The London School of Economics and Political Science

Essays on the economics of energy efficiency policies

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Abstract

This work presented in this thesis aims to provide a better understanding of how agents respond to policy incentives to encourage energy efficiency improvements. First of all, the way agents respond to policy incentives crucially depends on heterogeneity in characteristics determining their responsiveness to taxes and subsidies. Second, agents' heterogeneous responses to policy can undermine the cost-effectiveness of subsidies. Third, under conditions where the policy targeting is poor or agents are not very responsive to the traditional market-based instruments other policy instruments based on information provision or nudges may be more effective.

I propose a theoretical model on optimal tax and subsidy combinations to correct externalities from energy consumption and underinvestment in energy efficient technologies. I show that when agents misperceive their true energy efficiency, the targeting efficiency of policies based on subsidies is poor and consumers selection into adoption is adverse. Adverse selection arises because those more likely to adopt consume less energy and overvalue the benefit from adoption. In the second chapter, I present a discussion on energy policies in the United Kingdom and analyse the energy consumption and energy efficiency measures adoption patterns using data for households in England and Wales. This sets the stage for Chapter 3, where I present an empirical study to test whether selection into adoption is adverse or not. I find that early technology adopters consume more energy before adoption and experience higher energy consumption drops upon adoption. Thus, supporting the idea that consumers' heterogeneity plays a major role to explain the observed adoption patterns. The results suggest that adoption decisions are driven by heterogeneity in preferences rather than heterogeneity in beliefs. Hence, overall selection is not adverse and this suggests the role of misperceptions is dominated by the effect of preferences heterogeneity. This does not preclude, however, that biased beliefs may have a role at determining the adoption patterns and responses to policy interventions.

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Introduction

In the last decades, general interest in energy policy has grown dramatically. Energy policy has been placed at the center of the policy debate as a result of the increasing concerns about reducing global carbon dioxide and other greenhouse gas emissions directly related with Climate Change. In addition, governments are concerned about guaranteeing energy supply, reducing the degree of energy dependence on energy imports and addressing the impact of pollution emissions associated with energy consumption and production at a local level.

In this thesis, I focus on policies that promote investments in energy-efficiency improvements and efficient energy use in the residential sector. Using a behavioral economics approach, I provide a model to think about how households' heterogeneity affects the technology diffusion process and its relevance for policy design. Then, using residential energy consumption data I test the empirical predictions of the model.

Residential energy consumption is at least as important as transport energy efficiency policy or industrial sector energy efficiency policy. Energy consumption in residential buildings accounts for around 20% of the total energy consumption in the United States (Walls, 2014) and 29% in the United Kingdom (Energy consumption in the UK 2016 report). In addition, the residential sector is of particular interest to the research presented here, since the impact of psychological biases and the role of behavioral economics models might be of paramount importance to rethink how to design incentive schemes in a cost-effective manner.

Aside from changes in energy consumption behavior, reductions in energy consumption result mostly from the diffusion of enhanced energy efficiency technologies among firms and consumers. However, empirical evidence suggests agents often fail to make profitable technology investments. For instance, according to data reported by the Energy Saving Trust, loft insulation installation has a cost ranging from £285 to £395 and would pay out at £135-£240 in energy bill savings per year[1]. However, the data shows low adoption rates every year and a very slow gradual technology diffusion rate among households. UK National Energy Efficiency Data shows loft insulation yearly adoption rates are around 2%. At the same time, loft insulation would imply an associated reduction in CO2 emissions of 1000 kgCO2/year reduction, contributing in turn to reduce the impact on the environment. In the context of energy efficiency technology adoption market failures associated with suboptimal technology adoption rates interact with the energy consumption negative externality, leading to what is known as the energy efficiency gap.

Other areas of research, like development economics, have directed effort to understand why agents fail to adopt technologies for which the returns are expected to be high. Finding evidence that psychological biases lead agents to underinvest, see Mullainathan (2007) for a review. The development economics literature has placed a lot of attention on the technology adoption and input choice decisions by farmers. For instance, Duflo et al. (2008) and Suri (2011) provide experimental evidence that technology adoption is too low even when the returns are high. Bryan et al. (2014) provide a rationale and empirically find support for underinvestment in profitable technologies when experimenting is costly.

First references pointing at the energy efficiency gap go back to Hausman (1979), followed by a strand of literature supporting the idea that individuals behave as if they had a huge discount factor on future savings when making purchase decisions of durable goods. There are, however, many other possible explanations for the observed slow diffusion of energy efficiency improvements. Among them, consumers' preferences heterogeneity is of particular relevance for

[1]See Appendix A.2 for additional information on energy efficiency measures installation costs and expected returns

the work presented here. Hausman and Joskow (1982) argue that heterogeneous consumers might place different value on the benefits and costs of technology adoption and, as a consequence, this would generate an adoption pattern where initially only those who value more the new technology would adopt, followed by a gradual technology diffusion process. Hasset and Metcalf (1995) analyse the impact of tax credits on residential energy conservation investments, finding that accounting for unobserved heterogeneity plays an important role in energy conservation decisions and responses to policy.

More recently, the application of psychology insights to economics (behavioral economics) has led to the development of new rationales for the observed empirical facts. Models based on time-inconsistent preferences, reference-dependent preferences, limited attention decision making, non standard beliefs among others could lead to an undervaluation of the technology adoption benefits and, therefore, are able to provide an explanation for the energy efficiency gap. There is supporting evidence to the fact that agents might hold systematically biased beliefs. For example, DellaVigna and Malmendier (2006) provides evidence of overconfidence on future attendance to the gym, Spinnewijn (2015) on the fact that unemployed tend to be too optimistic about their prospects of finding a job. Specific to the energy policy context, Attari et al (2010) show evidence that consumers underestimate the energy use required to satisfy their energy services demand (heating, cooling, lighting).

In the public economics field, behavioral public economics has provided new insights on many areas relevant for public policy design. According to Chetty (2015), it provides a conceptual framework to think about new policy tools. For instance, defaults and automatic enrollment to pension schemes can be used to address the fact that agents save to little for retirement. Introducing behavioral aspects in the models allows to better match the empirical facts observed in the data.

Broadly speaking, the scope of energy efficiency policies spans from market-based policy instruments, mostly based on taxes and subsidies (price instruments), or regulations fixing quotas (quantity instruments), to purely informative policies or nudges aimed at raising awareness among agents of the potential benefits from investing in energy efficiency improvements.

Traditionally policies to encourage energy efficiency have been based on the use of taxes on energy consumption and subsidies on energy efficiency investments. Taxes have been widely used to correct the externalities of energy consumption following the idea of corrective taxation (Pigouvian taxes) introduced by Pigou (1920). Other work on corrective taxation has provided useful insights on optimal taxation under heterogeneity (Diamond, 1973), or on how to integrate corrective taxation within the second best optimal taxation system (Sandmo,1975). In a context where the only reason for agents to undervalue the benefit of adoption is the energy consumption externality, a corrective tax equal to the marginal externality would implement the efficient outcome. However, very often environmental policies for energy efficiency rely on subsidies helping agents face the technology adoption upfront cost.

The use of subsidies is justified on the basis that private agents underestimate the value of adoption and as a consequence underinvest in energy efficiency measures, as discussed earlier. One of the main policy design challenges when providing subsidies for adoption of technology is the cost-effectiveness of the subsidy. Key to this is how well the policy is targeted. When the government offers a subsidy, it is possible that agents who benefit from the subsidy would have invested in the technology improvement also in its absence (Stern, 1985). In this context, information provision policies might be superior from a cost-effectiveness perspective. Moreover, combining taxes and subsidies with information provision may improve the targeting efficiency of subsidies and the consumers responsiveness to taxes. Allcott (2011) provides evidence using a randomized experiment that consumers respond substantially to policy interventions based on providing information about social norms.

Therefore, whether the optimal policies should rely on market based instruments or on nudge policies addressing consumers' misperceptions is at the heart of the debate on energy efficiency policy. And understanding the forces driving the technology diffusion mechanism and the role of agents' heterogeneity is, therefore, of huge relevance for policy design.

I focus the attention on government provided incentives to encourage investments adoption of energy-efficient technologies in a context in which agents are heterogeneous in their current energy efficiency level. Under these conditions, the policy design process poses different challenges. First of all, heterogeneity in characteristics determines whether agents are going to take up a subsidy or not, or how responsive they are to a tax. Second, agents responsiveness to the policy instruments might undermine the policy cost-effectiveness when agents responding to policy incentives are those who would have adopted in the absence of the policy intervention. Third, under conditions where the policy targeting is poor or agents are not very responsive to the traditional market-based instruments it could be worth considering other types of policy instruments based on information provision or nudges.

I aim to shed some light on how policies that subsidize energy efficiency investments and impose taxes to correct externalities can become ineffective under some circumstances. In particular, first, I propose a conceptual framework where heterogeneity is driven by consumers' misperceptions on energy efficiency. Second, I provide empirical evidence on the role of consumers' heterogeneity in the selection into adoption mechanism.

Chapter 1 analyzes optimal energy policies to encourage purchases of energy-efficient durable goods in the presence of externalities and internalities. The focus of the chapter is on policies based on an energy consumption tax combined with a subsidy contingent on the adoption of energy efficiency improvements. I consider two extreme cases. One in which heterogeneity is the result of true energy efficiency differences among agents. In this case, the optimal policy is based on a corrective Pigouvian tax equal to the marginal externality and implements the first best level of adoption. More importantly, I consider the case in which the only source of heterogeneity is the result of biased beliefs about a common true energy efficiency level. I consider internalities arising from consumers' misperceptions about energy efficiency and analyze how heterogeneity driven by biased beliefs affects the optimal policy design. I find the optimal policy consists of a tax above the marginal externality level and a subsidy. The rationale for imposing a tax larger than the marginal externality is to address the internality effect resulting in energy overconsumption among non-adopters. Hence, the optimal tax exceeds the marginal externality by the average internality effect among non-adopters. The subsidy level, in turn, is targeted to the marginal adopter and offsets by how much the marginal adopter undervalues technology adoption. In addition, I identify two main reasons why energy taxes and subsidies are very ineffective when heterogeneity is driven by misperceptions. First, the model predicts a negative correlation between energy consumption and willingness to pay for the energy-efficient technology, thus, leading to an adoption pattern where heavy energy overconsumers are unlikely to adopt energy efficiency improvements. Second, the marginal adopter responsiveness to taxes and subsidies is low for agents with beliefs such that they overconsume energy. Thus, resulting in having to impose huge policy distortions on the inframarginal adopters to induce these types to adopt the energy efficiency measures.

Moreover, the theoretical analysis in Chapter 1 leads to concrete empirical predictions that allow to test for whether selection into adoption is driven by preferences heterogeneity or beliefs heterogeneity with a very simple correlation test that is closely related to the positive correlation test proposed in Chiappori and Salanié (2000) in the context of the insurance markets literature. In other words, the test allows to contrast whether selection into adoption is adverse or advantageous which is crucial to determine the policy cost-effectiveness.

Chapter 2 provides empirical evidence on the effectiveness of energy efficiency measures looking at energy consumption data from the UK. Moreover, it presents a discussion of the main energy efficiency policy interventions recently implemented in the UK and its potential as a source of identification of the impact of incentives on adoption and energy consumption patterns. For this purpose I use a data set

(National Energy Efficiency Data, NEED) covering a large sample of households in England and Wales. For approximately 4 million households, the data set keeps track of energy consumption and energy efficiency measures installation over the period 2005-2012.

Chapter 3 provides an empirical analysis based on the empirical predictions of the model presented in Chapter 1. The objective of the analysis is to test for the presence of adverse selection in the adoption of energy efficiency improvements among households under government provided incentive schemes. Following the insights of the model in Chapter 1, when heterogeneity is driven by misperceptions selection into adoption is adverse. In particular, early adopters exhibit lower levels of pre-adoption energy consumption and experience lower consumption drops upon adoption. On the contrary, if heterogeneity is driven by preferences, the opposite correlations are expected. To test which of the two sources of heterogeneity dominates I perform the following empirical analysis. First, I look at the levels of energy consumption prior to adoption and compare them across technology adoption year cohorts. Second, I look at the energy consumption drop upon adoption over time to see if those who adopt earlier experience lower energy consumption drops upon adoption. In both tests, I find evidence supporting that heterogeneity in preferences (in true energy-efficiency) might be the force driving selection into adoption. However, this evidence does not rule out that misperceptions play a role in the technology diffusion mechanism. Furthermore, I use policy variation from the Boiler Scrappage Scheme to analyse the role of incentives in the selection into adoption mechanism. My findings are that households adopting the technology under the incentive scheme exhibit lower pre-adoption levels of energy consumption and experience higher energy consumption drops between two years before and the year after technology adoption.

I contribute to the public economics literature on policy design with heterogeneous agents by providing a theoretical framework to think about optimal policy design under heterogeneity in perceptions about the energy efficiency of the in-house energy services production process and provides a rationale for the use of subsidies. The work presented in this thesis is closely related to Allcott et al (2014) where they analyze optimal energy policy with externalities and internalities, and Tsvetanov and Segerson (2013) where they present a welfare analysis of energy policies based on a model of temptation and self-control. In the last case, however, they focus on policies based on regulation of energy efficiency standards.

The suggested empirical test for adverse versus advantageous selection into technology adoption is related to the positive correlation test for asymmetric information Chiappori and Salanié (2000). It relates to work by Cohen and Einav (2007), Finkelstein and McGarry (2006) and Chiappori et al (2006) on preference heterogeneity. And also to more recent work by Spinnewijn (2013) on the role of misperceptions in the insurance markets. I apply these ideas to the context of technology adoption and use pre-adoption consumption comparisons, as post-adoption consumption is affected by technology adoption[2].

I also contribute to the literature on diffusion of energy efficient technologies [Hausman and Joskow (1982), Hasset and Metcalf (1995), Jaffe et al (2005)] and the energy efficiency gap [Allcott and Greenstone (2012), Jaffe (1994), Gillingham and Palmer (2014)]. I provide an heterogeneity based mechanism that is consistent with the gradual diffusion patterns observed in the data. In addition, the proposed model provides empirical implications that are in stark contrast with the predictions of a standard model where agents heterogeneity is driven solely by preference heterogeneity.

[2]This idea is analogous to using panel data in the insurance market context to discern whether the positive correlation between risk and insurance is driven by adverse selection or moral hazard

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Chapter 1

Energy efficiency policy and energy cost misperceptions

1.1 Introduction

Reducing residential energy use is one of the pillars of the strategy that most developed countries have adopted to address environmental issues, however how to design optimal policies to encourage households to reduce their energy demand remains an open question which is at the center of the policy debate. Residential energy demand is determined by decisions on technology (purchases of energy using durable goods) and energy use intensity. In both cases households' private decisions would lead to an inefficient outcome in the presence of negative energy consumption externalities. Moreover, there is potentially a second source of inefficiency in both consumption and investment decisions which is the presence of psychological biases leading households to make suboptimal decisions.

It is widely recognized that households' tend to underadopt available energy efficiency improved durable goods and underinvest in technologies that would reduce their energy bill and the environmental impact of their energy consumption. The idea that economic agents fail to invest in technology improvements that would result in a positive return goes back to Hausman (1979). Building up on previous work on durable purchasing decisions by Hausman and Wise (1978) and McFadden (1978), Hausman (1979) develops a model of consumer behavior on purchasing decisions and use of energy-using durable goods. The paper also provides estimates of a 20% implied discount factor of individuals' purchasing decisions.

This idea is also related to the double market failure discussed in Jaffe et al (2005). In the context of energy efficiency technology adoption the market failures associated with the energy consumption negative externality interact with market failures related with the slow rate of technology diffusion. The slow diffusion of energy efficiency technologies leads to the energy efficiency gap. Not only do agents fail to undertake efficient technology adoption decisions, but by doing so they fail to contribute to the reduction of the externality generated by energy consumption resulting from the increased energy efficiency. Hence, correcting this failure leads to a win-win situation. One in which the agent reduces expenditure in energy consumption and at the same time the externality damage associated with energy consumption is reduced. Following Gillingham and Palmer (2014), the main reasons that explain the gap can be divided in market failures and behavioral failures. Among the first it has been argued that imperfect information, principal-agent issues, credit and liquidity constraints and regulatory failures could explain why agents fail to adopt improved energy-efficiency technologies. On the other hand, non-standard preferences, non-standard beliefs or non-standard decision making can also contribute to explain the gap.

In addition, recent empirical evidence suggests large energy consumption responses to low-cost information provision interventions. Allcott (2011) finds that providing information about similar households energy consumption in the utility bill induced large energy consumption responses among households with pre-treatment energy consumption above average. This suggests that many households are poorly informed about changes in behavior they could adopt at a relatively low cost to reduce their energy consumption.

I propose a model to think about optimal policies to encourage the adoption of more efficient energy-using durable goods in the presence of externalities and internalities. The aim of the chapter is, first, analyse how the presence of internalities distorting the intensive (consumption) and extensive (investment in durable goods) margin choices affects optimal policies based on energy taxes and technology adoption subsidies. Second, analyse how the presence of such an internality affects the effectiveness of policy interventions via prices.

In the model presented here, consumers take two decisions, they choose their demand for energy services and decide on investments on energy efficiency improvements. Energy consumption is determined by the household technology which is characterized by its level of energy efficiency. Internalities result from misperceptions about the current energy-efficiency level and have two important effects on consumers' behavior. First, energy consumption choices based on their biased beliefs would result in over or underconsumption of energy relative to the efficient energy demand. Second, the bias in the energy consumption plan induces biased perceptions of the benefit from investing in energy efficiency improvements. The gap between the true energy efficiency and the beliefs can be thought as summarizing inattention to energy costs or bad habits in the use of energy-using durable goods that make the consumer deviate from his energy consumption plan. As a result of the discrepancy between true energy efficiency and the beliefs, the household actually consumes an amount of energy to satisfy its energy services demand that differs from the planned energy consumption. In particular, optimistic agents will overconsume energy relative to their targeted energy consumption level, whereas pessimistic agents will underconsume energy. Regarding investment decisions on energy efficiency improvements, optimistic agents will be less likely to invest as they underestimate the adoption benefits. Whereas, pessimistic agents will overinvest as the perceived adoption benefit overshoots the actual adoption benefit. This has important implications for the design of the optimal policy as the agents' response to policy instruments changes dramatically as a consequence of the internality. In a standard technology adoption framework with preference heterogeneity, one should expect agents who consume more energy to be the first to adopt the new technology as their potential benefit from adoption is larger. On the contrary, the model presented here predicts that one should observe the opposite, agents who consume more energy (optimistic agents) are less likely to adopt. The energy consumption externality together with the internality generate a discrepancy between private and social value of adoption.

The policy maker chooses a uniform tax and a uniform subsidy to correct the inefficiencies. In the absence of the internality, a Pigouvian corrective tax equal to the marginal externality would totally correct the choice inefficiencies both at the consumption and adoption margins. However, in the presence of the internality the optimal policy combines a tax above the marginal externality to address the effect of the internality and a positive subsidy. In general, the rate of adoption will be below the first best level of adoption, unless the policy maker has access to lump sum taxes to finance a sufficiently large subsidy. The optimal policy involves a positive subsidy, since it allows the policy maker to provide incentives for adoption without distorting too much the energy consumption choices. If the policy maker used only the energy tax, implementing the same proportion of adopters would require such a large tax that the efficiency cost imposed on unbiased adopters would be too high.

The main results of the optimal policy characterization are the following. With no misperceptions the optimal policy instrument is a corrective tax equal to the marginal externality (Pigouvian tax). This tax would correct both the intensive margin decisions and as a consequence also the technology adoption decisions. Similarly, if energy efficiency misperceptions were observable to the policy maker, then the first best allocation can be achieved by imposing a tax that can be decomposed into a Pigouvian tax addressing the externality correction plus an additional term that corrects the internality due to energy efficiency misperceptions. When the internality is uniform, the optimal policy combines a tax above the marginal externality level and a subsidy. The subsidy can be set at level such that the technology adoption decision is first-best efficient. Finally, in the presence of heterogeneous internalities the first best level of adoption can only be implemented if the government has access to large lump sum transfers. In that case, the optimal tax is set at the marginal externality level and the subsidy is set at a level such that the agents with the most extreme beliefs against adoption would be indifferent between adopting or not. On the contrary, if no lump sum transfers are available, the optimal budget balanced tax-subsidy combinations would not achieve the first best level of technology adoption. The resulting tax would be above the marginal externality level and the subsidy would be below the subsidy level that guarantees the first best level of adoption.

Beyond the optimal policy characterization, I provide important insights on the effectiveness of taxes and subsidies as policy instruments. First of all, in the presence of heterogeneous internalities, inducing the more optimistic agents to adopt the new technology requires a large subsidy. In addition, the subsidy is poorly targeted because the policy maker cannot prevent pessimistic consumers from taking the subsidy up. In particular, among the inframarginal adopters, the pessimistic agents would have adopted the energy efficient technology even if the subsidy was zero and the tax equal to the marginal externality.

Second, when agents exhibit biased beliefs, the correlation between the willingness to pay for the energy efficient technology and the social value of adoption is negative for optimistic agents and, therefore, energy taxes and subsidies induce a response to the policy instruments where severe overconsumers remain in the non-adoption state. At the same time, this implies that the correlation between the past history of energy consumption and investment in energy efficiency technologies should be negative. This feature distinguishes this model from a model where agents are heterogeneous in preferences and provides an interesting empirical implication of the model that could be tested using panel data containing information on individual energy consumption and decisions about purchases of energy efficient durable goods. This test can be linked to the standard positive correlation test of adverse selection proposed in Chiappori and Salanié (2000). The positive correlation test would prescribe that one should test for a positive correlation between the amount of insurance coverage and the probability of an accident in the insurance context. In this context, one could think of the positive correlation test when framing the test in terms of the correlation between the beliefs on energy efficiency and the social value of adoption, or the correlation between pre-adoption energy consumption and the social value of adoption which is directly related to the potential energy consumption drop the household would experience upon adoption of an energy efficiency measure. This is the idea behind the empirical study presented in Chapters 2 and 3.

The work presented in this chapter is related to the literature analysing the design of optimal policy interventions with behavioral agents. Chetty (2015) provides a review based on evidence for the relevance of psychological considerations when thinking about policy design[3]. For instance, O'Donoghue and Rabin (2006), Bernheim and Rangel (2004), Lockwood and Taubinsky (2017) analyse optimal taxation when some consumers overconsume a "sin good" because of time inconsistent behavior or addiction. Finkelstein (2009), Chetty et al (2009), Rees-Jones and Taubinsky (2016) study the implications of limited attention to taxes and its impact on behavioral responses to taxation. In the context of unemployment insurance, Spinnewijn (2015) analyses the policy implications of agents biased beliefs for the optimal design of unemployment insurance. Spinnewijn (2013, 2016) analyses the role of heterogeneous risk perceptions in insurance markets.

In the area of energy policy[4], recently, some papers have proposed theoretical models to think about optimal policy design with externalities and internalities that are closely related to the model developed in this chapter. Heutel (2011) develops a theoretical model with consumers who exhibit present bias and time inconsistency. Showing that in this context Pigouvian taxes are a suboptimal solution, and characterizes an optimal policy solution involving a tax above the marginal externality damage and a subsidy for energy efficient products.

Tsvetanov and Segerson (2013) , propose a model in which agents are subject to temptation and self-control and study under which circumstances policies based on minimum energy efficiency standards may be superior. They find that Pigouvian taxes do not lead to a first best outcome, and suggest that a policy combining

[3]Mullainathan et al (2012) provide also an excellent review on behavioral public finance.

[4]Other work on behavioral responses to policy and the role of psychological biases in energy policy include Allcott (2011), Allcott (2013), Allcott and Wozny (2013), Ito (2013), Ito (2015), Sallee (2012).

energy efficiency standards and Pigouvian taxes achieves a higher level of social welfare.

Allcott et al. (2014), probably the one closer to the model I present here, propose a model of energy-using durable goods where consumers undervalue energy costs. They show that in the presence of energy cost misperception, policies combining a tax targeting the energy consumption externality and product subsidies targeting the present bias.

However, none of these papers has analysed the implications of beliefs heterogeneity on optimal policy design in the presence of externalities and internalities affecting simultaneously the consumers' energy consumption choices and the investment decisions. The model I present aims to capture the idea that some agents overvalue the impact of their energy consumption decisions, leading them to energy saving behavior and to be prone to adopt energy efficiency measures. While others undervalue the impact of those decisions, leading them to exhibit a 'reckless' behavior. Based on this idea, I present a model of investment in energy efficiency measures where consumers exhibit a behavioral bias regarding energy costs. The main novelty of this model is that the behavioral bias is summarized in a single parameter that measures the perceived efficiency of the in-house energy services production technology. This parameter alone captures the implications of behavioral biases on the interaction between intensive margin decisions (energy use) and extensive margin decisions (energy efficiency measures adoption). First, the model allows me to show that policies based on an energy tax and a subsidy for energy efficiency measures investment would not achieve a first best outcome in a budget balanced way. Second, the model leads to clear empirical predictions that are in sharp contrast with those of technology adoption models where agents are heterogeneous in preferences, that can be indirectly tested using technology adoption and energy consumption data.

The research work presented in this thesis, also relates to the literature on policy design under adverse selection. In the context considered in this chapter, the idea of adverse selection is that agents for whom the social value of technology adoption is lower tend to be more responsive to policy interventions, whereas those for whom the social value of adoption is high are less prone to participate. Hence, those who adopt energy efficiency measures under subsidy schemes and benefit from the subsidy, are those who would probably have adopted anyway. This pattern reduces therefore the cost-effectiveness of the subsidies provided by the government (Stern, 1985).

The chapter is organized as follows. Section 2 introduces the model set up and discusses the policy-maker objective and the consumers' behavior for a given policy. Section 3 characterizes the optimal policy. Section 4 discusses alternative scenarios based on different assumption on learning. Section 5 compares the consumers' responses to taxes and subsidies in the two different scenarios (true energy efficiency heterogeneity versus biased beliefs/misperceptions) and briefly discusses the different policy implications of different heterogeneity sources. Section 6 discusses how the empirical implications of the model presented in this chapter could be tested. Section 7 concludes.

1.2 Model

I present a simple model aimed to better understand what are the implications of misperceptions on energy efficiency for the design of optimal policies to encourage the adoption of energy efficiency improvements among households. The main novelty of this model is that misperceptions enter the model affecting directly the intensive (energy consumption decision) margin and the internality induces a distortion on the extensive margin decision (technology adoption).

1.2.1 Consumers

Consumers make two decisions. They choose either to invest or not in a more energy-efficient durable good and they choose their demand for energy services taking the policy instruments as given. This section characterizes the consumption and adoption behavior of consumers for a given tax on energy consumption and a given subsidy on purchases of energy-efficient durable goods, denoted respectively by τ and σ. First, I provide the conditions that characterize the optimal consumption behavior for a given technology choice, and second, I characterize the optimal private adoption decision.

Energy consumption choice Consumers derive utility from a consumption good c and consumption of energy services s, according to the following quasi-linear utility function:

$$u(c, s) = c + g(s) \tag{1}$$

where $g(s)$ satisfies $g'(s) > 0$ and $g''(s) < 0$.

Consumers' endowment consists of a technology and an exogenous income y. The technology is characterized by the energy efficiency η. A consumer with energy efficiency η needs to use $e(s, \eta)$ units of energy to produce s units of energy services. I assume that the production function $e(s, \eta)$ satisfies $e_s > 0$, $e_\eta < 0$, $e_{ss} > 0$ and $e_{s\eta} < 0$. Hence, η is also closely related to the marginal cost of increasing the energy services demand measured in terms of the associated increase in energy consumption. The higher is η, the lower the amount of energy the household needs to purchase to produce an additional unit of energy services s. It is important that consumers do not derive utility directly from energy consumption, they only derive utility when they enjoy the energy services produced after consuming a particular amount of energy that is determined by their energy efficiency level.

Consumers also hold beliefs about their energy efficiency that are denoted by $\hat{\eta} \in [\underline{\eta}, \overline{\eta}]$. The distribution of beliefs is characterized by the cumulative density function H, satisfying that $E(\hat{\eta}) = \eta$. Consumers' private decisions on energy services demand and technology adoption come as the result of the consumers' optimal behavior given their beliefs about how efficient they are at converting energy into energy services. In other words, consumers' decisions are based on decision utility. However, the utility truly experienced by consumers holding biased beliefs about energy efficiency differs in general from the decision utility. Throughout this chapter, I refer to consumers with $\hat{\eta} = \eta$ as standard agents (or unbiased) and to consumers with $\hat{\eta} \neq \eta$ as behavioral (or biased) agents.

The price of the consumption good is normalized to 1. The unit price of energy is denoted by p, and consumers pay a tax τ per unit of energy consumed. Therefore, the consumers' budget constraint and energy services production function are given by:

$$c + (p + \tau)e \leqslant y \tag{2}$$

$$e = e(s, \eta) \tag{3}$$

For given beliefs $\hat{\eta}$, the consumer energy services demand is the solution to the utility maximization problem subject to 2 and 3. Hence, the energy services demand $\hat{s}(\tau, \hat{\eta})$ is defined by the following optimality condition:

$$g'[\hat{s}(\tau, \hat{\eta})] = (p + \tau)e_s(\hat{s}(\tau, \hat{\eta}), \hat{\eta}) \tag{4}$$

I assume that the energy services demand elasticity with respect to the energy efficiency ($\varepsilon_{s,\eta}$) is low enough to ensure that there is no energy consumption "rebound effect" when the energy efficiency increases. In particular, the condition $0 \leqslant \varepsilon_{s,\eta} < -\frac{e_\eta \eta}{e_s s}$ guarantees that energy consumption is decreasing in the energy efficiency level[5]. This condition implies that when energy efficiency increases, the demand for energy services increases less than proportionally and, hence, the corresponding energy consumption decreases. This assumption is crucial for the results in this chapter and for the empirical implications of the results presented here. If this assumption fails, then it is not necessarily true that energy efficiency increases lead to a decrease in energy consumption expenditure and therefore agents with quasi-linear utility might not benefit from technology adoption if the negative income effect more than offsets the substitution effect. In Chapter 2 I will provide empirical evidence based on the energy consumption profiles showing that

[5] In the particular case where the production function is $e(s, \eta) = \frac{s}{\eta}$, this condition becomes $0 \leqslant \varepsilon_{s,\eta} < 1$, and the values of the elasticity are consistent with empirical estimates (see Gillingham et al. (2009) (Gillingham, Newell, and Palmer 2009)).

the rebound effect is not observed empirically, and hence the empirical evidence suggests that the assumption holds.

The decision utility of a consumer with $\hat{\eta}$ beliefs is given by:

$$\hat{v}(\tau, \hat{\eta}) = y - (p + \tau)e(\hat{s}(\tau, \hat{\eta}), \hat{\eta}) + g(\hat{s}(\tau, \hat{\eta})) \quad (5)$$

The assumption underlying consumers' behavior is that a consumer chooses the optimal energy services demand given his beliefs, and he sticks to the planned energy services demand. As a consequence, a consumer who holds beliefs $\hat{\eta} > \eta$ consumes an amount of energy above the amount of energy he planned to consume to satisfy his demand for energy services. Similarly, a consumer who holds beliefs $\hat{\eta} < \eta$ would actually consume less energy than the amount he planned to satisfy his energy services demand (Figure 1). Therefore, for given beliefs about energy efficiency, there is a gap between decision utility given by (5) and experienced utility given by (6):

$$v(\tau, \hat{\eta}, \eta) = y - (p + \tau)e(\hat{s}(\tau, \hat{\eta}), \eta) + g(\hat{s}(\tau, \hat{\eta})) \quad (6)$$

Technology adoption decision Consider an improved energy-efficiency technology denoted by $\widetilde{\eta}$, such that $\widetilde{\eta} > \eta$. In addition, the new technology is assumed to provide an energy efficiency level such that the net social value of adoption is positive for some consumers.

At the technology adoption decision stage the consumer chooses either to adopt or not a more energy efficient technology (A) at a cost k. If the consumer decides to invest, then the energy efficiency improves to $\tilde{\eta} > \eta$. Moreover, I assume that in the adoption state the consumer beliefs are unbiased. On the contrary, if he chooses not to invest (N), he keeps the original technology endowment and beliefs. This assumption implies that through the adoption process the consumer also learns about the true energy efficiency of the new technology. The underlying idea is that when a consumer engages in the purchase of an energy efficient durable

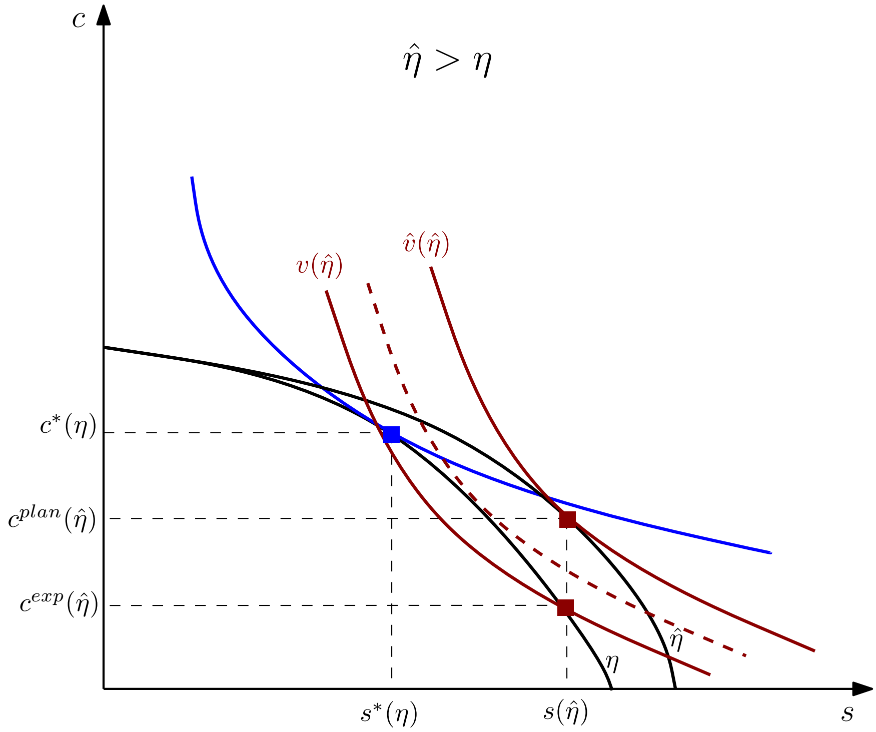


Figure 1: Consumer choice with externalities and internalities

Note: The figure illustrates the consumer choice in the presence of externalities and internalities for an agent with beliefs $\hat{\eta} > \eta$. Given her beliefs the agents demands $s(\hat{\eta})$ units of energy efficiency services and expects to consume $c^{plan}(\hat{\eta})$ units of the composite consumption good. As a result of her biased beliefs the agent consumes more energy than planned to satisfy the energy services demand and consumes $c^{exp}(\hat{\eta}) < c^{plan}(\hat{\eta})$ units of the consumption good.

good, the characteristics of the good and in particular its energy efficiency become fully salient to the consumer. When thinking about the overall energy efficiency of the in-house energy services production technology, this assumption might be less plausible. However, the assumption is made with simplifying purposes and should be taken as an assumption that sets an upper bound on the value of adoption of the energy efficiency measure. In addition, it does not affect the intuition behind the theoretical results presented later in this chapter. Nonetheless, I further discuss the implications of alternative learning hypotheses in Section 4 of this chapter.

