The London School of Economics and Political Science

Economic and non-economic drivers of the low-carbon energy transition: Evidence from households in the UK, rural India, and refugee settlements in Sub-Saharan Africa

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others.

I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

I declare that my thesis consists of approximately 72,000 words.

Statement of co-authored work

I confirm that Chapter 4 was jointly co-authored with Subhrendu K. Pattanayak, Ipsita Das, Jessica Lewis, and Ashok Kumar Singha, and I contributed 55% of this work. My contribution consisted of specifying the research question together with Subhrendu Pattanayak, analysing the data and writing the paper. Subhrendu Pattanayak, Ipsita Das, Jessica Lewis, and Ashok Kumar Singha contributed to define the broader research project of which this study is part and led the data collection.

Abstract

In this thesis I investigate the drivers of household clean energy technology adoption, looking at the role of economic variables, such as prices and monetary incentives, but also at non-strictly economic dimensions, such as geography, peer influence, health concerns, and heterogeneity in experience, priorities and perceptions of the technology.

The topic develops into two main lines of inquiry. The first one explores the uptake of residential solar PV systems in the UK. In Chapter 1 I look at how the UK feed-in tariff (FIT) scheme contributed to shape the distribution of decentralised electricity generation around the country. I ask in particular how effective the policy was at triggering the siting of solar installations in locations with better generation potential. In Chapter 2 I show that peer effects contribute to the diffusion of this technology, and they act as complements to the monetary incentives. I discuss two possible channels through which peer effects may operate – social utility derived from imitation, and social learning from information sharing among neighbours – and find evidence consistent with a dominant role of the latter.

The second line of research focuses on valuation of non-traditional cookstoves in Sub-Saharan refugee settlements (Chapter 3) and rural villages in Odisha, India (Chapter 4). I use stated preferences to investigate how different features of the cooking technologies and household heterogeneity affect willingness to pay. In the context of refugee settlements in Sub-Saharan Africa (Chapter 3), I complement the analysis by looking at how the non-traditional cookstoves distributed among the residents affect fuel efficiency, health and safety, time use and the gendered distribution of the cooking workload. In Chapter 4, I focus instead on how positive and negative experiences with biogas for cooking affect the stated willingness to pay for that technology in rural India, and how experience interacts with risk aversion, time preferences, and credit constraints.

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Introduction

Technological innovation is often cited in sustainable development discussions as the key to conciliate environmental protection with development objectives (Jaffe et al., 2003). If new inventions are fundamental to this purpose, attention must also be paid to the process of adoption and diffusion of the new technologies on the ground, and to the feedback that actual use under different circumstances may provide to innovation. To this purpose, behavioural and technical change need to go hand in hand.

Given the monetary but also cognitive investments needed to switch to a new, and therefore uncertain, technology, as well as the informational and economic externalities stemming from its adoption, diffusion is likely to be slower than the socially optimal path would recommend (Jaffe et al., 2005). This picture becomes even more complicated in the case of low-carbon energy technologies, as the issues linked to the diffusion of innovation are compounded by the environmental dimension, and in particular by the presence of environmental externalities and services whose benefits or costs are non-rival and non-excludable.

The result of this, as Jaffe et al. (2003) point out, is a paradox of low rates of adoption despite cost-effectiveness. Technological, organizational, social, and institutional path dependency have resulted in a carbon lock-in, which requires exogenous forces to be escaped (Unruh, 2000; Unruh, 2002; Unruh and Carrillo-Hermosilla, 2006).

From an academic standpoint, this thesis contributes new perspectives and new evidence to the literature on technology adoption, pro-environmental behaviour, and the costs and benefits of the sustainable energy transition. In particular, the thesis focuses on low-carbon energy generating technologies, and explores household preferences and decisions when they are offered monetary incentives to adopt (Chapter 1), when they interact with peers (Chapter 2), when they have heterogeneous expectations but also heterogeneous priorities with respect to the service the technology is offering (Chapter 3), and when they have different levels of relevant past experiences (Chapter 4).

From a policy perspective incentives, past experience, expectations and peer effects all contribute to shape the economic trade-offs and social norms that are critical in the transition towards a more sustainable and clean energy system. In each setting, I therefore acknowledge the role of economic drivers and market failures (in particular externalities, imperfect information, split incentives, and lack of access to credit), but also behavioural features (such as bounded rationality, inertia and default bias, risk and uncertainty aversion, myopia, environmental attitudes and social norms), and discuss how policy instruments may be designed to leverage the interdependencies between the two dimensions.

This thesis explores several of the "promising and unanswered research questions" identified by Greenstone and Jack (2015), which are relevant for countries at all income levels, as we grapple with the current climate crisis. In particular "What factors or design elements cause people [...] to make energy efficiency investments", "What are the costs and benefits of policies to improve environmental quality and access to energy?", "Will clean-energy products that work in the lab have the same results when real people use them in real world settings?", and "What policies can be effective for climate mitigation?".

In particular, Chapter 1 focuses on output-based incentives for small-scale renewables generation in the UK and their effectiveness in pushing the adoption of residential solar photovoltaic (PV) systems towards locations with better potential for electricity generation. Features of the UK Feed-in Tariff design and frequent updates to the amount of subsidies offered are used to identify the effects of the scheme on the geographical distribution of residential PV installations in the country. With the estimated parameters, I then predict the uptake of residential photovoltaic arrays under a hypothetical alternative policy scenario - a capacity-based subsidy - and compare the resulting geographical distributions of installations and the relative cost-effectiveness. The main contribution of this paper is the estimation of the responsiveness of residential PV demand to subsidy and installation price in a context where incentives are output-based. As predicted by the theory, I find a positive subsidy elasticity of demand, and a negative price elasticity. The geographical distribution of residential solar PV triggered by the policy appears to be only weakly correlated to the generation potential. This is the result of counteracting effects due to of socio-demographic composition, work arrangements and characteristics of the built environment. In fact, many of these contextual elements tend to be more favourable for solar adoption in areas with lower solar potential. As a consequence, the output-based subsidy is still more cost-effective than the hypothetical capacity-based one, which fails to counteract those effects and results in a negative correlation between installations and generation potential. On the other side, the estimated trade-off between the upfront price and periodic subsidies point towards a high implicit discount rate of households, suggesting that an upfront incentive adjusted according to generation potential would have been more cost-effective. The paper concludes with a discussion of the additionality of the policy and the amount and cost of averted emissions from offset generation.

Chapter 2 investigates how peer effects shape the spatial and temporal diffusion patterns of residential solar photovoltaic (PV) systems in the UK, while a monetary incentive scheme is in place. The literature suggests that household decision to install solar panels, as well as to adopt other innovative technologies or practices, is affected by peers who have already done so. This influence could operate through information sharing with neighbours or peers – the social learning channel – or because households obtain a non-monetary payoff when conforming with peers, that increases the utility of adopting – the social utility channel.

I set up a simple model of technology adoption which considers the two channels of peer influence, and obtain a set of hypotheses on the direction of peer effects, how they evolve over time, and how they interact with the monetary incentives. I then use spatial econometrics and purposely constructed estimators to test the hypotheses with data from the UK, and find that the social learning channel seems to be the dominant mechanism in the context under analysis. Of relevance for policy, I find that peer effects are economically significant, but they tend to be stronger in the early period of the policy and become weaker in later years. I also find that peer effects and monetary incentives act as complements, and discuss how this result could be leveraged in policy design.

The second half of the thesis focuses on a different set of energy-generating technologies – clean cookstoves in low and middle income countries – that is similarly associated to low rate of adoption, despite large potential private and social benefits. Chapter 3 investigates whether low willingness to pay for non-traditional cookstoves is linked to mismatches between expected and actual performances, and between the type of improvements promised and those each user is interested in. I use a new and rich dataset compiled from surveys in two refugee settlements in Burkina Faso and Kenya to test two competing interpretations: (i) users have low valuation for the improvements offered by non-traditional cookstoves, or (ii) users value the improvements but do not expect the stoves to deliver on them. In doing this, I show the importance of controlling for respondents' expectations regarding the technology offered, and heterogeneity of priorities on cooking.

In the second part of the paper, I look at whether the non-traditional cookstoves distributed in the camps (mainly basic models of fuelwood improved cookstoves, or ICS) delivers any significant improvement in four dimensions of welfare - fuel efficiency, health and safety, time use, and women and children workload. In the last part of the paper, I bridge the results on the benefits provided by non-traditional cooking systems with the stated preferences and show that women are relatively better than men at factoring the gains into their valuation.

Finally, Chapter 4 investigates preferences for small-scale biogas plants for cooking among households in rural India. In addition to improving health thanks to reduced smoke and indoor air pollution, biogas has the potential to be cheaper than other cooking fuels, improve waste disposal and provide high-quality fertiliser for agriculture. Data come from a discrete choice experiment (DCE) with over 500 households in rural Odisha, India, in an area that already has some penetration of biogas thanks to subsidisation schemes. Using a stratified random sample, the paper examines how previous experience with biogas is associated with the willingness to pay (WTP) for the technology.

My co-authors and I find that households have strong interest for decrease in smoke emissions and fuel savings, and appear to be highly interested in biogas rather than non-traditional biomass-fuelled cookstoves. Households who have no experience but are planning to build a biogas plant have similar preferences to households who already have biogas and did not experience any malfunctions, while households who had negative experience have a less enthusiastic taste for biogas. We also find that experience (both positive and negative) counteracts the negative effects on willingness to pay of risk aversion, impatience and concerns regarding access to credit, and find no evidence of price anchoring, i.e. respondents who already have biogas do not appear to tie their valuation to the price they paid. Policy implications are discussed for how to encourage uptake and use of the technology, and insights are provided on the risk of abandonment of the new technology and on why households engage in fuel stacking.

Chapter 1

Output-based incentives for residential solar PV: Demand responsiveness, geographical distribution, and alternative policy scenarios

1.1 Introduction

In the last two decades, governments around the globe – as well as local authorities, consumers' associations, and even utilities and private companies – have come up with a rich variety of policy tools and incentives in support of the uptake of residential solar photovoltaic (PV) generation to help decarbonise the energy system. This paper focuses specifically on output-based subsidies, a type of monetary incentive that is paid periodically – for example every quarter or every year – and depends on the amount of electricity generated by the PV system in each period. According to economic theory, this feature of the policy design should trigger more installations to occur where there is better potential for electricity generation, as in this case the system would produce more and the household would receive larger payments compared to a household in an area with lower solar potential (other things equal). At the same time, households have to face an inter-temporal trade-off between the costs and benefits of adopting solar PV, as the price for the system and its installation is mostly paid upfront (or over a short period), while the subsidy payments are received periodically over several years. I exploit these two features of the policy design to identify the effects of the output-based subsidy scheme on the geographical distribution of residential PV systems, and investigate the implicit trade-off between upfront costs and future benefits that is revealed by households' observed behaviour.

Data for the empirical analysis come from England and Wales[1], a territory where there is a relevant geographical variation in solar potential, and a *de facto* pure output-based subsidy scheme was in place between April 2010 and March 2019. Frequent changes in the FIT rate assigned to new adopters, combined with the expected electricity generation outcome of each location, provide the variation needed to identify the key parameters in the model, and estimate how the subsidy affects the decision to install. This estimation strategy faces a number of challenges that I address in the chapter, in particular endogeneity of the main regressors, self-selection and correlated unobservables, bunching, and the use of a count outcome variable.

The estimated parameters are then used to investigate the trade-off between upfront costs and future subsidies and estimate the implicit discount factor. If households discount future subsidies at a higher rate than the government can borrow at, then an upfront incentive would be more cost-effective than a periodic payment. Finally, the estimated model is used to predict and compare the uptake of residential solar PV under the observed policy scenario and under a hypothetical alternative scheme, with subsidies still paid periodically but independent of the output generated – i.e. a capacity-based scheme, as one kW of installed capacity is paid the same annual subsidy no matter how much it produces and where it is located in the country. For each scheme, I investigate the resulting geographical distribution of PV systems and the relative cost-effectiveness in terms of installed capacity and generated electricity. If the output-based incentive is more successful in triggering installations in locations with better solar potential than the capacity-based incentive, then the former should result in a lower marginal cost of generation.

The research questions explored in this Chapter contribute to our understanding of how centralised market-based incentives, such as Feed-in Tariff schemes, interact with the behaviour of decentralised agents, that are now both consumers and producers of electricity. More broadly, the paper contributes to the literature on the future

[1]Northern Ireland is excluded as it is not involved in the UK Feed-in Tariff scheme. Scotland is excluded because statistical areas in the country are constructed in a different way as compared to England and Wales.

of electricity system regulation, load and capacity management, and integration of renewables, and discusses practical policy alternatives to improve cost-effectiveness of renewable energy subsidies, given budgetary pressure.

The paper develops as follows: Section 1.2 presents the main literature of reference and details the research questions addressed in the rest of the Chapter, while Section 1.3 outlines the theoretical framework for the analysis. Section 1.4 provides information on the UK Feed-in Tariff policy and the data used; Section 1.5 focuses on the estimation of the parameters of interest, discussing the main challenges and the identification strategy, and presenting the results. Alternative policy scenarios and cost-effectiveness are then investigated in Section 1.6, while Section 1.7 concludes.

1.2 Motivation

1.2.1 Main literature of reference

This research builds on a growing body of literature investigating the demand for residential solar PV systems and the effectiveness of incentives for their adoption, with applications mainly to the US, and most frequently California – De Groote and Verboven (2019) on Flanders being a notable exception. The Flemish incentive scheme consists of a mix of output-based subsidies – similar to the UK scheme – and net metering – which is instead absent in the UK. In the US, support for residential solar systems is offered at the federal level through a tax credit for around 30% of the system cost. This is complemented by state-specific schemes, usually consisting of some form of subsidies and net metering. Under the California Solar Initiative (CSI) General Market Program, for example, residential solar PV owners can choose between an output-based subsidy called Performance Based Incentive paid monthly for 5 years, or an upfront lump-sum payment called Expected Performance-Based Buydown – with the vast majority choosing the latter (Hughes and Podolefsky, 2015). Although classified as a capacity-based subsidy, the Expected Performance-Based Buydown is actually adjusted depending on the expected generation of the solar array, calculated taking into account the characteristics of the system and the roof, as well as the solar insolation of the location where it is installed. In the rest of the Chapter, I will draw comparisons between the results reported by the literature on the CSI and the results obtained here for the UK, and I will discuss the strengths and weaknesses of each policy design.

The literature looking at the microeconomics of residential solar subsidies may be classified according to two main approaches – reduced-form models and static estimates on one side, and dynamic decision-making problems employing structural models on the other. Among the works in the first strand, Hughes and Podolefsky (2015) and Pless and van Benthem (2019) focus on the California Solar Initiative, using different empirical strategies. Hughes and Podolefsky (2015) exploit the difference in rebate amounts offered by different utilities to identify the effects of the rebate. As each utility serves a different territory, the boundaries of the catchment areas provide the discontinuity needed for identification. This is combined with time fixed effects and utility-specific time-varying fixed effects to control for unobservables that might bias the estimates. Allowing the elasticity parameter to vary, they find that a 0.10 USD (6%) increase in the rebate rate results in 20% more installations in the early periods of the policy, but this effects decreases to 8% in later times, corresponding to an average elasticity of -1.2. They estimate that the cost of the policy is 0.06 USD/kWh generated. Pless and van Benthem (2019) focus instead on the pass-through of the CSI rebate that is paid to the installers rather than to the end-users, and in their analysis they estimate a price elasticity of demand for solar panels of -0.85. Another important work to mention for its methodological as well as empirical contribution, is Gillingham and Tsvetanov (2019). The authors estimate the demand for residential PV in Connecticut, where systems are eligible for upfront rebates. Their estimation model addresses three main issues that commonly arise in this type of analyses, namely the use of a count outcome variable with excess zeros, unobserved heterogeneity, and endogeneity of the main regressor - the price of the PV installation. They develop a consistent estimator for an instrumental variable (IV) Poisson hurdle model with fixed effects, and use subsidy rates and roofing contractor wages after controlling for general local wages as instruments. The identification strategy relies on differences in the rebate levels over time – due to cuts to the incentives – and over different location – due to time lags in the incentive registration procedure. They estimate a price elasticity of -0.65.

Among the structural models, again focusing on California, Benthem et al. (2008) build an inter-temporal model to derive the optimal solar subsidy schedule in California, in the presence of environmental externalities and unappropriated learning-by-doing, and find that the existing incentive schemes in the state are very close to the model's optimum, while without learning-by-doing, environmental externalities alone cannot justify the high levels of subsidy. Burr (2016) analyses different types of incentives, concluding that upfront subsidies tend to result in more installations, but output-based subsidies are more efficient. She also notes that sub-optimal siting of residential PV results in high welfare cost. Langer and Lemoine (2018) estimate what the efficient subsidy schedule looks like when taking into account expectations about future subsidy and technology cost. Bollinger and Gillingham (2019) use a dynamic model of demand and supply to investigate the role of a rebate paid through the installers in fostering learning-by-doing in the industry. Allowing the elasticity to vary over time, they find values between -1.2 and -0.8, consistent with results from previous reduced-form analysis. In a recent working paper, Snashall-Woodhams (2019) uses highly disaggregated data on electricity consumption and estimates of solar generation potential at the rooftop level to model households' choice to adopt solar and compare the CSI with an optimally targeted subsidy. He finds that households discount heavily future benefits from solar, estimating an annual discount factor of about 82%. Finally, De Groote and Verboven (2019) use variation in subsidies for residential PV in the Flanders, Belgium, and a detailed structural model to identify the discount rate users appear to employ when choosing whether to install residential solar. As in the paper on California, they find the annual discount rate to be very high at 15% (equivalent to an annual discount factor of 0.86), and conclude that in cases in which the agents are myopic or discount heavily the future for other reasons, upfront subsidies are more cost-effective. On the issue of siting and geographical distribution of residential solar, it is worth mentioning recent work by Sexton et al. (2018), estimating the effects of solar electricity generation on averted pollution damages and on grid congestion, and how they vary over the US territory. They find substantial heterogeneity and spillovers across states, and conclude that incentives could be made more efficient and more environmental benefits could be achieved by better linking the level of subsidies to the location-specific outcome.

1.2.2 Research questions

Building on this literature, this Chapter aims to estimate the elasticity of residential solar demand to an output-based subsidy, such is the one employed in the UK, and to the investment price of the system. This first step serves then as an input to investigate and discuss how output-based subsidies shape the geographical distribution of solar PV systems over the country, and their effectiveness in triggering more installations in locations with better potential for electricity generation.

To delve deeper into what mechanisms might be at play I use event study analysis to test whether there is a bunching issue in the data and evidence of inter-temporal substitution, and I exploit features of the policy design to investigate time preferences and discounting, following a similar approach as De Groote and Verboven (2019). I also briefly start exploring the role of peer effects and heterogeneity of the elasticity parameters over time, which are the focus of the next Chapter, and I provide some estimates of the share of marginal and infra-marginal adopters (i.e. the additionality of the policy), and the rents appropriated by the latter group.

In the second part of the paper, I use the estimates for the parameters of interest to predict the pattern of installation under an alternative policy design – a capacity-based subsidy constant throughout the country, but paid periodically so to preserve the inter-temporal trade-off between costs and benefits. By keeping all else equal – i.e. the cost of the panels, geographic and climatic characteristics of each location, and the idiosyncratic 'preferences' of the residents of each area – I can therefore compare how linking the incentive to the solar potential of a location improves the cost-effectiveness of the scheme.

The UK FIT scheme is particularly interesting because it is an output-based incentive – a production subsidy is paid periodically for each kWh of generated electricity, according to the rate in effect at the date of installation. Variation in the level of (expected) subsidy results from differences in the expected electricity output in different locations in the country and from changes in the FIT rate over time. In fact, because the subsidy is output-based an installation in a location with high solar potential receives a higher subsidy than a location with low solar potential, all else equal. Similarly, a system installed in the early years of the programme receives a different subsidy than a system installed after the policy reforms.

Estimation in this setting presents a number of challenges. First, while the subsidy rate was progressively curtailed, the cost of PV systems has also been falling over time. I therefore control for changes in the cost. To control for potential endogeneity and measurement error in my main regressors, I use an instrumental variable approach. More specifically, I use local installers' wage, after controlling for general wage in the area, and price index of PV modules in international markets to instrument for the cost of installation. To instrument for the subsidy, I instead use relative latitude and longitude within municipalities and the FIT rate for different types of system. The former affects how much electricity the household can expect from the panels, due to the solar potential of the location, while the latter is a measure of government support for solar adoption and renewables in general and is therefore correlated to the FIT rate of residential panels. In turn, the amount of electricity generated and the FIT rate determine the subsidy the household receives.

Areas and time fixed effects are then used to correct for self-selection and correlated unobservables. Because the outcome is a count variable, I construct an estimator based on Gillingham and Tsvetanov (2019) that assumes a Poisson data-generating process, and provides consistent estimates when introducing IV and fixed effects. I then perform robustness checks to address bunching – in case households respond strategically to changes in the subsidy rate by installing later or earlier – and investigate two mechanisms that might cause heterogeneity in the effects of the main regressors, namely change in the parameters over time and peer effects.

Once I have estimated the parameters of interest, I use the fitted model to predict the number of installations that would have occurred without subsidy and when and where these installations would have occurred. I can then estimate the rent that is appropriated by these inframarginal adopters, and identify the marginal installations that have been induced by the policy, and would not have happened without it. In the last part of the paper I predict the geographical distribution of installations under an alternative policy scenario with a capacity-based subsidy. I then use the results of this analysis to discuss the cost-effectiveness of the policy, comparing the costs, the capacity installed and the electricity generated under each scenario. The cost of decreased GHG emissions is also discussed.

1.3 Theoretical framework

1.3.1 Single agent problem

In the context of small-scale electricity generation, it is becoming more and more common to refer to the owner of a system as a 'prosumer' - a portmanteau between the terms producer and consumer. The term aims to stress the change that these systems introduce in the relationship between the agent and the energy they consume and produce, introducing new processes and frameworks of analysis. According to this theoretical framework, the households involved in the decision to adopt a PV system may be modelled as profit-maximising and cost-minimising agents, following the theory of the firm in microeconomics:

$$\max_{q_k=\{0,1\}} \Pi(q_k, \psi_k) = S_k(y_k(q_k, \psi_k)) - C_k(q_k) \tag{1.1}$$

that is, agent k chooses whether to adopt ($q_k = 1$) or not ($q_k = 0$) – or the capacity to install – in the same way a firm may choose to 'enter the market' or to make an investment, so to maximise their profits (Π). ψ_k represents the solar generation potential of the location where the installation is being considered, and depends on conditions such as weather and cloud coverage, as well as tilt and azimuth of the roof, and shading.

Profits are given by the difference between the revenues that can be obtained from the production of electricity (i.e. the subsidy S) and the cost, or investment price, required to install (C). The cost includes the price of the modules, the inverter, and any other component of the system, as well as the service of getting the panels physically installed on the roof and the system up and running. In line with the information collected from in-depth interviews with UK prosumers,[2] the cost is assumed to be paid upfront and without taking loans – but the analysis can be easily adapted to accommodate instalments and loans. Given the specific case of solar PVs in the UK, the revenues correspond to the output-based FIT subsidy and depends positively on the electricity generated by the system (y_k), which in turns depends positively on the decision to install and on the solar potential of the location, i.e. $\frac{\partial S_k^{out}(y_k)}{\partial y_k} > 0$ and $\frac{\partial y_k(q_k,\psi_k)}{\partial \psi_k} > 0$. As the UK incentive is purely output-based and does not depend on the amount of electricity consumed by the household,[3] there is no need to model the consumption side in this framework. Therefore:

$$\frac{\partial \Pi^{out}(q_k, \psi_k)}{\partial \psi_k} = \frac{\partial S_k^{out}(y_k(q_k, \psi_k))}{\partial \psi_k} - \frac{\partial C_k(q_k)}{\partial \psi_k} = \frac{\partial S_k^{out}(y_k(q_k, \psi_k))}{\partial y_k(q_k, \psi_k)} \frac{\partial y_k(q_k, \psi_k)}{\partial \psi_k} > 0$$

To understand how this scheme differs from a capacity-based incentive, consider

[2]In-depth interviews were conducted as part of the ENABLE EU project. More information on the project and the methodology may be found in Standal et al. (2018, 2020).

[3]For example, the UK does not have any form of net metering, a scheme frequently used in other countries. More details on the policy background are presented in the next Section.

that under the latter the subsidy would only depend on the installation decision, i.e. $S^{cap} = S(q_k)$, and the solar generation potential parameter drops out of the profit formula, so that:

$$\frac{\partial \Pi^{cap}(q_k)}{\partial \psi_k} = \frac{\partial S_k^{cap}(q_k)}{\partial \psi_k} - \frac{\partial C_k(q_k)}{\partial \psi_k} = 0$$

That is, compared with capacity-based subsidies, output-based subsidies should trigger more installations in areas with higher solar potential, and the difference between the two distribution is larger the more variation in solar potential there is over the country (i.e. the larger $\frac{\partial y_k(q_k,\psi_k)}{\partial \psi_k}$ is), the higher the payment of an additional unit of electricity generation is ($\frac{\partial S_k^{out}(y_k(q_k,\psi_k))}{\partial y_k(q_k,\psi_k)}$), and the more responsive households are to the level of subsidy.

Output-based subsidies are paid periodically[4] in the case of the UK FIT for 20 years (or 25 for early stages of the scheme). The total subsidy S_k is therefore the present value of the flow of annual payments s_k. Each payment is calculated as the product between the FIT rate per kWh and the total amount of electricity generated in the corresponding period. The latter is not a pre-determined amount, but depends on several factors outside of the agent's control, including the solar potential of the location and actual weather conditions. When considering whether or not to install, the actual generation is therefore unobservable by the agent, and they consider instead an 'expected outcome'. I calculate the latter as the average estimated yearly amount of electricity generated by a system according to its geographical location, under some standard technical parameters.[5] This value approximates the estimates of electricity production that are provided by websites and solar installers.[6]

When the agent considers installing, the expected outcome is therefore the same in every year – as roof characteristics are fixed, there is no reason to expect systematic differences in the weather in one direction or the other between years, and the FIT rate per kWh generated is determined by the rate in place at the time of adoption and is held fixed throughout the subsidy period.[7] The annual subsidy can therefore be considered as an annuity, calculated as the product of the expected an-

[4]Payments are usually monthly, quarterly or annually – here I consider annually, but this does not affect the rest of the analysis.

[5]See Section 1.4 for more details.

[6]Interviews confirm that households in the UK consider these estimates when deciding whether to install PVs.

[7]The rate is indexed to the Retail Price Index (RPI) and is therefore adjusted for inflation on a yearly basis. There is therefore no need for the household to take inflation into consideration in their decision.

nual generation (a random variable) times the FIT rate at the time of the installation (a constant):

$$s_{k,t}(y_{k,t}(q_{k,t=0}, \psi_k)) = y_{k,t}(q_{k,t=0}, \psi_k) \cdot \mathrm{FIT}_{t=0} \tag{1.2}$$

and taking the expectation at the time of the adoption decision:

$$\begin{aligned} E[s_{k,t}(y_{k,t}(q_{k,t=0}, \psi_k)] &= E[y_{k,t}(q_{k,t=0}, \psi_k) \cdot \mathrm{FIT}_{t=0}] && = \\ &= E[y_{k,t}(q_{k,t=0}, \psi_k)] \cdot \mathrm{FIT}_{t=0} && = \\ &= s_k(\bar{y}_k(q_{k,t=0}, \psi_k) && \forall t = 1, ..., T \end{aligned} \tag{1.3}$$

The total subsidy is therefore the present value of an annuity over a finite period of time:

$$S_k(q_k) = \sum_{t=0}^{n} \frac{s_{k,t}(y_{k,t}(q_{k,t=0}, \psi_k)}{(1+r)^t} = \frac{1-(1+r)^{-T}}{r} \; s_k(\bar{y}_k(q_{k,t=0})) = \rho \; s_k(\bar{y}_k(q_{k,t=0})) \tag{1.4}$$

where T is the number of years the subsidy is paid for (in this case 20 years), and r is the discount rate. I do not make any assumption on the discount rate but consider it as one of the parameter to be estimated. In the estimation section I therefore calculate the implicit discount rate derived from the inter-temporal trade-off between upfront costs and future subsidies.

As the government sets the FIT rates, agents are 'subsidy-takers' (equivalent to price-takers firms in the theory of the firm). Similarly, agents can be considered to be cost-takers, as their individual choices are unlikely to affect the investment cost (in this case the price of the PV system and its installation). To support the latter assumption, it is worth remembering that PV modules and inverters are mostly imported from abroad and their price is determined in the international market.

1.3.2 Aggregate demand

The dependent variable for the empirical analysis is $Q_{i,t}$, the count of new installations in a location i at a given time t, so from the single-agent problem, I aggregate as follows:

$$Q_{i,t} = \sum_{k \in i,t} q_k \tag{1.5}$$

Changes in the subsidies and in the installation price result in changes in the profitability of the investment, and therefore trigger adjustment responses in how many prosumers decide to install, which can be captured by a total elasticity term:

$$\eta_\Pi = \frac{\Delta Q}{\Delta \Pi}\frac{\Pi}{Q} = \frac{\Delta Q}{Q}\frac{S - C}{\Delta S - \Delta C} = \frac{\eta_S\ \Delta S - \eta_C\ \Delta C}{\Delta S - \Delta C} \tag{1.6}$$

and substituting for the expression of S in equation 1.4:

$$\eta_\Pi = \frac{\eta_s\ \rho\Delta s - \eta_C\ \Delta C}{\rho\Delta s - \Delta C}$$

The parameters of interest in the estimation are therefore the partial elasticity of installations to changes in the annual subsidy:

$$\eta_s = \frac{\%\text{ change in }\#\text{installations}}{\%\text{ change in subsidy}} = \frac{\Delta Q}{\Delta s}\frac{s}{Q} = \beta_s\ \frac{s}{Q} \tag{1.7}$$

and the partial elasticity to changes in the cost of purchasing and installing a PV systems:

$$\eta_C = \frac{\%\text{ change in }\#\text{installations}}{\%\text{ change in cost}} = \frac{\Delta Q}{\Delta C}\frac{C}{Q} = \beta_C\ \frac{C}{Q} \tag{1.8}$$

I assume that agents display a constant response to changes in the levels of subsidies and installation cost (β), and the elasticity therefore varies depending on the value of these variables and of the number of installations (Q). I obtain estimates of the β coefficients through a reduced-form regression analysis in the next Section, and then calculate the elasticity at the means of the parameters.

Another element of interest is the discount rate r. It is possible to recover an implicit discount rate from the regression coefficients by imposing that agents respond in the same way to an increase (or decrease) in the total revenues S, as they respond to a decrease (or increase) of the same magnitude in the installation cost C (the same assumption is made implicitly in De Groote and Verboven, 2019). This implies that the only difference between changes in the annual subsidy and changes in the cost is that the former entails future cash flows that need to be discounted, while the latter is an upfront payment. Details of how the implicit discount rate is obtained are presented in Section 1.5 when the regression model is presented.

Within this framework, I consider the main decision for a household to be whether to install a PV system or not. I do not model the decision on the capacity, or size to be installed, as in the UK there is evidence that this is constrained by the available space on the roof and by the barrier of smaller FIT rates and authorisation requirements for systems larger than 4kW. In fact, under the UK FIT scheme (which applies to solar PV system up to 5MW), only systems 0-4kW are eligible for the highest subsidy rate and do not require any authorization to be installed and connected to the grid, so that over 90% of the installations eligible for FIT in the UK (i.e. solar PV systems up to 5MW) have a declared net capacity smaller than 4kW (see Figure 1.3).

The size of the system is therefore implicitly constrained to a maximum of 4kW in order to obtain the highest FIT rate and avoid the bureaucracy of obtaining the authorization. Within the 0-4kW range, I assume that the size of the system depends exogenously on the rooftop space available and is uncorrelated to the solar potential of an area. UK prosumers interviewed by the author (Standal et al., 2018, 2020) often mentioned that the number of panels installed was constrained by the size of their roof. I do take into consideration that as the technology evolves, a panel of the same surface area may correspond to greater installed capacity. To do this, I compute the median panel size installed in each local authority[8] in each year (see Figure 1.1) and use this value whenever I need to convert the number of installations into installed capacity.

The analysis can be easily extended to model the choice of the panel size, by considering a continuous q_k bounded at zero, rather than a dichotomous variable. In this case the aggregated demand $Q = \sum_k q_k$ would represent the installed capacity rather than the count of installations, and would be continuous, but still bounded at zero.

To estimate how responsive demand is to changes in the subsidy, I use a reduced-form model (described in more details in Section 1.5) with the number of new PV installations on the left-hand side, and the annual expected subsidy that could be received given the location and the date of the installation on the right-hand side. The dataset consists of a panel of installation counts for each location in England and Wales, observed at the monthly level. For each observation unit I calculate the corresponding expected annual subsidy given the location and date. The next Section provides additional information on the policy context and the data used.

[8]Local authorities are administrative areas at a higher aggregation level than the statistical areas considered as observation units.

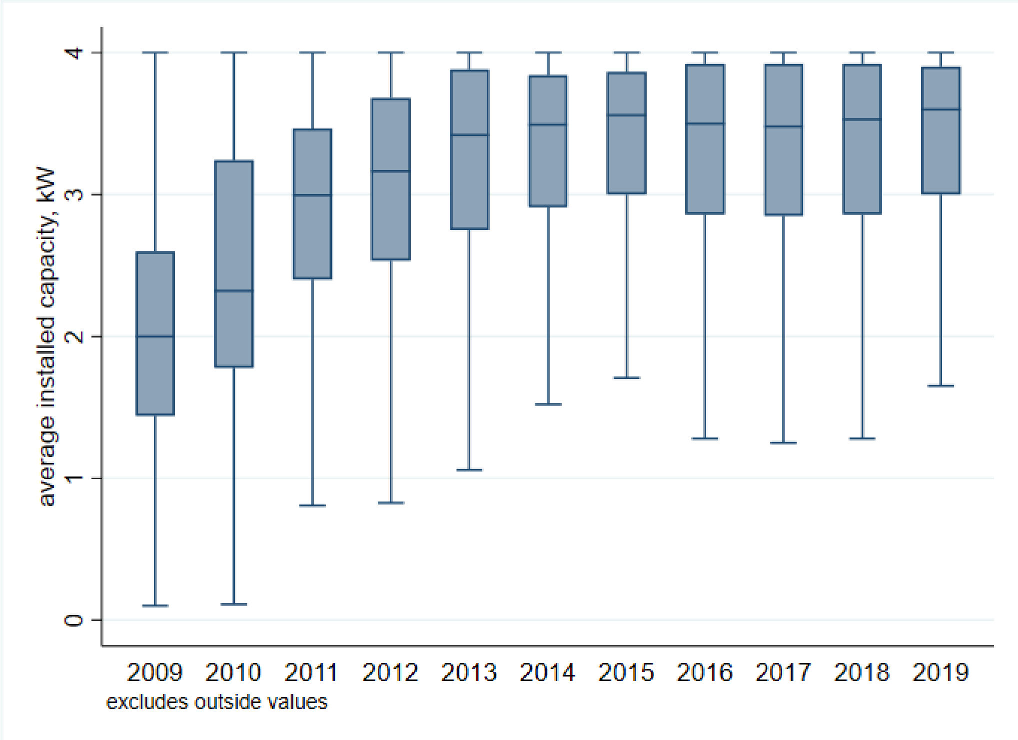


Figure 1.1: Distribution of system size in each year, in the 0-4kW category.

1.4 Policy background and data

1.4.1 The UK Feed-in Tariff scheme: a pure output-based subsidy

Between 2010 and 2019, the UK supported small-scale clean electricity generation through a Feed-In Tariff (FIT) scheme, which covered solar PV, wind turbines, hydroelectric, micro combined heat and power (CHP), and anaerobic digestion systems, up to 5MW. The scheme provides direct economic benefits to the owner of the system through two rates, the generation or production rate for generated electricity, and the export rate for the electricity that is sold to the grid. The production rate is paid on the total amount of generated electricity, recorded by an appropriate meter, while the export rate is paid on the assumption that 50% of the electricity generated is exported, as the quantity effectively exported is not currently metered for residential small-scale systems (McKenna et al., 2018). This makes the subsidy purely output-based, as its amount only depends on the electricity generated, and does not require to model and estimate how much of the electricity generated is used for self-consumption and how much is exported (in the UK there was no net metering scheme in place in the years included in the analysis).

The rates are assigned according to the date of the installation, with different values depending on the technology and the installed capacity of the system. These rates are then paid for 20 years (25 for solar installations in the early years of the scheme, later shortened to 20 for consistency with the other eligible technologies), and every year they are adjusted for inflation, according to the changes in the Retail Price Index over the previous year. The budget for the scheme comes from the general electricity bills of all energy suppliers' customers - as it is the case for other energy-related schemes in the country. This funding mechanism has attracted a lively political debate on the distributional equity of the scheme, and was one of the main arguments behind the closure of the scheme in 2019. While this issue is not convered in this Chapter, I refer to Grover and Daniels (2017) for a discussion on the UK, and Borenstein (2017) for California.

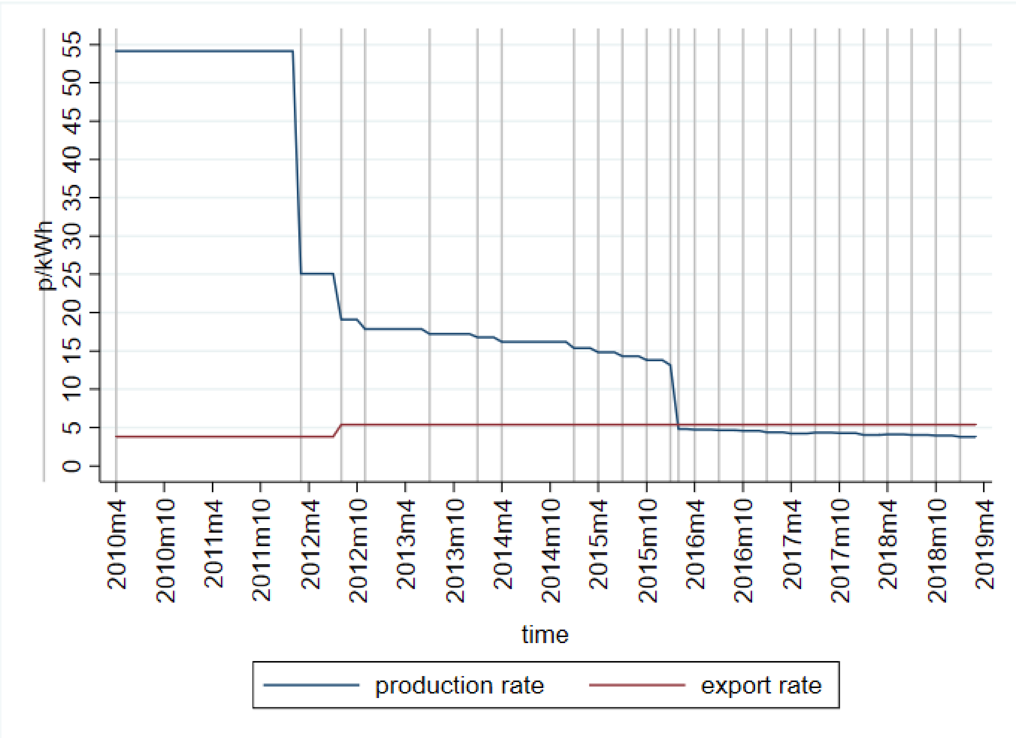


Figure 1.2: Changes in the FIT rates (production and export), for 0-4kW solar PV systems.

The FIT scheme was reformed various times since its introduction in April 2010.[9] The evolution of the rates for 0-4 kW solar PV systems, is shown in Figure 1.2. Quoting the sustained decrease in capital costs of solar PVs as the main rationale, the production rate has been repeatedly adjusted downward, moving from 54.17

[9]Details on the various phases and reforms of the policy have been collected from materials and reports by the UK Office of Gas and Electricity Market (Ofgem) and the former Department of Energy and Climate Change (DECC), now merged in the Department for Business, Energy and Industrial Strategy (BEIS).

p/kWh[10] in 2010 to 3.79 at the beginning of 2019, to be definitely phased out in March 2019. Major reforms to the rate and other features of the scheme were introduced in 2012 and 2016. In particular, an automatic and roughly quarterly degression mechanism was introduced at the end of 2012. The degression mechanism was pegged to pre-determined deployment objectives, that were nonetheless frequently modified. If these were not met and uptake was lower than the required threshold, the degression was postponed for up to two consecutive quarters. The rationale was that in this way the rate could be progressively reduced in line with the reduction in costs and increase in uptake without the need for government intervention, therefore reducing uncertainty in the sector. The scheme was initially intended until 2015, triggering a period of policy uncertainty as reforms to the system were discussed and the renewal of the scheme was questioned. The FIT scheme was then suspended at the beginning of 2016, before being reformed and re-instated in February.

Contrarily to the production tariff, the export tariff rate has undergone fewer amendments, and was adjusted upward, from 3.82 p/kWh to 5.38 p/kWh, in mid-2012. These progressive and sharp changes to the subsidy rate provide the main source of variation over time for the identification of the subsidy elasticity as explained in the following sections.

Aggregated data and trends on adoption of small-scale PVs in the UK are presented in Figures 1.3 and 1.4. Residential installations of less than 4kW constitute the vast majority (more than 90%) of small-scale electricity generating installations in the UK, both in terms of number and aggregated capacity. The trends in both figures show evident changes in correspondence of the major policy reforms.

1.4.2 Data

I compile two versions of my main dataset, one using as units of observation the Lower-layer Super Output Areas (LSOAs) as defined in the 2001 Census, and one using a higher level of aggregation, the Middle-layer Super Output Areas (MSOAs). The final dataset consists of observations for all the 34,378 LSOAs – or 7,194 MSOAs – in England and Wales.[11] Super output areas at different aggregation levels are

[10] The tariff is indexed to inflation and updated every year. All the tariff values are expressed at their 2019 level, at the time the FIT scheme was closed.

[11] Northern Ireland is excluded as it is not involved in the UK Feed-in Tariff scheme. Scotland is excluded because statistical areas in the country are constructed in a different way as compared to England and Wales.

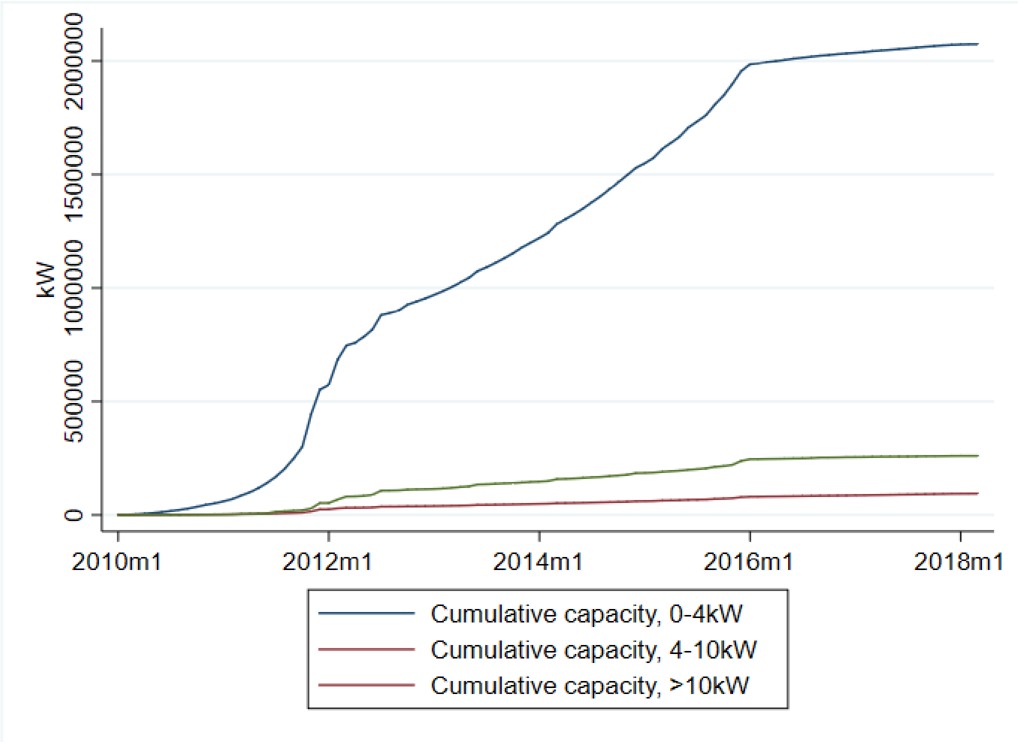


Figure 1.3: Cumulative installed capacity in the UK (kW), by month.

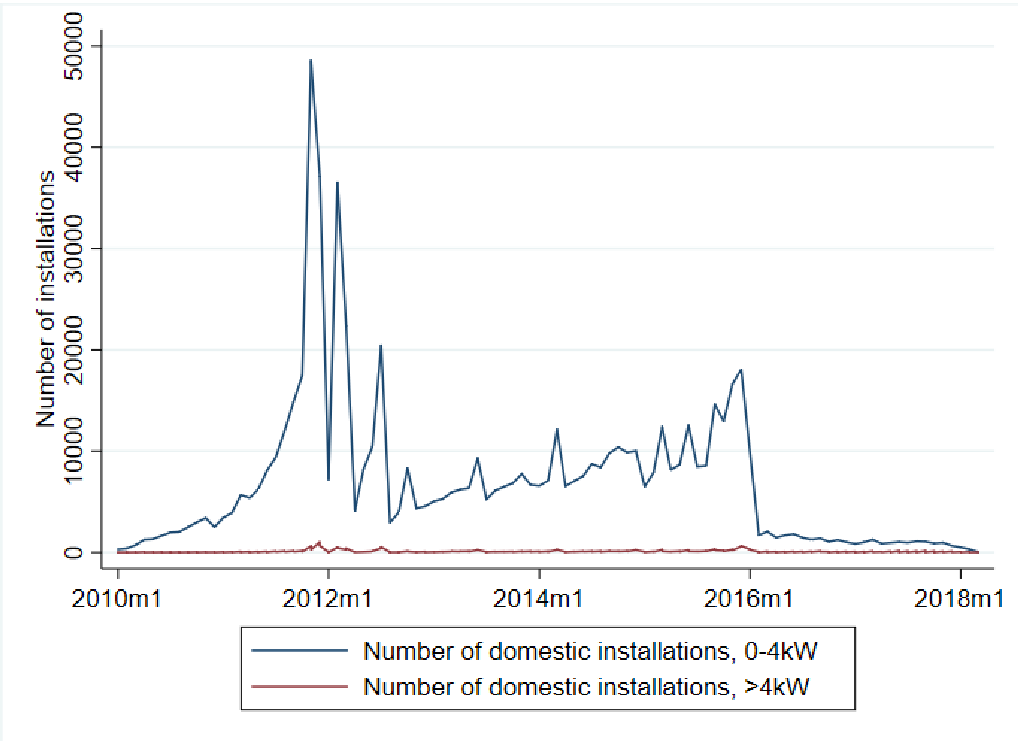


Figure 1.4: Number of installation in the UK, by month.

a statistical construct, developed for presenting local statistical information from different sources and offices in a standardized way.

The choice of LSOAs and MSOAs as aggregation levels is driven on one side by data availability, as these are the most granular level at which PV installation data could be obtained, but at the same time is preferred over post-code district (the other available unit) due to the way they are constructed. In fact, the LSOAs ans MSOAs are purposedly defined to insure within-homogeneity and between-comparability in the context of Neighbourhood Statistics and Census data collection, and to be roughly comparable to one another in terms of size of resident population. Geographical proximity and information on the prevalent type of dwelling, tenure, etc. are also used to ensure a compact shape and socio-demographic homogeneity[12]. LSOAs have a minimum of 1,000 residents, a maximum of 3,000 and an average of 1,500 (equivalent to 650 households, with a minimum and maximum of 400 and 1,200 respectively). MSOAs contain a minimum of 5,000 residents (or 2,000 households) and a maximum of 15,000 (or 6,000 households).

These are all desirable properties for an areal unit in spatial analysis, given that the exact coordinates of the installations are not available. Nevertheless, we must be aware of the Modifiable Areal Unit Problem which comes with such aggregations, as results may be sensitive to the level of aggregation as well as the shape and where the boundaries are set, and an extension of the present work may check the robustness of the results when other specifications are chosen (e.g. LSOAs, local authorities or postcode districts. See Briant et al., 2010 for the general issue and Flowerdew, 2011 for the specific case of UK Census data). Details of the main variables used for the analysis are described in the next paragraphs, while summary statistics are presented in Table 1.1.

Data on residential solar PV installations

Data on residential PV installations are obtained from the Ofgem Feed-in Tariff Installation Report, which contains information on the country's small-scale (i.e. below 5MW) renewable energy generation systems that are connected to the grid,

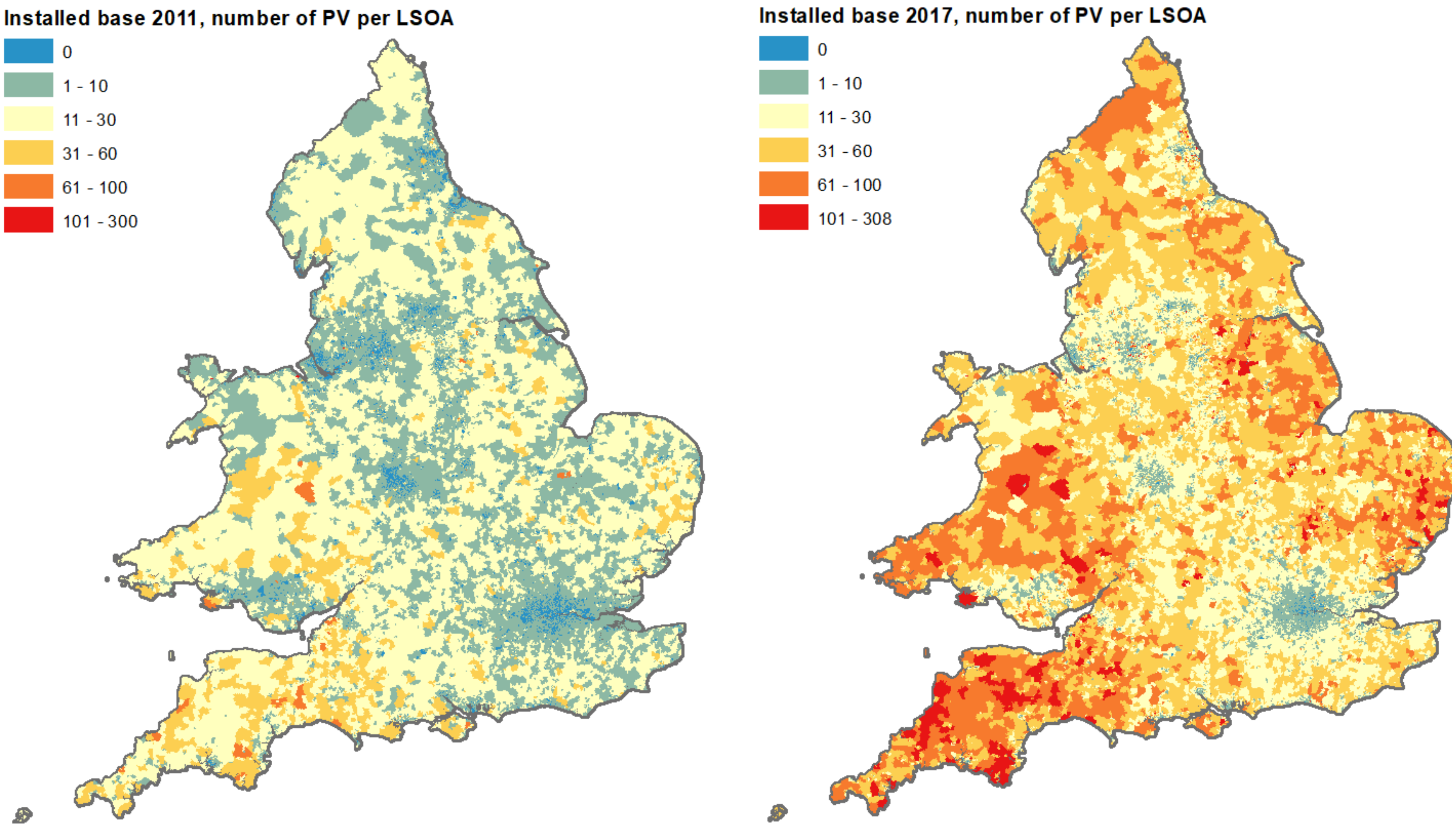
[12]The official definition and methodology are provided by the Neighbourhood Statistics division of the Office for National Statistics (ONS). Some LSOAs and MSOAs were merged or split in 2011, due to changes in their composition, however these changes only affected 2.5% LSOAs and 2.1% of MSOAs. See "Census geography - An overview of the various geographies used in the production of statistics collected via the UK census.", on the ONS portal.

Table 1.1: Summary statistics.

	mean	sd	min	p25	p50	p75	max
PV count	1.01	2.66	0	0	0	1	219
Installed base	38	46	0	5	21	54	474
Generation potential (kWh/year)	957.17	58.77	729.16	919.68	966.18	986.04	1121.76
Subsidy (100GBP/kW)	2.53	1.26	1.05	1.58	1.73	4.12	5.03
Install. cost (1,000GBP/kW)	2.23	0.71	.13	1.71	1.91	2.62	7.68
Pres.Value of Profitability (1,000GBP/kW)	0.45	0.86	-3.23	-0.13	0.06	1.03	4.58
Internal Rate of Return	0.09	0.05	0.00	0.06	0.07	0.11	3.60
Electricity price (p/kWh)	14.49	1.07	12.06	13.69	14.75	15.25	16.67
Av. electricity cons. 2010 (kWh/year)	3865.56	611.22	2388.93	3456.26	3734.87	4128.44	7779.3
Density	3265	3508	6	650	2466	4478	27673
Surface area (km^2)	21.01	52.78	0.29	1.73	3.19	11.86	1128.07
Owner-occupied houses	1906	695	24	1488	1926	2357	5182
Median house price (1,000GBP)	202.09	125.56	30.00	124.98	172.75	243.66	3500.00
Total resident population	7904	1694	2225	6618	7695	8867	25245
" 40-64 year old	2557	555	545	2165	2496	2882	6226
" $\geq$65 year old	1363	495	194	1015	1310	1642	4656
" socio-economic group A	179	112	16	96	153	235	868
" socio-economic group B	263	180	24	136	220	340	1593
" socio-economic group C	972	347	228	723	945	1186	2849
" socio-economic group D	491	163	70	375	470	586	2384
" socio-economic group E	365	154	81	260	336	438	1388
" socio-economic group F	374	130	55	282	365	456	1105
" socio-economic group G	611	199	121	467	597	736	1580
" socio-economic group H	474	223	59	304	442	611	1513
Flats	601	686	11	184	363	717	5725
Terraced houses	816	559	17	394	684	1112	3710
Semi-detached houses	989	508	11	646	939	1286	3569
Detached houses	713	593	3	199	546	1140	3716
Work from home	302	136	57	206	274	364	1167
Homemaker	340	114	46	261	323	398	1123
Retired	712	241	94	547	688	848	2445
Unemployed	175	95	18	104	148	224	838
Born in UK	6588	1395	2082	5583	6478	7399	13536
Born in EU	166	146	16	78	120	195	1550
Born elsewhere	480	660	17	121	213	470	6143
PV FIT rate, 1-5MW (p/kWh)	12.44	9.97	5.73	6.38	7.10	8.90	30.70
Wind FIT rate, 0-2kW (p/kWh)	26.22	9.31	13.73	17.78	21	36.2	36.2
Latitude	52.356	1.129	49.922	51.478	52.134	53.369	55.765
Longitude	-1.353	1.303	-6.312	-2.216	-1.382	-0.250	1.747
Chinese PV price index	0.81	0.38	0.53	0.55	0.57	0.98	1.62
Median earnings (GBP/week)	510.24	62.52	443.10	469.20	484.50	529.00	670.80
Median wage, electric (GBP/hour)	12.53	1.02	11.14	11.86	12.2	12.92	15.35
# Months	70						
# Statistical areas	7,194						
# Local authorities	348						
Tot. observations	503,580						

as well as stand-alone systems. Each installation record contains among other pieces of information the LSOA in which the system is located, the date the system was commissioned, the declared net capacity of the system, the technology,[13] and a code for the FIT rate it receives. To construct my dataset, I select the solar PV installations that receive the FIT rate for 0-4 kW systems. Of these, I remove the installations assigned to the "middle" rate, as this indicates the owner has 25 or more installations – and is therefore likely to be a solar company installing on rented rooftop space, rather than a household – as well as installations receiving the "lower" rate, meaning that the building where the solar PV system is being installed does not satisfy the minimum Energy Efficiency Requirement (this only affects 1% of installations in the 0-4 kW category).

[13]The report includes all the technologies eligible for FIT, i.e. solar PV, wind turbines, hydro-electric, micro combined heat and power (CHP), and anaerobic digestion systems.



(a) 2011

(b) 2017

Figure 1.5: Geographical distribution of residential solar PV systems in England and Wales.

The total stock of 0-4 kW solar PV systems in each LSOA is mapped in Figure 1.5 for 2011 and 2017. Comparing this Figure with Figure 1.6, it can be seen that installations appear to be mainly concentrated in rural and less dense areas, while the major cities - London in particular - display a substantially lower installed base, consistent with the literature (Graziano and Gillingham, 2015). Although income is considered as a key determinant of PV adoption – both directly, because of the investment required, and indirectly, as higher-income households are more likely to live in a house rather than in a flat and to be owners rather than tenants – there does not seem to be an evident correlation between the two variables (Figure 1.7), as the wealthy South-East has a relatively low number of adoptions, while the South-West and part of Wales have the largest installed base in the country, despite not being rich areas. At the same time, areas around Leeds are relatively wealthy and rich in residential PVs, while the northernmost parts of Wales and Yorkshire are neither.

Solar irradiation is another relevant variable, as it is the key determinant of PV electricity yield (see Figure 1.8). Again, if compared with the PV system distribution maps, it can be seen that although some areas, such as the South-West, have a consistent positive relationship between insolation and PV adoption, the situation in other areas is more puzzling, with the South-East showing substantial unexploited potential for solar power, while adoption is higher at the border with Scotland despite receiving considerably less solar radiation. Understanding the drivers behind the adoption of residential solar PV is therefore a less straightforward task than one might think, as socio-economic, demographic, geographical and built-environment characteristics all contribute to shape the uptake of this technology.

Annual (expected) subsidy and the investment cost of PV installations

To estimate the role monetary incentives play in this context, I need a measure of the annual subsidy (i.e. the 'revenues') that can be expected when installing a residential solar PV system at a given time and in a given location. I compute these annual potential revenues as the product of the estimated annual electricity output of a panel of 1kW of installed power at a given location, by the FIT rates applicable in a given month. The electricity output is measured in kWh/year for kW of installed power, and varies according to the geographical location and its solar insolation, as well as contextual factors such as cloud cover and rainy days, buildings

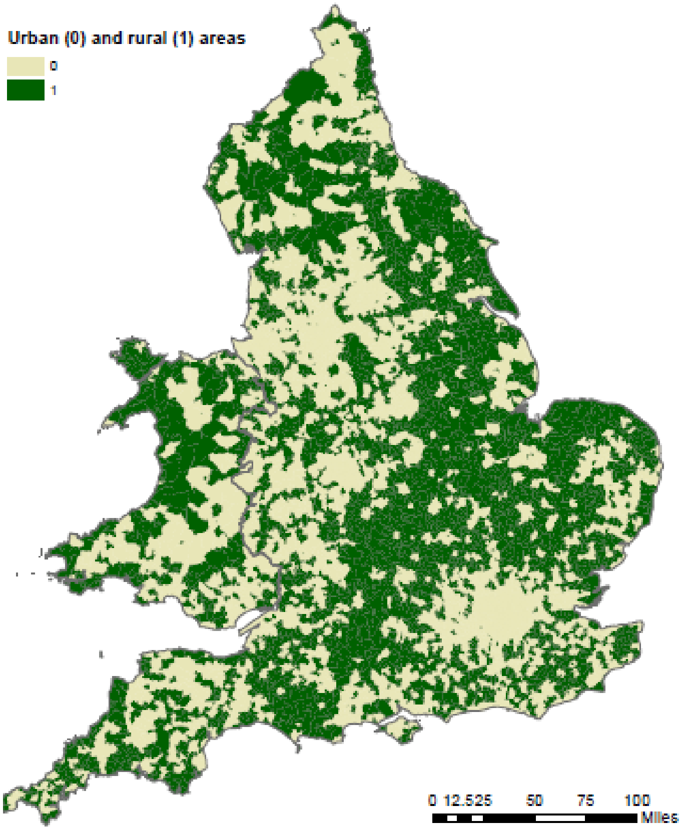


Figure 1.6: Geographical distribution of rural and urban areas in England and Wales.

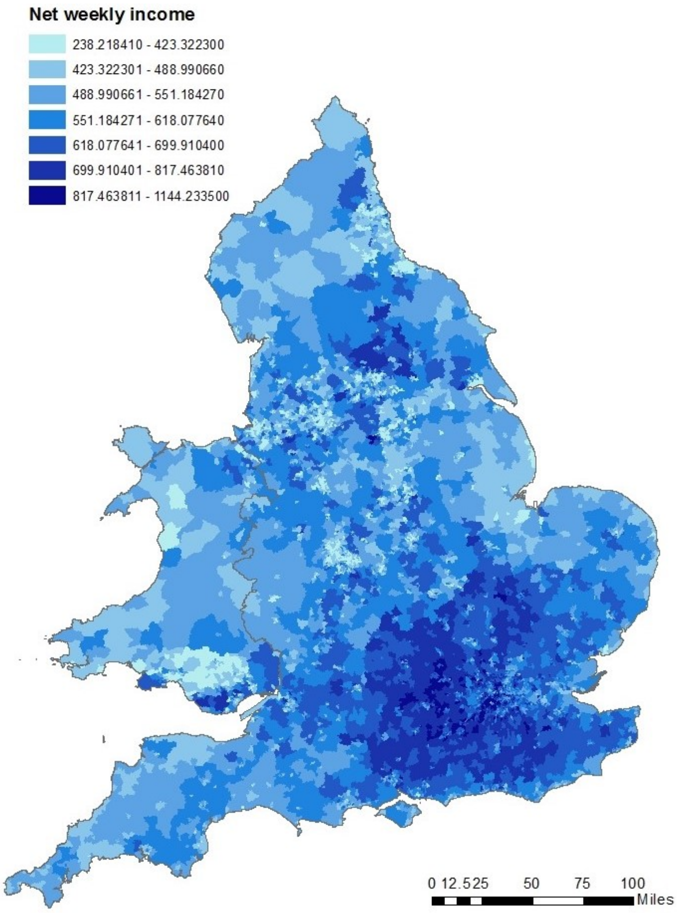


Figure 1.7: Geographical distribution of income in England and Wales.

and trees shadows, as well as the tilt, azimuth and direction of the roofs. Data on the output for each year between 2009 and 2016, under some standard installation conditions[14], were obtained from the Photovoltaic Geographical Information System (PVGIS European Communities, 2001-2017)[15] for each LSOA population-weighted centroid, and averaged over the different years to smooth the effects of meteorological factors. The resulting distribution of the electricity output over England and Wales is presented in Figure 1.8.

These values change over space, but are time-invariant. The FIT rates per kWh generated, on the contrary, are constant throughout the country, but vary in time. Each installation is assigned the FIT rate in place on the date of the installation, and that rate is paid for 20 years according to the kWh of electricity generated in each year. As described above, the owner of the system is paid a production rate for the electricity generated, and an export rate for 50% of the total generation, which is assumed to be the quantity exported to the grid, as the actual amount exported is not metered. I therefore obtain the annual expected revenue for each LSOA-month combination as the product of the yearly expected electricity generation for 1kW installed in that LSOA and the rate corresponding to that month (in p/year per kW of installed power). MSOA-level data are obtained as average of the LSOAs values. The total rate is given by the production rate plus 0.5 times the generation rate.

The resulting annual subsidy variable varies in both time and space – due to the changes in FIT rate and the variation in solar generation potential, respectively – and this variation is exploited to identify the effect of subsidy on adoption in the following section. The range of the expected revenues for each month across the different locations are presented in Figure 1.9, while summary statistics are presented in Table 1.1. The average subsidy varies from more than 400 GBP per year per kW of installed capacity at the start of the scheme, to between 150-200 GBP after the reforms in 2012, to only around 65 GBP after the 2016 reform.

The way subsidy data are calculated and the way subsidy rates are determined by the government may raise concerns of measurement errors and endogeneity. Mea-

[14]Peak power: 1kW; slope: 35 degrees; system losses: 14%. System losses gives an average of the performance over the 20 years the FIT is paid out, and include module degradation of about 0.5% per year.

[15]Data were obtained from the European Commission Joint Research Centre in Ispra. Values are based on the PVGIS SARAH database. Details on the methodology and the dataset can be found in Huld and Amillo (2015) and Huld et al. (2012). More information on the data and methodology can be found at https://ec.europa.eu/jrc/en/PVGIS/docs/methods.

surement errors may arise because the expected electricity outcome is obtained for standard parameters levels and at the population-weighted centroids, rather than using actual values (which are unobservables). Regarding endogeneity, the frequent adjustments and cut to the subsidy rate may have been affected by the demand for solar systems. Instrumental variables (IV) for subsidies are therefore introduced in the next Section.

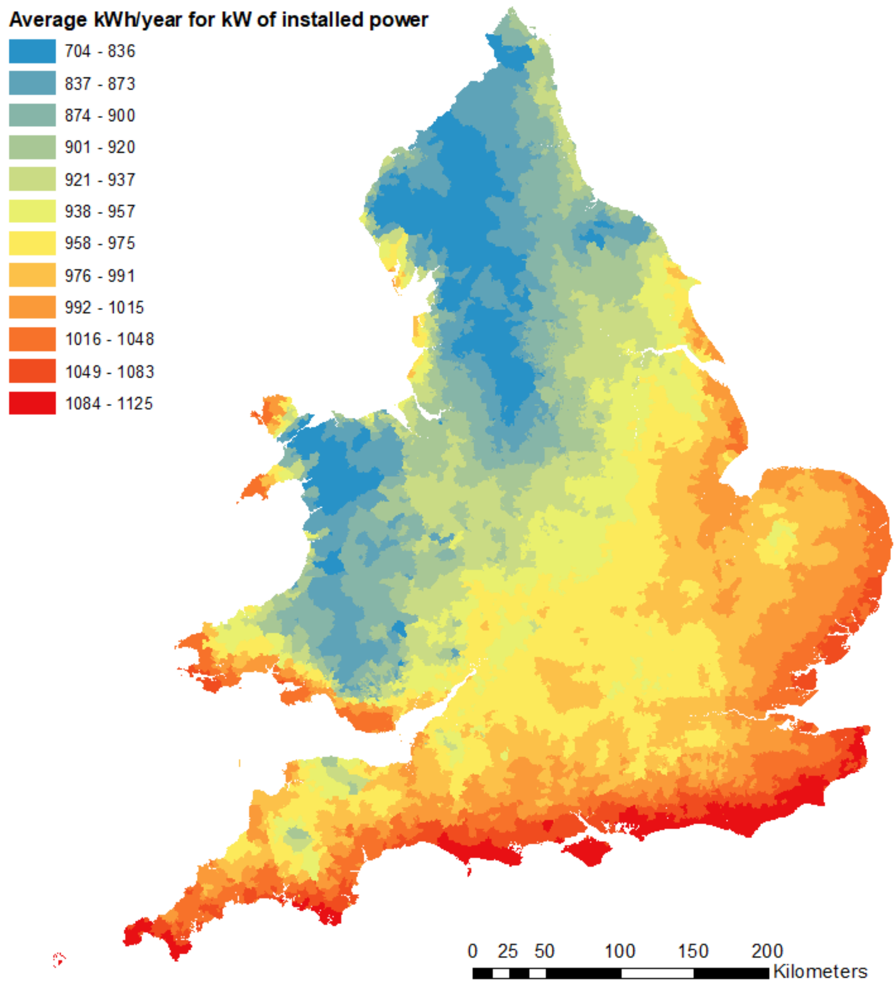


Figure 1.8: Map of electricity generation. Output, kWh/year for kW of installed power, average 2009-2016. Own elaboration on Photovoltaic Geographical Information System (PVGIS) data.

I refer to the price paid to purchase and install a solar system as 'cost' of the installation, as I am framing the installation problem as an investment decision with a trade-off between costs and future revenues. Data on the median cost for an installation per postcode area per quarter comes from the Micro Certification Scheme (MCS) to which each installation must register to be eligible for the FIT. Additional data on the countrywide average cost per month comes from the Department of Energy and Climate Change (DECC, now part of BEIS, the Department

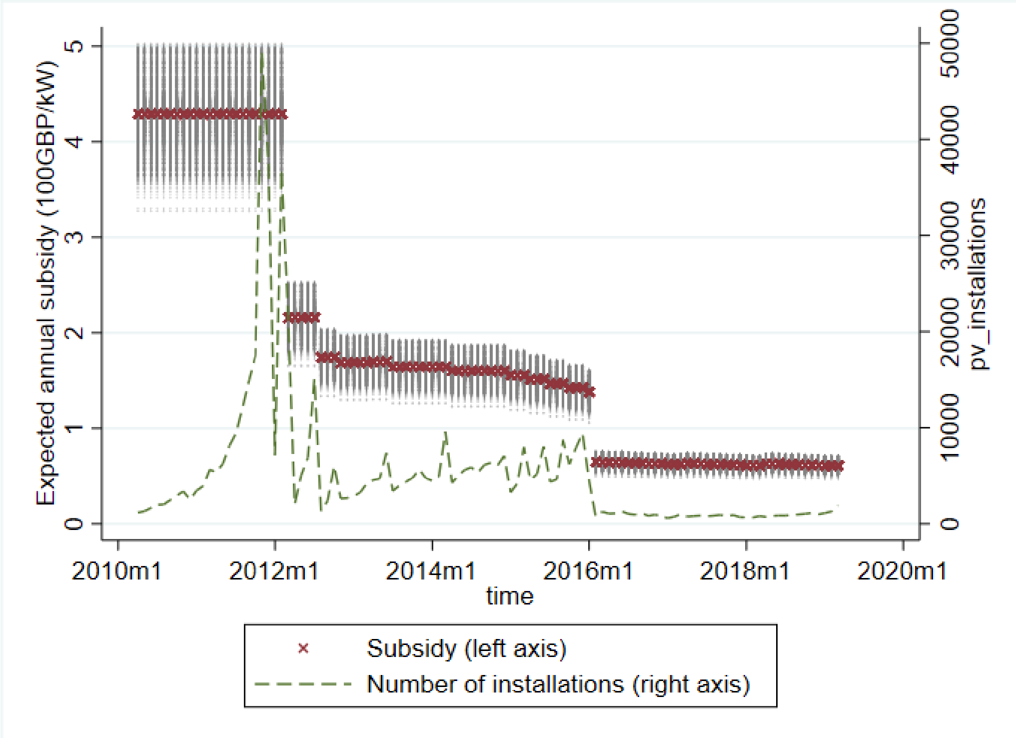


Figure 1.9: Expected annual FIT payments for kW of installed power, according to month of installation and location (left axis; average value highlighted), and number of residential PV installations in each month (right axis). Own calculation on Photovoltaic Geographical Information System (PVGIS) data and Ofgem data.

for Business, Energy and Industrial Strategy) "Annual Cost of Small-Scale Solar Technology Summary", May 2017. Cost data were only collected in a systematic manner starting from April 2013, and the Department does not provide data for previous years; for years before 2013, estimates of the average country-wide cost are obtained from the Green Business Watch report "UK residential solar panel costs and returns: 2010-2017". These are used for consistency checks.

MCS data are converted from cost per installation to cost per kW installed, by dividing them by the capacity of the median installation in the corresponding area and quarter. The resulting postcode-area-by-quarter dataset contains missing values for cases in which no installation was recorded or the price was not reported. I first assign the costs of each postcode area to all of the MSOAs within it, and the average price of multiple postcode areas to MSOAs that cross postcode boundaries. Imputing the postcode area-level data (this is a higher level of aggregation with respect to MSOAs, but is the most disaggregated level MCS agreed to disclose) to the MSOAs is a sensible approach in this setting, as installers compete over large areas and could carry out installations far from their headquarters.[16]. Moreover, the

[16]Based on interviews with prosumers (Standal et al., 2018, 2020) and information from installers'

supermarket chain Tesco, and more recently Ikea, sell solar panels throughout the country, contributing to make the cost of installations more uniform across larger areas. I then interpolate the existing data for each MSOA over time, to fill the gaps in the time series. This approach leaves missing data before the first price in a location is recorded and after the last one, as well as missing data for postcode areas with no cost data throughout the period. This missing data are imputed by using the average cost for the region[17] to which the MSOA belongs, for any given year, based on the same rationale of competition among suppliers discussed above.

Finally, the quarterly data are converted into monthly data using the moving average over the two months before and after each observation, to smooth the trends. The distribution of the final cost data for every year is presented in Figure 1.10 and summary statistics are presented in Table 1.1. The average cost across the country decreased from about 3,000 GBP per kW of installed capacity in 2010-2011 to about 2,000 in 2012-2015, to plateau around 1,600 GBP from 2016 onwards.

The need to use data at a higher aggregation level, impute missing data that cannot be observed and to smooth data trends to convert them from quarterly into monthly can be framed as an issue of measurement error, and might produce measurement error bias. The cost of the installations might also be affected by the demand for systems in each period, therefore challenging the assumption of exogeneity of this regressor – although most of the hardware components, inverter and PV modules are imported from other countries and their price is therefore determined in the international market. As for the subsidy variable, these issues are addressed using an instrumental variable (IV) approach, as illustrated in the next Section.

As shown in Section 1.3, installing a solar PV system can be thought of as an investment, as households pay the upfront installation cost, and then receive a return over time thanks to the FIT scheme, here approximated by constant expected annual revenues. To have an idea of how attractive this investment is, I build cash-flow vectors of the (negative) upfront installation cost and 20 successive constant (positive) payments of the expected annual revenues, and use them to calculate the internal rate of return (IRR) of the investment for each area-month combination. The results of the calculation are presented in Figure 1.11, comparing the trend in

websites.

[17]Regions are a more aggregated administrative level, in total there are 10 regions in England and Wales.

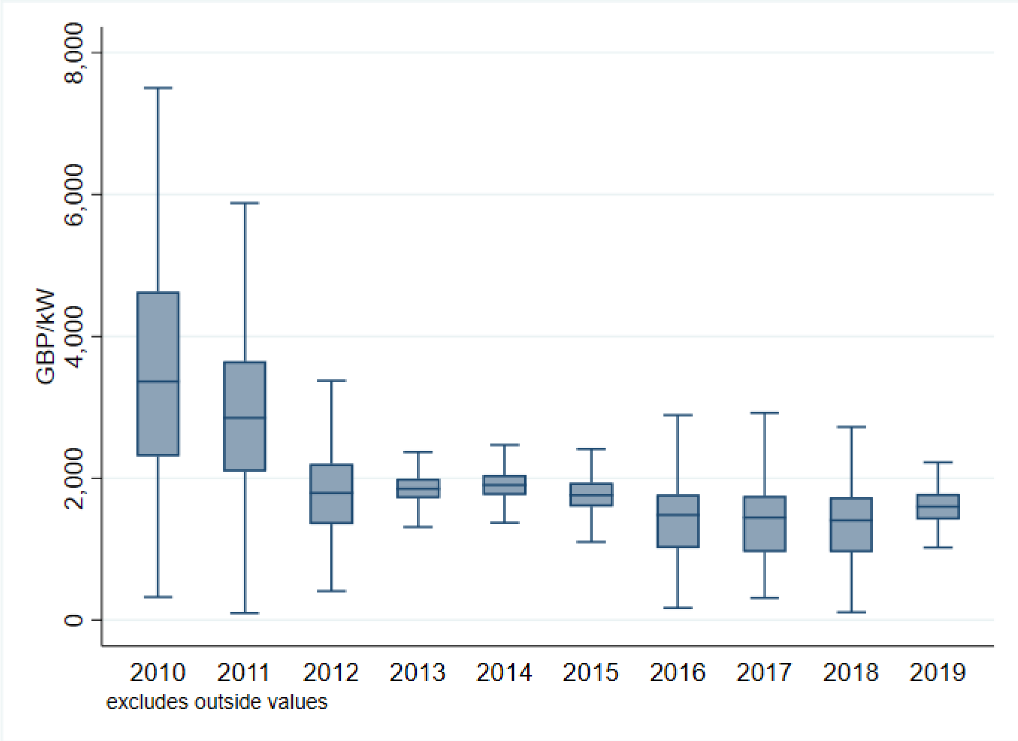


Figure 1.10: Trend in the cost of residential solar PV systems. Own elaboration on data from MCS.

the IRR with the observed trend in installations.

It can be noticed that the estimated IRR (calculated for every area-month, not just for those with a positive number of installations) before 2016 is almost always above 3%, and in the early period of the policy, when the tariff rates were held fixed while the cost was falling, it scored as high as 10-18% for the average area, well above the returns from low-risk investments in financial instruments in the country.[18] The trend in installations appear to follows the trend in the IRR, and the values are positively correlated.

Savings on electricity bills and other covariates

More indirect benefits of adopting residential solar are provided through savings in the electricity bills, as the generated electricity can be used for free reducing the amount of energy bought from the utility. In fact, given that export to the grid is 'deemed' and not actually measured, self-consumption does not affect the payment received through the generation and export rate, and it therefore has no opportunity cost.

[18]During in-depth interviews with households who installed residential PV at various moments, it was often mentioned that the solar panels were seen as a sensible investment and a better alternative than keeping money in the bank (Standal et al., 2020).

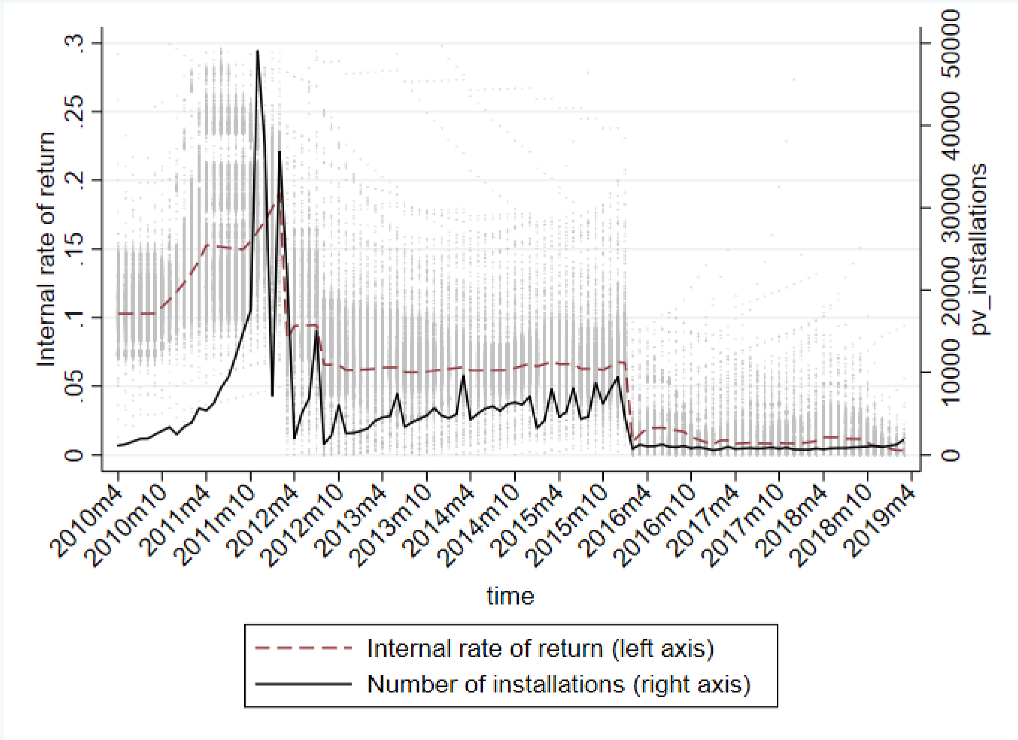


Figure 1.11: Internal rate of return, for kW of installed power, according to the month of installation and location (left axis, average value highlighted), and number of residential PV installations in each month (right axis). Own calculation on data provided by Photovoltaic Geographical Information System (PVGIS, Huld et al., 2012), Micro Certification Scheme and Ofgem.