Let $v_A(\tau, \tilde{\eta})$ and $\hat{v}_N(\tau, \hat{\eta})$ denote respectively the continuation value of adoption and the perceived continuation value of non-adoption. Then, a consumer optimal decision is to adopt if and only if

$$v_A(\tau, \tilde{\eta}) - (k - \sigma) \geq \hat{v}_N(\tau, \hat{\eta}) \tag{7}$$

In the remainder of the chapter, I will refer to agents with beliefs $\widehat{\eta} > \eta$ ($\widehat{\eta} < \eta$) as η-optimistic (η-pessimistic) consumers. Since energy services demand is increasing in the level of energy efficiency, η-optimistic (η-pessimistic) agents consume an amount of energy above (below) the one they would have consumed if they knew the true efficiency level. Regarding the adoption decision, η-optimistic (η-pessimistic) agents undervalue (overvalue) the benefit from adoption of the new technology.

Lemma 1. *There exists a cut-off value of energy efficiency $\hat{\eta}^a$ such that if $\widehat{\eta} \leqslant \hat{\eta}^a$, then the consumer private decision is to purchase the energy-efficient durable good.*

Proof. Consider the willingness to pay function $v(\hat{\eta})$. Consider $\hat{\eta}^a$ such that if $\widehat{\eta} \leqslant \hat{\eta}^a$, then$v_A(\tau, \tilde{\eta}) - (k - \sigma) \geq \hat{v}_N(\tau, \hat{\eta})$ and $v_A(\tau, \tilde{\eta}) - (k - \sigma) < \hat{v}_N(\tau, \hat{\eta})$ otherwise. Consider $\hat{\eta}' > \hat{\eta}^a$such that $v_A(\tau, \tilde{\eta}) - (k - \sigma) \geq \hat{v}_N(\tau, \hat{\eta'})$. By Lemma 4 (see Appendix A.1), the willingness to pay function is monotonically decreasing in η. Hence, this leads to a contradiction. □

Policy-maker The optimal policy analysis in this chapter is focused on policies based on two instruments, a per unit tax on energy consumption τ and a subsidy contingent on purchasing a high energy efficiency technology σ. The attention is restricted to uniform policies, in other words, the policy instruments cannot be made contingent on the consumers' type, so all consumers face the same tax per unit of energy consumption, and receive the same subsidy if they invest in energy efficiency improvements.

The policy-maker chooses the policy to maximize welfare subject to the government budget constraint. The social welfare function takes into account a negative externality from energy consumption that households do not take into account when making their choices on energy consumption and technology adoption. I assume the marginal externality damage to be constant and equal to θ, and therefore the externality imposed by energy consumption e is given by $-\theta e$. In addition, there is an internality because consumers have potentially biased beliefs about their current level of energy-efficiency, and consequently their energy consumption choices and the induced effect on the adoption decision impose an additional distortion that contributes to under-adoption of the high energy-efficiency technology. The true social welfare function is based on the true energy efficiency level and one of the aims of the policy-maker is to correct the consumption choices of biased consumers. Hence this is a paternalistic approach in the sense of Bernheim and Rangel (2009) where the government aims to maximize welfare based on experienced utility. The welfare contribution of a consumer with true energy efficiency η and beliefs $\hat{\eta}$ is given by:

$$w(\tau, \hat{\eta}, \eta) = y - (p + \tau)e(\hat{s}(\tau, \hat{\eta}), \eta) + g(\hat{s}(\tau, \hat{\eta})) - \theta e(\hat{s}(\tau, \hat{\eta}), \eta) \tag{8}$$

Hence, the optimal social adoption rule is that a consumer must adopt the energy efficient technology if the welfare contribution of the consumer upon adopting the energy efficient technology is greater or equal than that resulting from not adopting. This condition results in the following condition characterizing the optimal social adoption rule.

$$v_A(\tau, \tilde{\eta}) - \theta e(\tau, \tilde{\eta}) - (k - \sigma) \geq v_N(\tau, \eta) - \theta e(\tau, \eta) \tag{9}$$

This condition differs from the private adoption rule in two aspects. First, it includes the externality reduction benefit. And, second it is based on experienced utility instead of decision utility. This is it also includes the internality effect of consumers' biased perceptions on current energy efficiency.

The welfare function is the sum of consumers' experienced utility and net government revenues, minus the externality damage of energy consumption. Consider a population of size 1, with $\hat{\eta}$ distributed according to a cdf $H(\hat{\eta})$ with support $[\underline{\eta}, \overline{\eta}]$. Given the adoption behavior described in the previous section, there exists a marginal adopter denoted by $\widehat{\eta}^a \in [\underline{\eta}, \overline{\eta}]$ such that a consumer invests in the energy-efficient technology if he has beliefs $\hat{\eta} \leq \widehat{\eta}^a$ and keeps the current energy efficiency otherwise. The cutoff is implicitly determined by the private adoption rule and is a function of the policy instruments.

The government chooses (τ, σ) to maximize total welfare subject to the government budget constraint and to the consumers' adoption decision rule. Note that the private adoption rule (Rationality Constraint) implicitly pins down the marginal adopter identity as a function of the policy instruments, $\widehat{\eta}^a(\tau, \sigma)$. Hence, in general, when the policy-maker chooses a tax τ and a subsidy σ, the objective function can be expressed as follows:

$$
\begin{aligned}
W(\tau,\sigma) = & \underbrace{\int_{\underline{\eta}}^{\widehat{\eta}^a} \left[v_A(\tau,\widetilde{\eta}) - (k-\sigma)\right] dH(\hat{\eta}) + \int_{\widehat{\eta}^a}^{\overline{\eta}} v_N(\tau,\eta,\hat{\eta}) dH(\hat{\eta}) -}_{\text{Sum of agents utility}} \\
& \underbrace{- \int_{\underline{\eta}}^{\widehat{\eta}^a} \theta e(\tau,\widetilde{\eta}) dH(\hat{\eta}) - \int_{\widehat{\eta}^a}^{\overline{\eta}} \theta e(\tau,\eta,\hat{\eta}) dH(\hat{\eta}) +}_{\text{Externality damage}} \\
& \underbrace{+ \int_{\underline{\eta}}^{\widehat{\eta}^a} [\tau e(\tau,\widetilde{\eta}) - \sigma] dH(\hat{\eta}) + \int_{\widehat{\eta}^a}^{\overline{\eta}} \tau e(\tau,\eta,\hat{\eta}) dH(\hat{\eta})}_{\text{Net tax revenues}} \qquad (10)
\end{aligned}
$$

From the point of view of the policy maker, increasing the adoption of the new technology has a positive effect on welfare because of the externality benefit of energy consumption reduction. In addition, since upon adoption consumers perceive accurately the energy efficiency, it also corrects inefficiencies due to the internality. On the other hand, providing incentives has an efficiency cost as long as it implies charging an energy tax above the marginal externality for unbiased consumers.

1.3 Optimal policy

This section analyzes the optimal tax and subsidies in different scenarios. I consider two main cases, one where heterogeneity comes from consumers having initially different technologies, and the other where the source of heterogeneity is the heterogeneous biased beliefs that consumers may have about the same true technology.

To keep notation simpler, hereafter I denote adopters energy consumption by e^A, non-adopters energy consumption plan and actual energy consumption by $\hat{e}_N$

and e_N respectively. A superscript a identifies the marginal adopter. Whereas, a superscript $*$ identifies the first best marginal adopter and policy instruments. Also, the arguments of the energy consumption function (τ and η) are omitted to keep notation more compact.

1.3.1 Optimal policy with unbiased agents

First of all, I consider the case where consumers have unbiased beliefs about their current energy efficiency and there is heterogeneity in the true level of energy efficiency across consumers, hence for any consumer $\hat{\eta} = \eta$, and η is distributed according to cdf $F(\eta)$.

Proposition 1. *When there are no misperceptions, the optimal policy is $\tau^* = \theta$ and $\sigma^* = 0$. This policy achieves achieves the first best level of welfare.*

Proof. The proposition follows from the welfare maximisation problem. For a given policy (τ, σ), consider the problem where the government chooses the optimal cutoff η^* such that it is optimal to adopt when $\eta \leqslant \eta^*$ and it is optimal not to adopt otherwise. The first order condition with respect to η^* is given by:

$$v_A(\tau, \widetilde{\eta}) - v_N(\tau, \eta^*) + [(\theta - \tau)(e(\tau, \eta^*) - e(\tau, \widetilde{\eta})) - \sigma] = 0 \tag{11}$$

The government welfare maximization problem is

$$\begin{aligned} &\max_{(\tau,\sigma)} \quad W(\tau, \sigma) \\ s.t. \quad &v_A(\tau, \widetilde{\eta}) - (k - \sigma) \geqslant v_N(\tau, \eta) \end{aligned} \tag{12}$$

The first order conditions with respect to τ and σ are (using the envelope conditions from consumer utility maximisation):

$$\frac{d\eta^*}{d\tau}f(\eta^*)[(\theta-\tau)(e(\tau,\eta^*)-e(\tau,\widetilde{\eta}))-\sigma] = \int_{\underline{\eta}}^{\eta^*}(\theta-\tau)\frac{de(\tau,\widetilde{\eta})}{d\tau}dF(\eta)+ \\ +\int_{\eta^*}^{\overline{\eta}}(\theta-\tau)\frac{de(\tau,\eta)}{d\tau}dF(\eta) \quad (13)$$

$$\frac{d\eta^*}{d\sigma}f(\eta^*)[(\theta-\tau)(e(\tau,\eta^*)-e(\tau,\widetilde{\eta}))-\sigma] = 0 \quad (14)$$

Since $\frac{de(\tau,\eta)}{d\tau} < 0$ in general, the first order conditions necessarily imply that the optimal policy is $\tau^* = \theta$ and $\sigma^* = 0$.

Note that the private adoption decision rule evaluated at (τ^*, σ^*) becomes exactly equivalent to the socially optimal adoption rule that takes into account the externality damage reduction benefit from adoption:

$$v_A(\tau^*,\widetilde{\eta}) - k - v_N(\tau^*,\eta^*) = 0 \quad (15)$$

□

Hence, setting the policy instruments to $\tau^* = \theta$ and $\sigma^* = 0$ achieves the first best level of welfare. When the marginal externality is constant, imposing the Pigouvian tax will not only correct the energy consumption externality, but will also correct the extensive margin adoption decision. On the one hand, under this policy consumers' adoption response exactly coincides with the socially optimal adoption rule. Furthermore, the energy consumption externality is fully corrected by setting a tax equal to the marginal externality. When agents face such a tax they totally internalize the energy consumption externality and, as a consequence, they evaluate the technology adoption benefits as if they were taking into account the externality reduction benefit. Hence, this policy achieves as a decentralized equilibrium the same adoption rate that a welfare maximising social planner would have prescribed. Moreover, when consumption choice inefficiencies due to the externality have been corrected, efficiency at the adoption decision stage is recovered as the gap between the social value of adoption and the private value of adoption disappears.

Since consumers are initially heterogeneous in terms of their true energy efficiency, the optimal adoption rule does not necessarily imply that all the consumers should adopt the new technology. Indeed, adoption is optimal only for those consumers who are initially at low levels of energy efficiency and to whom the energy consumption savings plus the energy consumption externality reduction exceeds the adoption cost. Hence, the predicted adoption pattern involves that non-adopters are already at relatively high levels of energy efficiency and low levels of energy consumption. This fact is related to the positive correlation between the willingness to pay to adopt the energy efficient technology and the social value of adoption. As long as both of them are positively correlated, providing incentives through policy instruments like uniform taxes and subsidies induces an adoption pattern where consumers with poor initial energy efficiency adopt and those who are already efficient do not adopt. This adoption pattern implies that the correlation between energy consumption and willingness to pay is positive, as high energy consumption corresponds to low levels of energy efficiency initially and, hence, potentially high benefits from adoption of the high energy efficiency technology (Figure 2).

1.3.2 Optimal policy with biased agents

When the agents are biased about their energy efficiency, energy consumption decisions are distorted both by the effect of the externality and the internality. This generates a gap between the private benefit from adoption and the social benefit from adoption, that cannot be corrected imposing a Pigouvian tax equal to the marginal externality. In this case, correcting both consumption and adoption decisions requires the use of a richer set of policy instruments. However, if beliefs were observable, there would always exist a non-linear corrective tax schedule such that the efficient allocation is implemented. This tax schedule would have to components, a first term equal to the marginal externality that addresses the

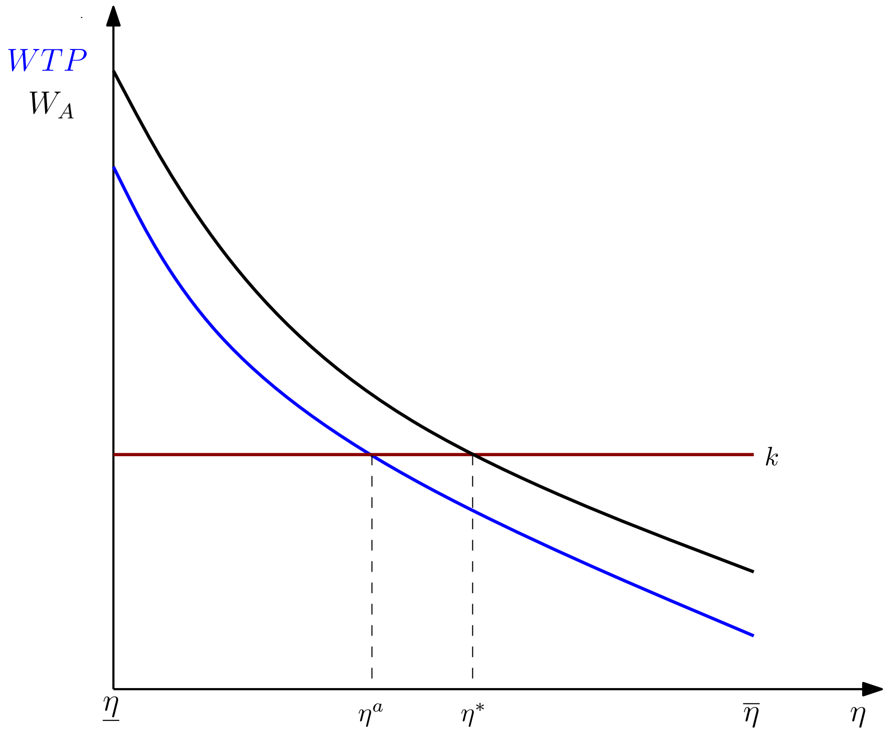


Figure 2: Social value of adoption and willingness to pay with unbiased agents

Note: The figure shows the social value of adoption and the private willingness to pay for the energy-efficiency technology with heterogeneous agents preferences. The gap between both is given by the externality effect on the adoption value. For a given investment cost k, η^a is the marginal adopter satisfying the optimal private investment decision rule. The figure shows how imposing a tax $\tau = \theta$ (equal to the marginal externality) implements the first best adoption level, the marginal adopter type from η^a to η^*.

externality and a second one addressing the internality.

Proposition 2. *If consumers' beliefs are observable to the policy maker, the optimal policy is given by a zero subsidy and the tax schedule* $\tau^*(\widehat{\eta}) = \theta + \frac{e_s - \hat{e}_s}{\hat{e}_s}(p+\theta)$. *Moreover, this policy achieves the first best level of welfare.*

Proof. Consider an agent with energy efficiency beliefs $\widehat{\eta}$ facing a tax τ. The first order condition for utility maximisation is $g'(s(\tau, \widehat{\eta})) = (p + \tau)e_s(\hat{s}(\tau, \hat{\eta}), \hat{\eta})$. Now consider the decision of an agent with the correct beliefs η facing the optimal Pigouvian tax equal to the marginal externality θ, the first order condition for utility maximisation is $g'(s(\theta, \eta)) = (p + \theta)e_s(s(\theta, \eta), \eta)$. By monotonicity of $g'(.)$, it follows a tax schedule replicating the first best energy services demand choices must satisfy the condition $g'(s(\tau, \widehat{\eta})) = g'(s(\theta, \eta))$. Hence, $(p + \tau)e_s(\hat{s}(\tau, \hat{\eta}), \hat{\eta}) = g'(s(\tau, \widehat{\eta})) = g'(s(\theta, \eta)) = (p + \theta)e_s(s(\theta, \eta), \eta)$. And the result in the proposition follows solving for τ and defining $e_s = e_s(s(\theta, \eta), \eta)$ and $\hat{e}_s = e_s(\hat{s}(\tau, \hat{\eta}), \hat{\eta})$. □

The idea is that for each value of the perceived energy efficiency level it is possible to find a tax such that the behavior of agents in response to that tax level is exactly the same as the one of an unbiased agent facing a tax equal to the marginal externality damage imposed by energy consumption. The optimal tax schedule is characterised by the condition $g'(s(\tau, \widehat{\eta})) = g'(s(\theta, \eta))$. From the first order condition for agent's utility maximisation, $g'(s(\tau, \widehat{\eta})) = (p + \tau)e_s(\hat{s}(\tau, \hat{\eta}), \hat{\eta})$ and $g'(s(\theta, \eta)) = (p + \theta)e_s(s(\theta, \eta), \eta)$.

The optimal tax schedule is the sum of the marginal externality plus a term capturing the internality due to the agents' misperceptions about their energy efficiency. Under this policy, optimistic agents ($\widehat{\eta} > \eta$) would face a tax higher than the Pigouvian tax because the tax needs to address also the energy consumption internality. The consumption internality originates in the fact that optimistic agents plan to consume too much energy services relative to the amount they would demand if they correctly perceived their true energy efficiency η. On the other hand, pessimistic agents ($\widehat{\eta} < \eta$) face a tax lower than θ. This policy would achieve the first best adoption rate as under this tax schedule every agent will internalize both the externality and the internality when making the adoption decision.

However, in what follows I focus the analysis on policies composed of a constant tax and a constant subsidy. In the remainder of the chapter, I discuss the characterization of optimal policies based on these two instruments, and how the presence of the internality affects the way consumers behave in response to the policy.

Heterogeneous internality In this section I consider the case where consumers are heterogeneous in their beliefs about their energy efficiency, $\hat{\eta} \in [\underline{\eta}, \overline{\eta}]$, but they all have a common true energy efficiency, η_0. It is assumed that for an unbiased consumer with energy efficiency η_0, the social value of adoption is positive and, hence, it is desirable to implement full adoption of the new technology with energy efficiency $\widetilde{\eta}$. First, this allows to analyse the effect of the presence of a heterogeneous internality on the optimal policy. Second, it provides predictions about the consumers' adoption behavior that are in stark contrast with the ones provided by a model where there is true heterogeneity in energy efficiency across consumers.

The key feature that differentiates this case from the ones analysed above is the fact that the correlation between the willingness to pay for energy efficiency improvements and the social value of adoption is negative for consumers who overconsume energy. From the policy maker point of view, the consumers for which the social benefit from adoption is larger are those ones who in the non-adoption state would overconsume energy, relative to what they would have consumed if they had known precisely their true energy efficiency. However, at the same time, for consumers who are optimistic about their energy efficiency it is more costly to induce them to adopt using policies based on taxes and subsidies.

In this case the perceived private value of adoption is decreasing in the perceived energy efficiency. This implies that agents who hold optimistic beliefs perceive the benefits from adoption to be low and are unlikely to invest in energy efficiency improvements. At the same time, these agents exhibit energy overconsumption and, from the policy-maker perspective are the ones for whom the social value of adoption is larger.

This negative relationship between the consumers' willingness to pay and the social value of adoption provides a rationale for the fact that many households energy efficiency is far below its potential. First, agents who believe themselves to be more efficient than they actually are, tend to overconsume energy relative to the energy consumption level they would need to satisfy their energy services demand if they had known their true energy efficiency. Second, agents who overconsume energy are relatively unlikely to invest in energy efficiency improvements. Even when these agents face policies that provide incentives to adopt based on uniform taxes and subsidies, the same adoption pattern remains, and these policies are proven extremely ineffective to encourage agents to adopt energy-efficiency enhanced technologies. (Figure 3)

The analysis presented here focuses on the case where agents become fully informed upon adoption, and therefore, the social value of adoption is larger as adoption provides both a better technology and corrects the choice inefficiencies due to biased beliefs. Nonetheless, I show AppendixA.1 that under some conditions, the model still satisfies the negative correlation between willingness to pay and social value of adoption property when misperceptions remain upon adoption.

First, I consider the case where the policy maker balances the budget with a lump-sum transfer. In which case, the government budget constraint is given by:

$$H(\widehat{\eta}^a)\,[\tau e_A - \sigma] + (1 - H(\widehat{\eta}^a))\,E\,[\tau e_N \mid \widehat{\eta} \geq \widehat{\eta}^a] = T \tag{16}$$

Proposition 3. *In the presence of heterogeneous internalities, full adoption of the energy-efficient technology is implemented by a policy consisting of a tax equal to the marginal externality damage and a subsidy $\sigma = (p+\theta)(e^a - \hat{e}^a)$. The lump sum transfer that balances the budget is given by $T = -(p+\theta)(e^a - \hat{e}^a) + \theta\tilde{e}$. When misperceptions are large enough, the full adoption implementation involves large*

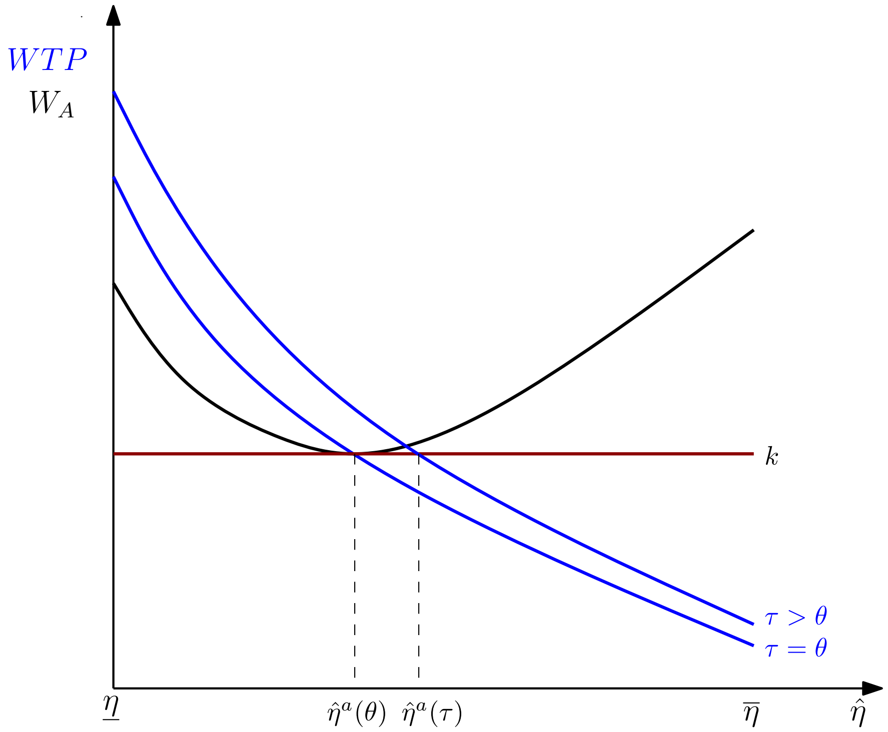


Figure 3: Social value of adoption (w_A) and willingness to pay with biased agents

Note: The figure shows the social value of adoption and the private willingness to pay for the energy-efficiency technology when heterogeneous agents in biased beliefs. For a given investment cost k, $\widehat{\eta}^a$ is the marginal adopter. The figure shows how imposing a tax $\tau > \theta$ (above the marginal externality) increases the marginal adopter type from $\widehat{\eta}^a(\theta)$ to $\widehat{\eta}^a(\tau)$. More importantly note that for $\widehat{\eta} > \widehat{\eta}^a(\theta)$, the gap between social value of adoption and the agent's WTP is positive and increasing.

lump-sum transfers to balance the budget.

Proof. Consider the welfare maximisation problem subject to the incentive compatibility constraint and the government budget constraint where the government has access to lump sum transfers T:

$$\max_{\mathbf{q}=(\tau,\sigma)} \quad H(\hat{\eta}^a(\mathbf{q}))\left[v_A(\tau,\tilde{\eta}) - (k(\tilde{\eta}) - \sigma) - \theta e(s(\tau,\tilde{\eta}),\tilde{\eta})\right]$$

$$+\int_{\hat{\eta}^a(\mathbf{q})}^{\overline{\eta}} \left[v_N(\tau,\hat{\eta}) - \theta e(s(\tau,\hat{\eta}),\eta)\right] h(\hat{\eta})d\hat{\eta} \tag{17}$$

$$\text{s.t. } H(\hat{\eta}^a(\mathbf{q}))\left[\tau e(s(\tau,\tilde{\eta}),\tilde{\eta}) - \sigma\right]+$$

$$+\int_{\hat{\eta}^a(\mathbf{q})}^{\overline{\eta}} \tau e(s(\tau,\hat{\eta}),\eta)h(\hat{\eta})d\hat{\eta} \geq T \qquad \text{(Lagrange multiplier: } \lambda) \tag{18}$$

$$T \geq 0 \qquad \text{(Lagrange multiplier: } \mu) \tag{19}$$

The first order conditions with respect to τ and σ are given by:

$$\hat{\eta}^a_\tau h(\hat{\eta}^a)\left[(p+\tau)(e^a - \hat{e}^a) - (\tau - \theta)(e^a - \tilde{e}) - \sigma\right] +$$

$$+(\tau-\theta)E\left[e_\tau|\hat{\eta}^a\right] - (p+\tau)\int_{\hat{\eta}^a(\mathbf{q})}^{\overline{\eta}} (e_\tau - \hat{e}_\tau)h(\hat{\eta})d\hat{\eta} =$$

$$= \mu\left[\hat{\eta}^a_\tau h(\hat{\eta}^a)\left(\tau(e^a - \tilde{e}) + \sigma\right) - E\left[e + \tau e_\tau|\hat{\eta}^a\right]\right]$$

$$\hat{\eta}^a_\sigma h(\hat{\eta}^a)\left[(p+\tau)(e^a - \hat{e}^a) - (\tau - \theta)(e^a - \tilde{e}) - \sigma\right] =$$

$$= \mu[H(\hat{\eta}^a) + \hat{\eta}^a_\sigma h(\hat{\eta}^a)(\tau(e^a - \tilde{e}) + \sigma)] \tag{20}$$

When the government has access to lump sum transfers the Lagrange multiplier $\mu = 0$ and the following conditions together with the government budget constraint and the incentive compatibility constraint characterize the optimal policy:

$$\tau = \frac{1}{1-\Gamma(\hat{\eta}^a)}\theta + \frac{\Gamma(\hat{\eta}^a)}{1-\Gamma(\hat{\eta}^a)}p \tag{21}$$

$$\sigma = (p+\theta)\left[(e^a - \hat{e}^a) - \frac{\Gamma(\hat{\eta}^a)}{1-\Gamma(\hat{\eta}^a)}(\hat{e}^a - \tilde{e})\right] \tag{22}$$

$$\Gamma(\hat{\eta}^a) = (1 - H(\hat{\eta}^a))\frac{E\left[(e_\tau - \hat{e}_\tau)|\hat{\eta} \geq \hat{\eta}^a\right]}{E\left[e_\tau|\hat{\eta}^a\right]} \tag{23}$$

Therefore, the first best is implemented setting $\tau = \theta$, $\sigma = (p+\theta)\left[(e^a - \hat{e}^a)\right]$ and $\Gamma(\hat{\eta}^a) = 0$. The budget constraint is satisfied then setting $T = -(p+\theta)(e^a - \hat{e}^a) + \theta\tilde{e} < 0$. $\square$

The intuition behind Proposition 3 is that when the adoption of the energy efficient technology is desirable from a social planner point of view, the socially optimal adoption rule would prescribe full adoption. Moreover, in the full adoption scenario, consumers become fully informed about their energy efficiency and the unique source of inefficiency is the energy consumption externality. Therefore, setting a large enough subsidy guarantees that even the most optimistic consumers invest in the new technology and become fully informed. And, hence, a tax equal to the marginal externality corrects the intensive margin energy consumption decisions. The main problem of using such a policy to implement full adoption is that it is very expensive. First of all, a potentially large subsidy is required to encourage the more optimistic consumers to adopt. And, second, once the subsidy is offered, there is no way to prevent the infra-marginal consumers from taking the subsidy up. For instance, consumers who are pessimistic about their energy efficiency before adoption would have invested in the new technology in the absence of the subsidy, however with the policy in place they all will adopt the new technology and get the subsidy.

The bottom line of this proposition, is that the policy-maker could always implement any level of adoption of his choice if he has access to lump sum transfers. In particular, among all the implementable levels of adoption, the one presented in Proposition 3 implements the first best.

Particular case: Uniform internality Here, I consider the case where agents are truly heterogeneous in their energy efficiency and there is a homogeneous bias in their beliefs. In particular, I focus the attention on a population composed of heterogeneous agents in η (true energy efficiency) and a uniform bias in energy efficiency beliefs b. Hence, the consumers' perceived energy efficiency is given by $\widehat{\eta} = \eta + b$. This case captures a situation in which, for instance, all consumers are optimistic about their energy efficiency and, hence, they tend to overconsume energy and undervalue the benefit from adoption.

Let define $\Gamma(\widehat{\eta}^a) = (1 - H(\widehat{\eta}^a)) \frac{E[(e_{\tau N} - \widehat{e}_{\tau N})|\widehat{\eta} \geq \widehat{\eta}^a]}{E[e_\tau|\widehat{\eta}^a]}$. For a given marginal adopter $\widehat{\eta}^a$, $\Gamma(\widehat{\eta}^a) \in [0, 1]$ is a measure of the average internality among non-adopters.

Corollary 1. *Let η^* denote the energy efficiency level such that for $\eta \leq \eta^*$ adopting the new technology is socially optimal. The optimal policy consisting of*

1. $\tau = \theta + (p + \theta)\frac{\Gamma(\eta^*+b)}{1-\Gamma(\eta^*+b)} > \theta$.
2. $\sigma = (p + \theta)\left[(e^a_N - \widehat{e}^a) - \frac{\Gamma(\eta^*+b)}{1-\Gamma(\eta^*+b)}(\widehat{e}^a_N - e_A)\right]$.

implements the socially optimal adoption rule. Moreover, the marginal adopter $\widehat{\eta}^a = \widehat{\eta}^* = \eta^* + b$ satisfies $(p + \theta)[e_N(\widehat{\eta}^*) - e_A] + g(s_A) - g(s_N(\widehat{\eta}^*)) = k$.

Proof. The corollary follows from evaluating the optimal policy result in Proposition3 when $\widehat{\eta} = \eta + b$. With heterogeneous agents in true energy efficiency η and a uniform internality b, such that the energy efficiency misperception $\hat{\eta} - \eta = b$ is constant, the only source of heterogeneity is the true efficiency level. However, the variable determining the optimal policy is $\widehat{\eta}$. Note that in this case, since the optimal adoption rule is determined by a cut-off rule on η, the equilibrium adoption pattern is that only consumers for whom $\widehat{\eta}^* = \eta^* + b \geq \widehat{\eta}^a$ adopt the technology. And therefore, in equilibrium $\Gamma(\widehat{\eta}^a) \in (0, 1)$. This results in a tax above the Pigouvian corrective tax level θ. □

The optimal policy when consumers have a homogeneous bias consists of a combination of a tax and a subsidy. The tax is set above the marginal externality to discourage energy overconsumption among non-adopters. Indeed, the expression for the optimal tax is equal to the sum of the marginal externality plus the average internality effect conditional on consumers with $\eta \leq \eta^*$adopting the new technology. The subsidy is set to the level such that the marginal adopter is $\widehat{\eta}^* = \eta^* + b$.

Note that in this case, non-adopters are consumers located originally at the top of the energy efficiency distribution. Hence, in spite of the presence of the homogeneous internality, this case shares common features with the unbiased heterogeneous agents case. As long as the internality is homogeneous, the willingness to pay is positively correlated with the social value of adoption and, hence, the pattern of technology adoption still satisfies that non-adopters do not represent an important problem in terms of energy overconsumption.

Optimal policy when no access to lump sum transfers In the next proposition, I focus my attention on the case where the policy-maker has no access to lump-sum transfers. Now, the policy-maker has to satisfy the budget constraint, i.e. the subsidy is financed only with the revenues raised by the tax on energy consumption.

Proposition 4. *When the policy-maker has no access to lump-sum transfers, the optimal policy must satisfy the following conditions:*

1. $\tau = \theta + (p+\theta)\frac{\Gamma(\widehat{\eta}^a)}{1-\Gamma(\widehat{\eta}^a)}$. *The optimal tax is strictly greater than the marginal externality.*

2. The subsidy is given by the government budget constraint,

$$\sigma = \tau e_A + \tau \frac{(1 - H(\widehat{\eta}^a))}{H(\widehat{\eta}^a)} E\left[e_N \mid \widehat{\eta} \geq \widehat{\eta}^a\right] \tag{24}$$

with $\sigma < (p+\theta)(e^a - \hat{e}^a) - (\tau - \theta)(e^a - \tilde{e})$ *.*

3. Rate of adoption below full adoption, $\hat{\eta}^a < \overline{\eta}$*.*

Proof. Consider the welfare maximisation problem subject to the incentive compatibility constraint and the government budget constraint where the government has no access to lump sum transfers T[6]:

$$\max_{\mathbf{q}=(\tau,\sigma)} \quad H(\hat{\eta}^a(\mathbf{q}))\left[v_A(\tau,\tilde{\eta}) - (k(\tilde{\eta}) - \sigma) - \theta e(s(\tau,\tilde{\eta}),\tilde{\eta})\right]$$

$$+\int_{\hat{\eta}^a(\mathbf{q})}^{\overline{\eta}} \left[v_N(\tau,\hat{\eta}) - \theta e(s(\tau,\hat{\eta}),\eta)\right] h(\hat{\eta})d\hat{\eta} \tag{25}$$

$$\text{s.t. } H(\hat{\eta}^a(\mathbf{q}))\left[\tau e(s(\tau,\tilde{\eta}),\tilde{\eta}) - \sigma\right] +$$

$$+\int_{\hat{\eta}^a(\mathbf{q})}^{\overline{\eta}} \tau e(s(\tau,\hat{\eta}),\eta)h(\hat{\eta})d\hat{\eta} \geq 0 \qquad \text{(Lagrange multiplier: } \lambda\text{)} \tag{26}$$

The first order conditions with respect to τ and σ are given by:

$$\hat{\eta}^a_\tau h(\hat{\eta}^a)\left[(p+\tau)(e^a - \hat{e}^a) - (\tau - \theta)(e^a - \tilde{e}) - \sigma\right] +$$

$$+(\tau-\theta)E\left[e_\tau|\hat{\eta}^a\right] - (p+\tau)\int_{\hat{\eta}^a(\mathbf{q})}^{\overline{\eta}} (e_\tau - \hat{e}_\tau)h(\hat{\eta})d\hat{\eta} = 0 \tag{27}$$

$$\hat{\eta}^a_\sigma h(\hat{\eta}^a)\left[(p+\tau)(e^a - \hat{e}^a) - (\tau - \theta)(e^a - \tilde{e}) - \sigma\right] = 0 \tag{28}$$

The government budget constraint is given by:

$$H(\widehat{\eta}^a)\left[\tau e_A - \sigma\right] + (1 - H(\widehat{\eta}^a))\, E\left[\tau e_N \mid \widehat{\eta} \geq \widehat{\eta}^a\right] = 0 \tag{29}$$

Combining the first order conditions and the government budget constraint it follows that the following condition must hold:

[6]Note that this can be seen as a particular case of the proof of proposition 4 where the constraint $T \geq 0$ is binding

$$\left[\widehat{\eta}^a_\tau + \widehat{\eta}^a_\sigma \frac{d\sigma(\tau)}{d\tau}\right] h(\widehat{\eta}^a)\left\{(p+\tau)(e^a - \widehat{e}^a) - (\tau-\theta)(e^a - e_A) - \sigma\right\}$$
$$= (p+\tau)\left[1 - H(\widehat{\eta}^a)\right] E\left[(e_{\tau N} - \widehat{e}_{\tau N}) \mid \widehat{\eta} \geq \widehat{\eta}^a\right] - (\tau-\theta) E\left[e_\tau \mid \widehat{\eta}^a\right] \tag{30}$$

And from the implicit differentiation of the budget constraint:

$$\frac{d\sigma(\tau)}{d\tau} = \frac{\widehat{\eta}^a_\tau h(\widehat{\eta}^a)\left[\tau(e^a - e_A) + \sigma\right] - E\left[e + \tau e_\tau \mid \widehat{\eta}^a\right]}{H(\widehat{\eta}^a) + \widehat{\eta}^a_\sigma h(\widehat{\eta}^a)\left[\tau(e^a - e_A) + \sigma\right]} \tag{31}$$

The optimal tax expression in the proposition follows from the first order condition with respect to τ. The expression for the subsidy then follows from the government budget constraint. The Lagrange multiplier λ is positive if and only if the condition $\sigma < (p+\tau)(e^a - \widehat{e}^a) - (\tau-\theta)(e^a - e_A)$ is satisfied. Hence, by comparison to Proposition 3, the subsidy is below the subsidy level that would implement full adoption.

Given these, equation 9 is satisfied when $\widehat{\eta}^a_\tau + \widehat{\eta}^a_\sigma \frac{d\sigma(\tau)}{d\tau} = 0$. From the implicit differentiation of the consumers' participation constraint, it follows that the change in the marginal adopter identity in response to the policy instruments must satisfy the following expressions:

$$\widehat{\eta}^a_\tau = -\frac{\widehat{e}^a - e_A}{(p+\tau)\widehat{e}^a_{\widehat{\eta}}} > 0 \tag{32}$$
$$\widehat{\eta}^a_\sigma = -\frac{1}{(p+\tau)\widehat{e}^a_{\widehat{\eta}}} > 0 \tag{33}$$

Hence it must be that $\frac{d\sigma(\tau)}{d\tau} < 0$ in equilibrium. □

When lump sum transfers are not available, the policy-maker can only consider revenue neutral changes in the tax and subsidy, and this introduces additional restrictions on the incentives that can be provided to induce optimistic consumers to purchase the energy-efficient technology. Furthermore, the welfare maximisation optimality conditions require that $\sigma < (p+\tau)(e^a - \widehat{e}^a) - (\tau-\theta)(e^a - e_A)$.[7]

[7] For the Lagrange multiplier on the government budget constraint to be positive this condition

To induce optimistic consumers to purchase the energy efficient technology, the policy-maker offers a subsidy that must be financed by the tax on energy consumption. However, the tax increase required to finance a larger subsidy, generates an increased efficiency cost due to taxing consumers who adopt the new technology above the marginal externality. At the same time, having a tax above the marginal externality has a positive welfare effect, as it discourages overconsumption among non-adopters. The idea behind the optimal policy proposed in Proposition 4, is that the tax must exceed the marginal externality by $(p+\theta)\frac{\Gamma(\widehat{\eta}^a)}{1-\Gamma(\widehat{\eta}^a)}$. This second term in the optimal tax expression depends on the average internality among non-adopters. Given that the marginal adopter is always optimistic about the energy efficiency level, this second term is always positive.

As the tax and subsidy increase need to increase in a balanced way to satisfy the government budget constraint, the proportion of adopters increases initially, as long as $\widehat{\eta}^a_\tau + \widehat{\eta}^a_\sigma \frac{d\sigma(\tau)}{d\tau} > 0$. To keep on increasing the number of adopters, larger tax revenues are required to finance a larger subsidy. However, the average energy consumption decreases for two reasons. First, more consumers adopt the energy efficient technology, leading to a reduction in energy consumption. Second, at the same time consumers cut energy consumption in response to the tax increase. Therefore, for large enough taxes the tax revenue is decreasing, and the subsidy has to decrease accordingly. This argument rules out the possibility of increasing the tax and the subsidy in a balanced budget way in order to achieve a full adoption implementation. Furthermore, the policy-maker will increase the tax until it reaches the level such that $\widehat{\eta}^a_\tau + \widehat{\eta}^a_\sigma \frac{d\sigma(\tau)}{d\tau} = 0$. Since both $\widehat{\eta}^a_\tau$ and $\widehat{\eta}^a_\sigma$ are positive, it must be that at the optimum $\frac{d\sigma(\tau)}{d\tau} < 0$. The policy-maker increases the tax and subsidy keeping the budget balanced as long as this has a positive effect on the marginal adopter. This implies setting a tax equal to the marginal externality plus the average internality among the non-adopters, and a subsidy that is strictly smaller that the one that would implement full adoption in the case discussed in Proposition 3 where lump sum transfers were available.

must be satisfied.

Therefore, the key trade off when choosing the policy instruments is between inducing energy consumption efficiency and adoption decisions efficiency. The first important consideration is that increasing the tax and/or the subsidy increases the adoption rate. In addition, the subsidy does not impose any distortion on energy consumption choices, however, to offer larger subsidies the policy maker needs to increase the tax in order to raise enough revenues to finance the cost of the subsidy. On the other hand, providing incentives taxing energy consumption requires increasing the tax above the marginal externality. Hence, imposing an excessively large tax on consumers who purchase the new technology, as this leads them to choose an inefficiently low energy consumption level.

Overconsumption and responsiveness to policy For optimistic agents (energy overconsumers), as the optimistic bias increases, the marginal adopter responsiveness to taxes decreases as consumers with large $\widehat{\eta}$ are less "attentive" to the energy cost. Due to their biased beliefs, they underestimate the marginal amount of energy required to produce an additional unit of energy services. For a fixed tax, the marginal adopter responsiveness to increases in the subsidy is increasing in $\widehat{\eta}$, since the private value of adoption curve becomes flatter as the bias increases. This is consistent with the optimal policy results in the previous section. In the case where the policy maker has access to lump sum transfer, the optimal policy involves a sufficiently large subsidy and the tax is kept at the level that corrects the externality and the average marginal internality among the non-adopters.

When the subsidy needs to be financed by the energy tax revenues, then there is an additional constraint on the feasible policies. Hence, it becomes of paramount importance for the optimal policy analysis how the marginal adopter responsiveness to the policy instruments changes when tax and subsidy change in a budget balanced way. From the last section, the marginal adopter responsiveness to the subsidy ($\widehat{\eta}^a_\sigma$) is decreasing in the energy tax. When the energy tax increases, the private value of adoption curve shifts outwards and at the same time becomes steeper. The rotation comes from the lower responsiveness of optimistic agents to the energy tax. Consequently, an increase in the subsidy has a smaller effect on the marginal adopter when combined with a large tax. This provides an argument in favor of keeping the tax low, however, to finance an increasing subsidy, the policy maker needs to increase the tax and this in turn reduces the effectiveness of the subsidy.

A second consideration, comes from the intensive margin energy consumption responses. As discussed before, the low responsiveness of optimistic agents' energy consumption plans to taxes arises because optimistic consumers undervalue the marginal energy consumption effect of increasing their demand for energy services, and therefore they perceive the impact of the tax on their budget to be very small. However, small responses to the energy tax in terms of planned energy consumption induce potentially large changes in the experienced energy consumption. This effect is due to the wedge between the responsiveness of experienced and planned energy consumption responses to the tax $(e_{\tau 0} - \widehat{e}_{\tau 0})$. This provides, therefore, an additional argument to set the energy tax above the marginal externality.

1.4 Learning alternative scenarios

I discuss in this section alternative assumptions on learning about the true energy efficiency parameter. I consider these alternative assumptions in the context of the model discussed previously. In particular, a model where the source of heterogeneity across agents is that they hold heterogeneously biased beliefs about their energy efficiency. The working assumption of the model discussed so far was that agents would eventually correct their biased beliefs upon adoption of the energy efficient technology. In the rest of this section I discuss how relaxing this assumption would affect the results of the model. I consider three alternative scenarios, one in there is an unconditional learning process (regardless of the technology adoption decision), one in which there is partial learning towards the true energy efficiency parameter upon adoption of the energy efficient technology, and a third one where there is no learning at all.

1.4.1 Unconditional aggregate learning

Suppose that regardless of the technology adoption decision, there is an underlying learning process that leads agents beliefs to converge towards the true energy efficiency parameter. Then, in future periods this would result in a lower internality effect. The energy consumption decisions of agents would be closer to the efficient level of energy consumption for a given level of energy efficiency. This would be the result of a smaller gap between the energy consumption plan and the experienced level of energy consumption. Therefore, the gap between the social value of technology adoption and the private value of technology adoption would be smaller.

Since the rational for the subsidy in the model is addressing the internality effect that leads agents to take suboptimal investment decisions, smaller behavioral biases would lead to an optimal policy involving a smaller subsidy.

The tax which is targeted to the average internality effect. In the presence of unconditional learning, regardless of adoption decisions, the average internality effect would be reduced and, therefore, the tax would be closer to the marginal externality (Pigouvian tax).

However, unless misperceptions are fully corrected, the model would still feature that those who invest in the energy efficient technology are those who would have invested in the absence of the subsidy. And those with biased beliefs such that they overconsume energy relative to the efficient level of energy consumption would be less likely to adopt the new technology.

1.4.2 Partial learning upon adoption

Suppose that there is partial learning towards the true energy efficiency parameter upon adoption of the new technology. Hence, non-adopters beliefs are preserved. Adopters, however, throughout the technology adoption process partially correct their misperceptions about their true energy efficiency.

According to the model, non-adopters are those who initially hold biased beliefs leading to energy overconsumption and undervaluation of technology adoption benefits, and adopters are those who initially hold beliefs such that they underconsume energy and overvalue the adoption benefits. As a consequence of this, after the adoption stage the distribution of beliefs would concentrate towards the true energy efficiency parameters for adopters and remain unchanged for non-adopters.

Even though both groups would still contribute to the average internality, the non-adopters group who is dominated by energy overconsumers would dominate the internality effect. As a result of this, in general the optimal policy should consist of a tax above marginal externality to address the overconsumption internality.

With regards to the subsidy, the social value of adoption is reduced compared to the case where adopters fully correct their misperceptions. Hence, the optimal policy subsidy should be smaller in the partial learning scenario. The subsidy should still be targeted at the marginal adopter internality. The rational for the subsidy is to encourage technology adoption, but also compensates adopters for the excessively high tax level that is imposed to address the average internality leading to energy overconsumption.

In this case, the negative correlation between the social value of adoption and the private value of adoption would be preserved under some conditions. In the next subsection I describe the limiting case in which there is no learning upon adoption. I provide in the Appendix a sufficient condition under which this negative correlation prevails in the no learning case. And, hence, that is also a sufficient condition for the negative correlation between the private value of adoption and the social value of adoption in the partial learning scenario.

1.4.3 No learning upon adoption

This can be considered an extreme particular case of the scenario just discussed. It is an interesting scenario as it sets a lower bound for the social value of technology adoption.

Suppose that there is no learning at all. Both adopters and non-adopters biased beliefs are preserved. As a consequence, new technology adopters will take inefficient utilisation decisions based on their biased beliefs.

Since the adoption decision is based on current beliefs, the model would still result on those who underconsume energy relative to efficient energy consumption to select themselves into technology adoption. This is a consequence of their overvaluation of the benefits of investing in the energy efficient technology. However, when operating the new technology, they will keep on taking decisions leading to inefficiently low levels of energy consumption. On the other hand, non-adopters who tend to be energy overconsumers will also keep making decisions leading to energy overconsumption in the second stage.

First of all, the fact that there is no learning induced by the adoption decision reduces the social value of adoption. Hence, the benefit of providing a subsidy from the policy maker point of view decreases. Selection into adoption is still adverse from a policy cost-benefit perspective. In addition, the potential welfare gain is reduced by the fact that adoption of technology does not correct energy cost misperceptions among adopters.

On the other hand, the effect on the tax will depend on the relative proportion of energy overconsumers and underconsumers. The tax should be equal to the marginal energy consumption externality plus an additional term targeting the average internality. Now, the internality effect is the result of behavioral biases among adopters and non-adopters. Under the model assumption, that energy overconsumers are less responsive to taxes (and subsidies), one could expect that the tax would still be above the marginal externality level as energy overconsumption deviations from the efficient level of consumption are likely to dominate. However, in general, whether the tax should be above of below the Pigouvian tax level would depend on the initial distribution of beliefs.

Furthermore, another force towards setting the tax above the Pigouvian tax level has to do with the revenue raising role of the tax to finance the subsidy. As discussed in the previous section, when the tax and subsidy policy is required to be budget balanced the policy maker wants to increase the tax to finance a larger subsidy and induce more agents to adopt the technology.

1.5 Policy (in)effectiveness: Preference heterogeneity vs Misperceptions about energy efficiency

The results from the optimal policy analysis presented above suggest key differential policy implications of the different sources of heterogeneity. First of all, a policy maker who ignores the presence of misperceptions among consumers would set a policy that does not provide enough incentives for the adoption of energy efficient technologies. If the policy maker sets a tax equal to the marginal externality, optimistic consumers will keep on undervaluing the benefits from adoption and overconsuming energy relative to what they would have consumed if their beliefs were accurate. Second, if the internality is taken into account the optimal policy will result in consumers underadopting the new technology. The reason behind this is that taxes and subsidies are very ineffective at encouraging adoption of energy-efficient technologies by optimistic agents.

In the presence of the internality, the marginal adopter responsiveness to both the subsidy and the tax is lower when optimistic biases are large. The more optimistic is the marginal adopter, the more one needs to increase the tax and/or the subsidy to increase the adoption rate. At the same time, the marginal adopter responsiveness to both additional tax and subsidy increases is decreasing in the energy tax. The idea is that as the tax increases the private benefit of adoption (willingness to pay) curve becomes steeper, making consumers less responsive to the subsidy. Similarly, when the tax is higher, the marginal adopter is more η-optimistic and, therefore, less responsive to tax increases as well. Although, increasing the tax and the subsidy provides more incentives to adoption, the policy maker has to keep in mind the negative effects. Increasing the tax above the marginal externality imposes an excessive tax on adopters generating an efficiency cost. In addition, if the tax grows too large, the tax revenues start decreasing and this limits how large the subsidy can be when the government has to keep a balanced budget. Finally, the inability to prevent inframarginal consumers from taking the subsidy up makes inducing severe overconsumers into adoption of energy-efficient technologies extremely costly.

Another way in which tax and subsidy policies are ineffective comes from the previously discussed negative correlation between adoption decisions and energy consumption. When agents are unbiased the willingness to pay and the social value of adoption are aligned. However, with misperceptions energy overconsumers do not adopt the energy-efficient technology and keep on overconsuming energy. If the policy could be better targeted to optimistic agents, the subsidy cost will be reduced dramatically. At the same time, the tax could be kept at lower level reducing the tax efficiency cost on adopters. Note that pessimistic agents would adopt the energy efficient technology even in the absence of the subsidy, and then the policy could be only focused on providing strong effective incentives to optimistic consumers.

1.6 Empirical test

One of the main insights of the previous analysis is that when agents are biased, providing incentives for technology adoption via taxes and subsidies is very expensive for the government. Moreover, the agents for whom the social value of adoption is higher are the ones who are less responsive to these policy instruments. On the other hand, the analysis above shows that when the marginal adopter is η-optimistic, the correlation between consumers' willingness to pay and the social value of adoption is negative and the wedge between them increases as the agents become more optimistic. Hence, in the presence of misperceptions about energy efficiency, the model predicts that heavy energy overconsumers are unlikely to adopt. This fact is in stark contrast with the implications of true technology heterogeneity and unbiased beliefs. In which case, non-adopters are those ones who find investing in the new technology not sufficiently profitable because their energy efficiency is already high or their energy use intensity is low. Hence, non-adopters are consumers that come from the lower end of the energy consumption distribution.

In this chapter I present two extreme cases, one in which there is only heterogeneity in the true energy efficiency, and another in which heterogeneity is driven only by heterogeneous misperceptions on energy efficiency. As discussed in the previous paragraph the two configurations have diametrically opposed predictions on the correlation between energy efficiency and energy consumption levels and changes in energy consumption upon adoption. With only preference heterogeneity the prediction is that the correlation is positive, whereas with only heterogeneous misperceptions the correlation is negative. The ideal empirical test I propose is based on analysing the correlations between energy consumption levels and energy consumption changes, and the energy efficiency type. Note, that this empirical test is not perfect, and a positive empirical correlation does not exclude the possibility that there is a role of misperceptions at explaining selection into adoption, however it would suggest that selection is dominated by heterogeneity in true preferences.

A first concern is that the preferences and beliefs on energy efficiency are not observable. This requires finding another source of variation that captures the potential sources of heterogeneity. For that purpose, I look at the timing of the adoption decisions as a reflection of consumers' heterogeneity. A second concern is that adoption decisions are endogenous. They are correlated with unobservable heterogeneity, that in turn is correlated with energy consumption decisions. However, the main advantage of this test is that it does not require any source of exogenous variation to overcome this endogeneity problem. Following this empirical predictions, in Chapter 3, I perform an empirical analysis using an event-study approach to conduct the test presented above. I estimate correlations between pre-adoption energy consumption levels and energy consumption changes upon adoption, and the timing of adoption decisions. The implicit assumption is that heterogeneity, in preferences or in beliefs, determines the timing of adoption decisions.

The test ideally requires using individual-level data on energy consumption and adoption of energy efficiency improvements. Ideally, one should be able to observe for each individual the past history of energy consumption before the individual purchases decides to invest in energy efficient durable goods. I believe it is crucial to control for individuals' socioeconomic characteristics, property characteristics, and geographic location, as many of this variables are likely to be correlated with energy consumption, but also might have an impact on the adoption decision.

The analysis presented in the rest of this thesis is based on the UK National Energy Efficiency Data. This data set will be described in detail in the next Chapter.

Another option I considered is the Residential Energy Consumption Survey (RECS). The RECS is conducted in the US every four years and contains information about households' characteristics, energy consumption and information about the type of energy-using durable goods purchased by each household. The main limitation imposed by this survey data is that it provides only aggregate information about energy consumption in the last four year-period for each household. However, when a household adopts an energy efficient technology, its energy consumption is expected to decrease. The information in this data set provides only the overall energy consumption in the same period where the adoption of the new technology took place, and this is likely to induce a negative correlation between energy consumption and adoption decisions which could have nothing to do with the implications of the model presented in this chapter. Even though, for the empirical application presented here, it is very important to observe energy consumption before adoption, since consumption after adoption is already affected by technology adoption. Nonetheless, the RECS survey data contains information about other interventions like energy audits and other smaller scale energy efficiency measures interventions that have potential to be used in further research.

1.7 Conclusion

This chapter proposes a theoretical model to think about energy policy in the presence of externalities and internalities. The main novelty of the chapter is that internalities affect directly the energy consumption decisions and induce a wedge between perceived and true benefits from adoption of energy-efficient technologies. The theoretical analysis is based on the fact that consumers' perceptions about their energy efficiency are biased and discusses the implications of the presence of this internality in the design of policies to encourage the adoption of energy-efficient technologies.

I find that when consumers' heterogeneity is driven by biased beliefs, the optimal policy is a combination of a tax greater than the Pigouvian corrective tax to discourage energy overconsumption among non-adopters, and a subsidy targeted at the marginal adopter internality.

I also show that whether heterogeneity is driven by misperceptions or by true heterogeneity in energy-efficiency makes a crucial difference for policy design. First, ignoring misperceptions and targeting the policy as if consumers where heterogeneous preferences (in the true energy efficiency) would lead to a level of adoption of the new technology far below what is socially desirable. Second, whilst energy taxes can fully correct inefficiencies due to the externality, this is no longer feasible when heterogeneity is driven by misperceptions. Moreover, the responsiveness of optimistic consumers to the proposed policy instruments is limited and decreases as the bias becomes more severe. Third, the model predicts a negative correlation between the new technology adoption likelihood and the current level of energy consumption. This implies that energy overconsumers are unlikely to adopt the energy-efficient technology under policies based on taxes and subsidies.

The findings in this chapter suggest that energy policy should perhaps combine taxes and subsidies with information policies like information campaigns, energy audits, use of devices like smart meters that make the energy costs more salient to households. This suggests also a rationale for the use of policies based on minimum energy-efficiency standards. Minimum standards would force households who undervalue the benefits from adoption to increase their level of energy efficiency when purchasing new durable goods because the current one broke down for instance. Hence, this would introduce some degree of random enforcement. An interesting question for future research is how to set optimal minimum energy efficiency standards in combination with other policy instruments.

Chapter 2

Energy consumption and energy policy in the UK

2.1 Introduction

This chapter discusses the energy consumption patterns and energy efficiency measures adoption in the UK. First of all, in Section 2, In Section 2, I review the evolution of how policy makers think about energy efficiency policy design in the light of the new theoretical developments and empirical evidence. In addition, I provide a review of energy efficiency policy in other developed countries to place energy efficiency policy in the UK in an international context.

The aims of this chapter are: first, identify energy efficiency policy interventions in the UK that could provide policy variation to identify the impact of incentives on technology adoption and selection into technology adoption, and second, analyse the energy consumption trends over time and the impact of technology adoption decisions. All in all, the analysis presented in this chapter sets the stage for the empirical analysis exposed in Chapter 3.

For this purpose I use a data set (National Energy Efficiency Data, NEED) covering a large sample of households in England and Wales. For approximately 4 million households, the data set keeps track of energy consumption and energy efficiency measures installation over the period 2005-2012. The data set is described in detail in Section 3 of this chapter, followed by a descriptive analysis of energy efficiency policies in the UK. Throughout the discussion in Section 4, I aim to emphasize the policy variation introduced by the government schemes in place. Data limitations, however, make difficult to use this policy variation to identify the behavioral responses of households to public incentive schemes using the National Energy Efficiency Data.

In the following sections I provide a detailed analysis of energy efficiency measures adoption and energy consumption patterns over time. More specifically, in Section 5 I focus on adoption patterns looking at adoption determinants and also at the timing of technology adoption. In Section 6, I turn the attention to the energy consumption profiles over time. Section 7 provides a discussion on the rebound effect based on the graphical analysis of the energy consumption profiles around the time of energy efficiency measures adoption.

With the aim of analysing the potential of households' heterogeneity at explaining the impact of energy efficiency measures adoption, in Section 8, I present a similar analysis grouping households according to different households' characteristics included in the dataset. In the absence of data on income and other socioeconomic characteristics of households, I focus the grouping analysis on the Index of Multiple Deprivation and the Fuel Poverty Index as variables that could proxy income heterogeneity. I also analyse the impact of the property type, main heating fuel and regional heterogeneity.

Section 9 analyses the role of information provision comparing groups of households that subject to information provision interventions to others who do not. In Section 10, I present the results of a household level fixed effects model estimating the aggregate impact of energy efficiency measures adoption. And Section 11 concludes.

2.2 Literature Review and International Context

From the early theoretical development of Pigouvian taxes as a way to correct externalities to the way policy makers think about energy efficiency policy there have been many contributions that have reshaped how policy makers think about optimal policy design.

The idea of Pigouvian corrective taxes as an instrument to correct market failures associated with the presence of externalities goes back to Pigou (1920). Following this idea it is argued that optimal Pigouvian taxes and/or subsidies would make agents fully internalize the externality and therefore achieve the first best outcome. Moreover, if the only reason why agents fail to invest in energy efficiency measures is the externality, Pigouvian taxes would suffice to restore the first best outcome on both the extensive margin (technology adoption) decision and the intensive margin (energy consumption) decision. Despite the theoretical appeal of Pigouvian taxes as a policy instrument, the information requirements necessary to find the optimal tax level and the political cost of implementing those taxes make them difficult to implement in reality. However, Pigou's idea provides the main rationale for the use of Pigouvian taxes to correct energy consumption externalities.

Instead, in the context of energy efficiency policy, we observe nowadays that policy makers are using a richer combination of policy instruments to try to correct externalities and close the energy efficiency gap. Hence, the policy design challenge is finding cost-benefit effective instruments that achieve the reduction in energy consumption targets. Key to the policy design process is understanding the mechanism underlying why agents tend to underinvest in energy efficiency measures relative to the socially optimal level of investment. However, as discussed in Allcott and Greenstone (2012) and Gillingham et al (2009) the empirical evidence on the size of the energy efficiency gap is situation specific and many times inconclusive. In this context, the recommendation is that the policy instruments should address the market or behavioral failures causing the energy efficiency gap as directly as possible. This is perhaps the main reason why energy efficiency policy relies on a combination of a number of instruments aimed to target the different sources of market and behavioral failures.

Following empirical evidence on large implicit discount factors when households make energy efficiency investment decisions (Hausman (1979)), early policies were mostly based on combinations of taxes and subsidies or regulation approaches based on efficiency standards. The idea behind this policy instruments being that subsidies should be effective when agents undervalue the benefit of energy efficiency measures adoption. Alternatively, one could regulate the level of energy efficiency of energy consuming appliances in the market and increase the overall energy efficiency.

In recent years, however, both policy makers and academic research have turned their attention to behavioral failures to better understand the energy efficiency gap and inform the policy making process. This newly developed area is obviously consistent with the earlier empirical findings of large implicit discount rates, and should be taken as an attempt to better understand the underlying behavioral process leading to an inefficiently low level of investment in energy efficiency.

Although direct evidence of behavioral biases or biased beliefs is not very extensive in the context of energy efficiency policy. There are many pieces of evidence that provide consistent suggestive evidence that behavioral biases may play an important role at explaining the energy efficiency gap. De Groote and Verboven (2016) analyse the effect of subsidies on the adoption of renewable energy technologies and find that households significantly undervalue the benefits of technology adoption. Allcott and Wozny (2013) find evidence that consumers slightly undervalue the future fuel operating costs of motor vehicles. Gallagher and Muehlegger (2011) analyse the effect of sales tax waivers, income tax credits and non-tax incentives on purchases of hybrid vehicles, finding an implicit discount rate of 14.6%.

Others have focused on evaluating the effectiveness of information provision policy interventions. Allcott (2011) provide experimental evidence that a program sending letters to households informing about the energy consumption social norm has a large impact on energy consumption at a very low policy intervention cost. Davis and Metcalf (2016) find that better information provision leads consumers to better energy efficiency investment decisions. Attari et al (2010) use an online survey to estimate that survey participants underestimate on average by a factor of 2.8 energy use and potential energy savings from energy consumption utilisation changes and investments on energy efficiency measures.

On the other hand, there is also empirical evidence that subsidies might prove an expensive way to provide incentives. Joskow and Marron show that households induced to adopt energy efficiency measures as a consequence of a subsidy would have invested also in the absence of the subsidy. They refer to this as a free riding problem, also called the additionality problem. Despite this, they argue that subsidies be effective at increasing the rate of diffusion of the new technology via information spillovers from early adopters. Boomhower and Davis (2014) use a regression discontinuity approach to study participation in a large scale energy efficiency program. They find that participation increases with large subsidies. However, most participants are non-additional, they would have participated with a lower subsidy or no subsidy at all. Ito (2015) analyses the effect of a large scale electricity rebate program, finding empirical evidence consistent with the fact that many program participants are non-additional. Concludes that this is a central problem when evaluating the cost effectiveness of incentive schemes. Davis et al (2014) analyse the impact of a large subsidy program in Mexico for appliance replacement and find that, although the program is effective, it is a very expensive way to achieve energy consumption savings.

To sum up, all this evidence, although not conclusive and context-dependent to a certain extent, has been taken into account by policy makers. In recent years, energy efficiency policy has been swinging towards policy instruments aimed at providing better information. Information provision, when effective, is extremely attractive from a policy design point of view as usually can achieve a potentially high impact at a lower cost than giving subsidies. In the light of the previously discussed evidence, subsidies may prove an expensive way to provide incentives for energy efficiency adoption.

As a result of this, the last decades have seen how energy efficiency policy has evolved towards a more extensive use of policies based on information provision.

And despite there are still many incentive programs providing subsidies to promote energy efficiency investment, governments are putting resources and effort in evaluating the potential of information provision interventions to address the energy efficiency gap. In the UK, the Department of Energy and Climate Change in collaboration with the Behavioral Insights Team has been running small scale experiments to gain insight on behavioral aspects crucial for energy efficiency policy design. For instance, a randomised control trial to test how the way energy efficiency information is presented affects the perception of cost savings related to the use of energy-efficient appliances. Other studies have included smart meters roll-out trials to evaluate the potential of smart metering to overcome housholds' lack of precise information on their current energy use. At the same time, other developed countries are also putting emphasis on the relevance of behavioral insights for better policy design. In Italy the regulatory authority has also been running experiments to test how individuals respond to different types of feedback on their energy use. A large experiment involving 10 EU countries has tested using an online experiment how provision of online information on appliances' energy efficiency affects consumers' decisions.

2.2.1 International Context

The empirical analysis presented in this thesis refers to energy efficiency measures adoption in the UK, in particular in England and Wales. However, the conceptual framework and the empirical results presented could be taken as a piece of evidence that could guide energy efficiency policy design in a broader context, this is for developed countries which are pursuing similar energy efficiency objectives. Other developed countries face similar challenges in the design of effective energy efficiency policies.

European Union directives prompt member states to implement policy measures to achieve carbon emission targets and reduce energy consumption. Among other measures, this includes providing incentives for a reduction in energy consumption in the residential sector, since it represents an important share of the total energy demand. Although changes in utilisation behavior can have a significant impact on energy demand, it is argued that the major energy savings potential resides in technological change. At the residential level, this involves basically adoption of energy efficiency measures like the ones considered here, i.e. insulation measures, purchase of higher energy efficiency boilers, heaters, etc. For these reasons, in the EU context, there is a large number of energy efficiency government policies similar to the ones implemented in the UK. In the UK, the Green Deal scheme, starting in 2013, introduces incentive programs and other measures to encourage investments in energy efficiency and energy consumption reductions in the residential sector. In the case of the UK, the Green Deal scheme follows other similar schemes that were in place in the previous years, and that I discuss in more detail later. Starting in 2003, the Flanders region in Belgium implemented a Rational Use of Energy scheme. A scheme that obligates electricity distributors to implement measures and encourage energy savings in the residential sector to achieve targets in energy consumption reduction. Starting in 2005, Italy introduced the "Titoli d'Efficienza Energetica" (Energy efficiency certificate) enforcing final consumption obligations on gas and electricity distributors. Also France and Denmark, starting in 2006, implemented similar programs shifting on energy suppliers and distributors the responsibility of achieving target reductions in energy consumption in the residential sector. Although this is not an exhaustive list, this are specific examples of how the EU Energy Efficiency Directive requirements has translated in the implementation of programs aimed to reduce energy consumption in the residential sector in most member states.