McKenna et al. (2018) monitored data from more than 300 UK households involved in a smart grid project, and found that on average the annual self-consumption level for households with solar PV systems is around 45% of the total PV generation, covering around 24% of households electricity demand. For reference, the yearly electricity demand of a household in the UK is around 4,000 kWh and the average retail price of electricity in the period of reference is around 15 p/kWh, resulting in estimated savings of around 138 GBP/year per household. This is equivalent to less than a third of the expected annual subsidy in the early period of the policy, while it is comparable with the expected annual subsidy in the last months of the policy. The relevance of bill savings with respect to the subsidy has therefore grown over time, as the amount of subsidies decreased. The study, together with other quantitative and qualitative work on the UK (see for example Standal et al., 2020, 2018; Bulkeley et al., 2016; Bell et al., 2015; Bulkeley et al., 2015) finds a large range for self-consumption values (both in absolute terms and as a percentage of total electricity demand), and show that the level achieved by a households is highly heterogeneous and depends on a wide variety of factors, including social, economic, educational, geographical, technical and demographic characteristics (including for example how much time member of the household spend at home during the day, i.e. when the system is generating; whether they have timers to schedule the use of appliances; age and gender composition; education level and background; load profile of the household and the type of appliances used), inter-household dynamics, the level of internalization of green preferences and of familiarity and understanding of 'smart' grid procedures and technical aspects of the grids. They find that the size and generation of the solar PV system are therefore only part of the explanation for the level of self-consumption and bill savings. Qualitative evidence from these studies also show that many UK households are unwilling to change their habits and to put much efforts in monitoring generation and shifting their electricity use accordingly. In particular, quoting Bulkeley et al. (2015): "The UK's feed-in tariff, particularly in the presence of low interest rates and insecurity about housing and financial markets, led to PV being regarded as one of the most secure and profitable forms of investment during 2010 –2011 [...] and has given rise to a logic of investing in PV and focusing on the export of power rather than any engagement with how using the electricity generated by PV could also lead to financial (and environmental) benefits". It should also be noticed that in the UK residential sector electricity is used for lighting and electrical appliances, while space heating – the demand for which is correlated to weather and climatic condition, and therefore to the generation of the solar module – is mainly achieved using natural gas (according to Palmer and Cooper, 2013, pp. 46-49, 90% of UK households had central heating in 2011, and of these 91% used natural gas; these shares are even higher if excluding flats and considering only houses). The need for space heating therefore does not directly affect electricity consumption, nor self-consumption of electricity generated by the solar PV system.

For all these reasons, I consider savings on the electricity bills as an indirect benefit of adoption rather than one of the main explanatory variables, and control for it in the regression analysis using:

- Average electricity price in each electricity Distribution Network Operator (DNO) region[19] in each year – as larger savings may be obtained in areas where

[19]Electricity distribution in England and Wales is divided in the following network regions: East Midlands; Eastern; London; Merseyside and North Wales; North East; North West; South East; South Wales; South West; Southern; West Midlands; Yorkshire.

electricity is more expensive. Data on the "average annual domestic standard electricity unit cost" in pence per kWh are obtained from BEIS (2018).

– Average electricity consumption in each location before the FIT scheme started – as households who consume more have more to gain from free electricity. Data on the "Average Ordinary Domestic Consumption" in kWh come from DECC (2012).

– Resident population working from home, working as homemakers, and retired – as they spend more time at home during daytime and therefore have the possibility to shift their energy demand to times when the panels are generating and to use the free electricity. Data are obtained from the UK Census (ONS, 2005).

Other control variables used in the regression analysis are:

– Population density, constructed by dividing the resident population by the surface area. Previous literature, for example Graziano and Gillingham (2015), found that households in areas with lower density and rural areas, are more likely to adopt solar PV, due to the characteristics of the built environment, more suitable housing stock, and less shading from nearby buildings.

– Number of owner-occupied houses, from ONS (2018) to control for the potential market size of residential customers. Tenants and households living in multi-apartment buildings suffer from split-incentive and coordination problems, and adoption of solar PV is therefore less likely.

– Median house price from ONS (2017)), to control for house value.

– Total resident population, population 40-64 and population above 65 years of age from ONS (2016) and previous editions, to control for demographic composition. People in these age brackets are more likely to own a house, to not be thinking about moving in the immediate future, and to have finished repaying the mortgage and therefore to have available liquidity to invest, all favourable conditions for purchasing solar PV.

– Socio-economic group A (Large employers and higher managerial and administrative occupations), B (Higher professional occupations), C (Lower managerial, administrative and professional occupations), D (Intermediate occupations), E (Small employers and own account workers), F (Lower supervisory and technical occupations), G (Semi-routine occupations), and H (Routine occupations) from ONS (2005), to capture household income and other socio-economic characteristics.

– Unemployment level from ONS (2005), to control for economic conditions in the area.

– Flats, Terraced houses, Semi-detached houses, Detached houses from ONS (2005). To control for house type and available rooftop space. Households living in flats are likely to suffer from a coordination problem or constraints on the use of the rooftop, so I expect less installations in areas with more flats.

– Born in UK, EU, or elsewhere from ONS (2005) to control for the likelihood of remaining in the country and in the same house until old age, and therefore to be able to appropriate the benefits from the solar system. Foreign-born residents may have family and connections in other countries and may therefore be more mobile.

It is to be noted that data from the 2001 Census (ONS, 2005), the number of owner-occupied houses and the average electricity consumption before the FIT scheme started are time invariant values. Summary statistics were presented in Table 1.1.

1.5 Estimation model

1.5.1 Identification strategy

Following from eq. (1.5) from the theoretical framework developed above, I specify a linear estimation equation to estimate the demand for residential PV. By developing the expression of the profitability in terms of subsidy and cost, and the total subsidy in terms of the annual payments, the regression equation becomes:

$$
\begin{aligned}
Q_{i,t} &= \beta_0 + \beta_\Pi \; \Pi_{i,t} + u_{i,t} = \\
&= \beta_0 + \beta_\Pi \; (S_{i,t} - C_{i,t}) + u_{i,t} = \\
&= \beta_0 + \beta_\Pi \left(\frac{1 - \frac{1}{(1+r)^n}}{r} \; s_{i,t} - C_{i,t} \right) + u_{i,t}
\end{aligned}
$$

I then re-name the coefficients to obtain the more familiar regression form:

$$Q_{i,t} = \beta_0 + \beta_s s_{i,t} + \beta_C C_{i,t} + u_{i,t} \tag{1.9}$$

with

$$\begin{aligned} \beta_s &= \beta_\Pi \left(\frac{1 - \frac{1}{(1+r)^n}}{r} \right) \\ \beta_C &= -\beta_\Pi \end{aligned} \tag{1.10}$$

where $Q_{i,t}$ is the number of new installations in location i at time t; $C_{i,t}$ is the cost for a 1kW installation in location i at time t; and $s_{i,t}$ is the expected annual subsidy for a 1kW system installed at time t in location i. β_s captures the responsiveness of demand to changes in the subsidy and β_C the responsiveness of demand to changes in the cost of the system, as described in Section 1.3. I run the regression in (1.9) to estimate $\hat{\beta}_s$ and $\hat{\beta}_C$ and use them to compute the partial elasticities at the mean. I then obtain the implicit discount rate $\hat{r}$ by solving the two-equation system in two unknowns in (1.10).

β_s is identified thanks to variation in the expected subsidy $s_{i,t}$ over time – due to changes in the FIT rate – and over space – because the subsidy is output-based and there is heterogeneity in the expected outcome at each location according to climatic and geographic conditions. In the case of β_C, there is an issue of measurement error, as I do not observe $C_{i,t}$, but only its median across postcode-areas:

$$C_{it} = \bar{C}_{jt} + v_{it}$$

Moreover, both regressors may be correlated with the error term, if for example the subsidy and the cost are adjusted by the government and the installers according to the demand for solar PV systems, casting doubts on whether the exogeneity assumption required for the identification and estimation of the parameters is valid. In the following paragraphs I present the main challenges for the estimation of these parameters and refine the regression model to obtain consistent estimates. The results of the regression analysis are then presented.

1.5.2 Estimation challenges

Bunching

Short-term dynamics - such as delaying or anticipating installations to benefit from a higher subsidy or a lower cost - might confound identification of long-term effects. Figure 1.12 plots the installation trend against the changes in subsidy, showing spikes in uptake in the months just before a subsidy change, and downturns just after. To investigate bunching in the data, I consider two main strategies:

- restrict the sample by dropping observations in the month before and after the tariff change (Hughes and Podolefsky, 2015); given the frequent subsidy updates, this technique reduces the sample size substantially, hindering the identification of the parameters;

- perform an event study analysis and control for time to/since subsidy change in the regression (Rogers and Sexton, 2014).

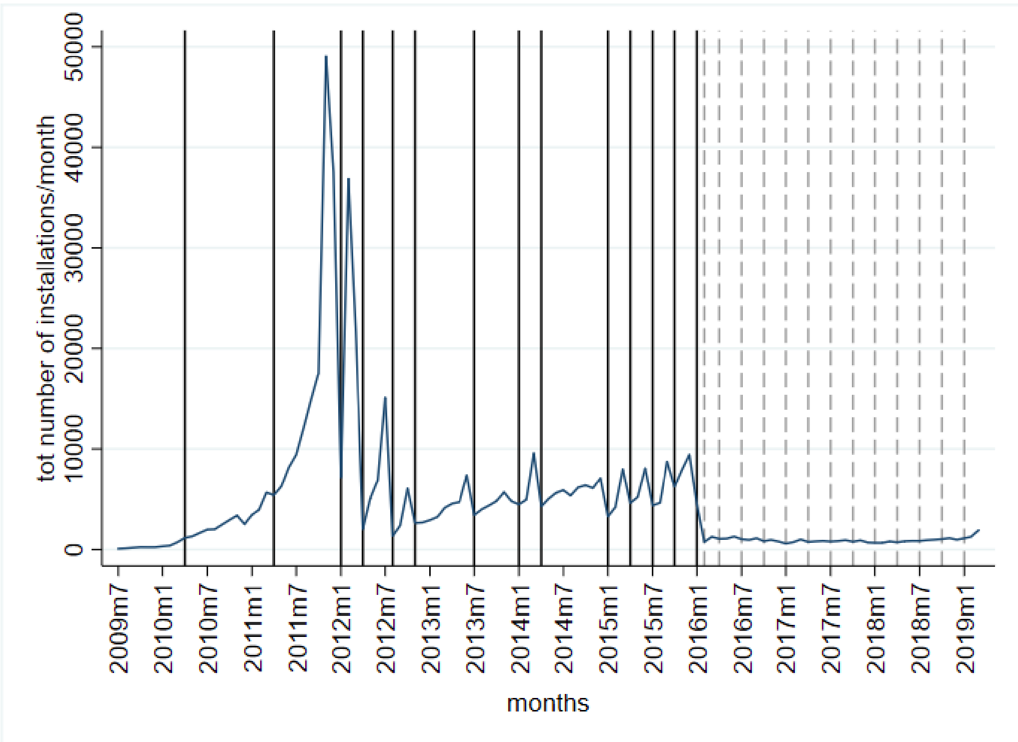


Figure 1.12: Trend in the monthly number of residential PV installations. The vertical lines highlight the months in which a change in the subsidy rate occurred (the dashed lines represent changes outside the time-frame considered in this paper).

The results from the event study analysis are reported in Figure 1.13. Regressing the number of adoptions over the number of months before or after the nearest tariff

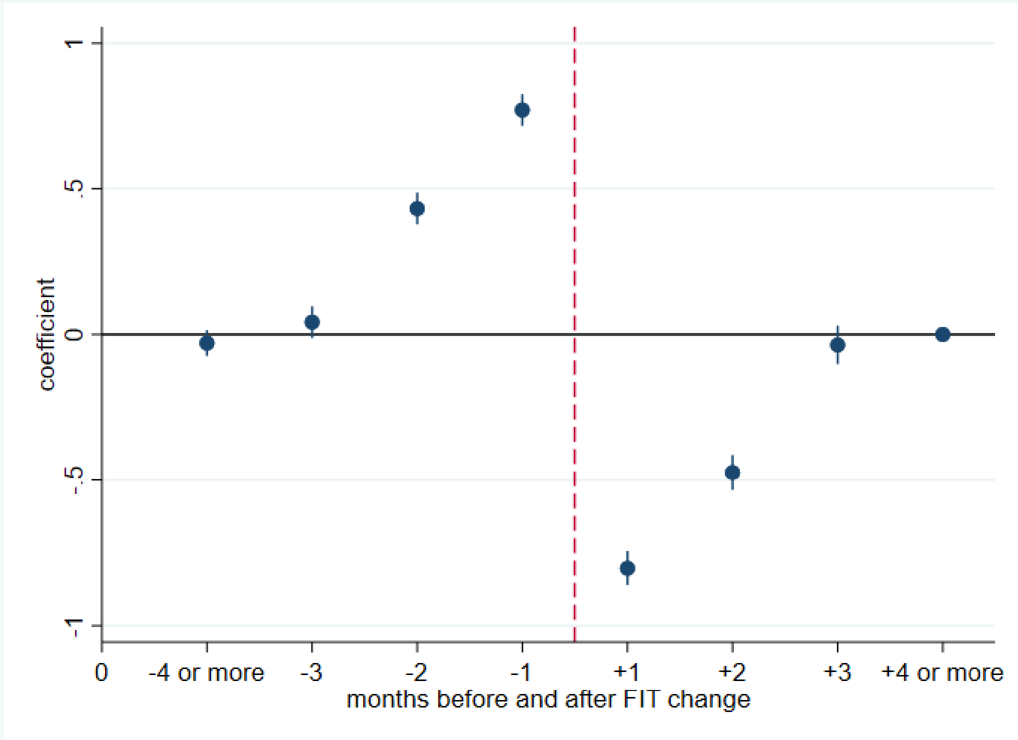


Figure 1.13: Event-study analysis. Results from regressing the number of installations per month per MSOA over the number of months before/after the nearest subsidy rate change.

change shows how a positive anticipation effect exists in the two months before the change, getting stronger as the event approaches. This effect is counterbalanced by lower than expected level of adoptions in the two months after the event, again stronger in size the closer the event is. These results suggest that households substitute adoptions over time, as the two effects almost exactly cancel each other out. No significant effect is detected for earlier or later months. In the regression I therefore include indicators to control for whether the observation is one month before a tariff change, two months before, one month after, or two months after, with any other time being the baseline.

Measurement error, Endogeneity and IVs

If the explanatory variables suffer from *classical errors-in-variables*, then OLS estimation results in an attenuation bias and the estimated $\hat{\beta}$ coefficient is biased towards zero (Pischke, 2007). I therefore use an instrumental variable (IV) strategy to obtain a consistent estimator in the presence of measurement error and, more generally, endogeneity. In order to use IVs, both the relevance and the exclusion assumption must hold, i.e. the instrument chosen must be correlated with the regressor (relevance assumption) and only affect the outcome through the regressor and no other channel (exclusion restriction).

Following the previous literature, I look for supply shifters to instrument for the cost of the installations. In particular, I use the monthly Chinese PV modules price index (as in De Groote and Verboven, 2018), and the regional median hourly pay for "Skilled Metal, Electrical and Electronic Trades" workers[20], a proxy for installers' wage. The latter is first regressed on the median general wage for the region to remove possible income effects, which would be correlated with the error term in the demand equation (as discussed in Gillingham and Tsvetanov, 2019). While the price index only varies over time, the wage data are disaggregated for each of the 10 regions of England and Wales, introducing variations over space, although they are not available at the monthly level, but only yearly. I perform robustness checks using the German-European and the Japanese-Korean PV modules price indices, and wage data at the 3- and 4-digits SOC, and results do not change.

To instrument for the subsidy, I use geographic location – and in particular the latitude and longitude of the population-weighted centroid of each area – and the FIT production rate for systems of larger size (1-5MW) and for a different technology (residential wind turbines, 0-2kW). As can be seen from Figure 1.8, the expected electricity generation, and therefore the subsidy, becomes larger when moving from North to South, and from West to East. Once area-specific fixed effects and location covariates are controlled for (see next paragraph), the relative latitude and longitude of the location with respect to the average of the fixed effect should only affect the demand for solar panels through the electricity output that may be expected from the panels, and therefore the subsidy that may be received. This instrument only varies over space, so I combine it with another instrument that captures variation over time. I use the FIT production rate for residential wind turbines with capacity 0-2kW and the FIT production rate for solar farm with capacity 1-5MW as proxies for the government's general support to residential-level smallest-scale distributed generation, and to solar generation respectively. This instrument controls for the fact that the government might change the FIT rate for residential solar PV systems depending on their demand, and therefore introduce endogeneity in the regression. I perform robustness checks using the FIT production

[20]Here I use data for the 2-digit Standard Occupational Classification (SOC): 52 "Skilled Metal, Electrical and Electronic Trades". Data at lower levels are missing for some regions. The codes for the lower levels are 3-digit SOC: 524 "Electrical and Electronic Trades"; 4-digit SOC: 5241 "Electricians and electrical fitters".

rates for 0-4kW systems and a draft of FIT rate changes pre-announced in 2010 as alternative instruments, and results do not change substantially. Summary statistics for the instrumental variables are also included in Table 1.1, previously presented.

The exclusion restriction cannot be tested, but it is credible that the price of PV modules on the international market can only affect the uptake of solar PV systems by affecting the cost of installing them, and possibly by affecting the subsidies, if the government decides to cut them as the technology gets cheaper. Raw data on installers' wages may reflect the living conditions in an area and the income of its residents, and would therefore violate the exclusion restriction; for this reason the wages are regressed on the median income of the area and only the residuals used. Similarly, the FIT rates and the latitude and longitude of a location should only affect the uptake through the subsidy channel, especially once fixed effects and location covariates are controlled for.

The result Section presents estimates for the first stage of the two-stage least-square (2SLS) regressions with IVs in Table 1.4, showing that the instruments chosen are significantly correlated with the regressors, and can explain changes in those variables. In fact, the price of the PV modules and the wage paid to installers are important components of the total installation costs (Gillingham et al., 2016; Seel et al., 2014). Similarly, due to the way the policy is designed, the only two components of the subsidy amount are the FIT rate and the electricity generated; as discussed above, latitude and longitude of the location are good predictors of the latter component, as it is highly affected by climatic and weather conditions, which in turn tend to worsen when moving towards the North and towards the West, i.e. towards the Atlantic Ocean. The second component – the FIT rate – is determined by the government as part of their strategy to support distributed renewable generation, and therefore the rates for different technologies and different capacity bands are likely to move in the same direction.

Another issue that may undermine the use of IVs, is the weak instrument problem – if the instrument has low explanatory power for the regressor, the regression may fail to detect the effect of the regressor on the outcome, even if in the true model the effect is significant. Diagnostic statistics and tests for weak instruments are presented in the result Section, in Table 1.4. When there is only one endogenous variable, a common statistics of reference for weak instruments is the F statistics of the excluded regressors. When there is more than one endogenous regressor, as in this case, Stock and Yogo (2005) tests can be used. Stock and Yogo (2005) provide critical values for a test of relative bias and for a test of size distortion induced by weak instruments, for different sets of parameters. The null hypothesis for both tests is that the instruments are weak, and the test statistic is given by the minimum eigenvalue statistic developed by Cragg and Donald (1993), which coincides with the F statistic of the excluded regressors when there is only one endogenous variable. If the test statistic is larger than the critical value, then weak instruments should not be an issue. I perform the test using the largest critical values reported by the software package[21], i.e. setting the largest tolerable bias of the 2SLS estimator at 5% for the "2SLS relative bias test", and the largest actual rejection rate for a 5% significance level Wald test at 10% for the "2SLS nominal 5% Wald test" (StataCorp, 2017). As a measure of correlation between the regressors and the excluded instruments, I calculate and report in the Table the partial R^2 statistic from Shea (1997), and the adjusted partial R^2 – which applies a correction according to the degrees-of-freedom of the estimation model, to account for the fact that the more instruments are used the larger the bias of the estimator becomes.

Unobserved heterogeneity and fixed effects

To control for unobserved heterogeneity, I introduce different sets of area-specific and time-specific fixed effects. Events that affect the whole country in a given period, or specific characteristics or local policies and institutions that make areas different from each other but are not observed in my dataset, would in fact bias the results of the analysis if not taken into consideration. In these cases, the error term in eq. (1.9) violates the assumptions required to have a consistent OLS estimator. I assume a basic specification of the error term as:

$$u_{i,t} = \mu_i + \gamma_t + \epsilon_{i,t} \tag{1.11}$$

where μ_i represents the time-invariant area-specific fixed effect and γ_t is a country-wide time fixed effect; $\epsilon_{i,t}$ is a zero-mean i.i.d. error.

In my preferred specification, I estimate the parameters using a regression specification with lower-tier local authority fixed effects. Local authorities are the administrative divisions corresponding to the local governments, and I expect differences in

[21] The model is etimated in Stata 15 using the *ivregress* and *estat firststage* packages.

local institutions and policies – if any – to occur at this level, while LSOAs, MSOAs, and statistical areas' boundaries in general do not have any administrative meaning. In total, there are 348 lower-tier local authorities in England and Wales, consisting of local authority (or non-metropolitan) districts, unitary authorities, metropolitan districts, and London boroughs.[22] location-specific covariates (where the location can be the LSOA or the MSOA, depending on the level of aggregation chosen; some of the covariates are time-invariant) and the main regressors are then used to control for the relevant drivers of PV adoptions within each location – built-environment, socio-economic characteristics, work arrangements and demographic composition, as described in the data section.

For time fixed effects I use year and month of the year fixed effect; the first is intended to control for macro-trends in the country, while the latter is used to control for seasonality effects.

As a robustness check, the regression is also estimated using two other alternative specifications for fixed effects, one using area fixed effects at the lowest level available (in this case any time-invariant variable is removed from the regression equation as they are absorbed in the fixed-effect term), and one with year-varying local-authority fixed effect, obtained by interacting local authority district with the year, rather than adding them separately. In all the specifications month-of-the-year fixed effects are used to control for seasonality in adoptions.

Count models, fractional models, and prevalence of zeros

Finally, another concern with the estimation model presented above is the use of a linear specification. In fact, a linear specification assumes that the outcome variable is continuous, unbounded and measured on an interval or ratio scale. Continuity and unboundedness are restrictive assumptions in this case, as the outcome variable is the count of installations, and therefore discrete and bounded at zero. Non-linear models for discrete and count outcome would be more appropriate in this case. Nevertheless, the linear model has the important advantages to be able to exploit the panel structure of the dataset to control for area-specific and time-specific fixed effects, while at the same time addressing the problem of endogenous subsidies and PV installation costs, which is more problematic to do with non-linear models. In

[22]For more information on local authorities see the Office for National Statistics (ONS) website: https://www.ons.gov.uk/census/2001censusandearlier/glossary.

particular, fixed effects do not simply cancel out as in a linear model, and non-linear models can suffer from the incidental parameters problem. To resolve these issues, I use a Poisson regression model, as the Poisson distribution is more appropriate for count outcome variables and at the same time a consistent estimator can be constructed to include fixed effects and endogenous regressors, as discussed in the next paragraph.

Using a Poisson distribution, the estimation equation (1.9) becomes:

$$Pr(Q_{i,t}|\lambda) = \frac{e^{-\lambda}\ \lambda^{Q_{i,t}}}{Q_{i,t}!} \quad \text{with } \lambda = e^{\beta_0+\beta_s s_{i,t}+\beta_C C_{i,t}} \tag{1.12}$$

where $Pr(Q_{i,t})$ is the probability of observing a count of $Q_{i,t}$ installations in a given area at a given time. While equation (1.10) used to estimate the time discount does not change.

A further issue is the large share of observations with zero new installations in the dataset, especially when LSOAs are used as units of analysis. I address this issue by aggregating the data at the MSOA-level, and restricting the sample of observations to the period between April 2010, when the FIT scheme started, to January 2016, just after a major reform took place and imposed severe cuts to the subsidy. After this time, installation rates in the country went substantially down (as can be seen in Figure 1.4 in the previous Section), and many solar installers filed for bankruptcy or moved out of the solar sector. This might have caused a structural break in the data and the mechanisms behind households' adoption behaviour might be different than in the previous period. Distribution of the observations at the LSOA-level, in this period contains 81% of zero, and only 14% of the observations have one installation, 3% have two, 1% three, etc.; more variation exists instead at the MSOA-level, as the share of observations with zero installations goes down to 58%, while 23% have one, 10% two, 4% three, etc. (see Figure 1.14).

In this case the dependent variable is not left-censored, but might also include structural zeros, as a different data generating process may be required to model whether the outcome is zero or non-zero, as opposed to how many installations there are conditional on there being at least one (see e.g. Gillingham and Tsvetanov, 2019). A strategy to deal with count data bounded at zero and structural zeros is the use of Tobit models, zero-inflated models and hurdle models, although these have less desirable properties when dealing with fixed effects and endogenous

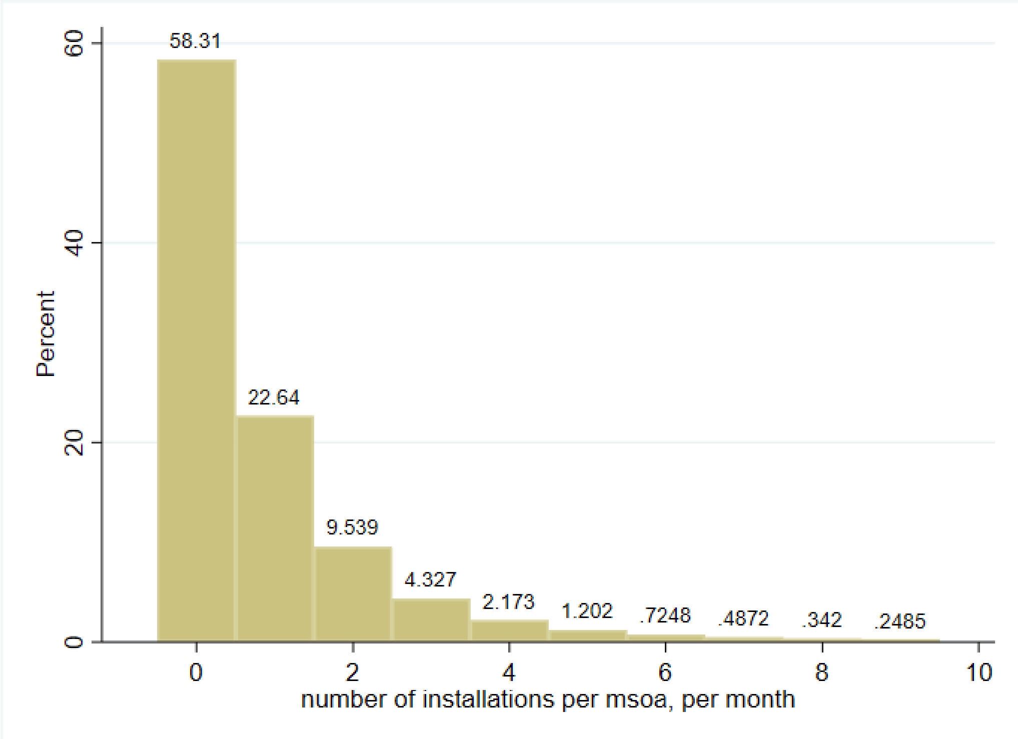


Figure 1.14: Histogram of the number of installations observed per MSOA per month (in the period 2010-2015).

regressors. Results from a Tobit model with and without instrumental variables (IV) but without fixed effects are presented in Table A.1 in the Appendix as robustness check.

I conduct further robustness checks using the proportion of households adopting PVs as dependent variable, instead of the count, as another way to address the issues posed by count outcome variables censored ar zero. To do this, I take the ratio of PV installations over the number of 'available' owner-occupied houses in each area in each month. The denominator is calculated using data on the number of owner-occupied houses in each area and subtracting the existing installed-base of PV systems to obtain the houses that are still available to host new installations. Owner-occupied houses are chosen as the reference market base because in the case of tenants and flats, split-incentives, property rights and coordination problems may arise. This is of course a proxy, as residential installations may still occur in other types of buildings and under other types of tenancy, and multiple installations may occur on the same building in case of enlargement of existing systems, nevertheless I believe this to be a reasonable assumption for the purpose at hand. In this case, the outcome variable is a share bounded between zero and one, and a fractional model based on a logistic or probit regression can be used. To address the issue of structural zeros in this context, I also estimate a zero-inflated beta model. Results from this robustness checks are presented in Table A.2 in the Appendix.

Consistent estimator for Poisson model with endogenous regressors and fixed effects

To incorporate the considerations presented in this Section, my preferred approach is to use a Poisson model with endogenous regressors and fixed effects, as presented in Gillingham and Tsvetanov (2019). Endogeneity of the regressors is addressed usins a control function approach. In the first stage, I regress the endogenous regressors on the excluded and included instruments, using a linear model with fixed effects, and recover the residuals. In the second stage, I use a Poisson model to regress the number of installations in each area and in each month on the main regressors, the estimated residuals from the previous stage, and the covariates and fixed effects. I assume a Poisson data-generating process, and use a maximum likelihood estimator, as Blundell et al. (2002) show that this does not suffer from the incidental parameter problem (the main concern which makes linear models preferable to non-linear ones when fixed effects need to be used) in this setting. I use bootstrapping to obtain standard errors. Gillingham and Tsvetanov (2019) provide details on the consistency of this estimator.

1.5.3 Results

Results from the regression analysis are presented in Tables 1.2-1.7 for the main specifications. Results from relevant robustness checks mentioned in the previous section are presented in Appendix A.1. Regression tables include estimates of the coefficients of the main regressors (subsidies and installation costs), as well as their partial elasticities evaluated at the mean (percentage change in the outcome variable due to a 1% change in the regressor, everything else being equal) and the mean values for the number of residential solar PV systems installed, the amount of the expected annual subsidy and the cost of installing, to facilitate interpretation. Standard errors are clustered at the MSOA level.

The model is estimated in levels, so elasticity is not constant but depends on the value of the variables. Regression tables show the elasticity calculated at the mean values to allow comparisons between linear and non-linear models, as in these cases the coefficients obtained from the regressions have different meanings and cannot be compared directly. In most cases, the values for the elasticity to the subsidy and to the cost are high and above 1. This is not worrying, as those values only represent partial elasticities. The parameter usually reported in the literature, especially in the case of rebates to the installation costs, is the total elasticity to the cost net of subsidies – or equivalent, but with opposite sign, the total elasticity to the subsidies net of the installation costs, i.e. η_Π in equation (1.6). To facilitate comparison with results from the literature, I re-estimate the model using the present value of subsidies net of installation costs, using a 7% discount rate (as assumed in Benthem et al., 2008) that take into consideration the opportunity cost of paying to install a solar PV system rather than investing the same amount in a financial instrument with a comparable risk profile. I can then directly estimate η_Π. Standard errors for the elasticity parameters are obtained using the delta method.

Finally, the tables also include the implicit annual discount rate and discount factor. This is obtained by solving the system of equations (1.10) for r, using the estimates for the beta coefficients obtained from the regression $\hat{\beta}_s$ and $\hat{\beta}_C$ in place of their true values β_s and β_C. Some regression specifications result in values of $\hat{\beta}_C$ that are too low compared to $\hat{\beta}_s$, so that the equation does not have any real positive solution. When this is the case, the implicit discount rate is missing.

Tables 1.2 and 1.3 shows the results for various specifications of the generalised linear model. The first table includes the coefficients and diagnostic statistics obtained from the regressions, while the second one includes estimates for the elasticity parameters and the implicit discount rate and factor. The first column (1) contains the results from a basic OLS regression of the number of PV installation in each area in each month on the expected annual subsidy (i.e. the annual 'revenue' the prosumer expects to make) and the cost of the installations. Models (2) and (3) includes local authority, year, and month fixed effects to capture unobserved geographical (but time-invariant) characteristics and temporal (but space-invariant) events, with a short and a longer set of covariates as controls. The short set of covariates include the price of electricity, the number of owner-occupied houses, and indicators of proximity to a change in the rate, as described in the Section on bunching. The longer set of covariates include all the other controls described in the Section on data. Model (4) is the traditional fixed-effects specification, with MSOA-level fixed effects. This model only includes time-varying covariates (price of electricity, the number of owner-occupied houses, and indicators of proximity to a change in the rate, median house price, density, population between 40-64 years old, and population above 65), as the others are absorbed by the fixed effects. The two final columns (5) and (6) use the interaction between local authorities and years instead of introducing them separately to control for time-varying fixed effects. Again, the two models differ by a shorter and a longer set of covariates.

Table 1.2: Regression table for the linear models with different specifications of the fixed effects.

	(1) OLS	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE
Subsidy (100GBP/kW)	0.810***	1.145***	1.141***	1.155***	1.201***	1.198***
	(0.013)	(0.021)	(0.021)	(0.011)	(0.022)	(0.022)
Install. cost (1,000GBP/kW)	-1.195***	-0.142***	-0.143***	-0.140***	-0.867***	-0.868***
	(0.021)	(0.022)	(0.022)	(0.013)	(0.059)	(0.058)
Covariates	No	Short	Long	Time-varying	Short	Long
MSOA FE	No	No	No	Yes	No	No
Local authority FE	No	Yes	Yes	No	No	No
Loc. auth. X Year	No	No	No	No	Yes	Yes
Year	No	Yes	Yes	Yes	No	No
Month of the year	No	Yes	Yes	Yes	Yes	Yes
N	503580	503580	503580	503580	503580	503580
R^2	0.05	0.18	0.19	0.12	0.22	0.23
adj. R^2	0.05	0.18	0.19	0.11	0.22	0.23
F	1852.5	390.5	268.4	2470.1	440.6	276.9
AIC	2388415.70	2312438.25	2308850.62	2295182.91	2286235.55	2282436.49
BIC	2388449.09	2312738.75	2309384.83	2295505.67	2286469.27	2282903.93

Standard errors (in parentheses) are clustered at the MSOA level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.3: Estimated elasticities and implicit discount rate for the linear models with different specifications of the fixed effects.

	(1) OLS	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE
mean values:						
PV count	1.01	1.01	1.01	1.01	1.01	1.01
Subsidy (10GBP/kW)	2.53	2.53	2.53	2.53	2.53	2.53
Install. cost (100GBP/kW)	2.23	2.23	2.23	2.23	2.23	2.23
partial elasticities:						
Subs.elasticity	2.04***	2.88***	2.87***	2.90 ***	3.02***	3.01***
	(0.033)	(0.054)	(0.054)	(0.027)	(0.056)	(0.055)
Cost elasticity	-2.65***	-0.31***	-0.32***	-0.30***	-1.92***	-1.93***
	(0.047)	(0.049)	(0.048)	(0.029)	(0.131)	(0.128)
overall elasticity[1]:						
Pres. value of net subsidy	0.275***	0.323***	0.323***	0.337***	0.490***	0.489***
	(0.003)	(0.007)	(0.007)	(0.004)	(0.010)	(0.010)
Impl.discount rate	13.6%				3.4%	3.4%
Impl.discount factor	88.0%				96.4%	96.3%

Standard errors (in parentheses) are calculated using the delta method. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[1]Elasticity to the present value of net subsidies (i.e. present value of subsidies net of installation costs), with 7% discount rate.

The coefficient of the annual subsidy (and therefore the corresponding partial elasticity) are robust through all the fixed effects specifications, and slightly lower in the basic OLS specification. The coefficient of the system costs are robust to the use of local authority or MSOA-level fixed effects in models (2), (3), and (4), but becomes larger when local authority fixed effects are interacted with years (models (5) and (6)), and even larger in the basic OLS specifications. The implicit discount rate and factor, and the overall elasticity parameter are lower than corresponding estimates for US and Belgium found in the literature.

As discussed in the previous Section, these model specifications are not satisfactory as they fail to address two main problems of the data, namely the fact that the outcome variable is a discrete count variable, bounded at zero, and that the main regressors may be endogenous. Tables 1.4 and 1.5 improve upon the analysis by addressing the endogeneity problem through the use of IVs in a two-stage least squares (2SLS) regression. To check for robustness, specifications with different sets of fixed effects are estimated. Model (1) and (2) include the preferred set: local authority, year, and month-of-the-year fixed effects. Model (3) uses MSOA-level fixed effects in place of the local authorities, while the last model (4) uses the interaction between local authorities and years.

Table 1.4: Regression table for the first stage of the linear models with IV.

	(1)		(2)		(3)		(4)	
	Subsidy	Install. cost	Subsidy	Install. cost	Subsidy	Install. cost	Subsidy	Install. cost
FIT production rate, 1-5MW	-0.0469***	-0.00656***	-0.0469***	-0.00655***	-0.0469***	-0.00656***	-0.0469***	-0.00656***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wind FIT productionrate, 0-2kW	0.00161***	-0.0182***	0.00159***	-0.0183***	0.00161***	-0.0182***	0.00161***	-0.0182***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Latitude	-0.187***	-0.0347	-0.191***	-0.0483*	.	.	-0.181***	-0.0276
	(0.014)	(0.024)	(0.014)	(0.024)	(.)	(.)	(0.014)	(0.024)
Longitude	0.0251*	0.0196	0.0250*	0.0185	.	.	0.0143	0.00707
	(0.010)	(0.017)	(0.010)	(0.017)	(.)	(.)	(0.010)	(0.017)
Chinese PV price index	2.243***	0.795***	2.244***	0.804***	2.243***	0.795***	2.243***	0.795***
	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)
Wage electric sector (residuals)	-0.0587***	0.122***	-0.0594***	0.114***	-0.0572***	0.123***	-2.328***	-1.402***
	(0.002)	(0.009)	(0.002)	(0.009)	(0.002)	(0.009)	(0.041)	(0.082)
Covariates	Short		Long		Short		Short	
MOSA FE	No		No		Yes		No	
Local authority FE	Yes		Yes		No		No	
Loc. auth. X Year	No		No		No		Yes	
Year	Yes		Yes		Yes		No	
Month of the year	Yes		Yes		Yes		Yes	
N	503580	503580	503580	503580	503580	503580	503580	503580
R^2	0.94	0.86	0.94	0.86	0.94	0.86	0.95	0.96
adj. R^2	0.94	0.86	0.94	0.86	0.94	0.86	0.95	0.95
Shea's Partial R2	0.10	0.03	0.10	0.04	.	.	0.10	0.08
Shea's Partial adj.R2	0.10	0.03	0.10	0.03	.	.	0.09	0.07
min eigenvalue stats	2887.15		2904.69		.		7134.42	
relative bias test crit.val.[1]	15.72		15.72		.		13.97	
nom.5% Wald test crit.val.[2]	21.68		21.68		.		19.45	

Standard errors (in parentheses) are clustered at the MSOA level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[1] Critical value for 2SLS relative bias test at 5%; [2] Critical value for 2SLS size of nominal 5% Wald test at 10%.

Results for the first stage are included in Table 1.4, showing the coefficients of the excluded instruments and diagnostic statistics. Reassuringly, the Shea's measure for correlation between the instruments and the regressors, and the two tests from Stock and Yogo (2005) do not point to a weak instrument problem. As expected, the annual subsidy is negatively correlated with the latitude and positively with the longitude (i.e. it is larger moving towards the South and the East), and is positively correlated with the FIT rate for small scale wind. The coefficient for the FIT production rate for larger scale solar has a negative sign – a possible interpretation for this result is that once covariates and fixed effects are taken into consideration, residential small-scale solar PV and larger scale solar farm are considered as substitutes to the government, and therefore they are negatively correlated, for example to make sure that sales of solar systems are stable over time and provide more certainty and stability to the solar sector and to installers. To make sure this is not problematic for the estimation, robustness checks using the FIT production rates for 0-4kW systems and a FIT rate schedule pre-announced in 2010 instead of the 1-5MW rate are presented in Table A.3 in the Appendix, confirming the same results. The subsidy is also positively correlated with the Chinese PV module price index, as both the subsidies and the price tend to decrease over time, and negatively correlated with the residuals of wage in the electric sector, although the latter coefficient is small in magnitude. Installation cost is strongly and positively correlated with the price index and the wage, as expected, with the exception of the last model with year-varying local authority fixed effects.

Results for the second stage are presented in Table 1.5. Coefficients are robust to the different specifications, and much larger in magnitude than the estimates without IV, consistent with an attenuation bias from *classical errors-in-variables*. The estimates suggest that a cut of 1 GBP in the annual expected subsidy per kW of installed capacity would result in around 0.026 fewer installations per MSOA, equivalent to 187 fewer installations across the country; while a decrease of 10 GBP in the upfront cost for installing would result in 0.079 more installations in each MSOA, i.e. 568 over the country. This time the implicit discount rate, and the overall elasticity parameter are larger than corresponding estimates for US and Belgium found in the literature, but again, results should be taken with caution due to issues of model misspecification.

Finally, Table 1.6 and 1.7 illustrate the results from the Poisson regression, with

Table 1.5: Regression table for the second stage of the 2SLS estimator, with IV. Estimated elasticities and implicit discount rate included.

	(1) IV,2SLS	(2) IV,2SLS	(3) IV,2SLS	(4) IV,2SLS
Subsidy (100GBP/kW)	2.584***	2.617***	2.675***	2.841***
	(0.057)	(0.057)	(0.044)	(0.057)
Install. cost (1,000GBP/kW)	-7.823***	-7.859***	-7.966***	-8.738***
	(0.171)	(0.169)	(0.092)	(0.169)
Covariates	Short	Long	Time-varying	Short
MSOA FE	No	No	Yes	No
Local authority FE	Yes	Yes	No	No
Loc. auth. X Year	No	No	No	Yes
Year	Yes	Yes	Yes	No
Month of the year	Yes	Yes	Yes	Yes
N	503580	503580	503580	503580
χ^2	1194226.0	38174.7	93437.6	356864.6
mean values:				
PV count	1.01	1.01	1.01	1.01
Subsidy (100GBP/kW)	2.53	2.53	2.53	2.53
Install. cost (1,000GBP/kW)	2.23	2.23	2.23	2.23
partial elasticities:				
Subs.elasticity	6.49***	6.58***	6.72***	7.14 ***
	(0.144)	(0.143)	(0.111)	(0.143)
Cost elasticity	-17.32***	-17.40***	-17.64***	-19.35***
	(0.378)	(0.374)	(0.203)	(0.374)
overall elasticity[1]:				
Pres. value of net subsidy	1.114***	1.129***	1.156***	1.143***
	(0.019)	(0.020)	(0.015)	(0.019)
Impl.discount rate	30.1%	29.9%	29.6%	30.6%
Impl. discount factor	76.8%	77.0%	77.2%	76.6%

Standard errors (in parentheses) are clustered at the MSOA-level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[1]Elasticity to the present value of net subsidies (i.e. present value of subsidies net of installation costs), using a 7% discount rate.

and without fixed effects, and with and without IVs, to better account for the discrete and bounded nature of the count outcome variable. The model is again estimated using different specifications of the fixed effects and covariate sets to check for robustness of the results. Specification (1) and (2) include the main set of fixed effects (local authority, year, and month of the year) with the short and long covariate set respectively; specification (3) is estimated using covariates but no fixed effects; while specification (4) uses MSOA-level fixed effects instead of the local authorities.[23]

The two final models, (5) and (6), take into consideration the potential endogeneity of the regressors, using a control function appraoch in a two-stage estimation procedure with fixed effects in both stages and a Poisson specification for the second stage, following Gillingham and Tsvetanov (2019) (see Section 1.5). Standard errors are bootstrapped. The former model uses the long covariate set and the preferred fixed effect specifications (local authority, year, and month of the year), while the latter replaces the local authority effects with MSOA-level, and therefore only includes time-varying controls. The first stage for these two models are the same as those used in specification (2) and (3) of the 2SLS linear model presented above (in Table 1.4). Coefficients are very similar in the two specifications. Results are robust across the different fixed-effects specifications without IVs, but the coefficients appear once again to be underestimated with respect to the regression models with IVs, consistent with the presence of attenuation bias from *classical errors-in-variables*. As for the linear specification, the model without fixed effects still result in an estimate for the subsidy coefficient that is very close to those obtained with fixed effects, while the cost coefficient is less robust.

[23]The specification with time variant local authority-level fixed effects could not be estimated due to lack of computational power.

Table 1.6: Regression table for the Poisson models.

	(1) Poisson	(2) Poisson	(3) Poisson	(4) Poisson	(5) Poisson w. IV, MLE	(6) Poisson w. IV, MLE
Subsidy (100GBP/kW)	0.704***	0.702***	0.615***	0.713***	1.907***	1.951***
	(0.004)	(0.004)	(0.006)	(0.004)	(0.027)	(0.022)
Install. cost (1,000GBP/kW)	-0.0399***	-0.0402***	-0.309***	-0.0586***	-4.182***	-4.245***
	(0.005)	(0.005)	(0.013)	(0.005)	(0.056)	(0.043)
Covariates	Short	Long	Long	Time-varying	Long	Time-varying
MSOA FE	No	No	No	Yes	No	Yes
Local authority FE	Yes	Yes	No	No	Yes	No
Year	Yes	Yes	No	Yes	Yes	Yes
Month	Yes	Yes	No	Yes	Yes	Yes
Var. instrumented					Subsidy Install. cost	Subsidy Install. cost
N	503580	503580	503580	502250	503580	502250
pseudo R^2	0.30	0.31	0.24		0.33	
χ^2	567162.9	584687.6	54713.3	335423.5	.	233670.8
AIC	1293795.18	1276312.46	1406601.00	1175195.14	1254529.88	1153547.38
BIC	1297957.61	1280708.61	1406946.02	1175506.69	1255075.22	1153881.19

Standard errors (in parentheses) are clustered at the MSOA-level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.7: Estimated elasticities and implicit discount rate for the Poisson models.

	(1) Poisson	(2) Poisson	(3) Poisson	(4) Poisson	(5) Poisson w. IV, MLE	(6) Poisson w. IV, MLE
mean values:						
PV count	1.01	1.01	1.01	1.01	1.01	1.01
Subsidy (100GBP/kW)	2.53	2.53	2.53	2.53	2.53	2.53
Install. cost (1,000GBP/kW)	2.23	2.23	2.23	2.23	2.23	2.23
partial elasticities:						
Subs.elasticity	1.78***	1.77***	1.56***	1.80***	4.82***	4.93***
	(0.010)	(0.010)	(0.014)	(0.010)	(0.069)	(0.055)
Cost elasticity	-0.09***	-0.09***	-0.69***	-0.13***	-9.31***	-9.45***
	(0.011)	(0.011)	(0.030)	(0.012)	(0.124)	(0.095)
overall elasticity[1]:						
Pres. value of net subsidy	0.203***	0.201***	0.251***		0.866***	
	(0.001)	(0.001)	(0.003)		(0.012)	
Impl.discount rate			0.05%		21.5%	21.3%
Impl. discount factor			99.95%		82.3%	82.4%

Standard errors (in parentheses) are calculated using the delta method. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[1]Elasticity to the present value of net subsidies (i.e. present value of subsidies net of installation costs), with 7% discount rate.

Coefficients from Poisson models are not directly comparable with those of linear models, due to the different meaning they have. For this reason, Table 1.7 reports estimates of the partial elasticity at the mean, as well as the overall elasticity estimated using net subsidies rather than subsidies and costs separately. Both the partial and overall elasticities and the time discount from the Poisson models without IVs are smaller in magnitude than the parameters obtained from the corresponding linear models. The same holds for the partial and overall elasticities and time discount from the Poisson models with IVs, which are smaller than those from the 2SLS linear models. Due to the theoretical considerations described in Section 1.5, the preferred specifications are the Poisson models with instrumental variables and fixed effects presented in column (5) and (6).

The coefficients estimated with this model have a less straightforward interpretation, as they show the the expected increase in log count for a one-unit increase in the regressor, all else equal. The estimates for elasticity at the mean show that a 1% cut in the annual subsidy would result in a much higher 4.82% decrease in installation, although if the installation costs also drop 1% at the same time, this would push adoption up 9.31%. At the mean values of 253 GBP of annual subsidy per kW of installed capacity, 2,230 GBP of installation costs per kW of installed capacity, and 1.01 installations per MSOA in each month, these results would translate into 0.19 fewer installations per MSOA (or 1,393 fewer installations over the whole territory) if the annual expected subsidy per kW of installed capacity decreases by 10 GBP, and 0.42 more installations per MSOA (or 3,032 over the whole territory) if the costs per kW of installed capacity decrease by 100 GBP, holding all the other variables constant.

Comparing estimates from model (5) with results from the literature, I find substantial similarities. The estimate of 0.87 for the overall elasticity to net subsidies at the means, can be interpreted as an elasticity of -0.87 to the cost of installing the system, net of the subsidy. This means that a 1% decrease in the overall costs net of subsidies – or equivalently a 1% increase in the overall profitability of the investment – results in 0.87% more installations. At the mean value of 1.01 installations per MSOA per month and 451 GBP of expected profits per kW of installed capacity, this is equivalent to 0.0195 more installations per MSOA, or 140 throughout the territory for a 10 GBP decrease in the cost of the system net of subsidies. In this sense, this result is very close to the estimate of -0.85 found using a dynamic structural model by Pless and van Benthem (2019) for the California rebate policy, and close to the -0.65 found by Gillingham and Tsvetanov (2019) for Connecticut, using reduced-form. In all of these cases, the main takeaway is that the elasticity parameter is high, pointing to the fact that households are highly responsive to changes in the subsidies and costs of solar PV systems.

The annual discount rate and discount factor estimated from the coefficients in model (5) are 21.5% and 82.3% respectively. This result is again very close to the estimated 82% discount factor on future electricity savings for California obtained by Snashall-Woodhams (2019). The discount rate is larger than – but still comparable to – the 15% discount rate for FIT payments estimated by De Groote and Verboven (2019) for Belgium. Both papers use dynamic structural models and are therefore better suited than the reduced-form analysis of this Chapter to identify the parameter; yet, it is reassuring that results are consistent, and contribute to the evidence that households 'behave as if' they discount heavily the future, when considering whether to adopt solar panels. It is worth remarking that this parameter can capture other behavioural features in addition to pure time preferences, so that it does not necessarily mean that agents are myopic. For example, it might capture time inconsistent discounting, such as hyperbolic discounting; mistakes in calculating the subsidies or undervaluation due to uncertainty and risk aversion, as future subsidies are not as certain as the upfront cost; default bias, as households might prefer to stick with their current energy setting rather than investing cognitive efforts in modifying it; unobserved search costs to obtain relevant information or other transaction costs; or households might be afraid they will not be able to appropriate all of the subsidies, for example if they think they may move out of the house before the end of the 20 year subsidy period. Such high trade-off between upfront costs and future benefits suggest that in general upfront subsidies are more cost-effective, as discussed in the next Section.

In the next section, I will use model (5) as the preferred specification for predictions rather than model (6), which uses MSOA-level fixed effects instead of local authority fixed effects, because the latter does not allow the use of latitude and longitude as instruments (as they are time invariant), and for the same reason, several covariates of interest cannot be included. This makes the interpretation of the mechanisms at play more difficult, as most channels get absorbed in the MSOA fixed effects. Moreover, MSOA level fixed effects may also absorb a substantial share of the variation in subsidies used for identification – especially in the months when there is no change in the FIT rate and the identification relies on spatial differences among the MSOAs. Nevertheless, it is reassuring that the estimates for the two models are very close.[24]

Robustness checks using a Tobit model bounded at zero, and fractional models with the shares of new installations as outcome variable, are presented in Tables A.1 and A.2 in the Appendix. The fractional models used are fractional logit, fractional probit and fractional probit with heteroskedasticity, with and without area- and time-specific fixed effects. To account for structural zeros, a zero-inflated beta model is also estimated.

Further analysis on the possibility that effects are heterogeneous is described in Appendix A.2. In particular, I test for the hypothesis that effects are heterogeneous over time, as found by Hughes and Podolefsky (2015), or depend on the existing installed base due to the presence of peer effects, as in Bollinger and Gillingham (2012); Richter (2014); Graziano and Gillingham (2015); Müller and Rode (2013); Rode and Weber (2016); Baranzini et al. (2017). These topics will be the focus of the next Chapter.

1.6 Cost-effectiveness and alternative policy design

1.6.1 Additionality of the subsidy, rent appropriation and comparison between FIT and upfront incentives

In this section, I discuss the cost-effectiveness of the UK FIT scheme given the results of the previous Sections. To start this analysis, I use the preferred specification – the Poisson model with endogenous regressors and fixed effects – to predict the number of installations that would have occurred even with no subsidies, to understand the additionality of the policy. In particular, I assume that the production rate is zero and only the export rate is paid for the electricity sold to the grid, estimated to be 50% of the total generation, as for the existing policy. Estimates have been repeated assuming not even the export rate is offered and the results are very similar.

Figures 1.15, 1.16, and 1.17 show the fitness of the estimated model, by compar-

[24]As a robustness check, the analysis in the next Section has been replicated using model (6), and the results are robust.

ing the observed and predicted number of installations over time (by month) and over space (by MSOA, and by local authority) respectively. In what follows I refer to the marginal adopters as the 'policy-induced' installations, computed by subtracting the number of inframarginal adopters from the number of installations predicted for each subsidy scenario. I predict that without the subsidy, 13,136 installations would have happened anyway in the period under consideration, corresponding to about 2.6% of the predicted total under the existing scheme.[25] Nevertheless, the rents appropriated by these inframarginal adopters are even lower than this share, because compared to the marginal installations they tend to occur in later times, when the cost of installing and the FIT rate are lower, and in areas with lower solar generation potential. I estimate that the amount of subsidy paid out to these households is 1.5% of the total, suggesting that the scheme has a very high additionality and not many households would have adopted without incentives to do so.

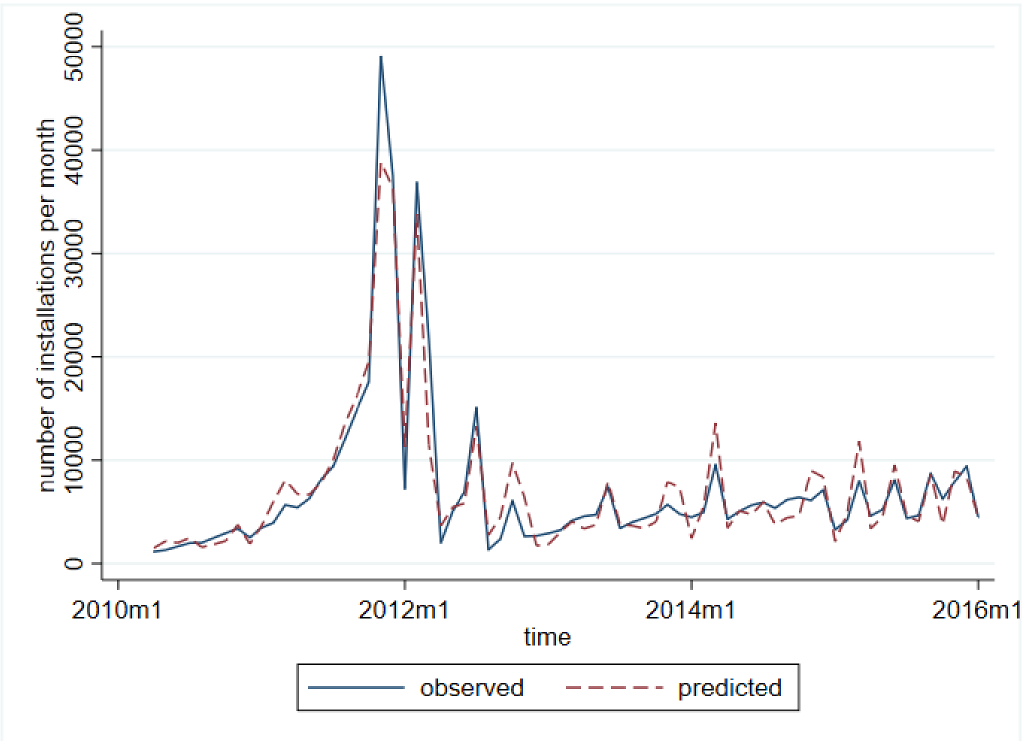


Figure 1.15: Comparison of the number of installed PV systems observed and predicted, in each month.

By inducing more installations, the objective of the scheme is to decrease emissions from electricity generation in the country. Before the introduction of the FIT

[25]The number of per capita installations predicted in absence of subsidies is comparable to the number of installations in Norway, a country with almost no support scheme for solar as of 2016 (Standal et al., 2020); in fact it is even larger, consistent with the better solar potential of the UK compared to Norway. This comparison suggests that the estimates are in a sensible range.

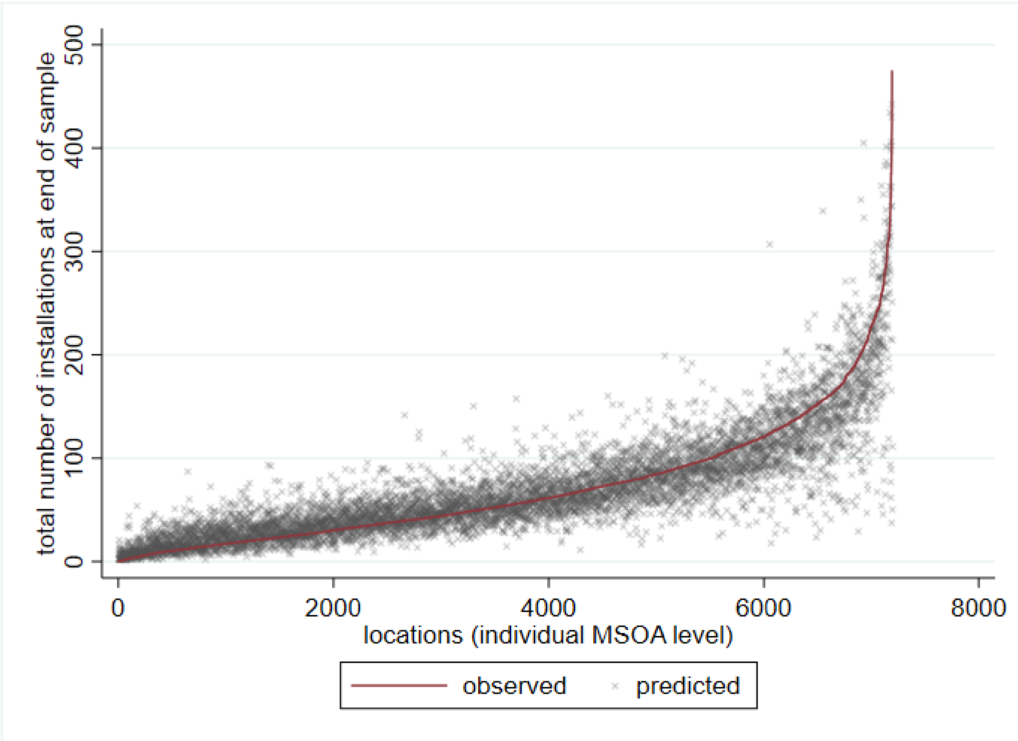


Figure 1.16: Comparison of the number of installed PV systems by the end of the sample observed and predicted, in each location.

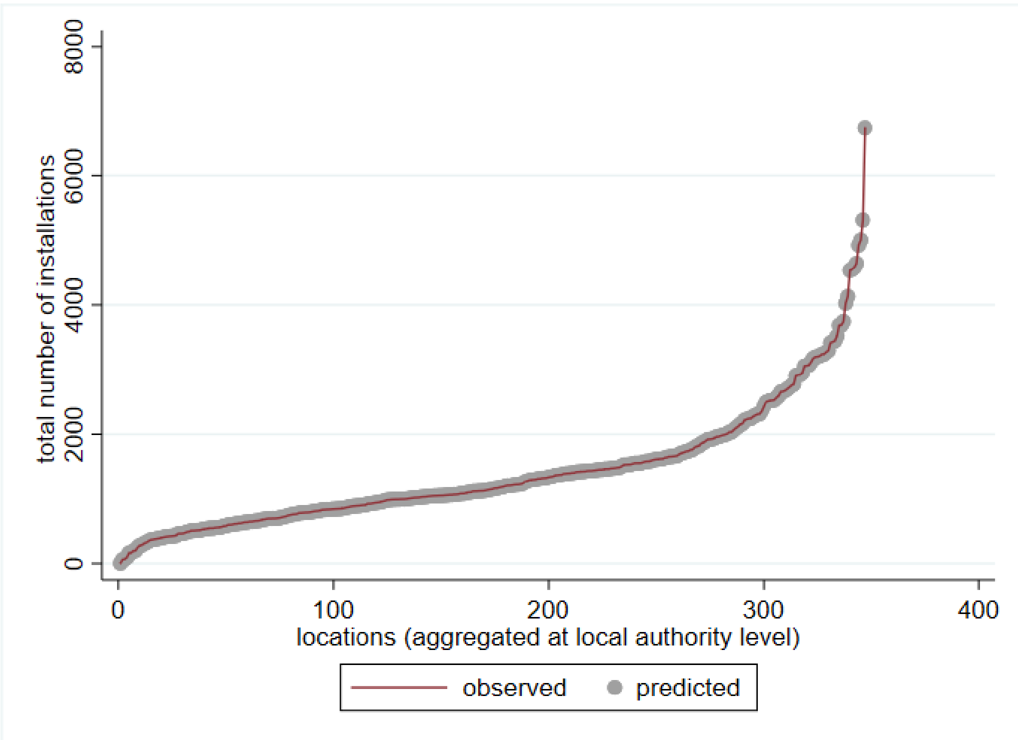


Figure 1.17: Comparison of the number of installed PV systems by the end of the sample observed and predicted, in each local authority.

scheme in April 2010, the carbon intensity of electricity generation in the UK was estimated to be around 500 grams of CO_2-equivalent per kWh (Staffell, 2017). I estimate that the installations of residential solar PV systems induced by the policy between April 2010 and January 2016 (i.e. the marginal installations) will have produced more than 46,700 GWh during their lifetime. Useful lifetime is assumed to be 30 years as in Benthem et al. (2008) and in the pessimistic scenario of Frischknecht et al. (2015) – although this assumption might be conservative, as the latter study considers 35 and 40 years in their realistic and optimistic scenario respectively. This is equivalent to 23.35 million metric tons of CO_2-eq emission avoided, as compared to the case in which the same amount of electricity was generated using the energy mix the country had in 2010.

This is achieved with an expenditure of around 7.31 billion GBP in FIT payments over the 20 years each installation is eligible for support (present value calculated using a 5% discount rate; this would be 5.23 billion GBP with a 10% discount rate – see Table 1.8). This is equivalent to approximately 313 GBP per metric ton of CO_2-eq avoided (224 GBP per metric ton, if considering a discount rate of 10%), more than twice as expensive as the California upfront rebate scheme, estimated at between 130 and 196 USD[26] by Hughes and Podolefsky (2015). In terms of electricity generated, I estimate a cost of the policy of 0.156 GBP per kWh (present value calculated using a 5% discount rate; this would be 0.112 using a 10% discount rate), about three times the cost per kWh of the California CSI, estimated at 0.06 USD in the same study.[27]

This difference can be explained by the fact that the California CSI consists of rebates on the upfront cost of the PV systems, while the UK FIT consists of subsidies paid periodically over a 20-year period. As households are estimated to have a high discount rate for the subsidy – which I have estimated at 21% per year for the UK – part of the subsidies in the FIT scheme end up paying for households' 'impatience', and other behavioural features that make households undervalue their future benefits (default bias, uncertainty and risk aversion, mistakes in calculating the present value, and so on). In fact, at a 21% discount rate, the cost of the policy drops to 0.06 GBP per kWh generated and 135 GBP per metric ton of CO_2-eq avoided, in line with the corresponding estimates for the upfront incentives in

[26]Equivalent to 100-150 GBP, at an exchange rate of 1.31 USD for 1 GBP.
[27]Equivalent to 0.046 GBP, at an exchange rate of 1.31 USD for 1 GBP.

California.

As long as this discount rate is higher than the interest rate on loans for the government or the utilities, upfront incentives would have been more cost-effective than the FIT scheme, all else equal. Even in this case, the policy remains very expensive if considered only as a tool to correct environmental externalities; as a reference point the European Union Emissions Trading System (EU ETS) carbon market price has never been above 25 GBP per metric ton of CO_2-eq avoided, and the estimates for the social cost of carbon (SCC) proposed in the Stern Review do not exceed 100 GBP (Stern, 2007). Yet, support for renewables provides additional benefits, including fostering innovation and learning-by-doing (Jaffe et al., 2005). In particular, Benthem et al. (2008) find that when both environmental externalities and unappropriated learning-by-doing are taken into account, the incentive schemes in California are very close to the optimal incentive schedule.

1.6.2 Alternative policy scenarios: output-based v. capacity-based

While the high estimated discount rate suggests that upfront incentives would have been more cost-effective than the existing FIT scheme, an advantage of the latter is that it provides stronger incentives to install in locations with higher solar generation potential. To assess the benefits of this feature, in this Section the existing FIT scheme is compared with an hypothetical alternative policy design that pays the same annual subsidy throughout the country, keeping the timeline and scale of changes as in the original. In what follows, I use again the preferred specification, the Poisson model with endogenous regressors and local authority-level fixed effects, to predict and compare the distribution of installations under the following conditions:

- annual output-based subsidy, as observed in the UK.
- annual capacity-based subsidy, set as the mean of the expected annual output-based subsidy over the country, in each month. In this case I use the newly created values for the subsidy and the original cost data to obtain the predicted number of installations.

Figure 1.18 shows the subsidy schedule under the two scenarios. The main objective of the following analysis is to investigate how linking the subsidy to electricity generation, and therefore implicitly to the solar generation potential of a location, affects the siting of installations. To do this, I look at how much solar capacity and electricity generation each subsidy induces, where the installations occur, and at what cost to the bill-payers.

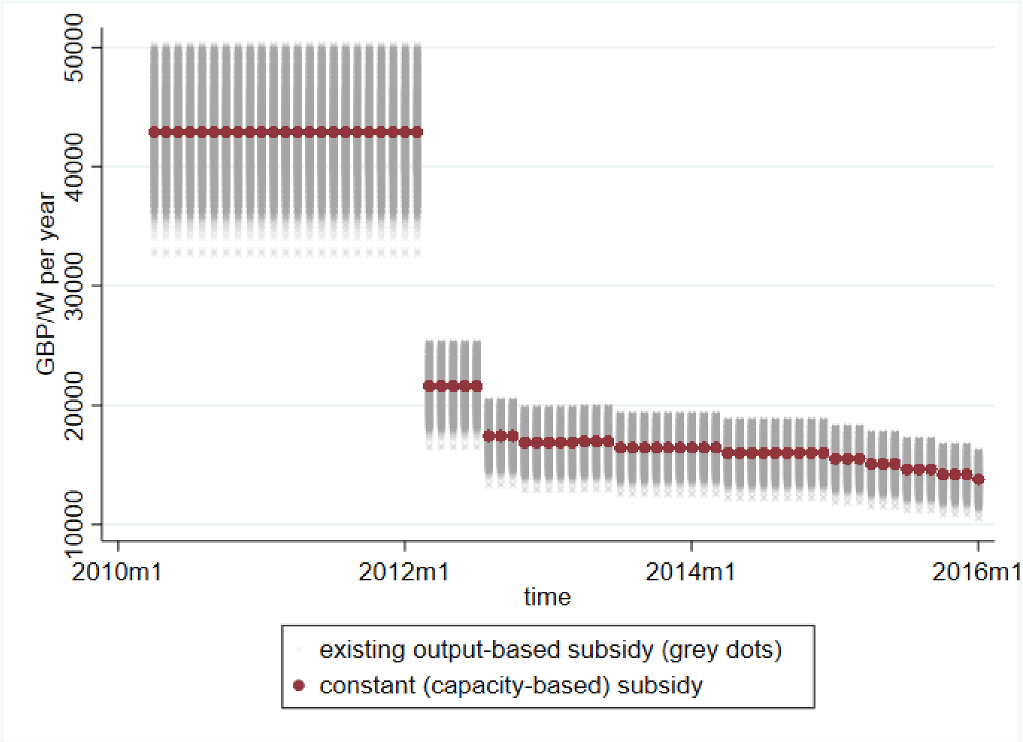
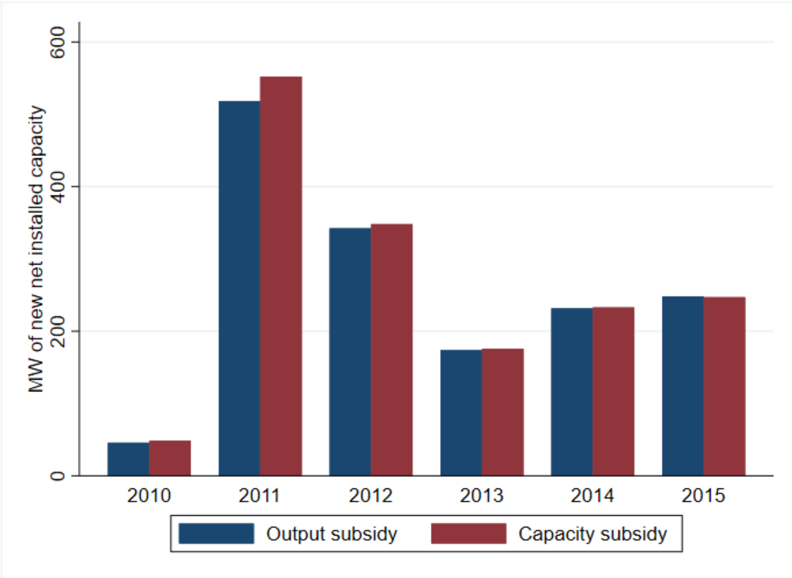


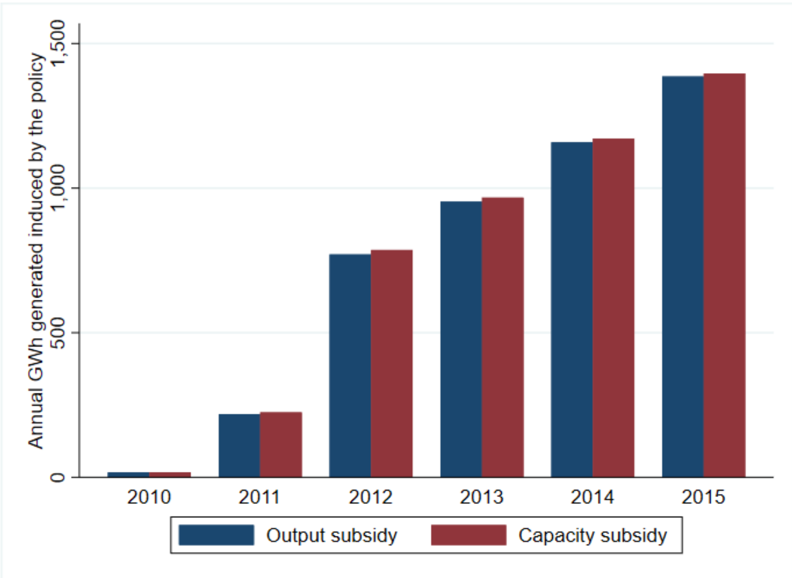
Figure 1.18: Schedules of subsidies under the different policy scenarios.

For each subsidy scenario, I fit the model using the two subsidy schedules and keep the rest of the variables as they are, and predict the number of installations in each MSOA in each month. I then net them out of the inframarginal adopters and convert them into equivalent installed capacity and generation. To obtain an estimate of the installed capacity, I multiply the count of installations by the median size of the observed installations in each year in each local authority area (see Figure 1.3). The use of year-specific size values should capture the technological improvements in the sector, as newer panels have a larger capacity than older ones. Generation is obtained by multiplying the estimated installed capacity in each MSOA for the average estimated output of that area. I then compute the total subsidies paid, the subsidy per 'induced' kW installed, and the subsidy per 'induced' kWh generated. Comparisons between the capacity and generation induced by each type of subsidy and the cost of the policy, are presented in Figure 1.19 and Table 1.8.

The first two panels of the Table show the total installed capacity net of inframarginal adoptions, and the electricity that is expected to be generated over the



(a)



(b)

Figure 1.19: New capacity (a) and generation (b) induced by different subsidies (net of inframarginal adopters) in each year.

Table 1.8: Subsidies per kW of installed capacity and per kWh generated, total capacity installed, total generation and total expenditures for each subsidy scheme, net of infra-marginal adoptions.

Total MW of (net) capacity installed between 2010-2015

	output-based subsidy	capacity-based subsidy
	1,575	1,620

Overall GWh generated assuming panel life is 30 years

	output-based subsidy	capacity-based subsidy
	46,781	47,028

Total subsidies for panels installed between 2010-2015, present value (billion GBP)

	output-based subsidy	capacity-based subsidy
disc. rate = 0	11.17	11.54
disc. rate = 5%	7.31	7.55
disc. rate = 10%	5.23	5.40

Subsidies per kW of installed capacity, present value (GBP/kW)

	output-based subsidy	capacity-based subsidy
disc. rate = 0	7,092	7,124
disc. rate = 5%	4,640	4,661
disc. rate = 10%	3,320	3,336

Subsidies per kWh generated, present value (GBP/kWh)

	output-based subsidy	capacity-based subsidy
disc. rate = 0	0.239	0.245
disc. rate = 5%	0.156	0.161
disc. rate = 10%	0.112	0.115

lifetime of the PV systems, assuming it to be 30 years. Consistent with findings in Burr (2016), the capacity-based subsidy induces more installed capacity than the output-based subsidy – in this scenarios, the capacity-based subsidy results in 3% more installations than the output-based subsidy. But if we look at the generation, the gap between capacity- and output-based subsidy becomes almost negligible, at only 0.5%; this is evidence that subsidies linked to generation are more effective at inducing installations in areas with higher generation potential, if compared with capacity-based incentives that are undifferentiated across the country. The third panel shows the overall amount of subsidies committed to the scheme (i.e. for all of the 20 years for which installations are eligible for FIT support), under three different values of the discount rate: 0, 5 and 10%, to show how the results change depending on assumptions made on this parameter. The fourth and fifth panels show the average cost of the policy per kW of installed capacity and for kWh of electricity generated. These are computed net of inframarginal adoptions, the adoptions that would have occurred even with no incentive. Once again in line with the theoretical results in Burr (2016), the output-based annual subsidy appear to be more cost-effective than the capacity-based annual subsidy.

Finally, I look at the geographical distribution of residential PV systems resulting under each policy scenario. The null hypothesis, according to economic theory, is that, all other things equal, output-based subsidies should result in a higher number of installations in locations with a better generation potential – and therefore there should be a positive correlation between the number of installations and the generation potential. The capacity-based subsidies on the contrary is indifferent between areas with larger or smaller potential and should therefore result in no correlation (other things equal). Looking at the empirical results, I find that the output-based subsidy is indeed better than the capacity-based subsidy in allocating installations according to the generation potential, but when fixed effects and other covariates are considered, the resulting geographical distribution is more complex than what the above hypotheses suggest. In fact, the correlation between installations induced by output-based subsidies and the generation potential of the area is close to zero in my data (0.085), while the correlation between the installations predicted under the capacity-based subsidy and the generation potential becomes strongly negative (-0.153). Interestingly, the inframarginal installations (i.e. the installations estimated to occur even without subsidies) are also negatively correlated with the generation potential although much closer to zero, with a correlation coefficient of -0.079. These results are illustrated in Figure 1.20, which shows the predicted number of installations in each area-month against the generation potential of the area, for each scenario. The plot lines represent the fractional polynomial fit lines. The difference is stronger when restricting the focus to the period with high subsidies – i.e. before the 2012-reform – with correlation coefficients of 0.108 and -0.219, respectively, while it is attenuated after the 2012-reform, when the correlation coefficients become 0.084 and -0.121 (Figure 1.21). This confirms that linking the subsidy to the actual generation or generation potential improves the cost-effectiveness of the incentive scheme and favours a more efficient[28] siting of the solar PV systems in terms of generation per kW installed, as compared to a geographically undifferentiated subsidy.

Overall, the analysis of this Section shows that cost-effectiveness of the incentive scheme could be improved by paying the subsidy upfront, but retaining the differentiation of the subsidy according to generation potential. This combination of features is exactly the solution adopted by California under the Expected Performance-Based Buydown – an upfront rebate that is adjusted according to the expected generation of the solar array, calculated taking into account the PV module type and the location, orientation and shading of the system. In fact, Benthem et al. (2008) find that this incentive scheme, as designed and realised in California, is very close to the optimal solar subsidy schedule resulting from their model (when accounting for environmental externalities and unappropriated learning-by-doing).

1.6.3 Determinants of PV siting: incentives, built-environment, work arrangements and socio-demographic conditions

To explain why the geographical distribution of residential solar PV adoptions induced by the policy is only weakly correlated to the generation potential, I look at the role of other covariates. In fact, the results from the scenario analysis suggest that while output-based subsidies are pushing installations towards locations with better generation potential, other elements are operating in the opposite direction. Even though there is no straightforward reason to expect that any of the covariates (besides the subsidy) is directly correlated with generation potential, in practice

[28] In this Section I consider 'efficient siting' purely in terms of maximisation of electricity generation given the investment in installed capacity in each month.

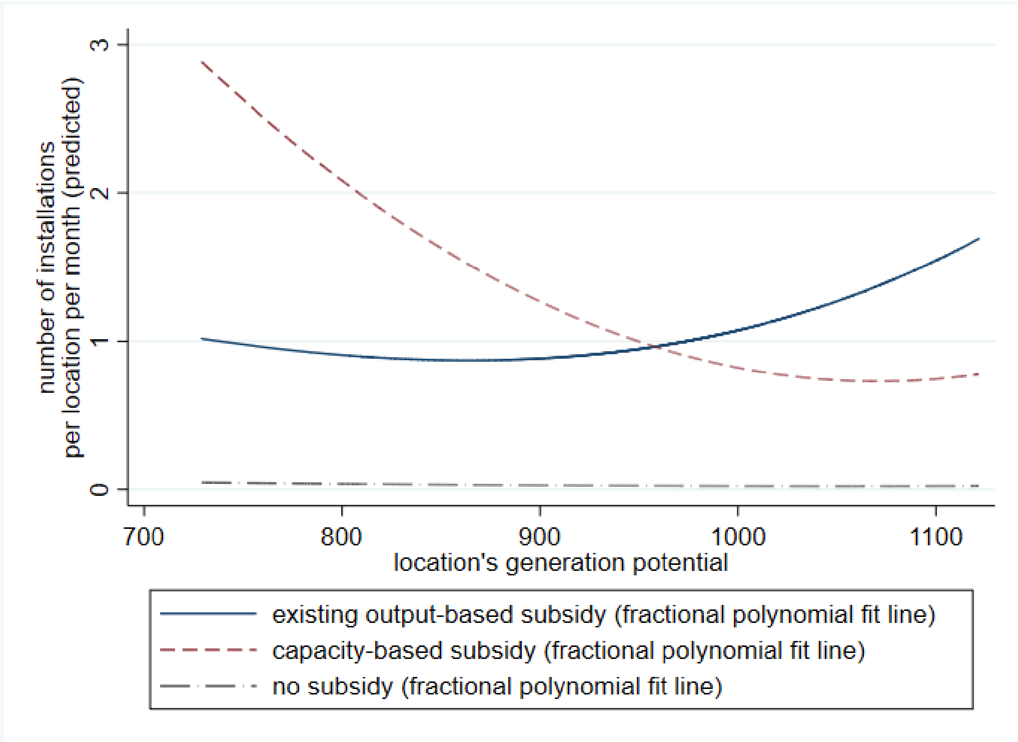
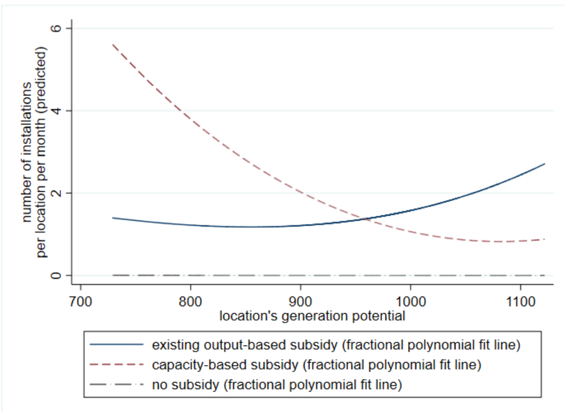
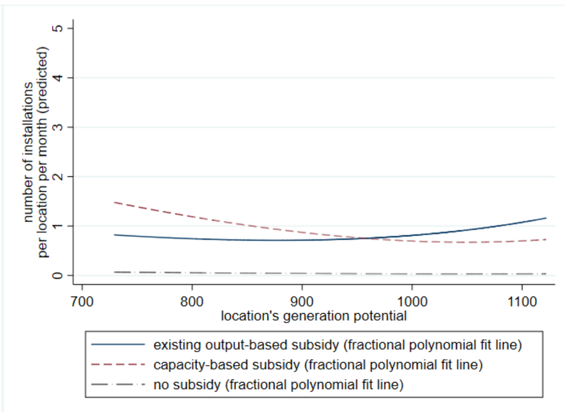


Figure 1.20: Correlation between installations and potential generation in the area in which they are installed, under the different subsidy scenarios (fractional polynomial fit lines).



(a)



(b)

Figure 1.21: Correlation between installations and potential generation in the area in which they are installed, under the different subsidy scenarios (fractional polynomial fit lines) before (a) ad after (b) the policy reform of 2012.

their distribution over the territory might be. For this reason, I obtain the partial correlations of all the covariates with the solar generation potential, and compare the signs of the correlation coefficients with the signs of the coefficients from the preferred regression model to see how they explain the resulting siting distribution of solar systems.

Results are presented in Table 1.9. As expected, subsidies are strongly correlated with the generation potential, due to the way they are designed, and have a positive effect on uptake. The two effects combined favour an efficient (in terms of total generation) siting of the solar systems in locations with larger generation potential. The same result is achieved by the installation costs, which have a negative effect on adoption and negative correlation with generation potential. Electricity price and electricity consumption in 2010 have a positive effect on solar PV adoptions, as they proxy for electricity bill savings, but they have opposite effects on the siting of the systems, as price tends to be higher in locations with larger generation potential, but consumption tends to be lower.