In the United States, under the Energy Independence and Security Act, one can also note policy interventions along the same lines. Among others, policies to encourage energy efficiency in the residential sector like standards in the form of building codes, or providing incentives for heating and cooling energy efficient technologies.

Other specific examples of policy interventions, also implemented both in most countries in Europe and in the US are information provision policies like the provision of information on appliances energy efficiency in labels. In Europe, the Energy Labeling Directive, or in the US, the Energy Star program introduced labels providing information about the carbon emissions and the energy efficiency rating of appliances with the aim of promoting the use of energy efficient appliances.

All in all, with its limitations, the analysis presented in this thesis should be taken as a relevant piece of evidence that could help guide energy efficiency policy design in a broader context than the UK.

2.3 National Energy Efficiency Data

In this section I provide a detailed description of the data set on which the empirical analysis presented in Chapters 2 and 3 is based. The data set is the National Energy Efficiency Data (NEED)[8], a publicly available data set produced by the UK Department of Energy and Climate Change (DECC) containing information on energy efficiency measures adoption, energy consumption and property characteristics.

The NEED version on which the analysis presented here is based is the End User Licence File covering a sample of more than 4 million households in England and Wales. NEED is an anonymised household level data set containing 25 variables for each household. These variables can be grouped in four categories: general variables, energy consumption variables containing historical gas and electricity consumption (2005-2012), property characteristics and energy efficiency measures installed.

The general variables include a unique household identifier, a region categorical variable indicating to which of the 8 former Government Office Regions each household belongs to, a categorical variable that takes discrete values from 1 to 5 indicating the Index of Multiple Deprivation quintile of the Lower Layer Super Output Area (LSOA) the household is located in [9], a categorical variable taking

[8]Department of Energy and Climate Change. (2014). National Energy Efficiency Data-Framework, 2014. [data collection]. UK Data Service. SN: 7518, http://doi.org/10.5255/UKDA-SN-7518-1

[9]Since household income or other socioeconomic characteristics is not available in the data

values from 1 to 5 identifying the quintile in the proportion of households in fuel poverty in the LSOA the household is located in and a categorical variable providing information on whether the household was subject to an Energy Performance Certificate inspection before 2010 or in 2010 or later[10].

The energy consumption variables contain information on annual gas and electricity consumption for years between 2005 and 2012 measured in physical units (kWh). The data set also includes an indicator variable indicating household records with valid gas and electricity consumption[11].

The data set contains information on the energy efficiency measures installed by households included the sample. The energy efficiency measures considered are cavity wall insulation, loft insulation and boiler installation. For each of these energy efficiency measures the data set contains a variable indicating if the household installed the measure through a government scheme and the year of installation. It is important to highlight at this stage that the sample included in the NEED dataset does only include households who adopted energy efficiency measures as participants of a government incentive scheme. Therefore, any estimates of the impact of the installation of energy efficiency measures presented in Chapters 2 and 3 should be interpreted as the impact of participating in a government scheme providing incentives to install the energy efficiency measures and, indeed, installing them. As opposed to installing the energy efficiency measure. This is an important caveat as this may introduce a selection bias, as households who select themselves into the incentives program participation might have different underlying characteristics affecting both their energy consumption choices and energy efficiency measures adoption decisions. In particular, it could be that those selecting themselves into the program are intrinsically more motivated

set, I include the Index of Multiple Deprivation variable in the regression analysis presented later to control for the level of income. The dataset includes two different variables for England and Wales. The IMD England variable is constructed based on the 2010 IMD for England, whereas the IMD Wales variable is based on the Welsh IMD in 2011.

[10]However, the data set does not contain information on the specific year when the inspection was conducted.

[11]The analysis presented in Chapters 2 and 3 is restricted to a subsample including only on households with valid consumption records

towards energy conservation behavior. Or, on the contrary, it could be that households adopting energy efficiency measures under the incentive scheme are less motivated, and chose to invest because of the financial incentives provided by the government program.

Based on this information I construct a variable containing time relative to adoption for each of the energy efficiency measures (time relative to event year) and on which I base the event study analysis presented here. This variables allow also me to control in a simple way for whether the household has adopted other energy efficiency measures and the timing of adoption.

Finally, the data set contains several variables providing information on property characteristics. These contain both characteristics of the building and energy consumption related features of the property. More specifically, the data set contains the following variables:

- A dummy variable identifying households with Economy 7 electricity meters.
- A variable identifying households' main heating fuel.
- Property age. A categorical variable grouping households in six bands based on the year of construction of the property.
- Property type. A categorical variable grouping households based on the property type.
- Floor Area variable that allocates each household to a floor area band. The data set does not contain information regarding the specific floor area of each household.
- Energy Efficiency band. Also a categorical variable that allows grouping households by different categories of energy efficiency.
- Depth of loft insulation. This variable identifies whether the property has 150mm or more, or less than 150mm.
- Wall construction. Identifies whether the property has a cavity wall or not.

The data set does not contain, however, information on households' demographic or economic characteristics. Being able to match the NEED information to demographic and socioeconomic household characteristics like income or household composition would definitely allow for a richer analysis of the questions I am addressing in these chapters, however because of confidentiality matters matching this data set to other data sets containing these sources of information or having access to more detailed geographic location of the households included in the NEED data set has not been possible.

2.4 Energy efficiency policy in the UK

Energy efficiency policy in the United Kingdom relies on the application of different policy instruments to different sectors and activities. The key components of the overall energy consumption are transport, domestic consumption, industrial consumption and the services sector (including public sector and commercial services) consumption. I focus on domestic energy consumption, which represents around 20% of total energy consumption, and on policies oriented to encourage energy savings and investment in energy efficient technologies. In the following paragraphs I discuss different policies that have been introduced in the UK during the period observed in the NEED sample.

In the following paragraphs I discuss different types of policies. On the one hand, policies that are based on providing subsidies to help households cover the investment cost. This is the case for the boiler scrappage scheme and the warm front scheme. On the other hand, policies based on information provision like the energy performance certificate. The Green Deal scheme provides financial aid and also advice to households on how to save energy. Another important distinction between policy interventions is whether they are targeted or universal. The Warm Front Scheme for instance targets households with low income level, the boiler scrappage scheme, on the contrary, offers a subsidy not targeted at any particular income level.

The Energy Performance Certificates were introduced in England and Wales on 2007. The energy performance certificate is required whenever a property is built, sold or rented, and consists of an evaluation of the property energy efficiency. The certificate awards each property an energy efficiency rating. The EPC was phased in between August and December 2007 for marketed sale of dwellings. For non-marketed sales or rental of dwellings it was implemented in October 2008. And the EPC on construction of dwellings on April 2008. The Energy Performance Certificate was initially introduced as part of the Home Information Pack. In 2010, the Home Information Pack was abolished and the EPC requirement continued.

The Community Energy Savings Programme (CESP) was announced in September 2008 and consisted of a package of measures to encourage investment on energy saving technologies among households. Part of the programme aid was targeted to low income households. However, every household was eligible for a 50% discount on cavity wall and loft insulation installation. The programme ran from January 2009 to December 2012.

The Green Deal scheme started at the end of the CESP. It provides loans for installation of energy efficiency improvements. The scheme was launched in October 2012, and is designed to facilitate consumers' investments in energy efficiency measures. The scheme loans are repaid through the energy bills.

The Warm Front Scheme was launched on June 2000 and closing in 2012/13. This program is targeted at reducing fuel poverty. It provides benefits to households installing energy efficiency improvements. Eligibility is based on income level as the program was set in place to address fuel poverty issues.

The Boiler Scrappage Scheme started on January 2010 and provided help to up to 125000 households to install fuel efficient boilers. Eligibility was based on having a G-rated boiler and substituting it for an A rated boiler or a renewable heating system. Successful applicants received a 400GBP voucher.

The policy variation introduced by these incentive schemes provide interesting further research opportunities to identify the impact of subsidies and information provision on the technology adoption patterns and energy consumption. However, the NEED data set is not rich enough to precisely identify which households are eligible and which ones actually benefited from them.

The Energy Performance Certificate introduction is an interesting source of variation to analyse the effect of information provision policies. The policy variation introduced by the phase in schedule is interesting as it introduces gradually an information provision policy that gives owners recommendations on how to reduce energy consumption and also makes them aware of potential energy efficiency improvements. The NEED data set contains information only on whether a household went through the certification process before 2010 or in 2010 or after, making it difficult to use the data to identify the effect of information provision on the adoption decisions and the intensive margin energy consumption decisions.

The major difficulty for using the Warm Front Scheme as a source of policy variation to identify the impact of incentives on energy efficiency adoption is that one needs to observe the households characteristics that determine program eligibility and take-up. The NEED data set contains only information on property characteristics and does not provide enough information to identify eligible households.

Regarding the Boiler Scrappage Scheme, in the NEED data set there is no information about program participation or any information that would allow to identify potentially eligible households which would be crucial to more precisely exploit this policy change empirically to identify how the introduction of a subsidy affects selection into adoption and the energy consumption change upon adoption. However, in the last section of Chapter 3, I use this policy change to obtain estimates for the intention to treat effect of the policy changes on energy consumption outcomes comparing those who install a boiler before 2010 to those who install it in or after 2010 under the Boiler Scrappage Scheme.

Incorporating households socioeconomic characteristics and more detailed household geographic location data would definitely be an important next step towards using this sources of policy variation to identify consumers responses to subsidies and information programs.

The NEED data set provides valuable information to study the adoption patterns, however connecting the observed adoption empirical patterns to the energy efficiency policy variation is not feasible with the available data. In contrast, in Chapter 3 I perform the correlation test proposed in Chapter 1 for which no policy variation is required.

2.5 Trends in adoption patterns

In this section, I present a discussion on the adoption patterns over time of cavity wall insulation, loft insulation and energy efficient boilers. The graphs presented in Figure 4 show the evolution of the adoption hazard rate over time. The hazard rates are calculated as the proportion between the number of adopters in year t over the number of households which have not adopted the energy efficiency measure before year t. The hazard rate for 2004 should be taken as the baseline hazard rate representing the proportion of adopters at the beginning of the sample period. For all three energy efficiency measures, the hazard rate has on overall increasing time trend showing that the proportion of households adopting the energy efficiency improvements increases.

When comparing the adoption patterns for the different energy efficiency measures, one finds that cavity wall insulation has a significantly higher baseline adoption hazard rate (slightly above 6%). Whereas for loft insulation and boiler the baseline hazard rates are at a significantly lower level, slightly above 2% and 1% respectively. This is likely to be related to the fact that during the sample period the adoption hazard rates increase significantly more for loft insulation and boiler than they do for the cavity wall insulation adoption hazard rate. The loft insulation adoption hazard rate remains at levels around 2% until 2010, to start then increasing sharply to peak in 2012 at a level close to 6% probably as the result of the 50% discount on insulation measures introduced by the CESP scheme. The boiler adoption hazard rates start increasing steadily from the beginning of the sample period (with the exception of 2008 when the adoption hazard rate falls by around 1.2%) to reach a level close to 5% by the end of the sample period. In contrast, the cavity wall insulation adoption hazard rate remains relatively stable around 2% for the whole sample period to show only a slight increase from 2010. A plausible explanation for this differential patterns is that the number of potential adopters for cavity wall insulation is much lower than it is for loft insulation and boiler adoption.

Before analysing the relationship between the timing of adoption decisions and the energy consumption levels and changes in energy consumption upon adoption, I study the impact of property characteristics on technology adoption decisions. For each of the energy efficiency measures included in the data set (boiler, cavity wall insulation and loft insulation) I run the following regression specification:

$$A_{itl} = X_{it}^{'}\omega + \gamma_l + \epsilon_{itl} \tag{34}$$

where A_{it} is a dummy variable taking a value of 1 in adoption years (and 0 otherwise), and X_{it} is a vector containing the property characteristics for household i and the year relative to year of adoption for the other two energy efficiency measures. The term γ_l includes region specific fixed effects. I provide regression estimates for a Probit model in Appendix A.3(Table 10). The results presented in Table 10 show that with very few exceptions the coefficients on all property characteristics are highly significant. More importantly, the coefficients on other energy efficiency measures time of adoption is always highly significant. This suggests that the adoption of the different energy efficiency measures is highly correlated. Therefore, in the event study regressions presented in the rest of this chapter and in Chapter 3 I always include controls for the timing of adoption of other energy efficiency measures observed in the data set.

2.6 Energy consumption

First of all, I discuss the energy consumption time series. In Figure 5 I present time series for total, gas and electricity consumption over time. Consumption is

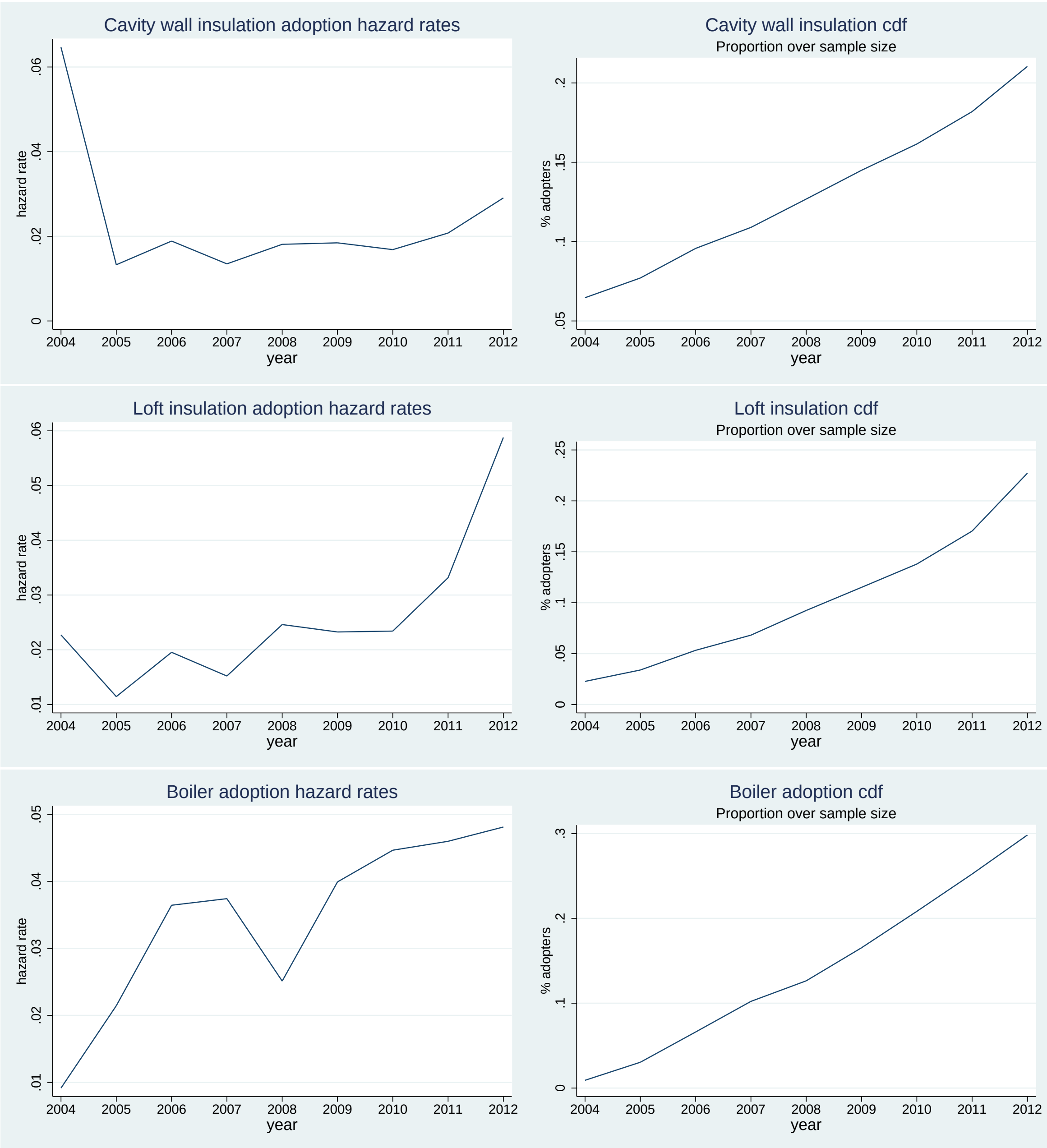


Figure 4: Adoption of energy efficiency measures (Hazard rates and cumulative rates of adoption)

Note: Graphs on the left show the adoption hazard rate for cavity wall insulation, loft insulation and boiler replacement throughout the sample period. The hazard rates have been computed using the sample information as number of adopters in year t over number of non-adopters at the beginning of period t. Graphs on the right show the cumulative proportion of adopters relative to the the sample size presented in physical units (kWh). The time profiles of energy consumption exhibit a clearly decreasing trend overtime. The decreasing trend in energy consumption is still present after decomposing energy consumption in gas consumption and electricity consumption. Therefore, one can discard the possibility that gas or electricity consumption are decreasing because households are substituting across different energy sources at an aggregate level. As discussed in the previous section, during the sample period 2005-2012 a number of households have been implementing energy efficiency measures, however the patterns in this graphs are not sufficient to claim that energy efficiency measures adoption led to a decrease in energy consumption. There are many confounding factors that could be having an impact on energy consumption at the same time. For instance, economic-cycle related factors or aggregated shocks affecting the capacity of households to produce energy services using raw energy inputs.

In the following sections, I present an event study approach to evaluate the impact of technology adoption on energy consumption. The main concern when analysing the impact of technology adoption on energy consumption is that decisions on installation of energy efficiency measures are endogenous. Both households technology adoption decisions and energy consumption are correlated with unobservable heterogeneity. Ideally one would want to randomize energy efficiency measures adoption to study the impact of technology adoption on consumption. Since this is not possible, I adopt an event analysis approach based on exploiting the sharp drops in energy consumption around the year of technology adoption[12].

At the same time, to control for other factors affecting the energy consumption profiles, I control for year fixed effects, region fixed effects and property characteristics. In the following analysis, therefore, I present graphs showing the residual variation in the energy consumption profiles over time relative to the adoption

[12]This approach has been used in similar environments. For instance Kleven et al (2016) study the effect of having children on labor market outcomes using an event-study approach.

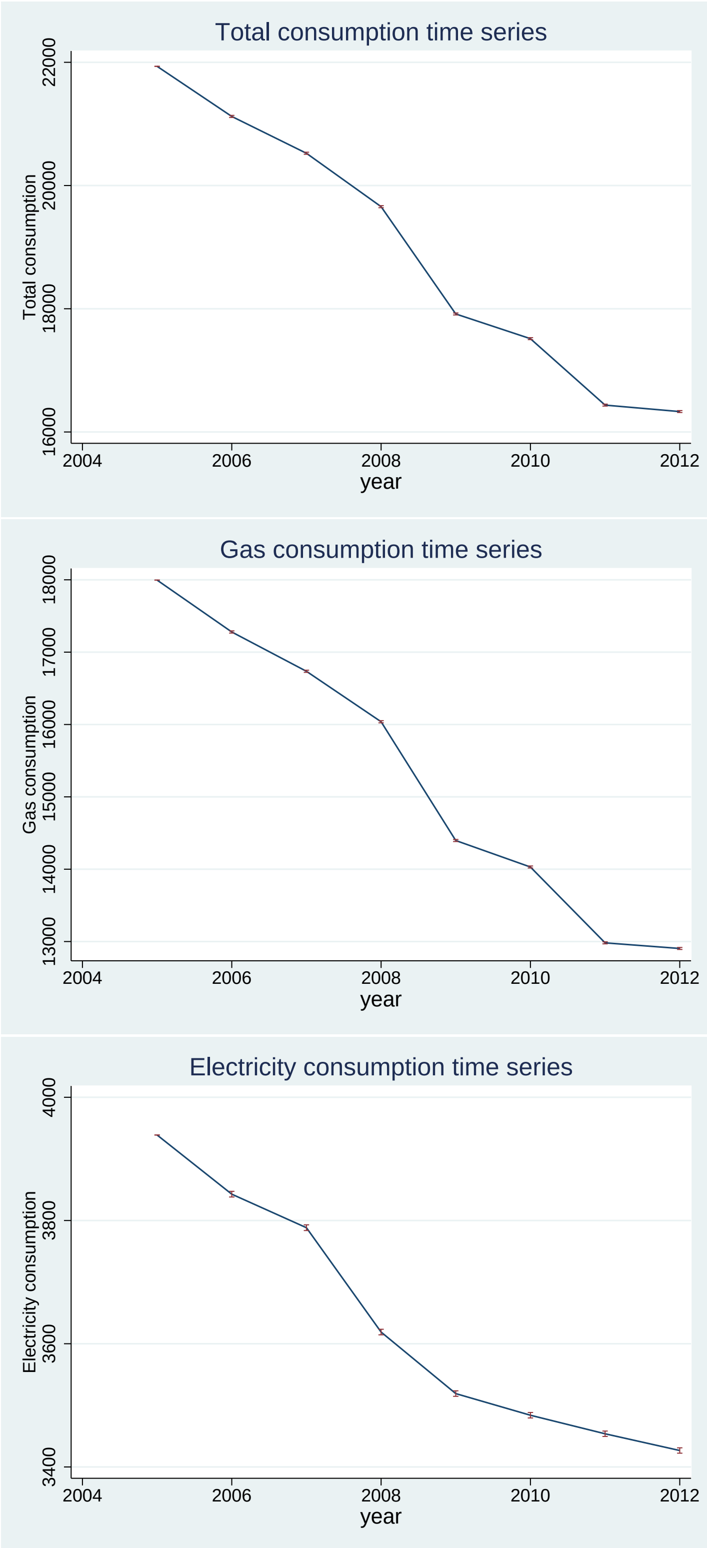


Figure 5: Energy consumption time series

Note: The graphs show the total, gas and electricity consumption profiles over time. The graphs are obtained using the raw NEED data and each data point represents the average energy consumption in each year with the corresponding 95% confidence interval.

year after controlling for these variables. This gives a more accurate idea of what is the variation in energy consumption around the year of adoption that could be attributed to the adoption of energy efficiency measures. I present the energy consumption profile around the year of adoption of each of the different energy efficiency measures included in the data set (cavity wall insulation, loft insulation and installation of an energy efficient boiler). I analyse separately the adoption of each of the energy efficiency measures for which the data set contains adoption information. For each household in the data set I denote by s=0 the year in which the technology has been adopted and represent energy consumption profiles over time relative to the adoption event time (s=0). Time relative to adoption runs from s=-7 (seven years before technology adoption) to s=7 (seven years after technology adoption). It should be noted that the panel is not balanced as the number of households observed at each time relative to adoption varies. For instance, at s=7 I observe only those households who adopt in 2005 (the first year in the data set). Hence the number of households observed is significantly larger for times around 0 (adoption time) and smaller for times relative to adoption far away from event time. Following this same approach, in chapter 3 I use the sharp changes in energy consumption at adoption time to estimate the impact of heterogeneity on the energy consumption drop upon technology adoption.

The graphs presented in the following subsections correspond to average energy consumption over event time. This is the β_s coefficients in the following regression specification and the corresponding 95% confidence interval.

$$c_{istr} = \sum_j \beta_j \mathbf{1}[j = s] + \sum_y \gamma_y \mathbf{1}[y = t] + \sum_k \delta_k \mathbf{1}[k = r] + X'_{it}\omega + \epsilon_{itl} \qquad (35)$$

The first term includes event time dummy variables and, therefore, the coefficients β_s capture the average energy consumption for each time relative to event time. The following terms include calendar year fixed effects, region fixed effects and the property characteristics control variables. Hence the coefficients of interest capture differences in average energy consumption across time relative to event time after controlling for everything else. The control variables include also for each observation the time relative to adoption for the other two energy efficiency measures to control for variation that might be driven by the interaction between the adoption of different technologies.

2.6.1 Cavity wall insulation

Figure 6 presents the residualised total energy, gas and electricity consumption. On the horizontal axis time is measured in years relative to the cavity wall insulation adoption year.

The graph for total consumption shows a sharp decrease in energy consumption around the cavity wall insulation adoption year. In years prior to adoption total energy consumption is exhibiting a decreasing trend. The consumption drop around adoption is concentrated in the adoption year and the year after adoption. From then onward, total consumption exhibits a slightly increasing trend. When one looks separately at gas consumption and electricity consumption, the first thing to note is that gas consumption shows a pattern very similar to total energy consumption. On the contrary, electricity consumption increases steadily until the year before adoption to then experience a sharp drop on the adoption year and keeps on decreasing until the third year after adoption. From then on electricity consumption starts trending up again.

2.6.2 Loft Insulation

The consumption patterns observed around the loft insulation adoption year (Figure 7) are similar to the ones for cavity wall insulation adoption. More specifically, total consumption presents a sharp decrease in energy consumption around the loft insulation adoption year. In years prior to adoption total energy consumption is exhibiting a decreasing trend. The consumption drop around adoption is concentrated also in the adoption year and the year after adoption. From then onward, total consumption exhibits an increasing trend. Compared to

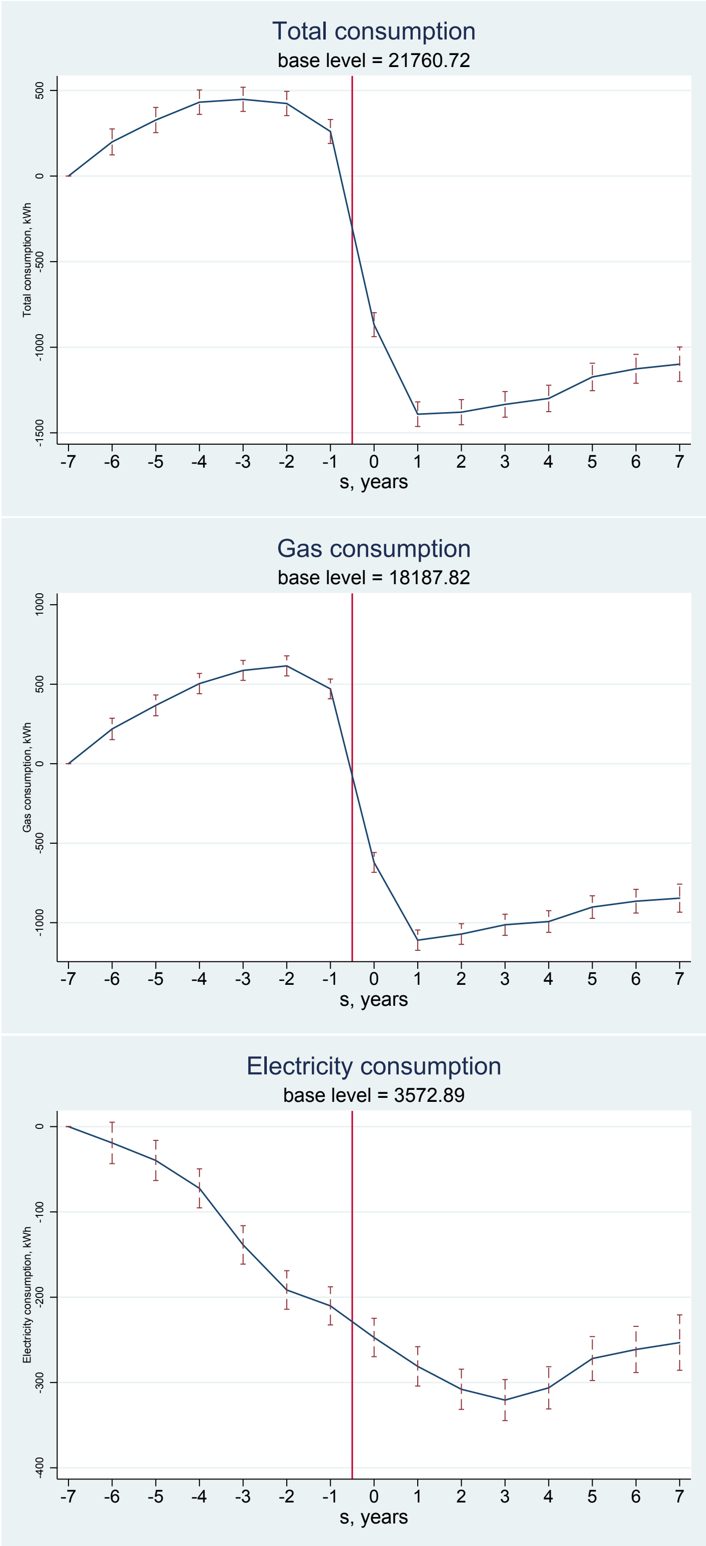


Figure 6: Consumption profiles over time relative to cavity wall insulation adoption year

Note: The graphs show the total, gas and electricity consumption profiles over time relative to adoption of cavity wall insulation. The data points represented in the graph should be interpreted as average energy consumption for households at time relative to event time s. The values are obtained from a regression including all the observations in the sample. The dependent variable is consumption and the independent variables include event time dummy variables, year fixed effects, region fixed effects and property characteristics controls. 95 % confidence intervals obtained using robust standard errors.

the case for cavity wall insulation, the post adoption trend in energy consumption slope is significantly larger. When one looks separately at gas consumption and electricity consumption, gas consumption shows a pattern very similar to total energy consumption. In this case, however, gas consumption decreases more gradually until the adoption year, exhibits a small sharp drop on the first year after adoption and then shows an increasing trend. The electricity consumption pattern instead increases steadily until the year before adoption to then experience a sharp drop on the adoption year and keeps on decreasing until the third year after adoption. From then on electricity consumption starts trending up again.

When comparing the consumption patterns for the two cases presented above, although they share many general features, one can also see from the graphs some differential features. The common features are that total consumption drops around the adoption year. This drop is both driven by a drop in gas consumption and a drop in electricity consumption. The drop in electricity consumption in both cases is very concentrated in the adoption year, whereas for gas consumption the graphs show a gradual pre-adoption decrease in gas consumption. In what the consumption patterns around adoption differ for cavity wall insulation and loft insulation is the intensity of these effects. In the loft insulation case, gas consumption starts dropping earlier before adoption and at a higher rate, whilst for cavity wall insulation the gas consumption drop is more concentrated around the adoption year. The slope of the post-adoption gas consumption trend is positive in both cases, however it is steeper in the loft insulation case. When considering electricity consumption, the upward pre-adoption trend is slightly steeper for loft insulation, and also the consumption drop upon adoption is larger in this case.

Even though the observed patterns are similar, this significant differences in the intensity of the effects prompt the necessity of analysing each of the two energy efficiency measures separately in the analysis to follow in this chapter and in the analysis presented in Chapter 3.

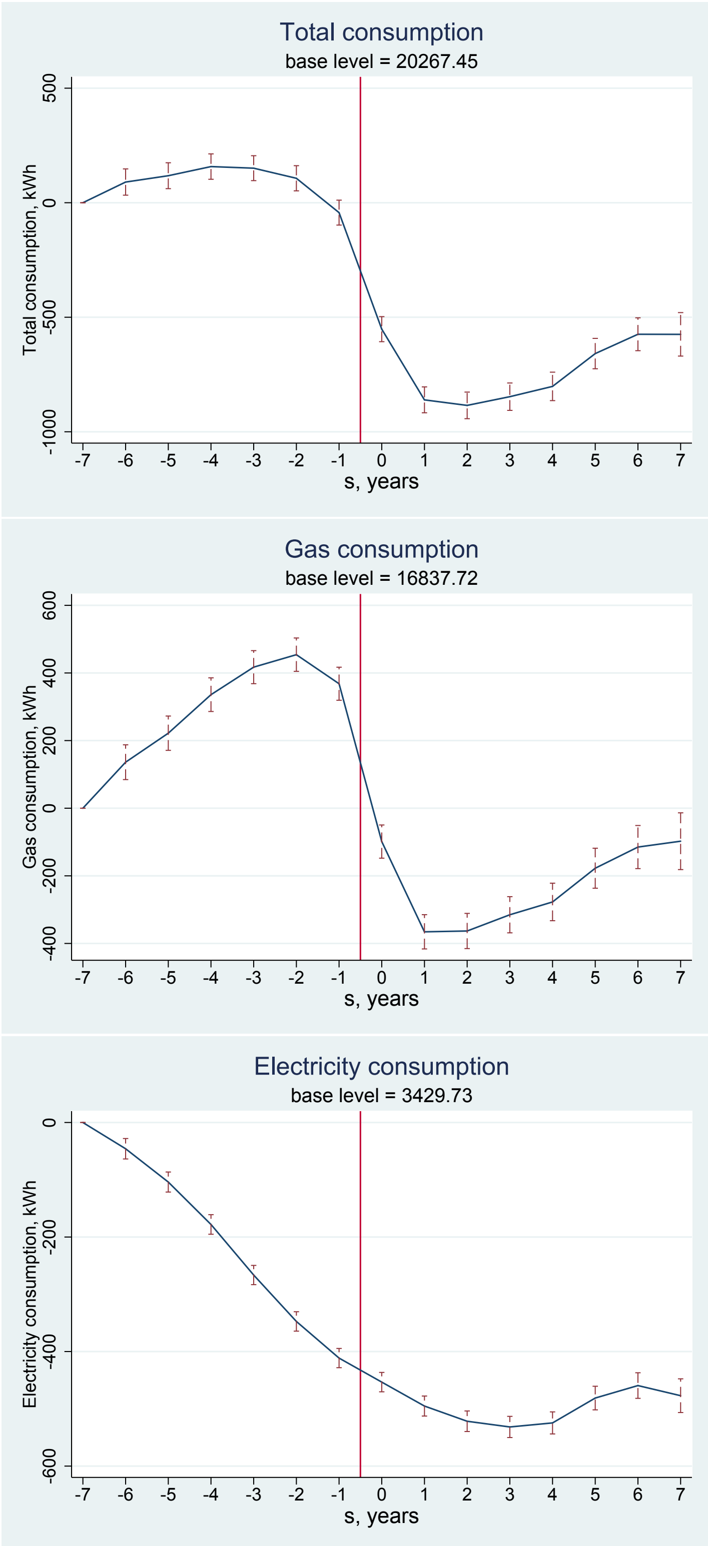


Figure 7: Consumption profiles over time relative to loft insulation adoption year

Note: The graphs show the total, gas and electricity consumption profiles over time relative to adoption of loft insulation. The data points represented in the graph should be interpreted as average energy consumption for households at time relative to event time s. The values are obtained from a regression including all the observations in the sample. The dependent variable is consumption and the independent variables include event time dummy variables, year fixed effects, region fixed effects and property characteristics controls. 95 % confidence intervals obtained using robust standard errors.

2.6.3 Boiler

Figure 8 shows the consumption profiles observed around the boiler adoption year. Total energy consumption shows a much less pronounced drop in the boiler adoption year. However, the decrease in the energy consumption level occurs very gradually starting as far as five years before adoption, in contrast with the insulation measures discussed in the previous sections. In years prior to adoption total energy consumption is exhibiting a significantly decreasing pattern. When decomposing consumption in gas and electricity consumption, one finds that gas consumption follows an almost identical pattern as total energy consumption. For electricity consumption, there is no sharp drop around the adoption year either. Electricity consumption is also decreasing gradually starting from five years prior to the adoption year. And electricity consumption starts then significantly increasing starting on the adoption year.

The energy consumption patterns observed around the boiler adoption year suggest that in many cases the installation of a new energy efficient boiler has an impact on the overall technology used by the household. The technology change results in higher electricity consumption probably as a result of substitution effects. However, another plausible explanation is that households implementing an energy efficient boiler might need to implement also at the same time other measures that lead to an increase in electricity consumption.

To sum up, the differential impacts of the adoption of the different energy efficiency measures suggest that each of them should be analysed separately. One reason being the completely different nature of the intervention, i.e. installing a new boiler has a completely different nature as installing wall or loft insulation. Second, among the insulation measures it has been also shown that the energy consumption patterns around the adoption year are sufficiently different, and therefore it makes more sense to also analyse them separately in the next chapter.

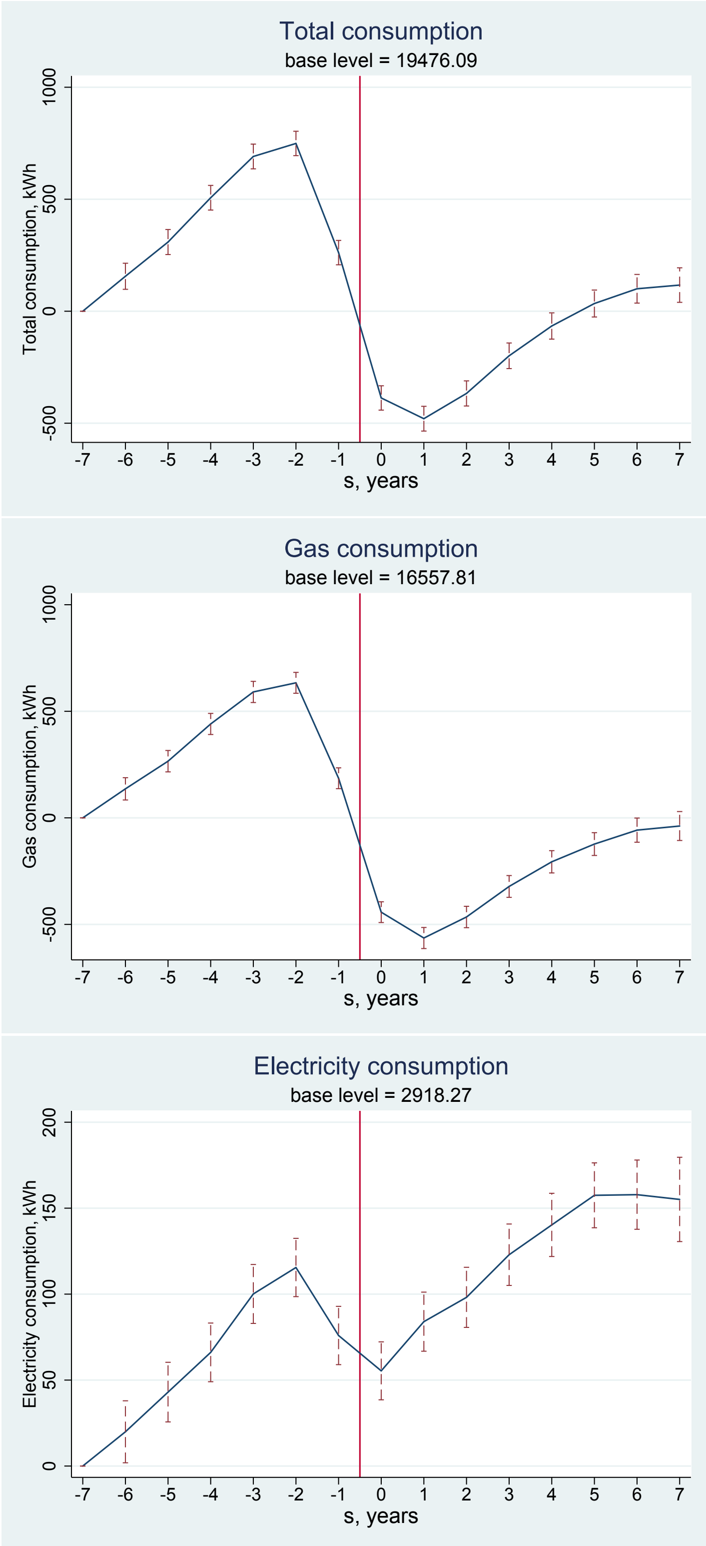


Figure 8: Consumption profiles over time relative to boiler adoption year

Note: The graphs show the total, gas and electricity consumption profiles over time relative to boiler replacement. The data points represented in the graph should be interpreted as average energy consumption for households at time relative to event time s. The values are obtained from a regression including all the observations in the sample. The dependent variable is consumption and the independent variables include event time dummy variables, year fixed effects, region fixed effects and property characteristics controls. 95 % confidence intervals obtained using robust standard errors.

2.7 Rebound effect

Another important aspect related to technology adoption in the context of energy consumption is whether there is a rebound effect. The rebound effect would imply that agents consume more energy after adopting a more efficient technology. From a theoretical point of view this is rationalized by the fact that when agents become more efficient at energy consumption they increase the consumption intensity. There are two opposing forces driving the change in energy consumption when the technology efficiency increases. On the one hand, they need to consume less energy to satisfy the same energy services demand. This has a negative impact on energy consumption. On the other hand, energy consumption becomes relatively cheaper and the substitution effect would lead them to consume more energy services and therefore demand more energy. If the second effect dominates, the net effect of technology adoption would be an increase in energy consumption.

The analysis presented so far in this chapter shows that, even though energy consumption stays at a lower level after adoption, there is a significant change in the energy consumption trend that could be seen as a weak version of the rebound effect. When comparing the pre-adoption trend and the post-adoption trend in Figures 6,7 and 8, in all cases the trend switches from a downward trend to an increasing trend of energy consumption around the technology adoption time. This evidence suggests there is a behavioral change upon adoption. The fact that energy consumption is lower in the post-adoption period, with the exception of energy consumption after boiler adoption, suggests that the "no rebound effect" assumption stated in the theoretical model in Chapter 1 holds. However, one can conclude that the substitution effect plays a role and households consume more energy when they become more energy efficient. Hence, there is no rebound effect in the levels, however there is a rebound effect in the trends.

The observed pre-adoption and post-adoption trends could be the result of households trying to cut energy consumption before adoption as they become aware their energy efficiency is relatively low. After adoption, households might stop restraining their energy consumption recognizing that they are now more energy efficient.

Developing a conceptual framework that rationalizes this behavioral change and explains the changes in the trends upon adoption is an interesting research question that I leave for future research.

2.8 Households' heterogeneity

Households' heterogeneity could explain different energy consumption patterns and different behavior across households. In this section, I exploit households' heterogeneity to analyse whether different household groups exhibit significantly different behavior, and discuss the potential policy implications. Throughout this section, I present and discuss the results of the regression analysis accounting explicitly for heterogeneity in household characteristics. The graphs presented in the following subsections present the energy consumption profiles over time relative to the adoption year for each group of households.

One surely relevant characteristic that may affect differences in energy consumption and energy efficiency measures adoption decisions is the income level. As previously discussed, the dataset does not include information on households' income. However, it includes the Index of Multiple Deprivation quintile and the Fuel Poverty Index quintile for the Lower Layer Superoutput Area in which the household is located.

Furthermore, I also consider a similar analysis grouping households according to geographical heterogeneity (region groups), property type and whether they use gas or another energy source as the main heating fuel.

For each grouping variable, I present the results of the regression model in equation (36). Where c_{itlg} is energy consumption for household i in year t that is located in region l and belongs to group g. The first term on the right hand side includes the interaction between a dummy variable S_{it} that takes a value of 1 when the observation corresponds to household i in year relative to energy efficiency measure adoption s and zero otherwise, and R_{it} takes a value of 1 when household i belongs to group r. The model includes also controls for property characteristics, adoption of other energy efficiency measures, calendar year fixed effects and region fixed effects.

$$c_{itlg} = \sum_s \sum_r \beta_r^s R_{is} S_{it} + X_{it}^{'} \omega + \alpha_t + \gamma_l + \epsilon_{itlg} \tag{36}$$

In the following subsections I present the results for each grouping criterion and further discuss the details specific to each case. Since the relevant findings are very similar for each of the three energy efficiency measures, I illustrate the argument presenting the figures for cavity wall insulation installation. The rest of the figures, that are omitted in the body of the chapter, are presented in Appendix 4.

2.8.1 Index of Multiple Deprivation

In an attempt to study the effect of income heterogeneity on energy consumption profiles, I consider the Index of Multiple Deprivation (IMD) as a proxy for income. Added to the fact that income is not directly observable in the dataset, there is one additional limitation of using the IMD as a measure of income. First of all, the IMD variable included in the dataset is just an IMD band classification based on the IMD for the Lower Layer Super Output Area in which the household is located. Therefore, it is not a direct measure of the household income, but just an aggregate measure of the index of multiple deprivation for the LLSOA. Despite this is potentially introducing a measurement error, this is the best proxy for income heterogeneity available in the dataset.

The results presented in Figures 9, 25 and 26 illustrate the energy consumption patterns over time relative to adoption of energy efficiency measures. The results show that pre-adoption energy consumption levels are significantly different across IMD groups. There is a clear monotonic ranking ranging from low energy consumption for households belonging to LLSOA in the first quintile of the IMD ranking, to higher energy consumption level for those in the 5th quintile. When looking separately at gas and electricity pre-adoption consumption levels, gas consumption exhibits the same pattern as total energy consumption. Electricity consumption, however, is not significantly different across groups and exhibits a smooth decreasing pattern in pre-adoption years. This is consistent to some extent with substitution from electricity consumption to gas consumption.

In the adoption year, the energy consumption drop is slightly higher for households in the higher quintiles of the IMD ranking. Showing, perhaps, that households with higher pre-adoption energy consumption levels have the potential to decrease energy consumption to a larger extent and still satisfy their energy services needs. This could be consequence of differences in quality of the same energy efficiency measure installed. In addition, it could also be a consequence of richer households cutting superfluous energy consumption due to the simultaneous implementation of other behavioral changes aimed at reducing energy consumption.

In post-adoption years, the energy consumption profiles tend to converge. As a consequence of the adoption of energy efficiency measures, the technology becomes more homogeneous. But the results also suggest there must be other behavioral changes that makes households energy consumption converge. The latter could probably be explained as a consequence of a learning process that makes households aware of the energy saving potential, not only of adopting energy efficiency measures, but also about better practices in the utilisation of energy services producing technologies.

It is also remarkable that electricity consumption profiles exhibit larger dispersion in the post-adoption years. In particular, the empirical results show that households in the the first quintiles of the IMD ranking become those ones for whom the level of electricity consumption is larger. At the same time they exhibit a non significant electricity consumption drop upon adoption. The reason for this may be that these households do not have a lot of margin to adjust their energy consumption downwards and experience an energy consumption drop close to the mechanical effect of the technological change.

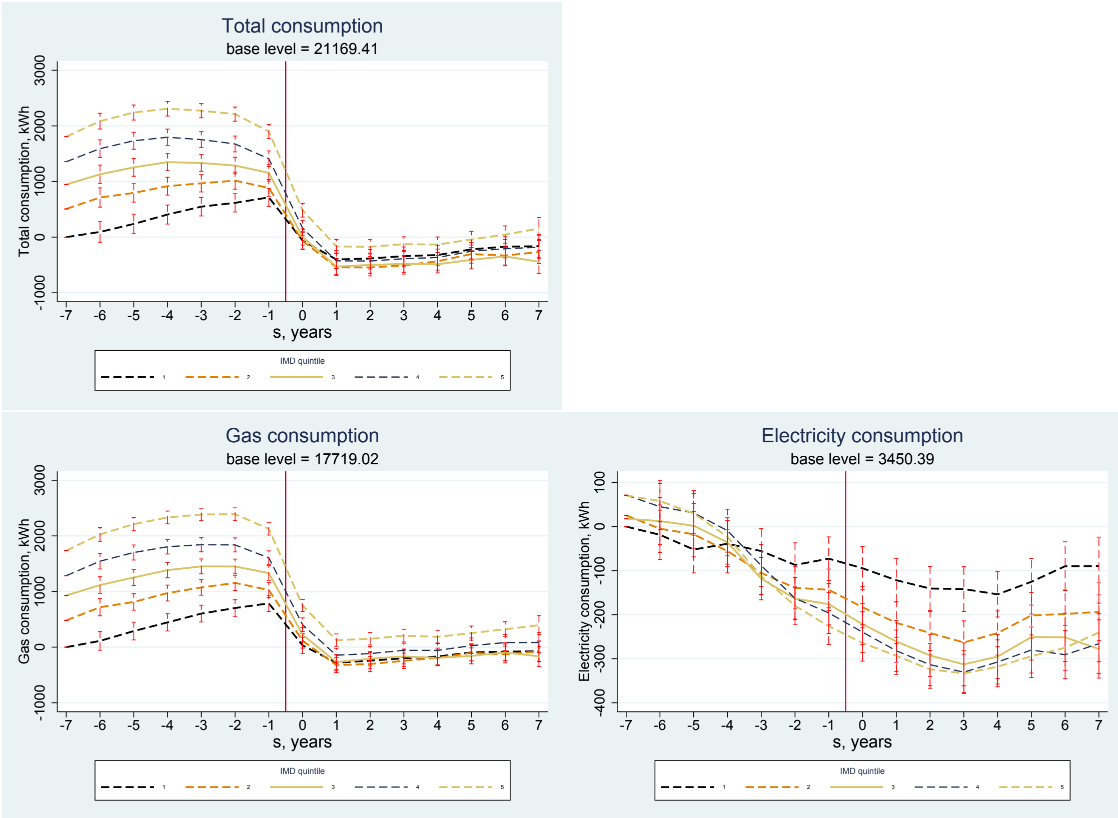


Figure 9: IMD groups (Cavity wall insulation adoption)

2.8.2 Fuel Poverty Index

The results presented here correspond to the comparison of different Fuel Poverty Index groups. The purpose of this analysis is to show how Fuel Poverty, understood here as a proxy for income heterogeneity might explain differences across household groups. As in the previous section, the Fuel Poverty Index variable included in the dataset is a categorical variable that identifies each household with the quintile in the Fuel Poverty ranking of the LLSOA in which the household is located.

The results presented in Figures 10, 27 and 28 illustrate the energy consumption patterns over time relative to adoption of energy efficiency measures for households grouped according to their Fuel Poverty band.

In general the empirical findings are similar to those obtained when grouping households according to their Index of Multiple Deprivation. In pre-adoption years, I observe that households in the first quintile of the Fuel Poverty Index ranking show levels of total energy and gas consumption significantly lower than the higher quintiles. Also, they consume on average larger amounts of electricity.

The energy consumption reduction in the adoption year is not significantly different across groups. One can see from the graphs that the total energy and gas consumption profiles, although they might differ in the levels, exhibit parallel behavior at the year of adoption of the energy efficiency measures.

In post-adoption years, in particular after adoption of insulation measures, the consumption profiles show a remarkably different behavior. It is worth noting that those in the first and second quintiles experience larger energy consumption growth in total and gas consumption. Again, the consumption patterns show that energy consumption levels tend to converge after adoption of the energy efficiency measures. In addition, in the case of insulation measures, the consumption profiles for the first and second quintile groups show that they experience a relatively large rebound effect compared to the other groups. Not only their energy consumption levels converge, but they end up exhibiting higher total and gas consumption than the third and forth quintiles groups. However, in many cases the post-adoption period differences across groups are not significantly different from zero at a 5% significance level.

In the case of electricity consumption, the consumption profiles show a smooth diminishing trend when considering insulation measures with no significant drop around the adoption year. For boiler replacement, the trends are slightly increasing. However given the precision of the estimates it is difficult to conclude the differences are significantly different from zero.

2.8.3 Geographical Heterogeneity

In this section I analyse the role of geographical heterogeneity. The results presented in Figures 11, 29 and 30 illustrate the energy consumption patterns over time relative to adoption of energy efficiency measures. The empirical results show that there is significant difference in energy consumption levels across regions. However, the total, gas and electricity consumption profiles evolve following a very similar pattern before, after and around the adoption year. These results

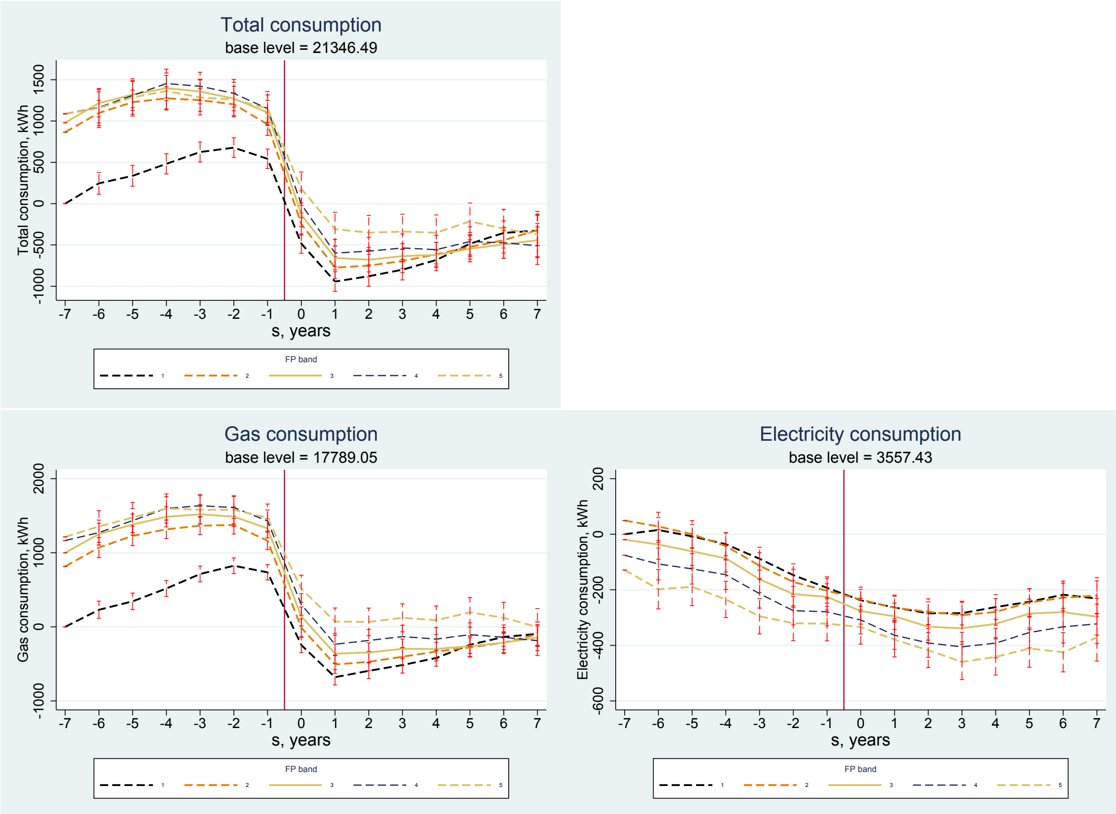


Figure 10: Fuel Poverty groups (Cavity wall insulation adoption)

suggest that after controlling for other sources of household heterogeneity, regional heterogeneity could explain variation in energy consumption levels, however, it does not seem to affect significantly the impact of energy efficiency measures adoption on energy consumption.

Despite the similar patterns in the energy consumption profiles, one remarkable deviation from the common pattern is the London region. When compared to the rest of the regions, London households' energy consumption exhibit a significantly different behavior. First of all, in pre-adoption years energy consumption increases at a higher rate. Second, significantly smaller energy consumption drops at the energy efficiency measures adoption year. Third, after adoption energy consumption tends to increase at a significantly higher rate than in the rest of the regions.

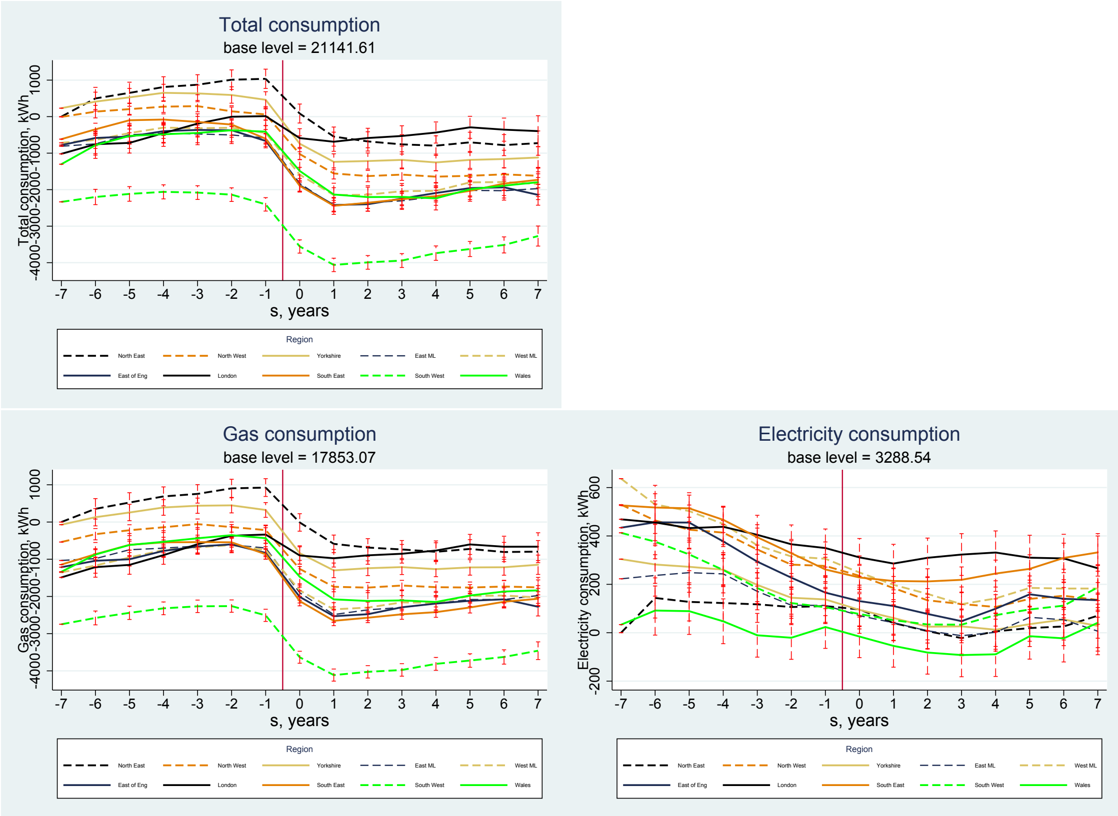


Figure 11: Region groups (Cavity wall insulation adoption)

2.8.4 Property Type

In this section I present the energy consumption profiles for different property type groups. The property types include Detached house, Semidetached house, End terrace house, Mid terrace house, Bungalow and Flat. The results presented in Figures 12, 31 and 32 illustrate the energy consumption patterns over time relative to adoption of energy efficiency measures.

The empirical results show that there is significant difference in energy consumption levels across different property types. Despite the differences in levels of energy consumption, the energy consumption evolution around the year of adoption of energy efficiency measures is similar. The two extreme cases are detached houses that exhibit the largest energy consumption level and significantly larger energy consumption drops around the adoption year, and flats that have the lowest level of energy consumption and consumption drops close that are not significantly different from zero. This shows that larger properties have a larger potential for

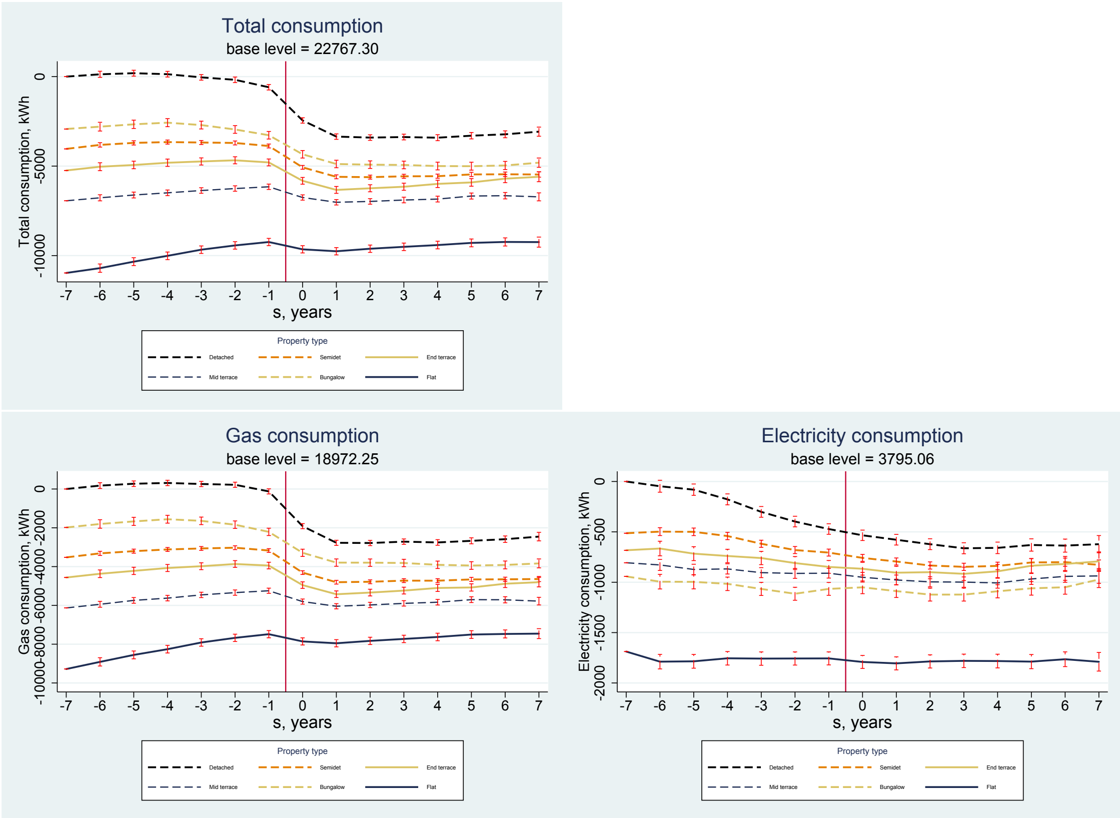


Figure 12: Property Type groups (Cavity wall insulation adoption)

energy consumption especially from insulation measures. When considering the installation of energy efficient boilers, the impact on energy consumption of the energy efficiency measures is very similar in absolute terms. This implies, however, larger energy savings for property types with low energy consumption levels.

2.8.5 Main heating fuel

In this section I compare households who use gas as the main heating fuel to households who use other main heating fuels. The results presented in Figures 13, 33 and 14 illustrate the energy consumption patterns over time relative to adoption of energy efficiency measures. First of all, it is important to note that households who use other main heating fuels present much lower levels of energy consumption in the pre-adoption years. Second, the number of observations in the other main heating fuels group is small leading to less precise estimates.

First I consider the profiles around the year of installation of insulation measures. In both cases, cavity wall insulation and loft insulation, I find significant drops in total and gas consumption at the adoption year for households using gas as the main heating fuel. However, the energy consumption drop at the adoption year for households using other heating fuels is not statistically significant at a 5% significance level. For electricity consumption I find that there is no change around the adoption of insulation measures for households using gas as the main heating fuel.

This empirical evidence suggests that the energy consumption drop around the adoption year is related to the mechanical effect of the insulation measure installation and potentially other behavioral changes mostly related with how households use the heating technology. If adoption of energy efficiency measures triggered a behavioral change affecting the overall household energy efficiency, one would expect to observe the impact of this changes in behavior also in the electricity consumption profile. On the contrary, the electricity consumption profile is flat for households using gas as the main heating fuel.

The consumption profiles over time relative to boiler replacement exhibit significant differences with the insulation measures case. For the group of households using gas as the main heating fuel, the consumption profiles are similar. However, for the group of households using other heating fuels I find, first, that total energy consumption post-adoption levels are higher than in the pre-adoption period. The pattern is driven by an increase in gas consumption in the adoption year and first year after boiler replacement. At the same time electricity consumption decreases upon boiler replacement. I interpret this patterns as the result of a technological substitution process resulting in those households relying more in gas consumption to satisfy their energy services demand after installing the boiler. This seems consistent also with the rebound effect idea. The fact that upon adoption there is an increase in total energy consumption might be the effect of an increased energy demand in response to a decrease in the effective cost of energy services production as the result of the technological change.

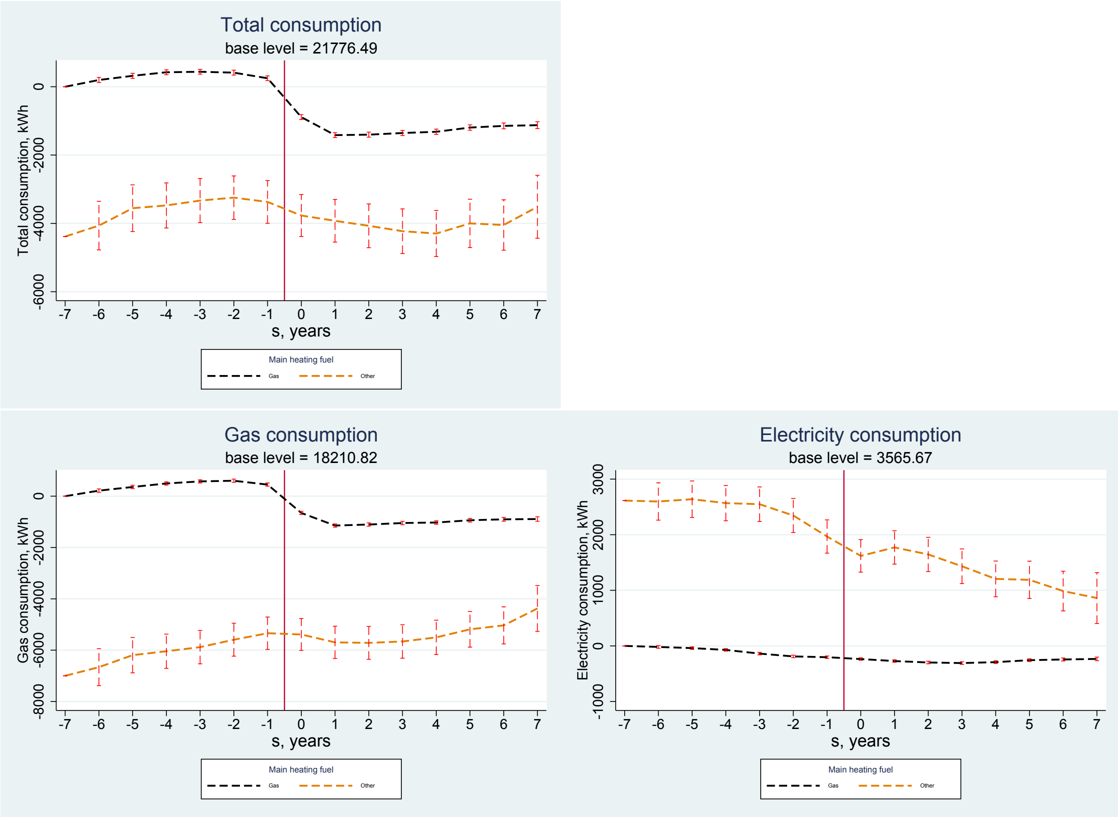


Figure 13: Main Heating Fuel groups (Cavity wall insulation adoption)

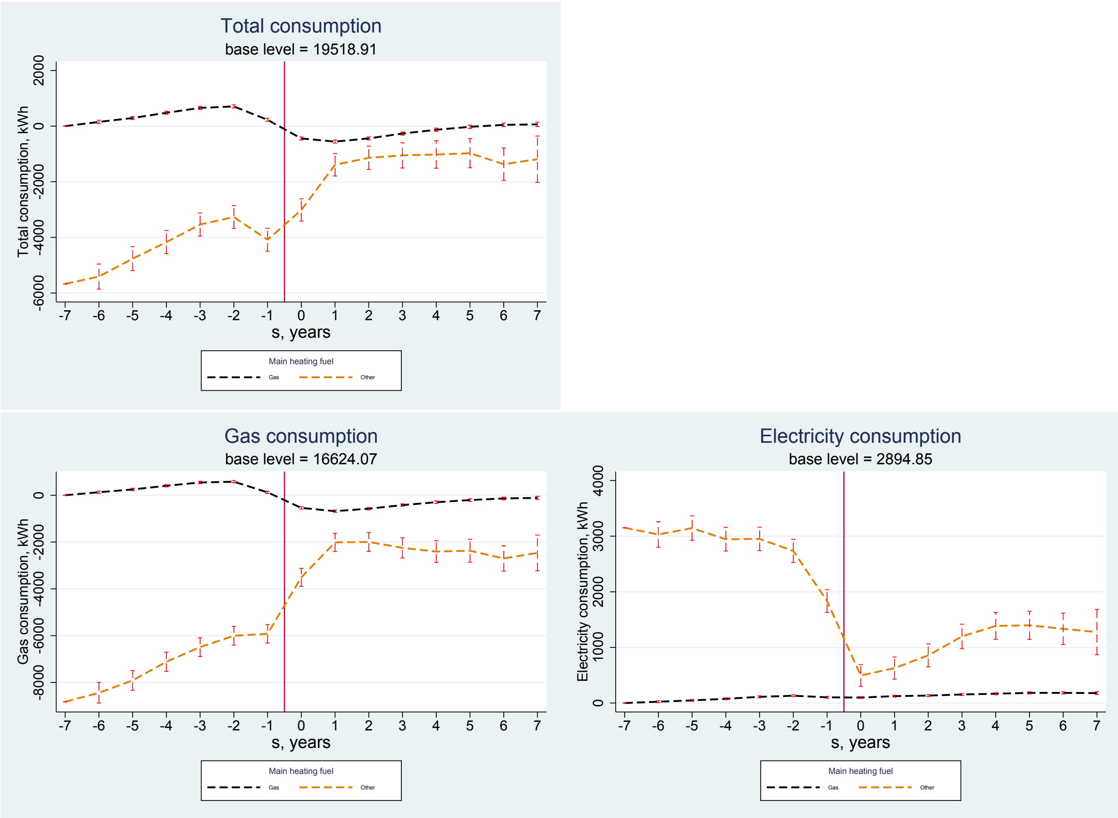


Figure 14: Main Heating Fuel groups (Boiler adoption)

2.9 Information Provision

In this section I analyse the effect of information provision on energy consumption. As discussed earlier, recently energy efficiency policy has evolved towards the use of policy instruments based on providing consumers better information about the potential benefits of installing energy efficiency measures and aiming to raise awareness of other behavioral changes towards a more efficiency utilisation of energy consuming technologies.