As found by Graziano and Gillingham (2015), population density has a negative effect on PV adoptions, which are more abundant in rural and sparse areas. Combined with a positive correlation with generation potential in the UK, density therefore contributes to inefficient system siting. Other covariates that have a negative effects on residential solar PV uptake but are positively correlated with generation potential are median house price,[29] population between the age of 40 and 64, and residents in the intermediate socio-economic groups C to F (lower managerial, administrative and professional occupations; intermediate occupations; small employers and own account workers; lower supervisory and technical occupations). On the other side, number of owner-occupied houses, residents working from home, and residents belonging to the social-economic group of large employers and higher managerial and administrative occupations (socio-economic group A) and to routine occupations (socio-economic group H) have a positive effect on PV adoption but are negatively correlated with solar electricity generation. All these drivers push installations towards locations with relatively worse generation potential.

[29]Note that in the UK historical houses, such as listed buildings and buildings in conservation areas, have stringent regulation on what modifications can be made and require authorisation for the installation of solar panels and other energy related measures (Hilber et al., 2019). Moreover, the aesthetics of the house is an important concern in the country, and many households oppose solar panels because they make the house look "hugly" or are afraid it might lower the value of the house (Standal et al., 2020). These concerns are likely to affect higher-value houses.

Table 1.9: Effects of covariates on solar PV uptake, partial correlation of covariates with the generation potential of locations, and resulting effect on siting.

	PV count (Poisson, IV)	Generation potential (partial correlations)	resulting effect on siting
Subsidy (100GBP/kW)	1.907*** (0.022)	10.23*** (0.101)	+
Install. cost (1,000GBP/kW)	-4.182*** (0.056)	-1.580*** (0.167)	+
Electricity price (p/kWh)	0.190*** (0.018)	8.020*** (0.118)	+
Electricity consumption in 2010	0.0001*** (0.000)	-0.015*** (0.000)	−
Density	-0.0001*** (0.000)	0.0003*** (0.000)	−
# Owner-occupied houses	0.0001*** (0.000)	-0.035*** (0.000)	−
Median house price	-0.000002*** (0.000)	0.0001*** (0.000)	−
Population 40-64	-0.0001*** (0.000)	0.011*** (0.000)	−
Population $\geq$65	0.0002*** (0.000)	0.059*** (0.000)	+
Residents in socio-economic group A	0.0002* (0.000)	-0.201*** (0.002)	−
Residents in socio-economic group B	0.0003*** (0.000)	0.0187*** (0.001)	+
Residents in socio-economic group C	-0.0000 (0.000)	0.049*** (0.001)	.
Residents in socio-economic group D	-0.0004*** (0.000)	0.012*** (0.001)	−
Residents in socio-economic group E	-0.0004*** (0.000)	0.120*** (0.001)	−
Residents in socio-economic group F	-0.0000 (0.000)	0.091*** (0.001)	.
Residents in socio-economic group G	0.0001 (0.000)	0.068*** (0.001)	.
Residents in socio-economic group H	0.0005*** (0.000)	-0.085*** (0.001)	−
Flats	-0.0002*** (0.000)	-0.009*** (0.000)	+
Terraced houses	-0.0001*** (0.000)	-0.022*** (0.000)	+
Semi-detached houses	0.0000 (0.000)	-0.039*** (0.000)	.
Detached houses	0.0003*** (0.000)	0.001*** (0.000)	+
Work from home	0.0011*** (0.000)	-0.238*** (0.002)	−
Homemaker	0.0001 (0.000)	0.181*** (0.001)	.
Retired	-0.0002*** (0.000)	-0.053*** (0.001)	+
Unemployed	-0.0003* (0.000)	-0.255*** (0.002)	+
Born in EU	0.0002* (0.000)	0.022*** (0.001)	+
Born in UK	0.0000 (0.000)	0.003*** (0.000)	.
N	503580	503580	
R^2		0.318	
adj. R^2		0.318	
pseudo R^2	0.325		
F		10676.0	

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The forces that push in the opposite direction – that is towards more efficient siting for electricity generation – due to positive coefficients for both adoption and generation potential are population older than 65 years old, residents in higher professional occupations (socio-economic group B) and homemakers spending time taking care of the home, residents born in the EU and UK, as opposed to outside of the EU, and the presence of detached houses. The same result occurs when both coefficients are negative, as in the case of areas with large presence of apartments (flats), terraced houses, retired residents and unemployment.

Besides the effects of these variables, the situation is likely to be further complicated by unobservables (variables that are not observed in the dataset), such as green preferences and local campaigns and initiatives, that are captured by area-specific fixed effects and contribute to shape the distribution of solar systems around the UK. Moreover, peer effects due to information sharing, social norms and imitative behaviour, might compound these mechanisms by triggering a domino effect, once solar PV systems start appearing in a neighbourhood.[30] Understanding the combined effects of these elements can therefore explain the puzzling distribution of residential solar PV around England and Wales.

Therefore, the distribution of residential solar systems appears to be shaped not only by the subsidy, but also by the counteracting effects of several other forces, including socio-demographic composition, work arrangements and characteristics of the built environment. Understanding the complementarities between these elements and the mechanisms behind these effects can therefore help design more effective and better targeted policies, which take into consideration the monetary and non-monetary incentives and the different physical, technological, socio-demographic and economic constraints at play.

1.7 Conclusion

The main contributions of this Chapter have been to estimate the responsiveness of demand for residential PV systems to the UK output-based subsidies, to identify what other forces shape the spatial distribution of solar installations around

[30]Evidence that peer effects play a significant role in the diffusion of new technology, and in particular of residential solar PV, is documented in the literature (Bollinger and Gillingham, 2012; Richter, 2014; Graziano and Gillingham, 2015; Müller and Rode, 2013; Rode and Weber, 2016; Baranzini et al., 2017), and suggested by the exploratory analysis presented in Appendix A.2. This is the topic of the next Chapter.

the country, and to understand the strengths and weaknesses of the policy design and how it could be changed to improve cost-effectiveness and achieve a more efficient siting of residential solar in terms of overall generation obtained from a given installed capacity.

As predicted by the theory, I find a positive subsidy elasticity of demand, with the number of installations decreasing in response to cut to the subsidies. This is counterbalanced by the negative elasticity to the cost of installing, with the number of installations increasing as the cost falls. Using a consistent estimator for a Poisson model with fixed effects and endogenous regressors, I estimate that on average a 1% cut in the annual expected subsidy results in a 4.82% drop in installations, but if the installation costs decrease by 1% then this boost adoption by 9.31% (when taking all variables at their mean values). These values represent partial elasticities. When considering the cost of installations net of the present value of all future subsidies as the main regressor – as commonly done in the literature, especially when rebate schemes are under analysis – the estimate for the overall elasticity at the mean is -0.87, meaning that a 1% decrease in the net costs, or equivalently a 1% increase in the profitability of the investment, results in 0.87% more installations. This value is comparable to estimates obtained in the literature for the US and Belgium, and suggest that a drop of 10 GBP in the net costs (or equivalently a raise of 10 GBP in the profitability) per kW of installed capacity would result in 140 more installations throughout the territory.

I have then used the resulting estimates to discuss the cost-effectiveness of the subsidy scheme and the degree of inframarginal adoptions and rent appropriation. The additionality of the policy appears to be very large, with only few installations predicted to have happened without any form of support, and mainly in later years, when the cost of PV systems was lower. Nevertheless, electricity generated by the residential PV installations appears to be more costly than other sources in the country, and even more expensive than residential solar electricity in other countries. I estimate a cost of the policy of 0.112-0.156 GBP per kWh generated (present value calculated using a 10% and 5% discount rate respectively), and of approximately 224-313 GBP per metric ton of CO_2-eq avoided with respect to the energy mix in place in 2010, before the FIT scheme started (present value calculated using a 10% and 5% discount rate respectively). On one side, it should be considered that solar PV systems are also linked to additional benefits in terms of technological innovation, learning-by-doing, social learning, and reduction of local pollutants and negative externalities that are associated with other energy sources (Jaffe et al., 2005; Benthem et al., 2008), and this would therefore justify a higher cost of solar energy with respect to other sources.

Yet, these benefits could likely be achieved at a lower cost than what UK energy bill payers have been paying, by providing incentives upfront, as in the case of the California Expected Performance-Based Buydown, or other rebate schemes in the US and around the world. In fact, I estimate that households behave 'as if' they were heavily discounting future subsidies, meaning that a large share of the subsidies end up paying for households' 'impatience', and other behavioural features that make households undervalue future benefits from adoption (default bias, uncertainty and risk aversion, mistakes in calculating the present value, and so on). High discount rates are a common feature in the literature on new technology adoption, and very similar values have been found in the context of residential solar PV systems for Belgium and California, using more complex structural models with dynamic optimisation of decisions. When calculating the present value of the policy expenditures using the estimated 21% discount rate households seem to be using, the cost drops to 0.06 GBP per kWh generated and 135 GBP per metric ton of CO_2-eq avoided, in line with the corresponding estimates for the policy cost of upfront rebates in California.

In terms of geographical distribution, I find that the existing output-based subsidy scheme is more cost-effective than the hypothetical alternative capacity-based subsidy considered. In fact, while capacity-based subsidies induce more installations than the standard output-based incentive, these occur in areas with worse generation potential. This is consistent with theoretical results from Burr (2016). Overall, retaining the differentiation of the subsidy according to generation potential is therefore helpful to improve the cost-effectiveness and efficiency of the subsidy. Nevertheless, there appear to be other mechanisms at play that result in a distribution of systems that is only weakly correlated to the generation potential. This is because in the UK several built environment, work arrangements and socio-economic characteristics that are associated with solar PV adoption – such as wealthier socio-economic groups, lower population density, more owner-occupied houses and more people working from home – tend to be negatively correlated with locations' generation potential. This result could be leveraged to target future policies and to design support schemes that take into consideration a broader set of monetary and non-monetary incentives and different physical, technological, socio-demographic and economic constraints.

At the same time, the observable characteristics included in the dataset are likely to be only a part of all the forces at play, as location specific fixed effects might be absorbing other relevant mechanisms that are unobserved in this analysis, such as green preferences, and local campaigns and initiatives. Peer effects, documented in the literature and detected through some preliminary analysis in this paper, might further compound the existing effect by triggering a chain reaction, once solar PV systems start appearing in a neighbourhood. More research on these channels would therefore be relevant.

In conclusion, the findings of this Chapter suggest that a combination of upfront incentives differentiated so to take into consideration generation potential would be a more cost-effective solution than both annual output-based subsidies and up-front capacity-based rebates. California Expected Performance-Based Buydown is an example of how such incentive could be designed, as it offers an upfront rebate calculated according to the expected generation of the solar array, taking into consideration the location, orientation and shading of the installation, and even the efficiency of the PV module purchased.

Future extensions of the research might integrate into the analysis grid network costs (generation, transmission, distribution, congestion, etc.), the geographical distribution of demand, and the potential solar energy generation in each location at a higher resolution (particularly useful would be at the week and weekend level, and by day and night time) to assess where a hypothetical central planner would have preferred to site the solar systems, and discuss how these 'optimal' distribution of installations across the country compares with the decentralised decisions triggered by different incentive designs.

The research questions explored in this Chapter contribute to our understanding of how centralised market based incentives, such as subsidy, interact with the behaviour of decentralised agents, that are now both consumers and producers of energy. It also discusses practical policy alternatives to improve cost-effectiveness of renewables subsidy, given budgetary pressure. More broadly, the paper contributes to the literature on technology adoption and policy intervention in the case of externality, the future of electricity system regulation, load and capacity management, and integration of renewables.

Chapter 2

The role of peer effects and monetary incentives in the diffusion of residential solar PV

2.1 Introduction

Together with externalities and non-rival and non-excludable benefits (Jaffe et al., 2005), incomplete information and information asymmetries, on one side, and decision heuristics and behavioural factors on the other, may also contribute to inertia and slow uptake in the diffusion of low-carbon innovations (Foster and Rosenzweig, 2010). While imperfect information is one of the causes of market failures listed in the standard economic models, and as such it has a longer tradition in economic literature, the discipline's focus on behavioural mechanisms is more recent. Both channels may have effects that spill over from an individual to the other through social interactions or simple physical proximity, therefore violating the standard assumptions of causal inference and requiring more complex estimation procedures and research designs. Moreover, the observational similarities of their effects make separate identification difficult.

This Chapter focuses on how these two channels may explain the presence of peer effects in the uptake of residential solar PV systems. I focus in particular on two spillover mechanisms, social learning through information sharing – within the more standard economic channel – and social utility derived from pressure to conform and imitation as a decision heuristic – representing the behavioural channel. To this aim, I choose residential solar PV systems as the focus of the analysis because it is a visible technology and as such knowledge of who has adopted can be transmitted even without communication. This means that geographical proximity can be used as proxy for the transmission of information and peer pressure rather than actual communication networks, that would be much more difficult to obtain data on.

This technology is also of particular relevance due to its promising role in reducing emissions from electricity generation and therefore in contributing to climate change mitigation. On this account, governments around the world have been experimenting with new measures to support its deployment, with a range of monetary incentives, informational interventions, financing mechanisms, and community initiatives. This provides a fertile setting for academic research, to understand and learn from what has been done and inform future policy design.

Compared to the existing literature, this paper adds more theoretical background to the analysis to suggest possible mechanisms behind peer effects in solar PV adoption. A simple static model sets up the household's decision to install solar panels given the subsidy offered, the upfront cost required to obtain the technology and the information the household has collected. The initial baseline model is then extended to include peer effects according to two different mechanisms. The first one is an imitation behaviour due to the utility premium obtained from conforming with peers and "keeping up with the Joneses" (the social utility channel); this utility premiums can also be seen as savings in the cognitive costs required to make the decision, achieved by using imitation of neighbours' behaviour as a decision heuristic. The second mechanism consists of information sharing at the local level, with peers who have already adopted the technology (the social learning channel). For each channel, propositions are derived on the direction of the peer effects, how they would evolve over time, and how the peer effects would affect the subsidy elasticity. While both mechanisms support the hypotheses that peer effects are present and significant, interact with subsidies and are not constant over time, they predict different patterns of evolution over time. I use these insights from the model to test which mechanism is more consistent with the results from the reduced-form regression analysis, and therefore find evidence on which one is dominant. This paper also looks explicitly at how peer effects and monetary incentives interact and whether they are complements or substitutes, and provides a discussion on how the result could be leveraged in policy design.

The research questions explored in this paper contribute to the broader research question of what are the economic and non-economic determinants of low-carbon technology adoption, at the household level, by combining more standard micro-economic theory of consumers' decisions with the literature on innovation spillovers, imitative behaviour, and social learning. In fact, in terms of policy implications, deployment subsidies are usually justified using environmental externalities or 'learning-by-doing' arguments, but if spillover effects are present then this may be an additional argument to consider, as they might act as a multiplier of the learning-by-doing effect. Any complementarity or substitutability between peer effects and monetary incentives should therefore be factored in when calculating the optimal level of the incentive, as well as its schedule over time.

Section 2.2 presents the main literature on peer effects and solar PV adoptions, as well as other technologies and practices, while Section 2.3 details the model and derive a set of propositions to be tested in the empirical part of the paper. Section 2.4 provides more information on the policy setting and the data used in the analysis, as well as a descriptive analysis of the spatial patterns of adoptions in the UK. Section 2.5 introduces the regression analysis, discussing the challenges to identification, the estimation strategy to address them, and how the estimators and the peer variables are defined; and Section 2.6 presents the results, as well as a series of robustness checks. Finally, Section 2.7 concludes with a discussion of the policy implications.

2.2 Peer effects and technology uptake

Peer effects and solar PV systems

Solar energy generation technologies have seen rapid improvements in the last decades, as well as a steep reductions in their price, making them a promising tool to help reduce emissions and mitigate the climate crisis. Policies that provide support to the development and deployment of these technologies have similarly been experimenting with different designs and frequent adjustments to keep up with the changing situation. This has provided fertile terrain to assess the effectiveness of different policy instruments and research the economic and non-economic mechanisms that drive the uptake of these technologies.

In this context, a literature on the role of peer effects in the adoption of residential solar PV systems and other energy efficiency technologies has developed in the last few years. Wolske et al. (2020) provide a multi-disciplinary review of the literature on peer effects in households' energy-related behaviours, covering studies more specifically on solar panels. Of relevance to this paper, they identify two main channels through which peer effects operate – social norms and interpersonal communication and persuasion – and describe different mechanisms behind each of them. Distinguishing the effects of the two channels using quantitative empirical analysis and observational data encounters several challenges, so that most of the economic literature so far has focused on identifying and quantifying peer effects in general, an already methodologically onerous task.

Bollinger and Gillingham (2012) is one of the very first papers in this literature, studying adoption of solar PV in California. They introduce the identification strategy that several subsequent papers, including this one, use. They exploit the time lag between the decision to adopt solar and the moment in which the panels are actually put on the roof and start producing, which is caused by administrative and bureaucratic requirements. In fact, a household can only be affected by their peers up to the moment in which the decision is taken. Yet, their solar panels will only start influencing others once they are visible on the roof and the household starts having information on their production. They conclude that peer effects are present and are stronger the larger the peer installations are and the closer to the reference household.

Graziano and Gillingham (2015), focus on Connecticut and extend the previous methodologies by applying spatial analysis tools and more explicit spatial variables. They study in particular the role of geography and the built environment and find that rural areas and smaller towns drive the diffusion of solar panels in the State. They confirm that peer effects are positive and significant and find that the influence of peers' installations become weaker the further away in space they are, and the further back in time they were installed.

To overcome the identification challenges of peer effects, Gillingham and Bollinger (2017) exploit the Solarize campaigns as a natural field experiment to study the uptake of solar panels, again in Connecticut. The Solarize scheme combines an informational campaign led by volunteer ambassadors, with group pricing to lower the price of installation, providing different level of price and peer interaction treatments, which the paper uses to estimate the effects. They find the intervention to be highly cost-effective. As the intervention explicitly increases information provision and information sharing, the main channel responsible for the effect appears to be social learning.

Other studies in Europe were conducted by Müller and Rode (2013) and Rode and Weber (2016) for Germany, Baranzini et al. (2017) and Carattini et al. (2018) for Switzerland, and Palm (2017) in Sweden. In particular, Müller and Rode (2013) focuses on only one city and use a discrete-choice framework to model the choice on whether to install or not, given policy support and existing nearby installations, while Rode and Weber (2016) set up an epidemic diffusion model enhanced with a spatial component to capture spatial and temporal patterns of adoption across the whole country. Palm (2017) uses a mix of qualitative interviews and quantitative survey methods in Sweden, and find that, according to households self-reported information, peer effects mainly operated through active interaction within existing social network, rather than passively through simple visibility of the panels, and that households rely on their peers mainly to confirm the functioning of the technology. Carattini et al. (2018) focus instead on Switzerland, and exploit cultural barriers and language differences within the country as a discontinuity design. They find that language barriers hampers adoption of solar PV, suggesting once again that social learning is a relevant mechanism at play. Baranzini et al. (2017) extends the analysis of peer effects in residential solar adoptions to the additional categories of businesses and farms, and to types of installation with different visibility, on the roof as opposed to integrated on the side of a building, and concludes that better visibility is associated with stronger effects, and that while households are influenced by installations in all categories, farms and businesses tend to be influenced only by installations in the same categories, that is farms and businesses respectively. All confirm that peer effects play a relevant role in the adoption of solar technologies.

The main study on the UK, and one of the first economic studies to identify peer effects in residential PV adoptions, is Richter (2014). While in this Chapter I use a similar identification strategies and estimators as in her paper, the key difference is that she uses more standard econometric techniques and does not take into consideration the spatial dimension of the diffusion process beyond the borders of the unit of analysis. Her analysis is also restricted to the first three years of the FIT scheme and uses postcode-districts, a much larger unit of aggregation than the LSOA I use in this paper – for comparison, there are 34,738 LSOAs in England

and Wales, but only 2,269 postcode-district. Spatial analysis on the diffusion of residential PVs in the UK is instead presented by Balta-Ozkan et al. (2015) and Westacott and Candelise (2016), but using cross-sectional data. They therefore provide a snap-shot of the situation in the country at one point in time, and do not research how changes in the policy affect the diffusion at different points in time

The evolution of peer effects in the adoption of residential PV has been investigated from an empirical perspective by Bollinger and Gillingham (2012), using year dummies interacted with the lagged installed base. They find that peer effects in California have strengthened over the years, consistently with the observed introduction of marketing strategies to leverage these effects. Similar results have been found by Graziano and Gillingham (2015) for Connecticut. Richter (2014) uses a similar method for the UK, but with quarter dummies, and finds that peer effects seem to be stronger in periods of policy changes, but overall decrease over time. Finally, Baranzini et al. (2017) estimate the coefficient for neighbouring installations in Switzerland using rolling 4-year samples, and again find evidence that peer effects in PV installations have decreased over time.

Peer effects and other 'green' technologies

Expanding the analysis to other 'green' technologies and spillovers from one technology to another, La Nauze (2019)'s paper on Australia studies how pro-social motivations and virtue signalling of installing solar panels affect purchase of green power in the neighbourhood, and find a positive spillover effect from one technology to the other. Narayanan and Nair (2013) focuses on the adoption of electric vehicles in California, using a clever identification strategy based on different brands of hybrid cars, one that is visibly hybrid and others that are indistinguishable from the regular fuel versions of the same car. Bollinger et al. (2019) focus instead on the adoption of water conservation practices in gardening in California. Their identification strategy is based on an instrumental variable approach, using households that have recently moved to a new neighbourhood.

Other studies rely on field experiments and RCTs to better control for confounders and endogeneity in the identification of peer effects. Alem and Dugoua (2019) for example, conducted an RCT in India offering solar lanterns, and divided their sample into control, unincentivised communication treatment and incentivised communication treatment. They find that communication strongly increases WTP.

Peer effects and agricultural and microcredit decisions

Similar research has been conducted in rural Asia and Africa to study the role of peer effects in the adoption of agricultural technologies and practices, with a particular focus on social learning. Bandiera and Rasul (2006) study peer effects in the adoption of a newly introduced crop, sunflower, using data on farmers' social networks in Mozambique. They find that while peer effects play a role, farmers who have better knowledge and information on the new crop are less influenced by peers. Similarly, Conley and Udry (2010) focus on peer effects in crop choices in Ghana, using explicit data on communication networks; they find positive social learning effects in the case of pineapples, a new crop, but no social learning in the case of crops that are already commonly used, suggesting that information from peers becomes redundant when individuals already have familiarity with the crop. Finally, Di Falco et al. (2020) identify peer effects in the number and type of climate change adaptation strategies adopted by farmers in rural Ethiopia, and construct a placebo test in which neighbours are re-assigned at random to corroborate the finding.

Another recent strand of research looks instead at whether different types of "peers" or information sources have different effects on the outcome. Krishnan and Patnam (2014) introduce a non-overlapping peer-of-peer IV strategy to identify social learning in the adoption of fertilizer and improved seeds in Ethiopia, and find that the effects evolve differently over time depending on whether the information came from neighbouring farmers or extension agents. BenYishay and Mobarak (2019) and Banerjee et al. (2013) study the role of the identity of the "injections points" of a new technology, or of information on a new technology, and use different definitions of social, cultural, and geographic networks to identify peers in agriculture and microcredit respectively.

The interaction between peer effects and monetary variables

To the best of my knowledge, the interaction between peer effects and responsiveness to subsidy has not been explored in the literature on residential PV installations. This paper challenges the null hypothesis of no interaction between the two effects.

The idea of an interaction effect between a monetary elasticity (usually price) and peer effects is not entirely new to the economic literature. One of the first to put the hypothesis forward was Leibenstein (1950). In the paper "Bandwagon, Snob and Veblen Effects in the Theory of Consumers' Demand", QJE, he integrates peer effects (called bandwagon effects in the paper) in the theory of demand, and shows how in the case of a change in price, the demand would change not only because of the direct price effect, but also because of the changes in other people's demand, so that the final elasticity of demand would capture both effects. Another interesting and relevant point is that of social taboos when bandwagon effects are present, i.e. at the beginning no one buys because no one else does, but for some price, enough people would buy despite the taboo triggering the taboo breaking points and starting the diffusion process. This could be relevant for the case of PV as a new technology that is initially frown upon. Following this theoretical framework, some empirical studies have been conducted, especially in the health economic literature, looking at alcohol and smoking. Relevant examples are Manning et al. (1995) and Ayyagari et al. (2013). The closest study in terms of the interaction effect considered is a recent working paper by La Nauze (2019). She finds that solar panels have a positive spillover effect on the purchase of green power, but the effect is smaller when subsidies are higher, possibly because virtue signalling become confused with profit maximisation.

Looking at the interaction between peer behaviour and subsidy is equivalent to ask whether responsiveness to subsidy is heterogeneous depending on how many peers are adopting. Investigating potential heterogeneity in the elasticity to subsidies is particularly relevant for welfare analysis and has important policy implications. In fact, it is critical to understand the impact of changes in the tariff, in terms of who will be more affected, the externalities generated, and the resulting welfare effects. These results could be a starting point to improve the efficiency of the current policy, as well as its distributional effects, or even thinking about new and more sophisticated policy mixes.

Some studies on heterogeneous price elasticity exist in the energy economics literature, although they mainly focus on the interaction with income (Archibald and Gillingham, 1980) or with the level of consumption (for example fuel price elasticity and driving intensity, in Frondel et al., 2012). Another relevant work that tested whether price elasticity changes depending on the level of information consumers have on the good, is Ashraf et al. (2013), in the context of a health product. They conduct a field experiment in Zambia offering water purification products households were not familiar with. The product was offered at different prices and coupled with different levels of information about its use, and the authors find that demand for the product is more elastic when information is provided, therefore suggesting that subsidies are more effective when complemented with informational treatments. Interestingly, they find that the informational effect in isolation does not have any direct effect on the demand for the product.

In order to contribute to this literature, my research focuses on decisional spillovers across space and time – whereby individuals affect each other's decisions via social interaction or simple geographic proximity, and technological choices made in the past provide information, as well as a reference point or 'default' options that will affect future decisions. The effect of social pressure, private and social learning, and information accumulation in these cases is not straightforward. Agents who have a behavioural bias towards the status quo technology (default bias) for example, will require very high net benefits before choosing to switch to the new technology, and may push others to do the same. Similarly, sharing information on the positive externality of the technology and the benefits that are difficult to exclude, may give rational agents an incentive to free-ride and the resulting diffusion of the technology will be socially sub-optimal. On the other side, information sharing and social pressure may trigger cooperative behaviours, via willingness to monitor and sanction, social preferences, or herding and reputational effects of the early adopters.

2.3 Theoretical framework

2.3.1 Model

The model is inspired by the formalisation of the decision to purchase a financial asset in the presence of social learning and social utility presented in Bursztyn et al. (2014, Appendix B), and of the role of peer effects in general in the decision to go see a movie at the theatre, in Moretti (2011). The theoretical framework used draws further inspiration from other relevant articles that model peer effects under social utility and/or social learning to derive hypotheses for empirical testing, in particular Sorensen (2006) for the case of health plan choices, and Young (2009), who characterises the shape of aggregate uptake under different peer effect mechanisms.

Given that economic benefits are often quoted as one of the main incentives in favour of residential PVs, and this was confirmed in qualitative interviews conducted by the author around the country (Standal et al., 2020), the baseline model formalises the decision to install or not install solar panels as a function of the subsidy and the cost of the technology at a certain time and location. The model is then extended to account for peer effects. In particular, I consider two different mechanisms through which peer effects may operate: social utility – which provides a premium for conforming with neighbours who have already adopted and triggers imitative behaviour – and social learning – where households who have already installed provide an additional source of information at the local level. These two mechanisms result in a set of hypotheses on the pattern of solar PV adoption that are then tested in the empirical section of the paper.

It is to be noted that this model regards decisions as static, i.e. households decide *whether* to install or not given present conditions, rather than *when* to install. Bollinger and Gillingham (2012) make the same assumption, supported by the specific context and information collected through a survey. This assumption is also consistent with qualitative interviews conducted by the author. Nevertheless, dynamic versions of this model could be explored in the future, as they would provide further insights into the diffusion of the technology. The framework could also be extended introducing environmental motivations as an additional non-monetary component of the payoff of adoption more generally. Heterogeneity of motivations and sophistication of the households would also be interesting extensions to explore in the future.

The model presented is intended to capture the main features of early stages of the adoption process, when saturation of the market is not yet an issue. This is appropriate for the UK in the period considered, as at the end of 2016 90% of the LSOAs had a penetration of residential solar panels of less than one system for every 10 owner-occupied houses, and half of the LSOAs had less than one solar installation for every 37 owner-occupied houses. And this is not considering houses occupied by tenants nor any block of flats, social housing or multi-family property or any other residential dwelling not classified as house. The potential market is therefore likely to be even larger.

Baseline model, no peer effects

In the case of innovative technology, it is common to assume that there is inertia in the diffusion process (Young, 2009; Richter, 2014). This can be included in the model by assuming that in each period and in each location, i.e. for each combination (l, t), only a fraction α of all the suitable households that constitute the potential market for solar PV systems consider installing solar panels. If household i is among those ones, they decide whether to install a solar PV system ($q_{i,l,t} = 1$) or not ($q_{i,l,t} = 0$) given the conditions in that location at that time. Aggregating the individual decisions gives $Q_{l,t} = \sum_{i\in(l,t)} q_i$, the total number of households installing in location l at time t. In what follows, I drop the subscript l and t for ease of exposition.

The decision set for household i is therefore $q_i = \{0, 1\}$. I assume that once a household has installed solar panels, they are out of the market. Installing the system provides a monetary payoff x, which in the case of the UK represents the periodic FIT payments. The payoff is risky and uncertain, and its realisation follows a probability density function $f(x)$, which is the same for all households within a given location-time combination (l, t), after controlling for covariates. To see why the payoff is risky and uncertain, consider that the FIT payments in the UK depend on the subsidy rate in place at the time the system is registered and the electricity generated by the system in each period. The latter depends in turns on characteristics of the systems, tilt and direction of the rooftop, solar irradiation at the location, but also contextual weather conditions. Moreover, once the household decides to install solar panels, the actual installation occurs at a lag, due to the bureaucracy involved and the time the installer needs to inspect the house, obtain all the components of the systems, connect the wires and inverter to the electric system, and place the solar modules on the roof. By the time the installation is completed and the system can be registered for the FIT scheme, the subsidy rate might have therefore been cut to a lower level. While this example is specific to the context studied in this paper, support schemes for renewable energy and new technologies in general tend to have similar elements of uncertainty and risks.

Household i's utility from installing is given by $u_i(x)$, so that higher payoffs provide more utility, but at a decreasing rate ($du(x)/dx > 0$ and $d^2u(x)/dx^2 < 0$), as commonly assumed in microeconomics. For simplicity, I assume that $u_i(x) =$

$u(x)$ for all i within a given location and time. Each i obtains information on the payoff they can expect given the present conditions, represented by a signal s_i. The signals for all households within a given location and time come from a common distribution, but each household has a different realisation, for example because they look for information from different sources, or ask different questions. Signals are informative, so that if payoff x is higher, households tend to observe higher values of the signal s_i. I follow Bursztyn et al. (2014) and formalise this condition by assuming that conditional density $f(x|s_i)$ satisfies the monotone likelihood ratio property (MLRP).

Household i will install only if the expected utility of adoption is larger than the opportunity cost of adopting, represented by $\bar{u}$. $\bar{u}$ includes the upfront cost of installing. In the baseline scenario, where households are not affected by the decisions of their peers, this translates into:

$$Pr(q_i = 1) = Pr(E(u(x|s_i)) > \bar{u}) \tag{2.1}$$

where

$$E(u(x|s_i)) = \int u(x)\ f(x|s_i)\ dx \tag{2.2}$$

so increases in x and relatedly more favourable signals s_i increase the probability of adoption.

As time passes, it is realistic that households across the country become generally more familiar with the solar PV technology and the support scheme offered, and their sophistication increases. As in Bursztyn et al. (2014), this is rendered in the model by assuming that as time passes the distribution of the signal becomes more precise and its variance decreases: $\sigma^s_{t_2} \leq \sigma^s_{t_1}$ if $t_2 > t_1$. Under continuity and differentiability assumptions this can be written as $d\sigma^s/dt \leq 0$. The precision of the signal per se does not affect $u(.)$, but only means that households make on average more 'correct' decisions, by installing if payoff is high with respect to the opportunity cost, and not installing if it is low, so that $\frac{\partial E(u(x|s_i))}{\partial \sigma^s} = 0$. This is consistent with the finding from Ashraf et al. (2013), reviewed above.

Model with social utility – peer effects as imitative behaviour

When social utility is at play, household i obtains extra utility if they can "keep up with the Joneses" by imitating or conforming to the behaviour of their neighbours (or peers). In this context it is reasonable to assume that utility from adoption – or equivalently the disutility of being the odd one out that does not have solar panels – is therefore higher the more widespread PV systems are in the neighbourhood and the stronger the "social norm" around solar panel is. Let us denote as γ the strength of the social norm, and as Q_{-i} the number of neighbours who have already installed solar panels on their rooftops at the time i is making the decision on whether to adopt. Note that Q_{-i} can be any form of aggregation of the individual installations already existing in the neighbourhood, for example the sum of the installations or the cumulative share, and installations could be weighted depending for example on the distance from i or on how far back in time they occurred. Note that a key identifying assumption in the paper is that an installation can affect peers living in the neighbourhood only once it has been purchased and installed on the roof, and therefore becomes visible to others. Then if $Q_{-i,2} > Q_{-i,1}$:

$$u(x|\gamma, Q_{-i,2})|_{q=1} - u(x|\gamma, Q_{-i,2})|_{q=0} \geq u(x|\gamma, Q_{-i,1})|_{q=1} - u(x|\gamma, Q_{-i,1})|_{q=0} \quad (2.3)$$

that is households who live in neighbourhoods with more installations get higher utility from installing (or higher disutilities from not installing) than households who live in neighbourhoods with lower penetration of the technology, given the same payoff and the same level of social norm; and similarly, if $\gamma_2 > \gamma_1$:

$$u(x|\gamma_2, Q_{-i})|_{q=1} - u(x|\gamma_2, Q_{-i})|_{q=0} \geq u(x|\gamma_1, Q_{-i})|_{q=1} - u(x|\gamma_1, Q_{-i})|_{q=0} \quad (2.4)$$

that is households who install when the social norm towards solar panels is stronger get higher utility from installing (or higher disutility from not installing) than households who install when the social norm is weaker, given the same level of penetration of the technology in the neighbourhood and the same payoff. These results rely on mild monotonicity assumptions on the utility function $u(.)$.

In particular, this can be specified as household i obtaining an additional non-monetary payoff from installing – or social payoff – on top of the monetary payments:

$$x^{social} = g(\gamma, Q_{-i}) \tag{2.5}$$

Function $g(.)$ aggregates the number of peer adoptions and translate them into the social payoff.[1] I do not impose a specific form for the aggregate function, but consistent with the specification commonly proposed in the literature I assume that the social payoff $g(.)$ increases the more peers have already installed: $\frac{\partial g(\gamma, Q_{-i})}{\partial Q_{-i}} \geq 0$. Similarly, the social payoff increases the stronger the social norm is: $\frac{\partial g(\gamma, Q_{-i})}{\partial \gamma} \geq 0$. The social norm acts as a multiplier, so that when the social norm is stronger, one extra installation in the neighbourhood has a stronger impact on i's decision, as compared to the case with a weaker social norm. This can be formalized using the cross derivative $\frac{\partial^2 g(\gamma, Q_{-i})}{\partial \gamma \partial Q_{-i}} \geq 0$. As $g(.)$ increases the total payoff, it also increases the expected utility, so that $\frac{\partial E(u(x|s_i))}{\partial g(.)} = \frac{\partial E(u(x|s_i))}{\partial x} \frac{\partial x}{\partial g(.)} \geq 0$. Utility therefore becomes a function of the two types of payoff, monetary and social:

$$u = u(x^{monetary}, x^{social}) = u(x^{monetary}, g(\gamma, Q_{-i})) \tag{2.6}$$

with utility increasing in each of the payoff ($\frac{\partial u(x^{mon}, g(.))}{\partial x^{mon}} > 0$ and $\frac{\partial u(x^{mon}, g(.))}{\partial g(.)} > 0$). The two payoffs may substitute each other, if keeping up with the neighbours is perceived as equivalent to an increase in the monetary subsidy; or complement each other, if they are perceived as complements, so that keeping up with the neighbours provide even more utility when the monetary payoff is also large, while the utility of conforming is not as large if the monetary payoff is low. The first case seems more intuitive for the setting of the paper, but I will discuss how each assumption affect the hypotheses of the model. If the two payoffs are substitute, increasing one of them results in diminishing marginal utility for the other, so that $\frac{\partial^2 u(x^{mon}, g(.))}{\partial x^{mon} \partial g(.)} \leq 0$ *[substitute case]*. If the payoffs are complement the opposite occurs; $\frac{\partial^2 u(x^{mon}, g(.))}{\partial x^{mon} \partial g(.)} \geq 0$ *[complement case]*. Note that if $g(\gamma, Q_{-i}) = 0$ – i.e. there is no social utility – then

[1]Different type of aggregations have been proposed in the literature, although in general effects are assumed to be cumulative, e.g. $g(q_{-i}) = \sum \theta q_{-i}$ where q_{-i} are the decisions of each of i's peer, and θ is some weighting parameter, representing for example some form of distance between i and each of their peer, or the total number of peers – therefore making the peer effects determined by the share of adoptions in the neighbourhood rather than the count. Cumulative effects can be linear, follow a concave/convex function, therefore becoming weaker/stronger the more adopters there are in the peer group, or act through a threshold effect, with $g(q_{-i}) = I[\sum \theta q_{-i} \geq threshold]$, so that peer adopters only affect decisions after they have reached a critical mass.

$u(x^{monetary}, g(.)) = u(x)$ and the model becomes the baseline model described above.

As in the baseline model, household i will install only if the expected utility of adoption is larger than the opportunity cost of adopting. If social utility is present, this translates into:

$$Pr(q_i = 1) = Pr(E(u(x|s_i, \gamma, Q_{-i})) > \bar{u}) \tag{2.7}$$

where

$$E(u(x|s_i, \gamma, Q_{-i})) = \int u(x^{monetary}, g(\gamma, Q_{-i}))\ f(x|s_i)\ dx \tag{2.8}$$

It is realistic to assume that the social norm around solar panels becomes stronger over time (Carattini et al., 2019), as the climate emergency become more severe and knowledge of their social benefits – such as positive externalities in the form of support to innovation, and reduction of negative externalities, by replacing fossil fuels in energy generation (Benthem et al., 2008) – increases. This is modeled as $\gamma = \gamma(t)$ such that $\gamma(t_2) > \gamma(t_1)\ \forall t_2 > t_1$. Under continuity and differentiability assumptions this can be written as $d\gamma/dt > 0$.

Model with social learning – peer effects as information sharing

In a model with social learning, household i obtains additional information from the actions of their neighbours. Again, the assumption is that an installation can only affect peers living in the neighbourhood once it has been purchased and installed on the roof, and the decision of the household therefore becomes visible to others. Households i therefore obtains information from installations that have already occurred and past actions or decisions of the neighbours, as the contemporaneous decision-making process is not visible. In particular, i infers that the more neighbours have adopted solar panels so far, the better the conditions in the area must be. In fact, neighbours' decisions depend (at least partly) on their private signals, and if they have installed solar panels it means they are likely to have received a favourable signal, given that $f(x|s_i)$ satisfies MLRP. If household i is one of the households considering whether to install solar panels at time t, they can therefore derive a 'social signal' s_i^{social} looking at how many solar panels have been installed in the neighbourhood so far (as only solar panels already installed and visible can provide a signal), and this signal is more favourable the more neighbours have adopted:

$s_i^{social} = h(Q_{-i})$ and $h(Q_{-i,2}) \geq h(Q_{-i,1})$ $\forall Q_{-i,2} > Q_{-i,1}$. Function $h(.)$ aggregates the installations in the neighbourhood in a similar way to function $g(.)$ in the social utility case, but in this case it translates them into an informational signal, rather than a payoff. Under continuity and differentiability assumptions, this can be written as $dh(Q_{-i})/dQ_{-i} \geq 0$.

In the baseline model, i only had a private signal $s_i = s_i^{priv}$. Now, the total information available to i is a combination of the private signal s_i^{priv} and the social signal s_i^{social}. Each signal carries more weight in the decision-making process depending on its precision. As described in the baseline model, the precision of the private signal increases with time, as households become more sophisticated. The total information can therefore be written as:

$$s_i = \phi(s_i^{priv},\ s_i^{soc}) = \omega^{priv}\ s_i^{priv} + \omega^{soc}\ s_i^{soc} = \omega^{priv}\ s_i^{priv} + \omega^{soc}\ h(Q_{-i}) \tag{2.9}$$

where $\phi(.)$ is an aggregation function – for simplicity I assume a weighted average – and ω^{priv} and ω^{soc} are weights, representing the importance given to each type of signal. I assume that weights depend on the precision of the signals, so that a more precise signal carries more weight in the final decision. The weights are constrained to be non-negative and no larger than 1, i.e. $0 \leq \omega^{priv} \leq 1$ and $0 \leq \omega^{soc} \leq 1$.

As remarked in the baseline case, increased precision of either signal implies that i is more likely to make the 'correct' decision according to the payoff, and does not affect utility directly. This means that weights actually reflect the 'relative' precision of the two signals, and if one weight increases the other must decrease. This insures that if the two signals have the same value, a change in their precision does not change the value of ϕ; intuitively, if both signals have the same values and provide the same information, changing the weight of one or the other should not affect the utility. I therefore impose that weights must sum to one: $\omega^{priv} + \omega^{soc} = 1$ or equivalently $\omega^{soc} = 1 - \omega^{priv}$. If $\omega^{soc} = 0$ – i.e. there is no social learning – then $\omega^{priv} = 1$ and $s_i = s_i^{priv}$, and the model becomes the baseline model described above.

The aggregate information is more favourable for the installation of solar panels the more favourable each of the signals is – all else equal – and as before, the expected utility tend to increase on average the more favourable the aggregate information is, because of the MLRP of $f(x|s_i)$, so that:

$$E(u(x|s_i^{priv},\ s_{i,2}^{soc})) \geq E(u(x|s_i^{priv},\ s_{i,1}^{soc})) \quad \forall\ s_{i,2}^{soc} > s_{i,1}^{soc} \tag{2.10}$$

As in the baseline model, household i will install only if the expected utility of adoption is larger than the opportunity cost of adopting. If social learning is present, this translates into:

$$Pr(q_i = 1) = Pr(E(u(x|s_i^{priv}, s_i^{soc}) > \bar{u}) \tag{2.11}$$

where

$$\begin{aligned} E(u(x|s_i^{priv}, s_i^{soc})) &= \int u(x)\ f(x|s_i^{priv}, s_i^{soc})\ dx = \\ &= \int u(x)\ f(x|(\omega^{priv}\ s_i^{priv} + (1-\omega^{priv})\ h(Q_{-i})))\ dx \end{aligned} \tag{2.12}$$

As in the baseline model, precision of the private signal increases as time passes and households become more sophisticated, i.e. $\omega^{priv} = \omega^{priv}(t)$ such that $d\omega^{priv}(t)/dt \geq 0$. In this case, this assumption means that the relative weights given to the private and social signals shift, so that the private signal carries more weight in the decision-making process, and the social signal becomes less important. In fact, $d\omega^{soc}/dt = -d\omega^{priv}/dt \leq 0$ The rationale is that as households become more sophisticated, they can extract more information from their private signal, so that information from the social signal becomes more and more redundant. Consistently, the social signal becomes less precise as time passes, because it depends on the stock of existing solar panels and therefore captures information that was available at different points in the past. In fact, the social signal is a synthesis of the private signals neighbours received at the time they decided to adopt and as the time range gets longer it becomes more and more likely that some of those pieces of information are not relevant any more. The implicit assumption is therefore that information obtained through private sources and through social learning are substitute.

Intuitively, the idea is that at the beginning of the period, solar panels and the subsidy scheme are still very novel and there is not much information available on them, so that households considering solar panels can learn a lot from neighbours who have already done so. As time passes, information on the technology and the subsidy scheme becomes more easily available and accessible everywhere in the country, thanks for example to the news or the internet, so that households can obtain more relevant information privately rather than learning from neighbours who have installed in the past, when the cost of solar panels, the subsidy rate and the technology were likely different from the current one. This assumption is sensible in the empirical setting considered, as the cost of solar panels have been decreasing quickly thanks to competition in the international markets, and the subsidy rate was changed on average once every three or four months between January 2012 and the end of the FIT scheme, in April 2019. This assumption is also consistent with results from the literature, such as Bandiera and Rasul (2006)'s study on the adoption of a new crop among farmers in Mozambique, which found that social learning had a weaker effect on the decision of farmers who started out with better information, and a stronger effect on farmers who had less information. Similarly, Conley and Udry (2010) found that peers' choices have an effect on the adoption of a new crop in Ghana, but no effect on decisions related to an already widespread and better known crop.

2.3.2 Predictions and hypothesis testing

The theoretical framework described above results in a series of propositions on the adoption patterns in the presence of peer effects, the evolution of peer effects over time, and the interaction between peer effects and subsidy responsiveness. The propositions provide hypotheses that can be tested in the empirical analysis, to check whether data are consistent with the presence of peer effects, and which of the two channels – social utility or social learning – is dominant. As the empirical section relies on a reduced form model and quasi-experimental data, the two channels cannot be separately identified, so that if both channels are relevant, the estimated coefficients represent the net effect.

Peer effects lead to clusters of adoption

The first proposition describes how peer effects shape the adoption patterns of residential solar PV systems over space. In this case, both channels lead to the same prediction, which can be used to test whether data are consistent with the presence of peer effects in general:

PROPOSITION 1: *If social utility or social learning are present, household i is more likely to adopt the more existing installations there are in the neighbourhoods, all else equal. If there are no peer effects, then the number of existing installations in the neighbourhood does not affect household i's decision, once all other characteristics are conditioned for. This is equivalent to state that if peer effects are present, then more new installations occur in areas where there is a larger installed base as compared to areas with a smaller installed base.*

Proof. (0) In the baseline case with no peer effects, i decides in isolation and the expected utility does not depend on neighbours' decisions, so $E_{Q_{-i,2}}(u(x|s_i)) = E_{Q_{-i,1}}(u(x|s_i))\ \forall\, Q_{-i,2} > Q_{-i,1}$. Under continuity and differentiability assumptions, and according to equations (2.1) and (2.2) and the way the elements of the model are defined, the same result can be written as:

$$\frac{\partial Pr(q_i = 1)}{\partial Q_{-i}} = \frac{\partial Pr(q_i = 1)}{\partial E(u(x|s_i))} \frac{\partial E(u(x|s_i))}{\partial Q_{-i}} = 0$$

(i) In the social utility case, the more neighbours have already adopted, the larger the non-monetary payoff is, by definition of social utility in the model, i.e. $\frac{\partial g(\gamma,\ Q_{-i})}{\partial Q_{-i}} \geq 0$. This increases utility i, according to equation (2.6), i.e. $\frac{\partial u(x^{mon}, g(.))}{\partial g(.)} \frac{\partial g(\gamma,\ Q_{-i})}{\partial Q_{-i}} \geq 0$. In turns, this pushes up the expected utility of i by mild monotonicity assumptions, and therefore the probability of adoption, according to equation (2.7). The overall result can be obtained by applying the chain rule for derivation on equation (2.8):

$$\frac{\partial Pr(q_i = 1)}{\partial Q_{-i}} = \frac{\partial Pr(q_i = 1)}{\partial E(u(x^{mon}, g(\gamma, Q_{-i})|s_i))} \frac{\partial E(u(x^{mon}, g(\gamma, Q_{-i})|s_i))}{\partial g(\gamma,\ Q_{-i})} \frac{\partial g(\gamma,\ Q_{-i})}{\partial Q_{-i}} \geq 0$$

because each element of the expression is non-negative.

(ii) In the social learning case, the more neighbours have already adopted, the more favourable is the social signal i receives, by definition of social learning in the model, i.e. $\frac{dh(Q_{-i})}{dQ_{-i}} \geq 0$. Household i's aggregate signal on the profitability of installing solar panels is therefore more favourable too, according to equation (2.9): $\frac{\partial s_i}{\partial h(Q_{-i})} = \omega^{soc} \geq 0$, as the weights are constrained between zero and one. Because $f(x|s_i)$ satisfies MLRP, this increases the expected utility of installing for i, as shown in equation (2.10). As a consequence, the probability that i adopts solar panels increases too, according to equation (2.11). Under stricter assumptions on the conditional distribution function, and on continuity and differentiability of the various elements, this result can be summarised using the chain rule for derivation on equation (2.12):

$$\frac{\partial Pr(q_i = 1)}{\partial Q_{-i}} = \frac{\partial Pr(q_i = 1)}{\partial E(u(x|s_i^{priv}, s_i^{soc}))} \frac{\partial E(u(x|s_i^{priv}, s_i^{soc}))}{\partial s_i^{soc}} \frac{\partial s_i^{soc}}{\partial h(Q_{-i})} \frac{\partial h(Q_{-i})}{\partial Q_{-i}} \geq 0$$

because each of the derivative is positive. □

Evolution of peer effects over time

Statically, both channels predict the presence of localised spillover effects that would result in cluster of adoptions, but when time is considered, the two mechanisms lead to different predictions on the evolution of peer effects:

PROPOSITION 2: *If social utility is the dominant channel through which peer effects operate, then the effect of a larger installed base in the neighbourhood becomes stronger over time. Conversely, if information sharing is the dominant mechanism through which peer effects operate, then the effect of a larger installed base in the neighbourhood becomes weaker over time.*

Proof. (i) In the social utility case, as time passes the social norm around solar panels becomes stronger, $\frac{d\gamma}{dt} \geq 0$. Because the social norm acts as a multiplier for the peer effects, when the social norm becomes stronger the effect of one extra installation in the neighbourhood becomes larger, i.e. it provides a larger non-monetary payoff:

$$\frac{\partial^2 g(\gamma, Q_{-i})}{\partial t \partial Q_{-i}} = \frac{\partial \frac{\partial g(\gamma, Q_{-i})}{\partial Q_{-i}}}{\partial \gamma} \frac{d\gamma}{dt} = \frac{\partial^2 g(\gamma, Q_{-i})}{\partial \gamma \, \partial Q_{-i}} \frac{d\gamma}{dt} \geq 0$$

by applying Young's theorem, and because the cross derivative is assumed to be non-negative $\frac{\partial^2 g(\gamma, Q_{-i})}{\partial \gamma \, \partial Q_{-i}} \geq 0$, as described in the set-up of the model. Therefore as time passes ($t \uparrow$) the effect on the social payoff of one additional installation in the neighbourhood increases ($\frac{\partial g(\gamma, Q_{-i})}{\partial Q_{-i}} \uparrow$), and as a direct consequence, the effect of one additional peer installation on the utility increases as well ($\frac{\partial u(x^{mon}, g(.))}{\partial Q_{-i}} \uparrow$). This result carries over to the expected utility ($\frac{\partial E(u(x^{mon}|s_i, \gamma, Q_{-i}))}{\partial Q_{-i}} \uparrow$), and by equation (2.7), to the probability of adoption. At the same time, sophistication of the households increases, which in the model translates into a more precise signal. But as described in the model, higher precision per se does not affect the payoff of i, but only decreases the standard deviation of the distribution function $f(x^{mon}|s_i)$. In the social utility case, neighbouring installations and signal do not interact, so changes in the precision do not affect the strength of peer effects. Therefore the overall result is that the strength of peer effects increases over time.

(ii) The opposite occurs in the social learning case, as there is no social payoff – i.e. $g(\gamma, Q_{-i}) = 0$ – and therefore the social norm does not enter the model, but peer installations do affect the signal. As described in the model, as time passes households' sophistication increases, translating into a more precise private signal, and therefore more weight being put on the private signal rather than on the social signal when making a decision, i.e. $\frac{d\omega^{priv}}{dt} \geq 0$ and $\frac{d\omega^{soc}}{dt} \leq 0$ because $\omega^{soc} = 1 - \omega^{priv}$. Peer installations do not interact with the private signal directly, so the effect of one additional installation in the neighbourhood always has the same effect on the private component of the signal, which is zero. Different is the situation for the social component of the signal, as the effects of time and additional installation are both relevant and move in opposite direction – in fact, one additional installation makes the social signal more favourable, therefore increasing the expected utility from adoption, but as time passes the weight given to the social signal is lower, therefore decreasing its effect on the final probability of adoption. This can be written using cross-derivatives, as:

$$
\begin{aligned}
\frac{\partial^2 s_i}{\partial t \partial Q_{-i}} &= \frac{\partial((1-\omega^{priv}(t))\ h(Q_{-i})}{\partial t \partial Q_{-i}} + \frac{\partial(\omega^{priv}(t)\ s_i^{priv})}{\partial t \partial Q_{-i}} = \\
&= \frac{\partial(1-\omega^{priv}(t))\ \frac{\partial h(Q_{-i})}{\partial Q_{-i}}}{\partial t} + 0 = \\
&= \frac{\partial(1-\omega^{priv}(t))}{\partial t}\ \frac{\partial h(Q_{-i})}{\partial Q_{-i}} + (1-\omega^{priv}(t))\ \frac{\partial^2 h(Q_{-i})}{\partial t \partial Q_{-i}} = \\
&= -\frac{d\omega^{priv}(t)}{dt}\ \frac{\partial h(Q_{-i})}{\partial Q_{-i}} + 0 = \\
&= -\frac{d\omega^{priv}(t)}{dt}\ \frac{\partial h(Q_{-i})}{\partial Q_{-i}} \leq 0
\end{aligned}
$$

which holds because $\frac{d\omega^{priv}}{dt} \geq 0$ and $\frac{\partial h(Q_{-i})}{\partial Q_{-i}} \geq 0$. Therefore as time passes ($t \uparrow$) one additional installation in the neighbourhood has a smaller effect on the overall signal ($\frac{\partial s_i}{\partial Q_{-i}} \downarrow$), which means that the effect on the expected utility – and by equation (2.11) on the probability of adoption – will also become weaker ($\frac{\partial E(u|s_i^{priv},\ s_i^{soc})}{\partial Q_{-i}} \downarrow$).

Therefore, one extra installation in the neighbourhood has a smaller effect on the probability of adoption, as time passes. This result relies on the assumption that information obtained through private sources and through social learning are substitute and that as time passes private information is more reliable than the social signal, because general knowledge of the topic is more widespread and sources of information are more accessible, facilitating private learning, while information provided by neighbours who have installed solar panels in the past becomes more and more out-dated. □

Interaction between peer effects and subsidy responsiveness

Predictions with respect to the interaction between peer effects and subsidy responsiveness depend on more specific assumptions on how elements of the model interact, but can still be helpful to characterise the empirical results:

PROPOSITION 3: *If social utility is the dominant channel then a change in subsidies – i.e. the monetary payoff – triggers a smaller response in areas with higher penetration of the solar panels if the monetary and social payoff are substitute; the opposite occurs if the two payoffs are complements. If information sharing is the dominant mechanism then the responsiveness to a subsidy can increase, decrease or stay the same where more neighbours have installed, depending on whether each additional installation carries more information than the previous one (for example because the more people install the more they prove that solar panels can be profitable for a wide range of house types and lifestyles), less (for example because information starts getting redundant), or the same.*

Proof. (i) In the social utility case, an increase in the monetary payoff increases utility, as does one extra installation in the neighbourhood, according to equations (2.5) and (2.6). In the *substitute case*, because of diminishing marginal utility, one extra installation in areas where the subsidy is larger has a smaller effect on i's expected utility if compared to the effect where the subsidy is lower. Equivalently, an increase in the subsidy has a smaller impact on i's expected utility if there are more installation in the neighbourhood, as compared to an area with fewer installation. The opposite occurs in the *complement case*, as more neighbouring installations and larger subsidies boost each other's effect. This can be formally shown as:

$$\begin{aligned}\frac{\partial^2 u(x^{mon}, g(\gamma, Q_{-i}))}{\partial x^{mon} \partial Q_{-i}} &= \frac{\partial \frac{\partial u(x^{mon}, g(\gamma, Q_{-i}))}{\partial Q_{-i}}}{\partial x^{mon}} = \frac{\partial \left(\frac{\partial u(x^{mon}, g(\gamma, Q_{-i}))}{\partial g(\gamma, Q_{-i})} \frac{\partial g(\gamma, Q_{-i})}{\partial Q_{-i}} \right)}{\partial x^{mon}} = \\ &= \frac{\partial^2 u(x^{mon}, g(\gamma, Q_{-i}))}{\partial x^{mon} \partial g(\gamma, Q_{-i})} \frac{\partial g(\gamma, Q_{-i})}{\partial Q_{-i}} + \frac{\partial^2 g(\gamma, Q_{-i})}{\partial x^{mon} \partial Q_{-i}} = \\ &= \frac{\partial^2 u(x^{mon}, g(\gamma, Q_{-i}))}{\partial x^{mon} \partial g(\gamma, Q_{-i})} \frac{\partial g(\gamma, Q_{-i})}{\partial Q_{-i}} + 0 \\ &= \frac{\partial^2 u(x^{mon}, g(\gamma, Q_{-i}))}{\partial x^{mpn} \partial g(\gamma, Q_{-i})} \frac{\partial g(\gamma, Q_{-i})}{\partial Q_{-i}} \end{aligned} \tag{2.13}$$

by applying Young's theorem and the fact that $\frac{\partial^2 g(\gamma, Q_{-i})}{\partial x^{mon} \partial Q_{-i}} = 0$ as the monetary payoff is not a direct component of the social payoff, even though the two payoffs interact. Given that $\frac{\partial g(\gamma, Q_{-i})}{\partial Q_{-i}} \geq 0$, the sign of expression (2.13) is determined by the cross-derivative of utility with respect to the two payoffs. By definition, the latter is negative if the two payoffs are substitute, and positive if the two payoffs are complements. If the effect on the expected utility becomes weaker/stronger, so does the effect on the probability of adoption, by equation (2.7).

(ii) While in the social utility case Q_{-i} only affects the total payoff, in the social learning case Q_{-i} only affects the signal the household receives. Both an increase in the payoff x and in the penetration of the solar panels in the neighbourhood Q_{-i} have a positive effect on the expected utility, but whether the two effects complement, substitute or are independent of each other depends on the functional form of $f(x|s)$. This can be seen, for example, by considering that if an area receives a relatively lower subsidy due to worse generation potential or because of a (past) change in the subsidy rate, this affects i, but would have also affected their neighbours in the same direction. This can be written as $Q_{-i} = Q_{-i}(x)$ with $\frac{dQ_{-i}}{dx} \geq 0$. The two variables are therefore interacting within the signal function. The interaction within the social signal can be written as a cross-derivative of the signal with respect to each of the two variables that are changing:

$$\begin{aligned}\frac{\partial^2 s_i^{soc}}{\partial x \partial Q_{-i}} &= \frac{\partial^2 h(Q_{-i}(x))}{\partial x \partial Q_{-i}} = \frac{\partial \left(\frac{\partial h(Q_{-i}(x))}{\partial x} \right)}{\partial Q_{-i}} = \frac{\partial \left(\frac{\partial h(Q_{-i}(x))}{\partial Q_{-i}} \frac{\partial Q_{-i}(x)}{\partial x} \right)}{\partial Q_{-i}} = \\ &= \frac{\partial h(Q_{-i}(x))}{\partial Q_{-i}} \frac{\partial \left(\frac{\partial Q_{-i}}{\partial Q_{-i}} \right)}{\partial x} + \frac{\partial Q_{-i}(x)}{\partial x} \frac{\partial^2 h(Q_{-i}(x))}{\partial Q_{-i}^2} = \\ &= \frac{\partial Q_{-i}(x)}{\partial x} \frac{\partial^2 h(Q_{-i}(x))}{\partial Q_{-i}^2}\end{aligned}$$

Given that $\frac{dQ_{-i}}{dx} \geq 0$, the sign of the cross-derivative is the same as the sign of the second derivative of the signal with respect to peer installations, which is undetermined unless more assumptions on $h(Q_{-i})$ are made. Therefore whether the effect of a change in subsidy increases, decreases or stays the same depending on the number of nearby installations – or equivalently, whether the influence of nearby installations is stronger, weaker or the same depending on the amount of subsidy offered – depends on whether each additional installation provides more, less or the same amount of information than the previous one, that is whether information travels faster, slower or at the same rate, when there are more installations in the neighbourhood. Given the general formulation of the model, the sign of the interaction is therefore not determined without imposing further assumptions on the functional form of $f(x|s)$. In this model I assumed for simplicity that the private signal and the precision of the signals do not depend on Q_{-i}, and that the aggregate signal s_i is linear in the private and social component. A different specification of the aggregate signal could introduce another channel of interaction between x and Q_{-i}, but the proposition would still be inconclusive unless more assumptions on the functional forms are made. □

2.4 Background information and data

Between 2010 and 2019, the UK supported small-scale clean electricity generation through a Feed-In Tariff (FIT) scheme, which covered solar PV, wind turbine, hydroelectric, micro combined heat and power (CHP), and anaerobic digestion. The scheme provides direct economic benefits for the owner of the system through two types of tariffs, the generation or production tariff, for generated electricity, and the export tariff, for the electricity that is sold to the grid. For residential solar PV, the production tariff is paid on the total amount of generated electricity, recorded by an appropriate meter, while the export tariff is paid on the assumption that 50% of the electricity generated is exported, as the amount effectively exported is not currently metered. Owners obtain further indirect benefits through savings in the electricity bills, as the generated electricity can be used for free reducing the amount of energy that has to be bought from the utility.

The tariff rates are assigned according to the date of the installation, with different values depending on the technology and the capacity of the system. These rates are then paid for 20 years (25 for solar installations in the early years of the scheme, later shortened to 20 as for the other eligible technologies), and are progressively adjusted for the inflation, according to the changes in the Retail Price Index over the previous year. The budget for the scheme came from the general electricity bills of all energy suppliers' customers - as it is the case for other energy-related schemes in the country. The scheme was reformed various times since its inception in April 2010, and closed to new applicants in March 2019.[2] The evolution of the FIT for residential solar systems (systems $\leq$4kW), is shown in Figure 2.1.

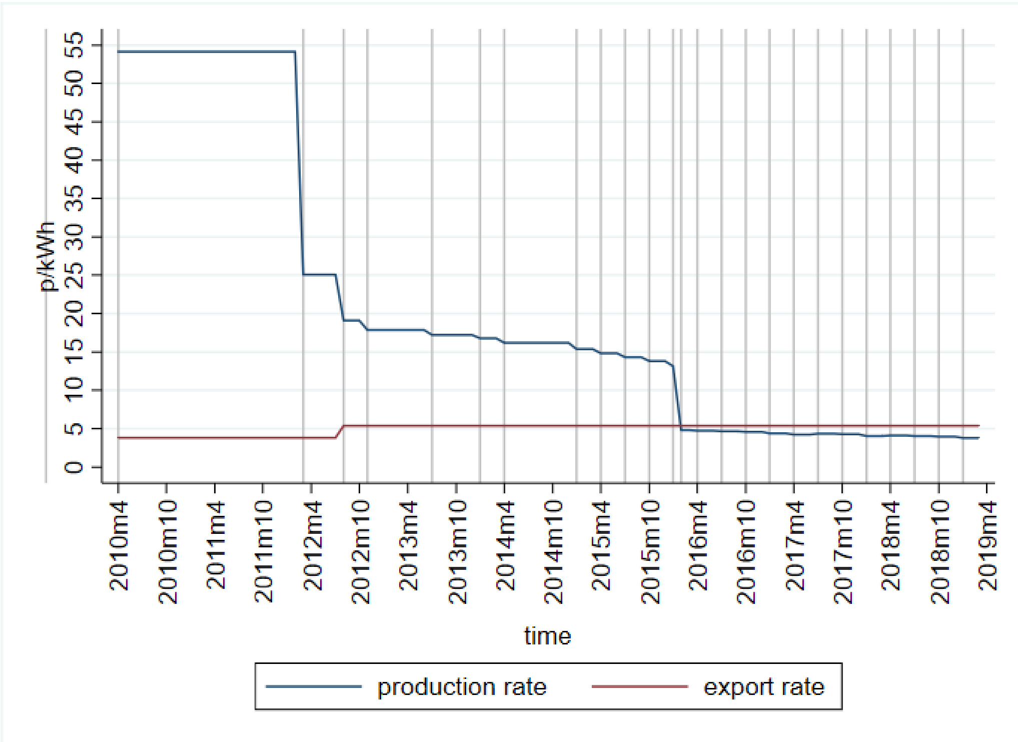


Figure 2.1: Changes in the FIT. Vertical lines represent the date the changes were implemented. Own elaboration on data from Ofgem.

Quoting the sustained decrease in the price of solar PV as the main rationale, the production tariff has been repeatedly adjusted downward, moving from almost 54 p/kWh in 2010 to 4 at the beginning of 2017.[3] Major reforms to the value of the tariff and other features of the scheme were introduced in 2012 and 2016. In particular, an automatic quarterly degression mechanism was introduced at the end of 2012. The degression mechanism was pegged to pre-determined deployment ob-

[2]Details on the various phases and reforms of the policy are provided by the Department for Business, Energy and Industrial Strategy (BEIS), into which the Department of Energy and Climate Change (DECC) was merged in 2016, and the Office of Gas and Electricity Markets (Ofgem).

[3]Rates are adjusted every year based on the retail price index (RPI), to account for inflation. In the Chapter the RPI-adjusted rates as they were at the time the scheme was closed in 2019 are used.

jectives. If these were not met and uptake was lower than the required threshold, the degression was postponed for up to two consecutive quarters. In this way, the tariffs could be progressively reduced in line with the reduction in costs and increase in uptake without the need for government intervention, therefore reducing uncertainty in the sector. The scheme was initially intended until 2015, triggering a period of policy uncertainty as reforms to the system were discussed and the renewal of the scheme was questioned. The FIT scheme was then suspended at the beginning of 2016, before being reformed and re-instated in February of the same year, to run until March 2019, after which the scheme was closed to any new applicant. Contrarily to the production tariff, the export tariff rate has undergone fewer amendments, and was adjusted upward, from 3.57 p/kWh to 5.03 p/kWh in 2012. These progressive changes to the policy provide the main source of variation over time for the identification of the responsiveness to subsidies (see following sections).

Aggregated data and trends on adoption of small-scale PVs in the UK are presented in Figg. 2.2 and 2.3. Domestic installations of up to 4kW constitute the vast majority of small-scale electricity generating installations in the UK, both in terms of number and aggregated capacity. The trends in both figures present evident changes in correspondence of the major policy reforms of 2012 and 2016. In the regression analysis I only use observations between April 2012 and December 2015, to avoid periods of policy uncertainty and instability in the solar market, and because there were no changes in the FIT rate before 2012. On top of the quantitative data described in the next paragraphs, the analysis and interpretation of results in this paper is informed by qualitative evidence from in-depth interviews conducted within the ENABLE.EU project and described in Standal et al. (2018) and Standal et al. (2020).

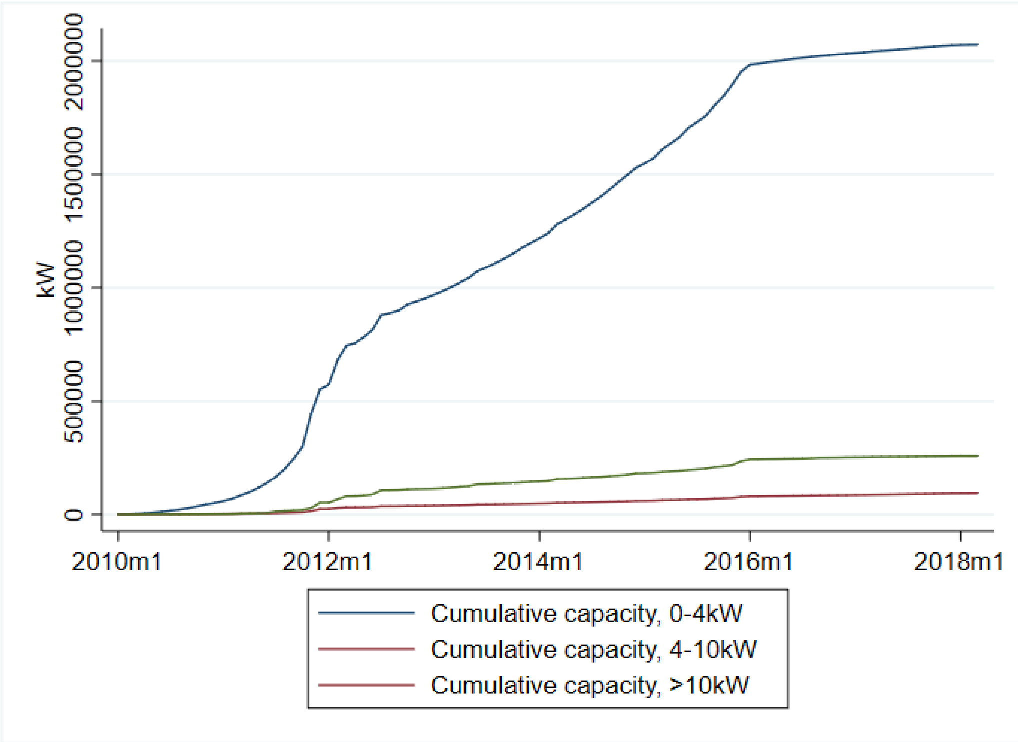


Figure 2.2: Cumulative installed capacity in the UK (kW), by month. Own calculation on Ofgem data.

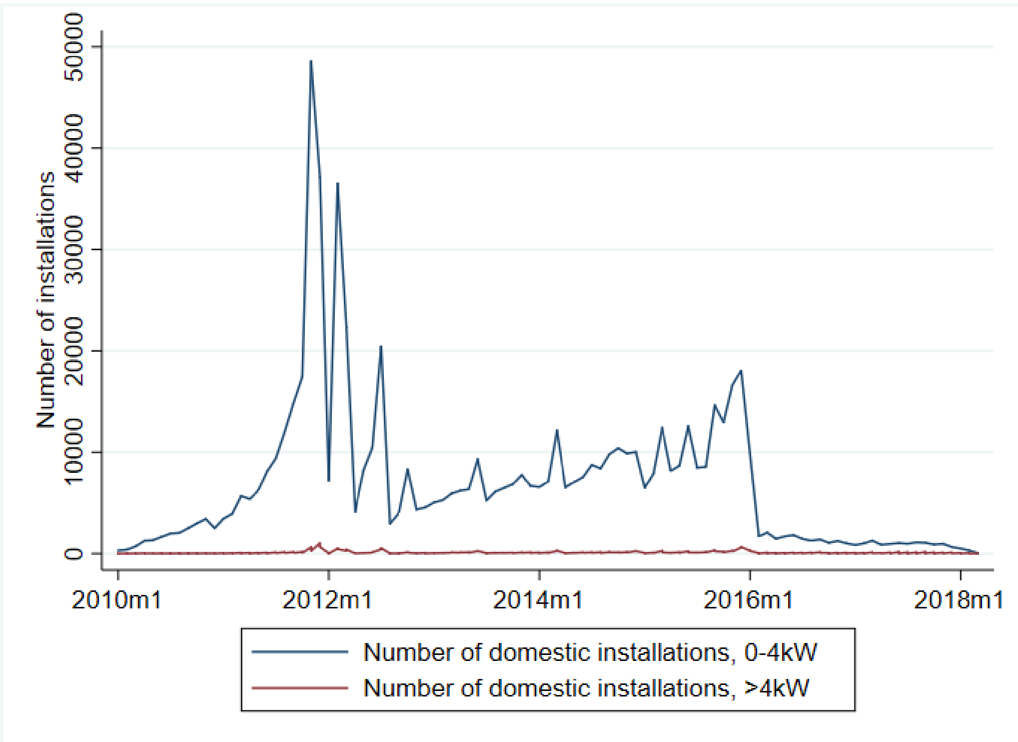


Figure 2.3: Number of installations in the UK, by month. Own calculation on Ofgem data.

2.4.1 LSOAs and distribution of the PVs

The units of analysis for the empirical specification are the Lower Layer Super Output Areas (LSOAs) as defined in the 2001 Census. The choice of LSOAs as aggregation level is driven on one side by the availability of geographic information for PV installations which could not be obtained at a more disaggregated level, but at the same time is preferred over post code district (the other available unit) due to the way they are constructed. In fact, the LSOAs are statistical units purposedly built to insure within-homogeneity and between-comparability in the context of Neighbourhood Statistics and Census data collection. Each LSOA contains typically four to six Output Areas so to be roughly comparable to the others in terms of resident population, with a minimum of 1,000 residents and an average of 1,500 (equivalent to 650 households). Geographic proximity and information on the prevalent type of dwelling, tenure, etc. are also used to ensure a compact shape and socio-demographic homogeneity[4]. These are all desirable properties for an areal unit in spatial analysis, given that the exact coordinates of the installations are not available. Nevertheless, we must be aware of the Modifiable Areal Unit Problem which comes with such aggregations, and an extension of the present work may check the robustness of the results when other specifications are chosen (e.g. MSOAs or postcode district. See Briant et al., 2010 for the general issue and Flowerdew, 2011 for the specific case of UK Census data).

The final dataset consists of a panel of monthly observations for the 34,378 LSOAs in England and Wales, according to the 2001 definition.[5] Some LSOAs were merged or split in 2011, due to changes in their composition, however, only 2.5 per cent of 2001 LSOAs were affected.

Data on residential PV installations are retrieved from the Ofgem databank of Feed-In-Tariff recipients. Each installation record contains among other pieces of information the LSOA and the commissioned date. I restrict the analysis to focus on solar PV systems classified as residential and up to 4kW of declared capacity, as this is the size that receives the highest FIT rate and does not require an authorization to be installed and connected to the grid. As seen in the previous section, this is by far the largest share of installations under 5MW in the country, both in terms of number

[4]The official definition and methodology are provided by the Neighbourhood Statistics division of the Office for National Statistics (ONS).

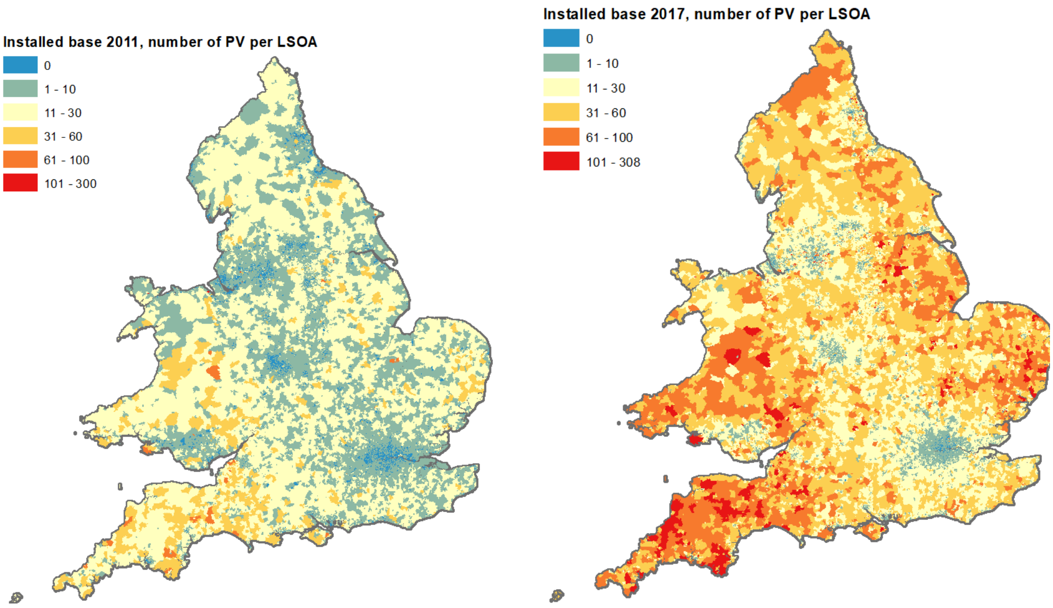
[5]No comparable units exist for Scotland and Northern Ireland.

and in terms of installed capacity. The total stock of PV systems in each LSOA is presented in Figure 2.4 for 2011 and 2017. Consistent with the literature, the installations are mainly concentrated in rural and less dense regions, while the major cities - London in particular - display a substantially lower installed base. Although income is often considered as a determinant of PV adoption, both directly, because of the investment required, and indirectly, as higher-income households are more likely to live in a house rather than in a flat and to be owners rather than tenants – both characteristics that economic theory would predict to be linked with increased adoption of solar PVs – there does not seem to be a visible positive correlation between the two variables, as the wealthy South-East has a relatively low number of adoptions, while the South-West and part of Wales have the highest installed base in the country, despite not being rich areas. At the same time the area around Leeds is relatively wealthy and rich in residential PVs, and the northernmost parts of Wales and Yorkshire are neither. Solar irradiation is another potentially relevant variable, as it is the key determinant of PV electricity yield. Again, if compared with the PV distribution maps, it can be seen that although some areas, such as the South-West, have a consistent positive relationship between insolation and PV adoption, the situation in other areas is more puzzling, with the South-East showing substantial unexploited potential for solar power, while adoption is higher at the border with Scotland despite receiving considerably less solar radiation.

The main outcome variable considered in the paper is the count of new installations in an LSOA in a given month. To check the robustness of the results and investigate additional hypotheses on how peer effects may work, in the regression analysis I consider alternative specifications using the total new installed capacity and the average size installed (both in kW) in an LSOA-month. Characteristics of the LSOAs, including mid-year population estimates and age distribution, and the number of houses (as opposed to apartments) inhabited by their owners are obtained from the 2011 Census and related databases. Summary statistics are presented in Table B.1.

2.4.2 FIT payments

To capture the effect of the monetary incentives offered for the adoption of micro-generation technologies, I need a measure of the potential revenues that can be



(a) 2011 (b) 2017

Figure 2.4: Geographical distribution or residential solar PV systems in England and Wales.

expected from the production and export tariff provided by the FIT scheme. I construct this variables in the same way as I did in the previous Chapter of this dissertation, but using data at the LSOA level instead of the larger MSOA level.

In particular, I obtain data on the estimated annual electricity output for a solar module of 1kW capacity situated at the population-weighted centroid of each LSOA, for each year between 2009 and 2016. This dataset is constructed using the Photovoltaic Geographical Information System (PVGIS) of the EU Joint Research Centre Institute for Energy and Transport (PVGIS European Communities, 2001-2017).[6] Details on the methodology and the dataset can be found in Huld and Amillo (2015) and Huld et al. (2012). Estimation are based on the solar irradiation of the location and the actual climatic and meteorologic conditions of the location during the year, assuming standard values for the tilt, azimuth and direction of the roofs.. I average these estimates through the available years to obtain a measure of "expected generation" per kW of installed capacity for each LSOA. The resulting distribution of average or expected generation over England and Wales is presented in Figure 2.5. I consider this to be the generation amount that households living in the LSOA consider when making their decisions to purchase solar panels or not.

[6]Data were obtained from the European Commission Joint Research Centre in Ispra. Values are based on the PVGIS SARAH database. More information on the data and methodology can be found at https://ec.europa.eu/jrc/en/PVGIS/docs/methods.

The average annual generation for each LSOA is then multiplied for the FIT rate in force in each month, to obtain the average annual subsidy a household installing in that LSOA and in that month can expect to receive in each of the 20 years covered by the FIT scheme. In particular, the owner of the system is paid a production rate for the electricity generated, and an export rate for 50% of the total generation, which utilities assume to be the quantity exported to the grid, as the actual exports are not metered. In this way, I obtain a panel dataset of expected or average annual subsidy per kW of installed power that varies in both space and time. This variation is exploited to identify how households' react to changes in subsidy.

Summary statistics are presented in Table B.1. The average subsidy varies from more than 1200 GBP per year for an average system of 3kW at the start of the scheme, to between 450-600 GBP after the reforms in 2012, to only around 195 GBP after the 2016 reform. In terms of variation in space, households in LSOA with the worst solar generation potential could expect to receive 1184 GBP per year for a 3kW system, while households in LSOA with the highest expected generation could expect 1893 GBP per year for the same system. The range of the potential revenues for each month are presented in Figure 2.6, together with the trend in adoptions around the country. It is easy to see how installations drop in correspondence with cuts in the subsidies.

2.4.3 Investment cost to adopt solar

For the cost of the system, I use data at the postcode distric per month level as constructed in the previous Chapter of this dissertation. Namely, I requested and obtained data on the median cost per residential installations under 4kW (the subset of installation I focus on in this paper) from the Micro Certification Scheme (MCS), a registry to which FIT-eligible micro-generation system must apply. Data were provided per postcode area per quarter, as the most disaggregated level the registry was willing to share. These data are provided per installation, and I convert them into cost per kW using information on the median installed system in the corresponding area in that given period. To check for consistency and obtain monthly variation, the monthly average and median costs per kW installed for the whole country were obtained from DECC (2017), for years between 2013 and 2017, and from Green Business Watch (2017) for years between 2010 and 2013.