For each household, the NEED dataset provides information on whether households had an Energy Performance Certificate inspection before 2010 or on 2010 or later. In this section, I use that information to provide evidence of the effect of information provision. I present the results of two different approaches. First, I consider households receiving the Energy Performance Certificate in the same period (2010 or later), and compare the group of households installing an energy efficiency measure in the EPC inspection period to those ones who installed the same measure before the EPC inspection. Second, I consider households installing an energy efficiency measure in the same period (2005-2009), and compare those who receive the EPC inspection in the same period to those who received it only in 2010 or later.

In the first case, therefore, I compare the energy consumption profiles of households who receive information in the adoption period to those who would only receive information later. The results of this empirical analysis, presented in Figures 15, 34 and 35, suggest that for households implementing an energy efficiency measure before the EPC inspection total and gas energy consumption drops around the adoption year are significantly larger.

One possible confounder in this empirical design is that each group is composed of households who adopt in different time periods. More, specifically the before EPC group is a group of households who adopt the energy efficiency measures in the period 2005-2009, whereas the group that adopts in the EPC inspection period ("After EPC" in the graph) contains households who install the measure in the

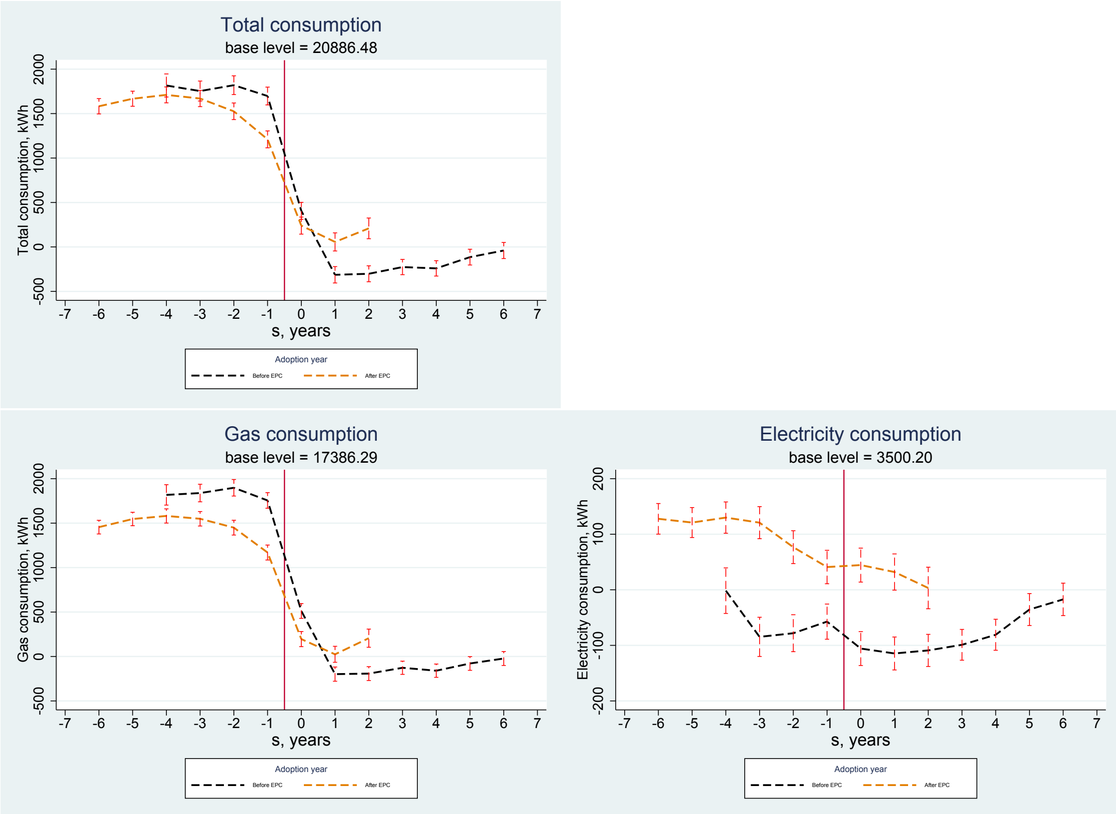


Figure 15: Adoption groups: Before EPC vs EPC period (Cavity wall insulation adoption)

period 2010-2012. Therefore, the comparison is between a group of "uninformed" early adopters and a group of "informed" late adopters. As a consequence, the observed differences might be the result of households differences in unobservable characteristics that determine their selection into early adoption versus late adoption. For instance, it could be that early adopters, despite having not been subject to the EPC inspection at the time of adoption, are intrinsically more motivated towards the potential benefits of the installation of energy efficiency measures. In an attempt to overcome this limitation, next I present a similar analysis comparing two groups of early adopters, one that receives the EPC inspection in the adoption period, the other receives it later.

Second, as previously discussed, I consider a subsample of households who implement an energy efficiency measure in the period 2005-2009 and receive the Energy Performance Certificate in that same period as a treatment group. As a control group, I consider the subsample of households who adopt the same energy efficiency measure but receive the Energy Performance Certificate only on 2010 or later.

In Figures 16, 36 and 37, I present the corresponding empirical results. For all the energy efficiency measures considered and for all types of energy consumption, the results show a very consistent pattern that I discuss in the following paragraphs.

First of all, the level of total, gas and electricity consumption before installation of the energy efficiency measure is higher for the group of households that adopts before the EPC inspection. Those who adopt before the EPC inspection exhibit on average slightly larger energy consumption levels. In the graph one can appreciate that the energy consumption levels are very similar three years before adoption. The gap between both increases in pre-adoption years perhaps as a result of the impact of information provision associated with the EPC inspection. This evidence would suggest that information provision has an impact on energy consumption and households respond to that implementing measures that result in energy consumption reductions.

Second, the energy consumption drop considering only the adoption year does not significantly differ across treatment and control group. Considering the years between one year prior to adoption and one year after adoption the consumption patterns are parallel. This shows that the effect of the energy efficiency measures installation has a similar impact on households who adopt in the same period, regardless on whether they receive the EPC inspection during the adoption period or later.

Third, in post-adoption years the treatment group, i.e. the group of households that does not receive the EPC inspection, exhibits an increasing trend in energy consumption. On the contrary, the group that receives the EPC inspection after adoption of the energy efficiency measure exhibits a flat or slightly decreasing energy consumption trend. One possible interpretation for this empirical fact is that households receiving the EPC inspection after adoption may be implementing changes in behavior in response to the information received that minimize the possible rebound effect associated with the increase in energy efficiency. On the

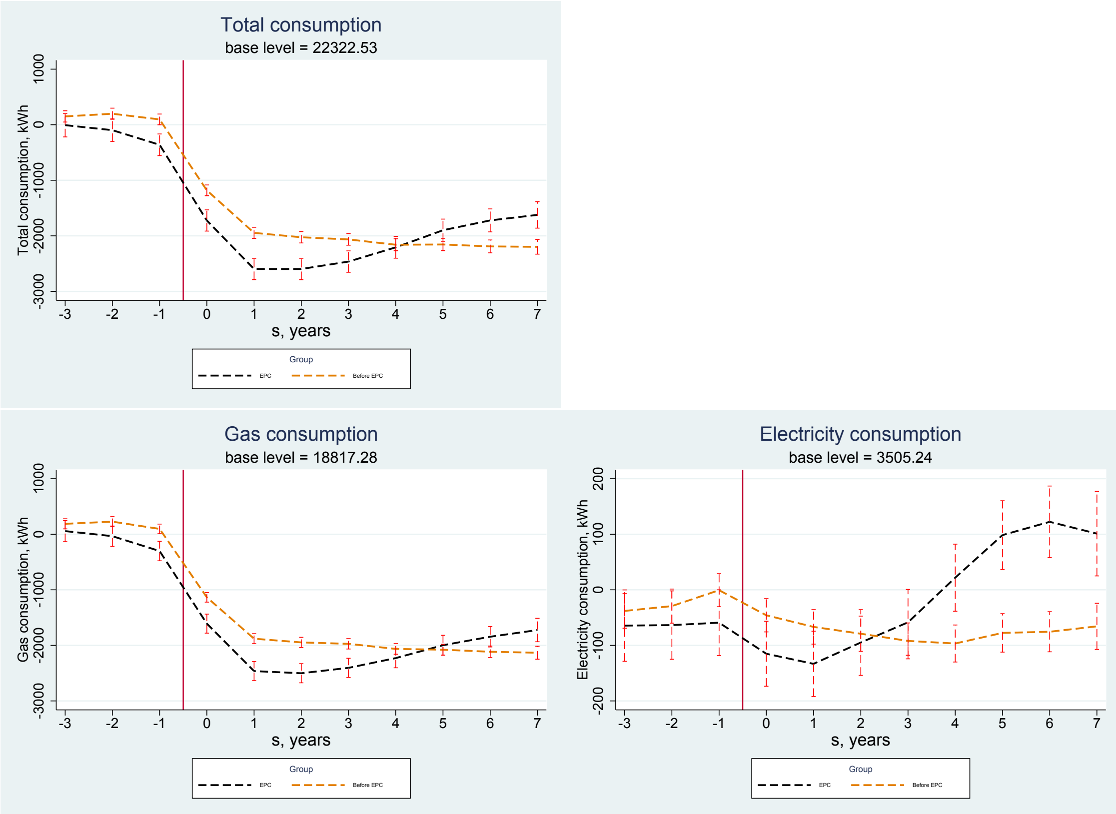


Figure 16: Early adopters (2005-2009): EPC vs Before EPC (Cavity wall insulation adoption)

other hand, households not receiving the EPC inspection after adoption exhibit a significant rebound effect in energy consumption. This suggests, on the one hand, that households do respond to information provision or that they install other energy efficiency measures as a result of the EPC inspection. On the other hand, the observed consumption patterns suggest that the effect of the EPC inspection on energy consumption behavior may not be persistent.

2.10 Aggregate impact of energy efficiency measures

In this section I present estimates of the impact of the installation of cavity wall insulation, loft insulation and boiler replacement at the aggregate level. Due to data limitations, it is not possible to directly control for household characteristics that are surely relevant for the adoption and energy consumption decisions of households. In this section, however, in an attempt to pin down the causal effect

Energy consumption (Fixed effects regression)									
	Gas			Electricity			Total		
Measure	Coeff	95% CI		Coeff	95% CI		Coeff	95% CI	
Cavity wall insulation	-3320.1	-3339.3	-3301.1	-248.97	-255.47	-242.47	-3569.2	-3590.3	-3548.0
Loft insulation	-2501.7	-2518.0	-2485.5	-192.62	-198.08	-187.16	-2694.3	-2712.2	-2676.5
Boiler replacement	-3502.6	-3516.7	-3488.5	-292.96	-298.03	-287.88	-3795.5	-3810.8	-3780.3
Constant	16583	16579	16586	3735.9	3734.7	3737.0	20319	20315	20322

Table 1: Impact of energy efficiency measures on energy consumption

Note: The table contains the coefficient on the interaction of the adoption year dummy variable and the event time group dummy variable for event time s = -1. The coefficients should be interpreted as the average energy consumption for each adoption cohort in the year before adoption of the corresponding energy efficiency measure. The table presents also the 95% confidence interval for the reported coefficient estimates.

of the energy efficiency measures, I present the estimates of the impact of energy efficiency measures on energy consumption resulting from a fixed effects model regression analysis. The regression equation I propose includes household level fixed effects and year fixed effects. Note, however, that since all the covariates included in the dataset do not present any variation at the household level, they need to be dropped out in this regression specification.

$$c_{ist} = \sum_s \beta_s \mathbf{1}[t \geq s] + \gamma_i + \delta_t + \epsilon_{ist} \tag{37}$$

Therefore the regressors include adoption dummy variable that take a value of 1 if calendar year is greater or equal than the year of adoption of efficiency measure s. γ_i are household level fixed effects and δ_t are calendar year fixed effects.

Based on the model presented in equation (37), I obtain estimates for the β_s coefficients from three regressions where the outcome variable is gas, electricity and total energy consumption respectively. The results are presented in table 1. The coefficients should be interpreted as the average energy consumption drop as a consequence of the adoption of each of the energy efficiency measures. All coefficients are negative and significant, implying that energy efficiency measures adoption proves effective at reducing energy consumption.

Furthermore, the size of the effect involves a total energy consumption drop relative to pre-adoption levels of 18% for cavity wall insulation, 13% for loft insulation and 19% for boiler replacement. When considering separately gas and electricity consumption, it should be noted that the energy consumption reduction comes mostly from changes in gas consumption. On average, households installing cavity wall insulation experience a gas consumption drop of 20%. The figure is 15% and 21% reduction in gas consumption upon installation of loft insulation and boiler replacement respectively. In contrast, electricity consumption reductions are smaller (7%, 5% and 8% for cavity wall insulation, loft insulation and boiler replacement respectively).

2.11 Conclusion

In this chapter I presented a discussion of the energy consumption and energy efficiency measures adoption patterns in the light of the information provided by the National Energy Efficiency Data. Besides that I also discuss the main residential level energy efficiency policy interventions in the UK to identify potential sources of policy variation to identify the role of incentives in the selection into technology adoption mechanism in the context of energy efficiency policy.

First of all, I find that overall the energy consumption profiles exhibit a decreasing time trend. From 2005 to 2012, I observe that total, gas and electricity consumption have been declining significantly.

When looking at the energy consumption data from an event study approach controlling for calendar year and region fixed effects, I find that energy consumption shows a drop around the technology adoption event time. The energy consumption drop is sharp for electricity consumption, whereas I find that gas and total energy consumption drops are much less sharp. The graphical evidence suggests that prior to technology adoption, there is a behavioral change among consumers that leads to a gradual reduction in energy consumption. A possible explanation for this could be that consumers' awareness about potential savings raises as the result of increased salience of energy consumption cost. Among other possible explanations, this might be the result of increased awareness of the energy costs when consumers start considering energy efficiency investments, or information spillovers from other consumers energy efficiency investment decisions.

From the NEED data analysis I can also conclude that there is no rebound effect after technology adoption when looking at the energy consumption levels. However, I find that the energy consumption trend is reversed upon adoption of energy efficiency measures. While energy consumption trends down in years before adoption, it starts slightly trending up after adoption of energy efficiency measures. I interpret this trend reversion as evidence of a weak version of the rebound effect.

Exploiting the variation in households' characteristics, I find that households' heterogeneity explains mostly differences in energy consumption levels, but has very little impact on the shape of energy consumption profiles over time relative to the adoption year. The empirical analysis shows similar energy consumption changes around the year of adoption for different groups of households. However, the energy consumption profiles provide suggestive evidence that is consistent with the idea that households implement other changes in energy consumption related behavior that could be explained by an underlying process of learning or correction of biased beliefs. In addition, the comparison of energy profiles between groups that implement energy efficiency measures before and after the Energy Performance Certificate inspection shows some differential patterns. Providing, therefore, evidence supporting the idea that households are responsive to information provision. Moreover, this response goes beyond the mechanical impact of energy efficiency measures installation.

The policy interventions to encourage energy efficiency measures adoption among households in the UK are an interesting source of policy variation to identify how incentives affect the selection into adoption mechanism when agents are heterogeneous. Although the information in the NEED data set turns out to be not rich enough to precisely exploit this policy variation, in Chapter 3 I analyse how incentives affect selection into adoption using the policy variation introduced by the boiler scrappage scheme.

The analysis presented in this chapter sets the ground for the empirical analysis presented in Chapter 3 where I propose an implementation to test the empirical implications of the model presented in the first chapter.

Chapter 3

Energy efficiency policy: Selection and Incentives

3.1 Introduction

The role for government provided energy efficiency incentive schemes is justified for two main reasons. First, there is evidence that agents tend to underinvest in profitable technologies. Second, the presence of energy consumption negative externalities reinforces the idea that agents do not fully internalize the benefit from investing in energy efficient technologies. In addition, when agents decisions are subject to mistakes, there is a third reason for the government to intervene based on paternalistic arguments.

One of the most commonly used policy instruments is subsidizing the adoption cost of energy efficiency measures. A subsidy should encourage households to install costly energy efficiency measures making up for how much agents undervalue the benefit of technology adoption. In Chapter 2, I show empirical evidence that technology adoption is effective at reducing energy consumption for different energy efficiency measures. However, the cost-benefit effectiveness of the policy relies heavily on the policy targeting efficiency. In other words, depends crucially on which types of consumers are cashing-in the subsidy and implementing the improvements. Therefore, it is important to understand what types of households select themselves into adoption under government incentive schemes and how large is the energy consumption drop upon adoption across different types of households.

In this chapter I provide an empirical test of the empirical predictions presented in Chapter 1. These analysis provides a piece of important information to shape the design of energy efficiency policies with heterogeneous agents. In addition, ideally, exploiting exogenous policy variation should allow to identify the impact of incentives on selection into adoption and on the energy consumption changes induced by adoption of energy efficiency measures. In the final part of this chapter I present estimates of the impact of incentives on energy demand outcomes comparing boiler adopters under the Boiler Scrappage Scheme to earlier adopters.

Using data on energy consumption and adoption of energy efficiency measures I aim to shed light on how to better understand the role of consumers' heterogeneity in the design of energy efficiency policies. Following Chapter 1 theoretical insights, I test whether selection into adoption is consistent with heterogeneity driven by biased beliefs on energy efficiency.

Based on the NEED data, I provide an indirect empirical test of the empirical implications of the model presented in Chapter 1. Using data on the history of energy consumption and the timing of energy efficiency measures adoption, I present an empirical test for the presence of adverse selection in the adoption of energy efficiency improvements among households under government provided incentive schemes. To tackle this question I consider, following the insights from the theoretical model presented in Chapter 1, two forms in which adverse selection could show up. The test relates to the positive correlation test for asymmetric information proposed in Chiappori and Salanié (2000). By analogy to the asymmetric information in insurance markets literature, I consider adopters and non adopters like insured and non-insured. The main concern is that adoption of energy efficiency measures affects energy consumption, it affects it mechanically because of the energy efficiency improvement and, in addition, it can potentially generate changes in energy consumption behavior among consumers. I address this taking advantage of the panel data structure of the data set. Observing households' energy consumption over time allows me to compare households pre-adoption energy consumption, and also compare early and late adopters to check if they experience heterogeneous effects of technology adoption. First, I look at the levels of energy consumption prior to adoption and compare them across adoption cohorts. Second, I look at the energy consumption drop upon adoption over time to test whether those who adopt earlier experience lower energy consumption drops upon adoption.

Exploiting the panel data nature of the data set, I find that pre-adoption energy consumption is decreasing in the year of adoption. Early adopters on average consume more energy than late adopters before adoption. Those who adopt a year later consume on average around 500 kWh less than adopters in the previous year. This difference is mostly driven by the change in gas consumption as it represents a huge share of the total energy consumption. When comparing energy consumption changes in the adoption year, I find that those who postpone adoption one calendar year experience a smaller consumption drop. The energy consumption drop experienced by those who adopt the technology a year later is on average about 200 kWh smaller. All in all, these results can be interpreted, in the light of the positive correlation test for asymmetric information, as evidence that selection into adoption is driven by preferences heterogeneity. However, this test does not preclude the possibility that heterogeneity in misperceptions does actually play a role in the selection mechanism that would point in the adverse selection hypothesis direction.

Using the policy variation introduced by the Boiler Scrappage Scheme I estimate the impact of cash incentives on selection into adoption. I find, first, that households replacing a boiler under the incentive scheme show lower pre-adoption levels of consumption. Second, the energy consumption drops experienced by those adopting under the scheme are not significantly different in the year of adoption. However, when considering the drop between a longer period of time around the adoption decision, they exhibit larger consumption drops.

The study presented in this chapter is related to the literature on selection into technology adoption. The key to understanding the selection mechanism is to understand how consumer heterogeneity is related to consumers' decisions on technology adoption. This is of particular relevance as it will determine the cost-effectiveness of an upfront subsidy offered by the government to those investing in energy efficiency measures. Consumer heterogeneity determines whether the subsidy paid by the government is cashed in by agents who would have invested also in the absence of the subsidy or it will be taken up by agents who would not have adopted the technology improvement (Stern, 1985).

The chapter is organized as follows. Section 2 presents the empirical analysis to estimate the impact of heterogeneity on selection into adoption analysing levels of energy consumption and energy consumption changes. In Section 3 I discuss how the estimated energy consumption profiles could be interpreted as evidence of learning consistent with the presence of initially biased beliefs. In Section 4 evaluate the effect of policy changes on the link between heterogeneity and selection into adoption using the Boiler Scrappage scheme as a source of policy variation. Section 4 concludes.

3.2 The role of heterogeneity: preferences vs misperceptions

In this section I present an empirical analysis to better understand the role of agents' heterogeneity in the technology diffusion process of energy efficiency measures. The specific goal is to provide empirical evidence on whether selection into adoption is adverse, driven by misperceptions in the cost of production of energy services, or advantageous, driven by true heterogeneity in energy efficiency, following the predictions of the model presented in Chapter 1.

The empirical analysis builds up on the National Energy Efficiency Data[13] presented in Chapter 2, an anonymised data set containing historical gas and electricity consumption (2005-2012), property characteristics and energy efficiency

[13] Department of Energy and Climate Change. (2014). National Energy Efficiency Data-Framework, 2014. [data collection]. UK Data Service. SN: 7518, http://doi.org/10.5255/UKDA-SN-7518-1

measures installed for a sample of 4 million households in the England and Wales.

The analysis is divided in two main parts. First, I focus the analysis on energy consumption levels and, later I look at the energy consumption changes focusing the attention on the energy consumption drop in the year of installation of the energy efficiency measures. Comparison of pre-adoption energy consumption levels across groups defined by the year of adoption of each technology allows one to test whether the timing of adoption is correlated with the energy consumption level. If the correlation is positive that provides evidence that selection is adverse and consistent with a model where selection is driven by heterogeneous misperceptions. A negative correlation would suggest that selection into adoption is dominated by preference heterogeneity (or heterogeneous true energy efficiency). When looking at the energy consumption first differences, I focus my attention on the first difference corresponding to the year of adoption of energy efficiency measures. This provides the energy consumption change upon adoption. If selection into adoption is adverse and driven by misperceptions, then the correlation between the energy consumption drop and the year of adoption should be positive, showing that early adopters experience smaller energy consumption drops upon adoption[14].

3.2.1 Levels analysis: Pre-adoption energy consumption

In this section I present the energy consumption levels empirical analysis. This analysis builds on the results discussed in the theoretical model presented in Chapter 1. The model predicts that when consumers hold heterogeneous beliefs on the energy efficiency of in-house energy service production, then those consumers who overestimate their energy efficiency are less likely to adopt and at the same time exhibit larger consumption levels before adoption. In this context households adopting energy efficiency measures and taking advantage of the government subsidies are those ones for whom the social benefit of adoption is lower. This is

[14]The empirical analysis presented here regarding the energy consumption drop upon adoption cannot be directly linked to the role of incentives. A potential avenue for future research is to see whether adoption under government provided incentives leads to smaller energy consumption drops. I provide an attempt to quantify that effect in the next section of this chapter using policy variation to identify the effect of incentives.

those underestimating their energy efficiency are more likely to adopt, however the potential benefit from adoption for them is lower. In this case there is adverse selection into adoption, and consequently in the type of agents who benefit from the public resources devoted to provide incentive for adoption of energy efficiency measures. As discussed in Chapter 1, this results in a negative correlation between the social value of adoption and the willingness to pay for energy efficiency measures (private value). In this conceptual framework this results in a negative correlation between energy consumption levels before adoption and adoption of energy efficiency measures.

To address this question, I perform an adoption cohort event study by adoption cohorts to analyse the role of agents heterogeneity at explaining the technology adoption patterns.

First of all, I look at the energy consumption profiles by adoption cohort (year of adoption). Figure 17 shows total energy consumption profiles over time relative to the adoption year. Each of the profiles corresponds to a group of adopters defined according to the year of adoption. The profiles in the figure correspond to the residual variation in energy consumption after controlling for property characteristics, time fixed effects and region fixed effects. I present the profiles of total energy consumption over time relative to adoption year by adoption year for all three energy efficiency measures. For each of the energy efficiency measures I obtain the average energy consumption as the beta coefficients (β_r^s) resulting from the following regression specification:

$$c_{itl} = \sum_s \sum_r \beta_r^s R_{it} S_{it} + X_{it}^{'} \omega + \alpha_t + \gamma_l + \epsilon_{itl} \tag{38}$$

The first term includes the interaction of time relative to adoption year dummies and calendar adoption year. S_{it} is a dummy variable taking a value of 1 when the observation corresponds to s years away from the adoption year and 0 otherwise. Whereas R_{it} is a dummy variable taking a value of 1 when the observation belongs to a household who adopted in calendar year r. X_{it} includes all the property characteristics controls and the time relative to the adoption of the other two energy efficiency measures included in the data, α_t are time fixed effects and γ_l region-specific fixed effects. Hence, the coefficients of interest are β_r^s as they provide the average difference in total consumption for each adoption calendar year and adoption event time combination relative to the base year 2005. Note that ideally one would want to identify separately all adoption year cohort and time relative to adoption β_r^s coefficients and the year fixed effects. However, this is not possible as any of the three variables (time fixed effects, time relative to adoption and adoption cohort year) is a linear combination of the other two. I identify year fixed effects and choose 2005 adoption cohort energy consumption as the base energy consumption profile. The justification for this choice is that raw energy consumption exhibits a strong time trend. Among the other regressors included there is no time variation, as they are property characteristics that do not change over time. However, I believe it is crucial to control for year specific fixed effects to get control for the variation in energy consumption that is related to time varying economic conditions, changes in policies and weather conditions across years. For the same reason, I believe it is crucial to control for region-specific fixed effects. As different regions have different weather conditions and differences in policies implemented at a local level that affect residential energy demand.

The coefficients corresponding to the year before adoption ($s = -1$) for each adoption cohort are presented in Table 2. The values of the coefficients suggest that in the year before adoption total energy consumption is decreasing in the year of adoption. Excluding the value for 2006, which is likely to be affected by the technology adoption decision, the coefficient estimates show a monotonic decreasing relation between pre-adoption energy consumption and the calendar year of adoption. This supports the hypothesis that selection into adoption is driven by preference heterogeneity. The graphs show that energy consumption levels before adoption are higher for early adopters, i.e. 2008 and 2009 adopters consume more energy in pre-adoption years than those who adopt in 2010 or later. In addition, from the graphs can be seen there is consistently a pre-adoption

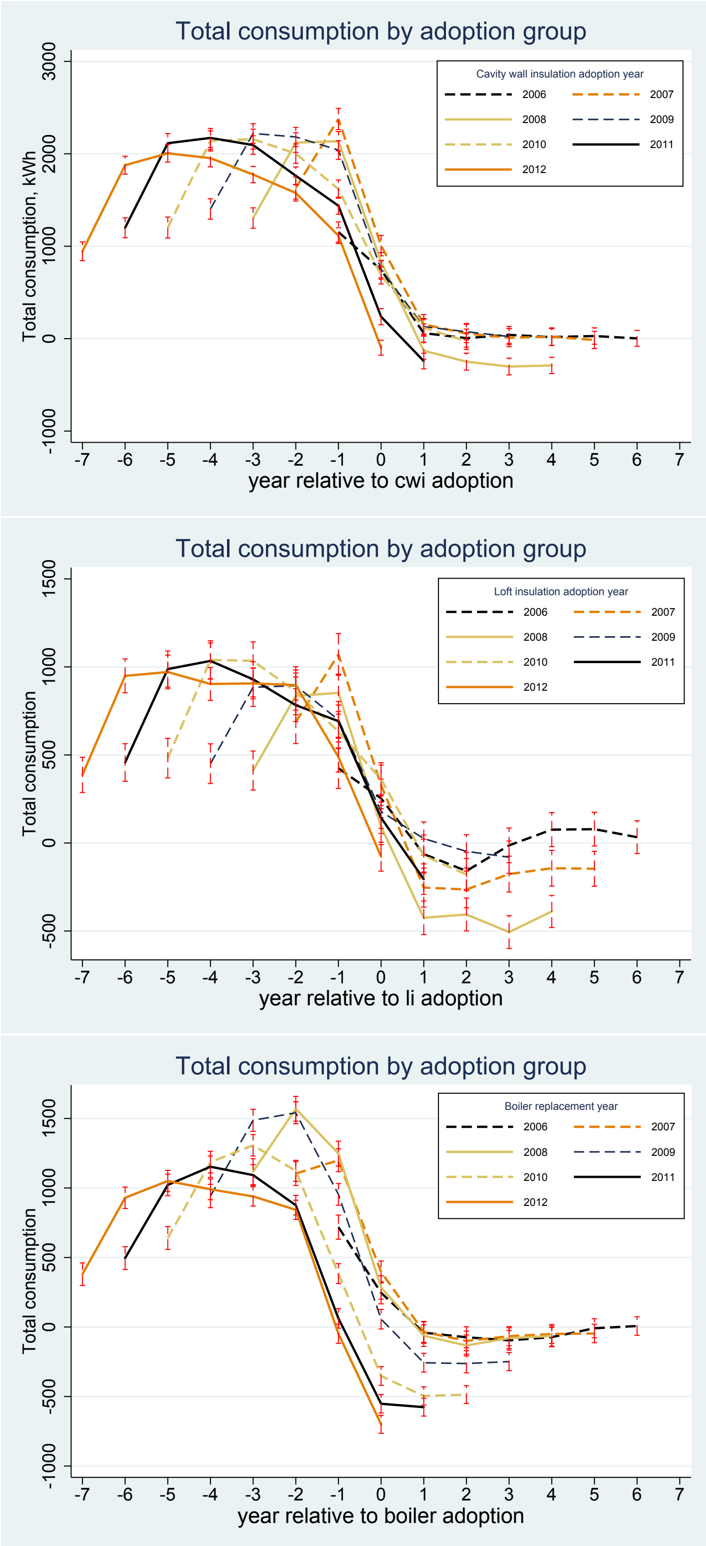


Figure 17: Total energy consumption by adoption cohort

Note: The graphs show total energy consumption profiles over event time (year relative to energy efficiency measures adoption). Each of the lines in the graphs represents the energy consumption profile for an adoption cohort (calendar year of adoption). Each value in the graph represents the average energy consumption for a particular adoption cohort (calendar year) and event time (year relative to adoption) combination. I also present in the graph the 95% confidence interval for each of them. The values are obtained as the coefficients on the adoption year dummy variable and the event time group dummy variable interaction in a regression of energy consumption that also includes year-fixed effects, region fixed effects and property characteristics as control variables.

Total consumption by adoption group pre-adoption year $(s = -1)$									
Adoption	Cavity Wall Insulation			Loft Insulation			Boiler		
year	Coeff	95% CI		Coeff	95% CI		Coeff	95% CI	
2005	base year			base year			base year		
2006	1154.37	1045.19	1263.55	424.61	309.53	539.70	718.38	631.59	805.17
2007	2376.74	2261.80	2491.69	1070.83	952.48	1189.19	1199.57	1117.39	1281.76
2008	2135.94	2031.64	2240.25	852.64	746.42	958.86	1247.42	1158.26	1336.59
2009	2040.42	1939.05	2141.79	699.35	594.89	803.81	954.00	875.90	1032.11
2010	1618.33	1520.31	1716.34	634.16	536.12	732.19	384.06	312.33	455.78
2011	1437.98	1345.83	1530.12	692.13	600.95	783.31	61.85	-8.644	132.34
2012	1114.63	1029.36	1199.91	488.51	403.04	573.98	-48.49	-117.31	20.32

Table 2: Total consumption in pre-adoption year by adoption cohort

Note: The table contains the coefficient on the interaction of the adoption year dummy variable and the event time group dummy variable for event time s = -1. The coefficients should be interpreted as the average energy consumption for each adoption cohort in the year before adoption of the corresponding energy efficiency measure. The table presents also the 95% confidence interval for the reported coefficient estimates.

energy consumption pattern showing and a sharp drop in energy consumption concentrated around the adoption year.