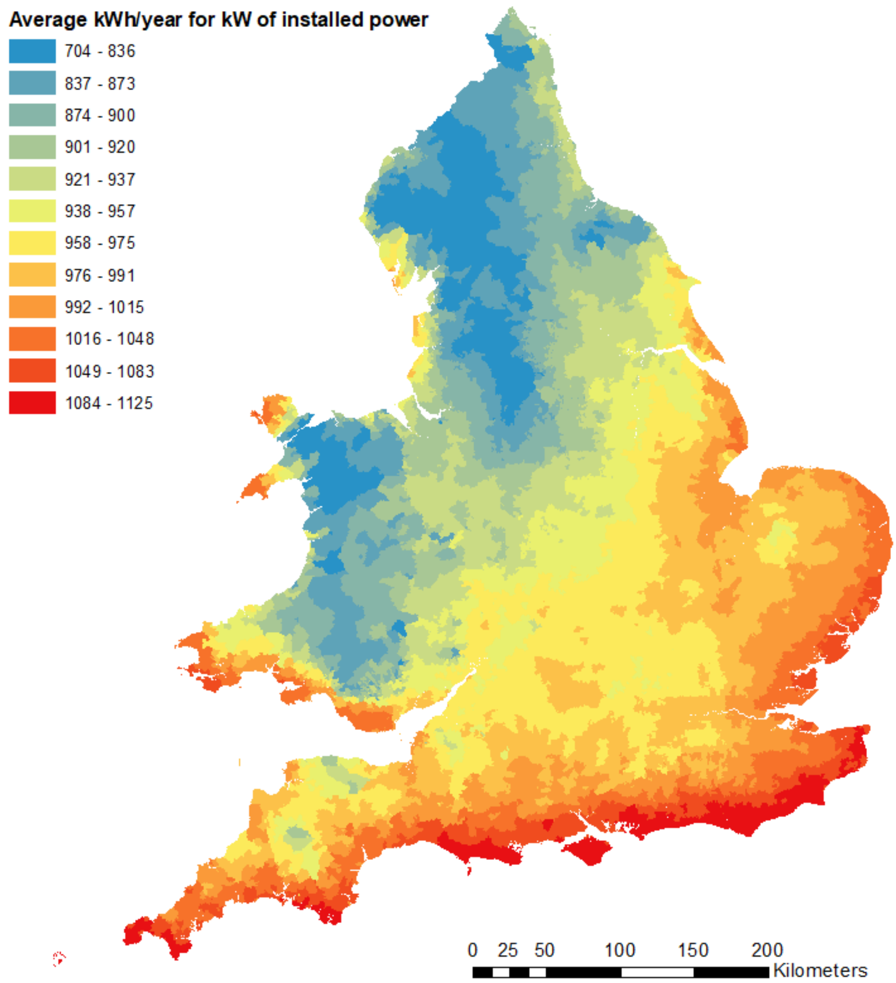


Figure 2.5: Annual electricity generation of residential solar PV systems, kWh/year for kW of installed power. The value is an average of estimates for 2009-2016. Own elaboration on Photovoltaic Geographical Information System (PVGIS) data.

The main issue to address to use this data in the analysis is the problem of missing values, due to cases in which the cost was not reported or simply there was no installation in the area and period considered. I therefore interpolate missing values within each area by using observations for periods before and after the missing observation in that same area, to fill the gaps in the time series. To convert these data from postcode areas into MSOA, I record for each MSOA the cost of the postcode area in which it is contained, or the average of different postcode areas if the MSOA crosses the postcode boundaries. For areas with missing data throughout the period, and for the months before the first recorded cost and after the last one, I impute the cost by using the average value for the administrative region[7] to which the MSOA belongs. To support the choice of this type of imputation, I consider evidence from several installers' websites and interviews with households who installed solar panels that confirmed that installers have large catchment areas, and given the margin of profits available on the service and the fact that some components need to be shipped from other countries or storehouses anyway, are willing to carry out installations even in areas quite far from their main location In addition to this, supermarket chains such as Tesco and later Ikea have been offering solar systems and installation services around the country, which should have insured a level of competition among suppliers, making the price required of customers more homogeneous.

As a last step, to obtain monthly data I first assign to each month the observation from the quarter it is in, and then replace it with the average over the two months before and two months after, using a moving average approach. In this way I smooth the trends and avoid having large changes from one quarter to the next and no changes within each quarter. Box-plots for the resulting variable is presented in Figure 2.7 and summary statistics are presented in Table B.1. The average costs obtained with this methods are very close to the official data on the monthly average for the country. Due to the measurement issues with this variable, I only use it as a control in the analysis and not as a regressor of interest. I conduct robustness checks dropping the cost variable and therefore implicitly assuming that the effect of the cost is captured in the time-varying fixed-effect component, and the results are not affected.

[7] England and Wales are divided into 10 administrative regions; this is therefore a higher level of aggregation with respect to either postcode areas or MSOAs.

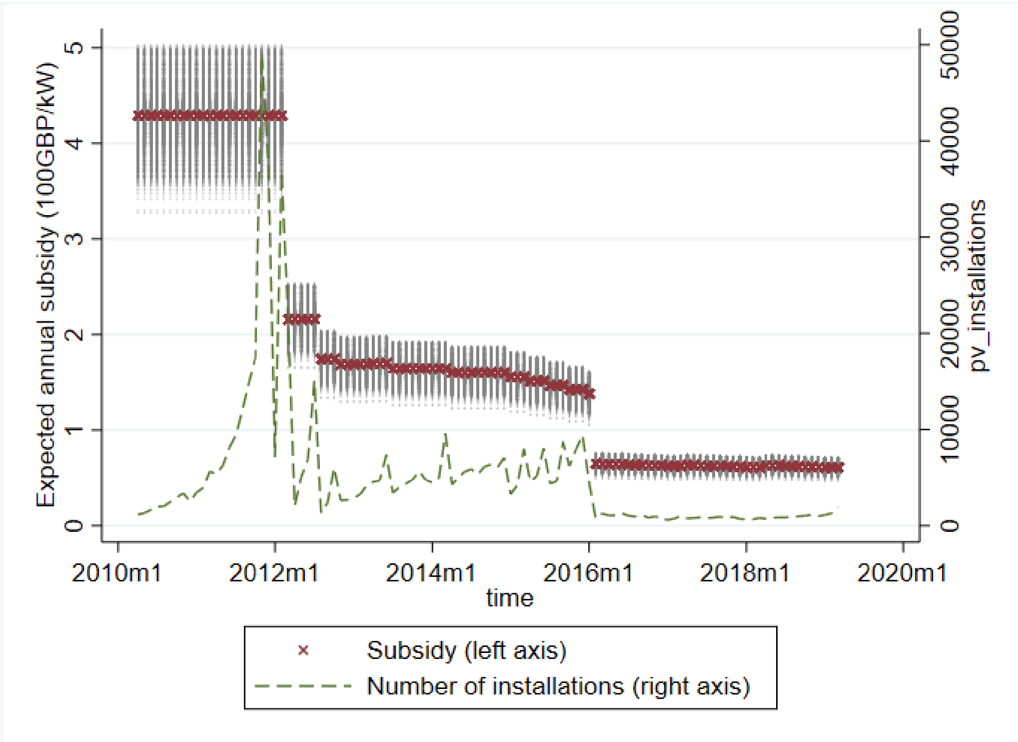


Figure 2.6: Expected annual revenues for kW of installed power, according to month of installation and location (left axis; average value highlighted), and number of residential PV installations in each month (right axis). Own calculation on Photovoltaic Geographical Information System (PVGIS) data and Ofgem data.

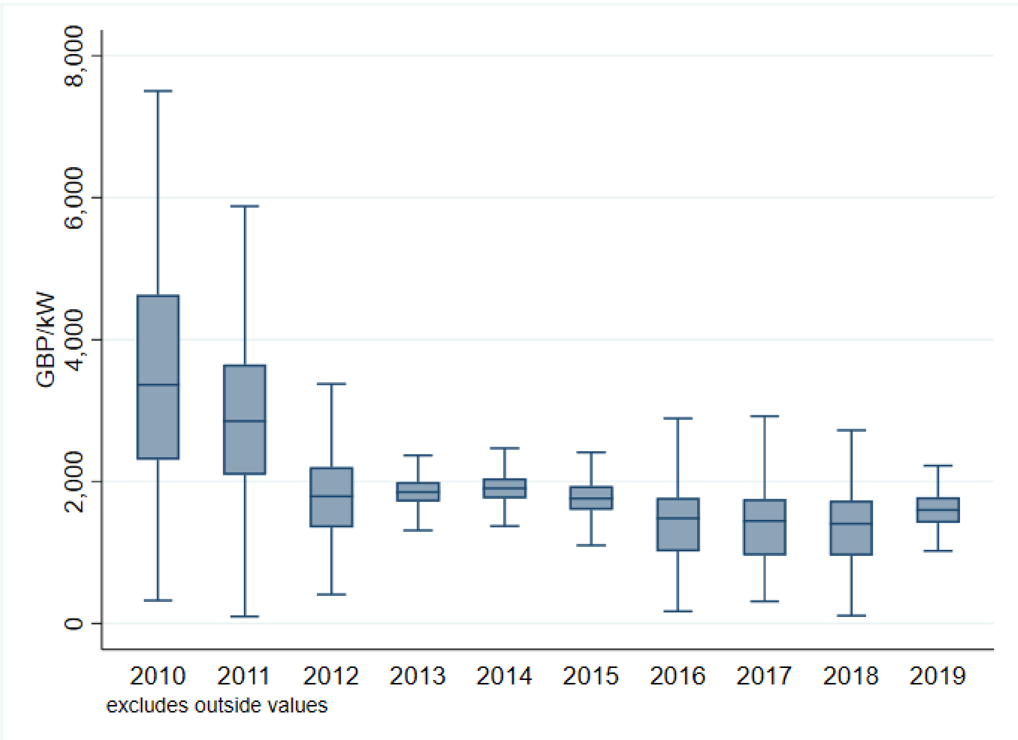


Figure 2.7: Trend in the cost of residential solar PV systems. Own elaboration on data from MCS.

2.4.4 Spatial patterns

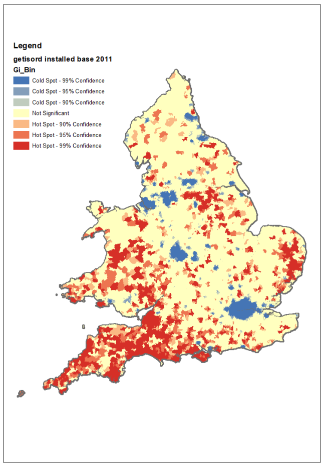
Getis-Ord hot-spot analysis

To confirm the presence of clusters of installations, or 'hot spots', I use the Optimised Getis-Ord method devised by Getis and Ord (1992) and Ord and Getis (1995), where the parameter for the threshold is determined within the system so to optimize the balance between the observation size and the statistical significance of the method. The results for spatial correlation of the installed base (stock variable) are presented in the top row of Figure 2.8 for the year 2011, 2013 and 2016. Clusters in the diffusion of PV systems appears to be pervasive throughout the period, with large hot spot areas in the South-West of England, and in central and south Wales, and clusters in the central-eastern part of the country that become increasingly more important as time passes. Cold spots are also present, although in smaller quantities, and are located in correspondence with the big cities. A possible explanation of such pattern is that urban areas have fewer buildings which are suitable for PV installations, for example due to shading from nearby buildings, and more tenants rather than owner-occupied dwellings, creating a split-incentive issue that acts as a barrier to adoption. The pattern is consistent with that identified by Graziano and Gillingham (2015) in Connecticut, where the diffusion of residential solar appears to be driven by rural areas, with lower population density.

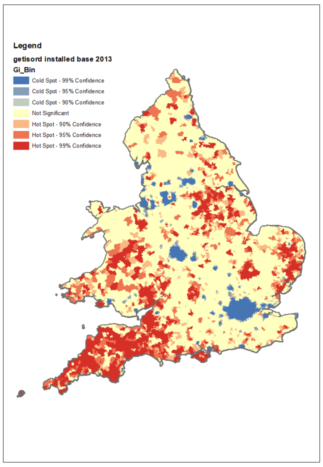
I repeat the hot-spot analysis on the number of yearly adoption in different years (flow variable) and the results are presented in the bottom row of Figure 2.8. The hot spots now identify the areas where high adoption rates are correlated with high adoption rates in the neighbouring areas. This time the picture changes substantially over the years. While there is strong evidence of clustering of adoption rates in 2011, this becomes weaker in 2013 for most of the country, with the exception of the north-east and extreme south-west, and by 2016 there is almost no correlation left. The evolution of cold spots is also particularly interesting, as these coincide with the major urban centres in 2011, but disappear almost everywhere by 2016, with the exception of London.

Moran's I and Local Moran's I

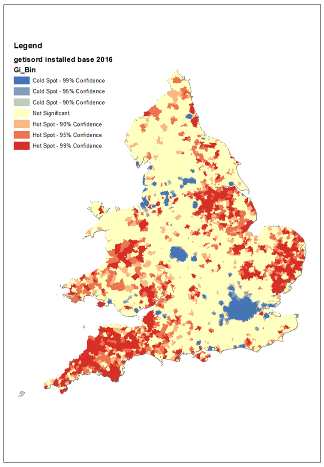
To further analyse whether there is any pattern of spatial auto-correlation and where they are located, global and local Moran's Is are computed, following Anselin (1995)



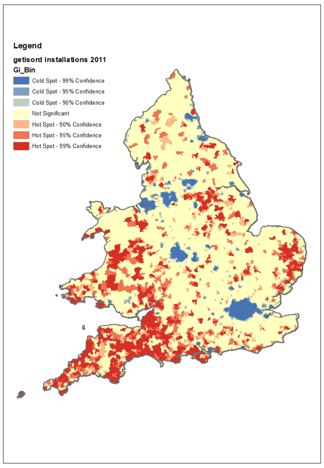
(a) installed base, 2011



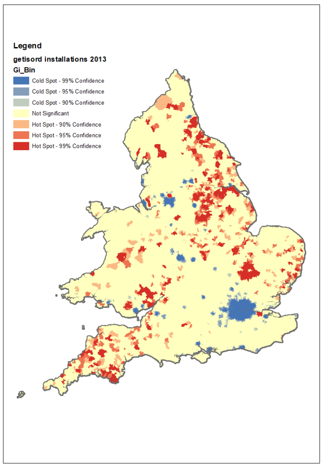
(b) installed base, 2013



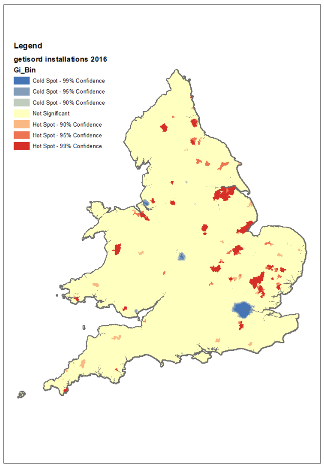
(c) installed base, 2016



(d) new installations, 2011



(e) new installations, 2013



(f) new installations, 2016

Figure 2.8: Optimised hot spot analysis, Getis-Ord Gi* index.

and Rey and Montouri (1999). These statistics rely on the covariances between neighbouring adoption of PVs and identify whether the adoptions are correlated in space rather than occurring at random locations. Spatial lags are obtained using the contiguity weight matrix. As in the hot-spot analysis, I repeat the analysis for different years so to check for persistence of the clusters, and apply it to both the stock variable and to the flow in new adoption in the year (i.e. the difference between the total installed base in one year and the total installed base in the year before) so to remove the effects of time-invariant variables and gain more insights on whether the clusterization can be attributed to spillover effects.

The global Moran's Is are presented in Table 2.1, where it can be immediately seen that a strong positive spatial correlation exists in the diffusion of PVs and is persistent in time. Focusing on the annual growth in adoption, the Moran's I is practically the same for the 2011-2012 period, while it becomes slightly smaller in 2014-2015.

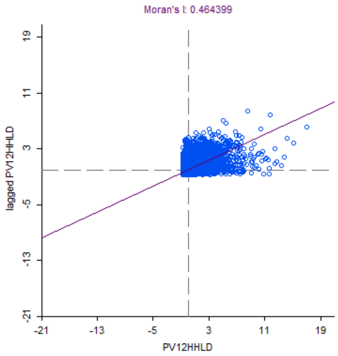
To identify the sources of the correlation, the Local Moran's Is are computed and mapped in Figure 2.9. The clusterization in the diffusion of PV systems appears to be pervasive, with large clusters of High-High adoption in part of Wales and the South-West (hot spots). Low-Low (or cold spots) are also present, although in fewer quantities, in the London area, South Wales, and around the big cities of the centre and north of England (Liverpool, Manchester, Newcastle, etc.), confirming the results of the Getis-Ord analysis.

Focusing on the annual adoption rate, the clusterization in 2011-2012 appears to be driven mainly by time-variant variables, as removing the fixed effects makes no difference in the Local Moran's Is, an evidence in favour of spillover effects. Different is instead the picture for 2014-2015, as the High-High clusters are still present but have shrunk to few areas in the South-West and in the East. This means that spillovers are now weaker and the underlying characteristics of the areas and of the individuals are becoming more important.

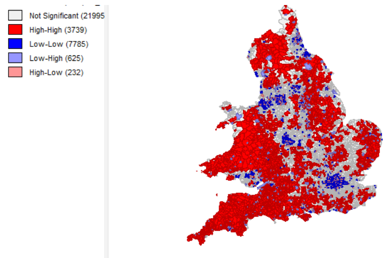
Table 2.1: Global Moran's I statistics.

	(Global) Moran's I			
	2012	**2015**	**2011-12**	**2014-15**
contiguity weights	0.464	0.521	0.442	0.359

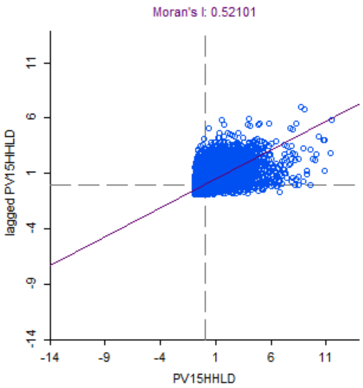
Significance maps are also generated using Montecarlo simulations to obtain 99 random permutations from which the expected random distribution of PVs adoption is derived so to obtain the p-values and confirm that the results are highly significant.



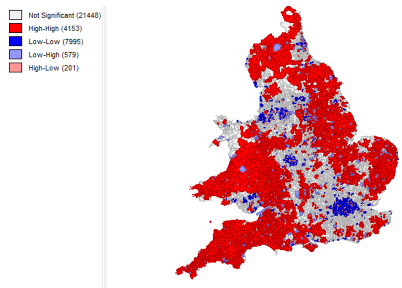
(a) 2012



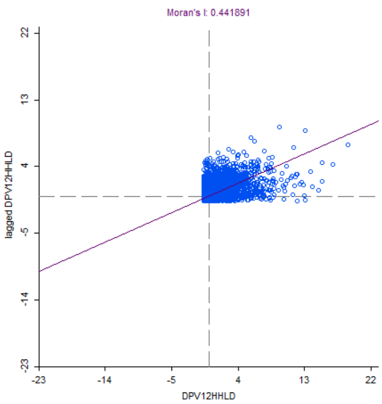
(b) 2012



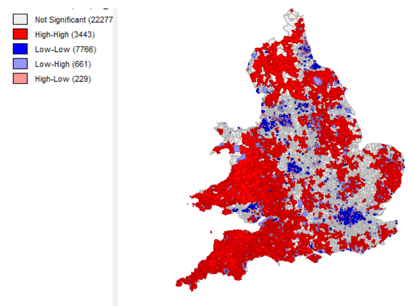
(c) 2015



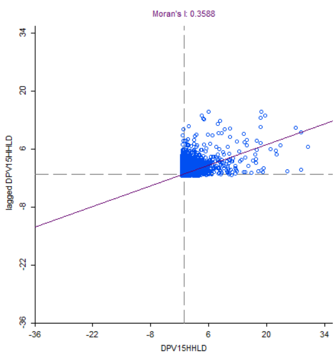
(d) 2015



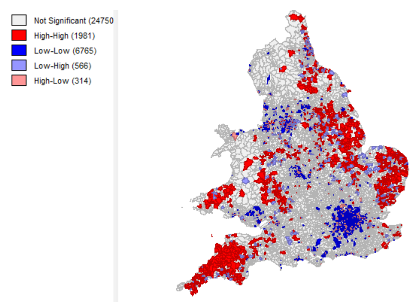
(e) 2011-2012



(f) 2011-2012



(g) 2014-2015



(h) 2014-2015

Figure 2.9: Local Moran's I, contiguity weights

Discussion

The evolution of the clusters is consistent with the hypothesis of peer effects that change over time, and suggests in particular that the effect becomes progressively weaker, consistent with the social learning channel described in the model.

As the technology was not widespread in the early years and households were less familiar with its functioning and the FIT scheme, the exchange of information between individuals may have had a leading role in the diffusion at this stage; on the contrary, when information becomes more widely spread, localised information sharing loses importance. Nevertheless, as time passes the subsidy is also being reduced, so that the diminished strength of the peer effect could also be associated to a lower subsidy, which would be consistent with both the social learning channel with information becoming more and more redundant the larger the installed base is, and with the social utility channel with monetary and social payoff perceived as complements. To obtain further insights on the issue, in the next Sections I therefore move to regression analysis.

2.5 Regression analysis

2.5.1 Identification of peer effects and estimation strategy

For the empirical estimation using regression analysis, I consider a reduced form equation for the problem of adopting residential PVs. Following Richter (2014), I use a linear estimation model:

$$Q_{l,t} = \alpha + \beta N_{l,t-s} + \gamma' X_{l,t} + u_{l,t} \tag{2.14}$$

where the error term is specified as:

$$u_{l,t} = \eta_{l,q} + \epsilon_{l,t} \tag{2.15}$$

$Q_{l,t}$ is the outcome variable, measuring new installations in location l during month t; $X_{l,t}$ contains covariates, including the economic regressors of interest, namely potential revenues from the adoption and the cost of the installation; and $N_{l,t-s}$ includes the neighbouring installations that have already been completed at the time in which the decision to adopt the new installations is made. The time lag between the decision to adopt and the actual completion of the installation is a technology-specific feature, due to the need to complete the purchase and the relative paperwork and bureaucratic procedures, and to schedule and complete the physical installation of the system on the rooftop. I assume the lag to be of three months $s = 3$. This assumption is also used in Richter (2014) for installation of PVs in the UK, and is consistent with qualitative evidence collected by the author. Peer effects are captured by the coefficient β. The error term $u_{l,t}$ contains a location-quarter fixed effect $\eta_{l,q}$, due to unobservable characteristics of each location, that may change over time, although we assume that the changes are slow and therefore negligible within each quarter, and a zero-mean i.i.d. component $\epsilon_{l,t}$, such that $E(N_{l,t-3}\epsilon_{l,t}) = 0$.

The identification of peer effects and the direction of causality present several challenges. First of all, the three issues highlighted by Manski (1993) and Gibbons et al. (2015) – reflection, self-selection into a peer group, and the problem of correlated unobservables – need to be addressed. Spatial sorting, also known as homophily, occurs as agents self-select into neighbourhoods. If characteristics and events related to the spatial sorting are also correlated with adoptions of PVs, there is a problem of endogeneity in the model that would bias the estimator if not properly addressed. The same goes if there are correlated unobservables that affect the rate of adoption in time – for example country-wide changes in the policy, or other macroeconomic trends – and/or in specific places – such as local programmes or marketing strategies. In the case of homophily and correlated unobservables, neighbouring installations are correlated with the unobservable error term, violating the exogeneity assumption required for consistent estimation of the peer effect β:

$$E(N_{l,t-3}u_{l,t}) = E(N_{l,t-3}\eta_{l,q}) + E(N_{l,t-3}\epsilon_{l,t}) = E(N_{l,t-3}\eta_{l,q}) \neq 0$$

Hartmann et al. (2008) show how these issues can be controlled for using time and area-specific fixed effects. To have a consistent estimate of the parameter of interest, I therefore control for unobservables using a flexible specification of the location fixed effect $\eta_{l,q}$ that allows the unobservables to be location-specific and time-varying, although I assume that they only change slowly over time, and changes are negligible within a quarter. Finally, if the effect of a peer relationship is bi-directional and contemporaneous, that is if agents can affect their peers and be affected at the same time, the simultaneity or 'reflection' issue challenges the identification of the parameter. The problem of simultaneity can be seen by thinking that the choice of agent i is being affected by a peer j, while affecting their choice at the same time. In this case we have that:

$$Q_{i,t} = \alpha + \beta N_{i,t} + \epsilon_{i,t} \text{ with } N_{i,t} = Q_{j,t}$$
$$Q_{j,t} = \alpha + \beta N_{j,t} + \epsilon_{j,t} \text{ with } N_{j,t} = Q_{i,t}$$

Taking the expected value:

$$\begin{aligned} E(Q_{i,t}) &= E(\alpha + \beta Q_{j,t} + \epsilon_{i,t}) = \\ &= \alpha + \beta E((\alpha + \beta N_{j,t} + \epsilon_{j,t})) = \\ &= \alpha + \beta E((\alpha + \beta Q_{i,t} + \epsilon_{j,t})) = \\ &= (1+\beta)\alpha + \beta^2 E(Q_{i,t}) \end{aligned}$$

So that:

$$E(Q_{i,t}) = \frac{\alpha}{1-\beta}$$

and the different parameters α and β cannot be separately identified. In the specific case of solar PV adoption, there is a lag between when a household decides to purchase, and when the panels are actually installed on the roof, therefore becoming visible to others and starting generating electricity. I assume that households may only be affected by peer installations up to the moment they make their choice, but they only start affecting others once their panels are installed, i.e. once they are visible and the household has some experience and information to share, so that simultaneity is not a problem. This is the key identifying assumption used in the estimation strategy, which follows Bollinger and Gillingham (2012). According to qualitative evidence collected by the author, this assumption appears to be realistic for the case of residential PVs in the UK.

In addition to these identification challenges, using the installed base to identify peer effects might incur in the Nickell's bias if the parameters are estimated using the usual fixed effect within-group estimator. In fact, as the installed base effectively consists of the lags of the outcome variable, the de-meaned installed base is correlated with the de-meaned error term (Nickell, 1981). The within-group estimator is therefore inconsistent, as the strict exogeneity assumption does not hold, as shown by Narayanan and Nair (2013). A similar issue applies to the random-effect estimator, as the random effect and the installed base are correlated by construction as they share the same random component, therefore violating the orthogonality assumption and resulting in inconsistent estimators. Bollinger and Gillingham (2012) and Richter (2014) provide proof that under some conditions on the order of autocorrelation of the errors, consistent estimates for the linear model specified above can be achieved using an adjusted first-difference estimator and a within-group estimator where the mean is defined at the area-quarter level. These estimators are presented in the next paragraph.

A final issue to consider is the incidental parameter problem, as location-specific fixed effects cannot be used in non-linear models such as the negative binomial, which might be a better fit for count data with several zeros and over-dispersion, such as those used to describe the uptake of a technology. To avoid this problem I only use linear models, while acknowledging the limitations of this specification when used with count data.

2.5.2 Estimators

As suggested by Gibbons and Overman (2012), the applied regression analysis of this Chapter is based on a quasi-experimental framework, which uses purposedly constructed first-difference and within-group estimators to identify the parameters of interests, and is used to test the propositions derived from a theoretical model based on the sign of coefficients, rather than trying to achieve model fit. The sources of exogenous variation in the regressors that are exploited for identification are changes in the subsidy decided by the government, differences in solar generation potential among locations due to geography, weather and climatic conditions, and changes in the cost of purchasing and installing solar panels, determined by the international market.

To test the hypotheses formulated in the previous sections, I adapt the estimation procedure presented by Richter (2014), using the identification strategy introduced by Bollinger and Gillingham (2012). The equation for the model is the one described in the previous section:

$$Q_{l,t} = \alpha + \beta N_{l,t-3} + \gamma' X_{l,t} + u_{l,t} \text{ where } u_{l,t} = \eta_{l,q} + \epsilon_{l,t} \tag{2.16}$$

As previously mentioned, the model includes LSOA-quarter unobservable fixed effects $\eta_{i,q}$ to control for self-selection of peers (homophily, or spatial sorting) and correlated unobservables. The main identification problem to address is the fact that the number of existing installations in the neighbourhood might be correlated with the fixed effect, and therefore with the error term of the model $u_{l,t}$. This happens if $E(N_{l,t-3}u_{l,t}) \neq 0$, which might be the case if installations included in $N_{l,t-3}$ occurred in the same location and in the same quarter as the outcome variable, so that they share the same fixed-effect $\eta_{l,q}$.

To address this issue, I use two different estimators constructed following Richter (2014). Both of them are used in the regression analysis, to check robustness of the results. The first estimator is a within-group estimator (WG) , where each term of the model in (2.16) is de-meaned using the average over the corresponding LSOA-quarter. As the unobservable fixed-effect is constant within each quarter, it cancels out. Because of the 3 months window considered in constructing the reference peer group, $N_{l,t-3}$ only includes installations up to the previous quarter, and is therefore not correlated with the error term $u_{l,t}$, which refers to the current quarter only.

$$Q_{l,t} - \bar{Q}_{l,q} = \beta(N_{l,t-3} - \bar{N}_{l,q-1}) + \gamma'(X_{l,t} - \bar{X}_{l,q}) + (\epsilon_{l,t} - \bar{\epsilon}_{l,q}) \tag{2.17}$$

with

$$t \in q \text{ and } t-3 \in q-1$$

This model can then be estimated as a pooled OLS.

The second estimator is an adjusted first-difference estimator (FD). After taking the difference of each term with its first lag, observations for the first month of each quarter are dropped and the model is estimated only for the remaining sample. In this way the LSOA-quarter fixed effect $\eta_{l,q}$ cancels out, and the first-differenced model can again be estimated as a pooled OLS:

$$Q_{l,t} - Q_{l,t-1} = \beta(N_{l,t-3} - N_{l,t-4}) + \gamma'(X_{l,t} - X_{l,t-1}) + (\epsilon_{l,t} - \epsilon_{l,t-1}) \tag{2.18}$$

with

$$t, t-1 \in q \text{ and } t-3, t-4 \in q-1$$

Richter (2014) and Bollinger and Gillingham (2012) provide a proof for the consistency of these estimators under certain conditions. The key requirement is that the order of autocorrelation must be less than 1 plus the number of months in the time window between the choice to adopt and the moment when the the adoption starts affecting others, which in this paper is set to be 3 months. As discussed by Richter (2014), the first-difference estimator is consistent under weaker assumptions than the within-group estimator, so the former will be my preferred estimator.

An important difference with respect to the empirical approach used by Richter (2014), is that the reference peer group is not defined simply as the installed base of the LSOA, but rather by constructing different types of buffers that are not restricted to the area's borders. The construction of the buffers and of the peer installation variable is presented in more detail in the next paragraph. Moreover, peer installations include all the solar systems classified as residential, as well as commercial and industrial systems up to 10kW of installed capacity, while the outcome variable is restricted to residential systems below 4kW, as these are the systems that receive the highest FIT rate and do not require previous authorisations for installation. Different model specifications and definitions of the outcome and neighbour variables are considered to investigate further features of the effects of interest and as robustness checks.

2.5.3 Definition of neighbourhood and measures of peers' installations

The main definition of 'neighbourhood' I use in this paper is based on a proportional buffer. For each LSOA, I obtain data on the surface area and calculate the radius that would generate a circle of the same area. I then construct a buffer of radius three times the reference radius, centred on the LSOA's population-weighted centroid. For example, the buffer of the average LSOA (surface area 4.4 km^2) is constructed using a radius of 3.55 km, while the buffer of the median LSOA (surface area 0.48 km^2) has a radius of 1.17 km. For each LSOA-month combination, all systems in the LSOAs with population-weighted centroids within the buffer are considered as belonging to the 'neighbourhood'. Those systems registered more than three months prior to the reference month are then summed together and constitute the peer group $N_{l,t-3}$. This definition of neighbourhood constructed using a proportional radius has the advantage of taking into consideration larger buffers for areas that are sparse and less densely populated, where residents are therefore more likely to travel further away in their daily routines, and smaller buffers for urban and dense areas, where residents can access most service nearby and are less likely to own a car or travel further away.

While the outcome variable only considers residential systems with capacity up to 4kW – as these are the ones receiving the highest tariff rate, do not require an authorization and are the most commonly used by households – the peer group also includes commercial and industrial systems up to 10kW, as a household who is considering solar panels might not necessarily be able to distinguish those systems from a residential one, and even if they can they might still be affected and obtain information from them, as they are still small scale and very similar to the one they are likely to be considering.[8]

Graziano and Gillingham (2015) and Baranzini et al. (2017) find evidence that peer effects are stronger not only the closer in space peer systems are, but also the more recently the installation occurred. To test the latter, in a set of specifications of the regression model I use the registration dates of systems in the neighbourhood to classify them into whether they had been purchased within the previous 6 months ($N_{l,t-3}^{<6-month}$), between 6 and 12 months prior ($N_{l,t-3}^{6-12-month}$), and over 12 months prior ($N_{l,t-3}^{>12-month}$). As in all the other specifications, only installations purchased at least 3 months prior are considered – as this is key to the identification of the model. In another specification, I split the buffer into three concentric rings of radius 1.5, 2, and 3 times the reference radius. The innermost ring represents the immediate neighbourhood, while the second and third rings are used to check how far the influence of neighbours extend, in case the inner circle is too small to capture the full effect. All installations that occurred in an LSOA whose population-weighted centroid lies within a ring are assigned to that ring. For each observation, all installations older than three months prior to the reference month and assigned to one of the three rings are summed into the peer installation variable $N_{l,t-3}^{ring1}$, $N_{l,t-3}^{ring2}$ and $N_{l,t-3}^{ring3}$. For reference, the buffers for the average LSOA (surface area 4.4 km^2)

[8]The share of systems between 4 and 10kW is nonetheless quite small compared to those up to 4 kW, as shown in the previous section.

have radius of 1.78, 2.37 and 3.55 km; for the median LSOA (surface area 0.48 km^2) the radii are 0.59, 0.78 and 1.17 km.

In the main analysis, I use the number of solar PV systems as unit of measure for the outcome variable and peers' installations. Results are presented in Section 2.6. To investigate whether larger installations produce larger spillover effects, another specification uses the installed capacity (in kw) rather than the count, as in Bollinger and Gillingham (2012) and Baranzini et al. (2017). This specification is nonetheless unable on its own to distinguish between a large number of small installations and a small number of large installation. To further investigate the effect of size, I therefore estimate yet another specification with the average newly installed capacity (obtained as newly installed capacity over the number of newly installed systems) as dependent variable, and the average installed capacity in the neighbourhood as regressor. Results using total capacity and average size are presented in Section 2.6.3.

Given the lack of information on the exact location of PVs within each LSOA, and given how the LSOAs are constructed to ensure within-homogeneity and between-comparability, the proportional buffer specification is preferred to a fixed-radius one. Nonetheless, I investigate two variants of the neighbourhood specification among the various robustness checks performed. First, I re-define the neighbourhoods as circular buffers of fixed radius 2km, around the population-weighted centroid of each LSOA ($N^{<2km}_{l,t-3}$). Again, given the lack of information on the exact location of solar PVs within each LSOA, the number of peer installations are calculated by including the total number of installations of each LSOA whose population-weighted centroid lies in the buffer.

To make sure that the results are robust to the simplifying assumption that all solar panels are concentrated in the centroid, I re-calculate the value of the spatial lag $N^{<2km}_{l,t-3}$, assuming that the PV systems are uniformly distributed over the LSOA. The new peer group is then constructed as the 'expected number' of completed installations in the buffer, that is a weighted sum of the number of nearby installations, where the weight is given by the probability that each installation belongs to the section of the LSOA that intersects the buffer:

$$N^{unif\ distr}_{l,t-3} = \sum_{j}^{J}(w_{lj} \cdot \sum_{\tau}^{t-3} Q_{j,\tau})$$

where $Q_{j,\tau}$ are the installations in LSOA j registered up to month $t-3$, and w_{lj} is the weight. Under the hypothesis that the PVs are uniformly distributed over the LSOA, the probability that each system lies in the intersection between the LSOA and the buffer is nothing else than the surface area of the intersection, over the area of the LSOA:

$$w_{ij} = \frac{area(i \cap j)}{area_j}$$

Due to the computation intensity of constructing these variables, these alternative measures of the reference group are obtained for a randomly extracted sample of 10% of the total LSOAs, that is 3,438 locations, rather than for the total population of LSOAs. The total population of observations is still used to calculate how many installations there are in each buffer, but the buffers are only constructed around the sampled LSOAs. Results using these alternative definitions of neighbourhood are presented in Section 2.6.3.

2.6 Results

2.6.1 Peer effects and their interaction with monetary incentives

Tables 2.2 and 2.3 present the results of different model specifications using a within-group and first-difference estimator, respectively. The outcome variable $Q_{l,t}$ is defined as the count of newly installed residential solar PV systems in each LSOA-month ($PVcount$), and the nearby installations $N_{l,t-3}$ as the count of small-scale systems in the neighbourhood with registration date before the 3-month window period. The 'neighbourhood' is identified using the proportional-radius buffer definition. Results from the two estimators are very close for the coefficients of the economic variables and almost identical for peer effects. Note that sample sizes are different as the first month of every quarter is excluded when using the first-difference estimator, to insure consistency.

Model (1) only includes the economic variables – the expected annual subsidy and the cost of purchasing and installing the system. The signs are as expected, positive for the subsidy and negative for the cost. Model (2), on the contrary, only includes the number of installations in the neighbourhood; the sign is positive, suggesting peer effects are present and operating as a bandwagon effect, with more existing installations triggering more new installations. Model (3) includes both the economic variables and peers' installations, and suggests that the coefficients of the economic variables are slightly underestimated in the first model, where peer effects are not taken into consideration. Similarly, peer effects appear to be underestimated in the second model, where the monetary dimension is not accounted for.

According to the estimates, a cut in the FIT rate that results in a reduction of 1 GBP per year per kW installed,[9] would lead to 0.008 fewer new installation per LSOA, equivalent to 275 fewer installations throughout England and Wales. As reference, consider that the expected annual subsidy decreased by almost 50 GBP/year/kW on average when the FIT was reduced in August 2012 – the largest cut in the time frame considered – and by around 4 GBP/year/kW on average when the FIT was cut in January 2014 – the smallest cut for the period under analysis. On the other side, a reduction of 10 GBP in the upfront cost of purchasing and installing the system,[10] would result in about 0.002 additional installations per LSOA, or 82 for all of England and Wales.

The coefficient of existing installations in the neighbourhood indicates that one additional system in the peer group is associated with 0.004 new adoptions in the reference LSOA. According to the coefficients of the economic variables just presented, the peer influence of one additional installation is therefore equivalent to a 0.5 GBP increase in the annual subsidy per kW installed – that is 1.75 GBP per year for the median system of 3.5kW – and a 17 GBP reduction in the upfront cost per kW installed – or 60 GBP for the median system. The effect is therefore economically significant, and is consistent with peer effects being a relevant driver of adoptions, but does not say anything with respect to the mechanism. A placebo test and robustness checks presented in Section 2.6.3 confirm this result. Having rejected the null hypothesis of no or negative effect, I can then move on to test the remaining two hypotheses and look for evidence on the dominant channel through which peer effects operate.

Model (4) extends the previous specification by including the squared term of existing nearby installations. The coefficient of $N_{l,t-3}$ is now larger than in the

[9] The average subsidy in the period under analysis is around 200 GBP per year per kW of capacity (Table B.1).

[10] The average cost of purchasing and installing a system in the period under analysis is around 1,850 GBP per kW of capacity (Table B.1)

Table 2.2: Regression table, proportional-area buffers, within-group estimator.

within-group estimator	(1) PVcount	(2) PVcount	(3) PVcount	(4) PVcount	(5) PVcount
subsidy (100GBP/kW/year)	0.783***		0.799***	0.802***	0.564***
	(0.006)		(0.006)	(0.006)	(0.007)
pvcost (1000GBP/kW)	-0.267***		-0.237***	-0.234***	-0.265***
	(0.010)		(0.010)	(0.010)	(0.010)
N		0.003***	0.004***	0.005***	-0.008***
		(0.000)	(0.000)	(0.000)	(0.000)
N squared				-0.000***	
				(0.000)	
subsidy X N					0.006***
					(0.000)
N	1546605	1546605	1546605	1546605	1546605
F	7888.632	527.229	5661.044	4345.467	4402.957
p	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: X represents an interaction between variables (here peer installations and subsidy).

Table 2.3: Regression table, proportional-area buffers, first-difference estimator.

first-difference estimator	(1) PVcount	(2) PVcount	(3) PVcount	(4) PVcount	(5) PVcount
subsidy (100GBP/kW/year)	0.812***		0.821***	0.823***	0.582***
	(0.009)		(0.009)	(0.009)	(0.010)
pvcost (1000GBP/kW)	-0.268***		-0.239***	-0.235***	-0.268***
	(0.016)		(0.016)	(0.016)	(0.016)
N		0.003***	0.004***	0.005***	-0.009***
		(0.000)	(0.000)	(0.000)	(0.001)
N squared				-0.000***	
				(0.000)	
subsidy X N					0.006***
					(0.000)
N	1031070	1031070	1031070	1031070	1031070
F	4188.325	240.258	2957.656	2250.623	2323.075
p	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: X represents an interaction between variables (here peer installations and subsidy).

previous specification, while the coefficient for $(N_{l,t-3})^2$ is negative. This suggests that the influence of one additional system has a diminishing effect on the outcome the more systems there already are in the neighbourhood. That is to say, peer influence is concave in the number of existing installations, and have diminishing marginal effect. The magnitude of the coefficients is nonetheless very small, so that the effect decreases only slowly. The sign is consistent with the literature on the UK, as Richter (2014) finds a decreasing effect of the installed base, which she interprets as potential evidence of satiation within post-code districts. Conversely, Bollinger and Gillingham (2012) find that the effect of the installed base in California is increasing in the number of installations, i.e. peer effects become stronger as more peers adopt the technology.

Finally, model (5), extends the specification in (3) by including an interaction term between the number of nearby installations and the level of expected annual subsidy. The coefficient of the interaction term is positive, meaning that peer effects are stronger when the subsidy level is higher; or equivalently, households are more responsive to changes in the subsidy if there are more installations nearby. In fact, the positive effect of nearby installations appears to be mainly driven by this interaction effect, as the coefficient for the remaining $N_{l,t-3}$ term is negative, meaning that when the subsidy is low, peer influence tends to die out or even have an overall negative effect on new installations. Given that the FIT is being progressively cut, a positive coefficient for the interaction term suggests that adoptions in areas with a larger installed base drop faster after a cut in the subsidy than areas with lower installed base. Taken together, these results help explain the finding from the hot-spot analysis conducted above that adoption rates are progressively less correlated in space. On one side, the increase in peer installations pushes new adoptions up, but at the same time periodic cuts in the subsidies push adoptions in the areas with larger installed capacity further down than in other areas, so that the two effects counter-balance each other.

This specification allows me to test the second proposition of the model, and I reject the null hypothesis of no interaction between adoption in the peer group and subsidy level. In particular, I find that this interaction is positive. This result does not provide evidence on which is the dominant channel, as it is consistent with both the social utility channel when the social payoff and the monetary payoff are complements (although this case is less intuitive in the setting under analysis than the substitute case, as discussed in the model Section), and with the social learning channel in the case in which more peer installations mean that information travel faster.

2.6.2 The evolution of peer effects

Finally, I investigate whether and how peer effects change over time, to test the last hypothesis of the model. To do this, I estimate the magnitude of peer effects separately by year, using the specification in model (3) in the previous Tables, in which peer effects enter linearly and subsidy and cost are controlled for. Estimating the model year by year has the advantage of allowing the responsiveness to subsidies and cost to change over time as well, and is therefore more flexible than interacting peer effects with a year dummy within the same model. For this analysis, I use data from January 2011 to December 2016.

The coefficients are obtained using the first-difference estimator. The results provide evidence against the null hypothesis that peer effects are constant over time. In particular, peer influence becomes weaker over time (Figure 2.10), as previously found by Richter (2014) for the UK, and Baranzini et al. (2017) for Switzerland. Peer effects appear to be strongest in 2011, then decrease steadily in the following two years, and plateau in the years 2013-2015 (coefficients for the three years are not statistically different from each other at 1% significance level), to then drop again in 2016. The coefficient for the latter year is not significantly different from 0 (point estimate of 0.00026, with a standard error of 0.00026).

This pattern is consistent with the information-sharing channel described in the model, in which peer effects weaken over time as households build-up their stock of private information that becomes more easily accessible over the years, and do not need to rely on localised social learning. This channel would also explain why peer effects drop to zero in the last year, as the the FIT policy was suspended at the end of 2015 and then a heavily reformed FIT scheme with a new queue system was re-instated in 2016, so that information from peers who installed before this date are less relevant to understand the new system. The social utility channel predicts instead the opposite result. Social learning through information-sharing appears therefore to be the dominant channel through which peer effects influence residential solar PV adoption.

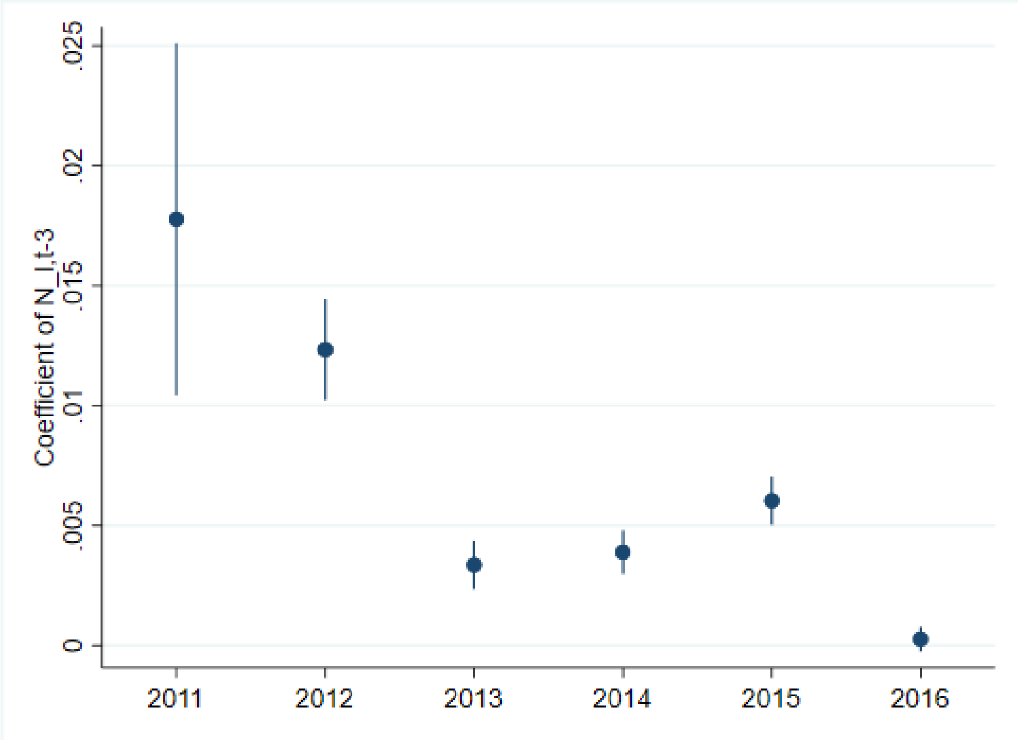


Figure 2.10: Year by year estimates of the peer effect coefficient. Bars represent the 95% confidence interval.

2.6.3 Robustness checks and further analysis

Placebo test with random assignment of neighbours

To further corroborate the finding of positive and statistically significant peer effects, a placebo test is performed. The placebo test is constructed by randomly re-assigning 'neighbourhoods', and is therefore similar in spirit to the placebo test in Di Falco et al. (2020). In particular, I randomly re-assign the number of neighbouring PV installations ($N_{l,t-3}$) or their first difference to the different LSOAs, and the model is then re-estimated using the first-difference estimator. The same procedure is repeated 100 times, obtaining 100 estimates of 'placebo' coefficients.

The distribution of the resulting estimates is shown in Figure 2.11, together with the original estimate of the coefficient (red line). In the top histogram, the random re-assignment was conducted through the entire sample, so that the first difference of each $N_{l,t-3}$ could end up being matched with the first difference in new installations of any LSOA and any month in the sample. The middle and bottom histograms are instead obtained by constraining the re-assignment within the same month, for a stronger test. In this case, the number of $N_{l,t-3}$ (bottom graph) or their first difference (middle graph) could be matched with any LSOA, but would always refer to month t. Randomly re-assigning within the same month means that the country-wide change in the number of solar PV installed is preserved at each point in time, therefore preserving any country-wide time trend in the rate of installation, such as seasonal effects, changes in the national policy, and macroeconomic events.

In the first version of the test (top graph), the first difference is re-assigned throughout the sample and the placebo coefficients are distributed almost symmetrically around a zero mean, and their values are well below the value of the estimated coefficient. In the second version (middle graph), the first difference is re-assigned within the same month and the placebo coefficients are positive and of larger magnitudes than in the previous case, but still substantially lower than the peer effect coefficient, providing further evidence of 'contagion' at the localised level. At the same time, the fact that the placebo coefficients are positive and significantly different from zero might suggest the existence of a more generalised and country-wide effect, where the increase in the number of installations anywhere in the country contribute to boost new adoptions even in regions that are further away. Several mechanisms could explain this effect. A larger installed base might contribute to construct and reinforce the social norm around residential solar PV systems throughout the country, as well as generate useful information that can be accessed and shared through the national media, social media, online forums and other types of networks that are not constrained by physical proximity. While this test still supports a positive and significant localised peer effect, it would suggests that its magnitude might be over-estimated.

The same test was then repeated by re-assigning the number of neighbouring PVs rather than the first differences, both throughout the sample (not presented) and constrained to the same month (bottom graph). Results are the same as in the top graph, with a distribution of the placebo coefficients around zero and orders of magnitude smaller than the peer effect estimate. The placebo tests overall reinforce the conclusion that peer effects are a significant driver of new adoptions.

Distance in time and space

In this paragraphs I present further analysis to corroborate the results obtained so far and test other hypotheses advanced in the literature. Tables with results for these analyses are included in Appendix B.

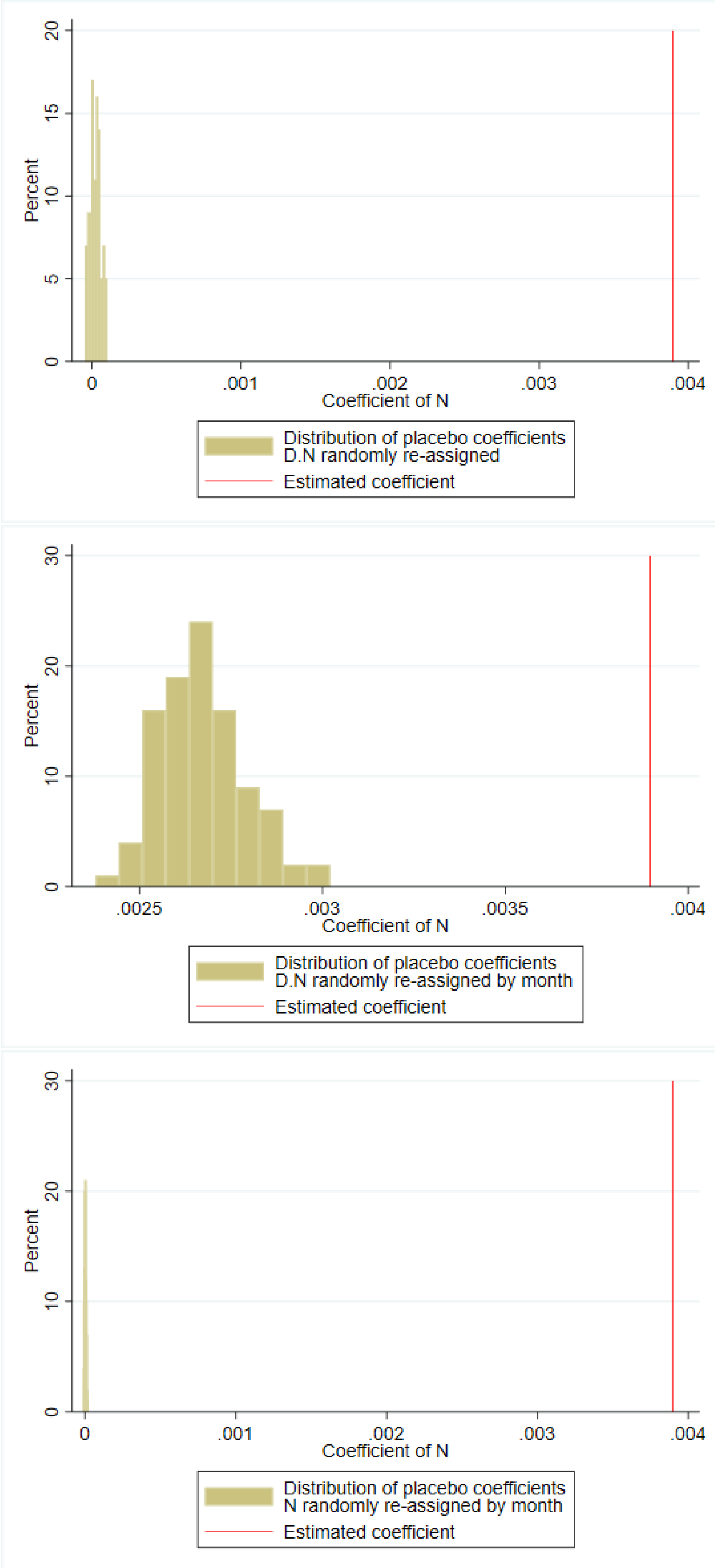


Figure 2.11: Distribution of coefficients estimated in the placebo tests, as compared to the original coefficient estimate (red line). First-difference of N is re-assigned at random throughout the sample (top) and within each month (middle); level of N is re-assigned at random within each month (bottom).

Graziano and Gillingham (2015) and Baranzini et al. (2017) find evidence that peer effects are stronger the closest in time the installations are. To investigate this hypothesis, in Table B.2 the peer variable is divided into three temporal intervals: systems completed within the past 6 months, between the past 6 and 12 months, and over 12 months prior. As in all the other specifications, only installations completed at least 3 months prior are considered – as this is key to the identification of the model. Estimates provided by the two estimators are very close, and the coefficients for the subsidy and PV cost are robust to this different specification. The coefficients for $N_{l,t-3}^{<6-month}$, $N_{l,t-3}^{6-12-month}$, and $N_{l,t-3}^{>12-month}$ are not statistically different from each other in specification (1). The same holds when the interaction term is included, in specification (2). This suggest that one additional installation in the neighbourhood has on average the same effects on the number of new adoptions, whether it was completed recently or more than one year prior. This could be the result of two forces pushing in opposite direction and therefore counteracting each other; on one hand, more recently installed system should be linked to more relevant information and therefore have a stronger effect, but older systems are more likely to have been noticed, as they have been around for longer and there is therefore a higher chance that the household passed by them even if they are not in their routine path.

In Table B.3 the neighbourhood is instead divided into three concentric rings, as detailed in Section 2.5.3, to investigate how far peer influence extends. Results from the two estimators are almost identical for peer effects, and the coefficients for subsidy and cost of purchasing and installing the system are close to the estimates in the previous Tables. Peer effects decrease when moving from the inner ring to the outer ones, confirming that influence becomes weaker when peers are further away. The coefficients for the outer rings are still positive and significant, and of economically relevant magnitude. This confirms that peer influence extends further away than the borders of the LSOA, and possibly even of the contiguous LSOAs. This is consistent with the fact that households are likely to communicate and be aware of adoptions by family, colleagues and friends that may not be their immediate neighbours but still live nearby, and that they might be affected by systems seen during their daily commute to work, which in England is on average 15 km (Le Vine et al., 2017).

The fact that the third ring's coefficient appears to be larger than that of the second one is counter-intuitive and might be due to the simplifying assumption used to construct the buffers – namely, that all installations in a LSOA are concentrated in the population-weighted centroid, and are therefore assigned to a ring if the centroid is within it. This means that some installations that are actually further away from the reference point might end up being classified as closer than they really are, and vice versa. This is a downside of the data, as the exact coordinates of the systems are not available.

To test for the robustness of results without this assumption, in one of the next paragraphs I use a different measure of peers' installations obtained by assuming that the installations are uniformly distributed in the LSOA, rather than concentrated in the centroid, and results are not only confirmed, but peer effects appear to be even stronger. Overall, the fact that peer effects appear to be significant through the three rings suggests that their influence extend outside the border of the LSOA, and possibly even further than the contiguous LSOAs. As the buffers used here are based on a radius whose length depends on the surface area of the LSOA of reference, one of the next paragraphs presents results using fixed-radius buffers for more insights into this issue.

Results for the installed capacity

To check the robustness of the results discussed so far and investigate additional hypotheses on how peer effects may work, the model was re-estimated using different definitions of the outcome and peer installation variable – namely using the installed capacity and the average size of the systems, in place of the count. As before, each specification is estimated using the within-group estimator and the first-difference estimator. Using capacity measures allows me to investigate whether larger installations produce larger spillover effects, as in Bollinger and Gillingham (2012) and Baranzini et al. (2017). Moreover, capacity has the advantage of making the outcome variable continuous, providing additional support for the choice of a linear model specification. While the outcome is still bounded at zero, a limitation that needs to be taken into account, the linear model has several advantages in terms of controlling for unobservables and correlated effects, and the properties of the two estimators used in this analysis are not easy to replicate in a non-linear model. With this caveat in mind, Table B.4 in Appendix B presents the results for each estimator. Again, the estimated coefficients are very close in the two cases, a good sign for the robustness of the results.

Column (1) and (2) use the total newly installed capacity in a LSOA-month as the outcome variable, and overall installed capacity in the neighbourhood (up to the previous quarter) as the peer variable. The main results from the previous Tables are replicated, as the more installed capacity there is in the neighbourhood the more new capacity is likely to be installed in the LSOA. The interaction effects estimated in column (2) are still positive, confirming the finding that households in areas with a larger installed base are more reactive to changes in the subsidies.

The effects of the economic variables have the expected sign in both specifications, but the coefficients are about three times larger in magnitudes than in the specification using the count of installations, consistent with the fact that the average size of installation is 3.25 kW. The coefficients of the peer variable are also slightly larger than in the count model. One additional kW installed in the neighbourhood leads to 0.006 new kW being installed; while one additional installation leads to 0.004 new installations. This suggests that larger peer installations have a slightly stronger effect on the newly installed capacity, although this specification is unable to distinguish whether this effect leads to larger installations or more installations.

To further investigate the effect of size, model (1) and (2) of Tables B.5 use the average newly installed capacity as dependent variable, and the average installed capacity in the neighbourhood as regressor. These are measures of the average size of the systems being installed, and are calculated as installed capacity over the number of systems when the number is positive. The dataset is therefore restricted to LSOA-month observations with a positive number of new installations and at least one nearby installation, to see whether new installations tend to follow the average size of installations in the neighbourhood. The coefficients for peer installations in model (3) and of both the peer installations and the interaction terms in model (4) are not significantly different from zero, with the only exception of the coefficient in the first specification estimated by within-group estimator, which is nonetheless only marginally significant.

These results suggest that when installations do occur, the size chosen is not affected by peers. This is consistent with qualitative evidence collected through interviews, as households did mention that their decision to adopt was affected by neighbours, family and friends who already had solar panels, but that the size of the system is mainly constrained by the available space on the roof, and by the 4kW threshold to obtain the highest FIT rate and avoid having to request authorisation for the installation and connection to the grid.

Larger subsidy per kW installed and a lower cost per kW installed appear instead to drive households to install larger systems. As the size of the annual subsidy depends on the generation potential of the area, this suggests that households living in area with better solar irradiation and a climate more favourable for solar generation tend to install larger systems. On the other side, the fact that lower cost per kW results in larger installations might suggest that households have liquidity constraints or a mental cap on the total amount they want to spend for solar panels, even after controlling for the returns they can get on their investment. In fact, the interviewed households stressed that they decided to install solar panels because they had available liquidity, and many explicitly mentioned that they did not want to take a loan to finance the installation. Overall, comparing the results from the count and capacity specifications, suggest that larger installations in the neighbourhood trigger more adoption rather than larger installations, as the size of the new adoptions is not affected by the average size of peers' installations.

Alternative 'neighbourhood' definitions

As a further robustness check, Table B.6 and Table B.7 in Appendix B use the two estimators to re-estimate the model using the count, capacity and average size of the installations, but with different definitions of the reference neighbourhoods, constructed using a 2km buffer for all the LSOAs, rather than buffers proportional to each LSOA size as in the previous models. Models (1), (3), and (5) impute systems to a neighbourhood assuming they are all concentrated in the population-weighted centroid of their LSOA. Models (2), (4) and (6) remove this assumption and instead consider that systems are uniformly distributed over the LSOA. Details on how the buffer and the variables are constructed were provided in Section 2.5.3. As specified in the same Section, this analysis is restricted to a random sample of the total LSOAs, due to computational reasons.

Results are again very similar to each other whether they are estimated with the within-group estimator (Table B.6) or the first-difference estimator (Table B.7). Estimated coefficients for subsidy and cost are almost identical to the ones obtained in the previous Tables, suggesting that restricting the analysis to a random sample is not affecting the final results. The general results on the existence of peer effects found in the previous Tables are confirmed, with peer effects being positive and significant. The estimated coefficient for peers' installations is even larger when estimated assuming that peer installations are uniformly distributed within their LSOA. As before, for households who adopt in areas where there is already at least one installation in the neighbourhood, the average size of the existing systems does not appear to have a significant effect on the size chosen for the new systems.

2.7 Conclusion

The present work contributes to the literature on the diffusion of residential solar PV systems, and the role peer effects play in it. While the literature on the topic has grown considerably in the last years, this paper adds more theoretical background to the analysis, to investigate the dominant mechanisms behind peer effects. As well as confirming that peer effects play a role in the diffusion of the technology, in this Chapter I also investigated how peer effects interact with monetary incentives and how peer effects evolve over time, and modelled the channels that may explain these patterns, a question that has not been investigated in depth in the literature, yet. Finally, I tested findings from existing papers based on different locations – mainly the US and Switzerland – in the case of the UK, which has a different policy to support residential solar PV systems.

The theoretical framework set up in the paper provides the motivation for the empirical analysis. In the baseline, a simple static model is set up to formalise how households are affected by economic variables on which policy makers have a leverage, namely monetary incentives for the adoption of micro-generation technologies, and the cost of investing in these technologies. The model is then extended to include peer effects triggered by existing solar panels in the neighbourhood. This is achieved by modelling the two main mechanisms through which this influence may arise: the social utility channel, in which households obtain a non-monetary 'social payoff' from conforming with the neighbours and "keeping up with the Joneses"; and the social learning channel, in which households obtain information from neighbours who have already installed, through localised information-sharing.

This model provides a set of hypotheses on how peer effects should affect the patterns of adoption over the country, how they interact with the elasticity to monetary incentives, and how their strength evolve over time, depending on what mechanism is dominant. In particular, both channels are consistent with peer effects that are positive and significant, are not constant over time, and interact with the monetary incentive, although they predict different patterns of evolution over time. These hypotheses are then compared with patterns identified in the data using a optimised hot-spot analysis with the Getis-Ord Gi* statistics, spatial correlation analysis using global and local Moran's I statistics, and regression analysis.

To overcome the different challenges of identifying peer effects, I have adapted the identification strategies and estimators presented by Richter (2014) and Bollinger and Gillingham (2012), and constructed different definitions of peer installations and neighbourhoods to check robustness of the results. The results of the empirical analysis robustly point towards the existence of positive and significant peer effects, with evidence that the influence of peers' decisions to adopt solar panels extends further than the boundaries of the LSOAs. Peer effects also appear to interact positively with the level of annual subsidy a household can expect to receive. This means that when the FIT rate is cut, areas with larger installed base experience larger drops in the number of new installations if compared to areas with lower installed base.

Finally, I find evidence that the strength of peer effects is not constant, but decreases over the years. This result suggests that information-sharing at the local level is the dominant channel through which the adoptions of peers tend to affect new installations in the neighbourhood. Taken together with results for the other hypotheses, this would suggest that information regarding cuts to the FIT rate spreads faster the more existing installations there are in the area, resulting in fewer installations than it would be the case in areas with a smaller installed base. Nevertheless, the effect of peers' decisions appears to fade out with time, possibly because households can obtain more and more up-to-date information from other sources so that localised social learning loses importance.

This is an important result in terms of policy implication, as it provides an additional motivation for subsidising residential solar panels and avoiding unpredictable and drastic cuts, especially in the early years of the scheme, as well as an additional element to take into consideration when setting the level and schedule of the subsidy. In fact, subsidies in the early years can 'buy' the boosting effect of peer influence and trigger a domino's effect in adoption, but when the subsidy is cut, the interaction effects between this variable and peer effects pushes in the opposite direction, slowing down new adoptions.

Another implication that can be derived for policy design is the importance of providing accessible information on the new technologies and the existing support schemes for their adoption, as well as visible and possibly trialable examples of them. In fact, if information-sharing is a relevant mechanism for peer effects, then areas in which social learning is not possible – because of the lack of peers who have already adopted – would experience a sub-optimal pattern of adoption than it would be the case in absence of imperfect and missing information. Given the strong evidence in the literature that inertia, default bias, and risk and uncertainty aversion make adoption of lower-carbon energy technologies slower than it would be optimal, this paper suggests that informational interventions and peer effects could be effective tools to help remove these barriers.

Chapter 3

Demand for 'improved' cookstoves or demand for improvements? Evidence from refugee settlements in Sub-Saharan Africa

3.1 Introduction

With almost 69 million individuals (UNHCR, 2016), if the forcibly displaced were a country, they would be the 21st largest country in the world by population, and one of the top countries for population growth. In fact, political and economic instability, wars, extreme climate events and changing environmental conditions continue to fuel displacement and migratory processes, adding to the victims of economic and political crises, new tides of climate and environmental refugees. Sub-Saharan Africa, where the refugee settlements studied in this Chapter are situated, is particularly hit by these trends, as the number of forcibly displaced people and the duration of the crises have kept growing in the last decades (Verwimp and Maystadt, 2015; Adepoju, 2019). In this context, actors involved in humanitarian responses are coming to the realisation that sustainable and clean energy provision is essential not only for the administration of the settlements, but above all to ensure the welfare of their inhabitants (Lahn and Grafham, 2015; Huber and Mach, 2019).

In fact, fuel efficiency and indoor air pollution are critical issues in developing countries, and are intimately related to the broader issues of poverty alleviation, environmental protection, and sustainable development. Cooking, in particular, is one of the main energy-consuming activities in households' everyday life, and can take up a substantial share of time and resources in developing countries. In refugee settlements, the problems linked to traditional forms of cooking are further exacerbated by the difficulties of humanitarian emergencies and displacement, in particular with respect to resource scarcity, potentially hostile host communities, high population density, and a large number of vulnerable individuals, such as children, women, the elderly and the infirm, and improvements are therefore even more urgent. Cookstoves are mentioned among the main energy challenges and solutions for refugee settlements in Lyytinen (2009).

At the same time, refugee settlements can provide interesting opportunities to introduce and develop new technological and organisational solutions (see for example Bellanca, 2014; Gunning, 2014; Lahn and Grafham, 2015; Grafham et al., 2016; Lehne et al., 2016; Vianello, 2016, for a review of cooking solutions and pilot programmes for refugee settlements and humanitarian settings). The benefits of these programmes could even spill over to the host communities and to family members in the countries of origin, triggering broader transition processes in both the receiving and sending countries (Alix-Garcia et al., 2018; Maystadt and Duranton, 2018). Moreover, refugee settlements are contexts where the provision and allocation of very scarce resources are a crucial issue and where central management and policy interventions are pervasive, making it an interesting setting for economic analysis and program evaluation.

Yet, economic and energy issues in these contexts are still under-researched – especially from a quantitative perspective – due to the difficulties in accessing the settlements to collect data and because the settlements are understood as temporary arrangements (Lahn and Grafham, 2015). To overcome the first hurdle, I rely on the effort of the recently formed Moving Energy Initiative (MEI) – a consortium of governmental and non-governmental organisations active in the energy and humanitarian spectrum – to close this knowledge gap. To this purpose a survey has been administered to representative samples in the Goudoubo settlement, in Burkina Faso, and in the Kakuma sub-camp one, a sector of the bigger Kakuma settlement, in Kenya, focusing on the current status of energy access and management, as well as the needs and priorities of households, enterprises and facilities on the ground. This survey provides the main information and data for the analyses in this Chapter. As for the temporary nature of the settlements, this is often more of a political label than a description of the actual situation. In fact, evidence cited by Vianello (2016) suggests that displaced people spend an average of 17 years as refugees, and UNHCR (2016) reports that "the average duration of the 32 protracted refugee situations at the end of 2015 is estimated at about 26 years". Consistently, the median arrival date in Kakuma for respondents in my sample is 2004, with several households having lived in the camp since the early 1990s, when the settlement was first established. The Goudoubo camp was opened in 2012; more than half of my sample reported living in the settlements since that year, suggesting that they might have already been living as refugees in the country before the camp was established. At the same time, about 5% of respondents in each settlement had arrived less than a year before the survey was conducted, evidence that the situations in the countries of origin had not yet been resolved – and in fact are still ongoing at the time of writing.

Despite evidence that there is much to be gained in improving cooking conditions for households in least developed contexts, the willingness to pay (WTP) for non-traditional stoves appear to be low, both in absolute and in relative terms (Mobarak et al., 2012; Whittington, 2010), and so is the take-up even when offered for free (Hanna et al., 2016). This result seems to be robust in rural and urban areas, although this has not been studied in the context of refugee settlements, yet. To understand the reasons behind this results, in the first part of this Chapter I investigate whether low WTP for non-traditional cookstoves[1] found in the data and more broadly in the literature, might be linked to the failure of these systems to live up to expectations, and more specifically to a mismatch between the performance of the stove and the features the user is interested in, such as fuel savings, smoke reductions, or compliance with traditions and habits. Using characteristic-demand theory I test two competing interpretations:

1. Households have low WTP for (i.e. low valuation of) the improved features (referred to as the 'characteristics' of the stoves, in the rest of the Chapter).

[1] For the purpose of this Chapter I refer to non-traditional stoves to indicate stoves that are different from the traditional three-stone fire. Whether a non-traditional cookstove constitute an improvement with respect to the traditional one, and what kind of improvements they provide, is an empirical question. For a similar argument, see Mobarak et al. (2012). I use the acronym biomass ICS (improved cookstoves) to indicate non-traditional cookstoves using solid fuels, such as firewood or charcoal, as this is the common name used to indicate these types of stoves.

2. Households value the improved features but do not think that non-traditional stoves provide them.

To do this, I use stated preferences for a set of seven different non-traditional cooking technology – basic solid-fuel ICS, enhanced firewood-ICS, enhanced charcoal-ICS, solar cookers, biogas stoves, LPG stoves, and electric stoves – and information on respondents' perceptions (or expectations) in terms of the characteristics of each cooking technology. I fact, different respondents have different perceptions of the characteristics of each type of cooking technology – for example because of heterogeneity of the stoves, or asymmetric information – and in the analysis I attempt to disentangle the premium respondents are willing to pay for each characteristics, from the technology-specific premium.

As a further refinement, I control for heterogeneity in priorities regarding the features of a cooking system. To see why this is important, consider for example that according to World Health Organization (2015) significant health improvements can only be achieved by moving away from solid fuel and switching to clean fuel such as LPG, biogas, and electric cooking. Respondents concerned with health issues might thus be expected to have a low valuation for solid-fuel non-traditional cookstoves, as they do not match with the respondents' priorities. Information is also obtained on whether the respondent has any previous experience with each technology. Given the setting and the technologies considered, this is often determined by participation in pilot schemes or donation programmes, rather than being the results of respondents' purchases in the private market.

In the second part of the Chapter, I use the same dataset to look at whether moving away from three-stone fires has delivered any significant improvements in each of four different dimensions of welfare - fuel efficiency, health and safety, time use, and the workload burden on women and children. The setting can be considered as a quasi-experiment, as non-traditional cookstoves have been mainly introduced in the camp through donation programs, and are not easily found in the local markets (neither within the settlement nor in the nearest towns). Finally, I conclude by bridging the results from the two analysis looking at the correlation between the predicted benefits provided by non-traditional cooking systems and the stated preferences. To do this I use household-specific estimates of the effect of using a non-traditional cookstove on different outcomes, and interact it with the gender of the respondent. The latter is used to see whether men or women are relatively better at factoring the gains into their valuation, and whether that depends on the outcome considered. In fact, it could be the case that the valuation increases more if the respondent is appropriating the benefits directly – which in the case of cooking means that women may be more responsive than men to improvements in health and safety and time savings, as they are the ones mainly affected.

The novelty of this research is two-fold. First, for its effort to bridge valuation of hypothetical products and improvements with estimates of actual improvements from the non-traditional cookstoves distributed in the camps. This is made possible thanks to the extensive scope of the survey data collected by the Moving Energy Initiative in terms of current level of access, multi-dimensional well-being information and valuation modules. Answering these questions with the same dataset provides interesting insights on whether a mismatch exists between the improvements supplied by the cookstoves actually deployed on the ground, and the improvements demanded by the users. To my knowledge, only one other study has focused explicitly on this connection so far, namely Berkouwer and Dean (2019)'s RCT in Nairobi, Kenya.

The second contribution, and key difference with respect to the above-mentioned work, is the focus on refugee settlements in developing countries. These are highly managed settings in which centralised interventions are pervasive and improvements in service provision are particularly urgent. Lessons can therefore be derived from past and current efforts, and be used as input in the design of future programmes, contributing to improve the life of a particularly vulnerable segment of the world population.

The questions investigated in this Chapter are meant to inform the more general question of whether low willingness to pay for non-traditional cookstoves found in the data and more broadly in the literature[2], might be linked to the failure of these systems to live up to expectations - consistent with the results by Mueller et al. (2011), Yu (2011), Hanna et al. (2016), and with the World Health Organization (2015) guidelines, stating that significant health improvements can only be achieved by moving away from solid fuel and switching to clean fuel such as LPG, biogas, and electric cooking.

This Chapter also contribute to the broader issue of economic and behavioural

[2]See for example (Mobarak et al., 2012; Beltramo et al., 2015).

drivers of adoption of low-carbon energy technologies in developing regions, and of the welfare effects that the low-carbon energy transition entails. At the same time, they are meant to shed light on the energy situation, needs, and demand of households in refugee settlements, as well as on energy-related welfare aspects of the everyday life of refugees. Both these topics are still under-researched – especially from a quantitative perspective. For this reason, while I acknowledge the limitation of cross-sectional survey data, I believe this is an important first step to start a conversation and inform future research on the topic.

3.2 Background and literature review

3.2.1 Willingness to pay and technology adoption

Low rate of adoptions and low WTP for technologies that are supposed to provide high returns and substantial improvements in the quality of life, are a puzzling result in the literature on energy efficiency and clean energy, in low and middle-income countries as well as in high-income countries. These results are especially robust in the case of biomass-fuelled non-traditional cookstoves, and has been found both in rural and urban contexts – see for example Mobarak et al. (2012); Whittington (2010); Beltramo et al. (2015).

Berkouwer and Dean (2019) conducted a randomised field experiment in Nairobi, Kenya's capital, in which they first confirm that the energy efficient cookstove being offered does in fact result in substantial fuel savings. Despite the high returns, they observe under-adoption and low WTP for the technology, and test for inattention to future savings and for credit constraints as potential explanations. While the former does not appear to be an important channel, the WTP is more than doubled when households have access to credit and the possibility to convert a large upfront payment into smaller instalments.

While low ability to pay is one of the key barriers to adoption, priorities and attitudes, experience, and expectations are other relevant factors. In the literature on determinants of WTP for clean energy and low-carbon technologies in general, Guo et al. (2014) find significant effects of knowledge and attitudes towards renewable energy in China, while Batley et al. (2000) document the effect of experience on WTP for renewable energy in the UK, and Claudy et al. (2011) shows how subjective consumer perception of product characteristics affects WTP for electricity micro-generation technologies in Ireland. Compliance with habits, traditions and cultural norms is another relevant factor that has been found to affect technology uptake in the global South, especially in the case of cookstove. Convenience of use, food taste and traditional food preparation have been cited as barriers to switch to non-traditional cookstoves (Sesan, 2012; Jeuland and Pattanayak, 2012), and efforts are now being put to design culturally appropriate and context-specific non-traditional stoves (Bensch et al., 2013).

Moreover, not all non-traditional cookstoves are created equal, and huge heterogeneity exists in terms of what type of improvement each stove provides, and whether they provide any improvement at all. If Berkouwer and Dean (2019) found that their cookstove effectively reduced charcoal use, Mueller et al. (2011), Yu (2011), Hanna et al. (2016) provide further evidence of interventions in China – the former two – and India – the latter – in which non-traditional cookstoves have failed to deliver on their promises of substantial health and fuel savings effects.

Hanna et al. (2016) is especially interesting, as they analyse an RCT conducted in rural Odisha, India, where the construction of a fixed non-traditional cookstove was offered at a highly subsidised cost, so to be almost free for the household. The stove was similar to the traditional one, in terms of materials and general design, but included a base for the fuel, so that it would burn more efficiently and contain the smoke into the fuel chamber, and a chimney to disperse the smoke away from the user. While some health improvements were found in the first year of use, the benefits faded away in the following period, due to lack of maintenance and correct utilisation. They also found that uptake was far from universal, even though the stove was offered for less than one dollar, and households often kept using their traditional stove side-by-side the new one – a practice known as stove or fuel stacking – and even abandoned the latter completely as time passed.

While non-traditional cookstoves have the potential to deliver important social benefits, especially in terms of environmental conservation, pollution and health, as discussed below, Jeuland and Pattanayak (2012) illustrate how the net effects of non-traditional cookstoves are far from certain, especially when focusing on the private and appropriable benefits and costs.

The problems of returns' uncertainty are compounded when quality of the product is not easily observable, and sub-standard or counterfeit models are present in the market, as Bensch et al. (2015) found in the case of non-traditional cookstoves in Burkina Faso, where a labelling scheme has been introduced for quality certification. This makes it more difficult for households to experiment and learn about the new technology and might even result in a generalised lack of trust in the product and its suppliers, as discussed by Bold et al. (2017) in the case of fertilizer and hybrid seeds.

Finally, even if non-traditional cookstoves effectively deliver improvements, these might be in areas users are less interested in, as a mismatch has often been reported between the solutions development organisations offer, and the priorities of the households they are targeting (Sesan, 2012). A similar mismatch might exist within the household, between the decision-making members and the members that are most likely to benefit from improved cooking conditions. In fact, in patriarchal societies women may lack the power or resources to make purchasing decisions, especially for durables and more expensive item, and men may overlook the health gains and time savings of non-traditional cookstoves as they are not the ones directly appropriating those benefits, as documented by Miller and Mobarak (2013).

3.2.2 Welfare improvements

Non-traditional cookstoves may be designed to achieve improved performance on a variety of dimensions, such as fuel efficiency and/or reduction in smoke emissions.[3] For the purpose of this Chapter I refer to non-traditional or 'improved' stoves as stoves that are different from the three-stone fires traditionally used in the regions under analysis. Fuel efficiency and indoor air pollution are especially relevant issues in developing countries, and are intimately related to the broader issues of poverty alleviation, environmental protection, and sustainable development. At the same time, cooking is one of the key activities in households' everyday life, and one that might take up a substantial share of time and resources – especially women's – in least developed contexts, and even more so in refugee settlements. As a consequence, various authors have studied the welfare effects of different cooking technologies in rural and urban settings in developing countries, but less research has been done

[3]Consider for example (Vianello, 2016) definition: "'improved' denotes positive changes in the efficiency, emissions, safety, durability, user acceptance, cost, fuel sustainability or other beneficial attributes that a new cooking system can offer. An 'improved cooking system' may use any type of fuel and may include options that meet internationally agreed standards for emissions and safety, as well as options that offer measurable benefits relative to traditional forms of cooking but do not necessarily meet internationally defined benchmarks."

on refugee settlements. I am specifically interested in the effects over the following dimensions: (i) fuel efficiency and environmental issues such as deforestation and environmental degradation, (ii) health and safety, (iii) time use, and (iv) gender issues.

Health and safety

Indoor (or household) air pollution (IAP) is at the moment one of the leading environmental causes of death, estimated to kill every year around 2 million people – roughly as many people as malaria and tuberculosis combined (World Health Organization, 2009; Martin et al., 2011). Medical studies have shown links between IAP and several health conditions, from acute respiratory infections and chronic lung disfunctions, to asthma, tuberculosis and several types of cancer. Most of the literature on the welfare effects of non-traditional stoves comes in fact from medical and health studies, some relevant examples being Diaz et al. (2007); Pennise et al. (2009); Gordon et al. (2014); Bruce et al. (2000). More recent literature focuses on health measurements conducted within randomised controlled trial (RCT), to minimise the effects of confounders.

In the flagship RESPIRE study, in Guatemala, for example, non-traditional cookstoves were provided to a random sample of households, and carbon monoxide exposure and health indices between the treated and untreated groups were compared. The results showed reduction in pollution exposure, linked to improvements in terms of eye issues, headaches and back pain (Diaz et al., 2007), women and children's respiratory issues (Smith-Sivertsen et al., 2009; Smith et al., 2011), as well as in a number of other health dimensions, although not always to a significant level. Duflo et al. (2008), Pattanayak et al. (2018) and Jeuland et al. (2015b) bridge the literature on air pollution and health effects with economics and development policies, through a survey of the evidence from the literature.