Second, I compare pre-adoption (2005) and post-adoption (2012) energy consumption levels across different groups of adopters (adoption calendar years) to check for differences in energy consumption behavior before and after adoption. More specifically, I compare energy consumption levels in the first sample year (2005) and in the last sample year (2012). I implement this in a regression specification where I regress the energy consumption level of interest on year of adoption dummy variables, region specific fixed effects and property characteristics control variables. Figure 18 shows the regression coefficients corresponding to each of the adoption year dummy variables in the linear regression in the following expression for $\tau = 2005$ and Figure 19 for $\tau = 2012$.

$$c^{\tau}_{irl} = \sum_j \beta_j \mathbf{1}[j = r] + \sum_k \delta_k \mathbf{1}[k = l] + X^{'}_{it}\omega + \epsilon_{irl} \qquad \forall \tau \in \{2005, 2012\} \quad (39)$$

c^{τ}_{irl} is the energy consumption in year τ for household i who belongs to adoption cohort r and region l. The first term includes the dummy variables for each adoption cohort. Hence, the graphs present the estimates for each of the β_r coefficients and their 95% confidence intervals. X_{it} includes all the property characteristics controls and the time relative to the adoption of the other two energy efficiency measures included in the data. The regression includes also region specific fixed effects.

Figure 18 shows that initial (2005) consumption, excluding the 2005 and 2006 coefficient values [15], is monotonically decreasing in the adoption calendar year in the cavity wall insulation and boiler adoption cases. This confirms that early adopters consume on average more energy before adoption than late adopters. The pattern observed in the case of loft insulation adoption is different. In this case, 2005 consumption is lower for 2008 loft insulation adopters and then increases. However, the 95% confidence interval shows that one cannot conclude that the consumption levels are significantly different with the exception of 2008 adopters. A plausible justification for this observation is that in 2008 the government introduced a policy consisting of a 50% discount on loft insulation. The fact that 2008 loft insulation adopters have lower energy consumption in 2005 can be interpreted as the impact of the subsidy on the adoption decision. In this case, the effect would go in the direction of pushing into technology adoption households who are less intensive in energy use and, therefore, find loft insulation adoption less profitable in the absence of the subsidy.

When looking at 2012 consumption, the energy consumption profile follows the same pattern. Figure 19 shows early adopters also tend to consume more on average in 2012 than late adopters. However, the gap between them is smaller. This indicates that adoption of the energy efficiency measures contributes to homogenize the energy consumption behavior of different ex-ante consumer types. There are many different potential explanations for this. One possibility is that during the adoption process consumers learn about the production process and

[15] 2005 and 2006 consumption includes the effect of technology adoption on 2005 consumption and therefore cannot be taken as a measure of pre-adoption consumption.

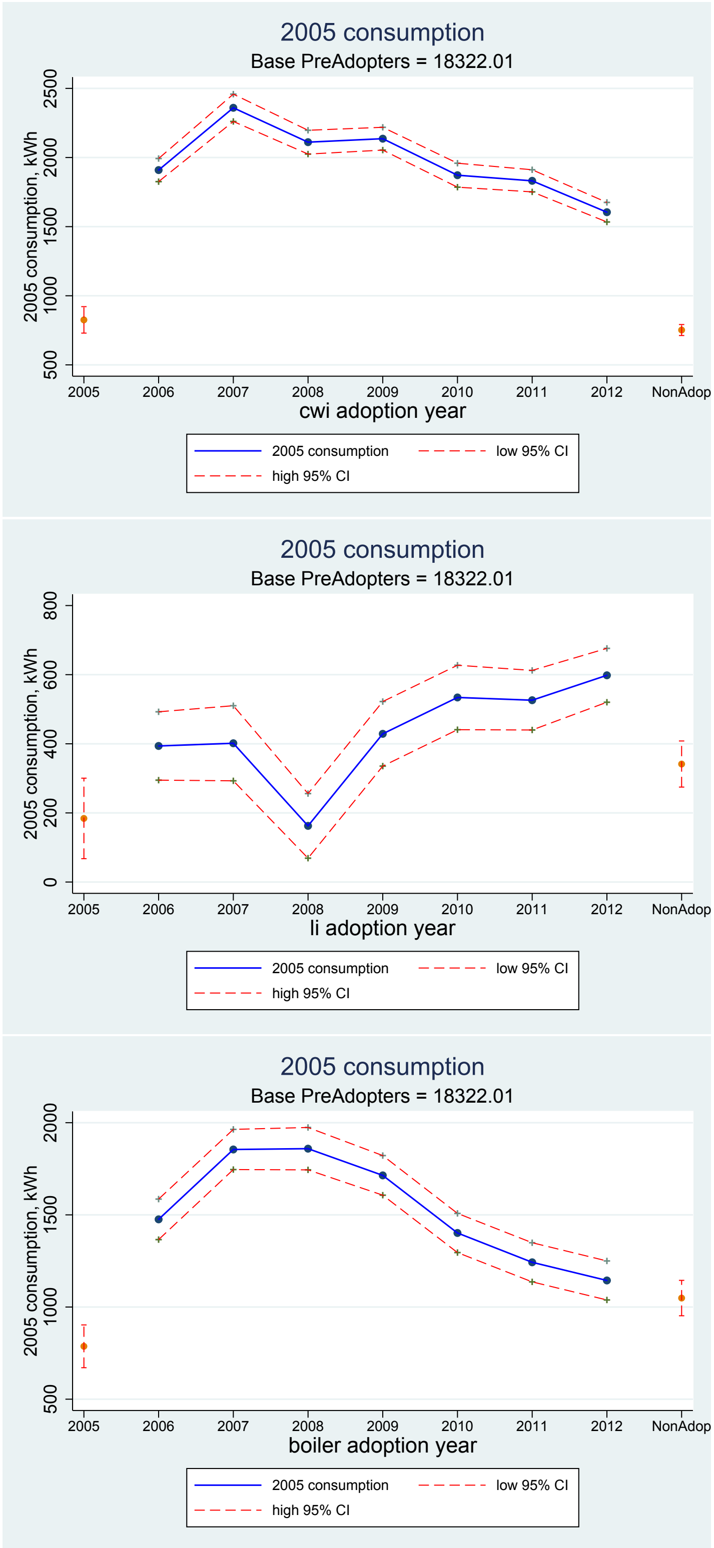


Figure 18: Pre-adoption 2005 consumption versus adoption year

Note: The values presented in the graph are obtained as the coefficients on year of adoption dummies in a regression of 2005 total energy consumption as the dependent variable on the year of adoption dummy variables, region fixed effects and property characteristics control variables. The dashed red lines represent the 95% confidence interval for those coefficients.

converge towards a more efficient use of the technology no matter the point in time where they adopt the improvements. Another possibility is that the change in the technology has a homogenization effect for mechanical reasons inherent to the implementation of the energy efficiency measures. Note that the last point in the graph corresponds to those who do not adopt the energy efficiency measure during the sample period. For those energy consumption in 2012 is substantially higher confirming the effectiveness of installing energy efficiency measures at reducing energy consumption. Note that non-adopters energy consumption in 2005 is lower than that for 2012 adopters, in 2012, however, their energy consumption level is significantly higher than any other group of adopters. This shows further evidence of the effectiveness of energy efficiency measures adoption at reducing energy demand.

To perform the correlation test, I compare the average total energy consumption in years before adoption. The main challenge to identify the effect of heterogeneity on selection into adoption is that technology adoption affects energy consumption. Therefore, to provide a compelling estimate of the correlation between energy consumption and technology adoption I compare energy consumption in years before the installation of energy efficiency measures across different adoption cohorts.

I implement this in a linear regression model where the left hand side variable is constructed as the average energy consumption before adoption for each household in the sample, $\bar{c}_{ilr,before}$. Note the sample is restricted to technology adopters in the period 2005-2012, excluding adopters in 2005 as energy consumption before adoption is not observed for the 2005 adoption group. In addition, I keep one observation for each household containing the average energy consumption before adoption at the time of adoption. Therefore, I estimate the linear correlation between the year of adoption of each of the measures and the average energy consumption in the pre-adoption years as the estimate for β in the following regression. The regressor of interest is the adoption year cohort R. The regression also includes year of adoption and region fixed effects, all property characteristics

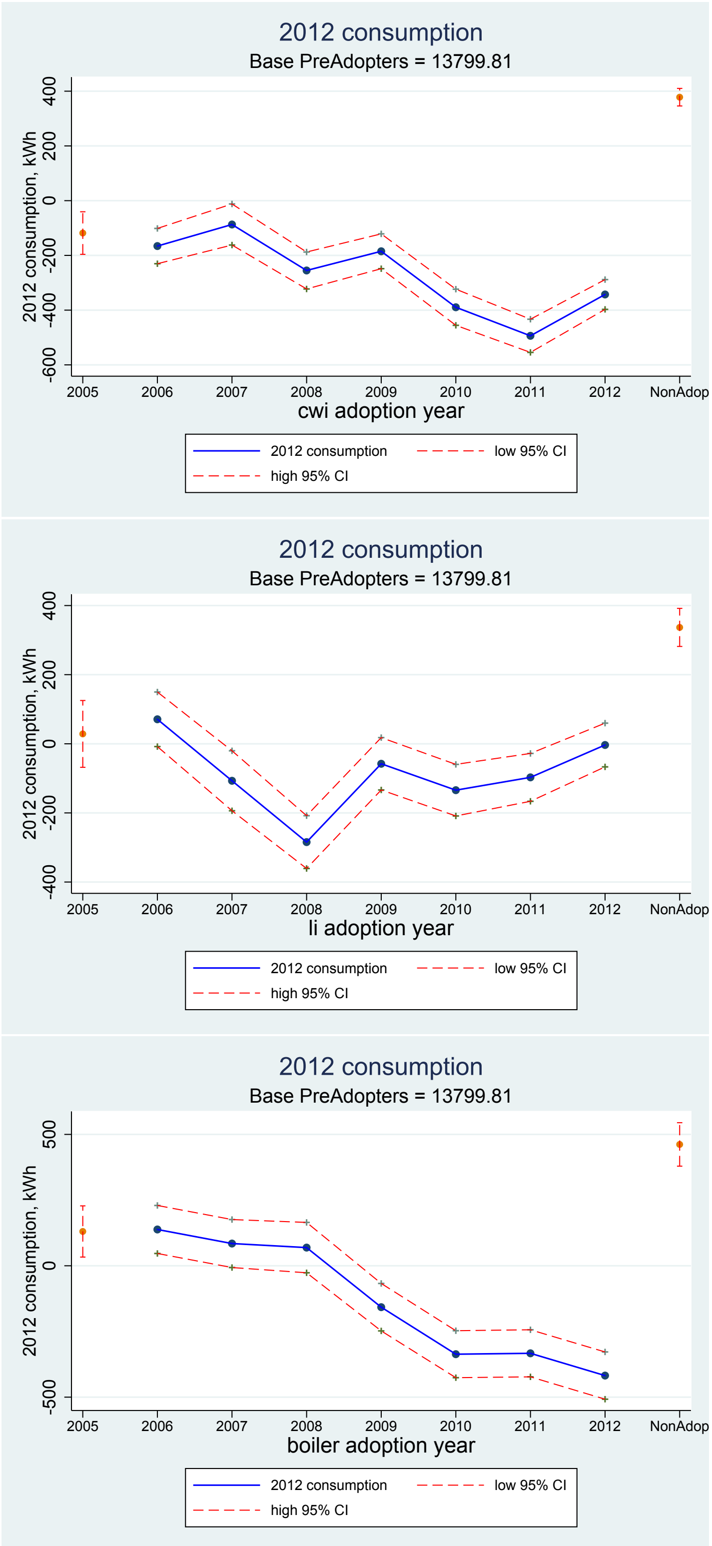


Figure 19: Post-adoption 2012 consumption versus adoption year

Note: The values presented in the graph are obtained as the coefficients on year of adoption dummies in a regression of 2012 total energy consumption as the dependent variable on the year of adoption dummy variables, region fixed effects and property characteristics control variables. The dashed red lines represent the 95% confidence interval for those coefficients.

Average energy consumption before adoption				
		Cavity wall insulation	Loft insulation	Boiler
Adoption year	Total consumption	-565.6***	-554.2***	-504.0***
		(9.605)	(8.156)	(7.335)
		$R^2 = 0.340$	$R^2 = 0.317$	$R^2 = 0.350$
	Gas consumption	-570.9***	-547.8***	-462.2***
		(8.660)	(7.416)	(6.654)
		$R^2 = 0.330$	$R^2 = 0.309$	$R^2 = 0.329$
	Electricity consumption	5.313*	-6.399***	-41.85***
		(2.818)	(2.383)	(2.232)
		$R^2 = 0.150$	$R^2 = 0.143$	$R^2 = 0.156$
Sample size		336,940	488,595	676,907
Property characteristics		X	X	X
Year FE		X	X	X
Region FE		X	X	X

Table 3: Average total energy consumption before adoption

Notes: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. Outcomes variables are average total energy consumption, gas consumption and electricity consumption before technology adoption, measured in kWh. The table presents in each column the coefficient estimates on the calendar year of adoption in a linear regression model where the independent variables are calendar year of adoption, control variables including property characteristics, year fixed effects and region fixed effects. Robust standard errors are presented in parentheses.

and variables to control for whether the household has previously adopted any of the other two energy efficiency measures in the past. The results are presented in Table 3.

$$\bar{c}_{ilr,before} = \alpha + \beta R_i + X_i^{'}\omega + \alpha_r + \gamma_l + \epsilon_{ilr} \tag{40}$$

The coefficients on the calendar adoption year show that the correlation is negative for total and gas consumption, the interpretation is that households who adopt measures later have lower average levels of energy consumption prior to adoption. For electricity consumption the correlation coefficient is positive when considering adoption of cavity wall insulation measures. The interpretation of the coefficients presented in Table 3 is those who adopt a year later have on average a pre-adoption total energy consumption level of approximately 500kWh lower than those who chose to adopt the same energy efficiency measure the year before. In all cases except one, the coefficient is significant at a 1% significance level. Thus supporting the hypothesis that heterogeneity in preferences (technology) is driving the selection mechanism. However, this does not preclude the possibility that heterogeneous misperceptions play a role in the selection into adoption mechanism. In the case of cavity wall insulation adoption, the coefficient on electricity consumption is positive and significant at a 10% significance level. This would suggest that early adopters consume on average less electricity than late adopters in the pre-adoption stage. This coefficient would be in line with the adoption pattern presented in chapter 1 when agents heterogeneous misperceptions dominate selection into adoption. However, the coefficient is small and of low economic significance.

The limitations of this approach are that year fixed effects and the coefficient on the time of adoption cannot be separately fully identified. The results should be interpreted as the timing of adoption variable is capturing the linear correlation between calendar year and average energy consumption before adoption. However, it is possible that part of this correlation is capturing just a time trend in energy consumption that is not necessarily related to heterogeneity across adoption cohorts.

To tackle this limitations, I provide further evidence exploiting the full variation in the data to identify separately year fixed effects and adoption cohort specific effects. For this purpose, I consider the following regression specification:

$$c_{itrl} = \sum_j \beta_j \mathbf{1}[s<0]\mathbf{1}[j=r] + \gamma \mathbf{1}[s<0] + \sum_j \mu_j \mathbf{1}[j=r] +$$

$$+ \sum_k \delta_k \mathbf{1}[k=l] + \sum_y \eta_y \mathbf{1}[y=t] + X_{it}^{'}\omega + \epsilon_{itrl} \tag{41}$$

The outcome variable c_{itrl} is energy consumption for household i at time t who belongs to year of adoption cohort r in region l. s represents time relative to adoption. Hence, the first term contains the interaction of a before adoption indicator variable (that takes a value of 1 if $s < 0$, and zero otherwise) and the adoption year indicator variables. The regression includes also the before adoption indicator, adoption year fixed effects, year fixed effects, region fixed effects and control variables (including property characteristics and controls for time relative to adoption for the other two energy efficiency measures observed in the data). I compare the estimates for β_r to show differences in average pre-adoption energy consumption among different adoption cohorts. The coefficient estimates and 95% confidence intervals are presented in Figure 20 (Total consumption) and Figure 21 (Gas and electricity consumption). Tables 11, 12 and 13 present the numerical values of the regression results in Appendix A.5.

The results presented in Figure 20 show the change in average energy consumption before adoption is decreasing in the year of adoption. In the case of cavity wall insulation adoption, it decreases from 2007 to 2010. To then slightly increase in 2011 and 2012. For loft insulation the trend is also declining, however from 2009 one cannot say the differences are statistically significant at a 5% significance level. The pattern observed when considering boiler replacement is very similar to the one for cavity wall insulation. In this case, excluding adoption years 2006 and 2007, the trend is declining until 2011. Note that those who adopt at the beginning of the sample period, in particular 2006, show lower average pre-adoption consumption. I believe the reason is that their energy consumption is already declining before actually installing the energy efficiency measure and there is only one or two pre-adoption observations.

Figure 21 presents the coefficient estimates in the case where the outcome variables are gas and electricity consumption respectively. The results in the case of gas consumption are very similar to those for total consumption. The electricity consumption case shows significant differences. Average energy consumption before cavity wall and loft insulation adoption is increasing in the year of installation of insulation measures. Hence, in this case the correlation is positive. This could be interpreted as evidence suggesting that selection into adoption is driven by misperceptions and that early adopters are actually those who consume less before adoption. However, electricity is only a small fraction of the total energy consumption. Together with the negative correlation between year of adoption and gas and total consumption, I interpret this as the effect of households substituting across different inputs, probably induced by the in-house technological change associated with the adoption of energy efficiency measures.

3.2.2 Energy consumption changes

Following the insights of Chapter 1, in this section I focus the analysis on energy consumption changes over time. The prediction of the model presented there was that agents who overestimate their energy efficiency perceive a lower private return on investments in energy efficiency measures. However, their true potential benefits (social value of adoption) is relatively high, as they overconsume energy and should be expected to experience large energy consumption drops upon adoption of energy efficiency measures when the adoption process leads them to also acquire information making them also more efficient at operating the technology. Hence, regarding consumption changes upon adoption, the testable empirical prediction is that one should expect a positive correlation between the energy consumption drop upon adoption and time of adoption. In consequence, in the presence of adverse selection driven by energy efficiency misperceptions, one should expect early adopters of energy efficiency measures to experience smaller drops in energy consumption upon adoption. On the contrary, when adoption is driven by heterogeneous preferences the correlation should exhibit the opposite sign.

In what follows in this chapter, energy consumption changes are drops in energy consumption, i.e. positive (negative) numbers should be interpreted as decreases (increases) in energy consumption in the adoption year.

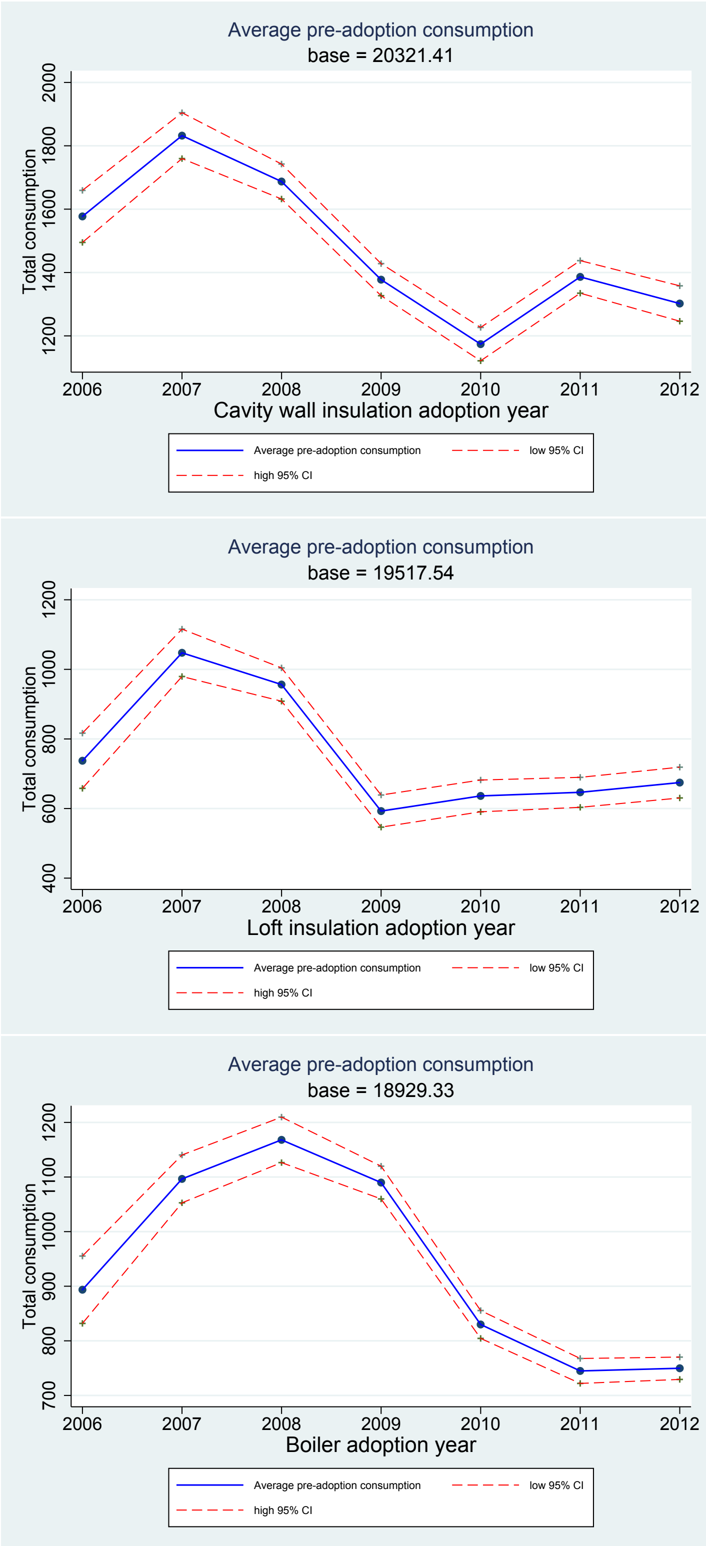


Figure 20: Pre-adoption total consumption by adoption year

Note: The graphs show the coefficient estimates and 95 % confidence intervals for the before adoption cohort specific effect obtained by regressing energy consumption on the interaction of a year of adoption indicator and the before adoption indicator. The regression model includes year fixed effects, region fixed effects and property characteristics.

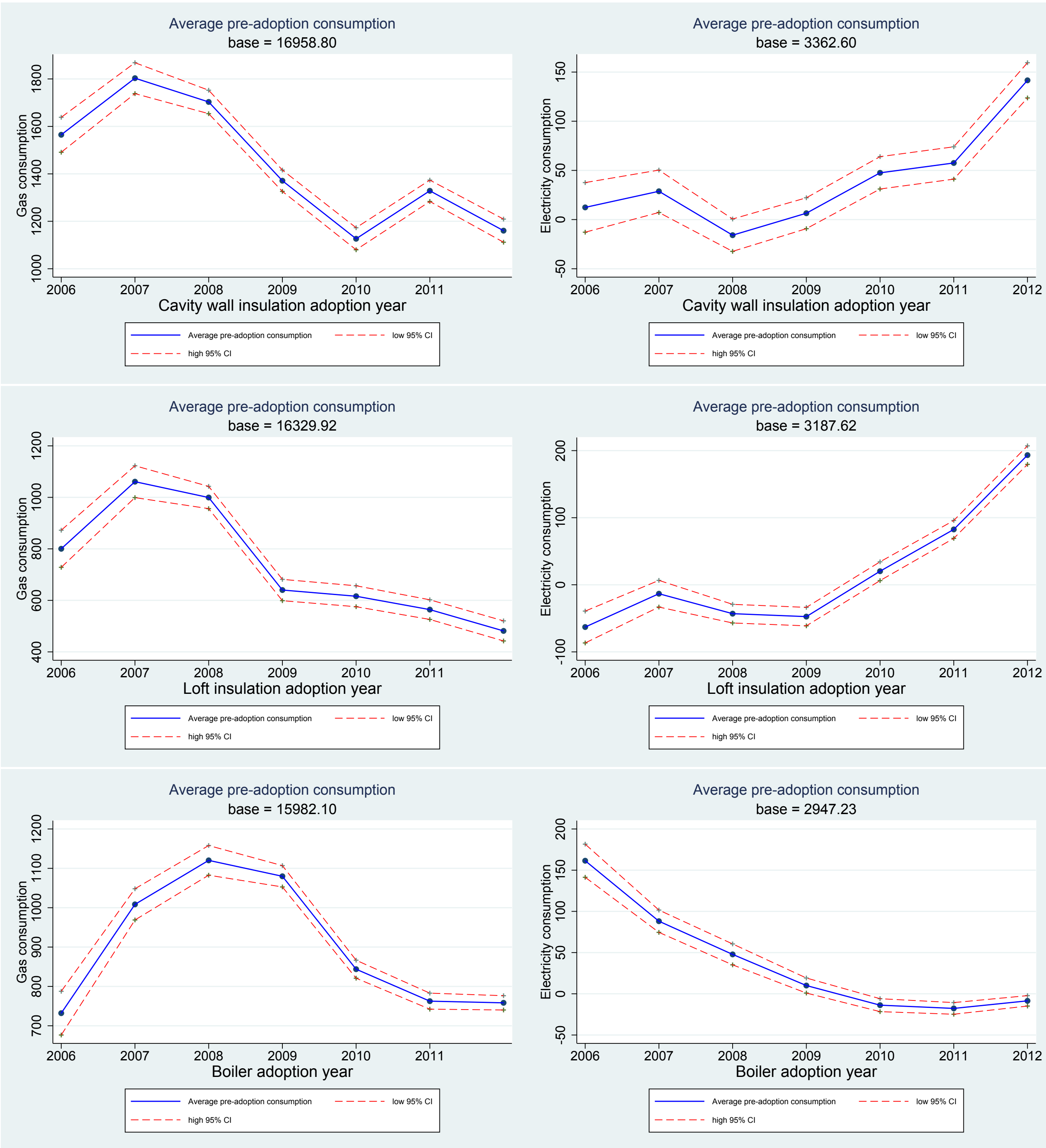


Figure 21: Pre-adoption gas (Left) and electricity (Right) consumption by adoption year

Note: The graphs show the coefficient estimates and 95 % confidence intervals for the before adoption cohort specific effect obtained by regressing energy consumption on the interaction of a year of adoption indicator and the before adoption indicator. The regression model includes year fixed effects, region fixed effects and property characteristics.

To estimate the impact of the adoption year on the energy consumption drop, I estimate the β parameter in the following regression. I run separate regressions for each measure of energy consumption and for each energy efficiency measure installed.

$$\Delta c_{ilt} = \alpha + \beta T_i + X_{it}^{'}\omega + \alpha_t + \gamma_l + \epsilon_{ilt} \tag{42}$$

The outcome variable is the energy consumption drop in the adoption year for household i in region l who adopts in calendar year t, calculated as consumption in the year before adoption minus consumption in adoption year. Therefore, β captures the correlation between the year of adoption and the energy consumption drop upon adoption. X_{it} includes all the property characteristics controls and the time relative to the adoption of the other two energy efficiency measures included in the data.

The parameter of interest provides an estimate of the correlation between adoption year and the energy consumption drop. Hence, it can be interpreted as the additional consumption drop upon adoption experienced when delaying adoption by one year. Table 4 (left panel) presents the coefficient estimates for β in each regression. The estimation results show a negative and significant correlation for all the energy efficiency measures considered and, therefore, provide evidence in favor of early adopters experiencing larger energy consumption drops in the adoption year.

From the graphical analysis presented above, in particular from Figure 17, the consumption drop around adoption seems to span over a larger period of time than just the year of adoption. This can be a consequence of other changes in energy consumption behavior that could potentially be correlated with the adoption of energy efficiency measures. For instance, considering the decision to invest on energy efficiency measures might be the result of an increased attention of a household to energy expenditures or an increased awareness of environmental

		Consumption drop on adoption year			Drop between $s = -2$ and $s = +1$		
		Cavity wall insulation	Loft insulation	Boiler	Cavity wall insulation	Loft insulation	Boiler
Adoption year	Total consumption drop	-218.2***	-228.7***	-195.7***	-423.7***	-433.1***	-297.1***
		(6.696)	(5.767)	(5.835)	(14.94)	(13.10)	(10.34)
		$R^2 = 0.023$	$R^2 = 0.017$	$R^2 = 0.012$	$R^2 = 0.037$	$R^2 = 0.027$	$R^2 = 0.021$
	Gas consumption drop	-199.2***	-206.3***	-157.8***	-344.70***	-346.2***	-219.9***
		(6.053)	(5.225)	(5.249)	(13.51)	(11.94)	(9.466)
		$R^2 = 0.027$	$R^2 = 0.019$	$R^2 = 0.015$	$R^2 = 0.043$	$R^2 = 0.031$	$R^2 = 0.031$
	Electricity consumption drop	-19.01***	-22.38***	-37.86***	-79.00***	-86.90***	-77.23***
		(2.425)	(2.076)	(2.258)	(4.987)	(4.268)	(3.536)
		$R^2 = 0.004$	$R^2 = 0.003$	$R^2 = 0.010$	$R^2 = 0.008$	$R^2 = 0.008$	$R^2 = 0.021$
Sample size		336,940	488,595	676,907	217,857	296,015	470,525
Property characteristics		X	X	X	X	X	X
Year FE		X	X	X	X	X	X
Region FE		X	X	X	X	X	X

Table 4: Consumption drop on adoption year

Notes: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. Outcomes variables are total energy consumption, gas consumption and electricity consumption drops at the time of technology adoption, measured in kWh. The table presents in each column the coefficient estimates on the calendar year of adoption in a linear regression model where the independent variables are calendar year of adoption, control variables including property characteristics, year fixed effects and region fixed effects. Robust standard errors are presented in parentheses.

related issues associated with energy consumption. Although the installation of energy efficiency measures might only materialise after some time, the household might start implementing other changes in behavior to cut energy consumption that are not observed in the data. In addition, observing only the year of adoption is a quite noisy measure of the timing of adoption. For instance, households adopting an energy efficiency measure at the end of the year will only experience the energy consumption drop the following calendar year, it will have, however, a very small impact on the adoption year energy consumption as reported in the data.

To address this I run the regression of energy consumption drops on adoption year considering the drop between two years before adoption and the year after adoption. The results are presented in Table 4 (right panel).

The results confirm the sign of the results presented in the Table 4. The size of the coefficients is significantly larger showing that in addition to the effect of adoption on the household technology, there is also an effect on energy consumption behavior associated with the adoption decisions. This empirical evidence is consistent with the idea that the technology diffusion process has associated knowledge spillovers and that decisions to invest in energy conservation are closely related to other changes in energy consumption habits, probably as the result of a process of information diffusion and acquisition by households on better practices regarding their energy consumption behavior.

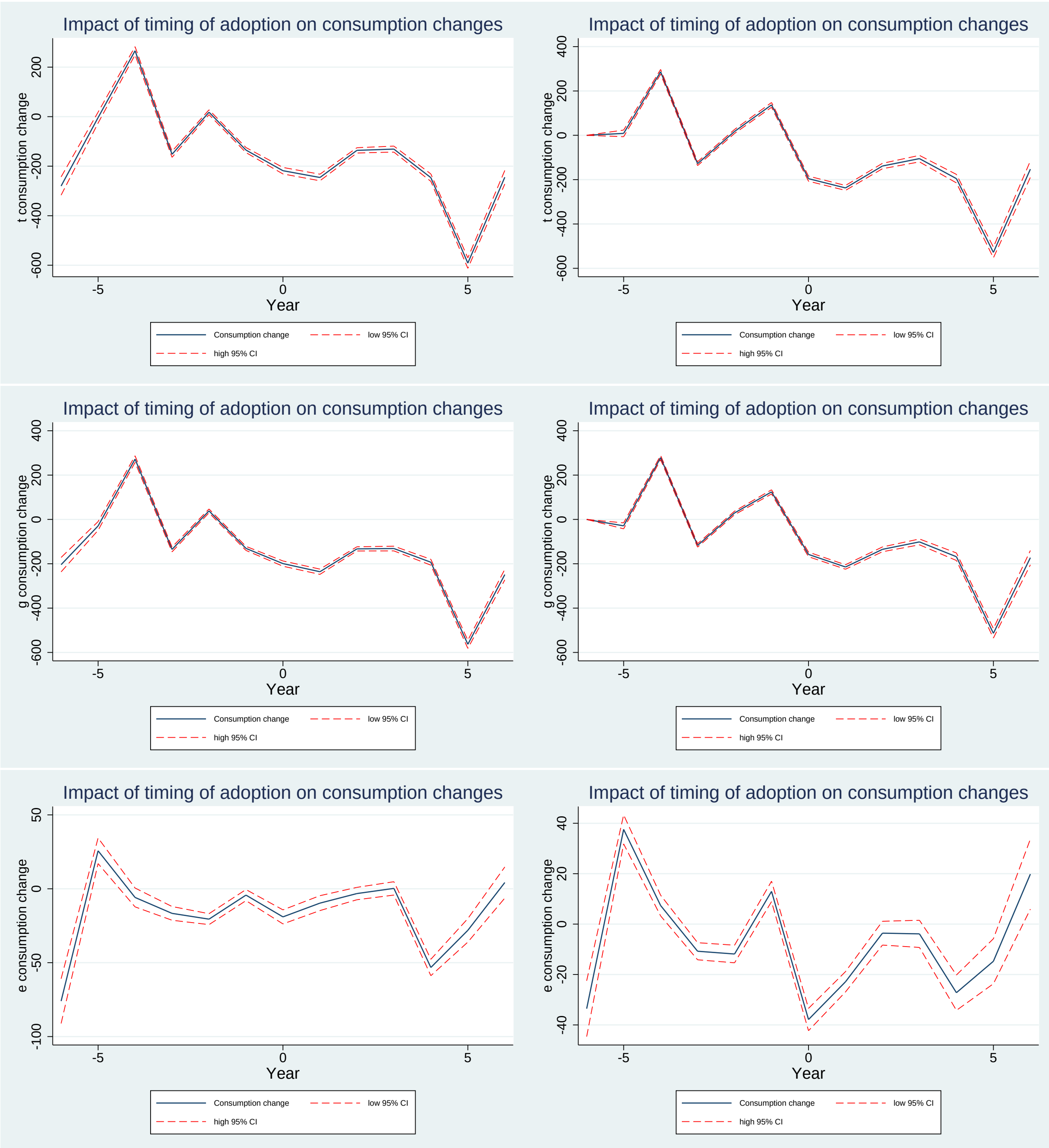
Finally, I present results for the same type of regression looking not only at the energy consumption drops in the adoption year, but also at the first differences for any time relative to adoption from six years before adoption to six years after adoption to test whether belonging to different adoption cohorts has an impact on consumption changes at any other point in time. To perform this analysis, I run the same regression specification by year relative to adoption and I present the beta coefficients on calendar year in Figure 22.

$$\Delta c^s_{ilt} = \alpha + \beta^s T_i + X^{'}_{it}\omega + \alpha_t + \gamma_l + \epsilon^s_{ilt} \qquad \forall s \in [-6, ..., 0, ..., 6] \qquad (43)$$

Figure 22 shows the coefficient on calendar year for each of the regressions specified above for cavity wall insulation (on the left) and boiler replacement (on the right). The graphs for loft insulation are very similar to the cavity wall insulation case and are presented in Appendix A.5. The interpretation of the coefficient estimates is the effect on year s (year relative to adoption time) energy consumption drop of postponing adoption by one year. In years around adoption time, the coefficient on calendar year is negative and significant, implying that adoption in late years leads to a smaller energy consumption drop confirming the results discussed earlier. Likewise, it can be noted that in years following adoption the coefficient is also negative and significant at a 5% significance level. On the contrary, in years before adoption the coefficients are, in general, positive with some exceptions and always significant. I conclude from this that preference heterogeneity seems to dominate selection into adoption and agents' heterogeneity has an effect not only on how effective technology adoption is, but also has persistent differential effects on their energy consumption patterns. In a scenario where, in contrast, selection into adoption is driven mostly by heterogeneous misperceptions, assuming that agents learn about the true energy efficiency as a result of the technology adoption process, then one should observe that the effect of the adoption timing vanishes in the post-adoption stage.