In absence of experimental data, as in the setting analysed in this Chapter, a few studies have applied quasi-experimental methods or statistical matching with observational survey data to evaluate the impact of non-traditional cookstoves in developing countries, but as far as I know, none in the context of refugee settlements. Importantly, Mueller et al. (2011) focus on the bias in health impact evaluation due to lack of control for health-relevant covariates (age, wealth, kitchen ventilation), which may affect who receives non-traditional stoves and who does not, as well as the outcome. Using Chinese data, they show that while simple difference-in-means estimators show no health improvements for the households with non-traditional stoves compared to those without, a positive effect is found when propensity score matching on health-relevant variables is used. In fact, households who use non-traditional cookstoves appear to be poorer and with worse kitchen ventilation, factors which bias the health effects if not adequately controlled for. Mueller et al. (2013) focus on bias caused by lack of controls for the heterogeneity between households who get the treatment - either through a donation or by purchasing non-traditional stoves themselves - and those who do not, using Chinese household survey data.

Yu (2011) uses data from various indoor air pollution reduction programs in rural China to evaluate the effects of stove improvements and behavioural interventions on children respiratory health, concluding that behavioural interventions are more cost effective, and no significant marginal benefits from the use of non-traditional cookstoves are found. In this case the assignment to different treatment was randomised and data were collected before and after treatment. The treatment groups consisted of subsidised stove and behavioural intervention, behavioural intervention only (stoves are available for purchase at full price, and in fact almost half of the households in this treatment group undertook some form of stove or ventilation improvement), and control. Nevertheless randomisation was not entirely successful in balancing pre-intervention differences (e.g. households in treatment group are poorer, larger, and in poorer health), and matching was therefore use to correct for this problem. Quansah et al. (2017) provide a meta-analysis of studies on the effects of traditional and non-traditional cooking systems on health and pollution exposure.

Further health and safety concerns are linked to firewood collection, as accidents are common, for example due to exhaustion and dehydration, attacks from wild animals, gender-based violence, and conflicts with neighbours, just to mention some. These issues are further exacerbated in refugee settlements, as refugees are less familiar with the surrounding environment, relations with the host communities are often tense, and camps are often located in resource-poor areas. Crisp (2000) for example mentions violence linked to firewood collection in the Dadaab and Kakuma refugee settlements in Kenya, where the host population increasingly attempts to prevent the refugees from accessing lands and forests outside the settlements, and Mulumba (2011) reports similar issues for refugee, especially women, in Uganda.

The refugee population also tends to comprise more vulnerable people, such as women, children, the elderly and individual with health conditions, making health and safety an even higher priority.

Context is relevant. In the sample, almost no accidents with the cookstoves were reported in Goudoubo and smoke is reported as a less severe issue, as almost all the households cook outside and exposure to air pollution is therefore lower, as documented by Langbein et al. (2017). Smoke and accidents are instead widely reported in Kakuma, where more than half of the respondents cook indoor.

Energy efficiency and fuel savings

The issue of fuel use, has attracted the interest of environmental economists and conservationists, as collection of firewood for cooking is leading to unsustainable forest exploitation and deforestation in some areas of the globe. On this matter, I cite Wallmo and Jacobson (1998) on fuel efficiency and conservation in Uganda, Tucker (1999) on solar cooking, and Bensch and Peters (2013) on reduction of deforestation in Senegal, thanks to charcoal savings induced by non-traditional cookstoves. This topic has also become popular - together with the health perspective - with international organizations and development banks (World Bank, 2011).

Adkins et al. (2010) conducted tests with different models of improved cookstoves in rural Uganda and rural Tanzania, and find that the non-traditional cookstoves have lower fuel requirements for the preparation of a standardised dish, in comparison with the traditional cookstove. Bluffstone et al. (2017) found similar results in Ethiopia, and attribute them mainly to the engineering of the stoves, as the results were not affected by the level of experience the cook had with the new stove.

The link between efficiency and fuel savings is nevertheless less straightforward than it might initially seem. Even when non-traditional cookstove are indeed more efficient than the traditional ones, this might not necessarily translate in an overall reduction of fuel used. In fact, as the more efficient cookstove uses less fuel to cook the same meal, it lowers the marginal cost of cooking, so that the new optimal level of cooking increases. In the new optimum, the household may end up consuming as much or even more fuel overall than they did with the traditional stove, a phenomenon known as 'rebound effect'. Evidence of this effect has been found for fuel-efficient cars and other appliances and energy services.

In the case of cookstove, evidence of rebound effect has been documented for example by Bensch and Peters (2013), using data on day-to-day cooking behaviours in urban Senegal, to verify whether the fuel savings obtained under laboratory conditions are replicated in a real world context. Their result is 25% charcoal savings thanks to ICS, less than in laboratory testing (where the savings were estimated to be around 40%). Following the same analytical design, Bensch et al. (2013) conduct an impact evaluation of a non-traditional stove designed to improve fuel efficiency (not designed to curb smoke emissions) in Burkina Faso. They rely on a cross-sectional dataset of survey data, and use propensity score matching and propensity score weighting to estimate the effect of ownership of a non-traditional cookstove.

Energy efficiency and fuel savings are particularly relevant issues for refugee camps in developing countries, as these are often set up in areas with very scarce resources or access to the local resources might be opposed by the host communities. The two settlements analysed in this Chapter are good examples of these issues. Goudoubo is situated in the dry and arid Sahel region, and lack of forested areas is a big problem for the host community as well as for the residents of the settlement, so much so that the firewood distributed to refugee households by humanitarian agencies is actually sourced from regions over 100km away from the settlement.[4] Fuel efficiency has become an even more urgent priority since free firewood distribution was discontinued at the beginning of 2017 (Vianello and Corbyn, 2018). Although resource availability is less dire in the area around Kakuma, the size of the refugee population and conflicts with the host communities over access to lands and forests outside the camp make the needs for fuel savings equally urgent (Crisp, 2000).

Scarce supply of fuel suggests that binding availability constraint might be an issue in the camps – simply improving the efficiency of the stoves might not change the amount of firewood consumed, because households may use all the fuel they have access to and still be short of the quantity they consider optimal given their utility function and budget constraints. In support of this hypothesis, insufficiency of fuel to cover the households' basic cooking needs is one of the main complaint by residents of both camps, and in both camps at least some respondents reported having to exchange foods to obtain fuel. Importantly, a large share of the food available in the camp cannot be consumed raw and require cooking, such as dry beans and grains. In Kakuma households receive 10kg of firewood for every member – equivalent to 60kg

[4]This was reported during key informant interviews in Goudoubo.

for the average 6-person household – every two months, while in Goudoubo the same amount is distributed every month (Vianello and Corbyn, 2018); according to focus groups and informants' interviews, this supply rarely lasts for the intended time and often only for half of it. Focus group participants in Kakuma, where charcoal is also commonly used (although firewood is still predominant), stressed that this fuel is subject to seasonal availability and price might even double when there are shortages. These circumstances make the refugee settings particularly interesting and important to look at.

Time use

On the importance of time saving and how freed-up time can be re-allocated to productive or leisure activities, I refer to Devoto et al. (2012). This aspect of the problem as related to cooking more specifically, has been investigated by Tinker (1987), focusing on time use of women. The use of non-traditional cookstoves may free up time by reducing cooking time itself, or by reducing the amount of fuel needed and therefore the time spent collecting it.

Referring again to Adkins et al. (2010) tests, the authors found the overall cooking time for a standardised dish tended to be longer for the non-traditional cookstoves when compared with the traditional one. Bluffstone et al. (2017) found similar results when the cooks were not familiar with the new stoves, but they report lower cooking time after the cook has gained more experience. On the second aspect, Lewis et al. (2016) document a reduction in time spent collecting firewood linked to the use of non-traditional cookstoves in rural India.

The effect on fuel purchase and fuel preparation time is even more ambiguous, as non-traditional cookstoves often require purposedly prepared fuel and/or fuel different from firewood that cannot simply be harvested and prepared by household members but has to be purchased. For example wood sticks might need to be cut and chipped into a smaller size, transformed into charcoal, or processed into pellets and briquettes. In this case households using non-traditional cookstove would have to dedicate more time to these activities.

Intra-household distribution of workload

Finally, it is to be noted that the consequences of unsustainable and unhealthy cooking practices, are likely not to affect every member of the household in the same way. In fact, women and children spend disproportionately more time indoor and in the vicinity of the stoves, and it is mainly on their shoulder that the responsibilities of firewood collection rest (Ryan, 2014; Batliwala and Reddy, 2003; Shailaja, 2000). Dankelman and Davidson (2013) provide a broader perspective on this topic as related to development, environment, and gender issues. A relevant issue in this context is the 'genderisation' of fuels and the gendered division of labour in the household (Matinga et al., 2016; Munro et al., 2017). Qualitative research in Sub-Saharan Africa has documented how firewood tend to be associated with women, and therefore activities related to it are perceived as being women's responsibilities. Charcoal and other modern fuel such as LPG tend instead to be perceived as more neutral or even associated with men (Troconis, 2017). Moreover, the introduction of a new technology in the household might trigger a process of re-negotiation and re-definition of gender division of tasks (Standal et al., 2020).

3.2.3 Context and dataset

Survey data collected by the Moving Energy Initiative provide the main dataset for the analyses in this Chapter. The surveys were conducted between the end of 2016 and the beginning of 2017 in the refugee settlements of Goudoubo, in Burkina Faso, and Kakuma sub-camp one, in Kenya. Goudoubo is situated in the Sahel region of northern Burkina Faso, in West Africa. The refugee settlement was established in 2012 to host Tuareg and other refugees from Mali that were previously hosted in the camps of Fererio, Gandafabou and Deou and had to be relocated further away from the Malian border to comply with international regulation (UNHCR, 2013). As the situation in Mali has not been resolved yet, new inflows of refugees have kept arriving in the camp since then. Kakuma is instead located in East Africa, in Turkana County, north west Kenya. Settlement of refugees started in 1992, to host forcibly displaced people from Sudan, and grew to assist refugees fleeing from conflicts and persecutions in various neighbouring countries, including the Democratic Republic of the Congo, the Central African Republic, and the new country of South Sudan. The two settlements are among the largest[5] and most important in the respective country, and have a population of around 11,000 and over 190,000 (considering all of Kakuma camp and Kalobeyei Integrated Settlement), respectively. Participants have been selected at random trying to ensure that the sample is representative, following a stratification procedure based on socio-economic clusters and housing blocks in the settlements. The sample size of completed questionnaires is 129 households in Goudoubo and 231 in Kakuma. In 70% of the cases, the questionnaire was answered by the head of the household.[6] Background information about the questionnaires and the data can be found in Vianello and Corbyn (2018).

These data are of particular interest for several reasons. Firstly, they come from two settlements that span different political, social and economic conditions, both in terms of the refugee and the host communities, allowing for comparisons and consistency checks of the results of the analyses. Secondly, the data are particularly relevant due to the specific focus on energy access and demand. The dataset compiled from the survey has a very rich set of variables on the current and desired energy situation of the participants, on their needs and priorities in terms of energy services, and their attitudes and experience with cooking technologies. Micro-data from refugee settlements are generally rare, and even more so micro-data on energy consumption, so that energy needs and energy preferences end up being often overlooked in the context of humanitarian interventions (Lahn and Grafham, 2015; Beogo et al., 2018). Lastly, the survey includes modules to elicit respondents' stated preferences in the form of ranking and willingness to pay for a large set of energy technologies for electricity access and for cooking. This Chapter focuses on the latter domain, where 10 different cooking options were considered – basic ICS (with and without fuel), enhanced ICS using wood (with and without fuel), enhanced ICS using charcoal (with and without fuel), solar cooker, biogas stove, LPG stove, and electric cooker. The ranking exercise includes the traditional three-stone fire as additional option – WTP for this cooking system was not asked, as it is effectively available for free.

[5]$\sim 1.26km^2$ Goudoubo; $\sim 4.17km^2$ Kakuma sub-camp 1, and $15km^2$ for the entire Kakuma complex.

[6]Note that several households identify one woman and one man as joint heads of the households.

Use of traditional and non-traditional cookstoves in the camps

People living in the refugee settlements under study rely on a mix of traditional and non-traditional cookstoves to meet their cooking needs. In both settlements, most of the non-traditional cookstoves have been received as donations, with only a small share being purchased by the households themselves. Three-stone fires are built by household members themselves, as no particular skills or materials are required. Table C.1 shows the penetration of traditional three-stone fires, biomass-based non-traditional cookstoves, and cleaner solar and LPG stoves. Summary statistics are also reported on whether the household cooks indoor and whether they use a chimney, the type of fuel used, fuel consumption, and reference prices for the basic biomass ICS used in the settlements. Photos of three-stone fires and the most common non-traditional cookstoves used in the camps are included in Appendix C.1.

As it is often the case in rural areas of developing countries, fuel and stove stacking are pervasive – households may use wood or charcoal depending on the type of food they are preparing, and often continue to use a traditional three-stone fire side by side a non-traditional cookstove. For instance, Malian refugees in Goudoubo use primarily firewood to prepare food, but switch to charcoal to make the traditional tea. At the time of the survey, 80% of the respondents in Goudoubo used a non-traditional stove, mostly some version of biomass-fuelled ICS, with only about 5% having LPG and 5% having a solar cooker (Blazing Tube, see Figure C.5 in Appendix C.1). The latter were introduced in refugee camps in Burkina Faso as a trial programme, but did not prove particularly successful, as they are very large and impractical to use, tend to break easily, and make it difficult to regulate the temperature and cook the food according to the household's habits and tastes – refugee women even reported receiving divorce threats from their spouses because of this issue (Troconis, 2017). The share of households using a three-stone fire as primary or secondary system is nevertheless still high, at 40%. Notably, almost none of the respondents cook indoor.

The share of households using biomass ICS in Kakuma is similarly 80%, but the level of stove stacking is lower – although still relevant – and only 28% of households still use a three-stone fire. No LPG or solar cookers were reported in the sample. The use of charcoal as main cooking fuel is more common in Kakuma than it is in

Goudoubo, as it is the use of chimneys or hoods to remove smoke from the cooking space. This is linked to the fact that over half of the households cook indoors (either in their dwelling or in a separate building), to avoid the strong winds of the region.

These trends regarding the prevalence of outdoor and indoor cooking are consistent with the general cooking habits of Burkina Faso and Kenya, as documented by Langbein et al. (2017). As measured by the same author, indoor cooking is linked with higher exposure to smoke and air pollution. Consistently, almost 70% of respondents from Kakuma reported experiencing smoke problems and more than 60% reported accidents, while the corresponding share are only 29% and 4% in Goudoubo. Information on these variables, as well as other characteristics of the households and their cooking habits and priorities are presented in Table C.2.

3.3 Part 1: WTP for non-traditional stoves and their characteristics

3.3.1 Theoretical framework: From the WTP for a product to the characteristics' premiums

Individual demand

To analyse the choices of the households, I use the characteristic-space framework, introduced by Lancaster (1966) and used for example in hedonic pricing models (Rosen, 1974). According to this theory, each product can be represented as a bundle of characteristics, and the utility of the agents depends on those characteristics, rather than on the product per se. I therefore define households' utility as a function of the 'improved' cooking service and of z, denoting any other good or service. The price of z is normalised to be 1 ($p_z = 1$). Each household decides how much of their income (M) to allocate to gain access to the cooking service, and how much to all the other goods and services. The 'improved' cooking service can be accessed by purchasing one of J different stoves, or not accessed at all - i.e. households can always choose to use a traditional three-stone fire which can be put together for free. Following the set up of the questionnaire used to produce the dataset I will use in the next Sections, I assume that only one of the J stoves will be made available. The choice of the household therefore simplifies to whether they want to buy stove j or not, if that is the only non-traditional stove available, rather than choosing which one to buy, i.e. $x_j = \{0, 1\}$ with $j = 1, ..., J$, where 0 means not buying, and 1 means buying. Each stove j can then be represented by a vector of K different characteristics, such as improved safety, convenience of use, reliability, etc: $x_j = x(c_{j1}...c_{jK})$. Again following the set up of the questionnaire, the characteristics are introduced as dummies, i.e. they are either present or not present $c_{jk} = \{0, 1\}$, with $k = 1, ..., K$. The consumer choice problem for each i is to choose x_j, so to maximise their utility:

$$U = U(x(c_{j1}...c_{jK}), z) = U(c_{j1}...c_{jK}, z)$$

subject to the budget constraint:

$$p_j x_j + z \leq M$$

The usual axiomatic characterisation of consumer's preferences is assumed, namely completeness, transitivity, monotonicity, and convexity of the indifference curves. Consistently, the utility function is non-decreasing in its arguments ($U(x_j = 1) \geq U(x_j = 0)$; $\frac{\partial U}{\partial z} \geq 0$). Given the local non-satiation assumption, in the optimum the agents will allocate the entire budget, so that the constraint becomes an equation, and I can rearrange it as:

$$z = M - p_j x_j(c_{j1}, ..., c_{jK})$$

Note that the quantity of stove purchased is either 0 or 1, so that the above translates into $z = M - p_j$ if the stove is purchased, and $z = M$ if not. Define the utility in the latter case as the outside option, or reference point $\bar{U}$:

$$U(0, M) = \bar{U}$$

The demand for cookstove j in the optimum can therefore be written as:

$$x_j^* = \begin{cases} 1 & \text{if } U(c_{j1}...c_{jK}, M - p_j) \geq \bar{U} \\ 0 & \text{if } U(c_{j1}...c_{jK}, M - p_j) < \bar{U} \end{cases}$$

That is, the consumer will buy the product as long as the utility they can get is no less than the utility obtained by spending that portion of the income on the other available goods and services. In this context, the WTP for product j is therefore nothing else that the price at which household i is indifferent between buying product j or spending the income on other things, that is they will buy the product as long as the price is lower or equal their maximum WTP, and will not buy if the price is higher:

$$maxWTP_j = \{p_j : U(c_{j1}...c_{jK}, M - p_j) = \bar{U}\}$$

So that I can re-write the demand for the product in a more familiar form, as a function of price :

$$x_j^*(p_j) = \begin{cases} 1 & \text{if } p_j \leq maxWTP_j \\ 0 & \text{if } p_j > maxWTP_j \end{cases}$$

Aggregate demand

Once the consumer choice problem for household i has been set up, it is easy to repeat the same process for each household and obtain the aggregate demand curve as the horizontal summation of each individual demand curve. When I extend the consumer problem to more than one household, I allow households to differ in the 'perception' of each stove's characteristics, and in their priorities with respect to the cooking experience. These elements allow to control for relevant household heterogeneity, together with observed households' characteristics such as income. The 'perceived' or 'expected' characteristics of each stove vary by households $x_{ij} = x(c_{ij1}, ..., c_{ijK})$; this variation is what allows the identification of the premiums the households are willing to pay for each characteristic, that is the quantity of interest. Finally, households have heterogeneous priorities in – or attitude towards – cooking, which I define to be represented by a vector ω_i so that $U_i(.) = U(\omega_i)$. These priorities are captured in the questionnaire by asking respondents "Which attributes of a cooking system are most important to you?".

Characteristics' premiums

Given that households' utility depends on the bundle of characteristics they can gain access to through the purchase of j, I am interested in the premium consumers attribute to each characteristic, i.e. whether and how the presence or absence of each characteristic affects the valuation of the cookstove in which they are embedded, all else equal. To do this, I start by setting up the conditional indirect utility function, or the highest utility level that can be achieved given the budget constraint. Starting with one consumer only:

$$\bar{U}_i = U(c_{ij1}...c_{ijK}, M_i - maxWTP_{ij}) \quad \forall i, j$$

where $maxWTP_{ij}$ represents the highest amount consumer i is willing to bid to obtain product j with characteristics $c_{ij1}...c_{ijK}$ in order to keep their utility at least at level $\bar{U}$. Each characteristic affects the utility level, which means that consumers might be willing to pay more or less for a cookstove if they believe characteristic c_k to be present, as opposed to missing. I define this additional amount as the premium associated with characteristic c_k. This is similar to the concept of indifference curve (but for a discrete 0-1 good), as it represents the trade-off between money and characteristic c_k, that maintains the utility at a given level. Inverting the utility function, holding all characteristics constant but c_k, I can write:

$$maxWTP_{ij} = f(c_{ij,k}, M_i \mid c_{ij,-k}, \bar{U}_i) \quad \forall i, j$$

where $-k$ means all the characteristics other than k. The premium for characteristics k is:

$$\begin{aligned} premium_{ijk} &= f(1, M_i \mid c_{ij,-k}, \bar{U}_i) - f(0, M_i \mid c_{ij,-k}, \bar{U}_i) \\ &= maxWTP_{ij}|_{c_{ij,k}=1} - maxWTP_{ij}|_{c_{ijk}=0} \quad \forall i, j, k \end{aligned} \tag{3.1}$$

For estimation purposes, I assume a functional form for $f(.)$ that allows each characteristic to increase the WTP incrementally, more specifically I consider the following linear model:

$$maxWTP_{ij} = \beta_0 + \sum_k \beta_k c_{ijk} + \mu_i(M_i) + \eta_j + \epsilon_{ij} \tag{3.2}$$

Given that each household provides a stated WTP and expectations on the characteristics for each product, I can rely on a within-subject framework for the analysis. The data for each household-product combinations are stacked, so to create a panel dataset over the two dimensions of households (indexed i) and products (indexed

j). When considering multiple individuals, the willingness to pay for each product ($maxWTP_{ij}$), as well as the 'perceived' characteristics (c_{ijk}), are household- as well as product-specific. Differences in households characteristics (both observable and unobservable) are captured by the household fixed-effects μ_i. These characteristics are household-specific and do not change depending on the product. Cookstoves fixed-effects (or alternative-specific constants) η_j are also introduced to capture characteristics of the products that are not already accounted for in the model, assuming that they are the same for every household. Observed households' priorities regarding cooking, ω_i, are captured by the household fixed-effects, if we assume that every cookstove satisfy each priority in the same way. Alternatively, priorities can be interacted with the cookstoves or with specific characteristics, generating the variable ω_{ij}, so that households with different priorities are allowed to value cookstoves and relevant characteristics differently. As an example, households who consider compliance with habits and traditions as a priority, might value cookstoves that are more similar to the traditional one (such as biomass-fuelled cookstoves) more than households who do not consider this to be a priority. Similarly, households who consider safety or smoke reduction as a priority, might be willing to pay a higher premium for the characteristic "health and safety". In some specifications I further distinguish the alternative-specific constant according to whether the household has had previous experience with that particular technology. ϵ_{ij} is the error component of the model, and assumptions on its distribution are made to ensure the consistency of the estimators for the various β_k which constitute the estimates of interest, according to the model specification used. The average premium for each characteristic c_k can therefore be obtained as:

$$premium_k = maxWTP_{ij}(c_{ijk} = 1|...) - maxWTP_{ij}(c_{ijk} = 0|...) = \beta_k \tag{3.3}$$

3.3.2 Data: WTP elicitation and descriptive statistics

Together with information on the current cooking situation, the questionnaire elicited the stated willingness to pay for different cooking technologies, using open-ended contingent valuation. Note that this Chapter uses secondary data and the survey was designed with the needs of the NGOs involved in mind, namely to gauge respondents' interest for a wide range of energy-access options, in the two domains of cooking, and electricity access and lighting.[7] In this respect, the open-ended contingent valuation has an advantage over auction-types elicitation methods recommended in the literature on valuation of private goods, such as the Becker-DeGroot-Marschak (BDM) auction, in terms of time and resource requirements and logistics. With respect to dichotomous choice questions, another methodology commonly recommended in the literature, there is evidence that for the valuation of a private good providing a service respondents are familiar with (such as cooking) the open-ended contingent valuation can perform as well, if not better (Loomis, 1990; Kealy and Turner, 1993; Frew et al., 2003; Whynes et al., 2005; Vossler and Holladay, 2018). The open-ended questions were designed following recommendations and best-practice from the literature, as described in this Section and further discussed in Section 3.3.3. In the latter I discuss the validity of the responses through a scope test comparing the stated WTP for cookstoves offered with and without the fuel, and through comparisons between the stated WTP and households' expenditures, stated WTP and estimates market price for the stoves, and between stated WTP in the two camps.

In terms of questionnaire design, the WTP module starts with a presentation of the scenario and the payment vehicle, and includes 'cheap talk' to reduce hypothetical bias. To allow for comparisons between stoves that use different fuels, respondents were asked to state a WTP for an all-inclusive service, including instalments to repay the cookstove and periodic supply of the necessary fuel. The payment vehicle used is explained carefully and with examples. A per day charge is used, as periodic payments tend to be preferable over upfront payments for people in poor and liquidity constrained situations. Moreover, in both camps under analysis, buying at credit to then repay periodically is common. Collecting or buying fuel periodically, often daily, is also common. The payment vehicle is therefore chosen to be consistent with payment arrangements and a temporal interval respondents are already familiar with. For each technology, an information card was first presented and respondents were encouraged to ask questions and clarifications. They were then asked what they liked and disliked about it, to make sure they were focusing on that specific stove. A reminder of the scenario, payment vehicle and 'cheap talk'

[7] In this case, 17 different WTP questions were asked, consisting of 10 different cooking options – basic ICS (with and without fuel), enhanced ICS using wood (with and without fuel), enhanced ICS using charcoal (with and without fuel), solar cooker, biogas stove, LPG stove, electric cooker – as well as six different electricity access options – basic solar lantern, system with multiple solar lanterns and connections, solar home system, and basic, medium, and high quality minigrid connections – and WTP for public street lighting.

were then repeated in the actual WTP question:

> "Assume that this technology is the only one that is made available. Given the benefits that this option would bring to your household, what is the highest price you would be willing to pay for it per day? Please think carefully and give an honest and realistic answer."

The possible options provided were "I would pay nothing for it and therefore not receive it", or, if the respondent was interested in the technology, an open-ended space to enter the monetary amount in local currency.[8] The option "I don't know" was also allowed. Responses have then been converted in USD per month for the present analysis. Given the peculiarity of refugee settlements, the valuation of non-traditional stoves in these settings has some commonalities with the valuation of non-market goods. In particular, there is hardly any supply chain and therefore market for most of the non-traditional stoves I consider in this analysis (in particular enhanced ICS, LPG, biogas systems, electric cookers, or solar cookers). For this reason, this Chapter focuses on stated preferences. While I acknowledge the limitations of this type of data as far as the cardinal values are concerned, what I am really interested in are the ordering and the trade-offs between different types of cooking technology and between attributes. Section 3.3.3 provides a discussion on the validity of the elicitation method in this specific context.

Regression analysis using the stated WTP is presented in Section 3.3.4. As a robustness check, and to gain further insights into respondents preferences, in Section 3.3.5 I apply regression analysis to the responses in the ranking exercise, conducted after the WTP elicitation module. Respondents were asked "If all these forms of energy access were available in what order of preference would you rank them?", and the alternatives to be ranked included the seven technologies for which WTP was elicited plus the traditional three-stone fire.[9] The ranking variable is therefore constructed so that the solution ranked as top has the highest score (i.e. 8), while the solution ranked last has a score of 1. Some households did not rank all the solutions, possibly because they had no interest in those they chose to leave out. These are given a score of 0 and considered as the least preferred options.[10] The

[8]West African CFA Franc in Goudoubo, and Kenyan Shilling in Kakuma.

[9]The three-stone fire can be assembled for free by members of the household, so WTP for this technology would not asked.

[10]I check the robustness of the results to this assumption, by repeating the test treating those observations as missing, and I find no significant differences in the results.

main difference between the scenarios presented in the willingness to pay module and in the ranking module is that in the former respondents were asked to answer considering a scenario in which the technology offered was the only type of stove available; in the latter they are asked to rank the options if all of them were available at the same time. The questionnaire also asked which stoves they would actually buy, if all were available. This question has a large share of missing values and respondents saying yes to all or none to all, so I do not use it as an outcome variable, but I use it to do consistency checks with the answers to the ranking question, as both are elicited with the same scenario. Answers to this latter question were used to construct a dummy for each solution, which takes the value 1 if the respondent chose that option among those they would buy, and zero otherwise. I then perform a t-test on the mean difference of the ranking position between households who are interested in buying the technology and those who are not. The mean ranking of households interested in buying the solution is always significantly higher than the mean ranking for those who would not buy it, with the exception of the basic non-traditional cookstove, where there is no significant difference in the ranking between the two groups. I checked the two settlements separately, and the results for this technology do not change. Possible explanations for this are that some households might be able to build this type of stove by themselves, and would therefore not be willing to buy one, even if they rank it high - or alternatively, that they already have a basic non-traditional cookstove, or are used to it being donated rather than purchased.

To avoid outliers skewing the results of the analysis, WTP responses for each technology are winsorised at 5% and 95%, that is values below the 5th percentile and above the 95th percentile are replaced with the value at the 5th and 95th percentile respectively. This is a common practice to deal with outlier in stated preferences studies (see for example Kahneman and Ritov, 1994; Halasa et al., 2014; Kirwan and Roberts, 2016; Moon and Nelson, 2019). This process only affects the top part of the distribution, as the values at and below the 5th percentile are zero for all technology, so no replacement occurs in this case. Summary statistics for the stated WTP are presented in Table 3.1. Reassuringly, the data do not show any apparent inconsistency. Willingness to pay for biomass-fuelled stoves is always greater when the fuel is included as compared to the case where only the stove is offered (a formal test is conducted in Section 3.3.3). In both settlements, the willingness to pay for a biomass stove including fuel averages around 5-6 USD per month, with charcoal being valued slightly more in both settlements. The respondents who are interested in more modern form of cooking such as biogas and LPG, appear to be willing to pay a 50-100% higher price for them. Electric cooking is valued even higher in Kakuma, while it attracts almost no interest in Goudoubo. Finally, the willingness to pay for solar cookers is rather low in both settlements, but it should be considered that this is potentially a very cheap technology, especially when the fuel is taken into consideration. More interesting in this regard is the share of respondents who show some interest in the technology. This is very low in Goudoubo, while it is comparable to the other non-biomass technology in Kakuma.

Table 3.1: Summary statistics for the observations with a positive willingness to pay for different cooking technologies in the two settlements (USD/month). WTP observations for each technology are winsorised at the 5th and 95th percentiles.

WTP for cookstoves in Goudoubo (USD/month)

	$WTP > 0$	Mean	SD	p25	p50	p75
basic ICS (stove only)	50%	3.52	4.06	1.27	2.54	4.45
basic ICS (with fuel)	41%	5.36	4.23	2.54	5.08	5.08
enhanced ICS, wood (stove only)	46%	4.43	4.15	1.53	2.54	5.08
enhanced ICS, wood (with fuel)	42%	6.21	5.00	2.54	5.08	7.63
enhanced ICS, charcoal (stove only)	52%	3.91	3.45	1.27	2.54	5.08
enhanced ICS, charcoal (with fuel)	45%	6.00	4.56	2.54	5.08	7.63
solar	8%	5.26	3.76	1.27	5.08	7.63
biogas	20%	14.8	9.97	7.63	10.2	25.4
LPG stove	47%	18.1	23.9	5.08	7.63	25.4
electric stove	6%	10.9	12.4	3.18	6.36	16.5

WTP for cookstoves in Kakuma (USD/month)

	$WTP > 0$	Mean	SD	p25	p50	p75
basic ICS (stove only)	52%	4.13	5.62	0.45	3	4.50
basic ICS (with fuel)	44%	7.93	7.30	3	4.50	10.5
enhanced ICS, wood (stove only)	42%	5.57	6.10	3	3.60	5.40
enhanced ICS, wood (with fuel)	40%	8.11	7.77	3	5.10	10.5
enhanced ICS, charcoal (stove only)	47%	4.82	5.83	1.80	3	4.50
enhanced ICS, charcoal (with fuel)	42%	8.76	7.66	3	6	11.1
solar	37%	4.15	4.00	2.10	3	6
biogas	31%	11.0	11.2	3	6	22.5
LPG stove	42%	35.1	37.8	3	15	63
electric stove	40%	25.3	23.7	3	15	58.5

Figure 3.1 shows a comparison of the aggregate demand curves for the different technologies, separately by settlement. Aggregate demand curves have been plot-

ted so that the x axis shows the share of the respondents willing to pay at least a certain price. In both settlements, the demand curve for LPG is dominant, while solar cookers attracts very low willingness to pay. The demand curves for biogas and biomass stoves are somewhere in between, with biogas eliciting higher willingness to pay from a smaller group of household in comparison with the biomass non-traditional-cookstoves. The demand curves for the two type of biomass non-traditional-cookstoves, wood-fuelled and charcoal-fuelled, follow each other very closely in both settlements. The biggest difference between the two settlements is in the demand for electric cookers, which is the lowest demand curve in Goudoubo on a par with solar cookers, and one of the highest demand curve in Kakuma, following closely the demand curve for LPG.

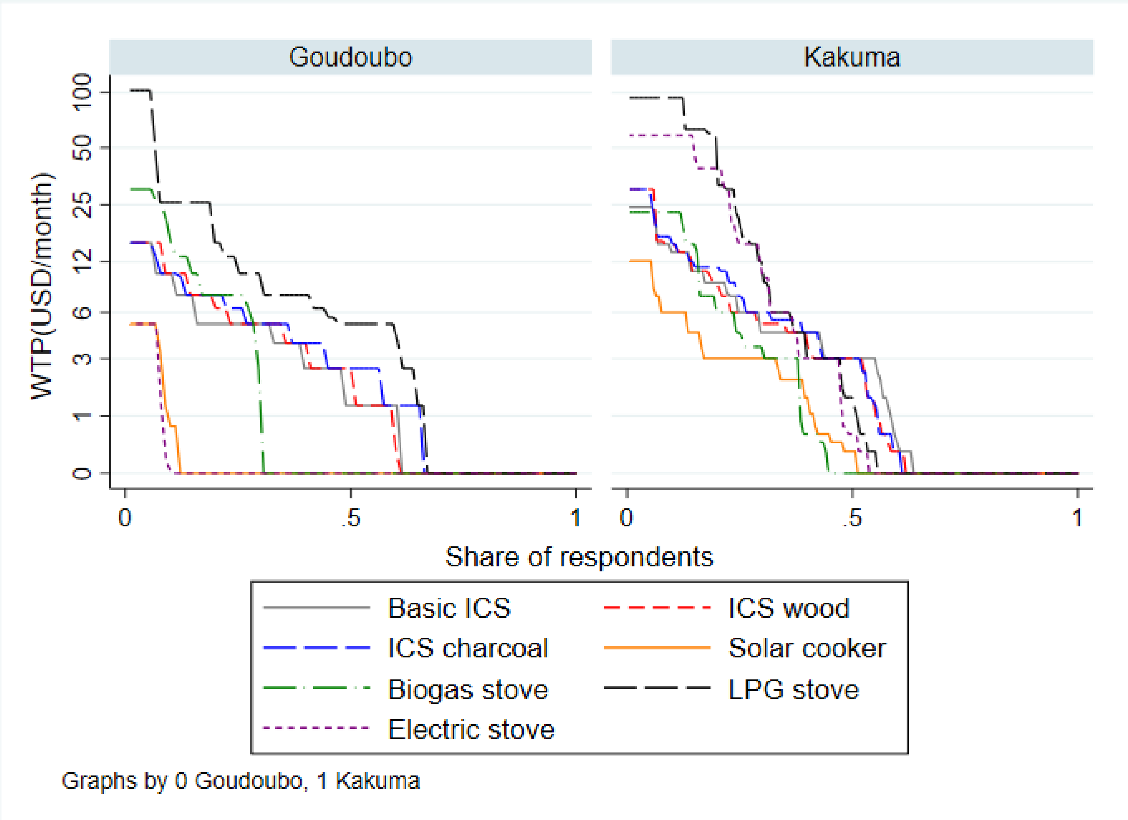


Figure 3.1: Aggregate demand curves for each technology.

As discussed in more details in Section 3.3.3, for a large share of respondents the willingness to pay is much lower than the cost of the technologies. But even more alarming is the finding that many are not interested in the non-traditional technologies no matter the price. This would not only predict a low take-up of the new systems if they were ever to be offered at market prices, but possibly a far from universal take-up even if they were to be distributed for free. As it has been frequently noted in the literature and in direct experiences on the ground, cultural acceptability and habits might be forces as strong as budget constraints in preventing the transition to cleaner cooking solutions. Another possible explanation, though, is that households do not believe the supposedly 'improved' systems actually deliver the promised improvements, or at least not to a level that would justify the high premium required for their purchase - as well as the cognitive effort of adopting them. In a similar vein, there might be a mismatch between the improvements the new stove provides, and the improvements the users are looking for.

To investigate these hypotheses, I look at the characteristics that respondents expect to find in each product. For each cookstove type households were asked "What do you like about this option?" and could choose more than one answer among the following list: "System capacity: which pots can be used", "Duration of energy supply", "Reliability", "Robustness", "Health and safety", "Convenience", or the outside option "No opinion". The list of characteristics was designed from responses from previous questionnaires administered by the same NGO in refugee camps and rural communities in different Asian and African countries, in which the question was left open-ended. As can be seen from Table 3.2, there is substantial heterogeneity in the perceived characteristics of each technology, providing the variation to estimate each characteristic's premium according to the characteristic-space framework developed in the previous section.

In fact, if households derive their utility from the characteristics of the product, rather than directly from the product itself, they will be willing to pay a different price depending on whether they believe the product to provide or not provide those characteristics. It is to be noted that characteristics of the cookstoves are self-reported perceptions, rather than exogenously controlled as in a discrete-choice experiment; endogeneity of perceptions might therefore be an issue and all results are to be interpreted as partial correlation. A similar caveat applies for whether respondents have previous experience with the technology, as in a normal situation this would be the result of households' deliberate decisions, and experienced and inexperienced households might therefore be different in some unobservable characteristics that might also affect the dependent variable. Nevertheless, in the refugee settlements under analysis previous experience is more often determined by participation in pilot schemes or donation programmes, rather than being the results of respondents' purchases in the private market, as the technologies considered are not easily found in the local markets, nor in the country of origins, especially if refugees come from rural areas. Despite these limitations of the data, the main purpose of this Chapter is to provide a first analysis of the situation in refugee settlements to better pinpoint the most relevant issues and knowledge gaps, and encourage further research and data collection efforts.

Table 3.2: Share of respondents who perceive the characteristics to be present in the technology.

Goudoubo

	(ics basic)	(ics wood)	(ics char)	(solar)	(biogas)	(LPG)	(electr)
convenience	45%	55%	53%	15%	22%	50%	9%
duration	2%	3%	2%	0%	4%	12%	1%
health	14%	16%	15%	2%	10%	19%	2%
reliability	4%	2%	5%	0%	11%	14%	2%
robustness	4%	9%	5%	1%	11%	23%	2%
capacity	12%	10%	8%	3%	11%	18%	6%
N	129	129	129	129	129	129	129

Kakuma

	(ics basic)	(ics wood)	(ics char)	(solar)	(biogas)	(LPG)	(electr)
convenience	35%	32%	32%	35%	23%	25%	26%
duration	23%	23%	23%	23%	21%	32%	30%
health	34%	34%	31%	41%	28%	35%	34%
reliability	42%	48%	49%	37%	33%	45%	39%
robustness	17%	14%	16%	10%	13%	18%	18%
capacity	8%	8%	9%	7%	7%	14%	20%
N	231	231	231	231	231	231	231

Finally, I include in the analysis the priorities expressed by the respondents in the multiple-answer question "Which attributes of a cooking system are most important to you? Rank at least three". Looking at the attributes ranked as top priority, the two settlements show different distributions. In Goudoubo, the greatest concern is to "save fuel" (21% of the respondents ranked it first), followed by "fast preparation of food" (13%), "suits our cooking habits" (11%), "stove is locally available" (10%), "less smoke" (9%), "easy to handle" (7%), "stove is easily transportable" and "can be used with different pot sizes" (6%), "safe to use" (4%), "traditional and familiar stove", "good taste of food" and "comfortable size of the stove" (3%), "affordable price" and "easy to repair" (2%). In Kakuma, the greatest concern is to have a stove that produces "less smoke" (18% of the respondents ranked it first), followed by "save fuel" and "fast preparation of food" (12%), "traditional and familiar stove" (10%), "safe to use" (9%), "affordable price" and "stove is locally available" (7%), "easy to handle" (6%), "comfortable size of the stove" (5%), "easy to repair" and "can be used with different pot sizes" (4%), "suits our cooking habits" (3%), "good taste of food" (2%), and "stove is easily transportable" (1%).

In both settlements, energy efficiency is in high demand - in line with the result from Mobarak et al. (2012), where most of the respondents listed reduced fuel cost and cooking time as the most valued characteristics – but health and safety concerns are not too far behind, especially in Kakuma, where indoor cooking increases the exposure to smoke and the risk of burns and other accidents. Compliance with habits and traditions, considered to include the two options "suits our cooking habits" and "traditional and familiar stove", appears also to be important for a share of the population, while less so the affordability of the stove. A possible explanation for the latter is that respondents value the quality of the stove and are therefore willing to pay more for a better service - but this could also be linked to the hope of receiving the stove for free or at a subsidised price, as it is common practice in the settlements. In the regression analysis I consider more specifically the respondents' priorities with respect to safety, reduced smoke emissions, reduced fuel use, cheap cooking, fast cooking, as these represent the type of improvements non-traditional cookstoves are designed to deliver. I also include compliance with habits and traditions, as this might be a barrier to adoption and might lead respondents to prefer biomass-fuelled stoves, that use the traditional fuels, rather than more modern and clean options.

3.3.3 Validity

The use of open-ended contingent valuation to elicit WTP for cookstoves

This section discusses the validity of stated preferences to infer information on households valuation of the cookstoves and their likely behaviour if they were to be provided for real, as well as the use of open-ended contingent valuation as a valid elicitation mechanism for stated preference.

On the first question, Griffin et al. (1995)'s study on piped water connections in India, compare stated preferences elicited from contingent valuation with actual behaviour once the service was provided, and find that the hypothetical responses are reliable predictors. Whittington (2010) similarly remarks that, although the literature is still scarce and mainly focused on industrialized countries, there is evidence that stated and revealed preference estimates for WTP tent to be similar.

Divergence between the two has mainly been reported when voluntary contributions are used as payment vehicle, which is mainly related to public goods, and in the case of laboratory experiments, as questions tend to be purely hypothetical and consequentiality is less credible. Neither of these concerns apply to my context. He further discusses how familiarity with the good or service being offered and cheap talk have been shown to reduce hypothetical bias, while dichotomous take-it-or-leave-it questions tend to result in overstated values because of a yes-saying bias. Moreover, in developing countries and for poorer segments of the population, liquidity constraints and low disposable income make large upfront payments less preferable, and this should be taken in consideration when choosing the payment vehicle for the valuation.

This provides further support for the validity of the valuation responses used in my analysis, which were obtained using open-ended questions rather than dichotomous choices, included cheap talk[11], focused on a familiar and salient aspect of refugees' everyday life, cooking, and used a periodic fee – presented as installment payments or repayments on a loans, which the respondents are familiar with – rather than a one-off price. The payment vehicle in particular is explained carefully and with examples, and respondents are reminded that they are asked for their

[11] 'Cheap talk' is used in the presentation of the scenario, as respondents are asked to "please, try to think carefully and give an honest and realistic answer. Honest answers are really valuable and important for us", and then again every time the willingness to pay question is asked, reminding to "please think carefully and give an honest and realistic answer".

willingness to pay as a daily charge in every question. In the specific contexts under analysis, buying at credit to then repay periodically is common, consistent with the presence of liquidity constraint and lack of disposable income. Collecting and buying fuel periodically, often daily, is also common.

On the use of open-ended contingent valuation, Vossler and Holladay (2018) find that this format tends to result in lower estimates than the more widely recommended single binary-choice referendum, and this seems to be because respondents are less likely to view the open-ended questions as consequential. The two tend to converge if consequentiality is made more credible, and their findings support the claim that open-ended contingent valuation do not require as large samples as other valuation methods.

The authors also identify four conditions under which open-ended questions are incentive compatible. First, the good or service offered need to be relevant and of interest to the respondents – which is the case with cooking technologies in refugee settlements, as households spend a substantial share of their resources and time to collect, purchase and prepare fuel, and to cook meals. Before providing their willingness to pay, respondents are asked what they like and dislike about the option offered, encouraged to ask questions and clarifications, and shown an information card with a photograph of the cookstove, and asked to think of the benefits that that particular cookstove would have for their household. This is to increase the concreteness and saliency of the good being offered, and to make respondents consider the costs and benefits of the offer.

Second, the payment must be credibly enforceable – households in the settlements are used to see non-traditional cookstoves as a market good (as opposed to the traditional three-stone fire, which is mostly built in-house) and to pay for any purchase they make, in kind if not using money; in both settlements, buying at credit and then repaying over time is also a common practice. A concern in the context of refugee settlements might be the expectation of receiving the cookstoves or the fuel as donations and free handouts, but in both camps and in the humanitarian sector more generally, the tendency is now to provide vouchers, rations and periodic allowances instead, so that residents can make decisions on what they want to purchase and in what quantity, theoretically improving the feeling of ownership and self-sufficiency over that of dependence.

Consequentiality is a further condition, that is respondents should believe that the proposed service is more or less likely to be implemented depending on how much interest it attracts, or in other words, they should believe that their answers matter in whether the project is realised or not.

The final condition, is that the answers should only affect whether the proposal is implemented or not, but not the price the respondent would have to pay, which should be communicated as being still uncertain but eventually determined by the actual cost of the implementation – and therefore exogenous to the valuation exercise. This is crucial to avoid strategic bias in responses, and can be effectively achieved using a BDM auction. This option was not feasible in the survey used for this Chapter, but as non-traditional cookstoves are a market good and would therefore be sold in the market, it is reasonable to believe that their price would indeed depend on the actual costs of providing the good, as it is the case for any market good, and not affected by the value stated in the valuation questions. To reinforce this view, organisations in the camps tend to support the creation of supply chains and help local businesses supply products rather than being directly involved in the sales, consistent with the approach to humanitarian intervention described above.

In line with these two final conditions, the valuation scenario was introduced as:

> "Discussions are being made on which energy sources could be of interest for people in the camp. We would therefore like to know, if each of these energy sources could be made available in the camp, whether you would be willing to pay something to have it, and how much you would be willing to pay"

stressing that the aim of the questions are to gauge the interest in the different technologies, rather than establishing a price for them.

Carson and Hanemann (2005) recognise that simple open-ended questions are the easiest to explain to respondents and provide more precise and readily interpretable information than dichotomous choice formats. Most of the critiques they review for this type of elicitation apply to the valuation of public goods, and are less of a concern for private goods.

A relevant downside of open-ended contingent valuation is the large rate of non-responses and zero answers. Large non-response rates are nevertheless less likely to occur with private goods and payment vehicles respondents are familiar with and that have tangible and salient costs and benefits for the respondents, as in the case of cookstoves. Moreover, in the survey in case of an “I do not know” answer, the respondents were then asked two or three dichotomous take-it-or-leave-it questions using a reasonable estimate of what the cookstove price might be in the camp, to be able to still gain some information on their willingness to pay. The large share of zero answers is consistent with the evidence that open-ended contingent valuation tend to produce lower estimates compared to other elicitation methods, although this would counteract the tendency to provide over-inflated estimates due to the hypothetical bias, as remarked by Whynes et al. (2005).

One issue that affects specifically private goods, is the incentive to behave strategically rather than reveal the true willingness to pay. If the respondents believe their answers would make it more or less likely than the good is produced and offered in the market, they might have an incentive to over-state their interest just to get the good as a further option in the market, and they can then decide whether they are indeed willing to pay its price or not once it is actually offered. Conversely, if they believe the aim of the survey is to determine the price of the good, then the incentive is to under-state the real willingness to pay, to try and make it cheaper.

Nevertheless, this concern affects mainly the credibility of the cardinal WTP, but the ordinal values between technologies and the trade-off between the different stoves and the different characteristics should not be affected – which is what matters for this Chapter’s analysis. Strategic behaviour should moreover be attenuated by the ‘cheap talk’ used in the questionnaire. Additional discussion on the credibility of the cardinal values elicited in the survey is presented in the following paragraphs. Other concerns raised by the authors regard incentive-compatibility, consequentiality, plausibility and saliency of the good offered, and payment vehicle – already addressed above – and the use of dichotomous rather than open-ended questions.

On this latter issue, Kealy and Turner (1993) compare open-ended and closed-ended contingent valuation for a private and a public good, and find no difference in results for the private good. They remark that incentives for strategic behaviour are less of a concern for private goods, and that valuation is more likely to be stable across elicitation methods the more familiarity and previous experience the respondent has with the good and the payment vehicle, and the more tangible and salient the good is – characteristics that apply to the cookstoves and the refugee settlements considered in this Chapter. Similar results on the reliability and convergence of values from open-ended and dichotomous choice questions have been obtained by Loomis (1990) using a test-retest procedure for the valuation of water quality in a lake.

Tests comparing different valuation methods have also been conducted in the health literature. Frew et al. (2003) show that open-ended valuation questions and payment scale questions result in similar answers, while valuations using dichotomous choices are significantly higher, possibly because of yes-saying and anchoring bias in the latter method. Whynes et al. (2005) compare valuation answers and the resulting demand curves elicited using open-ended contingent valuation, short and long payment scales, and dichotomous choice questions. They find that the different methods provide different results, with the answers to open-ended questions being the most conservative. As hypothetical bias would induce overstated WTP, and decision-makers tend to be risk averse, they choose the more conservative valuation from open-ended questions as their preferred one. Onwujekwe and Uzochukwu (2004) elicit WTP using binary with follow-up elicitation and open-ended questions, and compare them to respondents' actual behaviour once the payment is due. Again, they conclude that open-ended contingent valuation performs better than dichotomous choice, based on construct and criterion validity.

Scope test: WTP for stove only v. fuel included

To gather evidence in support of the validity of the answers, I compare the stated WTP when only the cookstove was offered, with the WTP for that same cookstove when a supply of fuel was also included. Each respondent was asked for their WTP in both of these scenario for the three different types of biomass cookstoves - basic ICS, enhanced ICS using wood, and enhanced ICS using charcoal. Firewood is sometimes framed as a 'free' fuel, as households can collect it from the surrounding of the settlement without paying any monetary price. A similar narrative applies to charcoal, as some households make their own using the firewood collected. Free distributions of firewood for cooking also occur periodically in the camps. At the same time, harvesting firewood can be a time consuming and dangerous activity, as vegetation around the camps becomes increasingly scarce - especially in the arid Sahel region, where Goudoubo camp is located - and accidents are common, for example due to exhaustion and dehydration, attacks from wild animals, gender-based violence, and conflicts with the host community, just to mention some. These questions were therefore added to gain insights on whether respondents see firewood and charcoal as 'free' resources, but can also be used to perform a scope test, to make sure that the 'larger' bundles - the cookstoves plus fuel supply - elicit a valuation higher or at least as high as the 'smaller' bundles - the cookstove alone. A t-test on the difference in mean for each technology, under the two different scenarios, confirms that the scope test has been passed, as the null hypothesis that the larger bundle is on average valued the same or less than the smaller bundle is always rejected with a confidence level of at least 90%. The results are reported in Table 3.3. Figure 3.2 plot the difference between the WTP under the cookstove plus fuel and cookstove only scenario for each respondent that expressed interest in that cookstove (that is, that was willing to pay at least something for it). All the respondents with the exception of a handful, reported a WTP for the cookstove plus fuel bundle that is at least as high as that for the cookstove only.

Table 3.3: T-test for the difference in mean between the WTP for cookstove with fuel supply, as opposed to cookstove only. The WTP for the two scenarios was only elicited for biomass cookstoves. All other cookstoves were presented as including fuel.

Goudoubo

	Mean w fuel (USD/month)	Mean w/o fuel (USD/month)	Diff. (USD/month)
WTP for basic ICS	3.23	2.23	+1.00**
WTP for enhanced ICS, wood	3.73	2.72	+1.00*
WTP for enhanced ICS, charcoal	3.91	2.62	+1.29**

*** p<0.01, ** p<0.05, * p<0.1; p-value based on one-sided test

Kakuma

	Mean w fuel (USD/month)	Mean w/o fuel (USD/month)	Diff. (USD/month)
WTP for basic ICS	4.99	2.79	+2.20***
WTP for enhanced ICS, wood	4.96	3.52	+1.44**
WTP for enhanced ICS, charcoal	5.29	3.07	+2.22***

*** p<0.01, ** p<0.05, * p<0.1; p-value based on one-sided test

Comparison between WTP and current expenditures

As additional evidence that the WTP values elicited are reasonable, Figure 3.3 compares the stated WTP per month with the reported total monthly expenditures for the household. In Goudoubo the valuations provided are all well below the house-

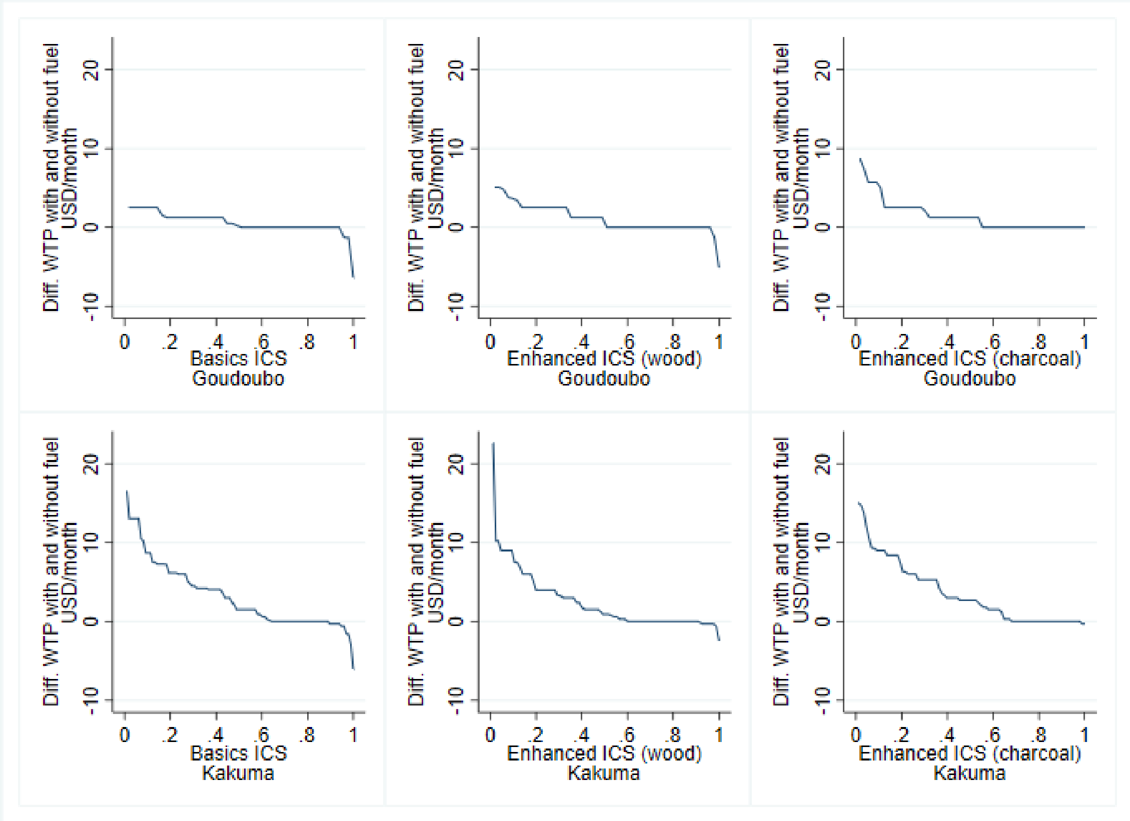


Figure 3.2: Distribution of the difference between each respondent's WTP for cookstove plus fuel, as opposed to cookstove only. Positive values mean that the respondent is willing to pay more when the fuel is included. Only respondents interested in buying the stove (i.e. with positive WTP) are included in this figure.

hold expenditures, used as proxy for the disposable income. Summary statistics for the WTP for each cookstove as a ratio of the total reported household expenditures are presented in Table 3.4. These statistics only include observations with positive WTP and expenditures. The current expenditures in energy for cooking – calculated as the sum of spending in firewood, charcoal, briquettes, LPG – as a ratio of total expenditures is also included for comparisons. Most ratios in Goudoubo are less than 10%, and comparable with what households currently spend in cooking fuels. Ratios for LPG and biogas are higher, but still within the household disposable income – this is consistent with the fact that those cookstoves and LPG refills are more expensive, and at the same time much cleaner than biomass cookstoves. In Goudoubo the median WTP for biomass cookstoves not including fuel is between 2.6 and 5% of the total monthly expenditures, rising to 6 to 7.6% for the same cookstoves including fuel, solar cookers, and electric cookers. The median WTP for biogas and LPG cookstoves is higher, at 18 and 12% respectively. In Kakuma this is not true for the whole sample, but it is to be noted that NGOs working in the camp remarked that the income and expenditures values reported by our respondents in Kakuma are much lower than expected. This is confirmed by other reports and surveys conducted in Kakuma in the last few years, which report a median income per household of between 30 and 50 USD per month, and a mean household income of between 50 and 70 USD per month (Guyatt et al., 2016; Samuel Hall, 2016; Betts et al., 2018; World Bank, 2018). Guyatt et al. (2016), who report specifically on expenditures in Kakuma sub-camp one, found a median expenditure of 20 USD per month, and a mean of 45 USD per month. This is compared to a median of 10 and mean of 35 for the same variable in my sample. As further evidence that the WTP values are within a reasonable range, but the total household expenditures in Kakuma are under-reported, the WTP to total expenditures ratios presented in Table 3.4 are mostly comparable with what households currently spend in cooking fuels, with the only exception of the cleaner and more expensive LPG and electric cookers, which elicit a higher WTP. Comparing the stated WTP with the current expenditures in cooking fuels in absolute terms in each camp (Table 3.5), it can be seen that the WTP for biomass cookstoves tend to be even lower than what households already spend for cooking. This is additional evidence that the stated WTP values are reasonable and within the respondents' ability to pay, and may even underestimate the actual demand – at least for the biomass cookstoves.

Table 3.4: Summary statistics of the WTP as share of total reported expenditures, for observations with a positive WTP.

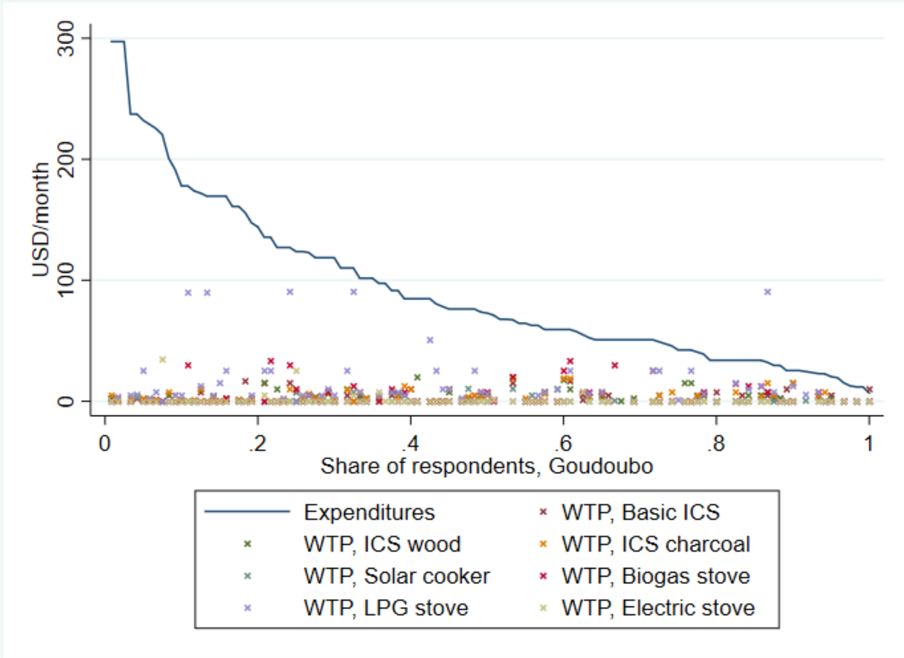
WTP as share of total reported expenditures, Goudoubo

	N	Mean	SD	p25	p50	p75
basic ICS (stove only)	62	0.08	0.17	0.01	0.03	0.10
enhanced ICS, wood (stove only)	57	0.07	0.08	0.02	0.05	0.09
enhanced ICS, charcoal (stove only)	64	0.06	0.09	0.01	0.03	0.08
basic ICS (with fuel)	53	0.11	0.21	0.02	0.06	0.12
enhanced ICS, wood (with fuel)	54	0.10	0.11	0.03	0.08	0.13
enhanced ICS, charcoal (with fuel)	58	0.10	0.12	0.02	0.06	0.13
solar	10	0.07	0.05	0.02	0.07	0.09
biogas	26	0.24	0.17	0.10	0.18	0.38
LPG stove	60	0.24	0.39	0.04	0.12	0.32
electric stove	8	0.09	0.07	0.03	0.06	0.15
current expend. in cooking fuels	105	0.14	0.15	0.05	0.10	0.17

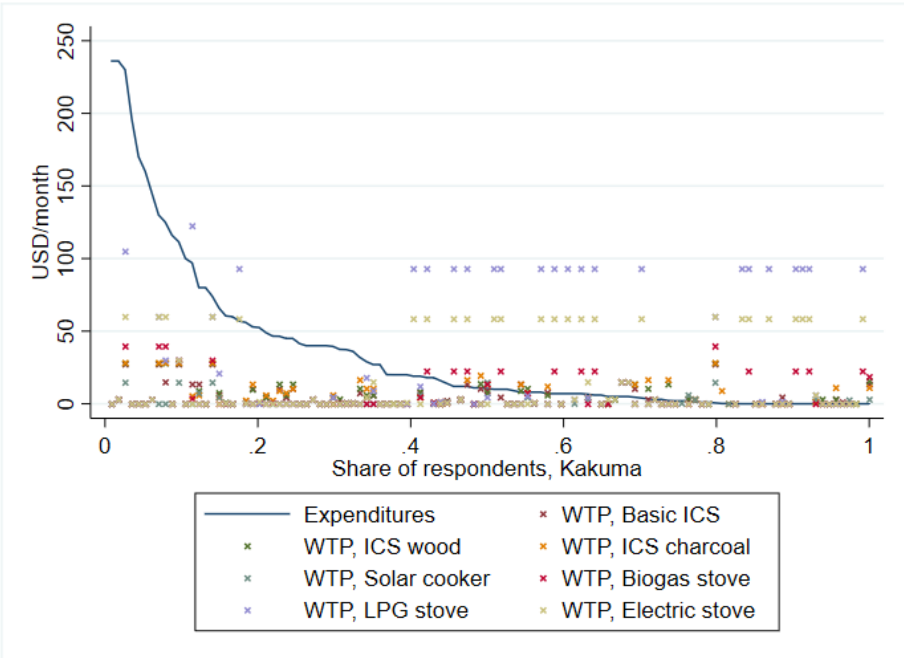
WTP as share of total reported expenditures[1], Kakuma

	N	Mean	SD	p25	p50	p75
basic ICS (stove only)	45	0.34	0.66	0.06	0.09	0.30
enhanced ICS, wood (stove only)	43	0.48	0.75	0.05	0.14	0.68
enhanced ICS, charcoal (stove only)	47	0.44	0.75	0.04	0.14	0.54
basic ICS (with fuel)	44	0.59	0.77	0.11	0.23	0.91
enhanced ICS, wood (with fuel)	44	0.77	1.22	0.09	0.24	0.93
enhanced ICS, charcoal (with fuel)	46	0.84	1.45	0.07	0.23	1.00
solar	29	0.57	0.94	0.04	0.11	0.56
biogas	32	0.91	1.19	0.03	0.26	1.58
LPG stove	41	3.69	5.61	0.24	0.63	5.17
electric stove	39	2.56	3.55	0.08	0.60	4.88
current expend. in cooking fuels	64	0.59	0.76	0.11	0.26	0.78

[1]Note: reported expenditures in Kakuma appears to be understated according to NGOs working in the camps, reports and other surveys.



(a)



(b)

Figure 3.3: Comparison between WTP for cookstoves and current expenditures. Note: current expenditures are likely to be under-reported in Kakuma, according to other reports, surveys, and personnel working in the area.

Comparison between reported WTP and estimated market price

Vianello and Corbyn (2018) provide estimates for the levelised cost of energy (LCOE) of different cooking technologies, that is the monthly cost of cooking based on the price of the stove spread over its lifespan, and the price of the fuel required to obtain a given amount of energy. Actual market prices for fuels, materials, etc. in the two settlements and nearest towns are used for the estimates. Table 3.5 compares those estimates with the respondents' stated WTP. The authors note that the average price of wood and charcoal is similar across the two camps, although it is subject to seasonal variations, and can change depending on the quantity and quality purchased. The market price of LPG is instead very different, as at the time of the study the fuel is subsidised in Burkina Faso, but not in Kenya. The LCOE takes into account the fuel efficiency of the different technologies and types of fuel to make the alternatives comparable despite the differences in upfront costs, fuel costs, and amount of fuel required. For this reason, the three-stone fire is one of the most expensive alternative, even though the upfront cost for the stove is basically zero. Most of the stated WTP are too low to cover the full cost of purchasing and operating any of the cookstove – with the exception of solar cookers, which are relatively cheap due to the basically null cost of fuel (although not many respondents are interested in this technology, no matter the price). Even the relatively high WTP for LPG cookstoves are low in absolute terms if compared to the technology's LCOE – only the top quartile of the interested respondents state a sufficient WTP.

Another source of reference market prices for non-traditional cookstoves and fuels in Sub-Saharan Africa, is Kammila et al. (2014). They estimate:

- Traditional three-stone fire: basically no upfront cost, but over 20 USD/month in operating costs;
- Basic ICS: range of 5–10 USD in upfront capital cost, plus 12–17 USD/month in operating costs;
- More enhanced ICS: range of 20–45 USD in upfront capital cost, plus 8–12 USD/month in operating costs;
- LPG: around 50 USD upfront capital cost, plus 17 USD/month in operating costs;

Table 3.5: Levelised cost of energy (LCOE) estimates and stated WTP.

LCOE and WTP Goudoubo (USD/month)

	LCOE[(a)]	Stated WTP				
		Mean	SD	p25	p50	p75
three-stone fire	27	-	-	-	-	-
basic ICS	9	5.36	4.23	2.54	5.08	5.08
enhanced ICS, wood	10.5	6.21	5.00	2.54	5.08	7.63
enhanced ICS, charcoal	9	6.00	4.56	2.54	5.08	7.63
solar	3	5.26	3.76	1.27	5.08	7.63
biogas	-	14.8	9.97	7.63	10.2	25.4
LPG stove	24[(b)]	18.1	23.9	5.08	7.63	25.4
electric stove	-	10.9	12.4	3.18	6.36	16.5
current expend. in cooking fuels		8.02	5.79	3.69	6.86	11.10

LCOE and WTP in Kakuma (USD/month)

	LCOE[(a)]	Stated WTP				
		Mean	SD	p25	p50	p75
three-stone fire	27	-	-	-	-	-
basic ICS	9	7.93	7.30	3	4.50	10.5
enhanced ICS, wood	10.5	8.11	7.77	3	5.10	10.5
enhanced ICS, charcoal	10.5	8.76	7.66	3	6	11.1
solar	3	4.15	4.00	2.10	3	6
biogas	-	11.0	11.2	3	6	22.5
LPG stove	60[(b)]	35.1	37.8	3	15	63
electric stove	-	25.3	23.7	3	15	58.5
current expend. in cooking fueld		7.84	5.00	4.50	7.00	10.00

[(a)]LCOE estimates from Vianello and Corbyn (2018).

[(b)]LPG is subsidised in Burkina Faso, but not in Kenya.

– Electric cooking: around 30 USD upfront capital cost, plus 25 USD/month, although this is highly variable depending on the cost and quality of electricity in the specific context.

These estimates remark once again that the stated WTP are generally low compared to the market prices, and a large share of the values are even below the operating costs, suggesting that respondents might be unable or unwilling to consistently use the cookstoves even if the cookstoves themselves were provided for free.

Comparison of answers between camps

Figure 3.4 compares the demand of each technology in the two settlements. Interestingly, the demand for biomass non-traditional cookstoves and biogas stoves –

the technologies with which the respondents are more familiar – are very similar in the two settlements, despite the differences in context (East versus West Africa, heterogeneity versus homogeneity of countries of origin and ethnicity, size of the settlements, geography, etc.). As for LPG, Kakuma appears to have a smaller share of respondents willing to pay higher prices with respect to Goudoubo, where instead a higher share is willing to pay at least something. The demand for solar cooking and electric cooking in Goudoubo are much lower than in Kakuma. A possible explanation is that Goudoubo hosted some not very successful trials with solar cooking that have made the technology unpopular in the settlement, while the low demand for electric cooking might be attributed to the nomadic lifestyle of a large part of the population in Goudoubo, meaning that they might be less likely to have had past experience with electric cooking or might consider it as not fitting with a nomadic lifestyle.

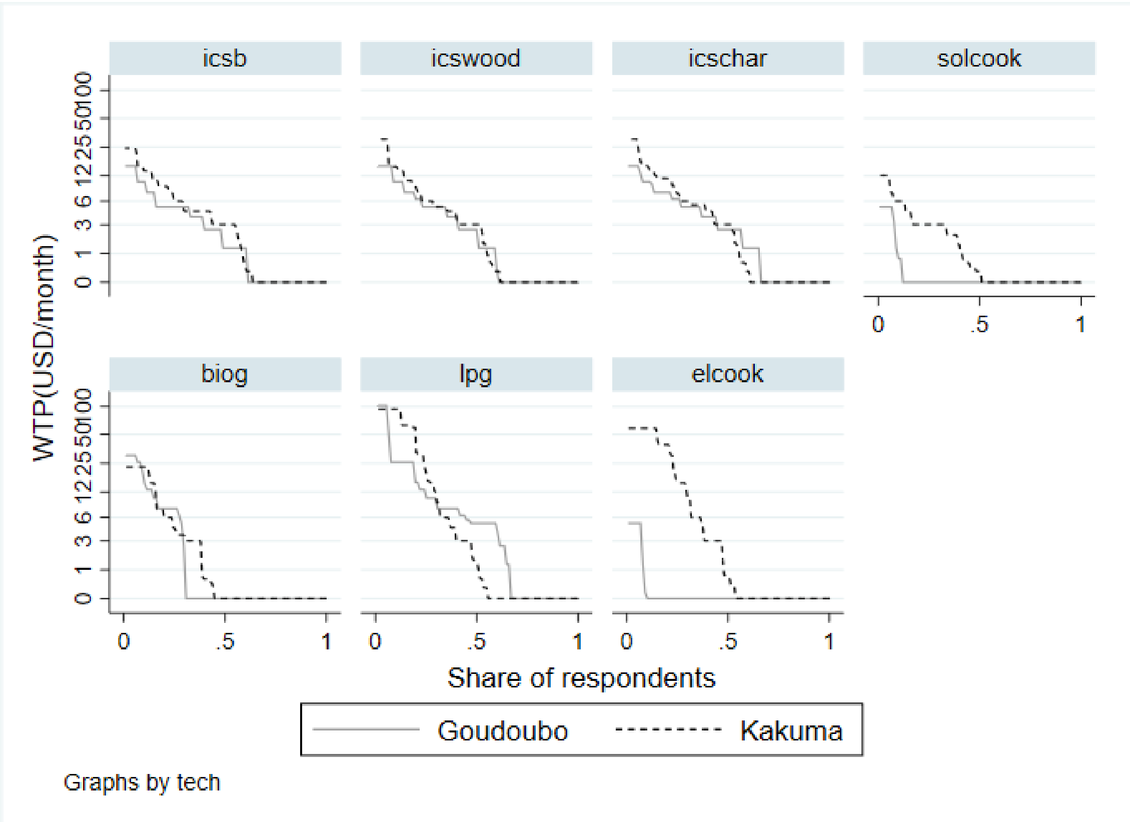


Figure 3.4: Comparison of WTP answers between camps.

3.3.4 Regression analysis

Estimation strategy

Exploiting the within-subject design of the WTP module, in which each respondent is asked the same question for each cooking technology, I stack each respondent's answers to create a panel dataset over the two dimensions of households (indexed i) and cooking technologies (indexed j). Each observation in the dataset is therefore a household-cookstove combination. The dependent variable is the (winsorised) stated WTP, and is therefore continuous, which allows me to use the linear fixed-effect model.

Following eq. 3.2, I estimate the coefficients of interest β_k using a linear fixed-effect within group estimator, with robust standard errors. Using a linear specification allows me to use technology fixed-effects (or alternative-specific constants, ASC) and household fixed-effects to control for 'objective' product characteristics that are the same for every household and are not explicitly captured by the 'perceived' characteristics, and for characteristics of the households that do not change with the cookstove considered (income, household size, etc.). Results are presented in Table 3.6 for Goudoubo and Table 3.8 for Kakuma.

One criticism towards the use of a linear model on the whole dataset could nonetheless be advanced, as the dependent variable is bounded at zero and there is a relevant share of zero answers (already presented in Table 3.1 and Figure 3.1), that is respondents who state they are not interested in the technology and would pay nothing for it. A first concern is that the outcome variable is not continuous but rather censored at zero, as negative responses are not allowed, although they could still represent valid preferences, for example in the case of respondents that would accept a stove they dislike in exchange for a monetary incentive – in fact, programmes that provide monetary incentive to switch to cleaner cookstoves are not hard to imagine (see for example Atkinson et al., 2004; Hanley et al., 2009, for the case of environmental amenities and disamenities). In fact, the distribution of the responses is not only strictly non-negative, but also skewed towards lower values, with a spike at zero.

A second criticism is that zeros in the dataset may be the results of a different data-generating process than the rest of the responses, as respondents may first decide whether they are interested in the technology or not, and only in the former case specify how much they are willing to pay for it (Martínez-Espiñeira, 2006). Zero answers might also include a mixture of respondents who have a 'true' zero valuation for the stove or respondents who have very low valuation, and 'protest' respondents who reject some element of the valuation process (Meyerhoff and Liebe, 2010 and Fonta et al., 2010 provide a review of the issue of protest zero in environmental valuation and healthcare valuation, respectively; Atkinson et al., 2012 discusses how to address the issue in the design of the questionnaire).[12]

To address these issues and provide a robustness check on the results of the linear model, I re-run the analysis using non-linear model specifications and two-stage models as suggested in the literature; the complication in this case is to select or adapt models so that they can still exploit the panel structure of the dataset and take into consideration the correlation between answers provided by the same respondent while avoiding the incidental parameter problem (Colin Cameron and Trivedi, 2010; Silva et al., 2015; Drukker, 2017). For this reason, I implement a random-effects tobit model, a fixed-effects Poisson model (quasi-maximum likelihood estimator), a zero-inflated Poisson model, and a double-hurdle regression model (bootstrap estimator).[13]

The random-effects tobit model extends the cross-sectional tobit model to account for the panel structure of the data through a respondent-specific random stochastic component in the error term, while addressing the fact that the outcome variable is left-censored at zero. The model considers the observed outcome variable as a censored version of the true but latent WTP of the respondents, that is observed above the censoring threshold, and unobserved below it. The tobit model still allows for only one type of zero observations, so does not address the problem of protest zeros.

The fixed-effects Poisson model estimated using a quasi-maximum likelihood estimator and robust standard error is becoming an increasingly popular option for modelling non-negative skewed outcome instead of using a logarithmic transformation of the dependent variable, as common in the past. While both approaches constrain the outcome to be non-negative and account for a skewed distribution towards smaller values, the first obvious advantage of a Poisson model over the use

[12]Note that the likelihood of this possibility should be smaller, as respondents could select "I don't know" as an answer instead of providing a specific amount.

[13]These regression models are implemented in Stata 15 using the commands *xttobit*, *xtpoisson*, *zip* and *bootdhreg* written by Engel and Moffatt (2014).

of a logarithmic transformation is that the latter does not admit zero responses, as the logarithm of zero is not defined. This application of the Poisson model to continuous censored data is encouraged for example by Silva and Tenreyro (2006); as specified by Nichols (2010) the model is equivalent to a generalised linear model using a logarithmic link and a Poisson-family distribution, and no assumptions are needed on the variance of the distribution.

In fact, an important advantage of the Poisson specification is that it requires relatively weak assumptions to ensures consistency and can accommodate fixed-effects without incurring in the incidental parameter problem, contrarily to other non-linear and two-stage models such as the hurdle or zero-inflated Poisson (Colin Cameron and Trivedi, 2010). Similar to the tobit specification, this model considers only one data-generating process and one type of zeros. One additional disadvantage of this model is that households who have a zero valuation for all the technologies are dropped from the sample (this explains the lower sample size for this model specification in the Tables).

To address this issue, the zero inflated Poisson (ZIP) model considers two stages in the decision-making process. First, each observation is considered to have a probability p of being zero (i.e. the probability of $WTP = 0$), and a probability of $1 - p$ of coming from a Poisson distribution. In the latter case, the response is constrained to be non-negative, but can still be a zero. This specification therefore allows for two type of zeros, distinguishing between the uninterested respondents and the low valuation respondents. Different regressors can be specified for the two parts of the models, one set to explain the probability p of being a zero-type, and one set to explain the realisation of the Poisson random variable. For the first component, I include a household wealth index, the size of the household, the respondent age, whether the respondent is a woman, household priority cooking concerns, and whether any of the stove the household has was received as a donation. As mentioned above, fixed-effects or random-effects cannot be included in this model, as the incidental parameter problem would make the estimator inconsistent. I cluster the standard error at the respondent level to capture correlation between choices made by the same person, although this does not eliminate the limitation of this estimator when applied to a panel dataset.

Finally, the double-hurdle specification was introduced by Cragg (1971) models the decision-making problem in two steps. The first hurdle distinguish between respondents who are uninterested and would therefore not pay for any of the cookstoves (zero-type respondents), and respondents who are interested and therefore potentially willing to pay. Conditional on being in the latter group, the second hurdle determines how much the respondent is willing to pay for a specific technology or not. Again, the result of the second hurdle can be a zero, but with a different meaning than the zeros resulting from the first hurdle. The first hurdle is modelled as a probit on whether $WTP = 0$ or not; the second hurdle is modelled as a tobit, to account for the censoring at zero. Different set of covariates can be used to explain the outcome of each hurdle; I use the same as described for ZIP model. To adapt the estimator to the panel structure of the data, standard errors are estimated as standard deviation of bootstrapped coefficients, considering respondents as clusters and sampling a set of responses from each of them, therefore allowing for correlation between choices made by the same respondents. Bootstrap is performed with replacement and allows to estimate the model non-parametrically and therefore with fewer assumptions on the structure of the error term (Engel and Moffatt, 2014).

Results for these four non-linear estimators are presented in Table 3.7 for Goudoubo and Table 3.9 for Kakuma. Comparing the estimates of the different models specifications provide an indication of which results are sensitive to different assumptions on the data-generating process and which ones are robust. Overall, I consider the linear within group estimator the preferred one for my analysis, due to its small-sample properties, better control over respondent-specific fixed-effects and ease of interpretation of the resulting estimates.

Detailed results for the models are presented below, while Section 3.3.5 introduces the analysis and results from the ranking exercise, and broader patterns and implications from the WTP and ranking analyses are discussed in Section 3.3.6.

Results

Goudoubo

After illustrating the estimation strategy, I now discuss the results for each camp in more details. Starting with Goudoubo, Table 3.6 presents the results from the linear fixed-effects within estimator. The specification in column (1) includes only the alternative-specific constants – that is the technology-specific fixed effects – and their interaction with the gender of the respondent, as well as the respondent-specific fixed effects. The baseline technology is the basic biomass ICS. Column (2) extends the first specification including interactions between technologies and level of experience (note that there are some technologies for which fewer than two respondents have experience; interactions are therefore not included for these cookstove types). Column (3) excludes the experience interaction and includes instead the perceived characteristics of each cookstove, together with an interaction between whether the household's top priority is smoke reduction[14] and the cookstove is perceived as having health-improving characteristics ($healthXtop1lesssmoke$) and an interaction between whether habits and tradition compliance is the top priority and the cookstove considered is a non-biomass cookstove ($top1tradXnon-biomasstech$). Further interactions between priorities and technologies are included as controls. Finally, column (4) includes the experience interaction as well.

The estimates suggest that households are willing to pay an average premium of about 10 USD/month for a LPG stove (including fuel supply), and this is robust through all the different specifications. While solar and electric cookers seem to attract a negative premiums when characteristics are not controlled for, this result disappears once the latter are introduced, suggesting that respondents do not dislike these technologies per se but rather have a negative perception of their characteristics. In fact, once characteristics are controlled for, women appear to be willing to pay a positive premium for this technology (consistent with qualitative evidence that men are the main opponents to this technology). There are no other significant differences between men and women respondents in terms of technology-specific premiums. The coefficient for biogas is also positive once characteristics are accounted for. Households who have previous experience with charcoal ICS appear to be willing to pay a premium for this cookstove, although this result disappears once the perceived characteristics are controlled for, in the last column; again, this suggests that having experience with charcoal improves the perception of the characteristics of the stove, rather than creating a favouritism for the technology per se. With respect to characteristics, convenience and capacity appears to be the most relevant ones, each associated with a premium of $\sim$5 USD/month. Health attracts a similar premium of about 6 USD/month, but only among households whose top priority is smoke reduction (this result is only marginally significant though). The remaining

[14]Whether safety is a priority is not included in the specification for Goudoubo as only very few respondents chose it.

characteristics have positive coefficients, as predicted by the theory, but the null hypothesis that the coefficients are equal to zero cannot be rejected at conventional significance levels. Finally, as predicted, households who consider habits and tradition compliance as the top priority have lower WTP for non-biomass technology compared to households who have different priorities.

As a robustness check, I compare these results with estimates from the non-linear regression models for Goudoubo, presented in Table 3.7. Note that the magnitude of coefficients from the Poisson models (fixed-effects and zero-inflated) cannot be directly compared to the estimates in the linear model, as they have a different meaning, but the sign still give the average direction of the effect; Tobit model and the second-hurdle of the double-hurdle model can instead be directly interpreted as premiums, in the same way as the linear model. Overall, the results from the linear model are confirmed. I find once again a strong premium for LPG, here estimated at around 6-8 USD/month, quite close to the estimate in the linear model. The results also provide further evidence for the presence of a negative premium for electric cooking and, only among male respondents, for solar.

The two Poisson models detect a large negative premium for solar among respondents who have previous experience with the technology – the sign of this effect is consistent throughout all the linear and non-linear specifications[15] although not significant in any of the others. As in the previous table, all the characteristics have positive coefficients, and convenience and capacity have the strongest effects, all else equal, followed by reliability. Again, there is some evidence that households whose top priority is smoke reduction value stoves perceived to be healthy and safe more than the rest of the sample, on average, although the coefficient is not always significant.

Kakuma

The specifications included in Table 3.8 for Kakuma are the same as previously described for Goudoubo, with the only differences being the addition of an interaction between whether the household's top priority is safety and the cookstove is perceived as having health-improving characteristics ($healthXtop1safe$). A very limited num-

[15]The interaction terms $experienceXsolarcooker$, $experienceXLPG$ and $healthXtop1lesssmoke$ are dropped in the double-hurdle model as convergence could not be achieved when they were included.

Table 3.6: Regression table, fixed-effects model. Outcome is (winsorized) WTP. Goudoubo camp.

	Goudoubo (1) linear,fe	Goudoubo (2) linear,fe	Goudoubo (3) linear,fe	Goudoubo (4) linear,fe
2.tech (wood ics)	-0.28	-0.27	-0.24	-0.19
	(0.593)	(0.593)	(0.950)	(0.893)
" X female respond	1.76	1.75	1.81	1.77
	(1.255)	(1.259)	(1.192)	(1.171)
3.tech (charcoal ics)	0.19	-1.97	-0.47	-0.43
	(0.558)	(1.347)	(0.739)	(1.065)
" X female respond	0.98	1.01	1.77	1.62
	(1.072)	(1.092)	(1.172)	(1.111)
4.tech (solar)	-3.01***	-3.83***	-0.45	-0.41
	(0.651)	(1.063)	(1.184)	(1.243)
" X female respond	0.26	-0.12	2.72*	2.46*
	(0.972)	(1.065)	(1.049)	(1.071)
5.tech (biogas)	0.53	-0.30	2.91*	2.53*
	(1.143)	(1.260)	(1.212)	(1.269)
" X female respond	0.97	0.64	-0.22	-0.13
	(1.817)	(1.869)	(1.364)	(1.305)
6.tech (LPG)	10.17**	9.42**	10.50*	10.62*
	(3.275)	(2.893)	(4.820)	(4.398)
" X female respond	-1.68	-1.61	-0.07	-0.05
	(5.185)	(5.521)	(4.115)	(4.432)
7.tech (electric)	-2.86***	-3.69***	0.03	-0.37
	(0.601)	(0.982)	(1.288)	(1.292)
" X female respond	0.01	-0.32	0.55	0.69
	(0.943)	(1.004)	(1.096)	(1.113)
experience X non-charcoal ics		-1.66		-0.13
		(1.486)		(0.985)
experience X charcoal ics		3.05**		0.00
		(1.140)		(1.057)
experience X solar cooker		-0.09		-1.58
		(1.846)		(1.743)
experience X LPG		-4.67		-3.47
		(4.316)		(5.126)
convenience			5.05**	5.05**
			(1.835)	(1.855)
duration			4.05	4.25
			(3.344)	(3.428)
reliability			4.49	4.70^{+}
			(2.713)	(2.695)
robustness			1.67	1.56
			(2.187)	(2.197)
capacity			5.79*	5.67*
			(2.875)	(2.837)
health			-0.20	-0.19
			(1.953)	(1.961)
" X top1 less smoke			6.16^{+}	5.78
			(3.632)	(3.704)
top1 trad. X non-biomass tech			-3.18^{+}	-2.95^{+}
			(1.617)	(1.504)
Other cooking priorities X tech	No	No	Yes	Yes
N	624	624	624	624
R^2	0.163	0.168	0.355	0.354
adj. R^2	0.146	0.147	0.299	0.300

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.7: Regression table, non-linear models. Outcome is (winsorized) WTP. Goudoubo camp.

	Goudoubo (1) xttobit	Goudoubo (2) xtpoisson	Goudoubo(3) zip	Goudoubo (4) double-hurdle
2.tech (wood ics)	-1.49	-0.19	0.01	0.51
	(2.958)	(0.212)	(0.140)	(2.656)
" X female respond	5.48	0.54^{+}	0.27	0.65
	(4.631)	(0.293)	(0.215)	(3.907)
3.tech (charcoal ics)	1.16	0.19	0.41	4.04
	(3.694)	(0.394)	(0.270)	(3.245)
" X female respond	2.04	0.35	0.59^{**}	-3.41
	(4.721)	(0.276)	(0.224)	(4.135)
4.tech (solar)	-12.79^{**}	-1.96^{**}	-1.34	-9.42^{*}
	(4.652)	(0.609)	(1.386)	(3.982)
" X female respond	14.02^{*}	2.05^{**}	1.29	7.46
	(6.523)	(0.708)	(1.434)	(5.564)
5.tech (biogas)	-3.02	-0.19	1.10^{***}	1.05
	(3.813)	(0.472)	(0.260)	(3.195)
" X female respond	2.94	0.80^{+}	0.14	-7.93
	(5.320)	(0.446)	(0.286)	(5.042)
6.tech (LPG)	7.24^{*}	0.58	1.43^{***}	6.43^{*}
	(3.272)	(0.398)	(0.324)	(2.859)
" X female respond	2.03	0.37	0.22	-8.46^{*}
	(4.776)	(0.411)	(0.383)	(4.221)
7.tech (electric)	-12.03^{*}	-1.83^{**}	-1.79^{+}	-5.94
	(4.708)	(0.618)	(0.992)	(3.891)
" X female respond	6.03	1.09	0.94	-5.93
	(6.835)	(0.769)	(1.505)	(6.702)
experience X non-charcoal ics	1.94	0.14	0.56^{*}	3.67^{+}
	(2.811)	(0.316)	(0.233)	(2.226)
experience X charcoal ics	0.36	-0.24	-0.18	0.04
	(3.392)	(0.217)	(0.178)	(3.059)
experience X solar cooker	-50.78	-13.05^{***}	-15.28^{***}	
	(1287.478)	(0.617)	(1.050)	
experience X lpg	-4.32	0.44	-1.07^{**}	
	(7.102)	(0.467)	(0.347)	
convenience	16.75^{***}	1.82^{***}	-0.33	11.20^{***}
	(2.032)	(0.313)	(0.221)	(1.530)
duration	2.69	0.05	0.03	1.23
	(3.134)	(0.240)	(0.232)	(2.612)
reliability	9.12^{***}	0.30	0.21	13.97^{***}
	(2.471)	(0.199)	(0.262)	(2.272)
robustness	4.09^{+}	0.19	0.05	3.33^{+}
	(2.249)	(0.165)	(0.171)	(1.935)
capacity	11.57^{***}	1.22^{***}	0.65^{**}	9.42^{***}
	(2.419)	(0.349)	(0.199)	(1.829)
health	3.49	0.47^{*}	-0.31^{+}	2.25
	(2.162)	(0.227)	(0.189)	(1.621)
" X top1 less smoke	14.23	1.25	0.97^{***}	
	(10.558)	(1.238)	(0.280)	
top1 trad. X non-biomass	0.22	-0.08	0.21	-0.64
	(3.117)	(0.343)	(0.147)	(2.631)
N	624	607	624	569
AIC	2425.20	2007.32	3440.29	1934.08
BIC	2549.41	2113.12	3604.43	2086.12

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

bers of respondents had previous experience with any of the non-biomass stoves, so only interactions between experience and biomass ICS are included.

Again, households appear to be willing to pay an average premium of 8 USD/month for a LPG stove (including fuel supply), and have instead a negative WTP for solar cookers of 3 USD/month. Both are robust through all the different specifications. In the first two specifications biogas appears to be associated with a negative premium, which disappears when characteristics are considered. The opposite occurs for electric cookstoves, which are associated with a positive premium only in the last two columns. This suggests that households do not perceive these two technologies to have many positive characteristics, but when the characteristics are held constant the valuation for these technologies increases. There are no significant differences between men and women respondents in terms of technology-specific premiums, while households who already have experience with charcoal are willing to pay a premium of about 2 USD/month on average for this technology.

In terms of characteristics, health attracts the highest premium, at 4.5 USD/month, and this becomes three times larger for households whose top priority is safety; households whose top priority is smoke reduction do not appear to have a higher valuation for the health characteristics than the rest of the respondents. The premium for capacity is also positive and significant, at about 4 USD/month, as are the premiums for robustness, reliability and convenient, at about 2 USD/month. Respondents who prioritise habits and tradition in cooking tend to value non-biomass stoves 2-3 USD/month less than the rest of the sample, although the coefficients are not significantly different from zero even at 10% significance level.

Comparing these results with the coefficients estimates in Table 3.9 confirm the findings from the linear model. The non-linear regression models confirm the presence of a strong positive premium for LPG, estimated here at 12-14 USD/month and not significantly different from the estimates in the linear model. The estimates for the negative premium for solar and the positive premium for electricity are also very close to the linear model, although only significant in the two Poisson specifications. Similarly, biogas does not appear to suffer any negative premium if characteristics are controlled for. As in the previous model, I find that the alternative-specific constants are no significantly different between men and women, while respondents who are familiar with charcoal ICS are willing to pay a positive premium for it, and households who prioritise habits and traditions have a lower valuation for non-

Table 3.8: Regression table, fixed-effects model. Outcome is (winsorized) WTP. Kakuma camp.

	Kakuma (1) linear,fe	Kakuma (2) linear,fe	Kakuma (3) linear,fe	Kakuma (4) linear,fe
2.tech (wood ics)	0.78	0.77	0.81	0.82
	(0.556)	(0.556)	(0.833)	(0.837)
" X female respond	0.26	0.27	-0.80	-0.80
	(0.810)	(0.807)	(0.943)	(0.946)
3.tech (charcoal ics)	1.13	0.56	1.28	0.66
	(0.815)	(0.769)	(0.999)	(0.985)
" X female respond	0.35	0.40	0.26	0.36
	(0.986)	(0.997)	(1.026)	(1.036)
4.tech (solar)	-3.12**	-2.99**	-3.69*	-3.49*
	(0.962)	(1.034)	(1.462)	(1.386)
" X female respond	1.07	1.06	1.35	1.32
	(1.184)	(1.194)	(1.246)	(1.244)
5.tech (biogas)	-2.41+	-2.28+	0.85	1.08
	(1.349)	(1.359)	(1.507)	(1.366)
" X female respond	-0.96	-0.96	-1.28	-1.30
	(1.625)	(1.626)	(1.342)	(1.339)
6.tech (LPG)	8.78**	8.92***	8.23*	8.48**
	(2.737)	(2.636)	(3.246)	(3.078)
" X female respond	-1.01	-1.03	-0.54	-0.57
	(3.363)	(3.369)	(3.154)	(3.149)
7.tech (electric)	1.73	1.86	4.42+	4.66*
	(1.743)	(1.703)	(2.411)	(2.294)
" X female respond	0.42	0.41	0.35	0.33
	(2.201)	(2.204)	(2.147)	(2.141)
experience X non-charcoal ics		0.25		0.36
		(1.070)		(1.043)
experience X charcoal ics		1.75		2.27*
		(1.154)		(1.047)
convenience			2.28*	2.41*
			(1.088)	(1.087)
duration			1.20	1.24
			(0.965)	(0.972)
reliability			2.52**	2.50**
			(0.804)	(0.817)
robustness			2.14+	2.17*
			(1.097)	(1.099)
capacity			4.34*	4.34*
			(1.839)	(1.841)
health			4.52**	4.50**
			(1.557)	(1.555)
" X top1 safe			11.80+	11.88+
			(6.299)	(6.336)
" X top1 less smoke			-0.41	-0.31
			(2.590)	(2.580)
top1 trad. X non-biomass tech			-2.49	-2.60
			(1.866)	(1.831)
Other cooking priorities X tech	No	No	Yes	Yes
N	1155	1155	1155	1155
R^2	0.139	0.140	0.252	0.254
adj. R^2	0.130	0.129	0.218	0.218

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

biomass stove, although the latter is only significant in some specifications.

In terms of characteristics, health is again one of the most-valued ones, and the Tobit and double-hurdle models confirm that respondents who prioritise safety have an even larger valuation for this characteristics; this latter result is not replicated in the two Poisson models. Results for the other characteristics are also broadly confirmed, with capacity being among the most valued, followed by robustness, reliability and convenience.

3.3.5 Ranking exercise

To analyse the responses to the ranking exercise, I use a rank-ordered logistic (ROL) regression model (also known as the Plackett-Luce model or the exploded logit model) and estimate the coefficients using the maximum likelihood estimator introduced by Beggs et al. (1981).[16] This model can be seen as an extension of McFadden (1981) conditional logit model, where the characteristics of each alternative on offer explain the decision of which alternative is selected as the preferred one, but rather than using the preferred option as outcome it uses the position in the preference ranking. As in the conditional logit model, an idiosyncratic additive random effect is included to capture preference heterogeneity between individuals. The ranking position of each cookstove is therefore a function of its characteristics, for simplicity assumed to be linear (similar to the way the maximum WTP was defined in eq. 3.2) and the stochastic random term ϵ_{ij}:

$$r_{ij} = \sum_{k=1}^{K} \beta_k c_{ijk} + \epsilon_{ij}$$

where r_{ij} is the ranking position of technology j according to respondent i. Following the set-up of the conditional logit, if ϵ_{ij} are independent and identically distributed (i.i.d.) following a type 1 extreme value distribution, then the probability that alternative j is ranked higher than any other can be expressed using the conditional logistic function:

$$Pr[r_{ij} = 1] = \frac{\exp(\sum_{k=1}^{K} \beta_k c_{ijk})}{\sum_{l=1}^{J} \exp(\sum_{k=1}^{K} \beta_k c_{ilk})}$$

[16] I perform the rank-ordered logistic regression in Stata 15, using command *rologit*. See Fok et al. (2012) for an example of application of the technique.

Table 3.9: Regression table, non-linear models. Outcome is (winsorized) WTP. Kakuma camp.

	Kakuma (1) xttobit	Kakuma (2) xtpoisson	Kakuma (3) zip	Kakuma (4) double-hurdle
2.tech (wood ics)	2.37	0.21	0.03	0.39
	(2.911)	(0.129)	(0.145)	(3.726)
" X female respond	-1.81	-0.07	0.04	0.08
	(3.492)	(0.156)	(0.171)	(4.789)
3.tech (charcoal ics)	1.77	0.14	-0.05	-0.89
	(3.214)	(0.158)	(0.164)	(4.252)
" X female respond	-0.31	0.04	0.21	-0.18
	(3.477)	(0.188)	(0.160)	(4.794)
4.tech (solar)	-3.77	-0.80***	-0.75***	-1.42
	(3.132)	(0.213)	(0.206)	(3.959)
" X female respond	-0.29	0.17	0.32+	-3.43
	(3.506)	(0.226)	(0.192)	(4.804)
5.tech (biogas)	-2.10	-0.00	0.25	-0.46
	(3.287)	(0.183)	(0.210)	(4.142)
" X female respond	-2.68	-0.23	0.14	1.18
	(3.701)	(0.206)	(0.210)	(4.859)
6.tech (LPG)	14.03***	0.95***	1.34***	12.20**
	(3.027)	(0.222)	(0.245)	(3.896)
" X female respond	-3.04	-0.05	0.06	10.10*
	(3.364)	(0.250)	(0.251)	(4.551)
7.tech (electric)	4.93	0.55*	1.12***	4.47
	(3.095)	(0.218)	(0.200)	(3.983)
" X female respond	-2.89	-0.10	-0.09	6.05
	(3.481)	(0.252)	(0.225)	(4.700)
experience X non-charcoal ics	2.37	0.19	0.08	3.12
	(1.926)	(0.172)	(0.184)	(2.403)
experience X charcoal ics	5.72*	0.45**	0.19	6.13+
	(2.544)	(0.168)	(0.175)	(3.479)
convenience	5.14***	0.20*	-0.30*	5.67***
	(1.338)	(0.102)	(0.142)	(1.357)
duration	3.34**	-0.03	0.01	3.33*
	(1.267)	(0.074)	(0.108)	(1.380)
reliability	6.82***	0.23**	0.20	9.01***
	(1.188)	(0.086)	(0.124)	(1.300)
robustness	6.06***	0.19+	0.49***	11.86***
	(1.605)	(0.106)	(0.130)	(1.687)
capacity	8.14***	0.14	0.63***	24.12***
	(1.805)	(0.114)	(0.121)	(2.105)
health	7.43***	0.40**	0.42**	2.11
	(1.587)	(0.147)	(0.141)	(1.500)
" X top1 safe	14.09**	-0.21	-0.11	17.66**
	(4.921)	(0.191)	(0.168)	(5.883)
" X top1 less smoke	2.31	-0.03	0.09	7.29*
	(4.124)	(0.183)	(0.180)	(3.420)
top1 trad. X non-biomass	-3.11	-0.21	-0.41*	-5.60*
	(2.287)	(0.198)	(0.207)	(2.565)
N	1155	855	1155	1249
AIC	5793.61	4409.65	10515.46	7229.29
BIC	5930.01	4518.92	10702.38	7429.36

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

After the top-ranked cookstove has been selected, the second-ranked stove is nothing else than the preferred among the remaining options, and so on in a sequential way. The probability of observing a given ranking sequence is therefore the product of the probability of each rank position, that is the product of conditional logit probabilities[17]:

$$Pr[\{r_{i1}, ...r_{iJ}\}] = \prod_{j=1}^{J-1} \frac{\exp(\sum_{k=1}^{K} \beta_k c_{ir_{ij}k})}{\sum_{l=j}^{J} \exp(\sum_{k=1}^{K} \beta_k c_{ir_{il}k})} \tag{3.4}$$

The coefficients of interest $\beta_1...\beta_K$ can then be estimated using maximum likelihood.

Results are presented in Table 3.10 for Goudoubo, and Table 3.11 for Kakuma. As remarked in the data Section above, the three-stone fire is now included among the cookstove alternatives household are asked to rank.

Column (1) of each table estimate the model including the traditional three-stone fire. This specification does not include perceived cookstove characteristics as these were not asked for the traditional stove, but introduces an additional interaction term between whether the alternative is a traditional three-stone fire and whether the respondent selected tradition and habits compliance as their top priority ($top1tradXtradstove$). Column (2) excludes the three-stone fire and includes the perceived cookstove characteristics and the interaction between the health characteristic and dummies identifying whether the household chose less smoke and safety as their top priority.

Both models include alternative-specific constants (ASCs), interactions between ASCs and the gender of the respondent, and between ASCs and the experience level, and the interaction on whether the alternative being considered is a non-biomass cookstove and the respondent selected tradition and habits compliance as their top priority. According to the model specification, only regressors and interaction terms that vary by cookstove enter the model, while respondent's specific characteristics that are constant over the different alternatives are dropped.

Goudoubo

Results for Goudoubo (Table 3.10) show that enhanced firewood ICS tend to be the preferred cookstove type, followed by the enhanced charcoal ICS, and basic ICS (reference technology). The higher preference for charcoal with respect to the

[17]Notation is adapted from Fok et al. (2012).

basic ICS becomes close to zero for women respondents, confirming that charcoal is a fuel that attracts men preferences, as documented by qualitative research on genderisation of fuel.

The only clean technology that has an average ranking as high as the basic ICS is LPG, while all the other clean technologies have higher probabilities to be ranked below the biomass cookstoves. In particular, electric cookers and biogas are associated with the lowest ranking positions, while solar performs slightly better, especially once the perceived characteristics of the stoves are controlled for.

Interestingly, the traditional three-stone fire tends to be ranked below the biomass ICS and LPG, but still above the rest of the options, and women tend to rank it lower than men. This supports the finding of studies on intra-household preferences and decision-making such as Miller and Mobarak (2013) that women tend to be more interested in non-traditional stoves than men, but they may lack the agency to make decisions for the household and resources to purchase the new cookstove.

In terms of previous experience, respondents who are familiar with non-charcoal ICS tend to rank these technologies lower, while those who have experience with charcoal ICS rank it higher. The coefficients for the interaction between experience and solar cookers, and experience and LPG are similarly positive, but not significant.

Consistently with what would be expected, perceived positive characteristics are on average positively (or at most insignificantly) associated with an improved ranking of a cooking solution. The strongest effect is achieved when stoves are perceived to be 'convenient' to use – interestingly, this was the characteristic with the largest coefficient in the WTP analysis, as well.

As for priorities, respondents who want smoke reduction do not seem to rank stoves they perceive to deliver "health and safety" higher than other respondents – the sign of the coefficient is even negative in this case. Respondents whose priority is habits and tradition compliance do not appear to rank biomass and non-biomass technologies differently from other respondents.

Kakuma

Table 3.11 presents the results for Kakuma. Again, enhanced firewood ICS is associated with higher ranks, followed by enhanced charcoal ICS, the basic ICS (reference technology), solar cookers and LPG, with no significant difference in average rank-

Table 3.10: Regression table, rank-ordered logit. Outcome is ranking position of each cooking technology. Goudoubo camp.

	Goudoubo (1) rank-ordered logit		Goudoubo (2) rank-ordered logit	
2.tech (wood ics)	1.14***	(0.178)	1.32***	(0.212)
" X female respond	0.02	(0.260)	-0.14	(0.315)
3.tech (charcoal ics)	0.73**	(0.232)	0.82**	(0.262)
" X female respond	-0.55*	(0.276)	-0.70*	(0.321)
4.tech (solar)	-1.48***	(0.334)	-0.92**	(0.336)
" X female respond	-0.58	(0.410)	-0.62	(0.435)
5.tech (biogas)	-1.77***	(0.321)	-1.31***	(0.312)
" X female respond	0.57	(0.437)	0.37	(0.434)
6.tech (LPG)	-0.17	(0.272)	-0.17	(0.293)
" X female respond	-0.47	(0.313)	-0.54	(0.358)
7.tech (electric)	-1.81***	(0.308)	-1.29***	(0.331)
" X female respond	-0.43	(0.464)	-0.59	(0.512)
8.tech (traditional)	-1.09***	(0.232)		
" X female respond	-0.55+	(0.298)		
experience X non-charcoal ics	-0.39+	(0.202)	-0.47*	(0.228)
experience X charcoal ics	0.56+	(0.324)	0.59*	(0.293)
experience X solar cooker	0.25	(0.451)	0.11	(0.462)
experience X LPG	1.23	(0.837)	1.07	(1.047)
convenience			1.05***	(0.197)
duration			0.85+	(0.504)
reliability			0.59+	(0.338)
robustness			0.15	(0.271)
capacity			0.51	(0.331)
health			0.02	(0.256)
" X top1 less smoke			-0.85*	(0.380)
top1 trad. X non-biomass tech	0.34	(0.395)	0.02	(0.353)
top1 trad. X trad stove	0.14	(0.397)		
N	1032		903	
pseudo R^2	0.205		0.269	
AIC	1890.73		1444.56	
BIC	1989.51		1559.90	

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
X in the name of a regressor indicates interactions between variables.

ing among these technologies. As before, the alternative-specific constant for the traditional three-stone fire is negative, indicating that this stove tends to be ranked below the basic ICS and the other stoves mentioned above, and women tend to rank this stove lower than men, although the difference in this case is not significantly different from zero at conventional significance level. Biogas and electric stoves tend to have the lowest ranking.

Households who have previous experience with non-charcoal biomass ICS tend to rank these technology lower than households who have no experience, suggesting that experience has not been satisfactory and might have created skepticism towards this type of cookstoves.

In terms of characteristics, all the coefficients are positive and significant, with the strongest being convenience and reliability, followed by health, robustness and capacity, and duration of energy supply. Results on the significance of the different characteristics confirm the results from the valuation analysis. Contrarily to the valuation analysis though, in the ranking exercise households who prioritise safety and smoke reduction do not rank stove perceived to match these characteristics any higher than households with different priorities. Finally, consistent with expectations, households whose priority is habits and tradition compliance tend to rank the three-stone fire higher and the non-biomass clean cookstoves lower than households with different priorities.

3.3.6 Discussion of results

Overall, these results confirm the same qualitative pattern as the valuation analysis, with several similarities between the two camps. My findings point towards a preference for good quality enhanced biomass-ICS, that can be used with the fuel households are familiar with, but also for LPG, that emerges as a technology households value and are interested in in all the analyses. Nevertheless, it might be more difficult to trigger the switch to cleaner cookstoves and fuels in households who value habits and traditions, as this appear to have a significant negative effect on households preferences for non-traditional stoves.

Despite the evidence for a certain willingness to pay a premium for LPG in the previous section, here I found no statistically significant difference in the ranking for LPG stoves if compared to basic ICS. The two facts can be reconciled by looking at

Table 3.11: Regression table, rank-ordered logit. Outcome is ranking position of each cooking technology. Kakuma camp.

	Kakuma (1) rank-ordered logit		Kakuma (2) rank-ordered logit	
2.tech (wood ics)	0.37***	(0.108)	0.44***	(0.128)
" X female respond	0.02	(0.134)	-0.01	(0.158)
3.tech (charcoal ics)	0.35^{+}	(0.178)	0.32	(0.221)
" X female respond	0.03	(0.173)	-0.08	(0.204)
4.tech (solar)	-0.25	(0.196)	-0.34	(0.240)
" X female respond	-0.06	(0.219)	-0.03	(0.254)
5.tech (biogas)	-1.38***	(0.299)	-1.28***	(0.336)
" X female respond	-0.43	(0.368)	-0.44	(0.397)
6.tech (LPG)	-0.42	(0.282)	-0.50	(0.313)
" X female respond	-0.03	(0.318)	0.06	(0.337)
7.tech (electric)	-1.18***	(0.305)	-1.11**	(0.342)
" X female respond	0.02	(0.355)	-0.08	(0.376)
8.tech (traditional)	-0.78***	(0.173)		
" X female respond	-0.08	(0.182)		
experience X non-charcoal ics	-0.24	(0.148)	-0.61**	(0.198)
experience X charcoal ics	-0.07	(0.138)	-0.17	(0.170)
convenience			0.71***	(0.105)
duration			0.38**	(0.126)
reliability			0.63***	(0.106)
robustness			0.49***	(0.140)
capacity			0.48**	(0.164)
health			0.48***	(0.125)
" X top1 safe			-0.01	(0.475)
" X top1 less smoke			0.17	(0.340)
top1 trad. X non-biomass tech	-0.61*	(0.239)	-0.79**	(0.270)
top1 trad. X trad stove	1.01**	(0.350)		
N	1800		1575	
pseudo R^2	0.095		0.134	
AIC	3826.99		3004.54	
BIC	3925.91		3127.87	

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
X in the name of a regressor indicates interactions between variables.

the different scenarios they refer to and at the practice of stove stacking. In fact, households appear on average to be willing to pay a premium for LPG when this is the only technology available, but if they are asked to consider a scenario in which all the products are available, they tend to rank LPG below the enhanced biomass ICS.

Yet, stove stacking, as well as fuel stacking, are a common practice in the settlements (in Goudoubo, more than 30% of the respondents have used at least one secondary stove in the past year, while this is slightly less than 20% in Kakuma), as well as in the global South in general, so that households preferred solution might well be to have both a biomass and an LPG stove, especially if supply of LPG is unreliable.

Another possibility is that this difference between the two analysis is the result of a trade-off between higher-value but more expensive stoves, such as LPG, and more affordable biomass ICS that deliver less improvements. The WTP analysis confirm that households recognise and value the benefits of LPG stoves, but the ranking exercise suggests that if they have the choice they might opt for more affordable and more familiar options instead, highlighting how lack of resources and purchasing power might be a strong issue.

A possible explanation for the strong LPG premium in both camps is that there are other characteristics associated with LPG stoves that raise their values and are not controlled for in the model - for example LPG might be considered as a 'status' or aspirational good, as in Lee et al. (2016), following Veblen's theory of conspicuous consumption, or it could be the result of the use of dummies variable to define the characteristics rather than a continuous measure.

The striking difference in the importance of health between the two settings can instead be explained looking at the specific context of the two settlements, as well as to the perceptions of respondents about the urgency of the health consequences of cooking – households in Kakuma cooking indoor and reporting more issues with smoke and accidents, while households in Goudoubo tend to cook outdoor and report fewer problems.

Overall, respondents appear to value perceived characteristics and low valuation for a stove is explained by the perceived absence of those characteristics. I found no significant differences between men and women in their preferences for specific technology type, with the exception of men appearing to like charcoal ICS and traditional three-stone fire slightly more than women in Goudoubo.

In both camps, households with experience with firewood ICS tend to rank them lower than households who have no experience. This might suggest that cookstove models introduced in the camp have failed to meet household expectations and needs, and have created skepticism towards this technology among the households who have used them. There are evidence that the opposite occurred for charcoal ICS, as households with experience value them more. To investigate this latter evidence in more details, in the next part of the Chapter I assess the performance of the non-traditional cookstoves already used in the camps over the different dimensions of fuel savings, health and safety, time use, and women and children workload.

3.4 Part 2: Benefits of non-traditional cookstoves

3.4.1 The promised land: hypotheses on the benefits of non-traditional cookstoves

In the second part of the Chapter, I look for evidence that the non-traditional cookstoves in use in the camps are effectively associated with improvements in the lives of their users, with respect to the traditional (and free) alternative of the three-stone fire. Information on the cookstoves used by respondents in the sample have been provided in Section 3.2.3, Table C.1 and photographs in Appendix C.1. Most of the non-traditional stoves used by respondents in the sample are basic ICS models which can accommodate both charcoal and firewood, although the latter tend to be by far the most popular fuel for cooking meals in both camps. Following the main research questions explored in the literature on cookstove benefits, I consider four dimensions of welfare – namely, energy efficiency and environmental gains, health and safety, time use, and the workload burden on women and children. As informed by the existing literature on the topic, I formulate the following sets of hypotheses:

HP1: Energy efficiency Do households who use non-traditional stoves consume less firewood? Given that almost all of the stoves in the sample are biomass-fuelled, this question is really related to whether the non-traditional cookstoves use the fuel more efficiently. In addressing this question I take into consideration two issues. On one side, the main complaint by residents of both settlements is the insufficiency of firewood to cover for their basic needs, meaning that binding availability-constraints might be an issue. There may be no difference in quantity consumed by households using different stoves, simply because households may consume all the fuel they have access to and still be short of the amount they would consider optimal, given their utility and budget. On the other side, more efficient stoves would make cooking cheaper at the margin, and may push households to use the stove for longer hours and cook more, triggering a 'rebound effect'. To account for these possibilities, I test two hypotheses: (i) households who use non-traditional stoves consume less firewood overall, and (ii) consume less firewood per hour of use of the stove. Evidence on the rebound effect is further investigated under the time use hypothesis.

HP2: Health and safety Are households who use non-traditional stoves less exposed to health and safety hazard? In particular, I check whether these households are less likely to report accidents related to stove use and problems with smoke than households who use a three-stone fire.

HP3: Time use Do households who use non-traditional stoves spend less time in cooking-related activities (cooking, and fuel collection, purchase and preparation)? As mentioned in the literature review, a few issues should be accounted for in this case. On one side, improved energy efficiency could make the actual cooking of a meal faster, and therefore reduce the number of hours a stove is used. Yet, if a rebound effect were present, the sign of the relationship might be reverted, as households might decide to cook more food or cook for longer in the new optimum. At the extreme, if the rebound effect results in even more fuel being used than before, households might need to spend more time finding firewood to collect or purchase. Longer times might also result from the need to prepare the fuel in specific ways (for example making wood chips and cutting the wood at the appropriate size for the stove, or make charcoal out of wood) or procure fuel that is more difficult to find in the local markets (such as briquettes and pellets, or charcoal), depending on the cookstoves requirements. Moreover, in some cases longer times have been reported to cook the same meal with a non-traditional stove, as documented for example by Adkins et al. (2010).

HP4: Gender and children workload Women and children are the ones most affected by efficiency and health gains, as they are the ones who traditionally spend more time carrying out cooking-related activities and firewood collection. A part from the efficiency and health channels, the introduction of a technological innovation such as a non-traditional stove, may shift the gender balance of cooking-related activities. For example, preparing and purchasing the fuel for non-traditional stoves may be perceived as activities that require a different set of skills, and may therefore entice a greater involvement of men than it would be the case with traditional stoves and traditional fuel. The 'genderisation' of fuel, with firewood associated with women, and charcoal and LPG being more neutral or even associated with men, is documented in the literature.

3.4.2 Estimation strategies

To investigate these hypotheses, I refer to the potential outcome framework and Rubin's Causal Model (Rubin, 1974; Holland, 1986). Following the notation and terminology of Angrist et al. (1996), I define the exclusive use of non-traditional cookstoves as my treatment indicator (D_i), and various indicators for energy efficiency, health and safety, time use, and women and children workload as the realised and observed outcome (Y_i). Every observation unit can then be thought of as having two potential outcomes, Y_{0i} and Y_{1i}, indicating respectively the outcome if the unit were not subject to the treatment, and the outcome if they were. In this case, Y_{0i} represents the outcome if the household were using a non-traditional cookstove and Y_{1i} as the outcome if the same household were instead using the traditional three-stone fire. The effect of the treatment on that household can then be obtained as the difference in potential outcomes:

$$\alpha_i = Y_{1i} - Y_{0i}. \tag{3.5}$$

Of course, for each household only one of the potential outcomes can be observed, i.e. the realised outcome Y_i, and the problem of estimating the effects of the treatment becomes one of correcting for these 'missing' or unobservable counterfactual observations - the 'fundamental problem of causal inference'. Under specific identification assumptions, I can still estimate the Average Treatment Effect (ATE) by comparing the outcomes of treated and untreated units:

$$\alpha_{ATE} = E[Y_1 - Y_0]. \tag{3.6}$$

The gold standard for this type of causal inference analysis is to conduct a

Randomised Controlled Trials (RCTs), in which treatment is assigned at random:

$$(Y_1, Y_0) \perp\!\!\!\perp D$$

Random assignment (i.e. independence of assignments) may then be used as an identification assumption to prove that the ATE can be estimated as a simple difference in means between the treated and untreated groups:

$$E[Y|D=1] - E[Y|D=0] = \alpha_{ATE}. \tag{3.7}$$

and a simple OLS estimator can be used:

$$Y_i = \beta_0 + \beta_D D_i + \epsilon_i$$

When RCT-like studies are unfeasible and only observational data are available – as in my case – the identification assumption is likely to be violated and a difference in means may result in biased estimates. The main threat to identification is sample-selection, as households that decide to purchase a non-traditional cookstove are effectively self-selecting themselves into the treatment sample, and some of the characteristics that make them want to have a non-traditional cookstove might then affect the outcome as well.

As an example, households concerned with health issues or who already suffer from respiratory problems might be more interested in purchasing a non-traditional cookstove, but they might also use the cookstove more carefully or adopt other behavioural adjustments to reduce smoke exposure and accidents no matter what the stove is, and therefore affect the outcome. In this case, the results of a simple OLS, unconditional and conditional on covariates, should be interpreted as simple correlations, unless it can sensibly be argued that the allocation of traditional and non-traditional cookstoves among the households in the settlement is as good as random - or only determined by characteristics that are orthogonal to the outcome. This might not be the case in the context under analysis, as the type of stove used by a household (D) is the result of purchase decisions, product availability, households' preferences and characteristics, and budget constraints. This means that treated and untreated households are not directly comparable groups.

I therefore have a problem of endogeneity and sample-selection, and the main task of this Section is to present ways to address this problem and how ignoring it would lead to misleading conclusions for the analysis. A number of methodologies have been proposed in the literature to achieve this purpose, and Greenstone and Gayer (2009) and Mueller et al. (2011) in particular present a survey of the most relevant ones in the fields of environmental economics – the former – and health benefits linked to stove use – the latter.

Given that my dataset consists of cross-sectional survey data, I am not able to track households over time nor to use pre- and post-intervention observations for the same households. I therefore cannot use panel data analysis and the difference-in-difference methodology to control for unobservables confounders such as the idiosyncratic characteristics of each households, but I have to rely mainly on selection on observables to indirectly control for them. To do this, I rely on a wide set of relevant socio-demographic and economic characteristics and household-specific information on cooking-related activities to make the treated and untreated groups more comparable, at least with respect to their observable characteristics. I also use free cookstove distribution programs that happened in the past and information on whether the stoves were received as a donation, possibly at random, as instrument to predict the treatment and correct for sample-selection, following an instrumental variable (IV) approach.

Nevertheless, I acknowledge the limitation of the dataset to identify causal effects and results should therefore be considered as exploratory. I believe that given the rarity of datasets on energy-related issues in refugee settlements, this analysis can still provide interesting insights in an understudied context, but I encourage further research on the topic and hope that future data collection efforts in refugee camps will adopt a design better suited to perform causal inference.

With this caveat in mind, I now show how an instrumental variable approach and treatment-effects estimators based on observation re-weighting can address the issue of sample-selection, and what assumptions need to hold.

Instrumental variable approach using cookstove distribution programmes as instrument

Even though the purchase of non-traditional cookstoves is hardly random, receiving one as part of a distribution program in the context of refugee settlements might be as good as random, if every household has the same likelihood of receiving one. Receiving a non-traditional cookstove as donation[18] could therefore be used as the exogenous instrument in an IV regression model. Following the notation and methodology in Angrist et al. (1996), I define the instrumental variable as Z or 'encouragement', and define D_z as the potential treatment status given the realisation of the encouragement, i.e. D_0 if the household does not have a donated stove, and D_1 if they have. I estimate this model using a 2-stage least squares (2SLS) estimator and using the indices versions of the treatment variable, as described in the data section. A continuous treatment is better suited for this type of models as the both stages in a 2SLS are estimated using linear models.

The validity of the instrumental variable approach relies on three assumptions: the exclusion restriction, or independence assumption; the first-stage or relevant-instrument assumption; and the monotonicity assumption (Angrist et al., 1996). The assumption that donations are as good as random and all households are as likely to receive one corresponds to the independence of the instrument, or 'ignorability' assumption required for identification of the estimator. The assumption of independence of the instrument implies 'exclusion restriction', i.e. the excluded instrument Z can have no effect on Y except through D, which is to say that donations of a cleaner stove can only affect the welfare outcome Y through the actual utilization of the stove, which - although untestable - is clearly a sensible assumption to make. As a consequence, any correlation between stove donations (Z) and the welfare outcome (Y) can be attributed to the use of the stove (the actual treatment, D):

$$(Y_0, Y_1, D_0, D_1) \perp\!\!\!\perp Z$$

The first stage or relevance of the instrument assumption require that the instrument must induce variation in the treatment:

$$0 < P(Z = 1) < 1 \text{ and } P(D_1 = 1) \neq P(D_0 = 1)$$

Monotonicity implies absence of 'defiers', individuals that would not use a cleaner stove if donated one, but would use it if they were not donated one ($D_0 = 1$ and

[18] In practice, I use data on whether the household has a primary or secondary stove that was donated. I acknowledge that this is not ideal, as this indicator does not include households who received a stove donation but are not using it for whatever reason. Unfortunately, I have no data on the latter.

$D_1 = 0$, therefore $D_1 < D_0$). Although not testable, this seems a sensible assumption in this setting:

$$D_1 \geq D_0$$

The first-stage assumption can be tested by regressing the treatment on the instruments. Nevertheless, even if the excluded instrument is significantly correlated with the treatment, the instrument might be weak, i.e. the instrument might explain only a small proportion of the variation in the treatment. This might indeed be the case in the setting considered in this Chapter as many NGOs and agencies active in the settlements have moved from donation-based to market-based interventions, and as a consequence donations might not be a dominant driver of the adoption of non-traditional cookstoves.

As a rule of thumb, this problem can be diagnosed if the F-statistic of the excluded instrument obtained in the first stage of a 2SLS estimator is less than 10 (Stock et al., 2002). If the instrument is weak the confidence intervals for the IV estimator might then be unreliable and the variance too large. To address this issue, I test the null hypothesis that the treatment coefficient is not significantly different from zero using Anderson-Rubin (AR) test statistic (robust to weak instruments, see Finlay and Magnusson, 2009), and report the corresponding p-value[19] (indicated as *weak IV - robust p-value*) below the p-value of the Wald test.

The exclusion restriction requires that donations of a cleaner stove can only affect the welfare outcomes through the actual utilization of the stove, which - although untestable - seems a sensible assumption to make. Nevertheless the exclusion restriction may be violated if households who received the donated stove were also provided with health and safety information, and other type of training or education which might affect the outcome independently from the stove used. If so, it would be impossible to attribute the welfare effects to the phasing out of three-stone stoves rather than to these additional features. This assumption is not testable.

The independence of the instrument may also not hold if donations are not random, for instance if they are targeted on characteristics that might affect the outcome as well. In this case, endogeneity would bias the estimator.

[19] The AR test is conducted in Stata 15 using the command *weakiv* written by Finlay et al. (2013) and based on Finlay and Magnusson (2009).

Double-robust treatment-effects estimators

Without more detailed information on the donation programmes, I cannot exclude that donations were targeted, for example by giving priorities to households with a female head, or with higher dependency ratio, or larger household size. To control for these possibilities, I estimate the average treatment effect using two 'double-robust' treatment-effects estimators for observational data: the inverse-probability weighting regression-adjusted (IPWRA) estimator, introduced by Wooldridge (2007, 2010) and the augmented inverse-probability weighting (AIPW) estimator, based on Robins et al. (1995). Treatment-effects estimators are designed for binary, or at most categorical, treatment variables.

These estimators combine two models, one to predict the treatment status of each household and one to predict the potential outcome under the treatment and under the control scenario for each household. A convenient property of IPWRA and AIPW estimators is that they are 'doubly robust', meaning that they provide correct estimates of the treatment effect as long as at least one of the two models is correctly specified. Or equivalently, they are robust to misspecification in one of the two models (as long as the other one is correct).

Estimation of the ATE follows a three-step approach. First, the treatment model is estimated using a a logistic regression and the predicted probability of being in the treatment group (or propensity score) is used to construct the inverse-probability weights. The following steps include estimating the regression model for the potential outcomes in each treatment status, conditioned on covariates, and then comparing the mean predicted outcome under treatment with the mean under control to obtain the ATE. These two steps are different depending on the estimator used (StataCorp, 2014).

The inverse-probability weighting component of both estimators helps address the endogeneity issue introduced by the problem of sample selection of households into the treatment. The intuition is that after conditioning on covariates in both models, the treatment and the potential outcomes should be independent from each other, the assumption required for identification of the ATE. It is effective as long as participation in the programme is induced by 'observable' characteristics of the households, such as in the example of donations targeted to large households, and as far as the observables considered in the analysis can control or proxy for relevant unobservable confounders (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 2002).

Similar to matching estimators, the main identification assumptions for the identification of the ATE rely on conditional independence or selection on observables:

$$(Y_1, Y_0) \perp\!\!\!\perp D|X$$

and on the common-support, or overlap assumption, stating that every household has a positive probability of being selected in the treatment group, or in the control group:

$$0 < Pr(D = 1|X) < 1 \text{ for (almost all) } X$$

To select the covariates and the functional form for the treatment model, I use a Bayesian information criterion (BIC) minimisation procedure, as suggested by Cattaneo et al. (2013) in the context of treatment-effects estimators. I consider polynomials including different combinations of covariates and interaction terms up to the second order, and use the one with the minimum BIC as preferred specification for the treatment model. I specify the treatment model as a logit, and the outcome model as a linear, logit or fractional logit specifications depending on whether the outcome is continuous, binary or fractional. The overall model is estimated using moment conditions on estimating equations and a GMM estimator, and a robust sandwich estimator for the standard errors, corrected for the three-step procedure.

As a diagnostic tool for the overlap assumption, I plot the densities of the estimated probability of being in the treatment or control group, as estimated in the treatment model component of the regression. The resulting plots are shown in Figure 3.5 and do not raise concerns against the validity of the overlap assumption. To confirm that the inverse-probability weighting is successful in balancing the distribution of the covariates between the treatment and control group, I run the overidentification test for covariance balance, introduced by Imai and Ratkovic (2014).

Endogenous treatment-effects estimator

As a further robustness check, I use an endogenous treatment-effects estimator that accounts for the endogeneity of the treatment using a control-function approach (Wooldridge, 2010). Similar to the other estimators described in this Section, this estimator consists of a treatment model to estimate the likelihood of belonging to the treatment group, using a probit model; and an outcome model to explain the final outcome under treatment and control condition, estimated using a linear, probit or fractional regression depending on whether the outcome is continuous, binary, or fractional. Applying the control-function approach, the residuals from the treatment model are included in the outcome model as additional regressors. In this way the model controls for the correlation between unobservables included in the error term of the treatment model and the unobservables included in the error term of the outcome model. This correlation is what causes the endogeneity problem discussed above.

Under the control-function approach, an endogeneity test can be performed by checking if the correlation between the unobservables in the two models – estimated as an auxiliary parameter in the regression – is significant.[20] The null hypothesis is that the correlation is not significant, and there is therefore no endogeneity. In this case, the results from the double-robust treatment-effects estimators are to be preferred. The χ^2 statistics and the p-value of the endogeneity test are included in the Tables presented below.

Adjustment for multiple hypothesis testing

Because I test the effect of using a non-traditional cookstove on multiple outcomes, significant effects may be found simply due to chance; for example, at a 10% significance level, I can expect to mistakenly reject one null-hypothesis[21] out of every ten hypotheses I test. To address this issue, I correct the p-values of my tests to control for the false discovery rate (FDR). Compared with other type of adjustments, such as the Bonferroni correction, FDR-corrections do not reduce dramatically the power of the test, which is important in my setting, due to the small sample size.

More specifically, I follow Anderson (2008) and Baird et al. (2019) and use the two-stage q-values introduced by Benjamini et al. (2006). The procedure is a "sharpened" version of the FDR correction in Benjamini and Hochberg (1995), and is implemented using the code provided by Michael Anderson, as used in Anderson (2008). The *sharpened q-value* is included in the Tables with estimates of the ATE,

[20] The endogenous treatment-effects estimator and the endogeneity test are implemented in Stata 15 using the command *eteffects* and the corresponding post-estimation options.

[21] The null hypothesis is that the treatment has no effect on the outcome.

below the p-value.

3.4.3 Data: outcomes, 'treatment' and covariates

To test the hypotheses listed in the previous section, I construct a set of outcome indicators, twof for each welfare dimension considered: total quantity of firewood consumed per month and quantity of firewood consumed per hour of use of the stove for energy efficiency; whether smoke problems were reported and whether cooking-related accidents were reported[22] to explore health and safety benefits; how many hours per day the stove is on and the total time spent in cooking-related activities by all the members of the household (including cooking and fuel collection, purchase and preparation) to investigate time savings; and finally the share of the total time that is contributed by female members of the household, and whether children are involved in firewood collection for the last dimension.

The main treatment (*treatment*) is an indicator of whether the respondent reports their cookstove to be different from the three-stone fire. For households that use a secondary stove, the treatment is an indicator of whether both stoves are different from the three-stone fire. Due to the heterogeneity of the stoves and fuels used in the camp, and the difficulty of identifying the quality tier of the products from just one question, I use further information on the material of the stove and how it was produced, the fuel used, whether the household cooks indoor and whether a chimney is used, to construct three other versions of the treatment, and use them to assess the robustness of the results. More specifically, I construct another binary indicator that reassigns stoves of lower quality (for example artisanal and self-built) to the control group (*treatment adjusted*), and two continuous indices, the first one as a summative index that assigns a +1 score for characteristics associated with higher quality and -1 for indicators of lower quality (*treatment index*), and the second one as a weighted average of the quality scores determined using factor analysis and extracting the first factor using the Bartlett method (*treatment pca*)

To account for sample-selection into the treatment group using an instrumental variable approach, I use whether the cookstove was received as a donation as instrument. Detailed definitions of the treatment and outcome variables and how they are constructed are provided in Appendix C.3, while summary statistics for these

[22] Almost no accidents were reported in Goudoubo, so this outcome is only analysed for Kakuma.

variables and other characteristics of the sample are presented in Table C.2.

Several covariates representing households' characteristics such as wealth, demographics, decision-power and priority concerns around cooking, are used as controls to model either the outcome or selection into the treatment. Due to the small sample size, I use factor analysis to synthesize information on the economic situation of the household, and on the level of female empowerment, into indices.

The female empowerment index is constructed using information on whether the head of the household is a woman, whether women in the household go out at night, work outside the house, are studying, or their main activity is housekeeping, whether large purchase decisions are responsibility of the woman or the man, whether everyday purchases are responsibility of the woman or the man, and the gender-ratio in the household.

The wealth index is constructed using information on the natural logarithm of the per capita income of the household[23], share of adults in the household who are working, whether the household has a radio, tv, and lighting, how many mobile phones per capita they have, whether they have a solar lamp or solar-home system they purchased themselves (not received as donations).

The variables used for these indices are a mix of continuous and categorical variables, so a matrix of polychoric correlation is constructed before running factor analysis. After applying factor analysis, the first factor for each group of variables is extracted using the Bartlett method. The wealth and female empowerment indices are then constructed as weighted sums of the original variables, according to the loading factors obtained.

3.4.4 Estimations of the average treatment effects

In this Section I present the results of the estimations of ATEs (average treatment effects) using the estimation strategies presented in Section 3.4.2. Consistent with the design of the different estimators, I use the binary versions of the treatment with the IPWRA, AIPW and endogenous treatment-effects estimator, and the continuous indices in the IV and OLS specifications, the latter presented for comparison. I use the different definitions of the treatment defined above as robustness checks. Estimated ATEs and potential outcome under no treatment, obtained with the

[23]The income is only used in Goudoubo, as the variable has many missing values in Kakuma and has been found to be under-reported.

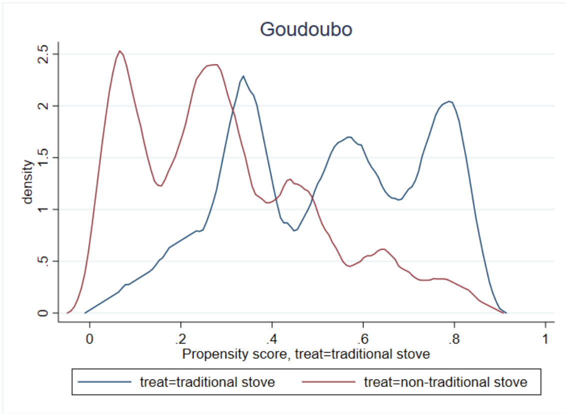
treatment-effects estimators, are presented in Tables 3.12 to 3.15 for Goudoubo and 3.16 to 3.19 for Kakuma, including both the regular p-value and the sharpened q-value adjusted for multiple-hypotheses testing in brackets.

The Chi square statistics and p-value for the endogeneity test when using the endogenous treatment-effects estimator are also included in the Table. I fail to reject the null hypothesis that the treatment is not endogenous at 10% significance level in all cases, and in all but one case at the 5% significance level. The IPWRA and AIPW are therefore my preferred estimators and I discuss those results in more details for each camp; for all outcomes, results estimated with the IPWRA and the AIPW estimators are very close. Figure 3.5 shows the overlap plots as a diagnostics in favour of the validity of the overlap assumption.

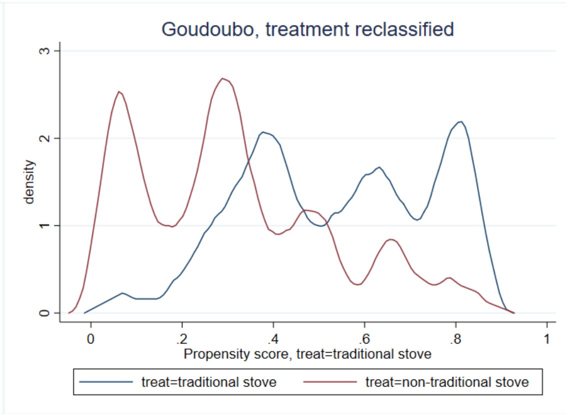
Finally, Tables C.3 and C.8 show results for the first stage of the 2SLS used for the IV specification, for Goudoubo and Kakuma respectively, while Tables C.4 to C.7 present the results of the second stage (only the coefficient for treatment index) for Goudoubo and C.9 to C.12 for Kakuma, including also results from an OLS model for comparison. Although the first-stage regressions support the relevance of the instrument (stove donation is a positive and significant predictor of the treatment index), the F-statistics for the excluded instruments is small and less than 10 in both camps, suggesting that the 2SLS estimates suffer from a weak instrument problem. The result Tables therefore include a weak-instrument-robust p-value obtained from the Anderson-Rubin (AR) test, and the sharpened q-values are calculated based on these values rather than the Wald-test p-values. Due to the weak instrument problem, these results are presented as a robustness check, and the IPWRA and AIPW are confirmed as the preferred specifications for the analysis.

Goudoubo

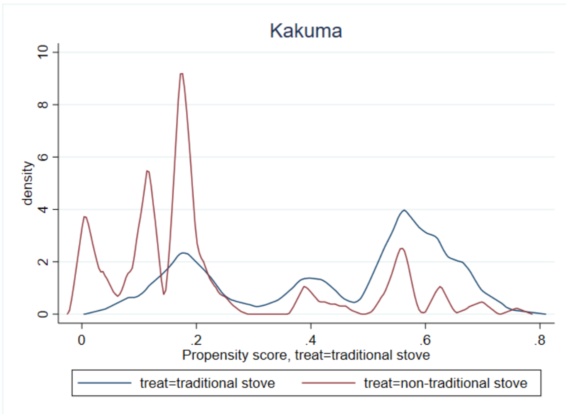
In Goudoubo, the use of non-traditional cookstoves appears to be associated with significant improvements in energy efficiency, both in terms of total firewood use, and of firewood per hour of use of the cookstove. Results estimated with the IPWRA and the AIPW estimators are very close, and they are significant even after correcting for multiple-hypothesis testing with the sharpened q-values. Households who still cook on a traditional cookstove are estimated to use on average around 130 kg of firewood per month and around 0.8 kg per hour when the stove is in use, while households who



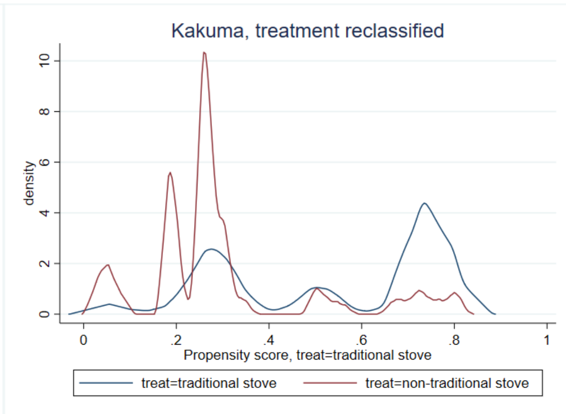
(a)



(b)



(c)



(d)

Figure 3.5: Plots of the estimated density of the probability of belonging to the treatment group and to the control group.

only use non-traditional cookstoves save on average 48 kg of firewood per month, and 0.25 kg per hour of stove use (Table 3.12). The savings are even larger when only higher quality non-traditional stoves are considered as treatment (the *treatment, adjusted* variable). These savings are equivalent to a 30-40% reduction in fuel use; this is still shorter than the 40-60% decrease[24] that the most common metallic biomass ICS introduced in the camp was supposed to deliver.

In terms of health and safety, I only test the effect of the treatment on the likelihood of reporting smoke problems, as almost no accidents were reported in the survey, and using non-traditional stoves is again significantly associated with improvements in this dimension, with a sharpened q-value smaller than 0.01 (Table 3.13). Households cooking with a traditional cookstove are estimated to have on average a 50% chance to have reported smoke problems, while this is only 20% on average for households using non-traditional cookstoves. Again, the benefits are esti-

[24] According to key informant interviews conducted by the Moving Energy Initiative.

Table 3.12: Estimated ATE on energy efficiency, Goudoubo.

tot firewood qty	ipwra treat.	ipwra tr. adj.	aipw treat.	aipw tr. adj.	eteffects treat.	eteffects tr. adj.
ATE	-47.92*	-63.81**	-47.61*	-60.72*	-9.30	-21.23
	(20.889)	(20.885)	(24.002)	(24.237)	(73.550)	(58.421)
p-value	[0.022]	[0.002]	[0.047]	[0.012]	[0.899]	[0.716]
sharp.d q-value	[0.038]	[0.004]	[0.086]	[0.016]	[1.000]	[1.000]
POmean (t=0)	129.99***	135.57***	124.92***	127.47***	131.79*	107.68*
	(18.557)	(19.229)	(20.357)	(21.557)	(58.958)	(48.673)
N	104	104	104	104	104	104
endog. chi2 [p-value]					1.17 [0.56]	0.88 [0.64]

firewood per hour	ipwra treat.	ipwra tr. adj.	aipw treat.	aipw tr. adj.	eteffects treat.	eteffects tr. adj.
ATE	-0.26*	-0.43**	-0.25+	-0.40*	0.11	-0.05
	(0.120)	(0.151)	(0.137)	(0.156)	(0.455)	(0.333)
p-value	[0.031]	[0.005]	[0.068]	[0.010]	[0.805]	[0.884]
sharp.d q-value	[0.041]	[0.006]	[0.093]	[0.016]	[1.000]	[1.000]
POmean (t=0)	0.76***	0.84***	0.73***	0.79***	0.72*	0.58*
	(0.082)	(0.137)	(0.096)	(0.137)	(0.311)	(0.263)
N	104	104	104	104	104	104
endog. chi2 [p-value]					1.38 [0.50]	1.36 [0.51]

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

mated to be even larger when only higher-quality stoves are considered as treatment, and results are almost identical between the IPWRA and AIPW estimator.

Table 3.13: Estimated ATE on health and safety, Goudoubo.

smoke problems	ipwra treat.	ipwra tr. adj.	aipw treat.	aipw tr. adj.	eteffects treat.	eteffects tr. adj.
ATE	-0.31***	-0.34***	-0.31***	-0.33***	-0.26	-0.26
	(0.075)	(0.061)	(0.067)	(0.065)	(0.203)	(0.204)
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.198]	[0.194]
sharp.d q-value	[0.001]	[0.001]	[0.001]	[0.001]	[0.495]	[0.830]
POmean (t=0)	0.51***	0.51***	0.51***	0.51***	0.46*	0.37+
	(0.064)	(0.057)	(0.057)	(0.060)	(0.193)	(0.195)
N	126	126	126	126	126	126
endog. chi2 [p-value]					0.07 [0.97]	0.44 [0.80]

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results are less encouraging with respect to time savings and share of the workload shouldered by women, while further benefits appear in terms of children involvement in firewood collection (Tables 3.14 and 3.15). The estimators detect a reduction of a little more than 1 hour in the number of hours per day the stove is in use, from an estimated baseline of almost 7 hours per day for traditional cookstoves, but the difference is only marginally significant (p-values and sharpened q-values are all close to or slightly above 0.1). Differences in the tot amount of time spent in cooking-related activities are not statistically significant, although the sign of the ATE is again negative, consistent with time savings; the total amount of time spent by all household members in these activities is estimated to be 50 hours per week.

Results in the following Table confirm that this workload is not shared equally among the members, as on average 75% of these hours are inputted by female members – note that on average 52% of the household members are female, and the median household has exactly the same number of female and male members. This outcome does not appear to change depending on the type of stove used. The likelihood that children participate in firewood collection is instead significantly lower in households that use non-traditional cookstoves (sharpened q-values < 0.5), possibly related to the fuel savings found above. For households using traditional stoves there is a 40% probability that children are involved in firewood collection; this is less than 20% in households using non-traditional cookstoves. Again, the benefits are slightly larger when considering the adjusted treatment.

Table 3.14: Estimated ATE on time use, Goudoubo.

	ipwra		aipw		eteffects	
hours of stove use	treat.	tr. adj.	treat.	tr. adj.	treat.	tr. adj.
ATE	-1.19^{+}	-1.16^{+}	-1.46	-1.51	2.95^{+}	2.43
	(0.668)	(0.665)	(0.913)	(0.965)	(1.721)	(1.544)
p-value	[0.075]	[0.080]	[0.109]	[0.118]	[0.086]	[0.115]
sharp.d q-value	[0.058]	[0.051]	[0.123]	[0.076]	[0.431]	[0.830]
POmean (t=0)	6.61***	6.58***	6.84***	6.86***	2.16	2.58^{+}
	(0.571)	(0.569)	(0.832)	(0.887)	(1.684)	(1.480)
N	126	126	126	126	126	126
endog. chi2 [p-value]					4.51 [0.11]	4.24 [0.12]

	ipwra		aipw		eteffects	
tot time	treat.	tr. adj.	treat.	tr. adj.	treat.	tr. adj.
ATE						
r1vs0.treat	-1.99	-4.35	-1.38	-4.19	15.55	14.40
	(5.983)	(5.900)	(6.265)	(6.311)	(14.718)	(15.080)
p-value	[0.739]	[0.461]	[0.825]	[0.507]	[0.291]	[0.340]
sharp.d q-value	[0.268]	[0.152]	[0.309]	[0.197]	[0.571]	[0.830]
POmean (t=0)	49.71***	50.80***	48.65***	50.04***	32.14**	31.00*
	(5.516)	(5.393)	(5.684)	(5.567)	(12.268)	(12.444)
N	125	125	125	125	125	125
endog. chi2 [p-value]					1.55 [0.46]	2.06 [0.36]

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

None of the estimated ATE is significant when using the endogenous treatment-effects estimator, but given that the endogeneity test in this model fails to reject

Table 3.15: Estimated ATE on women and children workload, Goudoubo.

	ipwra		aipw		eteffects	
female share of work	treat.	tr. adj.	treat.	tr. adj.	treat.	tr. adj.
ATE	0.05	0.05	0.04	0.06	-0.15^{+}	-0.12
	(0.045)	(0.044)	(0.058)	(0.056)	(0.082)	(0.085)
p-value	[0.300]	[0.234]	[0.482]	[0.314]	[0.062]	[0.145]
sharp.d q-value	[0.118]	[0.127]	[0.192]	[0.187]	[0.431]	[0.830]
POmean (t=0)	0.75***	0.74***	0.76***	0.75***	0.90***	0.88***
	(0.037)	(0.035)	(0.052)	(0.049)	(0.040)	(0.042)
N	124	124	124	124	124	124
endog. chi2 [p-value]					4.49 [0.11]	4.63 [0.10]

	ipwra		aipw		eteffects	
children involv.	treat.	tr. adj.	treat.	tr. adj.	treat.	tr. adj.
ATE	-0.22**	-0.26***	-0.24**	-0.29**	0.02	-0.01
	(0.073)	(0.072)	(0.091)	(0.095)	(0.225)	(0.214)
p-value	[0.003]	[0.000]	[0.007]	[0.002]	[0.937]	[0.956]
sharp.d q-value	[0.010]	[0.001]	[0.023]	[0.007]	[1.000]	[1.000]
POmean (t=0)	0.39***	0.42***	0.41***	0.45***	0.18	0.16
	(0.067)	(0.067)	(0.088)	(0.093)	(0.202)	(0.188)
N	126	126	126	126	126	126
endog. chi2 [p-value]					0.84 [0.66]	1.44 [0.49]

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the null hypothesis of non-endogeneity of the treatment, I consider the IPWRA and AIPW as preferred estimators. As a robustness check, I compare these results with estimates from a simple OLS model and a 2SLS model for IV using the indices representing the quality of the cooking system. The magnitude of the estimates are not directly comparable with the results in the previous tables, as the treatment here is a continuous index and not a binary indicator, but I can compare the sign and significance of the results. The general results obtained in the previous analysis are confirmed by both the OLS and the 2SLS estimators, but none of the treatment coefficients in the IV models is significant, especially after correcting for multiple-hypothesis testing with the sharpened q-values (Table C.4-C.7).

Kakuma

The average firewood consumption in Kakuma is much lower than in the other camp, with household cooking on a traditional three-stone fire estimated to use around 40 kg of firewood per month and 0.20 kg per hour of use of the cookstove (Table 3.16). This difference is possibly due to a larger use of charcoal in Kakuma.

Contrary to the results in Goudoubo, in Kakuma I find no significant differences in terms of the total firewood consumed in a month, and even find an increase of about 100 grams in the amount of firewood needed to fuel the stove for one hour, although the latter is only marginally significant, especially when considering the sharpened q-values.

As discussed in the hypothesis Section, these results do not necessarily mean lack of improvement in energy efficiency, although this is certainly one of the potential explanation. In fact, households already consume much smaller amounts of firewood compared to the other camp (although this is partly due to the larger use of charcoal in Kakuma) and given the large number of reported accidents and smoke problems in Kakuma, camp administrators might have prioritised the introduction of cooksoves that improve health and safety issues rather than fuel efficiency.

Another possible explanation is that there are constraints to the availability of firewood and households optimal choice would be to consume more if there was more available; in this case, even if the non-traditional stoves are more efficient, the households would still consume all the fuel they can get access to, and there would be no difference in the total amount of fuel used. In support of this explanation, focus group participants have been very vocal in complaining that firewood distributed in the camp is insufficient to cover basic needs, and that the host community is preventing firewood collection in the local forests.[25]

The increase in firewood used per hour may be reconciled with the lack of differences in the overall amount of firewood used if the non-traditional stoves cook faster than the traditional ones and are therefore used for fewer hours. At the same time, if there are binding availability constraint and the non-traditional cookstoves burn the fuel faster, then the households have no choice but to use the stoves for a shorter time. Without further information on the amount of food cooked and whether households cannot purchase more fuel even if they want to, I cannot draw any conclusion on energy efficiency.[26]

In terms of health and safety, non-traditional cookstoves are associated with a smaller probability of smoke problems – from about 70-80% for households using a three-stone fire to 60% for households in the treatment group – but no significant differences in the probability of accidents – around 60-70% for all the households (Table 3.17).

[25]From focus group discussions conducted by the Moving Energy Initiative.

[26]The fact that charcoal is often used instead of firewood adds an additional nuance to the issue,

Table 3.16: Estimated ATE on energy efficiency, Kakuma.

	ipwra		aipw		eteffects	
tot firewood qty	treat.	tr. adj.	treat.	tr. adj.	treat.	tr. adj.
ATE	-2.95	1.68	-4.80	3.58	-38.16	1.97
	(7.261)	(5.727)	(7.683)	(7.298)	(28.079)	(16.526)
p-value	[0.684]	[0.769]	[0.532]	[0.624]	[0.174]	[0.905]
sharp.d q-value	[0.416]	[0.478]	[0.438]	[0.368]	[0.685]	[1.000]
POmean (t=0)	42.07***	36.86***	43.87***	35.51***	84.21**	50.27***
	(6.289)	(3.990)	(6.617)	(5.679)	(27.322)	(14.359)
N	175	175	175	175	175	175
endog. chi2 [p-value]					3.40 [0.18]	3.71 [0.16]
	ipwra		aipw		eteffects	
firewood per hour	treat.	tr. adj.	treat.	tr. adj.	treat.	tr. adj.
ATE	0.12*	0.13*	0.09	0.12+	-0.14	-0.01
	(0.056)	(0.055)	(0.060)	(0.066)	(0.258)	(0.151)
p-value	[0.029]	[0.023]	[0.115]	[0.058]	[0.584]	[0.949]
sharp.d q-value	[0.038]	[0.074]	[0.168]	[0.133]	[1.000]	[1.000]
POmean (t=0)	0.19***	0.20***	0.22***	0.21***	0.49+	0.33**
	(0.041)	(0.031)	(0.045)	(0.043)	(0.248)	(0.110)
N	175	175	175	175	175	175
endog. chi2 [p-value]					1.73 [0.42]	1.80 [0.41]

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.17: Estimated ATE on health and safety, Kakuma.

	ipwra		aipw		eteffects	
smoke problems	treat.	tr. adj.	treat.	tr. adj.	treat.	tr. adj.
ATE	-0.19**	-0.03	-0.19**	-0.01	-0.04	-0.14
	(0.071)	(0.068)	(0.072)	(0.081)	(0.191)	(0.174)
p-value	[0.007]	[0.652]	[0.010]	[0.859]	[0.854]	[0.435]
sharp.d q-value	[0.015]	[0.478]	[0.021]	[0.476]	[1.000]	[1.000]
POmean (t=0)	0.83***	0.67***	0.83***	0.67***	0.56**	0.60***
	(0.058)	(0.051)	(0.060)	(0.065)	(0.194)	(0.138)
N	213	213	213	213	213	213
endog. chi2 [p-value]					3.22 [0.20]	1.97 [0.37]
	ipwra		aipw		eteffects	
accidents	treat.	tr. adj.	treat.	tr. adj.	treat.	tr. adj.
ATE	-0.08	0.09	-0.07	0.11	-0.17	-0.19
	(0.065)	(0.070)	(0.075)	(0.081)	(0.127)	(0.134)
p-value	[0.231]	[0.202]	[0.366]	[0.168]	[0.171]	[0.165]
sharp.d q-value	[0.182]	[0.193]	[0.355]	[0.202]	[0.685]	[1.000]
POmean (t=0)	0.70***	0.58***	0.69***	0.57***	0.79***	0.72***
	(0.051)	(0.057)	(0.063)	(0.067)	(0.105)	(0.071)
N	213	213	213	213	213	213
endog. chi2 [p-value]					0.44 [0.80]	3.11 [0.21]

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimates of the ATEs for the time use outcome, in Table 3.18 confirm that non-traditional cookstoves are indeed used for shorter time: around 9 hours per day against the 10-14 hours per day of the traditional stoves. The difference is smaller and only marginally significant when using the adjusted treatment, suggesting that the cookstoves that have been re-assigned to the control group in this treatment definition might actually be of good quality.

In terms of overall time spent in cooking-related activities, the sign of the estimated ATE is negative, but the effects are not significant, and much smaller in magnitude than would be predicted by the reduction in hours of stove use found above. To further investigate the issue I repeat the analysis for each cooking-related activity separately – cooking, firewood collection, fuel purchase and fuel preparation – and find that while cooking time decreases slightly, fuel purchase and fuel preparation for non-traditional cookstoves take up more time if the household uses a non-traditional cookstove (tables not presented due to space constraints). This is consistent with the fact that some non-traditional cookstoves use charcoal or specially-prepared firewood.

Table 3.18: Estimated ATE on time use, Kakuma.

	ipwra		aipw		eteffects	
hours of stove use	treat.	tr. adj.	treat.	tr. adj.	treat.	tr. adj.
ATE	-4.96***	-1.75+	-4.78***	-1.64	-2.97	-2.95
	(0.969)	(0.978)	(1.056)	(1.019)	(4.431)	(2.673)
p-value	[0.000]	[0.073]	[0.000]	[0.108]	[0.503]	[0.269]
sharp.d q-value	[0.001]	[0.102]	[0.001]	[0.185]	[1.000]	[1.000]
POmean (t=0)	13.66***	10.50***	13.53***	10.37***	11.73**	12.31***
	(0.840)	(0.813)	(0.936)	(0.834)	(4.201)	(2.164)
N	213	213	213	213	213	213
endog. chi2 [p-value]					0.20 [0.91]	1.02 [0.60]
	ipwra		aipw		eteffects	
tot time	treat.	tr. adj.	treat.	tr. adj.	treat.	tr. adj.
ATE	-1.28	-1.48	-2.60	-5.90	-0.17	3.76
	(5.112)	(3.719)	(5.213)	(5.127)	(20.671)	(12.695)
p-value	[0.803]	[0.690]	[0.619]	[0.250]	[0.993]	[0.767]
sharp.d q-value	[0.431]	[0.478]	[0.448]	[0.263]	[1.000]	[1.000]
POmean (t=0)	24.27***	25.42***	25.52***	29.63***	31.68	27.29**
	(4.721)	(3.121)	(4.840)	(4.729)	(19.381)	(10.419)
N	200	200	200	200	200	200
endog. chi2 [p-value]					3.07 [0.22]	1.62 [0.44]

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The share of the total time shouldered by women is again 70-80%, although in

which I do not explore in this Chapter.

Kakuma as well as in Goudoubo the median household has exactly the same number of female and male members, and on average women and girls represent 52% of the household members; when using the adjusted treatment, there are some evidence that men contribute more in households with non-traditional cookstoves, but this is only marginally significant when considering the sharpened q-value. Significant and robust improvements are instead found in terms of children involvement in firewood collection – from a 50% probability of participating in households using three-stone fires, to 20-25% in households with non-traditional cookstoves (Table 3.19).

Table 3.19: Estimated ATE on women and children workload, Kakuma.

	ipwra		aipw		eteffects	
female share of work	treat.	tr. adj.	treat.	tr. adj.	treat.	tr. adj.
ATE	0.09	-0.08*	0.06	-0.09*	0.45**	0.13
	(0.059)	(0.039)	(0.067)	(0.039)	(0.154)	(0.106)
p-value	[0.131]	[0.030]	[0.392]	[0.023]	[0.004]	[0.212]
sharp.d q-value	[0.118]	[0.074]	[0.355]	[0.086]	[0.030]	[1.000]
POmean (t=0)	0.66***	0.81***	0.69***	0.81***	0.29+	0.65***
	(0.054)	(0.033)	(0.063)	(0.034)	(0.149)	(0.102)
N	192	192	192	192	192	192
endog. chi2 [p-value]					2.48 [0.29]	5.19 [0.07]
	ipwra		aipw		eteffects	
children involv.	treat.	tr. adj.	treat.	tr. adj.	treat.	tr. adj.
ATE	-0.29***	-0.27***	-0.25***	-0.25***	-0.06	-0.02
	(0.065)	(0.057)	(0.071)	(0.064)	(0.202)	(0.151)
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.757]	[0.891]
sharp.d q-value	[0.001]	[0.001]	[0.002]	[0.001]	[1.000]	[1.000]
POmean (t=0)	0.50***	0.46***	0.47***	0.47***	0.31+	0.28*
	(0.054)	(0.043)	(0.060)	(0.049)	(0.183)	(0.116)
N	213	213	213	213	213	213
endog. chi2 [p-value]					0.89 [0.64]	2.75 [0.25]

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Again, none of the estimated ATEs is significant when using the endogenous treatment-effects estimator, but the endogeneity test in this model fails to reject the null hypothesis of non-endogeneity of the treatment, supporting the use of the IPWRA and AIPW as preferred estimators. Similarly, none of the estimated treatment coefficients is significant when using an IV model in Tables C.9-C.12 (the only exception is for the children outcome, but becomes insignificant too when correcting for multiple-hypothesis testing). The OLS model confirms that non-traditional cookstoves are associated with significantly fewer hours of stove use, smaller probability of children participation in firewood collection, and less smoke problems (the latter only marginally significant) but finds no significant effects on the other outcomes (using the sharpened q-values as reference for significance).

3.5 Part 3: Linking stated preferences and predicted benefits

In this last Section, I bridge the results on the predicted benefits – or lack thereof – of using non-traditional cookstoves with the stated preferences for hypothetical improvements. To do this, I use the estimates from Wooldridge's double-robust IPWRA estimator to predict the treatment effect for each household in the various outcomes. The distributions of the benefits across the two samples are plotted in Figure 3.6. Notably, there is some variation in whether transitioning to the non-traditional cookstoves results in gains or losses.

I then test whether respondents from households who are predicted to have the most to gain from moving away from the three-stone fires are also the ones who have higher willingness to pay for non-traditional cookstoves. I limit the analysis to the WTP for biomass-fuelled ICS (basic; enhanced using wood; enhanced using charcoal) as these represent the non-traditional cookstoves on which the treatment effects estimates are based. To obtain the partial correlation coefficients, I use an OLS regression with WTP as the dependent variable and the predicted outcomes as regressors. Given that the total quantity of firewood used in a month and the amount of firewood per hour of stove use are highly correlated, I only use the latter to avoid collinearity problems. For the same reason, I only use the predicted effect on total time use and exclude the number of hours the stove is used for. The predicted outcomes are interacted with the gender of the respondent, to investigate whether men or women are better at factoring the predicted gains into their valuation, especially considering that some outcomes affect each gender differently – women would benefits more directly from reduction in smoke exposure and cooking time, while men may benefits more directly from reductions in fuel expenditures. As additional controls, the regressions include the wealth index, the size of the household in adult-equivalent term (with children weighted as 0.5 adults and the elderly as 0.8), the respondent's age and gender, an interaction between whether the respondents is a woman and the female empowerment index, and the cooking priorities of the household.

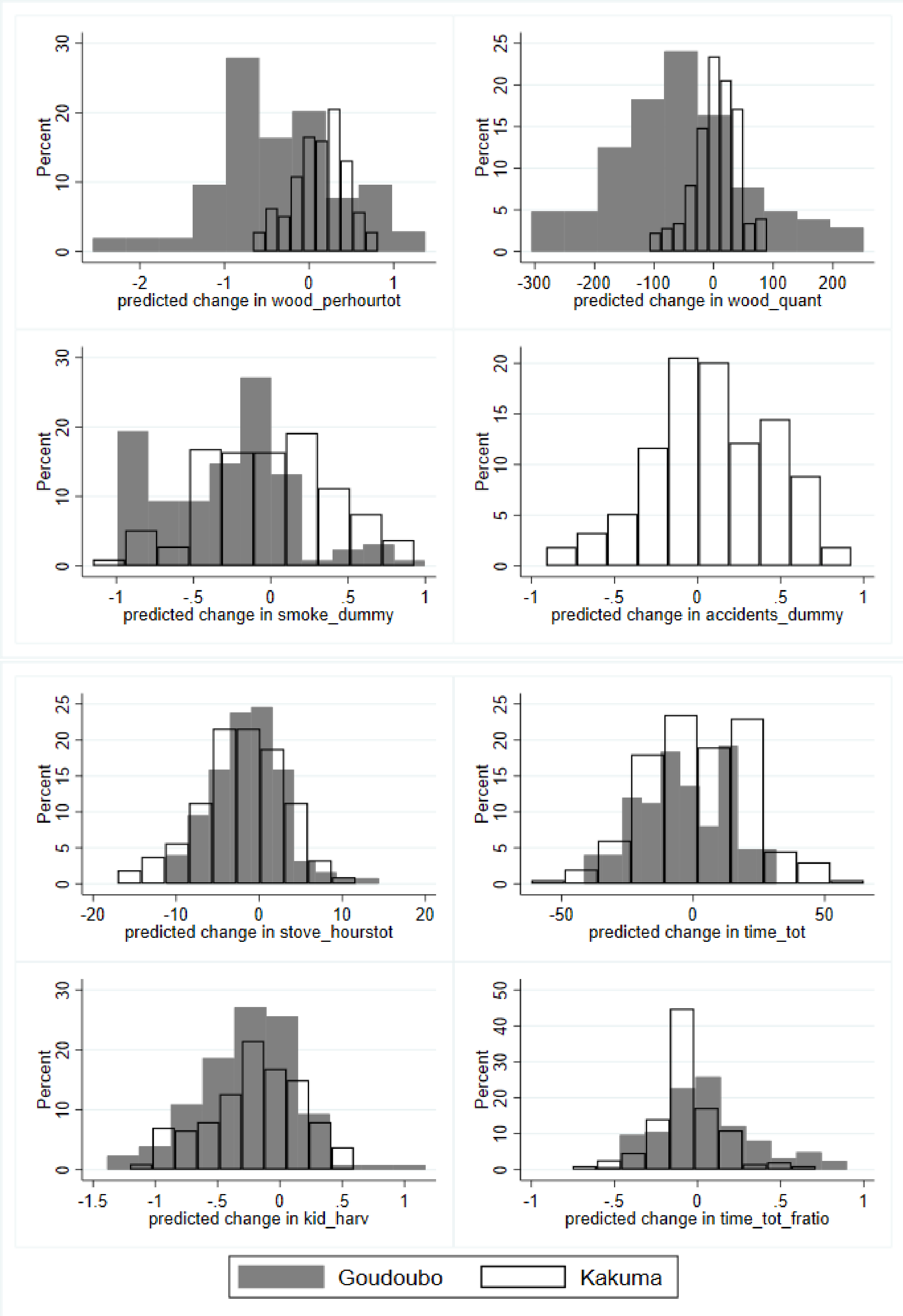


Figure 3.6: Distribution of the predicted gains for households in each camp.

In Goudoubo (Table 3.20) women's WTP for each stove tend to be higher when there are larger predicted reductions in firewood use, probability of smoke problems and time spent in cooking-related activities, although these coefficients are ony significant for the enhanced firewood-ICS. The coefficients for smoke problems and time use even switch sign for men, suggesting that they are less successful at predicting the improvements and factoring them in their valuation. Similarly, in Kakuma (Table 3.21) women's WTP for all three cookstoves are significantly correlated with predicted reductions in firewood use, smoke problems, and accidents (the latter only marginally significant). Again, the sign of the same coefficients are switched for men.

3.6 Conclusion

While cultural acceptability and budget constraints have often be mentioned in the literature as the main hurdles to transition towards cleaner energy solutions, low expectations regarding the performances of the new systems contribute to explain low willingness to pay and low take-up. On one side, the innovations currently marketed might not actually deliver the improvements they promise, or at least not to a level that would justify the high premium required for their purchase – as well as the cognitive effort of adjusting habits and behaviours. On the other side, even if they do deliver on their promises, the improvements and features of the new technologies might not match households' priorities and preferences.

In this Chapter, I investigate these issues in a context where resources are particularly scarce, and transitioning to a cleaner energy system is especially urgent, namely refugee camps in Sub-Saharan Africa. Given the substantial amount of time and resources refugees spend on cooking, the essential services cooking provide to everyday life, and the range of negative impacts linked to the use of three-stone fires and biomass-fuelled cookstoves, the technological innovations I focus on are non-traditional cookstoves. To this purpose, I use a novel dataset based on a survey administered in Goudoubo camp (Burkina Faso) and Kakuma camp (Kenya), which includes modules to elicit respondents' stated preferences for a range of non-traditional cooking systems: LPG, biogas, solar cooker, electric cooker, and different types of biomass-based ICS.

Analysing respondents' valuation of these technologies, I find a strong interest for LPG in both camps, while any favouritism or dislike for the other technologies tend to fade away once the perceived characteristics of the system are accounted for. I further find that priority heterogeneity affects the valuation of specific technologies

Table 3.20: Partial correlations between predicted benefits and (winsorized) WTP for non-traditional biomass cookstoves (OLS model). Goudoubo.

	Goudoubo (1) Basic ICS	Goudoubo (2) Enhanced ICS, wood	Goudoubo (3) Enhanced ICS, coal
pred. effect on wood per hour	-7.53	-1.91	1.21
	(5.364)	(3.828)	(1.977)
" X female respond	-4.05	-1.59	-1.81
	(3.884)	(2.018)	(2.666)
pred. effect on smoke	0.47	5.80*	0.88
	(1.527)	(2.760)	(1.480)
" X female respond	-0.48	-6.75*	-2.08
	(2.853)	(3.193)	(2.656)
pred. effect on tot time	0.16	0.08	0.10
	(0.110)	(0.091)	(0.070)
" X female respond	-0.13	-0.35*	-0.05
	(0.119)	(0.153)	(0.109)
pred. effect on children involv.	13.02	4.71	-5.64
	(14.230)	(10.457)	(5.671)
" X female respond	6.49	13.02*	3.33
	(8.664)	(6.412)	(7.084)
pred. effect on fem. share of work	-1.59	3.19	-3.65
	(4.369)	(4.194)	(2.195)
" X female respond	4.97	0.21	3.60
	(4.440)	(5.256)	(4.360)
wealth index	-0.83	-0.96	0.37
	(1.536)	(1.369)	(1.125)
adult-equiv size	1.32+	-0.22	0.01
	(0.757)	(0.751)	(0.355)
respondent's age	-0.12	-0.08	0.01
	(0.084)	(0.057)	(0.033)
female respondent	-0.30	-5.79	0.78
	(2.860)	(4.092)	(2.076)
" X fem empower index	15.97	9.47	-0.31
	(12.958)	(8.352)	(7.321)
top safe	-2.11	-2.84	0.90
	(1.828)	(2.208)	(1.671)
top less smoke	0.91	-0.80	1.59+
	(1.215)	(1.189)	(0.919)
top cook fast	0.44	3.89	-2.53
	(3.108)	(3.124)	(1.643)
top traditions & habits	-0.32	1.35	0.05
	(0.923)	(0.923)	(1.006)
top less fuel	-10.47*	0.85	-0.72
	(5.175)	(4.534)	(2.908)
N	101	96	100
r2	0.25	0.30	0.14
r2_a	0.06	0.11	-0.08

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.21: Partial correlations between predicted benefits and (winsorized) WTP for non-traditional biomass cookstoves (OLS model). Kakuma.

	Kakuma (1) Basic ICS	Kakuma (2) Enhanced ICS, wood	Kakuma (3) Enhanced ICS, coal
pred. effect on wood per hour	5.91	6.71	6.56
	(7.290)	(7.174)	(6.885)
" X female respond	-15.52**	-18.01**	-16.08*
	(5.677)	(6.131)	(6.235)
pred. effect on smoke	16.36*	21.12***	19.12**
	(6.335)	(5.827)	(5.937)
" X female respond	-11.91*	-12.76*	-10.77*
	(4.610)	(5.059)	(4.876)
pred. effect on accidents	-0.94	1.61	-0.09
	(2.375)	(2.535)	(2.536)
" X female respond	-0.38	-4.44+	-2.79
	(2.310)	(2.601)	(2.495)
pred. effect on tot time	-0.08	-0.08	-0.09
	(0.064)	(0.078)	(0.077)
" X female respond	0.06	0.07	0.08
	(0.077)	(0.095)	(0.092)
pred. effect on children involv.	-0.89	-0.12	-0.91
	(4.682)	(5.117)	(4.575)
" X female respond	0.09	-0.81	-0.95
	(4.622)	(5.153)	(4.580)
pred. effect on fem. share of work	13.53**	16.03***	14.34**
	(4.710)	(4.340)	(4.382)
" X female respond	-7.34	-4.76	-3.75
	(5.197)	(5.870)	(5.714)
wealth index	-0.29	-0.11	1.15
	(2.176)	(2.267)	(2.177)
adult-equiv size	1.73*	2.32***	1.94**
	(0.730)	(0.657)	(0.713)
respondent's age	-0.07+	-0.13**	-0.10*
	(0.042)	(0.047)	(0.042)
female respondent	-5.31+	-5.91*	-5.45+
	(3.168)	(2.970)	(2.998)
" X fem empower index	8.16*	10.00**	8.11*
	(3.335)	(3.758)	(3.646)
top safe	1.42	2.52	1.63
	(2.529)	(2.269)	(2.401)
top less smoke	5.07*	8.23***	7.39**
	(2.385)	(2.114)	(2.343)
top cook fast	0.91	1.34	0.67
	(1.834)	(1.910)	(1.933)
top traditions & habits	2.27*	3.33**	2.37*
	(0.981)	(1.118)	(1.012)
top less fuel	-3.87*	-4.32*	-4.12*
	(1.697)	(1.906)	(1.902)
N	174	150	166
r2	0.27	0.39	0.34
r2_a	0.17	0.29	0.24

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

and characteristics, with households prioritising smoke reductions and safety having higher valuation for related characteristics, and households prioritising habits and traditions having lower valuation for non-biomass cookstoves than the rest of the sample. This also holds in terms of broader priorities of the two settings, with households in Kakuma displaying a stronger interest for health and safety improvements than households in Goudoubo, consistent with the difference between the two camps in terms of indoor cooking and prevalence of smoke problems and cooking-related accidents. Previous experience with a technology is not necessarily associated with higher valuation, and the coefficient is even negative for some technologies, suggesting that unsuccessful trials and the introduction of cookstoves that do not perform as expected might have deleterious effects and induce even more skepticism towards related products.

In the second part, I then estimate how the supposedly 'improved' cooking systems currently used in the two locations perform compared to the traditional three-stone fires in terms of energy efficiency, health and safety, household time use, and women and children workload. I find that the use of (mostly biomass-fuelled) non-traditional cookstoves in Goudoubo is associated with lower firewood use, lower incidence of smoke problems and smaller likelihood of children participating in firewood collection. In Kakuma I find some improvements in terms of smoke problems, shorter use of the cookstove, and less involvement of children in firewood collection for households using non-traditional cookstoves, but no evidence of fuel savings or smaller incidence of accidents, and possibly even an increase in the time spent preparing and procuring fuel.

In the last part of the Chapter, I link the results on the estimated benefits of using non-traditional cookstoves with the stated preferences for hypothetical improvements, and look at whether the households who are predicted to have more to gain from the non-traditional stoves introduced in the camps are also the ones who value them higher. I find that women seem to be on average better than men at factoring the benefits into their valuation. This is especially true for smoke reduction and time savings for women in Goudoubo, and smoke and accident reductions and fuel savings for women in Kakuma. This is consistent with the fact that women are the one shouldering most of the responsibilities of cooking and fuel collection and that their time use and health are impacted more directly.

While this research provides some initial insights on the energy situation, needs and preferences in humanitarian settings, I acknowledge the limitation of the data available to draw any general conclusion. To better understand these issues, more research is needed on preferences and performances of non-traditional stoves in the field, especially in understudied but vulnerable settings such as refugee camps, as well as more rigorous evaluation of the interventions being trialled. With this caveat in mind, in terms of policy implications the results of this Chapter point towards a need for better quality controls, information, and hand-on experience with non-traditional stoves, to fight skepticism towards the new technologies; but also towards the importance of considering heterogeneity in individual preferences and priorities. On the latter aspect, it should be acknowledged that mismatches often exist between who has the resources and decision-making power – often men and adults of the family – and who suffers more directly from the use of traditional cookstoves – often women and the younger members, whose preferences may remain unrevealed and unsatisfied.

A more participatory approach to the design and provision of new technological solutions would therefore make sure that the products that reach the households and the local markets are compatible with the local circumstances and offer variety rather than a one-size-fits-all solution. At the same time, access to information and first-hand trialling of the stoves would help make informed decisions, but in contexts where resources and purchasing power are extremely tight, as it is often the case among refugees, financial arrangements and subsidies would still be needed if households are even to consider switching to modern cookstoves and fuels, especially for systems that generate positive externalities such as the more modern and cleaner non-biomass stoves. Finally, more and more evidence is being found that intra-household dynamics are an important dimension of the low-carbon energy transition, and that negotiation, decision-making power and financial resource access for the members who are suffering the most from the use of traditional and biomass cookstoves are crucial to make sure their voices are heard and they have the means to choose according to their needs and priorities. Ultimately, these complementary steps might prove key to make sure that non-traditional technologies are accepted, understood and used correctly, and that sustained welfare improvements are therefore achieved.

Chapter 4

Preferences for cooking with biogas in rural India: the role of positive and negative experience

4.1 Introduction[1]

Burning fuelwood and other solid biomass, such as dung or crop residues, in inefficient stoves with no ventilation systems is still a common practice worldwide, especially among rural populations in lower income countries. This persistent and pernicious trend has negative consequences on several dimensions, from the health and safety of the household members (Gordon et al., 2014; Jeuland et al., 2015b; Lewis et al., 2016), and the expending of scarce time and resources to find fuel (Tinker, 1987; Lewis et al., 2016), to negative environmental externalities such as deforestation (Bensch and Peters, 2013), local pollution and climate change (Jeuland and Pattanayak, 2012; Pant et al., 2014). Policy interventions and campaigns to encourage households to adopt cleaner cookstoves and correct negative externalities through subsidies are therefore underway in several countries. India, as one of the world hot-spot for biomass burning and persistent use of traditional and inefficient

[1]The research presented in this Chapter is the result of a collaboration with Subhrendu K. Pattanayak and Ipsita Das (Sanford School of Public Policy, Duke University, United States), Jessica Lewis (World Health Organization, Geneva, Switzerland), and Ashok Kumar Singha (CTRAN Consulting, Bhubaneswar, India), with support from SANDEE (the South Asian Network for Development and Environmental Economics). My contribution consisted of specifying the research question together with Subhrendu Pattanayak, analysing the data and writing the paper. Subhrendu Pattanayak, Ipsita Das, Jessica Lewis, and Ashok Kumar Singha contributed to define the broader research project of which this study is part (together with Somnath et al., 2014 and Lewis et al., 2016) and led the data collection.

cookstoves, has long been at the forefront of action, with the national and local governments and several NGOs and international organisations providing generous incentives for cleaner fuels such as LPG, kerosene, and biogas, as well as information and awareness campaigns.

Yet, improvements often fail to materialise, both in terms of uptake of the cleaner technologies, and in terms of results once they enter the house (Whittington, 2010; Mobarak et al., 2012; Jeuland and Pattanayak, 2012). On the latter issue, recent studies have highlighted how households tend to keep using the traditional cookstoves side by side the new ones rather than switching completely, a practice defined as fuel-stacking (Jeuland et al., 2015a). In some cases the use of the cleaner cookstove has even been seen to decline over time, often due to loss of functionality because of lack of proper maintenance or repair services, supply-constraints on the fuel, or just loss of interest and negative perception of the taste of food cooked with the new systems (Hanna et al., 2016).

The continuous use of inefficient and polluting cookstoves and solid biomass fuel, even if only for a share of total cooking, is still enough to generate harmful indoor air pollution, and consequent health problems (World Health Organization, 2015). In fact, indoor air pollution is currently one of the main health problems in the developing world (World Health Organization, 2009).

On the issue of low uptake and low willingness to pay (WTP) for non-traditional cookstoves, studies have pointed towards affordability and credit constraints, lack of awareness of the negative impacts of traditional cooking, supply-side constraints and therefore unavailability of clean fuels and clean cookstoves, as well as the fact that some of the technologies offered are not appropriate for the context in which they are introduced, for example in terms of households' needs and size, cultural background, and type of food cooked (Beltramo et al., 2015; Bensch et al., 2015; Miller and Mobarak, 2015). Another understudied issue that compounds these challenges, is that households have heterogeneous preferences for cooking and cookstoves, even within relatively homogeneous population such as that of a village. So one-size-fits-all solutions are unlikely to exist and care must be used to understand the specific needs, tastes and situations on the ground (Pant et al., 2014).

In this study, we focus in particular on heterogeneity in terms of previous positive and negative experience (or no experience) with the cooking technology offered, risk aversion, time preferences and perceived credit constrains. Relevant studies in this respect are Atmadja et al. (2017), who analyse the relationship between time discount and the adoption of environmental and health-related behaviours, including fuel choice, and Jeuland et al. (2015a) and Jeuland et al. (2019), who compare stated and revealed preferences for different types of improved cookstoves, looking at the role played by risk aversion, time preferences, gender, and other socio-economic characteristics of the respondents; all these studies use data from India.

The main contribution of this Chapter is twofold. First, we use a stratified random sample to classify households according to the type of experience they already have with the technology of interest, biogas for cooking. In particular, we look at households who have had a positive experience, as their system has never broken down, households who have had a negative experience, in the form of malfunctions and failures, and finally households who have no experience with the technology. We then look at how the different levels of experience correlate with the valuation of the technology, and how the level of experience interacts with risk aversion, impatience and perceived credit constraints, to test whether familiarity with the technology attenuates the negative impact of these variables. While this interaction has been suggested in other studies, we are not aware of any that test it explicitly. The asymmetric role of positive and negative past experience is similarly an understudied topic, and complements the literature on asymmetries in the effect of positive and negative information derived from peer adopters, as studied by Miller and Mobarak (2015).

Second, while most of the literature on clean cookstoves tend to focus on improved fuelwood-fired cookstoves and LPG, we focus on household biogas for cooking (household 'self-produced' biogas), a technology with the potential to deliver important co-benefits and positive externalities. Biogas digesters are used to transform livestock manure and other agricultural waste into gas for cooking, which can then be used in the same way as LPG and burnt without producing smoke emissions. Biogas has been shown to deliver substantial benefits in rural contexts with a hot and humid climate, such as many parts of India, not only in terms of reduced smoke emissions from cooking, cheaper energy and reduction in the use of fuelwood, but also in terms of waste disposal (and therefore sanitation) and high-quality fertiliser for agriculture as a byproduct of the anaerobic digestion (Brown, 2006; Chen et al., 2010; Somnath et al., 2014; Insam et al., 2015; Lewis et al., 2016). An important advantage with respect to LPG is that biogas does not use fossil fuel, and is therefore not affected by the price of oil nor its supply chains, and can instead contribute to mitigate climate change.

Relevant studies on the benefits of the use of biogas for cooking, and variables associated with its adoption are Pant et al. (2014), Somanathan and Bluffstone (2015), and Meeks et al. (2019), all with a focus on Nepal. Bond and Templeton (2011) provide an overview on the use of domestic biogas plants in the developing world, with details on the case of India and China and the policies introduced by the respective governments to support their uptake. Yet, the existing studies on biogas tend to pay limited attention to household preferences for specific attributes of the biogas systems, and even less to how those preferences might vary even within seemingly homogeneous populations, as remarked above for the cookstove literature in general.

To address these gaps in the literature, we use stated preferences elicited via a discrete choice experiment (DCE), using a similar design as in Jeuland et al. (2015a) and Jeuland et al. (2019). The DCE consisted of a series of choice cards, in which respondents were presented with three alternative options: a biogas plant for cooking, an improved firewood cookstove, and a traditional *Chulha* as the outside option. Each alternative came with a specified price, and level of maintenance assistance, smoke emissions, and fuel requirements, which varied in each choice card. On this basis, respondents were asked to select their preferred option in each set presented. The DCE was conducted with 503 households in rural Odisha in India (more information on the survey and the context are presented in Somnath et al., 2014), and used sample stratification to obtain information from households with different types of experience.

The Chapter develops as follows: Section 4.2 presents the theoretical framework for the analysis and details on the estimation models used; Section 4.3 provides information on the study area, the sample stratification, the design of the DCE and the modules to elicit risk aversion and time preferences; while Section 4.4 provides a descriptive analysis of what factors and characteristics are associated with type of experience with biogas, and ownership and use of cookstoves. Section 4.5 discusses the results of the regression analysis for the DCE, and translate them into willingness to pay (WTP) for different attributes of the cookstove, and for biogas in particular, for different 'types' of households. Section 4.6 concludes with the main takeaways from the Chapter and practical implications of the results.

4.2 Theoretical framework

4.2.1 Research question

The research question we investigate in this Chapter is how preferences for clean cooking varies (i) depending on the attributes the cookstove has, in particular in terms of price, maintenance assistance, smoke emissions, and fuel requirements; (ii) according to the type of technology offered, i.e. traditional, improved fuelwood cookstove (ICS) or biogas; and (iii) by the level of experience the respondent has with the technology, namely positive, negative or no experience[2].

We also formulate the hypothesis that familiarity with a technology mitigates uncertainty concerning its value, and test it by examining how valuation of a technology is affected by risk aversion, impatience, and perceived credit constraints, separately by level of experience. Finally, we test whether the price paid for a biogas plant (in the case of households who already have one) has an 'anchoring' effect on valuation, making biogas more or less likely to be chosen in the DCE depending on whether the price attribute presented is below or above this reference point.

4.2.2 The random utility model

The design of the experiment follows Jeuland et al. (2015a) and Jeuland et al. (2019), who conducted a DCE to elicit preferences for fuelwood ICS in Northern India, with the key differences being the introduction of biogas as an alternative, and the use of maintenance assistance as an attribute in place of number of burners. In fact, while focus groups conducted for those two studies suggested that maintenance is not among the major determinants of fuelwood cookstove choice, in our case focus groups' discussions highlighted the importance of conducting proper maintenance and having repair services for biogas plants. The analysis is similarly based on Jeuland et al. (2015a), as well as on the literature on best practices for DCE in general (Hauber et al., 2016; Johnston et al., 2017; Lancsar et al., 2017).

The theoretical framework of reference is a random utility model (Manski, 1977), where household i's utility can be decomposed into a non-stochastic indirect utility component $V_i(.)$, and a stochastic term ε_i that captures how the idiosyncratic tastes

[2]Heterogeneity in terms of experience level is only analysed in the case of biogas, as less than 1% of the sample own a fuelwood improved ICS, and no information on previous experience or perception of the technology was collected.

of each i differ from the average household.[3] We then consider the good to be valuated as a bundle of attributes, each of which contributes to the household utility, following Lancaster (1966):

$$U_{ijt} = V(X_{jt}, \beta_i) + \varepsilon_{ijt} \tag{4.1}$$

In particular, we assume that the indirect utility of each stove offered (jt, that is technology j in choice-card t) is a function of observable characteristics of the stove – in this case the price, the level of the other attributes included in the card (maintenance, smoke emissions, and fuel requirements) and the type of technology (biogas, fuelwood ICS, and traditional cookstove) – included in vector X_{jt}, and β_i, the vector of parameters to be estimated, representing the marginal utility of each attribute and the alternative-specific premiums.

4.2.3 Estimation models: conditional logit and random parameter logit

McFadden (1981) shows that when the stochastic term follows an i.i.d. type 1 extreme-value error distribution and households choose the alternative that maximises their utility in each choice-task, the probability that alternative k is chosen among all the J alternatives in a given choice-task t is given by the conditional logit model (CL):

$$Pr(\text{choice } j = k \text{ by } i \text{ in task } t) = Pr(U_{ikt} > U_{ijt}\ \forall j \neq k) = \frac{e^{V(X_{ikt},\beta)}}{\sum_{j=1}^{J} e^{V(X_{ijt},\beta)}} \tag{4.2}$$

i.e. the probability of choosing an alternative over the others is a function of the characteristics of the alternative itself, but also of the characteristics of all the other available alternatives. In this case, $j = \{biogas, fuelwoodICS, traditionalstove\}$. This model can be estimated using maximum likelihood.

While the conditional logit has important advantages in terms of ease of interpretation and estimation, it relies on two particularly restrictive assumptions: i.i.d. error terms, and independence of irrelevant alternatives (IIA). The latter has often been found to be violated when tested in real-life decision-making situations, while the former is especially unrealistic when the same respondent makes repeated

[3]Notation is largely based on Hole et al. (2013).

choices, as in the DCE analysed in this Chapter, and decisions are therefore likely to be correlated (Lancsar et al., 2017). For this reason, we relax these assumptions and use a random parameter logit (RPL, also called mixed logit, introduced by Revelt and Train, 1998) model instead, as common in the analysis of DCE data, such as Greene and Hensher (2003) in the field of transportation, Hole (2008) in health economics, and MacKerron et al. (2009) in payments for carbon offsets in environmental economics.

In this model, different households are allowed to have different preferences by modelling β as random parameters with density function $f(\beta|\theta)$, rather than as fixed parameters. To obtain an expression for the probability of each choice, the previous expression needs to be integrated over the distribution of the unknown random parameter:

$$Pr(\text{choice } j \text{ by } i \text{ in task } t) = \int \frac{e^{V(X_{ijt}, \beta)}}{\sum_{j=1}^{J} e^{V(X_{ijt},\beta)}} \; f(\beta|\theta) \; d\beta \tag{4.3}$$

This expression cannot be solved analytically to obtain an explicit likelihood function to maximise. We use maximum simulated likelihood, as detailed in Train (2009).[4] This model is better suited to capture heterogeneity of preferences across respondents, as parameters (either some or all) are allowed to be randomly distributed across households according to a given continuous distribution (in our case we assume a normal distribution), rather than being constrained into a single value, as in the CL model. The model can also take into account the panel structure of the data, by considering the probability that an individual makes a sequence of choices, rather than the probability of a single choice:

$$S_i = \int \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{e^{V(X_{ijt}, \beta)}}{\sum_{j=1}^{J} e^{V(X_{ijt},\beta)}} \right]^{\mathbb{I}_{ijt}(k=j)} \; f(\beta|\theta) \; d\beta \tag{4.4}$$

where $\mathbb{I}_{ijt}(k = j)$ is an indicator function that equals 1 if household i selected alternative $k = j$ in choice task t, and 0 otherwise. Note that in the CL model, error terms are assumed to be independent and the parameters are fixed, so that there would be no need to integrate over the distribution of β and the probability of a sequence of choices would simply be equal to the product of the probability

[4] All the models in the Chapter are estimated in Stata. RPL models are estimated using the *mixlogit* package developed by Hole (2007).

of each choice. This means that the likelihood function for repeated choices by the same respondents would be the same as for independent single choices by different respondents, and the resulting estimate is therefore not taking into consideration the panel structure of the data.

In the empirical analysis, we start by comparing two basic specification of CL models and RPL models, to assess their differences. Standard errors for the CL models are calculated clustering at the household-level; in the RPL models, standard errors are clustered at the village-level, as the model acknowledges the panel structure of the data and already takes into consideration the correlation between decisions made by the same respondent. The regression models estimated are all linear in the parameters (Lancsar et al., 2017). Under this assumption, the coefficients of the attributes represent their marginal utility, and provide a measure of how much the utility of the respondents changes (on average) for a one-unit increase in the value of the attribute.

The coefficients can then be translated into a monetary measure of the marginal willingness to pay (WTP) for the attribute by dividing them for the coefficient of the price (i.e. the marginal utility of money). Standard errors are computed using the delta method. The same can be done for the alternative-specific constants (ASC), to obtain the premium respondents are (on average) willing to pay for the specific technology (as opposed to the outside option), when the attributes offered by all the alternatives are the same. In the RPL specifications, when the coefficients of the attributes or the ASCs are modelled as random and normally distributed, the mean marginal WTP is obtained by using the mean of the parameter estimate. The price coefficient is modelled as a fixed parameter unless otherwise specified, for ease of interpretations and of deriving the WTP.[5]

4.3 Background and data

4.3.1 Dataset and data collection

Data for this Chapter come from a survey administered in 42 villages in 8 different districts of Odisha, in eastern India. The survey was conducted between Novem-

[5]Robustness checks are conducted assuming the price coefficient to be a random parameter with a normal and log-normal distribution of the negative of the price – the latter to insure that the sign of the marginal utility of the price is always negative. Results are robust to these changes in the specification.

ber 2011 and February 2012. The household sample was stratified in four groups, according to the type of stoves the household has: group 1 and 2 include households with working and broken biogas plants respectively; households in group 3 use clean stoves different from biogas; and group 4 represents households who only have traditional cookstoves. The enumerators were asked to interview 3 households for each group in each village, although this was not always possible. The final sample includes 503 households, of which 133 in group 1 (working biogas plant), 120 in group 2 (broken biogas plant), 121 in group 3 (other clean stoves) and 129 in group 4 (traditional stoves). Whenever possible, the interview was conducted with the head of the household. The survey, stratification and sampling strategy, and sample characteristics are described in more details in Somnath et al. (2014).

The part of the dataset used for this research project contains information on socio-economic characteristics of the households – including assets, land and livestock ownership, community engagement, and access to credit – and details on their energy use and cooking habits, especially the different types of biomass and cleaner fuel used, the types of cookstoves owned and how often and for how long they are used, where in the house is the cooking done, ventilation systems (including simply opening windows while cooking), and the amount of expenditures and subsidies received for cookstoves and cooking fuel. Households in sample group 1 and 2 (i.e. with working or broken biogas plant) are asked detailed information about their biogas plant and the reasons they considered when deciding to install it. Households in sample group 3 and 4 are asked whether they are planning to install a biogas plant (variable *plan biogas*). A description of the characteristics of the households and of the biogas plants is provided in Appendix D.2, highlighting the main elements of interest for the Chapter; descriptive statistics are presented in Tables D.1, D.2 and D.3, in Appendix D.2.[6]

4.3.2 Time preference and risk aversion elicitation

The data also include the results from a risk aversion and a time preference elicitation exercise, using two hypothetical dichotomous choices for each module. In both modules, a scenario is presented and the respondent is asked to imagine someone is offering them a gift in the form of an amount of money, remarking that there

[6]Tests of difference-in-means (t-tests and tests of proportions) between the stratification groups are available from the authors upon request.

are no right or wrong answers but it is only a matter of personal preferences. In the time preference module, the respondent is first asked to choose whether they would prefer a smaller amount of money (1,000 INR, equivalent to about 19 USD at the time of the survey[7]) tomorrow or wait for 12 months to receive double that amount (2,000 INR, or 38 USD). For reference, consider that the median monthly expenditures excluding food, a proxy for the household disposable income, is 1,350 INR (26 USD), so the amount offered is substantial. If they choose the smaller amount tomorrow, they are asked the question again increasing the amount after 12 months to 2,500 INR (48 USD). If they choose to wait in the first question, they are asked the question again, but decreasing the amount to be received after 12 months to 1,500 INR (29 USD). Using the responses, I create an *impatience* index with value 1 if the respondent chooses to wait in both questions (low impatience); 2 if they choose to wait in the first question but prefer to receive the money sooner in the second question; 3 if they choose the smaller amount sooner in the first question, but would rather wait in the second question; and 4 if they prefer the smaller amount sooner in both questions (high level of impatience).

The risk aversion module first asks the respondent to choose between a smaller but certain amount now (500 INR, or 9.6 USD), or to flip a coin and receive a larger amount (1,200 INR, or 23 USD) if it is head and nothing at all if it is tail (the expected value of this option is therefore 600 INR, or 11.5 USD), again to be paid out immediately. If they prefer the safer option, they are then asked the question with the option to have again 500 INR (9.6 USD) as a certain amount, or to flip the coin to receive 1,250 INR (24 USD) if it is head or only 250 INR (5 USD) if it is tail (the expected value is 750 INR, or 14 USD). If they instead prefer the riskier option in the first question, they are then asked to choose between the certain 500 INR (9.6 USD), or to flip a coin for a 1,000 INR (19 USD) if head, and nothing at all if tail (the expected value is 500 INR, the same as the certain amount). The responses were then used to create a *risk averse* index, in the same way detailed in the previous case. Households were also asked to self-assess their risk aversion and impatience before the elicitation modules, and robustness checks for the analyses in the following sections are conducted using these self-reported measures in place of the elicited ones.

[7]The conversion rate used in the Chapter is 52 INR for 1 USD, the approximate rate in effect during the study period November 2011 and February 2012.

4.3.3 The discrete choice experiment

Finally, and the core component of this Chapter, the dataset includes responses from a discrete choice experiment (DCE) to assess households' preferences for different cookstoves' attributes and technologies. The technologies we were interested to test are the biogas plant and a biomass-fuelled improved cookstove (ICS), while the most commonly used traditional cookstove (biomass-fuelled) was used as outside option. Before the survey, focus groups on the key obstacles to biogas adoption and use were conducted in the study area (Somnath et al., 2014). The main issues stressed by participants concerned the lack of quality assurance and the lack of adequate repair and maintenance services; affordability, as the upfront construction costs are still too high for the lower income households, even after factoring in the available subsidies; alternative uses of dung as fertiliser or dung-cake to be burnt for energy, which although less efficient than a biogas digester, require less time and upfront expenses to make; and finally the fact that the biogas plants commonly used in the area and the amount of dung available to a household are usually insufficient to cover the cooking energy needs of the family, so that households usually continue to use traditional stoves as well. Information from the focus groups were used to design the DCE.

The DCE consisted of 5 hypothetical decision scenarios, each presented through a choice-card. The 3 alternatives in each choice-card are 'labelled' using the names of the most common cookstove available in the sample area for each type: Rocket Stove (biomass-fuelled ICS), Gobar Gas (biogas plant), and the outside-option Chulha (traditional biomass cookstove). Each alternative is presented with a picture of the stove, followed by its price as a number and in pictures, and pictures for the maintenance assistance, smoke emissions, and fuel requirement (4 attributes). Each stove and each attribute is explained in details using information cards complete with pictures, before the DCE module is started.

The attributes for the traditional stove (Chulha) are fixed for all the decisions and are set to low maintenance, high smoke emissions, medium fuel requirements and a price of 100 INR (1.9 USD). The attributes and attribute levels used are summarised in Table 4.1, while the script and choice-cards used in the DCE are included in the Appendix D.1 (in both English and Odia). A total of 25 combinations of attributes for the ICS (Rocket Stove) and biogas plant (Gobar Gas) are obtained using an efficient fractional factorial design. The 25 choice cards are grouped into 5 sets of 5 cards each, and respondents in each stratification group are randomised into a choice set. The final dataset consists of 503 respondents, each presented with 5 choice cards, resulting in 2,515 choices.

Table 4.1: Attributes and attribute levels used in the discrete choice experiment (DCE).

Attributes	Levels for biogas/ICS	Reference level (traditional stove)
Price	4,000 / 7,000 / 10,000 INR (77 / 135 / 192 USD)	100 INR (1.92 USD)
Maintenance	Low / High	Low
Smoke	Low / High	High
Fuel requirement	Low / Medium / High	Medium

In the empirical analysis, attributes are dummy-coded as being lower or higher than the baseline attributes of the traditional stove (i.e. alternative 3: low maintenance, high smoke, medium fuel use), which are fixed across all questions. Price is considered a continuous variable.[8]

The outcome variable is the alternative chosen among the Gobar Biogas, the Rocket Stove, or the traditional Chulha. After the respondent selects their preferred alternative for a choice card, they are asked to confirm whether they would indeed purchase that cookstove at the proposed price[9], and in 73% of the cases the respondent answers affirmatively. Most of the no answers are in cases in which the respondent selected the biogas plant but already has a working one, or when the selected option is the Rocket stove. As a robustness check, the analysis is repeated including the intention to purchase. In particular, we repeat the analysis excluding the choices for which intention to purchase is not confirmed, and results are robust in terms of coefficients and WTP for the biogas stoves, while WTP for attributes are between 20-40% lower. Tables available on request.

4.3.4 Levels of experience

We use the sample stratification together with information from the survey to classify households in three different levels of experience with biogas. Households who have

[8]As a robustness check, we run additional regressions using price as a categorical variable, as suggested by Lancsar et al. (2017), and find that the coefficients respond close to linearly. For this reason, in the main specifications presented in the Chapter price enters the models linearly and as a continuous variable.

[9]"Would you purchase the alternative you have chosen at the given price?".

experienced malfunctions in the biogas plant – i.e. all the households in group 2, whose biogas plant is currently broken, plus the households in group 1 that experienced malfunctions in the past – are classified as *bad experience*, while the remaining households in group 1, who have a biogas plant that has never broken down, are considered as *good experience*. Households in group 3 and 4 are classified as having *no experience*; in some specifications and robustness checks this sample is further divided by sample group (no experience, group 3; and no experience, group 4), or by intentions to install biogas in the future (no experience, plan to install; no experience, no plan to install).

4.4 Cookstoves' ownership and use, experience with biogas, and intention to adopt

This section provides a descriptive analysis of what factors and characteristics are associated with the type of experience a household has with biogas. In particular, we look at the type of cookstove owned and their use, fuel-stacking behaviour, plans to install a biogas plant (for the households who do not already have one), and functionality of the existing biogas plants (for the households who already have one). The insights obtained provide helpful guidance to interpret the results of the DCE analysis.

4.4.1 Factors associated with types of cookstove owned and their use

Type of stove used

To parse out the role of each characteristic when considered together with the others, I use multivariate regression analysis. In all the regressions that follow, errors are clustered at the village level. First of all, I use a multinomial logit regression to assess which observable characteristics are associated with the likelihood of having a biogas plant (sample group 1 and 2) as opposed to other types of clean stove (group 3) or traditional stove only (group 4). This is a categorical outcome variable with three categories; having a biogas plant is used as the baseline. Model (1) in Table D.4, Appendix D.3, reports the results of this analysis.

The main variables correlated with the type of cooking system owned are wealth and income, and the count of large animals. Predictably, the more large animals the household has, the more likely it is to have a biogas plant as opposed to other clean cookstoves, and as opposed to traditional cookstoves only. This makes sense, as large animals provide the 'fuel' needed to feed the biogas plant and are therefore a *de facto* prerequisite for adoption. In fact, dung availability is cited as one the leading motivations for adoptions among households using biogas.

A larger disposable income, measured by the natural log of non-food expenditures in a year, is positively correlated with the odds of having other clean cookstoves rather than having biogas. Smaller wealth, as measured by the asset ownership index, is an indication that the household is more likely to only have traditional cookstoves, as opposed to biogas. This suggests that biogas is more likely to be used by households in the lower and middle part of the income and wealth distribution, while higher income households tend to use LPG, kerosene and electric cookstoves. Results are robust to using self-assessed risk aversion and impatience instead of the elicited index – the coefficients of these variables are not significant in either case.

Fuel-stacking

Next, I investigate fuel-stacking behaviour in the sample, looking at what characteristics are associated with the likelihood of having only one type of cookstove, two different types, or three or more. Note that cookstove types correspond to different fuels, namely fuelwood, biogas, kerosene, LPG and electricity. I first consider the outcome as categorical and use a multinomial logit regression, where having one type of cookstove is the baseline. The odds of having two stove types rather than one and the odds of having three or more rather than one are both strongly associated with the asset ownership index and the index for the quality of housing materials.

The magnitude of the coefficients for these variables are double when comparing one stove to three or more, than they are when comparing one stove to two. For this reason, I choose to use an ordinal logit as the preferred specification for the analysis, as it is more efficient and should not sacrifice on insights on the dynamics of fuel stacking, given the results from the multinomial logit. Results are presented as Model (2) in Table D.4, Appendix D.3. Wealthier households appear to be more likely to stack different types of stove, as indicated by the positive coefficient of the asset ownership index, and negative coefficient for low quality housing material. Households who live closer to the village centre are also more likely to engage in stove (and fuel) stacking, possibly because proximity to the market provides better access to different stoves and fuels. These results could suggest that households who do not engage in stove and fuel stacking do so because they are constrained by affordability and access to different options.

For further insights on this hypothesis, I investigate fuel stacking behaviour in households who have at least one clean cookstove. To do this, I estimate the multinomial logit model excluding households in sample group 4 (households who only have a traditional cookstove), and find that the probability of using only one type of cookstove rather than two is strongly associated with having difficulty in accessing credit, while the probability of having three or more types of cookstoves rather than two is again positively associated with asset ownership and negatively associated with low quality housing material and distance to the village center.[10] This is consistent with the above hypothesis.

Intention to install biogas

Model (3) in Table D.5, Appendix D.3, only considers the sample of households without a biogas plant (group 3 and group 4) and shows what characteristics of the households are associated with the likelihood that the household is planning to install a biogas plant, using a logistic regression. In general, none of the variables is significant at the 1% significance level, so the households are quite similar along the observable characteristics considered. Households that are planning to adopt biogas appear to be less credit-constrained than those who are not, and to be less impatient (although the latter is only significant when using a 5% significance level). Robustness checks are conducted using self-assessed risk aversion and impatience instead of the elicited variables, ownership of each type of cookstove, and number of stove types owned, and results are robust to the different specifications.

Time stoves are used

Finally, Table D.6, Appendix D.3, show the results of regressions for the total time of use (in minutes per day) of all the stoves for the entire sample (4a), for time of use

[10] Table not reported, but available from the authors upon request.

disaggregated by clean stoves (4b) and biomass stoves (4c), and for the share of time clean stoves are used rather than biomass stoves (4d). The size of the households (more exactly the number of people to be cooked for everyday, adjusted so that children count for half a adult) only affects the amount of time biomass stoves are used (and through that channel, the time of use of all stoves, which is the sum of biomass and clean stoves), while it has no effect on the use of clean stoves.

This suggests that biomass stoves are used as 'residual' cookstoves, to complement clean stoves when they are insufficient to cover the entire energy demand of the household. The use of clean stoves therefore appear to be determined by constraints, possibly the availability of fuel, as it was highlighted by focus groups in the case of biogas. This hypothesis is supported by the fact that having a traditional biomass cookstove per se does not affect the amount of time clean cookstoves are used, while on the other side having clean cookstoves substantially decreases the amount of time traditional stoves are used.

The fact that economic variables do not seem to be substantially correlated with the time or the share of use of clean stoves, once the cookstove types are controlled for, further suggests that in this case constrained fuel availability might play a larger role than fuel affordability in the decision of what cookstoves to use and for how long. This would also provide an explanation for fuel stacking. The other covariates associated with the outcomes are of course the type of cookstoves the household has, represented by ownership of cookstoves types and by the sample group (because of the way stratification was conducted).

4.4.2 Factors associated with biogas functionality

In model (5a) of Table D.7, Appendix D.3, I restrict the sample to households who already have a biogas plant and use a logistic regression for the probability that the plant is broken. I include the same characteristics of the households as in the previous models, and add variables on the characteristics of the plant, its use, and the motivations for installing.

The main variable associated with a working biogas plant are a more recent installation year, larger plant size, more time spent feeding the dung into the plant and cleaning the plant, and less time spent collecting the dung. If the model is run using the overall time spent in the three activities as one aggregated variable, this is not significant any more (results not reported), suggesting that while households spend on average the same overall time in activities related to the plant, those who now have a broken biogas plant tended to spend *relatively* more time collecting dung and less in actually operating and maintaining the plant.

The price paid by the household and the amount of subsidy are not significant, once the other covariates are controlled for; while having a higher livestock counts, mainly small animals, are positively correlated with having a working plant. A higher disposable income (as measured by the natural log of yearly expenditures in non-food items) and smaller distance to the village centre are also associated with a working biogas plant, which might suggest that it is easier for these households to have the plant repaired or serviced, or it might be an indication of higher quality of the plant, as better materials and better installers might have been hired for the same price.

Although lack of data on servicing, other type of maintenance and direct measures of the quality of the plant prevents looking at these channels in more details, further investigations go against the hypothesis that income and proximity to the village centre are associated with the likelihood of having the system repaired rather than experiencing malfunctions in the first place. Firstly, column (5b) looks at whether the biogas plant ever broke down, rather than whether it is not working at the moment. The results are substantially unchanged, possibly because only 8 households in the sample ever experienced a break down and repaired it, with the exception of the coefficient of the time spent cleaning the plant, which is now significantly larger in magnitude, suggesting that proper maintenance is the main driver of plant functionality.

I then restrict the sample to the households whose biogas plant has ever been broken and regress whether it has been repaired or not on the log of the expenditures and distance to the village (alone and with covariates). The former has a positive correlation with the likelihood of the system being repaired, while the latter a negative one, but none of the coefficient is significant at conventional significance level (results not reported); these results should be taken with caution due to the very small number of cases of repaired plants.

Overall, the households with a broken biogas plant and households with a functioning one appear to be quite similar along the observable characteristics considered, and the age of the plant and the time spent cleaning it seem to be the main driver of malfunctions. These are the only variables that are still significant at the more conservative significance level of 0.1%. It should be noted that all the results in this section are correlations, rather than causal effects, as data are observational. They nonetheless provide interesting insights on the issue, and could be a starting point for designing an experimental or quasi-experimental investigation on the causal effects at play.

4.5 Preferences for biogas, biomass-ICS and traditional cookstoves: results from a discrete choice experiment

4.5.1 Results

This Section presents results on the DCE analysis, using random parameter logit models (RPL). Conditional logit (CL) specifications are presented for comparisons. The estimated coefficients are then translated into WTP amount for each attribute and technology, by different 'types' of households, in the following Section.

Valuation of attributes and stove-specific premiums: strong interest in lower emissions, fuel savings, and biogas

Table 4.2 compares estimates from conditional logit (CL) models (1 and 3) and random parameter logit (RPL) models (2 and 4). The RPL specifications model the alternative-specific constants (ASC) and the coefficients of the attributes, with the exception of price, as random normally distributed parameters; for the random parameters, both the mean of the coefficient and the standard deviation are presented. The likelihood ratio chi-square test comparing the log-likelihood value of the CL model with that of the 'empty' model without covariates ($ll(0)$) rejects the null hypothesis that the two models are not significantly different. This holds for all the specifications. Comparing the log-likelihood of the CL with that of the RPL model with the same regressors, further suggests that the latter is to be preferred (Greene and Hensher, 2003).

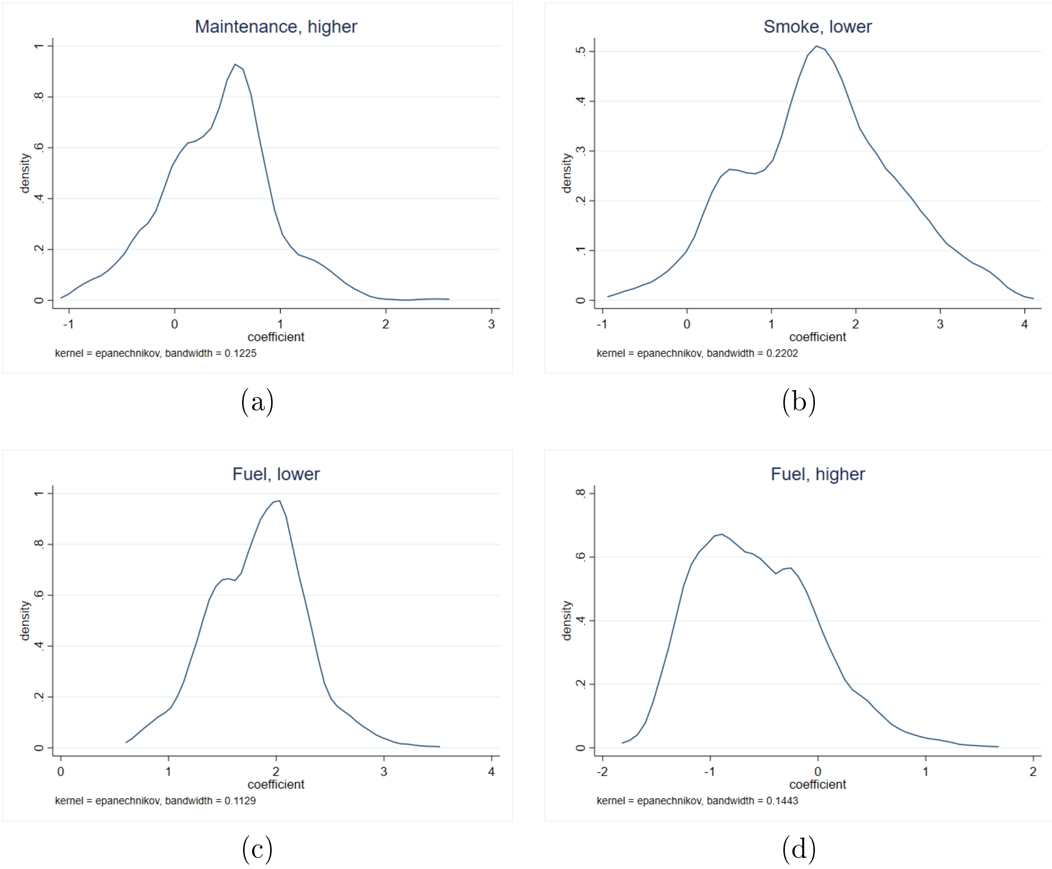
The first specification (columns 1 and 2) looks at how different values of the attributes affect the likelihood of choosing a cookstove over the other two alternatives, while the alternative-specific constants (ASC) represent cookstove-specific tastes, after controlling for the attributes. In the second specification (columns 3 and 4) each attribute is interacted with whether the cookstove chosen is the biogas plant, to investigate whether households are willing to pay a larger or smaller premium for each attribute, depending on the fuel (i.e. biogas as opposed to fuelwood, used in the ICS Rocket Stove and in the traditional stove).

The signs of the attribute coefficients are as expected, negative for higher prices and higher fuel requirements, and positive for maintenance service, lower smoke emissions, and lower fuel consumption. There is nonetheless heterogeneity in the valuation of each attribute, as indicated by significant estimates for the standard deviations. The distributions of the coefficients in model (2), estimated using Epanechnikov kernel density, are plotted in Figure 4.1 – for the attributes. The ASC for the Rocket stove is significantly negative, suggesting that the traditional stove (baseline) is strongly preferred to the fuelwood ICS. Biogas on the contrary, attracts a strong positive valuation. Again, there is substantial heterogeneity in tastes regarding the different technologies, as indicated by the the standard deviation of the coefficient on the ASC.

In the second specification (3 and 4) households are willing to pay extra for maintenance services only in the case of biogas, as only the coefficient for the interaction term is significant. In fact, other DCEs and preparatory focus groups conducted in India suggests that maintenance is not strongly relevant to respondents, at least in the case of fuelwood stoves (e.g. Jeuland et al., 2015a), while focus groups in our study area highlighted that maintenance is a key factor for biogas. None of the other interactions is significant, suggesting that smoke emissions and fuel savings are valued independently from the specific stove.

Negative experience corresponds to less enthusiastic preferences for biogas; households who intend to install a biogas plant have similar preferences to households with positive experience

We next investigate whether previous experience with biogas, either positive or negative, contribute to explain households' preferences for biogas. In Table 4.3 the attributes' coefficients and stove-specific constants are estimated separately depending on whether the alternative chosen is the biogas stove or not, and when it is the



(a) (b) (c) (d)

Figure 4.1: Distributions of the estimated parameters for the maintenance (a), smoke (b) and fuel (c, d) attributes, estimated in the random parameter logit.

biogas stove it is further interacted with the type of experience with biogas the household has had: *positive, negative, or no experience*. The model in column (2) extends this specification by splitting the households in the *no experience* group according to whether they plan to install a biogas plant or not, while in column (3) they are further distinguished by stratification group, that is whether they have a clean cookstove or only traditional ones.

Table 4.2: Regression table for the DCE. Baseline specifications, with attributes and ASCs. Conditional logit (1 and 3) and random parameters logit (2 and 4).

	(1)	(2)		(3)	(4)	
	outcome	outcome		outcome	outcome	
	outcome	Mean	SD	outcome	Mean	SD
price_thousands	-0.13***	-0.27***		-0.13***	-0.26***	
	(0.01)	(0.03)		(0.02)	(0.03)	
maint_higher	0.23***	0.32*	1.35***	0.02	0.01	1.40***
	(0.07)	(0.15)	(0.22)	(0.11)	(0.20)	(0.25)
" Xbiogas				0.33*	0.59*	1.61***
				(0.13)	(0.25)	(0.26)
smoke_lower	0.90***	1.70***	1.72***	1.06***	1.69***	1.53***
	(0.07)	(0.17)	(0.23)	(0.12)	(0.28)	(0.21)
" Xbiogas				-0.21	-0.02	-0.15
				(0.15)	(0.25)	(0.22)
fuel_lower	1.00***	1.92***	1.13***	0.93***	1.64***	1.56***
	(0.08)	(0.14)	(0.19)	(0.12)	(0.26)	(0.23)
" Xbiogas				0.13	0.53	-0.28
				(0.15)	(0.35)	(0.31)
fuel_higher	-0.30***	-0.65***	1.35***	-0.28*	-0.45*	0.91**
	(0.08)	(0.17)	(0.25)	(0.14)	(0.21)	(0.31)
" Xbiogas				-0.03	-0.18	0.05
				(0.16)	(0.26)	(0.20)
ICS ASC	-0.71***	-1.19***	2.04***	-0.67***	-0.98*	1.77***
	(0.14)	(0.30)	(0.27)	(0.17)	(0.44)	(0.36)
biogas ASC	0.51***	1.09***	1.96***	0.46***	0.81**	1.85***
	(0.13)	(0.27)	(0.26)	(0.14)	(0.27)	(0.26)
N	2515	2515		2515	2515	
r2_p	0.18			0.18		
ll	-2274.49	-1998.91		-2270.53	-2001.33	
ll_0	-2763.01			-2763.01		
p	0.00	0.00		0.00	0.00	
aic	4562.99	4023.83		4563.06	4044.67	
bic	4611.49	4113.90		4639.27	4190.17	

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: *" Xbiogas* means the attribute in the previous row has been interacted with the biogas dummy, representing whether the alternative from the choice card is labelled as a biogas stove.

Table 4.3: Regression table for the DCE. Interactions with prior experience. Random parameters logit.

	(1)				(2)				(3)			
	Mean		SD		Mean		SD		Mean		SD	
price_thousands	-0.27***	(0.04)			-0.26***	(0.03)			-0.26***	(0.03)		
maint_higher	0.04	(0.19)	1.21***	(0.29)	0.03	(0.16)	1.18***	(0.20)	0.05	(0.20)	1.30***	(0.21)
" XbiogasXgoodexper	0.69*	(0.35)	0.71	(0.45)	0.61	(0.37)	1.03	(0.65)	0.64	(0.33)		
" XbiogasXbadexper	1.11**	(0.36)	1.02	(0.52)	1.05**	(0.34)	1.56*	(0.67)	0.98**	(0.33)		
" XbiogasXnoexper	0.27	(0.38)	1.40	(0.80)	0.52	(0.33)	1.27**	(0.46)	0.35	(0.32)		
smoke_lower	1.58***	(0.22)	1.45***	(0.35)	1.38***	(0.18)	1.67***	(0.26)	1.72***	(0.27)	1.17***	(0.21)
" XbiogasXgoodexper	0.23	(0.39)	0.75	(0.46)	0.64	(0.47)	1.05	(0.81)	-0.15	(0.36)		
" XbiogasXbadexper	0.20	(0.39)	-0.12	(0.47)	0.25	(0.34)	-0.81*	(0.41)	-0.17	(0.38)		
" XbiogasXnoexper	0.18	(0.29)	0.41	(0.75)	0.55*	(0.27)	-0.53	(0.43)	0.03	(0.28)		
fuel_lower	1.54***	(0.32)	1.63***	(0.20)	1.40	(.)	1.44***	(0.20)	1.44***	(0.25)	-1.34***	(0.29)
" XbiogasXgoodexper	0.81	(0.44)	-0.37	(0.29)	0.90*	(0.41)	-0.71	(0.43)	0.64	(0.43)		
" XbiogasXbadexper	1.44**	(0.49)	-0.70	(0.38)	1.50**	(0.46)	0.37	(0.39)	1.24**	(0.41)		
" XbiogasXnoexper	0.28	(0.44)	-0.24	(0.29)	0.56	(0.36)	0.85*	(0.36)	0.14	(0.35)		
fuel_higher	-0.41	(0.22)	-0.61**	(0.21)	-0.33	(0.24)	-0.83**	(0.29)	-0.49*	(0.22)	1.13*	(0.45)
" XbiogasXgoodexpe	-0.15	(0.39)	-0.52	(0.43)	-0.19	(0.32)	-0.87*	(0.41)	0.09	(0.30)		
" XbiogasXbadexper	-0.23	(0.46)	0.26	(0.77)	-0.26	(0.46)	-0.45	(0.80)	-0.04	(0.41)		
" XbiogasXnoexper	-0.35	(0.28)	-0.44	(0.30)	-0.45	(0.29)	0.16	(0.26)	-0.33	(0.29)		
ICS ASC	-0.60	(0.42)	-1.63***	(0.31)	-0.25	(0.31)			-0.83*	(0.38)	1.82***	(0.34)
biogas ASC	1.66***	(0.37)	1.96***	(0.52)	1.51***	(0.40)	1.69***	(0.26)	1.66***	(0.40)	1.38***	(0.29)
" Xbadexper	-1.03*	(0.52)	-0.14	(0.24)	-0.96	(0.53)	0.06	(0.54)	-1.01*	(0.50)	0.35	(0.44)
" Xnoexper	-1.20	(0.64)	0.77	(1.77)								
" Xplanbg					-0.22	(0.37)	1.52***	(0.37)				
" Xotherclean									0.44	(0.41)	-1.18*	(0.55)
" Xtradonly									-0.42	(0.47)	-1.06**	(0.34)
" Xnoplanbg					-2.74***	(0.62)	1.83***	(0.39)				
" Xotherclean									-1.69***	(0.50)	-1.62***	(0.44)
" Xtradonly									-3.19***	(0.69)	-1.20*	(0.51)
N	2515				2515				2515			
aic	4002.76				4019.16				3933.52			
bic	4286.83				4303.23				4176.02			

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Note: *" X[dummy]*: variable in previous row is interacted with [dummy].

While the interactions between attributes and experience are not significant for the smoke and higher fuel requirement attributes (and their valuation is similar to the estimates in the previous table), they provide interesting insights regarding the preferences for maintenance services and fuel savings. Households who already have experience with the biogas plant are willing to pay more for maintenance of the biogas stove, and the amount is even larger for households who had a negative experience, suggesting that households who own a biogas plant realise how important careful and frequent maintenance is for the correct functioning of the plant. In the case of the biogas stove for households who have no experience with biogas the valuation of maintenance is still positive, but not as high as for experienced respondents, while in the case of the fuelwood stoves (the baseline category) the valuation of the maintenance attribute is very close to zero.

Households who have experience with biogas also have larger coefficients for fuel savings from a biogas plant, compared to the other categories, with negative experience playing once again a larger role than positive experience.

Finally, negative experience with the technology appears to be associated with less enthusiastic preferences for biogas, compared to households with positive experience (the baseline category). In fact, in model (1) households who have not experienced malfunctions are willing to pay a larger premium for the technology, as compared to households with negative experience or no experience at all.

Model (2) and (3) shows that this result is nonetheless more nuanced, as households who have no experience with biogas but are planning to adopt it are willing to pay a premium for biogas almost as large as households who have it and have had a positive experience. Among the former, this result is driven in particular by households who have a clean cookstove different from biogas, rather than households who are currently only using traditional stoves. Yet, all the households who have no experience but are planning to install biogas, independently of what stoves they currently use, have more enthusiastic preferences for biogas than households who experienced malfunctions. Finally, households who have no experience and no intentions to install have the lowest willingness to pay for a biogas-specific premium, with the valuation for households who have other clean stoves close to zero, and the valuation for households who are only using traditional stoves even reverting the sign to negative.

This set of results suggests that in general households who are cooking with clean cookstoves (biogas or other) have a stronger dislike for the traditional stove (the outside option), and are willing to pay more to avoid choosing that option – consistent with their revealed preferences. Yet, the intention to install is more strongly associated with stated preferences for biogas than it is whether households have a clean cookstove different from biogas or are only using traditional stoves at the time of the survey. This finding is corroborated by a robustness check in which the model is first estimated splitting the households with no experience according to their stratification group.[11]

Across the specifications, it is a robust result that households who have no experience but are planning to adopt display similar preferences to those who have already adopted and had no malfunctions, while households who experienced malfunctions have less enthusiastic preferences than either of them. This finding suggests that negative and positive experience – as defined in this Chapter – might have asymmetric effects on the preferences for biogas. Or similarly, households who are planning to install might be optimistic about the technology, so that a smooth experience largely confirms their expectations, while a negative experience leads them to update their preferences downward. This explanation is consistent and complements results from the field experiment on improved cookstoves in rural Bangladesh by Miller and Mobarak (2015), who find that households are asymmetrically affected by the positive and negative information received from their social network, with only the latter playing a significant role. It is to be noted that, due to the nature of the data, our results are partial correlations rather than causal effects, and we cannot rule out that households who experienced plants malfunctions had systematically different preferences for biogas to start with, or that a more pessimistic opinion about the technology is what led to the malfunctions in the first place. More research is needed to understand the direction of causality between these variables.

Experience (positive and negative) counteracts risk aversion, impatience and concerns on access to credit

In Table 4.4 we investigate the role of risk aversion, time preference, and perceived credit constraints on households' stated preferences, as very little evidence exists in the literature on these regards. To do this, we interact the attributes and each cookstove-specific constant with a risk aversion dummy (column 1), an impatience

[11] Results from this specification not shown.

dummy (column 2), and a perceived credit constraint dummy (column 3). Risk aversion and time preference elicitation are described in Section 4.3. The credit constraint dummy is based on a self-assessment of how difficult it would be for the respondent to obtain a 5,000 Rupees loan through formal channels, that is excluding borrowing from family or friends: “If you have to borrow Rs. 5000 (from a money lender or micro-finance groups, not from the family member and friends) for one month, would this be possible?”, with possible answers (1) yes, quite easy, (2) yes, but not easy, (3) may be not sure, (4) not possible; 2 is the average and median response in the sample. We classify households who answered 3 or 4 as credit-constrained. To delve deeper in the role of experience, the biogas-specific constant is further interacted with the type of experience, in all three models.

The results from model (1), (2) and (3) suggest that while risk aversion, impatience and concerns regarding access to credit are all negatively correlated with preferences for biogas, experience of any kind counterbalances these effects. The result is even stronger for positive experience, which reduces the difference to very close to zero. In fact, in model (1) the biogas-specific constant is lower but not significantly different from zero for more risk averse respondents in the case of households who have had positive experience and in the case of households who have had negative experience, while risk averse households who have had no experience have a substantially lower biogas-specific constant than their less risk averse counterparts with no experience. The same occurs when considering impatience in model (2), and perceived credit constraints in model (3); these characteristics are all associated with a smaller biogas premium, but the effect is much larger and significant (at 5% significance level) only in the case of households with no experience.

Finally, more impatient households have on average a stronger dislike for the Rocket stove than those who are more patient, and the same occurs for more risk averse households and for households who have more concerns with credit access, although the differences in these cases are smaller and not significantly different from zero, at conventional levels. None of the interactions with the attribute are significant at the 5% significance level in any of the three models.

Table 4.4: Regression table for the DCE. Interactions with risk aversion, impatience and perceived credit constraints. Random parameters logit.

	(1)				(2)				(3)			
	Mean		SD		Mean		SD		Mean		SD	
price_thousands	-0.17***	(0.02)			-0.17***	(0.02)			-0.18***	(0.02)		
maint_higher	0.24	(0.15)	0.70*	(0.30)	0.08	(0.14)	0.50	(0.29)	0.32*	(0.14)	0.92***	(0.27)
" Xriskaverse	0.02	(0.18)	1.03**	(0.34)								
" Ximpatient					0.28	(0.17)	1.19***	(0.22)				
" Xcreditconstr									-0.11	(0.23)	0.95*	(0.40)
smoke_lower	1.17***	(0.14)	0.86**	(0.27)	1.08***	(0.10)	0.80**	(0.26)	1.06***	(0.14)	1.28***	(0.13)
" Xriskaverse	-0.02	(0.22)	1.26**	(0.42)								
" Ximpatient					0.16	(0.19)	1.35***	(0.35)				
" Xcreditconstr									-0.10	(0.35)	1.64***	(0.27)
fuel_lower	1.29***	(0.19)	0.99***	(0.20)	1.30***	(0.21)	0.86***	(0.24)	1.39***	(0.15)	1.30***	(0.14)
" Xriskaverse	0.18	(0.25)	0.98*	(0.43)								
" Ximpatient					0.13	(0.25)	1.16***	(0.33)				
" Xcreditconstr									-0.45	(0.23)	0.41	(0.52)
fuel_higher	-0.47**	(0.18)	0.92***	(0.24)	-0.68***	(0.20)	1.06***	(0.26)	-0.46**	(0.14)	1.07***	(0.19)
" Xriskaverse	0.04	(0.22)	-0.90**	(0.30)								
" Ximpatient					0.35	(0.21)	-0.63	(0.37)				
" Xcreditconstr									-0.43	(0.33)	-1.35	(0.82)
ICS ASC	-0.51	(0.30)			-0.21	(0.27)			-0.39	(0.37)		
" Xriskaverse	-0.37	(0.36)										
" Ximpatient					-0.88**	(0.34)						
" Xcreditconstr									-0.16	(0.35)		
biogas ASC X goodexpe	1.50***	(0.24)			1.45***	(0.33)			1.51***	(0.27)		
" Xriskaverse	-0.08	(0.29)										
" Ximpatient					-0.04	(0.39)						
" Xcreditconstr									-0.02	(0.37)		
biogas ASC X badexper	1.09***	(0.27)			1.28***	(0.29)			1.05***	(0.22)		
" Xriskaverse	-0.22	(0.28)										
" Ximpatient					-0.56	(0.31)						
" Xcreditconstr									-0.12	(0.37)		
biogas ASC X noexp	0.77**	(0.26)			0.91**	(0.31)			0.90***	(0.24)		
" Xriskaverse	-0.49*	(0.25)										
" Ximpatient					-0.73*	(0.34)						
" Xcreditconstr									-1.22***	(0.31)		
N	2515				2515				2515			
aic	4308.75				4296.76				4239.57			
bic	4481.97				4469.97				4412.78			

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Note: *" X[dummy]*: variable in previous row is interacted with [dummy].

No evidence of 'anchoring' valuation to the price of existing biogas plant

In our final specifications, we test whether for households who already have a biogas plant the price they paid for their plant has an "anchoring" effect (or reference-dependent effect) on their choices in the DCE, and therefore on their valuation of biogas.[12] In particular, we test whether the biogas alternative is less likely to be selected in the DCE when the price presented is above the price the household paid for their own biogas plant, after controlling for the general effect of price (as higher prices already have a negative effect on the probability of choosing an alternative).

To do this, the baseline model specification with attributes and ASCs is modified as follows. The biogas ASC is interacted with the type of experience, and for households with positive and negative experience it is further interacted with whether the price attribute is above the price the household paid for their existing plant. The same is done for the price attribute, after interacting it with whether the alternative is biogas. In this specification, the coefficient for price is modelled as a random parameter to allow for unobserved heterogeneity. Results are presented in Table 4.5 – model (1) uses the price actually paid by the household (*pricepaid*) as reference, while model (2) uses the price inclusive of subsidies (*pricetot*) as reference.

Whether the price in the choice-card is above or below the price originally paid appears to be insignificant, when controlling for the general price effect, the rest of the attributes, and experience level. The result is robust if only the price interactions are introduced in the model or if only the interactions with the biogas ASC are included (results not shown). We therefore find no evidence that the price of the household's own biogas plant anchor the valuation of biogas in the DCE.

[12] See Maniadis et al. (2014); Fudenberg et al. (2012) for a review on anchoring effect and reference-dependent preferences, and recent results from testing anchoring effect in stated preferences experiments.

Table 4.5: Regression table for the DCE. Testing for price 'anchoring', using the price paid as reference (1) and the total price – price paid plus subsidies – as reference (2). Random parameters logit.

	(1)				(2)			
	Mean		SD		Mean		SD	
price_thousands	-0.25***	(0.05)	0.24***	(0.03)	-0.25***	(0.05)	0.26***	(0.03)
" Xifbiogas Xgoodexper	-0.46	(0.29)	0.22***	(0.05)	0.02	(0.26)	0.14	(0.10)
" Xabovepricepaid	0.54	(0.28)	0.09*	(0.04)				
" Xabovpricetot					-0.07	(0.13)	0.14*	(0.06)
" Xifbiogas Xbadexper	0.10	(0.38)	0.04	(0.02)	0.10	(0.15)	0.07	(0.04)
" Xabovepricepaid	-0.11	(0.38)	-0.05	(0.03)				
" Xabovpricetot					-0.10	(0.10)	-0.02	(0.03)
" Xifbiogas Xnoexper	-0.00	(0.06)	0.09**	(0.03)	-0.02	(0.07)	0.10	(0.06)
maint_higher	0.37**	(0.14)	0.69*	(0.31)	0.38**	(0.14)	-0.72	(0.47)
smoke_lower	1.58***	(0.16)	1.15***	(0.19)	1.55***	(0.15)	1.18***	(0.21)
fuel_lower	1.76***	(0.13)	0.10	(0.34)	1.77***	(0.13)	0.01	(0.72)
fuel_higher	-0.50***	(0.14)	-1.02**	(0.35)	-0.56***	(0.15)	-1.19***	(0.28)
ICS ASC	-0.82*	(0.38)	1.20***	(0.29)	-0.77*	(0.38)	1.05***	(0.26)
biogas ASC Xgoodexper	4.29**	(1.31)	-0.87**	(0.27)	1.87*	(0.89)	-1.21**	(0.45)
" Xabovepricepaid	-3.10*	(1.31)	-0.04	(0.37)				
" Xabovepricetot					0.49	(1.05)	-1.73	(0.98)
biogas ASC Xbadexper	1.09	(1.67)	0.61*	(0.30)	1.19*	(0.48)	0.66	(0.38)
" Xabovepricepaid	0.11	(1.75)	0.06	(0.16)				
" Xabovepricetot					-0.26	(0.36)	-0.40	(0.53)
biogas ASC Xnoexper Xplanbg	1.52***	(0.41)	1.52***	(0.29)	1.63***	(0.45)	1.49***	(0.38)
biogas ASC Xnoexper Xnoplanbg	-0.53	(0.39)	-1.58***	(0.33)	-0.63	(0.40)	-1.65***	(0.31)
N	2515				2515			
aic	3933.30				3933.44			
bic	4168.88				4169.01			

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: *" X[dummy]*: variable in previous row is interacted with [dummy].

4.5.2 Estimates of the WTP for changes in the attributes and technology-specific premiums

To understand the magnitude of the estimates and convert them into monetary measures, we calculate the WTP for a one-unit change in each attribute, and for moving from the traditional cookstove to each of the non-traditional technology. When the coefficient of references are modelled as random, the measure provided is the mean WTP. Results are reported in Tables 4.6, 4.7, and 4.8, in 1,000 Rupees. Note that when conducting the robustness check and excluding the observations for which the choice was not validated in the follow-up question on whether they would indeed purchase that cookstove at that price (28% of the cases), the estimated WTP for the attributes tend to be between 20% and 40% lower than the estimates for the whole sample, while estimates for the biogas-specific premiums are more similar, mostly within a +/-10% interval. Except for this difference, the general results discussed in this and the previous section are robust.

Households appear to be willing to pay for more frequent maintenance services only for the biogas stove, in the amount of 2,300 Rupees, on average (column (4) in Table 4.6). As can be seen in the models with interaction terms with experience level (Table 4.7), this result is mainly driven by households who already have experience with the technology, and in particular those who experienced malfunctions – the latter are willing to pay 4,200 Rupees on average for the more frequent service. This suggests that households who are not familiar with the technology might underestimate the level of work required for operating and maintaining a biogas plant. In terms of respondents' characteristics, maintenance service tend to be of interest to more impatient and less credit-constrained households (Table 4.8).

WTP for smoke reduction is even larger, at 6,250 Rupees, and is less dependent on the type of fuel, level of experience, risk aversion, time preference, or perceived credit constraints. As seen in the previous section, there is nonetheless unobserved heterogeneity in the estimate, although not along the lines analysed in this Chapter. As an extension, estimates for this attribute could be obtained by health status of the household, in particular in terms of respiratory issues, and by households' beliefs of how harmful indoor pollution is, as in Jeuland et al. (2015a, 2019).

Table 4.6: WTP estimates (in 1,000 Rupees, ~19 USD) for the models in Table 4.2.

	(1)	(2)	(3)	(4)
maintXhigher	1.84***	1.17*		
	(0.55)	(0.55)		
mainthigherXwood			0.14	0.02
			(0.85)	(0.77)
mainthigherXbiogas			2.70***	2.33**
			(0.68)	(0.74)
smokeXlower	7.07***	6.25***		
	(0.98)	(0.96)		
smokelowerXwood			8.28***	6.58***
			(1.30)	(1.46)
smokelowerXbiogas			6.63***	6.49***
			(1.02)	(1.07)
fuelXlower	7.87***	7.06***		
	(1.05)	(0.85)		
fuellowerXwood			7.28***	6.40***
			(1.31)	(1.30)
fuellowerXbiogas			8.31***	8.47***
			(1.12)	(1.15)
fuelXhigher	-2.39***	-2.41***		
	(0.68)	(0.66)		
fuelhigherXwood			-2.17*	-1.76*
			(1.07)	(0.86)
fuelhigherXbiogas			-2.43**	-2.45**
			(0.78)	(0.80)
ICS ASC	-5.60***	-4.37**	-5.29**	-3.82
	(1.60)	(1.48)	(1.76)	(2.01)
biogas ASC	3.97***	4.03***	3.62***	3.18***
	(0.77)	(0.70)	(0.88)	(0.84)
N	2515	2515	2515	2515

Standard errors in parenthese; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.7: WTP estimates (in 1,000 Rupees, ∼19 USD) for the models in Table 4.3.

	(1) outcome		(2) outcome		(3) outcome	
mainthigherXwood	0.16	(0.72)	0.12	(0.63)	0.18	(0.77)
mainthigherXbiogasXgoodexper	2.70*	(1.25)	2.46	(1.34)	2.64*	(1.29)
mainthigherXbiogasXbadexper	4.27***	(1.20)	4.17***	(1.22)	3.96**	(1.20)
mainthigherXbiogasXnoexper	1.15	(1.17)	2.13	(1.10)	1.55	(1.05)
smokelowerXwood	5.87***	(1.21)	5.34***	(1.00)	6.66***	(1.30)
smokelowerXbiogasXgoodexper	6.71***	(1.73)	7.82***	(2.30)	6.07***	(1.43)
smokelowerXbiogasXbadexper	6.61***	(1.62)	6.32***	(1.58)	6.02***	(1.43)
smokelowerXbiogasXnoexper	6.55***	(1.14)	7.46***	(1.26)	6.78***	(1.17)
fuellowerXwood	5.69***	(1.34)	5.41***	(0.64)	5.56***	(1.12)
fuellowerXbiogasXgoodexper	8.67***	(1.04)	8.90***	(1.57)	8.04***	(1.29)
fuellowerXbiogasXbadexper	11.02***	(1.89)	11.21***	(2.02)	10.38***	(1.48)
fuellowerXbiogasXnoexper	6.72***	(1.19)	7.58***	(1.58)	6.12***	(1.22)
fuelhigherXwood	-1.51	(0.86)	-1.29	(0.94)	-1.90*	(0.87)
fuelhigherXbiogasXgoodexper	-2.08	(1.27)	-2.02	(1.14)	-1.54	(1.00)
fuelhigherXbiogasXbadexper	-2.35	(1.46)	-2.28	(1.52)	-2.04	(1.43)
fuelhigherXbiogasXnoexper	-2.81**	(1.02)	-3.05**	(1.11)	-3.16**	(0.99)
ICS ASC	-2.22	(1.71)	-0.99	(1.28)	-3.23	(1.69)
biogas ASC X goodexperience	6.16***	(1.29)	5.84***	(1.36)	6.42***	(1.30)
biogas ASC X badexperience	2.35	(1.53)	2.14	(1.59)	2.49	(1.45)
biogas ASC X noexperience	1.71	(1.84)				
biogas ASC X noexp X planbg			5.00***	(1.25)		
biogas ASC X noexp X planbg X otherclean					8.14***	(1.70)
biogas ASC X noexp X planbg X tradonly					4.80**	(1.69)
biogas ASC X noexp X noplanbg			-4.75*	(1.91)		
biogas ASC X noexp X noplanbg X otherclean					-0.12	(1.96)
biogas ASC X noexp X noplanbg X tradonly					-5.91**	(2.20)
N	2515		2515		2515	

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.8: WTP estimates (in 1,000 Rupees, ∼19 USD) for the models in Table 4.4.

	(1)		(2)		(3)	
mainthigherXlessriskaverse	1.40	(0.81)				
mainthigherXriskaverse	1.50	(0.81)				
mainthigherXpatient			0.45	(0.78)		
mainthigherXimpatient			2.06**	(0.77)		
mainthigherXunconstrain					1.73*	(0.69)
mainthigherXcreditconstr					1.14	(1.04)
smokelowerXlessriskaverse	6.74***	(1.08)				
smokelowerXriskaverse	6.61***	(1.46)				
smokelowerXpatient			6.24***	(0.94)		
smokelowerXimpatient			7.17***	(1.56)		
smokelowerXunconstrain					6.42***	(1.08)
smokelowerXcreditconstr					5.87**	(2.09)
fuellowerXlessriskaverse	7.39***	(1.27)				
fuellowerXriskaverse	8.40***	(1.37)				
fuellowerXpatient			7.57***	(1.51)		
fuellowerXimpatient			8.34***	(1.26)		
fuellowerXunconstrain					8.29***	(1.13)
fuellowerXcreditconstr					5.84***	(1.29)
fuelhigherXlessriskaverse	-2.71*	(1.12)				
fuelhigherXriskaverse	-2.47**	(0.91)				
fuelhigherXpatient			-3.93**	(1.33)		
fuelhigherXimpatient			-1.92*	(0.87)		
fuelhigherXunconstrain					-1.99*	(0.88)
fuelhigherXcreditconstr					-4.31**	(1.45)
ICS ASC Xlessriskaverse	-2.92	(1.83)				
ICS ASC Xriskaverse	-5.03**	(1.93)				
ICS ASC Xpatient			-1.20	(1.59)		
ICS ASC Ximpatient			-6.32**	(2.14)		
ICS ASC Xunconstrain					-3.38*	(1.50)
ICS ASC Xcreditconstr					-4.23	(2.20)
biogas ASC XgoodexpXlessriskaverse	8.60***	(1.53)				
biogas ASC XgoodexpXriskav	8.12***	(1.44)				
biogas ASC XgoodexpXpatient			8.39***	(1.98)		
biogas ASC XgoodexpXimpatient			8.19***	(1.46)		
biogas ASC XgoodexpXunconstr					8.24***	(1.36)
biogas ASC XgoodexpXcreditcstr					8.14***	(1.57)
biogas ASC XbadexpXlessriskaverse	6.24***	(1.46)				
biogas ASC XbadexpXriskav	4.99***	(1.14)				
biogas ASC XbadexpXpatient			7.45***	(1.63)		
biogas ASC XbadexpXimpatient			4.22***	(1.15)		
biogas ASC XbadexpXunconstr					5.71***	(1.06)
biogas ASC XbadexpXcreditcstr					5.05**	(1.87)
biogas ASC XnoexpXlessriskaverse	4.45***	(1.30)				
biogas ASC XnoexpXriskav	1.66	(1.14)				
biogas ASC XnoexpXpatient			5.27**	(1.68)		
biogas ASC XnoexpXimpatient			1.05	(1.17)		
biogas ASC XnoexpXunconstr					4.90***	(1.04)
biogas ASC XnoexpXcreditcstr					-1.77	(1.37)
N	2515		2515		2515	

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In terms of fuel savings, the WTP appears to change non-linearly, as a reduction in fuel requirements elicit a much larger coefficient than an increase in the attribute (in absolute value). In the former case, the average household is willing to pay around 7,000 Rupees on average for a one-unit decrease in fuel (equivalent to a 33% reduction in the total), while the mean negative WTP for a one-unit increase is only 2,400 Rupees (Table 4.6). Again, as noted in the previous section results are not significantly different by fuel, level of experience or any of the respondents' characteristics considered, with the exception of households who had a negative experience with biogas, who are willing to pay 50% more for a reduction in fuel requirements. An interpretation for this result is that households might consider it an indicator of higher efficiency of the stove and therefore higher quality.

Finally, in terms of technology-premiums, households' dislike for the fuelwood ICS translates into a negative WTP of between 0 and -6,000 Rupees to be convinced to move from a traditional cookstove to the ICS, with the more negative values associated with more risk averse and more impatient households (Table 4.8). Lack of interest for fuelwood ICS, especially when compared to cleaner fuel stoves such as LPG or electric, has emerged in several studies using either stated or revealed preferences, especially in India (Hanna et al., 2016; Jeuland et al., 2019, 2015a).

As highlighted by the estimates for the standard deviations, presented in the previous section, there is substantial unobserved heterogeneity in the taste for ICS. Given the results we obtained regarding the importance of experience in the valuation of biogas plants, it would be interesting to see if the same applies to ICS. Unfortunately, we could not explore this hypothesis in the present work as less than 1% of the sample households had a fuelwood ICS at the time of the survey and no information was collected on previous experience with the technology.

Although, interest appears to be much higher for biogas, this result actually masks substantial heterogeneity. Households who have had a smooth experience with their biogas plant have an estimated WTP of 6,000 Rupees more, on average, than for the traditional cookstove, after controlling for attributes (Table 4.7). A slightly lower value of 5,000 Rupees is elicited for the households who have no experience with biogas but plan to install it. The WTP goes down to 2,000 Rupees for households who have had a negative experience (although a valuation of 0 is within the confidence interval at 5% significance level), and becomes strongly negative for households with no experience and no intention to adopt the technology.

This suggests that households with experience and households with no experience but a pre-existing interest in the technology are aware of the additional co-benefits of biogas that are not captured by the attributes presented in the DCE, such as waste disposal and fertiliser as a by-product of gasification – although the fact that only a small share of the households with biogas actively use the slurry as fertiliser suggests that these co-benefits might still be not fully utilised and therefore undervalued. This positive effect appears to be counteracted by the negative effect of malfunctions and failures of the systems, suggesting that it is very important to insure that the plants are of good quality and that repair and maintenance services are available, in order to avoid discontent and abandonment of the technology. In fact, 16% of the households who have experienced malfunctions stated that they have no interest in repairing the plant.

Further heterogeneity in the taste for biogas exists at the level of household characteristics. Larger risk aversion, impatience and perceived credit constraints are associated with lower WTP (Table 4.8). Nevertheless, this difference appears to be significant only in the case of households with no experience, suggesting that familiarity with the technology, even when malfunctions occur, mitigates the scepticism associated with these variables.

4.6 Conclusion

In this Chapter, we use a discrete choice experiment to understand household preferences for 'clean' cookstoves. On average, respondents' WTP for a biogas-premium is quite high, depending on the group considered, showing that there is substantial interest in the technology and appreciation for the co-benefits it brings. Although some heterogeneity exists, interest in rocket stoves (an alternative promoted by the private sector) is instead much lower, with households tending to prefer the traditional stove. In terms of attributes, households appear to assign a high value to smoke reduction and fuel savings, two dimensions on which biogas can deliver substantial improvements.

Nevertheless, these general results hide substantial heterogeneity in the taste for specific technologies, especially with respect to the type of experience the household has had with the stove. Households who are planning to build biogas appear to have a valuation of the technology that is almost as high as the households who already have a plant (this is in contrast with those who do not have nor plan to have biogas). However, "already having clean cookstoves" rather than "only using traditional stoves" is not correlated with the outcome of the choice experiment, once intentions to install are controlled for. This suggests that households who only have traditional cookstoves, do not have a idiosyncratic preference for those types of stoves, or fuelwood-based stoves in general, once the attributes – and especially the price – are controlled for, but might be instead constrained by availability, and budget and credit constraints, as emerges from the analysis in Section 4.4.

Preference for biogas is substantially lower for households who experienced malfunctions (all other attributes held constant). This result suggests that a negative experience is reducing the interest in the technology. In fact, negative experience might even lead to abandonment, as several respondents stated they have no interest in repairing their broken plant. Households who have had a smooth experience, on the contrary, have a more favourable opinion of the technology with respect to households with no experience, although the difference with households who are planning to adopt is less marked.

The asymmetric effect of positive and negative information is consistent with results from other works in the cookstove literature, especially on social learning and marketing messages, and in general with prospect theory and loss aversion in behavioural economics. This suggests that it is very important to insure that the plants are of good quality, that they are appropriate for the context and the household-specific needs, and that repair and maintenance services are available, in order to avoid discontent with the technology, and ultimately abandonment and lower uptake if negative opinions spread.

Finally, experience of any kind, either good or bad, appears to counterbalance the negative effects of risk aversion, impatience and concerns regarding access to credit on preferences for biogas. These results suggest that monetary incentives for adoption of biogas could be successfully complemented with information schemes to raise awareness on the co-benefits of the technology and schemes that allow households to gain experience with the technology and trial it before committing.

Regarding the existing situation on the ground, the type of cookstove owned appear to be driven mainly by economic characteristics such as disposable income, wealth and credit constraints; plus, in the case of biogas, having cattle. Fuel stacking is pervasive, and there is evidence to suggest that clean cookstoves and clean fuels available, including biogas, are not sufficient to cover the full energy need of the households, so that the vast majority of households continue to use traditional cookstoves for at least some of the cooking. Malfunctions of the biogas plants seem to be linked to age and quality of the plant and less time spent maintaining them.

Overall, the Chapter contributes to the literature on cookstove adoption and use, providing insights on preferences for biogas and on the role of previous positive and negative experience with the technology being offered, two elements on which not much research has been done. While the results presented are mainly correlational, they provide an important first step for designing causal studies and formulating hypotheses to test.

Biogas has the potential to deliver important benefits in rural contexts with a hot and humid climate, which often tend to be the hotspot for biomass burning, especially in India. The main takeaway of the Chapter is that while interest in such a technology is significant in the study area, its penetration could be improved by complementing the existing subsidy schemes with information campaigns and above all trials of the technology, as experience appears to mitigate risk aversion, present-oriented time preferences, and concerns regarding access to credit. Yet, these are unlikely to substitute for monetary incentives, as the elicited WTP are still often short of the total cost of installing a biogas plant, and the upfront payment is likely to be too burdensome for many households. The results of our analysis further suggest that attention should be paid to ensure positive experiences with the technology if its use is to be sustained, as malfunctions and failures might cause discontent and abandonment. In particular, good quality of the biogas systems, detailed instructions on how to operate and maintain it, and accessible and affordable repair services, are key elements in this direction.

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Appendix A

Appendix to Chapter 1

A.1 Robustness checks

Table A.1: Regression table, Tobit and Tobit with IV.

	(1) Tobit	(2) Tobit	(3) Tobit,IV	(4) Tobit,IV
Subsidy (100GBP/kW)	2.305***	2.222***	5.245***	5.461***
	(0.0450)	(0.0428)	(0.150)	(0.148)
Install. cost (1,000GBP/kW)	-0.410***	-0.0713*	-6.227***	-8.412***
	(0.0468)	(0.0378)	(0.213)	(0.277)
Covariates	Short	Long	Short	Long
Local authority	No	No	No	No
Year	Yes	Yes	Yes	Yes
Month of the year	Yes	Yes	Yes	Yes
Var. instrumented			Subsidy Install. cost	Subsidy Install. cost
N	503580	503580	503580	503580
F	168.1	127.0		
Impl.discount rate			10.2%	14.3%

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Regression table, models for fractional outcome variable.

	(1) FracLogit	(2) FracProbit	(3) FracProbit,HET	(4) FracLogit	(5) FracProbit	(6) FracProbit,HET	(7) ZeroInflBeta	(8) ZeroInflBeta
Subsidy (100GBP/kW)	0.000272***	0.000286***	0.000303***	0.000238***	0.000263***	0.000142***	0.000233***	0.000347***
	(0.00000265)	(0.00000294)	(0.00000330)	(0.00000529)	(0.00000573)	(0.00000640)	(0.00000152)	(0.00000310)
Install. cost (1,000GBP/kW)	-0.000404***	-0.000431***	-0.000461***	0.00000466	0.00000006	-0.0000169**	-0.000432***	-0.00000480
	(0.00000407)	(0.00000452)	(0.00000508)	(0.00000517)	(0.00000562)	(0.00000674)	(0.00000289)	(0.00000355)
Covariates	No	No	No	Yes	Yes	Yes	No	Yes
Local authority	No	No	No	No	No	No	No	No
Year	No	No	No	Yes	Yes	Yes	No	Yes
Month of the year	No	No	No	Yes	Yes	Yes	No	Yes
N	503580	503580	503580	503580	503580	503580	503580	503580
mean values:								
Fraction of houses installing PV	0.00052	0.00052	0.00052	0.00052	0.00052	0.00052	0.00052	0.00052
Subsidy (100GBP/kW)	2.53	2.53	2.53	2.53	2.53	2.53	2.53	2.53
Install. cost (1,000GBP/kW)	2.23	2.23	2.23	2.23	2.23	2.23	2.23	2.23
partial elasticities:								
Subs.elasticity	1.466***	1.541***	1.623***	1.750***	1.894***	1.165***	1.163***	1.982***
	(0.0136)	(0.0152)	(0.0171)	(0.0443)	(0.0470)	(0.0515)	(0.00762)	(0.0177)
Cost elasticity	-1.919***	-2.043***	-2.173***	0.0302	0.000393	-0.122**	-1.902***	-0.0241
	(0.0210)	(0.0233)	(0.0258)	(0.0336)	(0.0357)	(0.0484)	(0.0130)	(0.0178)
Impl.discount rate	13.7%	13.9%	14.1%				17.8%	

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The coefficients represent the average marginal effects calculated at the mean. Elasticities are calculated at the mean.

Table A.3: Robustness checks on choice of instruments.

	(1) first stage Subsidy	(1) first stage Install. cost	(1) second stage PV count	(2) first stage Subsidy	(2) first stage Install. cost	(2) second stage PV count	(3) first stage Subsidy	(3) first stage Install. cost	(3) second stage PV count
Subsidy (100GBP/kW)			1.962***			0.966***			0.866***
			(0.014)			(0.004)			(0.010)
Install. cost (1,000GBP/kW)			-4.194***			-4.031***			-4.110***
			(0.031)			(0.030)			(0.030)
FIT production rate, 1-5MW	-0.0355***	-0.00519***							
	(0.000)	(0.000)							
FIT production rate, 0-4kW				0.0725***	0.00378***				
				(0.000)	(0.000)				
2010 Pre-announced FIT rate, 0-4kW							0.351***	-0.00223	
							(0.000)	(0.001)	
Wind production FIT rate, 0-2kW	0.00179***	-0.0183***		-0.00255***	-0.0179***		-0.00346***	-0.0173***	
	(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)	
Latitude	-0.191***	-0.0483*		-0.192***	-0.0484*		-0.191***	-0.0483*	
	(0.014)	(0.024)		(0.014)	(0.024)		(0.014)	(0.024)	
Longitude	0.0250*	0.0185		0.0248*	0.0185		0.0250*	0.0185	
	(0.010)	(0.017)		(0.010)	(0.017)		(0.010)	(0.017)	
Chinese PV price index	2.157***	0.803***		-0.0172***	0.524***		1.830***	0.536***	
	(0.002)	(0.005)		(0.000)	(0.005)		(0.001)	(0.008)	
Wage electric sector (residuals)	-0.0594***	0.114***		-0.0599***	0.114***		-0.0595***	0.114***	
	(0.002)	(0.009)		(0.002)	(0.009)		(0.002)	(0.009)	
N	503580	503580	503580	503580	503580	503580	503580	503580	503580
R^2	0.94	0.86		1.00	0.86		0.95	0.86	
adj. R^2	0.94	0.86		1.00	0.86		0.95	0.86	
pseudo R^2			0.33			0.33			0.33
χ^2			605517.9			605732.1			604741.0

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.2 Heterogeneous effects

In this section, I investigate the possibility that responsiveness to changes in the subsidy and costs of installing PV systems is heterogeneous over time, as found by Hughes and Podolefsky (2015), or depends on the existing installed base due to the presence of peer effects, which have been detected by Bollinger and Gillingham (2012); Richter (2014); Müller and Rode (2013); Graziano and Gillingham (2015); Rode and Weber (2016); Baranzini et al. (2017). I formulate and test the following hypotheses regarding how responsiveness to economic incentives and costs changes over time, and how they interact with peer effects. These effects and the underlying mechanisms are investigated in more details in the next Chapter, addressing concerns of endogeneity and spatial correlation.

Heterogeneous effects over time:

[H_0] The responsiveness parameters are constant over time, all else equal;

[H_1] Responsiveness to subsidy and/or system costs changes over time, all else equal.

Heterogeneous effects depending on the neighbourhood's installed base:

[H_0] No interaction between responsiveness to incentives and costs, and the existing installed base;

[H_1] Responsiveness to changes in the subsidy and/or responsiveness to changes in the costs are heterogeneous depending on the number of previous installations in the neighbourhood.

Results are presented in Table A.4 and A.5. To investigate the first hypothesis, I construct an indicator for three different time periods, so that each period contains four reforms to the FIT production rate, and the time between consecutive rate changes that belong to different time periods are evenly split between the two. This results in the following subdivision: period 1, from April 2010 to February 2013; period 2, from March 2013 to February 2015; and period 3, from March 2015 to January 2016. I then interact the time period indicator with the subsidy and with the cost and run the regression analysis using a Poisson model with the main set of fixed effects, to see whether the responsiveness coefficients are stable over the three periods (model (1) in Table A.4).

Hughes and Podolefsky (2015) find that responsiveness to rebate rates in California decreases over time. Similarly, I found that the coefficient for the annual subsidy decreases substantially from period 1 to period 2, but there are no significant differences between the coefficients for period 2 and 3. The opposite occurs for the cost coefficient, which is smaller and not significantly different from zero in the first and second period, and becomes larger and significantly negative in the last period. This result does not depend on the fact that subsidies and costs were much smaller in later time and so were changes in their absolute levels; in fact, the same result emerges when calculating the elasticities at the mean for each time period (model (1) in Table A.5). This suggests that subsidies were the main driving force behind adoption in the early time of the policy, while in the later stages costs reductions and subsidies were both important.

To investigate the second hypothesis, I first check for evidence that peer effects are at play. For every observation, i.e. for every MSOA-month combination, I calculate how many PV systems had been installed up to that point and use this as an additional regressor in the equation. [1] Consistent with the literature on peer effects in the adoption of residential solar PV, in column (2) I find that the existing installed base has a positive coefficient. I therefore construct a new indicator for whether each MSOA at the end of 2011 – before any change in the FIT rate had occurred – had more or fewer installations than the median area. The indicator is interacted with the subsidy and the installation cost in the regression model presented in column (3). I find that responsiveness to the subsidy is higher in areas with higher existing installed base, while the opposite happens for costs, as responsiveness is higher in areas with lower existing installed base and is not statistically different from zero in areas with higher installed base. This suggests that peer effects help move the focus from the upfront cost to the future benefits provided by the subsidies.

[1] This analysis is only exploratory, as I am not addressing endogeneity and spatial correlation issues (see for example Manski, 1993; Bollinger and Gillingham, 2012; Richter, 2014), which are discussed in the next Chapter.

Table A.4: Heterogeneous effects over time and by installed base (as a measure for peer effects). Poisson model, no IVs.

PV count	(1) Poisson	(2) Poisson	(3) Poisson
Subsidy (100GBP/kW), – period1	0.735*** (0.008)		
Subsidy (100GBP/kW), – period2	0.372*** (0.045)		
Subsidy (100GBP/kW), – period3	0.358*** (0.057)		
Subsidy (100GBP/kW)		0.721*** (0.007)	
Subsidy (100GBP/kW), – low installed base			0.651*** (0.014)
Subsidy (100GBP/kW), – high installed base			0.711*** (0.008)
Install. cost (1,000GBP/kW), – period1	-0.0266 (0.014)		
Install. cost (1,000GBP/kW), – period2	-0.0384 (0.034)		
Install. cost (1,000GBP/kW), – period3	-0.286*** (0.044)		
Install. cost (1,000GBP/kW)		0.0177 (0.015)	
Install. cost (1,000GBP/kW), – low installed base			-0.145*** (0.021)
Install. cost (1,000GBP/kW), – high installed base			-0.0246 (0.013)
Existing installed base		0.00604*** (0.000)	
N	503580	503580	503580
pseudo R^2	0.31	0.33	0.32

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.5: Heterogeneous effects over time and by installed base (as a measure for peer effects). Poisson model, no IVs. Estimates of the partial elasticities at the mean.

PV count	(1) Poisson	(2) Poisson	(3) Poisson
mean values:			
PV count	1.01	1.01	1.01
Subsidy (100GBP/kW)	2.53	2.53	2.53
Install. cost (1,000GBP/kW)	2.23	2.23	2.23
partial elasticities:			
Subs.elasticity, period 1	2.59***		
	(0.027)		
Subs.elasticity, period 2	0.61***		
	(0.733)		
Subs.elasticity, period 3	0.53***		
	(0.084)		
Subs.elasticity		1.82***	
		(0.019)	
Subs.elasticity, low installed base			1.63***
			(0.034)
Subs.elasticity, high installed base			1.81***
			(0.019)
Cost elasticity, period 1	-0.07		
	(0.039)		
Cost elasticity, period 2	-0.07		
	(0.063)		
Cost elasticity, period 3	-0.47***		
	(0.071)		
Cost elasticity		0.04	
		(0.032)	
Cost elasticity, low installed base			-0.33***
			(0.048)
Cost elasticity, high installed base			-0.05
			(0.030)
Installed base elasticity		0.23***	
		(0.007)	

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Elasticities are calculated at the mean.

Appendix B

Appendix to Chapter 2

Table B.1: Summary statistics, LSOA-level.

	mean	sd	median (p50)
number of new PV/LSOA/month	0.19	0.69	0
new capacity installed kW/LSOA/month	0.60	2.01	0.00
average capacity of installations kW	3.25	0.76	3.50
system cost GBP/kW	1,852	289	1,820
subsidy GBP/kW/year	206	75	187
existing installed base in the LSOA	0.70	4.01	0
owner occupied houses	401	165	414
LSOA surface area km2	4.40	14.82	0.48
population	1631	383	1565

Table B.2: Regression table, proportional-area buffers, within-group (WG) and first-difference (FD) estimator. Peer installations are divided according to how recently they had been installed.

	(1,WG) PVcount	(2,WG) PVcount	(1,FD) PVcount	(2,FD) PVcount
subsidy (100GBP/kW/year)	0.798***	0.565***	0.817***	0.581***
	(0.006)	(0.007)	(0.009)	(0.010)
pvcost (1000GBP/kW)	-0.231***	-0.224***	-0.232***	-0.225***
	(0.010)	(0.010)	(0.016)	(0.016)
N_<6m_ring	0.004***	-0.012***	0.004***	-0.010***
	(0.000)	(0.001)	(0.000)	(0.001)
N_6-12m_ring	0.004***	-0.010***	0.004***	-0.010***
	(0.000)	(0.000)	(0.000)	(0.001)
N_>12m_ring	0.004***	-0.009***	0.004***	-0.011***
	(0.000)	(0.001)	(0.000)	(0.001)
subsidyXN_<6m_ring		0.007***		0.006***
		(0.000)		(0.000)
subsidyXN_6-12m_ring		0.007***		0.007***
		(0.000)		(0.000)
subsidyXN_>12m_ring		0.007***		0.008***
		(0.001)		(0.000)
N	1546605	1546605	1031070	1031070
F	3501.763	2299.088	1833.013	1206.502
p	0.000	0.000	0.000	0.000

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: X represents an interaction between variables.

Table B.3: Regression table, proportional-area buffers, within-group (WG) and first-difference (FD) estimator. Peer installations are divided in three concentric rings.

	(1,WG) PVcount	(2,WG) PVcount	(1,FD) PVcount	(2,FD) PVcount
subsidy (100GBP/kW/year)	0.800***	0.544***	0.822***	0.560***
	(0.006)	(0.007)	(0.009)	(0.010)
pvcost (1000GBP/kW)	-0.237***	-0.268***	-0.238***	-0.271***
	(0.010)	(0.010)	(0.016)	(0.016)
N_ring1	0.005***	-0.019***	0.005***	-0.020***
	(0.000)	(0.001)	(0.001)	(0.002)
N_ring2	0.003***	-0.003*	0.003***	-0.003
	(0.000)	(0.001)	(0.001)	(0.002)
N_ring3	0.004***	-0.006***	0.004***	-0.006***
	(0.000)	(0.001)	(0.000)	(0.001)
subsidyXN_ring1		0.012***		0.012***
		(0.001)		(0.001)
subsidyXN_ring2		0.003***		0.003***
		(0.001)		(0.001)
subsidyXN_ring3		0.005***		0.005***
		(0.001)		(0.000)
N	1546605	1546605	1031070	1031070
F	3401.468	2217.043	1777.633	1169.755
p	0.000	0.000	0.000	0.000

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: X represents an interaction between variables.

Table B.4: Regression table, proportional-area buffers, within-group (WG) and first-difference (FD) estimator. Installations are measured in kW rather than count.

	(1,WG) PVtot_kw	(2,WG) PVtot_kw	(1,FD) PVtot_kw	(2,FD) PVtot_kw
subsidy (100GBP/kW/year)	2.647***	1.794***	2.716***	1.848***
	(0.021)	(0.027)	(0.030)	(0.040)
pvcost (1000GBP/kW)	-0.834***	-0.945***	-0.839***	-0.956***
	(0.034)	(0.034)	(0.054)	(0.054)
N_ring	0.005***	-0.009***	0.005***	-0.010***
	(0.000)	(0.000)	(0.000)	(0.001)
subsidyXN_ring		0.007***		0.007***
		(0.000)		(0.000)
N	1546605	1546605	1031070	1031070
F	5668.853	4492.498	2930.601	2347.854
p	0.000	0.000	0.000	0.000

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: X represents an interaction between variables.

Table B.5: Regression table, proportional-area buffers, within-group (WG) and first-difference (FD) estimator. Installations are measured in average kW installed rather than count, to investigate the effect of size.

	(1,WG) PVav_kw	(2,WG) PVav_kw	(1,FD) PVav_kw	(2,FD) PVav_kw
subsidy (100GBP/kW/year)	0.070***	0.068***	0.719***	0.923***
	(0.007)	(0.013)	(0.091)	(0.173)
pvcost (1000GBP/kW)	-0.190***	-0.190***	-0.847***	-0.843***
	(0.026)	(0.026)	(0.217)	(0.217)
N_ring	0.008*	0.006	-0.076	0.074
	(0.004)	(0.010)	(0.069)	(0.126)
subsidyXN_ring		0.001		-0.065
		(0.004)		(0.043)
N	200970	200970	28303	28303
F	52.667	39.552	25.686	19.337
p	0.000	0.000	0.000	0.000

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: X represents an interaction between variables.

Table B.6: Regression table, fixed-radius buffers, withing-group (WG) estimator. Different specifications of the installations measures (count, total kW and average kW) and different assumptions on distribution of systems in neighbourhood. Analysis is conducted on a random sample of total observations.

within-group estimator	(1) PVcount	(2) PVcount	(3) PVtot_kw	(4) PVtot_kw	(5) PVav_kw	(6) PVav_kw
subsidy (100GBP/kW/year)	0.824***	0.867***	2.739***	2.834***	0.115***	0.114***
	(0.020)	(0.020)	(0.068)	(0.069)	(0.021)	(0.021)
pvcost (1000GBP/kW)	-0.254***	-0.151***	-0.823***	-0.543***	-0.101	-0.080
	(0.033)	(0.033)	(0.108)	(0.109)	(0.082)	(0.082)
N_<2km	0.005***		0.008***		0.008	
	(0.001)		(0.001)		(0.007)	
N_<2km_unifdistr		0.024***		0.023***		0.270
		(0.001)		(0.001)		(0.138)
N	154710	154710	154710	154710	20381	20381
F	597.421	711.772	596.163	677.681	10.933	11.624
p	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: X represents an interaction between variables.

Table B.7: Regression table, fixed-radius buffers, first-difference (FD) estimator. Different specifications of the installations measures (count, total kW and average kW) and different assumptions on distribution of systems in neighbourhood. Analysis is conducted on a random sample of total observations.

first-difference estimator	(1) PVcount	(2) PVcount	(3) PVtot_kw	(4) PVtot_kw	(5) PVav_kw	(6) PVav_kw
subsidy (100GBP/kW/year)	0.854***	0.877***	2.825***	2.885***	0.832*	0.870***
	(0.029)	(0.029)	(0.097)	(0.097)	(0.259)	(0.261)
pvcost (1000GBP/kW)	-0.259***	-0.176***	-0.845***	-0.661***	-0.681	-0.602
	(0.052)	(0.053)	(0.174)	(0.175)	(0.670)	(0.674)
N_<2km	0.004**		0.007***		0.053	
	(0.001)		(0.001)		(0.122)	
N_2km_unifdistr		0.020***		0.017***		0.715
		(0.002)		(0.002)		(0.646)
N	103140	103140	103140	103140	1357	2960
F	314.847	348.845	307.946	324.379	3.697	4.051
p	0.000	0.000	0.000	0.000	0.011	0.007

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: X represents an interaction between variables.

Appendix C

Appendix to Chapter 3

C.1 Examples of stoves from the settlements

Figure C.1: Example of a three-stone stove (in the background) and a portable metallic improved cookstove (ICS) in the forefront. Source: Practical Action, Moving Energy Initiative.

Figure C.2: Example of fixed outdoor cookstove, self-built by a refugee household in Goudoubo. Source: Practical Action, Moving Energy Initiative.

Figure C.3: Example of metallic portable improved cookstove (ICS) fuelled with firewood, manufactured by blacksmiths in Goudoubo. Source: Practical Action, Moving Energy Initiative.

Figure C.4: Example of portable improved cookstove (ICS) fuelled with firewood, Kakuma. Source: Practical Action, Moving Energy Initiative.

Figure C.5: Example of Blazing Tube (solar cooker) trialled in Saag-Nioniogo Camp, Burkina Faso. The same model was also trialled in Goudoubo. Source: UNHCR via Clean Cooking Alliance; accessed on February 10, 2020 at the link: https://www.cleancookingalliance.org/about/news/10-20-2015-blazing-tube-solar-cookers-in-burkina-faso-refugee-camps.html.

C.2 Willingness to pay and valuation

Table C.1: Summary statistics of cooking-related variables. Prices, consumption quantities and expenditures statistics are calculated only for households reporting positive and non-missing values.

Goudoubo

	count	mean	sd	p25	p50	p75
has a three-stone (0/1)	126	0.38	.	.	.	.
has a biomass ICS (fixed) (0/1)	126	0.18	.	.	.	.
has a biomass ICS (portable) (0/1)	126	0.61	.	.	.	.
has a solar cooker (0/1)	126	0.05	.	.	.	.
has a LPG stove (0/1)	126	0.05	.	.	.	.
has a purchased stove (0/1)	126	0.15	.	.	.	.
has a donated stove (0/1)	126	0.71	.	.	.	.
uses firewood (0/1)	126	0.94	.	.	.	.
uses charcoal (0/1)	126	0.08	.	.	.	.
cooks indoor (0/1)	126	0.03	.	.	.	.
uses chimney (0/1)	126	0.01	.	.	.	.
firewood used (kg/month)	91	89.71	115.04	23.00	39.50	150.00
charcoal used (kg/month)	27	34.70	33.40	10.00	25.00	30.00
firewood expenditures (USD/month)	99	7.79	7.69	4.24	6.78	8.47
charcoal expenditures (USD/month)	39	3.70	2.09	1.69	3.39	5.08
briquettes expenditures (USD/month)	38	0.50	0.41	0.17	0.34	0.85
tot. expend. in cooking fuels (USD/month)	112	8.02	5.79	3.69	6.86	11.10
basic ICS's price (USD)	16	5.30	2.33	3.39	4.24	8.47
tot. household expend. (USD/month)	120	91.20	66.00	42.40	72.00	123.70

Kakuma

	count	mean	sd	p25	p50	p75
has a three-stone (0/1)	223	0.28	.	.	.	.
has a biomass ICS (fixed) (0/1)	223	0.05	.	.	.	.
has a biomass ICS (portable) (0/1)	223	0.75	.	.	.	.
has a purchased stove (0/1)	223	0.20	.	.	.	.
has a donated stove (0/1)	223	0.70	.	.	.	.
uses firewood (0/1)	223	0.80	.	.	.	.
uses charcoal (0/1)	223	0.32	.	.	.	.
cooks indoor (0/1)	223	0.56	.	.	.	.
uses chimney (0/1)	223	0.16	.	.	.	.
firewood used (kg/month)	159	46.60	45.50	10.00	25.00	80.00
charcoal used (kg/month)	71	33.80	26.20	2.00	45.00	50.00
firewood expenditures (USD/month)	38	3.94	3.55	2.00	2.75	5.00
charcoal expenditures (USD/month)	78	7.25	3.94	5.00	7.00	9.50
tot. expend. in cooking fuels (USD/month)	93	7.84	5.00	4.50	7.00	10.00
basic ICS's price (USD)	36	4.10	2.25	3.00	4.00	5.00
tot. household expend. (USD/month)*	94	40.70	54.40	7.00	18.50	49.00

* Note: Household expenditures in Kakuma are likely under-reported according to other data sources, reports, and private conversation with personnel in the field.

C.3 Effects of stove use

Treatment

– *treatment* - dummy that takes the value 1 if only non-traditional cookstoves are used, and 0 if three-stone fire is used for cooking (either as primary or secondary cooking system, or both).
– *treatment adjusted* - same as above, but cookstoves that are artisanal or self-built are reclassified as traditional three-stone fires.
– *treatment index* - summative index constructed by assigning a score of +1 for each characteristic associated with an improved cooking system (any of the primary or secondary stove is a fixed ICS, a portable ICS, a non-biomass stove, manufactured, branded, purchased, the household uses charcoal as a cooking fuel, cooks outdoor, uses a chimney to remove smoke), and -1 for each characteristic associated with traditional cookstoves and indoor pollution (any of the primary or secondary stove is a three-stone fire, is artisanal, is self-built, the household uses firewood as a cooking fuel, cooks indoor). The index can therefore take values from -5 to +9.
– *treatment pca* - index constructed by using factor analysis on the same dummies used for *treatment index* and extracting the first factor using the Bartlett method.

Instrument

– *stove donated* - whether the primary or secondary cookstove was received as a donation.

Outcome variables

Energy efficiency:
– $firewood(kg/month)$ - quantity of firewood consumed per month, using responses to the question "How much does your household consume in a typical month on the following fuels for the cookstoves? FIREWOOD". The question distinguishes between the amount purchased, donated, and collected, and the three have been aggregated for the purpose of this analysis.
– $firewood(kg/hour\ of\ cooking)$ - quantity of firewood consumed per hour, computed as the ratio between the quantity of firewood consumed per month divided by 30 to obtain the average daily consumption, over the number of hours the primary and secondary stove are lit per day. This measure allows to investigate the fuel ef-

ficiency of the stoves without being affected by binding availability constraints and the rebound effect. Nevertheless, this measure misses some aspects of fuel efficiency such as shorter time required to warm up the stove. Some information on the latter can be obtained by looking at the time use outcomes.

Health and safety:

– *smoke problems* (*dummy*) - dummy that takes the value 1 if any smoke issue was reported related to any of the primary or secondary stove (stove "caused a lot of smoke") or to the fuel used for cooking ("chest infections/lung disease, due to indoor air pollution" and "eye infections, smoke-related").

– *accidents* (*dummy*) - dummy that takes the value 1 if any accident was reported related to any of the primary or secondary stove (stove "caused unintended fire", "damaged home", "caused burns", "caused permanent physical damage to any person in the household") or to the fuel used for cooking ("burns").

Time use:

– *hours/day of stove use* - number of hours the primary cookstove is lit per day, plus the hours the secondary cookstove is lit per day (using responses to the question "In the last 7 days, how many hours per day on average was the primary/secondary cookstove lit?").

– *total time* (*hours/week*) - sum of the time spent by all the members of the household in all cooking-related activities ("In a normal week, how many hours does each household member spend cooking (food, tea, boiling water) / collecting or gathering fuel / purchasing fuel - including travel time / producing and preparing fuel?", hours for all the members are summed).

Workload burden on women and children:

– *children involved* - dummy that takes the value 0 if the household reports that children are "never involved" in fuelwood collection, and 1 otherwise.

– *female share of total work* measures the percentage of the total time dedicated to cooking-related activities (cooking, fuel collection, fuel purchase and preparations) that is contributed by female members of the household.

Table C.2: Summary statistics for variables used in the estimation of the benefits of using non-traditional cookstoves.

	Goudoubo		Kakuma	
	mean	sd	mean	sd
– treatment –				
treatm. (non-trad stove)	0.62	0.49	0.72	0.45
treatm. adjusted	0.60	0.49	0.61	0.49
treatm. index	0.92	2.42	0.94	2.61
treatm. pca	0.66	0.43	0.71	0.44
– instrument –				
stove donated	0.69	0.46	0.68	0.47
– outcomes –				
fuelwood(kg/month)	108.79	151.21	40.94	45.32
fuelwood(kg)/hour cooking	0.62	0.83	0.28	0.41
smoke (dummy)	0.29	0.46	0.66	0.487
accidents (dummy)	0.04	0.19	0.61	0.49
hours/day stoves are on	5.61	2.71	9.87	8.20
hours/week cooking activities	46.52	32.24	22.78	26.03
female/tot cooking activities	0.82	0.21	0.74	0.36
children involv.	0.25	0.43	0.32	0.47
– other variables –				
female respond.	0.43	0.50	0.67	0.47
female head of h.	0.35	0.48	0.58	0.49
respond. age	42.09	14.47	31.08	12.88
head of h. age	42.99	14.52	34.20	13.16
hh size	5.50	3.37	6.04	2.84
hh size, female	2.79	1.81	3.12	1.90
hh size, male	2.71	2.15	2.73	1.83
mobile dummy	0.81	0.40	0.88	0.32
radio or tv dummy	0.20	0.40	0.24	0.43
expend. (usd/month)	91.93	68.43	36.30	66.58
top priority safe	0.14	0.35	0.13	0.33
top priority less smoke	0.21	0.41	0.12	0.32
top priority less fuel	0.09	0.28	0.17	0.38
top priority cook cheap	0.04	0.19	0.08	0.28
top priority cook fast	0.13	0.34	0.11	0.32
top priority trad. & habits	0.02	0.15	0.07	0.25
N	129		231	

C.3.1 Robustness checks - Goudoubo

Table C.3: First stage of the 2SLS IV estimator; *stove donated* is the instrument.

	Goudoubo (1) treatm. index		Goudoubo (2) treatm. pca	
stove donated	2.15***	(0.558)	0.24*	(0.094)
wealth index	1.22*	(0.490)	0.15+	(0.079)
adult-equiv. size	0.16	(0.391)	-0.03	(0.067)
adult-equiv. size^2	-0.02	(0.026)	-0.00	(0.004)
number of children	-0.03	(0.176)	0.00	(0.031)
head's age	-0.01	(0.014)	-0.00	(0.003)
fem empower index	2.87*	(1.446)	0.60*	(0.287)
female respondent	-0.50	(0.497)	-0.07	(0.092)
" X fem empower index	-1.32	(1.653)	-0.37	(0.326)
top safe	-0.14	(0.586)	0.03	(0.107)
top less smoke	-0.97*	(0.431)	-0.20*	(0.078)
top less fuel	-0.68	(0.442)	-0.11	(0.077)
top cheap	-0.68	(0.637)	-0.07	(0.129)
top cook fast	-0.23	(0.459)	-0.10	(0.088)
top traditions & habits	-0.18	(0.495)	-0.06	(0.091)
_cons	-0.77	(0.958)	0.78***	(0.181)
N	129		129	
F	3.46		4.43	
p	0.00		0.00	
r2	0.29		0.29	
r2_a	0.19		0.20	

Standard errors in parentheses
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.4: Estimates of treatment effects on energy efficiency, Goudoubo.

	OLS		IV,2sls	
tot firewood qty	(treatm. index)	(treatm. pca)	(treatm. index)	(treatm. pca)
treatment	-11.44**	-91.57***	-7.35	-60.50
	(4.321)	(24.762)	(10.654)	(88.312)
p-value	[0.010]	[0.000]	[0.490]	[0.493]
" weak IV-robust			[0.505]	[0.505]
sharpened q-value	[0.073]	[0.003]	[0.674]	[0.674]
N	104	104	104	104
r2	0.50	0.52	0.49	0.52
r2_a	0.41	0.44	0.41	0.43

	OLS		IV,2sls	
firewood per hour	(treatm. index)	(treatm. pca)	(treatm. index)	(treatm. pca)
treatment	-0.06*	-0.46***	-0.02	-0.16
	(0.025)	(0.133)	(0.063)	(0.518)
p-value	[0.032]	[0.001]	[0.752]	[0.751]
" weak IV-robust			[0.758]	[0.758]
sharpened q-value	[0.105]	[0.003]	[0.674]	[0.674]
N	104	104	104	104
r2	0.36	0.38	0.35	0.36
r2_a	0.25	0.27	0.24	0.25

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.5: Estimates of treatment effects on health and safety, Goudoubo.

	OLS		IV,2sls	
smoke problems	(treatm. index)	(treatm. pca)	(treatm. index)	(treatm. pca)
treatment	-0.05**	-0.43***	-0.07+	-0.59+
	(0.016)	(0.095)	(0.037)	(0.329)
p-value	[0.002]	[0.000]	[0.076]	[0.073]
" weak IV-robust			[0.105]	[0.106]
sharpened q-value	[0.014]	[0.001]	[0.590]	[0.590]
N	129	129	129	129
r2	0.35	0.41	0.35	0.39
r2_a	0.27	0.33	0.26	0.31

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.6: Estimates of treatment effects on time use, Goudoubo.

	OLS		IV,2sls	
hours of stove use	(treatm. index)	(treatm. pca)	(treatm. index)	(treatm. pca)
treatment	-0.11	-1.16	0.26	2.15
	(0.117)	(0.794)	(0.223)	(1.979)
p-value	[0.337]	[0.148]	[0.248]	[0.278]
" weak IV-robust			[0.230]	[0.230]
sharpened q-value	[0.410]	[0.227]	[0.590]	[0.590]
N	126	126	126	126
r2	0.15	0.17	0.06	.
r2_a	0.03	0.05	-0.07	.
	OLS		IV,2sls	
tot time	(treatm. index)	(treatm. pca)	(treatm. index)	(treatm. pca)
treatment	-0.33	-2.37	1.16	9.88
	(1.079)	(5.776)	(2.418)	(20.638)
p-value	[0.760]	[0.683]	[0.630]	[0.632]
" weak IV-robust			[0.633]	[0.633]
sharpened q-value	[0.484]	[0.519]	[0.674]	[0.674]
N	125	125	125	125
r2	0.35	0.35	0.34	0.33
r2_a	0.26	0.26	0.25	0.24

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.7: Estimates of treatment effects on women and children workload, Goudoubo.

	OLS		IV,2sls	
female share of work	(treatm. index)	(treatm. pca)	(treatm. index)	(treatm. pca)
treatment	-0.01	-0.01	-0.04^{+}	-0.30
	(0.008)	(0.049)	(0.020)	(0.189)
p-value	[0.268]	[0.878]	[0.080]	[0.112]
" weak IV-robust			[0.076]	[0.076]
sharpened q-value	[0.192]	[0.336]	[0.590]	[0.590]
N	124	124	124	124
r2	0.28	0.27	0.20	.
r2_a	0.18	0.17	0.09	.
	OLS		IV,2sls	
children involv.	(treatm. index)	(treatm. pca)	(treatm. index)	(treatm. pca)
treatment	-0.03*	-0.17*	-0.04	-0.37
	(0.014)	(0.086)	(0.032)	(0.299)
p-value	[0.031]	[0.050]	[0.205]	[0.221]
" weak IV-robust			[0.195]	[0.195]
sharpened q-value	[0.042]	[0.053]	[0.590]	[0.590]
N	129	129	129	129
r2	0.32	0.32	0.32	0.29
r2_a	0.23	0.23	0.23	0.20

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.3.2 Robustness checks - Kakuma

Table C.8: First stage of the 2SLS IV estimator; *stove donated* is the instrument.

	Kakuma (1) treatm. index		Kakuma (2) treatm. pca	
stove donated	1.30**	(0.428)	0.34***	(0.064)
wealth index	-0.86	(0.534)	-0.13	(0.080)
adult-equiv. size	0.11	(0.475)	0.03	(0.068)
adult-equiv. size^2	-0.03	(0.044)	-0.01	(0.007)
number of children	-0.04	(0.114)	0.02	(0.018)
head's age	-0.00	(0.015)	-0.00	(0.002)
fem empower index	-1.11	(0.761)	-0.17	(0.131)
female respondent	0.34	(0.524)	0.04	(0.082)
" X fem empower index	0.39	(0.963)	0.03	(0.159)
top safe	-0.08	(0.387)	-0.02	(0.062)
top less smoke	-0.68+	(0.409)	-0.12*	(0.063)
top less fuel	0.66+	(0.356)	0.06	(0.063)
top cheap	0.14	(0.428)	-0.00	(0.070)
top cook fast	0.18	(0.460)	-0.06	(0.073)
top traditions & habits	-0.05	(0.404)	-0.06	(0.063)
central_africa (baseline)	.		.	
eastern_africa	-0.07	(0.789)	0.06	(0.158)
somalia	1.45*	(0.704)	0.30**	(0.108)
south_sudan	0.57	(0.655)	0.16	(0.111)
sudan	-1.20+	(0.638)	-0.09	(0.107)
N	214		214	
F	4.80		6.48	
p	0.00		0.00	
r2	0.25		0.30	
r2_a	0.17		0.23	

Standard errors in parentheses
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.9: Estimates of treatment effects on energy efficiency, Kakuma.

	OLS		IV,2sls	
tot firewood qty	(treatm. index)	(treatm. pca)	(treatm. index)	(treatm. pca)
treatment	-0.90	2.48	15.78	47.88^{+}
	(1.504)	(7.645)	(11.711)	(26.117)
p-value	[0.551]	[0.746]	[0.035]	[0.067]
" weak IV-robust			[0.035]	[0.035]
sharpened q-value	[0.649]	[0.511]	[0.256]	[0.256]
N	175	175	175	175
r2	0.26	0.26	.	0.10
r2_a	0.17	0.17	.	-0.01

	OLS		IV,2sls	
firewood per hour	(treatm. index)	(treatm. pca)	(treatm. index)	(treatm. pca)
treatment	0.01	0.13^{+}	0.01	0.02
	(0.015)	(0.071)	(0.071)	(0.215)
p-value	[0.629]	[0.060]	[0.936]	[0.936]
" weak IV-robust			[0.936]	[0.936]
sharpened q-value	[0.649]	[0.136]	[0.650]	[0.650]
N	175	175	175	175
r2	0.22	0.24	0.22	0.23
r2_a	0.13	0.15	0.13	0.13

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.10: Estimates of treatment effects on health and safety, Kakuma.

	OLS		IV,2sls	
smoke problems	(treatm. index)	(treatm. pca)	(treatm. index)	(treatm. pca)
treatment	-0.03^{+}	-0.09	0.02	0.07
	(0.014)	(0.077)	(0.054)	(0.203)
p-value	[0.053]	[0.258]	[0.738]	[0.735]
" weak IV-robust			[0.731]	[0.731]
sharpened q-value	[0.140]	[0.275]	[0.650]	[0.650]
N	214	214	214	214
r2	0.18	0.17	0.13	0.15
r2_a	0.10	0.09	0.05	0.07

	OLS		IV,2sls	
accidents	(treatm. index)	(treatm. pca)	(treatm. index)	(treatm. pca)
treatment	0.02	0.09	-0.04	-0.17
	(0.014)	(0.077)	(0.055)	(0.202)
p-value	[0.212]	[0.230]	[0.427]	[0.414]
" weak IV-robust			[0.409]	[0.409]
sharpened q-value	[0.362]	[0.275]	[0.650]	[0.650]
N	214	214	214	214
r2	0.16	0.16	0.07	0.11
r2_a	0.07	0.07	-0.02	0.02

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.11: Estimates of treatment effects on time use, Kakuma.

hours of stove use	(1) OLS (treatm. index)	(2) (treatm. pca)	(3) IV,2sls (treatm. index)	(4) (treatm. pca)
treatment	-0.44*	-2.89*	0.97	3.55
	(0.211)	(1.157)	(0.955)	(3.281)
p-value	[0.038]	[0.013]	[0.311]	[0.279]
" weak IV-robust			[0.246]	[0.246]
sharpened q-value	[0.113]	[0.05]	[0.420]	[0.420]
N	213	213	213	213
r2	0.34	0.35	0.19	0.25
r2_a	0.28	0.28	0.11	0.17

tot time	OLS (treatm. index)	(treatm. pca)	IV,2sls (treatm. index)	(treatm. pca)
treatment	1.15	0.65	-8.08	-22.30
	(1.055)	(5.055)	(7.114)	(16.294)
p-value	[0.277]	[0.897]	[0.256]	[0.171]
" weak IV-robust			[0.155]	[0.155]
sharpened q-value	[0.383]	[0.511]	[0.420]	[0.420]
N	200	200	200	200
r2	0.16	0.15	.	0.03
r2_a	0.07	0.06	.	-0.07

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.12: Estimates of treatment effects on women and children workload, Kakuma.

female share of work	OLS (treatm. index)	(treatm. pca)	IV,2sls (treatm. index)	(treatm. pca)
treatment	-0.01	-0.06	0.07	0.17
	(0.009)	(0.050)	(0.068)	(0.146)
p-value	[0.413]	[0.215]	[0.321]	[0.253]
" weak IV-robust			[0.224]	[0.224]
sharpened q-value	[0.525]	[0.275]	[0.420]	[0.420]
N	192	192	192	192
r2	0.46	0.47	0.25	0.40
r2_a	0.40	0.41	0.17	0.34

children involv.	OLS (treatm. index)	(treatm. pca)	IV,2sls (treatm. index)	(treatm. pca)
treatment	-0.04**	-0.26***	-0.10+	-0.38*
	(0.013)	(0.072)	(0.055)	(0.191)
p-value	[0.006]	[0.000]	[0.069]	[0.045]
" weak IV-robust			[0.051]	[0.051]
sharpened q-value	[0.055]	[0.004]	[0.256]	[0.256]
N	214	214	214	214
r2	0.21	0.23	0.11	0.22
r2_a	0.14	0.16	0.02	0.14

Standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix D

Appendix to Chapter 4

D.1 Discrete-choice experiment material

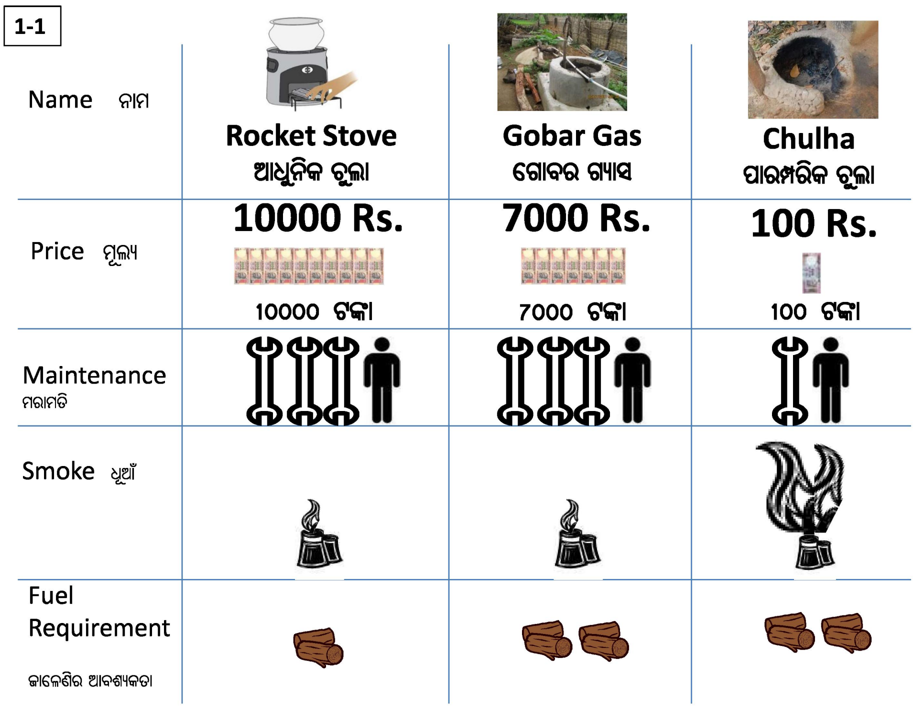

Figure D.1: Example of choice-card used in the discrete-choice experiment.

I. CHOICE SETS

We will now have a different exercise. This exercise involves three different cooking options: a traditional chulha, gobar gas, and a rocket stove.

Traditional Chulha **(give the participant the card):** This stove is homemade. It burns wood and other fuels. Most of you are currently using it or have used it before, hence are familiar with this cooking option.

Gobar Gas **(give the participant the card)**: This stove is built outside of your house. You must put the dung from your cattle into the inlet, and mix it with water. Through an opening in the inlet, the mixture will go beneath this dome and generate gas below. The gas formed is transferred through this pipe **(point to the pipe in the card)** to a stove in your kitchen. You can use this gas to cook. Everyday, you must spend about 30-60 minutes to add the dung, mix it with water, and keep the gobar gas plant functional.

Rocket Stove **(give the participant the card)**: In this stove, you have to place small pieces of wood on this tray and light it the way you would light your chulha. This stove is designed in a way that makes it easier to start a fire quickly and produces a much hotter and cleaner fire that uses significantly less fuel. This means faster cooking, time and fuel savings. This stove is portable- you can use it inside or outside your house.

Do you understand each of the different cooking options?

Each option has four features: price, repair, smoke, and fuel requirement.

Price: Price is how much you must pay for the stove. This is shown using thousand rupees notes or hundred rupee notes. ***(Please show the card which explains the price attribute)***
Do you understand the price attribute?

Maintenance: The next attribute is maintenance. ***(Please show the card which explains the maintenance attribute)***

- 1st symbol represents few maintenance visits to ensure operation of the stove
- 2nd symbol represents regular and thorough maintenance visits to ensure operation of the stove

Do you understand the maintenance attribute?

ଚୁଲି ମନୋନୟନ କାର୍ଯ୍ୟକ୍ରମ

ଆମ୍ଭେ ବ ର୍ତ୍ତମାନ ଗୋଟିଏ ଭିନ୍ନ ଧରଣର ମାନସିକ କସରତ କରିବା । ତିନି ପ୍ରକାରର ରନ୍ଧନ ପ୍ରଣାଳୀ ସଂପର୍କରେ ଏହି କାର୍ଯ୍ୟକ୍ରମ କରାଯାଉଛି । ଗୋଟିଏ ହେଉଛି ପାରମ୍ପରିକ ଚୁଲା, ଗୋଟିଏ ଗୋବର ଗ୍ୟାସ ଚୁଲା ଓ ଅନ୍ୟଟି ରକେଟ୍ ଷ୍ଟୋଭ୍ ବା ଆଧୁନିକ ଚୁଲା ।

ପାରମ୍ପରିକ ଚୁଲା : (ଲୋକଙ୍କୁ ଚିତ୍ର ଥିବା କାର୍ଡ଼ ଦେଖାଇ) ଘରେ ଘରେ ତିଆରି କରାଯାଏ । ଏଥିରେ କାଠ, ବାଉଁଶ, କୁଣ୍ଡା, ଘସି ଆଦି ଜଳେ । ଆମ୍ଭମାନଙ୍କ ମଧ୍ୟରୁ ଅନେକ ଏହି ପ୍ରକାର ଚୁଲା ସହିତ ପରିଚିତ । ଆଗରୁ ଆମେ ଏହାକୁ ବ୍ୟବହାର କରୁଥିଲେ, ଏବଂ ଏବେ ମଧ୍ୟ ବ୍ୟବହାର କରୁଛନ୍ତି ।

ଗୋବର ଗ୍ୟାସ୍ : (ଅଂଶ ଗ୍ରହଣ କରିଥିବା ଲୋକମାନଙ୍କୁ ଚିତ୍ର ଥିବା କାର୍ଡ଼ ଦେଖାଇ) ଗୋବର ଗ୍ୟାସ ପ୍ଲା ଆମ୍ଭମାନଙ୍କ ଘର ବାହାରେ ବସାଯାଇଥାଏ । ଏଥିରେ ଆମ ଗାଈ ଗୋରୁମାନଙ୍କର ଗୋବର ପାଣିସହ ମିଶାଇ ପୁରାଯାଏ । ଏହି ମିଶ୍ରଣ ଗମ୍ବୁଜରେ ଟାଙ୍କିର ତଳ ଅଂଶକୁ ଯାଏ । ସେଠାରେ ଏଥିରୁ ଗୋବର ଗ୍ୟାସ ନିର୍ଗତ ହୁଏ । ଟାଙ୍କି ସହ ପାଇପ୍‌ର ଗୋଟିଏ ମୁହଁ ସଂଯୋଗ କରି ରୋଷେଇ ଘର ଭିତରେ ଥିବା ଚୁଲି ସହ ଆଉ ଗୋଟିଏ ମୁହଁ ସଂଯାଗ କରାଯାଏ । (ଚିତ୍ର ଦେଖାଇବ) ଏହି ଗ୍ୟାସ ଚୁଲିରେ ଜଳେ ଏବଂ ଏହି ଚୁଲି ସାହାର୍ଯ୍ୟରେ ରନ୍ଧନ କାର୍ଯ୍ୟ କରିହୁଏ । ପ୍ରତିଦିନ ୩୦ ରୁ ୬୦ ମିନିଟ୍ ପର୍ଯ୍ୟନ୍ତ ସମୟ ଦେଇ ଗୋବର ସହ ପାଣି ମିଶେଇ ଗୋବର ଗ୍ୟାସ ପ୍ଲା ଭିତରକୁ ଛଡ଼ାଯାଏ ଏବଂ ସେଥିରୁ ଯେପରି ଗ୍ୟାସ୍ ପ୍ରସ୍ତୁତ ହୁଏ, ତାହା ସୁନିଶ୍ଚିତ କରାଯାଏ ।

ରକେଟ୍ ଷ୍ଟୋଭ୍ / ଆଧୁନିକ ଚୁଲା : (ଅଂଶ ଗ୍ରହଣ କରିଥିବା ଲୋକମାନଙ୍କୁ ଚିତ୍ର ଥିବା କାର୍ଡ଼ ଦେଖାଇ) ଏହି ଷ୍ଟୋଭ୍‌ରେ ଥିବା ପାତ୍ରରେ ଛୋଟ ଛୋଟ କାଠଖଣ୍ଡ ରଖି ପାରମ୍ପରିକ ଚୁଲି ଲଗାଇବା ଭଳି ଏଥିରେ ନିଆଁ ଲଗାଯାଏ । ଏହା ଏପରି ତିଆରି ହୋଇଛି ଯେ ସଙ୍ଗେ ସଙ୍ଗେ ନିଆଁ ଧରିଯାଏ । ଏଥିରୁ ଅଧିକ ଉ ାପ ଦେଉଥିବା ନିଆଁ ବାହାରେ । କମ୍ ଜାଳେଣିରେ ଏଥିରେ ରୋଷେଇ ହୋଇଯାଏ । ସୁତରାଂ କମ୍ ଜାଳ ଖର୍ଚ୍ଚ, କର୍ମ ସମୟରେ ରୋଷେଇ ହୋଇଥାଏ । ଏହା ଛୋଟ ଆକାରର । ତେଣୁ ଏହାକୁ ଗୋଟିଏ ଜାଗାରୁ ଅନ୍ୟ ଯାଗାକୁ ସହଜରେ ନେବା ଆଣିବା କରିହୁଏ । ଏଥିରେ ଘର ଭିତରେ ଓ ଘର ବାହାରେ ରୋଷେଇ କରିହେବ ।

ତୁମେମାନେ ବିଭିନ୍ନ ପ୍ରକାରର ରନ୍ଧନ ଚୁଲି ସଂପର୍କରେ ବୁଝି ପାରିଲ ତ ?
ପ୍ରତ୍ୟେକ ପ୍ରକାରର ରନ୍ଧନ ଚୁଲିକୁ ଆମେ ପା ଟି ଦିଗରୁ ବିଚାର କରିବା । ତାହାହେଲା ମୂଲ୍ୟ, ମରାମତି ସୁବିଧା, ଧୂଆଁ, ଜାଳକାଠ ବା ଜାଳେଣୀର ଆବଶ୍ୟକତା ଏବଂ ରନ୍ଧନ କ୍ଷମତା ।

ମୂଲ୍ୟ : ପ୍ରତ୍ୟେକ ଚୁଲାର ବିଭିନ୍ନ ପ୍ରକାରର ମୂଲ୍ୟ ରହିଛି । ପ୍ରତ୍ୟେକ ଚୁଲାର ମୂଲ୍ୟ ହଜାରେ ଟଙ୍କିଆ ନୋଟ୍‌ର ଚିତ୍ର ସାହାଯ୍ୟରେ ଦେଖାଇ ଦିଆଯାଇଛି । (ଚିତ୍ର ଦେଖାଇବେ, ଯାହାକି ମୂଲ୍ୟକୁ ବୁଝାଉଥିବ)
ବ ର୍ତ୍ତମାନ ଆପଣ ବୁଝିଲେତ, କେଉଁ ପ୍ରକାରର ଚୁଲା ପାଇଁ କେତେ ମୂଲ୍ୟ ଦେବାକୁ ହେବ ?

ରକ୍ଷଣାବେକ୍ଷଣ: ବ ର୍ତ୍ତମାନ ଏହି ଚୁଲାମାନଙ୍କର ରକ୍ଷଣାବେକ୍ଷଣ କଥା ବିଚାର କରିବା । **(ବିଭିନ୍ନ ପ୍ରକାର ଚୁଲା ରକ୍ଷଣାବେକ୍ଷଣ ହେଉଥିବା ଚିତ୍ର ପ୍ରଦର୍ଶନ)**

- ପ୍ରଥମ ସଙ୍କେତରୁ ଜଣାପଡ଼ିବ, ରକ୍ଷଣାବେକ୍ଷଣ ପାଇଁ କମ୍ ଥର ପରିଦର୍ଶନ କରନ୍ତି ।
- ଦ୍ୱିତୀୟ ସଙ୍କେତରୁ ଜଣାପଡ଼ିବ ଯେ, ରକ୍ଷଣାବେକ୍ଷଣ ପାଇଁ ଅଧିକ ଥର ପରିଦର୍ଶନ କରନ୍ତି ।

ବ ର୍ତ୍ତମାନ ବିଭିନ୍ନ ପ୍ରକାରର ଚୁଲାର ରକ୍ଷଣାବେକ୍ଷଣ ସଂପର୍କରେ ବୁଝି ପାରିଲ ତ ?

Smoke: The third attribute is smoke. ***(Please show the card which explains the smoke attribute)*** This attribute is determined by the amount of smoke that is generated during cooking.

- 1st symbol represents low amounts of smoke.
- 2nd symbol represents a lot of smoke

Do you have any questions about the smoke attribute?

Fuel Requirement: The next attribute is fuel requirement. ***(Please show the card which explains the fuel requirement attribute).*** Each option will show the fuel needed for cooking with this stove – both the amount and the time required to collect and prepare .

- 1st symbol represents a small amount of fuel and time.
- 2nd symbol represents a medium amount of fuel and time.
- 3rd symbol represents a large amount of fuel and time.

Do you have any questions about the fuel attribute?

I will now show you cards with the three different cooking options each with varying features. I would like you to choose which option you would prefer. There is no wrong or right answer. ***(Enumerator: please give the first choice card)***

ଧୂଆଁ : ତୃତୀୟ ବିଷୟର ବିଷୟ ହେଲା ଧୂଆଁ । (ବିଭିନ୍ନ ପ୍ରକାର ଚୁଲିରୁ ଧୂଆଁ ନିର୍ଗତ ହେଉଥିବା ଚିତ୍ର ପ୍ରଦର୍ଶନ କରାଇବେ)

ବର୍ତ୍ତମାନ ଦେଖନ୍ତୁ କେଉଁ ପ୍ରକାର ଚୁଲିରୁ କେତେ ପରିମାଣର ଧୂଆ ବାହାରୁଛି :-

- ପ୍ରଥମ ଚିତ୍ର: କମ୍ ପରିମାଣ ଧୂଆଁ ବାହାରୁଛି ଦେଖାଇ ଦିଆଯାଇଛି
- ଦ୍ୱିତୀୟ ପ୍ରକାର ଚୁଲିରୁ ଅଧିକ ପରିମାଣରେ ଧୂଆଁ ବାହାରୁଛି ।

ଆପଣମାନେ ବିଭିନ୍ନ ପ୍ରକାର ଧୂଆଁ ବାହାରିବା ସଂପର୍କରେ ଆଉକିଛି ପଚାରିବେକି ?

ଜାଳେଣି ଆବଶ୍ୟକତା : ବର୍ତ୍ତମାନ ବିଭିନ୍ନ ପ୍ରକାରର ଚୁଲି ନିମନ୍ତେ ଜାଳେଣି ଆବଶ୍ୟକତା ସଂପର୍କରେ ବିଚାର କରିବାର କଥା । (ବିଭିନ୍ନ ପ୍ରକାର ଚୁଲି ଆବଶ୍ୟକ କରୁଥିବା ଜାଳେଣି ସଂପର୍କରେ ଚିତ୍ର ପ୍ରଦର୍ଶନ କରନ୍ତୁ)
ପ୍ରତ୍ୟେକ ଚିତ୍ର ଚୁଲା ଚଳିବା ପାଇଁ ଦରକାର ହେଉଥିବା ଜାଳେଣି ବିଷୟରେ ଦର୍ଶାଉଛି – ସଂଗ୍ରହ ଏବଂ ତିଆରିକରିବା ପାଇଁ ଦରକାର ହେଉଥିବା ପରିମାଣ ଓ ସମୟକୁ ଦର୍ଶାଉଛି ।

- କମ୍ ପରିମାଣର ଜାଳେଣି ଏବଂ ସମୟକୁ ପ୍ରଥମ ଚିତ୍ରରେ ସୂଚୀତ କରାଯାଇଛି ।
- ମଧ୍ୟମ ପରିମାଣର ଜାଳେଣି ଏବଂ ସମୟକୁ ଦ୍ୱିତୀୟ ଚିତ୍ରରେ ସୂଚୀତ କରାଯାଇଛି ।
- ଅଧିକ ପରିମାଣ ଏବଂ ସମୟକୁ ତୃତୀୟ ଚିତ୍ରରେ ସୂଚୀତ କରାଯାଇଛି ।

ଆପଣମାନେ ଜାଳେଣି ସମ୍ବନ୍ଧରେ ଆଉକିଛି ପଚାରିବେ କି ?

ମୁଁ ବର୍ତ୍ତମାନ (ସାକ୍ଷାତ୍‌କାରୀ) ଆପଣମାନଙ୍କୁ ତିନୋଟି ଚୁଲିର ଚିତ୍ର ଦେଖାଉଛି । ପ୍ରତ୍ୟେକ ଚୁଲିର ବିଭିନ୍ନ ପ୍ରକାରର ଗୁଣ ଓ ଦକ୍ଷତା ରହିଛି । ଏହାକୁ ଭଲ ଭାବେ ଦେଖିସାରୁ କୁହ – କେଉଁ ଚୁଲିଟି ତୁମର ପ୍ରଥମ ପସନ୍ଦ । ଏଥିରେ ଭୁଲ ଓ ଠିକ୍ ଉତ୍ତର ନାହିଁ । (ଗଣନାକାରୀ : ଦୟାକରି ପ୍ରଥମ ପସନ୍ଦ ଚିତ୍ର ଦେକାନ୍ତୁ) ।

Figure D.2: Script used to introduce the discrete-choice experiment, in English and Odia.

D.2 Description of the sample

D.2.1 Characteristics of the respondents

Table D.1 shows descriptive statistics for the demographic and socio-economic characteristics of the respondents, community engagement, safety nets, risk aversion and impatience, cookstove and fuel use, and cooking behaviours. As a general description of the sample, respondents (whenever possible the survey was conducted with the head of the household) are on average 43 years old, with half the sample between 32 and 53, and less than a third are women.

Most households cook for 4-5 members every day (*hhsize_cookedfor*), live in houses with an estimated value between 50,000 and 200,000 INR (~600-2500 GBP) and 2 to 4 rooms. The caste composition of the sample is 8% scheduled castes, 12% scheduled tribes, 63% other backward castes, and 17% open or general. 40% of the households are below the poverty line. Further information on the wealth of the household are provided by an asset-ownership index (constructed as the number of different types of assets the household owns in a given list, which includes different electrical appliances, transportation means, phones and television sets, different pieces of furniture, etc.) and low quality of housing material index (higher value means lower quality materials are used; the index is constructed using information on the materials used for the floor, walls, and roof of the kitchen and of the living area).

Expenditures in non-food items, a proxy for disposable income, are on average 27,000 INR (340 GBP) per year, with a median of 16,200 INR (200 GBP) denoting a skewed distribution; expenditures for electricity and/or fuels for lighting are on average 1,800 INR (23 GBP) per year, and 86% of households in the sample have electric lighting. The credit constraint index measures how difficult it is for households to access credit, and is constructed using answers to the question "If you have to borrow Rs. 5000 (from a money lender or micro-finance groups, not from the family member and friends) for one month, would this be possible?", with values (1) yes, quite easy, (2) yes, but not easy, (3) may be not sure, (4) not possible, and 2 being the average and median response in the sample.

30% of the households are members of a self-help group and 28% participate in community or neighbourhood cleaning activities, a signal of community engagement and awareness of hygiene and health issues. Most households live within a 3-10 minute walk from the center of their village, 1-10 minute from the nearest all-weather road, and 5-20 minute from a mason or plumber. 23% of the respondents reported cooking inside the living areas (i.e. the kitchen and living rooms are the same, with or without a partition to separate them, but no walls). Fuel-stacking behaviour is pervasive; details on the combination of cookstove technologies used by sample households are presented in Table D.2. Values for cooking and fuel-related variables are described by sample group in the next sub-section, as they are related to the way the stratification groups are defined.

D.2.2 Characteristics and use of the existing biogas plants

Table D.3 presents descriptive statistics for variables related to the biogas plant and the motivations for its adoption, for households in the sample groups with working and broken biogas. All the biogas plants are fixed-dome (Deenbandhu model); with a capacity of either 1 m^3 (15% of the households) or a larger 2 m^3 (85% of the households; the variable *biogasplantsize* is coded 1 for the larger size, and 0 for the smaller size). Most plants were installed between 2004 and 2010, with some going back as far as the 1980s. On average, households paid 3,500 INR (44 GBP) out of their own pockets for the plant, while the average subsidy was around 3,700 INR (47 GBP). Everyone in the sample received subsidies for the construction of the plant, ranging from 17% to 82% of the overall cost; the vast majority (91%) received them from OREDA, and the remaining 9% from other support schemes from the government of Odisha. OREDA also played an important role in spreading awareness about the subsidy scheme, as 72% of the households heard about the program from them, while 22% found out through the person who installed the plant and and 6% through family or friends.

On operation and maintenance, households with a broken biogas plant were asked to answer with reference to when the plant was working properly. Households spend between 2 and 6 hours each week (equivalent to about 15-50 minutes a day) operating and maintaining the plant, of which 0.5-2 hours collecting the dung, 0.5-2.5 hours feeding it into the plant, and 1-1.5 hours cleaning. Only one household in the whole sample reported having to purchase dung for the biogas plant, while the others have dung available that only needs to be collected (not reported in the table). One of the important co-benefits of using biogas, is that the slurry resulting from the gasification process can be used as fertiliser in agriculture, and in fact this is often of higher quality than the fertilisers available at the local markets or undigested manure (Insam et al., 2015; Chen et al., 2010; Brown, 2006). 83% of the respondents say they have noticed that agricultural yield increases with the slurry if compared to purchased fertilisers or animal manure, while the remaining has either noticed no difference or has no experience to makes the comparison; only one respondent claimed that the yield decreases compared to the other fertiliser options. Yet, only 14% purposefully use the slurry as fertiliser, while most households (82%) simply dump it in the field. 9% of the respondents make it into cakes to be burned as fuel for cooking or other energy purposes[1].

Finally, households with a biogas plant were asked what factors they had considered when deciding to install a biogas plant, and to rank the relevant ones in order of importance. Table D.3 reports those that are listed as the top three. The most cited factor is dung availability (88% of respondents), followed closely by saving on fuelwood (80%). Important is also the cost factor, cited by about half of the respondents (48%). Maintenance costs and health benefits were considered as top 3 motivations by 24% of respondents each, while air quality and credit availability by 11% and 10% respectively.

D.3 Additional tables

[1]Households were allowed to select more than one option, and 7.5% selected both dump it in the field and make it into cakes for fuel, which is why percentages add up to more than 100

Table D.1: Summary statistics of the sample of 503 households.

	mean	sd	min	p25	p50	p75	max
age_respondent	43.38	14.19	16	32	42	53	85
female_respondent	0.30	0.46	0	0	0	1	1
hhsize_cookedfor	4.62	1.25	1	4	5	5	9
children_cookedfor	0.70	0.94	0	0	0	1	4
general_caste	0.17	0.38	0	0	0	0	1
OBC_caste	0.63	0.48	0	0	1	1	1
SCST_caste	0.20	0.40	0	0	0	0	1
belowpovertyline	0.40	0.49	0	0	0	1	1
lowqltyhousematerial (index)	26.09	10.87	8	17	26	36	44
assetsownership (index)	9.19	3.98	2	6	9	12	21
housevalue (1,000 INR)	154.83	144.81	10.00	50.00	100.00	200.00	800.00
numberrooms	3.00	1.30	1	2	3	4	7
expenditures (1,000 INR/year)	26.97	31.30	2.55	8.90	16.21	32.69	343.00
electrnlightexp (1,000 INR/year)	1.79	0.95	0	1.10	1.68	2.30	4.90
electriclight (dummy)	0.86	0.34	0	1	1	1	1
receivelpgsubs (dummy)	0.09	0.28	0	0	0	0	1
receivekerosubs (dummy)	0.92	0.28	0	1	1	1	1
receivefoodsubs (dummy)	0.41	0.49	0	0	0	1	1
receiveemploymsubs (dummy)	0.09	0.29	0	0	0	0	1
creditconstr (index)	2.16	1.02	1	1	2	3	4
shg_member (dummy)	0.30	0.46	0	0	0	1	1
cleancommunity (dummy)	0.28	0.45	0	0	0	1	1
distancevillagecentre (min. walking)	6.46	5.24	0	3	5	10	31
distanceroad (min. walking)	7.41	8.24	0	1	5	10	45
distancemason (min. walking)	15.71	18.83	0	5	10	20	130
plotarea (1,000 sq foot)	1.87	1.70	0.16	0.80	1.20	2.20	9.00
livestockqty_small	1.53	4.75	0	0	0	0	45
livestockqty_big	2.98	3.22	0	0	2	4	25
selreportriskaverse	2.76	1.34	0	2	3	4	5
riskaverse	3.28	1.10	1	3	4	4	4
selfreportimpatient	2.18	1.24	0	1	2	3	5
impatient	3.34	1.08	1	3	4	4	4
numberstovetypes	1.87	0.75	1	1	2	2	5
hastraditional (dummy)	0.91	0.28	0	1	1	1	1
haskerosene (dummy)	0.18	0.39	0	0	0	0	1
haslpg (dummy)	0.20	0.40	0	0	0	0	1
haselectric (dummy)	0.07	0.26	0	0	0	0	1
timeuseallstove (minutes/day)	237.34	77.13	0	180	240	280	910
timeusebiomassstove (minutes/day)	147.71	87.48	0	60	150	210	445
timeusecleanstove (minutes/day)	89.62	82.44	0	0	90	150	610
ventilqty (index)	0.93	0.52	0	1	1	1	4
cookinlivingareas (dummy)	0.23	0.42	0	0	0	0	1
believesmokeunhealthy (index)	2.23	0.85	1	2	2	3	5
woodqtyused (kg/week)	30.50	15.88	0	20	30	40	80
collectwood (dummy)	0.74	0.44	0	0	1	1	1
qtywoodcollect (kg/year)	1414.36	1559.89	0	0	1200	2250	12800
woodhardtofind (dummy)	0.67	0.47	0	0	1	1	1
usedailywood (dummy)	0.69	0.46	0	0	1	1	1
usedailylpg (dummy)	0.11	0.31	0	0	0	0	1
usedailykeros (dummy)	0.04	0.20	0	0	0	0	1
usedailyelectr (dummy)	0.04	0.19	0	0	0	0	1
N	503						

Table D.2: Fuel-stacking: combination of cookstove technologies for the full sample (503 households).

group # stove types		include traditional	clean only
group 1			
	1		biogas (11%)
	2	trad+biogas (66%)	LPG+biogas (4%) electric+biogas (1%)
	3+	trad+biogas+keros (7%) trad+biogas+LPG (3%) trad+biogas+electric(1.5%) trad+biogas+keros+LPG (3%) trad+biogas+keros+LPG+electric (2%)	keros+LPG+biogas (1.5%)
group 2			
	1		biogas (2%)
	2	trad+biogas (78%)	LPG+biogas (4%) keros+biogas (1%)
	3+	trad+biogas+keros (7%) trad+biogas+LPG (5%) trad+biogas+keros+LPG+electric (2%)	LPG+electric+biogas (1%)
group 3			
	1		LPG (3%) kerosene (1%)
	2	trad+LPG (31%) trad+keros (25%) trad+electric (10%) trad+ICS (2%)	keros+LPG (2%) LPG+electric (1%)
	3+	trad+keros+LPG (11.5%) trad+keros+electric (6.5%) trad+LPG+electric (1%) trad+ICS+keros (1%) trad+keros+LPG+electric (3%)	keros+LPG+electric (2%)
group 4			
	1	trad. (100%)	
total		91%	9%

Table D.3: Summary statistics of the variables related to the existing biogas plants in the sample (253 households).

	mean	sd	min	p25	p50	p75	max
installationyear	2005.74	6.36	1982	2004	2009	2010	2011
biogasplantsize_large	0.85	0.35	0	1	1	1	1
price_paidbyhh[1] (INR)	3506.50	1746.31	580	2170	3225	4000	12000
subsidies[1] (INR)	3731.61	1437.65	1300	2750	3510	4500	8000
subspriceratio (%)	0.52	0.14	0.17	0.46	0.50	0.59	0.82
time_total (hours/week)	4.34	0.97	2.10	3.50	4.50	5.00	6.00
time_collectdung (hours/week)	1.40	0.51	0.50	1.00	1.50	2.00	2.00
time_feedplant (hours/week)	1.46	0.62	0.50	1.00	1.00	2.00	2.50
time_cleaning (hours/week)	1.49	0.06	1.00	1.50	1.50	1.50	1.50
slurry_dumpinfield	0.82	0.39	0	1	1	1	1
slurry_fertilize	0.14	0.35	0	0	0	0	1
slurry_cakeforenergy	0.09	0.29	0	0	0	0	1
increased yield	0.83	0.37	0	1	1	1	1
top3_dungavailability	0.88	0.32	0	1	1	1	1
top3_woodsavings	0.80	0.40	0	1	1	1	1
top3_cost	0.48	0.50	0	0	0	1	1
top3_maintenancecost	0.24	0.43	0	0	0	0	1
top3_health	0.24	0.43	0	0	0	0	1
top3_airquality	0.11	0.32	0	0	0	0	1
top3_creditavailability	0.10	0.30	0	0	0	0	1
N	253						

[1] Subsidies are defined as additional to the price paid by the household. The total price is therefore the price paid by the household plus the subsidy.

Table D.4: Regression table. Model (1) is a multinomial logit with outcome "having a biogas plant" (baseline), "other clean stoves" and "traditional only"; model (2) is an ordinal logit model for whether the household has only one type of cookstove, two types, or three or more.

	(1)		(2)
	stovegroup		stovestacking
	other clean	traditional only	stovestacking
age_respondent	0.004	0.004	-0.011
	(0.009)	(0.010)	(0.006)
female_respondent	-0.087	0.152	-0.394*
	(0.277)	(0.246)	(0.171)
distance_roadallweather	-0.006	-0.019	-0.009
	(0.015)	(0.013)	(0.011)
OBC_caste	0.725*	0.736	-0.123
	(0.319)	(0.404)	(0.337)
SCST_caste	0.021	0.506	-0.034
	(0.528)	(0.509)	(0.484)
belowpovertyline	-0.235	0.149	-0.070
	(0.355)	(0.272)	(0.250)
healthbelief	-0.057	0.126	0.005
	(0.184)	(0.190)	(0.144)
hhsize_adj_cookedfor	-0.269	0.143	-0.137
	(0.153)	(0.141)	(0.091)
children_cookedfor	0.082	0.001	0.040
	(0.159)	(0.130)	(0.088)
assetsownership	0.030	-0.188**	0.141***
	(0.058)	(0.058)	(0.042)
numberrooms	0.116	-0.039	0.122
	(0.126)	(0.131)	(0.086)
lowqltyhousematerial	-0.029	0.027	-0.036**
	(0.016)	(0.016)	(0.012)
lnyearexp	0.851**	0.243	0.103
	(0.266)	(0.220)	(0.175)
creditconstr	0.305	0.116	-0.128
	(0.159)	(0.134)	(0.098)
shg_member	0.040	0.153	-0.013
	(0.294)	(0.279)	(0.255)
cleancommunity	-0.146	-0.195	0.352
	(0.377)	(0.283)	(0.182)
distancevillagecentre	-0.046	0.003	-0.043**
	(0.026)	(0.024)	(0.016)
plotarea	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
livestockqty_small	-0.040	-0.028	0.031
	(0.028)	(0.022)	(0.022)
livestockqty_big	-0.393***	-0.268*	0.054
	(0.090)	(0.110)	(0.029)
riskaverse	-0.266*	0.057	-0.036
	(0.133)	(0.147)	(0.113)
impatient	0.081	-0.094	0.008
	(0.156)	(0.163)	(0.106)
_cons	-7.004**	-3.078	
	(2.602)	(2.262)	
N	503		503
pseudo R^2	0.23		0.13

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.5: Regression table. Logit estimates for the likelihood of "planning to build a biogas plant", for households who do not currently have biogas.

	(3) plan to install biogas	
plan_biogas		
group4 (trad. only)	0.360	(0.358)
age_respondent	0.002	(0.014)
female_respondent	-0.378	(0.384)
distance_roadallweather	0.014	(0.025)
OBC_caste	0.015	(0.508)
SCST_caste	0.217	(0.585)
belowpovertyline	0.451	(0.338)
healthbelief	-0.218	(0.171)
hhsize_adj_cookedfor	-0.012	(0.142)
children_cookedfor	0.066	(0.150)
assetsownership	0.043	(0.069)
numberrooms	0.266	(0.153)
lowqltyhousematerial	-0.026	(0.015)
lnyearexp	-0.073	(0.264)
creditconstr	-0.351*	(0.145)
shg_member	0.474	(0.358)
cleancommunity	-0.198	(0.330)
distancevillagecentre	-0.032	(0.024)
plotarea	0.000	(0.000)
livestockqty_small	0.064	(0.087)
livestockqty_big	0.103	(0.103)
riskaverse	0.053	(0.135)
impatient	-0.232	(0.146)
_cons	1.437	(2.852)
N	250	
pseudo R^2	0.14	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.6: Regression table. OLS estimates for time and share of time stoves are used.

	(4a) time, all stoves		(4b) time, clean		(4c) time, biomass		(4d) share, clean	
2.samplegroup	31.0**	(11.02)	-48.2***	(11.33)	79.2***	(8.32)	-0.3***	(0.04)
3.samplegroup	-35.0*	(16.28)	-78.1***	(13.17)	43.1***	(9.63)	-0.2***	(0.03)
4.samplegroup	-8.4	(9.35)	-128.4***	(7.58)	120.0***	(9.25)	-0.5***	(0.03)
hastraditional	38.5*	(16.35)	-15.7	(13.71)	54.2***	(10.69)	-0.2***	(0.04)
haskerosene	36.5**	(11.21)	29.1**	(9.27)	7.5	(7.00)	0.0	(0.02)
haslpg	13.8	(13.78)	54.8***	(10.96)	-41.0***	(10.02)	0.2***	(0.03)
haselectric	1.9	(21.80)	31.4*	(15.02)	-29.5*	(11.69)	0.1***	(0.03)
age_respondent	0.2	(0.27)	0.1	(0.20)	0.2	(0.18)	-0.0	(0.00)
female_respondent	-5.8	(7.07)	1.6	(4.90)	-7.4	(5.42)	0.0	(0.02)
distance_roadallweather	0.0	(0.48)	0.4	(0.34)	-0.4	(0.29)	0.0	(0.00)
OBC_caste	-2.6	(9.26)	7.4	(8.43)	-10.0	(8.05)	0.0	(0.03)
SCST_caste	6.0	(9.91)	14.3	(9.80)	-8.3	(9.43)	0.0	(0.04)
belowpovertyline	6.3	(7.58)	5.8	(5.62)	0.5	(7.15)	0.0	(0.02)
healthbelief	-2.7	(3.75)	-0.0	(3.42)	-2.7	(3.37)	0.0	(0.01)
hhsize_adj_cookedfor	17.0***	(3.31)	2.9	(2.82)	14.0***	(2.86)	-0.0	(0.01)
children_cookedfor	0.0	(2.84)	-2.1	(2.80)	2.1	(3.19)	-0.0	(0.01)
assetsownership	3.1*	(1.46)	1.9	(1.18)	1.2	(1.22)	0.0	(0.00)
numberrooms	0.2	(4.10)	1.3	(3.12)	-1.1	(2.44)	0.0	(0.01)
lowqltyhousematerial	0.4	(0.33)	-0.3	(0.34)	0.7*	(0.32)	-0.0	(0.00)
ln yearly expenditures	-10.4	(5.48)	0.2	(3.70)	-10.6	(5.69)	0.0	(0.02)
creditconstr	2.4	(3.53)	-0.7	(2.32)	3.1	(3.20)	-0.0	(0.01)
shg_member	-8.9	(9.41)	-7.6	(6.53)	-1.3	(7.73)	-0.0	(0.02)
cleancommunity	9.3	(6.11)	-6.0	(5.35)	15.3*	(6.38)	-0.0	(0.02)
distancevillagecentre	-1.7*	(0.76)	-1.0	(0.49)	-0.8	(0.58)	-0.0	(0.00)
plotarea	0.0	(0.00)	-0.0	(0.00)	0.0	(0.00)	-0.0	(0.00)
livestockqty_small	-0.6	(0.71)	-0.5	(0.41)	-0.1	(0.62)	-0.0	(0.00)
livestockqty_big	-1.6	(1.29)	-0.8	(0.92)	-0.7	(0.86)	-0.0	(0.00)
riskaverse	-3.0	(2.99)	0.0	(2.39)	-3.1	(2.48)	0.0	(0.01)
impatient	-2.8	(3.74)	-0.0	(2.70)	-2.8	(3.12)	0.0	(0.01)
N	503		503		503		498	
adj. R^2	0.16		0.56		0.54		0.69	

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.7: Regression table. Logit estimates for the likelihood of having a working biogas plant, as opposed to broken (baseline).

	(5a) working biogas v. broken (baseline)		(5b) never broken v. has broken (baseline)	
age_respondent	0.002	(0.011)	0.009	(0.011)
female_respondent	0.327	(0.354)	0.530	(0.360)
OBC_caste	0.654	(0.519)	0.893	(0.463)
SCST_caste	0.093	(0.760)	0.161	(0.646)
belowpovertyline	0.227	(0.344)	0.199	(0.296)
hhsize_adj_cookedfor	-0.089	(0.170)	-0.113	(0.160)
children_cookedfor	-0.007	(0.230)	0.003	(0.212)
assetsownership	-0.044	(0.054)	-0.048	(0.057)
numberrooms	-0.283*	(0.132)	-0.305*	(0.139)
lowqltyhousematerial	-0.026	(0.022)	-0.023	(0.021)
lnyearexp	0.815**	(0.308)	0.789**	(0.304)
creditconstr	-0.258	(0.227)	-0.240	(0.190)
shg_member	-0.443	(0.560)	-0.508	(0.549)
cleancommunity	0.720	(0.496)	0.559	(0.466)
distancevillagecentre	-0.082**	(0.028)	-0.062*	(0.024)
distance_roadallweather	-0.008	(0.019)	0.002	(0.020)
plotarea	0.000	(0.000)	-0.000	(0.000)
livestockqty_small	0.077**	(0.025)	0.081**	(0.026)
livestockqty_big	0.075	(0.052)	0.057	(0.047)
healthbelief	0.341	(0.237)	0.433*	(0.218)
riskaverse	-0.483	(0.250)	-0.429	(0.243)
impatient	0.280	(0.217)	0.294	(0.242)
top3_cost	-0.400	(0.463)	-0.418	(0.433)
top3_maintcost	0.405	(0.469)	0.117	(0.409)
top3_dungavailab	1.059	(0.562)	0.945	(0.533)
top3_creditavail	-0.193	(0.746)	-0.293	(0.736)
top3_woodsaving	0.671	(0.501)	0.423	(0.500)
top3_health	0.157	(0.410)	0.011	(0.426)
top3_airqlty	0.029	(0.528)	0.283	(0.466)
slurry_fertilize	-1.079**	(0.379)	-1.188**	(0.395)
slurry_cakeforenergy	1.091	(0.698)	1.181	(0.642)
noteyieldsup	-0.610	(0.606)	-0.548	(0.601)
biogasplantsize_large	1.460**	(0.535)	1.213*	(0.497)
totbiogasprice_imputed	-0.000	(0.000)	-0.000	(0.000)
totbiogassubs_imputed	0.000	(0.000)	0.000	(0.000)
subspriceratio_adj	-2.105	(5.605)	0.719	(5.810)
timebiogas_collectdung_imputed	-1.574***	(0.409)	-1.385***	(0.377)
timebiogas_feedplant_imputed	0.845**	(0.325)	0.834*	(0.338)
timebiogas_cleaning_imputed	7.086***	(2.140)	12.882***	(2.344)
installationyear	0.154***	(0.040)	0.133***	(0.033)
N	253		253	
pseudo R^2	0.33		0.30	

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$