Similar to the previous section, the interpretation of these correlations as evidence of the impact of the year of adoption on energy consumption outcomes is subject to some limitations. As the sample is restricted to just the adoption year observation for each household adopting the energy efficiency measures, it is not possible to guarantee that the coefficient on the adoption timing variable capture only the year of adoption on the energy consumption drops. The reason again is that I cannot separately identify year fixed effects from the adoption cohort effect.

As in the previous section, to address the limitations, I provide further evidence exploiting the full variation in the data to identify separately year fixed effects and adoption cohort specific effects. For this purpose, I consider the following



Cavity wall insulation Boiler replacement

Figure 22: Adoption cohort effect on energy consumption change

Note: The graphs present the values of the coefficient estimates and 95% confidence intervals for calendar year in a linear regression model. The coefficient corresponding to year s is the result of a regression considering all observations for which year relative to event time is s. In each of the regressions, the outcome variable is the consumption change in first differences and the regressors include property characteristics control variables, year fixed effects, region fixed effects. The confidence interval is constructed based on robust standard errors.

regression specification:

$$\triangle c_{itrl} = \sum_j \beta_j \mathbf{1}[s=0]\mathbf{1}[j=r] + \sum_j \mu_j \mathbf{1}[j=r] +$$

$$+ \sum_k \delta_k \mathbf{1}[k=l] + \sum_y \eta_y \mathbf{1}[y=t] + X_{it}^{'}\omega + \epsilon_{itrl} \tag{44}$$

The outcome variable $\triangle c_{itrl} = c_{t-1} - c_t$ is the energy consumption drop for household i at time t who belongs to year of adoption cohort r in region l. s represents time relative to adoption. Hence, the first term contains the interaction of an adoption indicator variable (that takes a value of 1 if $s = 0$, and zero otherwise) and the adoption year cohort indicator variables. The regression includes also the adoption year cohort fixed effects, year fixed effects, region fixed effects and control variables (including property characteristics and controls for time relative to adoption for the other two energy efficiency measures observed in the data). I compare the estimates for β_r to show differences in energy consumption drops in the year of adoption across different adoption cohorts. The same analysis is also done for a long difference in energy consumption (between two years before adoption and one year after adoption), $\triangle c_{itrl} = c_{t-2} - c_{t+1}$.

The coefficient estimates and 95% confidence intervals are presented in Figure 23 for total consumption drops. Figures 38 and 39 show the results for gas consumption and electricity consumption changes in Appendix A.5. Coefficient estimates and standard errors are included in Appendix A.5 in Tables 14, 15 and 16.

In Figure 23 (left column) I present the average energy consumption drops on the adoption year for each adoption cohort (adoption year groups). The figure shows that late adopters experience smaller consumption drops upon adoption of energy efficiency measures. This is true for drops on the adoption year until 2010 when considering cavity wall and loft insulation adoption, and until 2011 in the case of boiler adoption. Thus, supporting the hypothesis of a negative correlation between timing of adoption and energy consumption drops at the time of technology adoption. This would be consistent with selection being dominated by preferences heterogeneity. However, by the end of the sample period, the graphs show that this trend is reversed and adopters in 2011 and 2012 experience larger consumption drops in the adoption year. This coincides with the introduction of the Boiler Scrappage Scheme and at the end of the sample period the Green Deal scheme was introduced. Connecting this change in the pattern to policy changes provides an opportunity to identify the impact of incentives on selection into technology adoption and the cost effectiveness of incentive schemes. In the last section of this chapter I provide an attempt to shed some light on that using the introduction of the Boiler Scrappage scheme as a source of policy variation.

The right column of Figure 23 presents the same results for the long differences in energy consumption. As discussed previously, the long difference aims to capture additional change in behavior that are associated with adoption decisions and have an effect on energy consumption. In this case, the graphs show that the drop in energy consumption around adoption is larger and decreasing in the year of adoption. From 2010 a reversal in the trend is observed, however in this case it is smaller. This suggests that when considering a broader impact of adoption on energy consumption, early adopters seem to experience larger energy consumption drops. I attribute the drop in the adoption year to a mechanical response of energy consumption to the technological change, whilst the drop considering additional years could include also other behavioral responses, like changes in the energy consumption habits. This results suggest that for early adopters the behavioral responses are higher relative to the mechanical effect of adoption. This would be consistent with the idea that early adopters are more attentive to energy costs, have larger concerns about the impact of energy consumption on the environment and, in general, energy efficiency issues are more salient to them. As a consequence, they probably implement changes in energy consumption behavior and further energy efficiency intervention, at the same time they decide to invest in the observed energy efficiency measures.

The patterns observed in gas and electricity consumption drops are very similar and are presented in Appendix A.5.

3.3 Evidence of Learning

In the light of the empirical evidence presented in both Chapter 2 and Chapter 3, one can argue that the observed consumption patterns around the installation of energy efficiency measures suggests that the consumption changes are not only the consequence of the technological change, but also a consequence of other changes in energy consumption behavior that could be linked to learning. Learning understood in a broad sense could include that households learn more precisely about their true energy efficiency, or that, for instance, they may be learning about the energy consumption social norm. In either case, one can interpret those patterns in energy consumption as a correction in the beliefs about the true cost of production of energy services. In the following paragraphs, I further discuss the link between the features observed in the data and the learning process that could be underlying them.

The data analysis presented previously shows consistently that in pre-adoption years there is an inverted U-shaped pattern in the energy consumption profiles. This can be interpreted as evidence of an underlying learning process. The U-shaped pattern could be the result of the reversion of an upward trend in energy consumption that is reverted as households learn about their true energy efficiency, i.e. they become aware of the energy savings potential of energy consumption behavioral changes in the utilisation of the current technology. That effect shows up in the energy profiles as a reversion in the energy consumption trend and decline of energy consumption that begins in the years prior to adoption of energy efficiency measures. Although it is not possible to disentangle the mechanism that is causing this, it is consistent with a learning process by which households misperceptions about the cost of production of energy services production is

Drop on adoption year **Drop between $s = -2$ and $s = +1$**

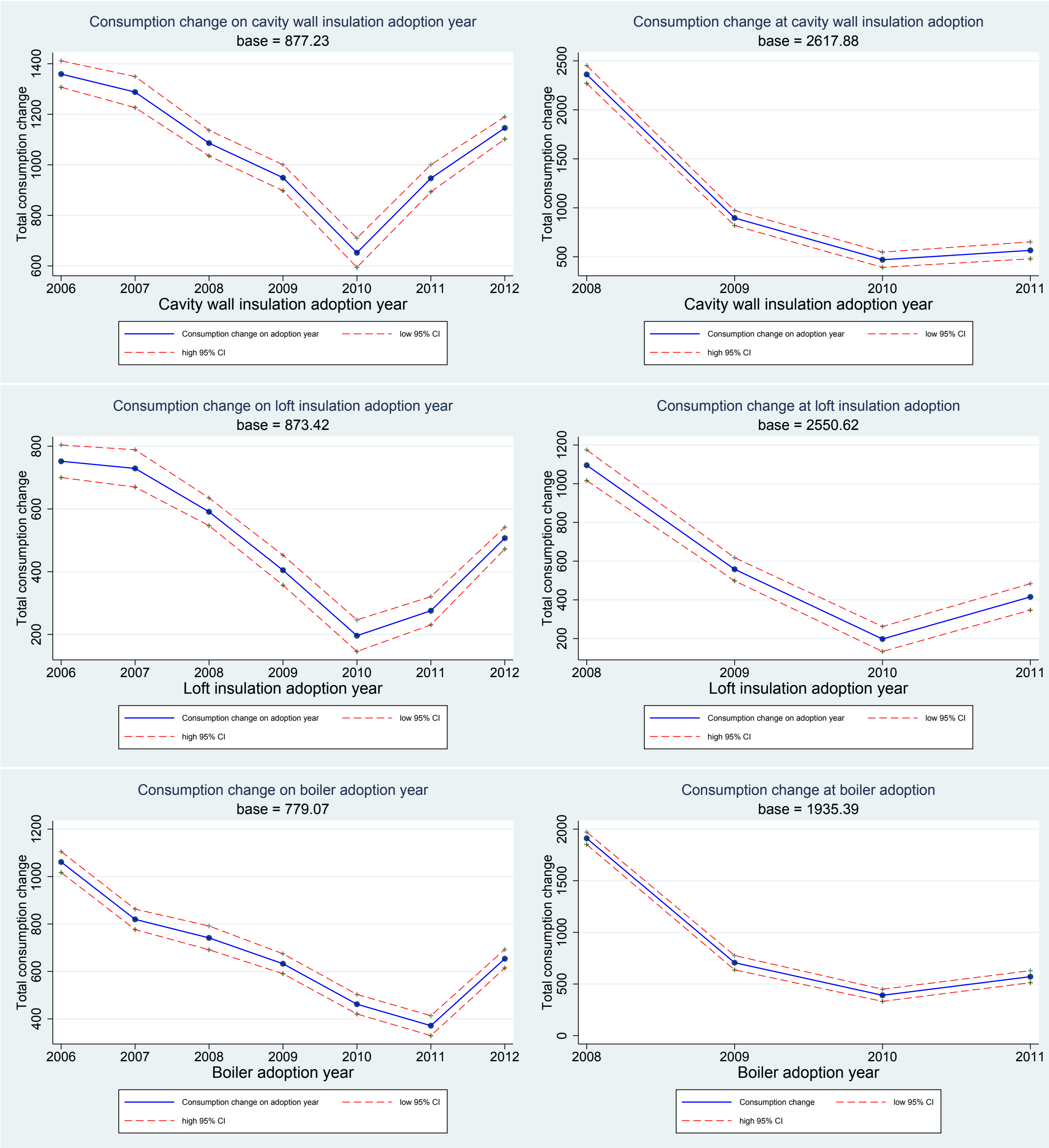


Figure 23: Total consumption change upon adoption

Note: The graphs show the coefficient estimates and 95 % confidence intervals for the year of adoption specific effect obtained by regressing changes in energy consumption upon adoption on the interaction of a year of adoption indicator and the time of adoption indicator. The regression model includes year fixed effects, region fixed effects and property characteristics.

gradually corrected. The source of information leading to the exhibited behavior could be varied, ranging from information provision to knowledge spillovers across households.

Another feature observed in the empirical analysis is the convergence of energy consumption profiles in post-adoption years. The differences in energy consumption levels between household groups is significantly larger in pre-adoption years than it is in the post-adoption period. Again, this could be reflecting that throughout the adoption process, households learn about their true cost of production of energy services. As a consequence of that, the distribution of energy consumption across groups is more homogeneous. It should also be noted that the installation of energy efficiency measures might also lead to this convergence in energy consumption across groups of households as a consequence of a pure mechanical effect of the technological change. After installing the energy efficiency measures, there is also more homogeneity in the true energy efficiency of households.

3.4 Role of incentives: Using policy variation from the Boiler scrappage scheme

In this section I perform an empirical analysis to address the role of government provided incentives on selection into adoption. Considering the policy variation introduced by the "Boiler Scrappage Scheme" I provide estimates of the impact of the policy change on pre-adoption energy consumption and energy consumption changes upon adoption. To determine the relevance for policy design of consumers' heterogeneity, it is important to understand the effect of incentive provision on selection into adoption. With heterogeneous agents this determines the energy consumption savings upon adoption of energy efficiency measures.

The Boiler Scrappage scheme introduced starting from 2010 a subsidy for households replacing an old low efficiency boiler with an energy efficient boiler. The scheme offered up to 125000 subsidies of 400GBP to those replacing a G-rated boiler with an A-rated boiler. To analyse the effect of the Boiler Scrappage

Scheme I group households in five groups. The groups are defined as: Pre-adopters (adopted the measure before 2005), Early I (adopted in the 2005-2007 period), Early II (adopted in the period 2008-2009), Late (adopted in the 2010-2012 period when the Boiler Scrappage Scheme was in place) and Never (those who do not adopt the measure during the sample period 2005-2012).

Figure 24 represents the energy consumption profiles over time relative to boiler adoption for each of the groups. The graphs show energy consumption drops around boiler replacement for all groups of adopters. It is interesting to observe that groups Early I and II show a very similar energy consumption profile but earlier adopters have a lower energy consumption level after adoption. Late adopters exhibit lower pre-adoption energy consumption levels and experience a significant drop around boiler replacement. To further analyse this, in the following subsections I present a regression analysis to quantify the difference in pre-adoption energy consumption levels and energy consumption drops between those who adopt in the Boiler Scrappage scheme period and those who adopt before.

Note that the data does not identify which households received the subsidy. The results, therefore, should be interpreted as an intention to treat effect.

3.4.1 Pre-adoption levels of consumption

In this section I propose a Difference in Difference approach to obtain estimates for the effect of the Boiler Scrappage Scheme on selection into adoption studying changes in pre-adoption average energy consumption levels. The estimates are obtained using observations in Early I (boiler replacement in period 2005-2007), Early II (boiler replacement in period 2008-2009) and Late (boiler replacement in period 2010-2012) adoption groups. Early I and Early II adoption groups replace the boiler before the Boiler Scrappage scheme and I compare them to control for the pre-policy trend in pre-adoption energy consumption.

The identifying assumption underlying the Difference in Difference estimate is that absent the policy change, Late adopters pre-adoption consumption would

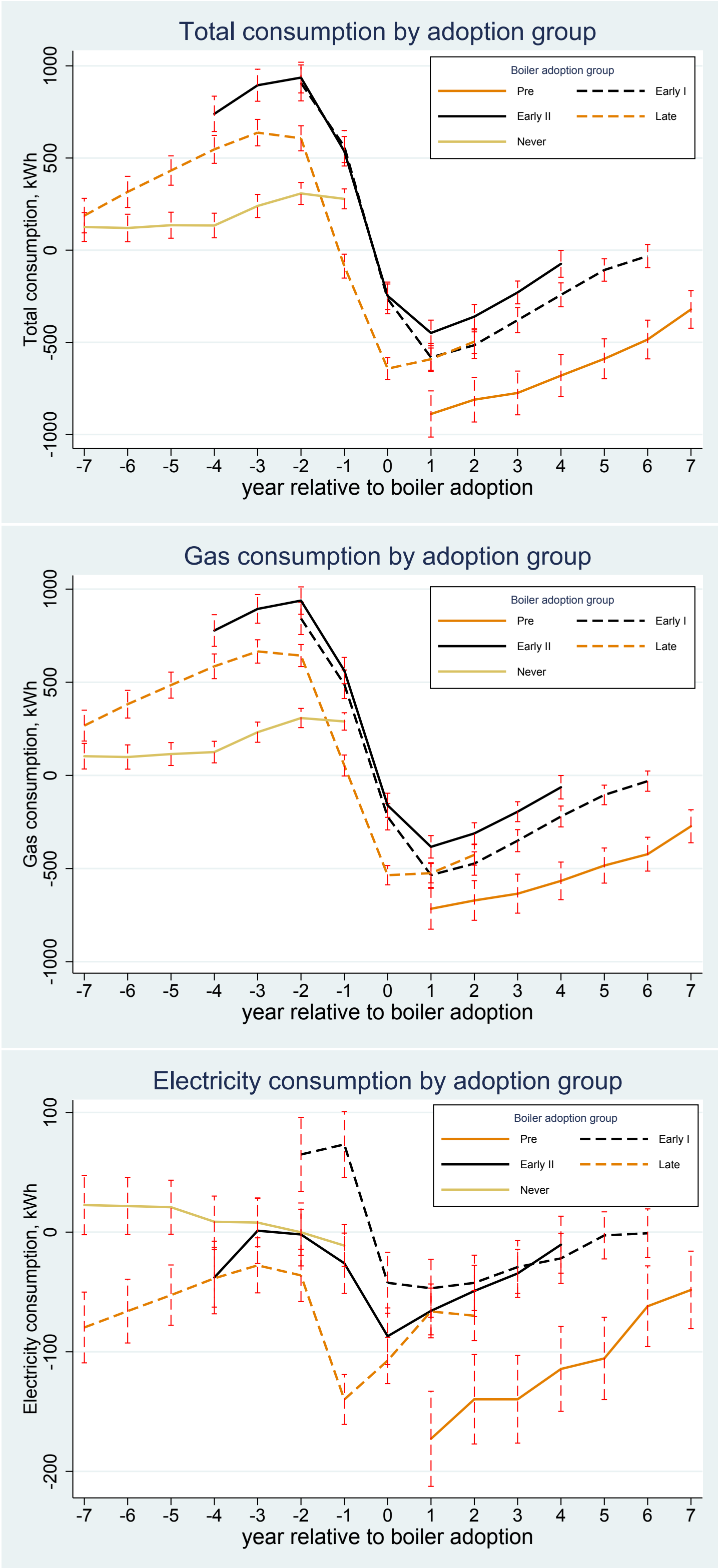


Figure 24: Energy consumption by boiler adoption groups

Note: The graphs present the values of the coefficient estimates and 95% confidence intervals for the interaction of the adoption group dummy variable and the year relative to boiler adoption in a linear regression model. The outcome variables are total, gas and electricity consumption and the regressors control variables: property characteristics, year fixed effects and region fixed effects. The confidence interval is constructed based on robust standard errors.

have followed the pre-policy trend.

For the mentioned adopters groups I use all the information on energy consumption included on the data set, to separately identify time fixed effects and adoption-group specific effects.

I estimate the following regression model:

$$c_{itgl} = \sum_j \beta_j \mathbf{1}[s < 0]\mathbf{1}[j = g] + \gamma \mathbf{1}[s < 0] + \sum_j \mu_j \mathbf{1}[j = g] +$$

$$+ \sum_k \delta_k \mathbf{1}[k = l] + \sum_y \eta_y \mathbf{1}[y = t] + X_{it}^{'}\omega + \epsilon_{itrl} \qquad (45)$$

The outcome variable c_{itgl} is energy consumption for household i at time t who belongs to adoption group g in region l. s represents time relative to adoption. Hence, the first term contains the interaction of a before adoption indicator variable (that takes a value of 1 if $s < 0$, and zero otherwise) and the adoption group indicator variables. The regression includes also the before adoption indicator, adoption group fixed effects, year fixed effects, region fixed effects and control variables (including property characteristics and controls for time relative to adoption for the other two energy efficiency measures observed in the data). I compare the estimates for $\beta_g + \mu_g$ across groups to show differences in average pre-adoption energy consumption among different adoption groups. The coefficient estimates are presented in Table 5.

I use the coefficient estimates to construct a Difference-in-Difference estimate as $[(\beta_{LATE} + \mu_{LATE}) - (\beta_{EARLY2} + \mu_{EARLY2})] - [(\beta_{EARLY2} + \mu_{EARLY2}) - (\beta_{EARLY1} + \mu_{EARLY1})]$. These coefficients are presented in bold in the Table 5. The difference between the Late group and Early 2 group shows that late adopters consume on average 353 kWh less in the pre-adoption period. The Difference-in-Difference estimate aims to control for the pre-policy trend. The identifying assumption is that in the absence of the policy change the difference between Late and Early 2 adopters would have been the same as for Early 2 and Early 1 adopters. This provides a Difference in Difference estimate of the policy impact on pre-adoption consumption of -438.8 kWh. This would suggest that as a consequence of cash incentive provision, households who consume less before adoption decide to invest in energy efficiency measures as a consequence of the subsidy. On the one hand, this can be interpreted as the result of households with low energy intensity use who found replacing the boiler not profitable enough, decide to invest in energy efficiency measures. Alternatively, it could be also interpreted as leading households who consume less to adopt and cash the subsidy in, when they would have adopted any way.

Note that these results are in line with the results of the previous section, this is late adopters consume less energy before adoption than early adopters. However, the Difference in Difference estimate should be taken carefully, as it may be that the pre-trend is not properly captured as a consequence of the short pre-adoption time series for early adopters. In particular, I find that the difference between Early 2 and Early 1 adopters is positive, meaning that Early 2 adopters consume more on average before boiler replacement. However, this is very likely to be as a result of the Early I group pre-adoption consumption being already affected by the technology adoption decision. As a consequence, it is difficult to interpret this estimate as an unbiased estimate of the policy effect. This could be addressed with a longer time series of energy consumption before adoption to potentially guarantee that pre-adoption consumption is unaffected by the technology adoption decision.

3.4.2 Energy consumption changes

In this section, I present a similar analysis using as outcome variables the energy consumption drop on the boiler adoption year and the drop in consumption between 2 years before and 1 year after boiler adoption. The graphs for energy consumption presented in Figure 24 suggest that the energy consumption drop around the boiler replacement year is not fully concentrated in the adoption year. For that reason, I also consider the consumption drop between two years before and one year after adoption.

Pre-adoption consumption			
Boiler replacement	Total	Gas	Electricity
Group*Pre-Adoption			
Early I group	1005***	906.3***	98.31***
	(19.91)	(17.95)	(6.22)
Early II group	1063***	1025***	37.95***
	(15.67)	(14.01)	(4.83)
Late group	1051***	1014***	36.23***
	(12.38)	(10.83)	(3.92)
Group (Early I base)			
Early II	27.19***	54.52***	-27.33***
	(10.25)	(8.93)	(3.27)
Late	-313.3***	-249.4***	-63.93***
	(11.19)	(9.71)	(3.59)
Constant	18922***	15964***	2958***
	(38.50)	(34.31)	(11.81)
Late - Early2 Diff	**-353.0*****	**-314.7*****	**-38.32*****
	(12.50)	**(11.33)**	**(3.81)**
Early2 - Early1 Diff	**85.81*****	**173.5*****	**-87.70*****
	(19.94)	**(18.08)**	**(6.23)**
Diff-in-Diff	**-438.8*****	**-488.2*****	**49.38*****
	(27.69)	**(25.13)**	**(8.55)**
Sample size		5415255	
R^2	0.379	0.368	0.135
Property characteristics	X	X	X
Year FE	X	X	X
Region FE	X	X	X

Table 5: Pre-adoption consumption by boiler adoption group

Notes: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. Outcome variables are total energy consumption, gas consumption and electricity consumption, measured in kWh. The table presents in each column the coefficient estimates for the before adoption group specific effect, and the adoption group specific effect. Regressors include also year fixed effects, region fixed effects and control variables including property characteristics and controls for adoption of cavity wall and loft insulation measures . Robust standard errors are presented in parentheses.

I propose the following regression specification using all the time variation for all three groups of adopters over time.

$$\triangle c_{itgl} = \sum_j \beta_j \mathbf{1}[s=0]\mathbf{1}[j=g] + \sum_j \mu_j \mathbf{1}[j=g] +$$

$$+ \sum_k \delta_k \mathbf{1}[k=l] + \sum_y \eta_y \mathbf{1}[y=t] + X'_{it}\omega + \epsilon_{itrl} \qquad (46)$$

The differences in coefficient estimates β_g, are interpreted as the differences in energy consumption drops experienced by different adoption groups upon boiler replacement. The coefficient estimates are presented in Table 6. I compare the estimates for $\beta_g + \mu_g$ across groups to show differences in the energy consumption drops among different adoption groups.

The coefficient estimates are used to construct a Difference-in-Difference estimate as $[(\beta_{LATE} + \mu_{LATE}) - (\beta_{EARLY2} + \mu_{EARLY2})] - [(\beta_{EARLY2} + \mu_{EARLY2}) - (\beta_{EARLY1} + \mu_{EARLY1})]$. These coefficients are presented in bold in the Table 6. The difference between the Late group and Early 2 group shows that late adopters experience consumption drops on average 187 kWh smaller in the adoption year, and 498.9 kWh larger when considering the long difference between two years before and one year after adoption.

When controlling for the pre-policy trend in energy consumption drops, the resulting difference in difference estimate is not significantly different from zero when considering consumption drops at the boiler replacement year. However, when considering the longer period the difference in difference estimate is 1280 kWh. The interpretation is that those who replace a boiler under the Boiler Scrappage scheme experience significantly larger energy consumption drops than those who replace a boiler earlier.

Note that the average energy consumption drops when considering a larger period around adoption time are significantly larger than those considering only the drop on boiler replacement year. This evidence suggests that there are other behavioral changes associated with technology adoption decisions affecting the energy consumption patterns other than the installation of energy efficiency measures itself. The result suggest that a large proportion of the energy consumption drop experienced between two years before adoption and one year after adoption is not concentrated in the year of boiler replacement, but are related to other energy consumption behavioral changes. With the information available in the data set it is not possible to identify them separately. First of all, the data does not provide detailed information about financial aid received by each household to implement the energy efficiency measures. Second, it does not provide information about which households actually benefited from the Boiler Scrappage scheme. However, the results suggest that those who adopt under the incentive scheme tend to experience higher energy consumption savings.

A possible explanation for this large effect could be that under the policy scheme, more adopters replace a low energy efficiency boiler for a high efficiency one as this is the main eligibility requirement. If this is the case, however, one would expect the change in energy consumption to be more concentrated at the installation year.

Another potential confounder comes from the fact that it is not possible to observe whether a household installed the new boiler at the beginning or at the end of the year, as this would make a huge difference on which year energy consumption reflects the impact of the technology improvement in the data. Higher frequency data would help to better identify the impact of the technology adoption on energy consumption.

An alternative explanation is that households who adopt under the scheme are at the same time exposed to other incentives at the same time. This could include policies based on providing information on how to improve the household energy efficiency and as consequence of that are substantially changing energy consumption behavior in the years around boiler replacement.

Again, the Difference in Difference estimate should be taken with care as it is difficult to guarantee that the trend in energy consumption drops changes only as a consequence of the policy. Also, since the number of years observed in the pre-policy period is small, it is not possible to check in a compelling manner that the pre-trend changes at the time of the policy intervention. This could be improved with a longer time series before the policy intervention, as that would allow to provide clearer evidence to support the identifying assumption.

3.5 Conclusion

This chapter presents an empirical analysis to test whether adoption of energy efficiency measures is adversely selected. When selection into adoption is adverse, the pattern one should observe in the data is that the correlation between energy consumption before adoption and the year of adoption is positive. In contrast if the correlation is negative, that would show evidence supporting that those who consume more energy adopt energy efficiency measures earlier. Second, I also look at the change in energy consumption at the time of adoption of energy efficiency measures as it represents a measure of the energy consumption reduction related to the adoption decision. In this case, the adverse selection hypothesis implies that early adopters should experience smaller energy consumption drops upon adoption.

For this purpose I use the NEED data set containing information on adoption of energy efficiency measures, energy consumption and property characteristics for households in England and Wales between 2005 and 2012. In contrast with Chapter 2, in this chapter I split the data in groups based on the year of adoption of energy efficiency measures in order to compare the patterns of energy consumption around the adoption year for each of the adoption cohorts. I present coefficient estimates from linear regressions, controlling for property characteristics and year fixed effects, for the correlation between energy consumption before adoption and the adoption year, and also for the energy consumption drop upon adoption and the adoption year.

I find evidence that, with the exception of the case of electricity consumption around cavity wall insulation, the correlation between the year of adoption and

Boiler scrappage scheme consumption drop

	At adoption year			Between $s=-2$ and $s=+1$		
Boiler replacement	Total	Gas	Electricity	Total	Gas	Electricity
Group*Adoption year						
Early I group	940.0***	806.7***	133.3***	1704***	1575***	129.0***
	(15.70)	(14.29)	(6.08)	(31.97)	(29.40)	(10.99)
Early II group	676.2***	615.3***	60.97***	296.2***	300.9***	-4.673
	(16.34)	(14.84)	(6.06)	(23.18)	(21.23)	(7.76)
Late	497.7***	539.9***	-42.24***	972.2***	922.5***	49.73***
	(11.81)	(10.47)	(4.40)	(31.17)	(28.22)	(10.35)
Group (Early I base)						
Early II	77.77***	77.92***	-0.155	627.1***	594.1***	33.01***
	(7.16)	(6.35)	(2.65)	(15.41)	(13.85)	(5.14)
Late	69.31***	58.75***	10.56***	450.0***	435.0***	14.93***
	(6.27)	(5.57)	(2.31)	(17.21)	(15.50)	(5.77)
Constant	848.2***	801.4***	46.78***	2263***	2188***	74.63***
	(27.90)	(25.05)	(10.29)	(61.95)	(56.35)	(20.49)
Late - Early2 Diff	**-187.0*** **	**-94.53*** **	**-92.49*** **	**498.9*** **	**462.6*** **	**36.32*** **
	(19.22)	**(17.33)**	**(7.14)**	**(35.52)**	**(32.34)**	**(11.78)**
Early2 - Early1 Diff	**-186.0*** **	**-113.5*** **	**-72.46*** **	**-781.2*** **	**-680.5*** **	**-100.7*** **
	(21.48)	**(19.57)**	**(8.16)**	**(35.99)**	**(33.18)**	**(12.31)**
Diff-in-Diff	**-1.065**	**18.97**	**-20.04**	**1280*** **	**1143*** **	**137.0*** **
	(36.18)	**(32.85)**	**(13.54)**	**(58.84)**	**(53.94)**	**(19.79)**
Sample size		4738349			1796525	
R^2	0.013	0.016	0.002	0.028	0.032	0.009
Property characteristics	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Region FE	X	X	X	X	X	X

Table 6: Consumption drops upon adoption by boiler adoption group

Notes: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. Outcome variables are energy consumption drop on the adoption year and energy consumption drop between two years before and one year after boiler replacement, measured in kWh. The table presents in each column the coefficient estimates for the adoption time group specific fixed effect and the adoption group specific effect. Regressors include also year fixed effects, region fixed effects and control variables including property characteristics and controls for adoption of cavity wall and loft insulation measures . Robust standard errors are presented in parentheses.

the average energy consumption before adoption is negative. The results also provide evidence of a negative correlation between the year of adoption and the energy consumption drop upon adoption. Implying, therefore, that late adopters experience smaller drops in energy consumption upon adoption.

However, the correlation test performed in this analysis is not a perfect test. Hence, this results do not rule out the fact that misperceptions may still play an important in the selection into adoption mechanism.

Furthermore, I provide evidence on the impact of the calendar year on the energy consumption drop by adoption cohorts. I find that the consumption changes experienced by different adoption cohorts in years other than the adoption year differ significantly. This provides further evidence of heterogeneity across adoption cohorts.

In addition, using policy variation from the introduction of the Boiler Scrappage Scheme, I attempt to estimate the effect of incentives provision on selection into adoption. The results show that consumers replacing the boiler before the incentive scheme exhibit larger energy consumption before technology adoption. When looking at the energy consumption drop upon adoption, I find that adopters under the policy scheme experience larger energy consumption drops around the year of adoption. In the year of adoption, however, the estimate is not significantly different from zero. The Difference in Difference estimates, however, rely on a strong identifying assumption, namely that pre-policy trends in pre-adoption consumption and energy consumption drops upon adoption would have remained the same in the absence of the policy intervention. It is plausible that the assumption is not satisfied, and the trends are changing for other reasons. Having further data on pre-policy years would help to provide evidence to validate the identifying assumption.

Estimating precisely the impact of incentives on selection is a very relevant question for policy design, and I leave for further research finding compelling strategies and data sources to quantify this effect.

Conclusion

I present in this thesis research work on the impact of agents heterogeneity on energy efficient technology adoption and design of incentives for investment in energy efficient technologies at the residential level. The thesis presents a theoretical model to analyse the role of heterogeneity driven by psychological biases on the energy efficiency perceptions. Followed by a critical discussion on energy policy, energy consumption and technology adoption patterns in the United Kingdom based on the National Energy Efficiency Dataset. Finally, in the third chapter I present the results of an empirical study using the NEED data providing evidence on the correlation between energy consumption profiles and the timing of adoption decisions and the role of incentives in the selection into adoption mechanism.

More specifically, the work presented in this thesis provides a conceptual framework to think about the optimal design of incentive schemes to encourage investment in energy efficiency technologies. The model presented in Chapter 1 presents a behavioral public economics approach showing that when agents misperceive their true energy efficiency policies based on taxes and subsidies only achieve constrained efficient outcomes at a very large cost for the government. The results of the model show that agents who tend to overconsume energy are at the same time very unresponsive to this type of policies. This results, together with recent empirical evidence showing that residential consumers seem to be quite responsive to information based policies, suggest that providing information is a more compelling way to encourage adoption rather than providing financial incentives via subsidies to reduce the upfront cost consumers face when considering investments in energy efficient technologies.

The main novelty of the model presented here is that, in contrast to similar models, the heterogeneous psychological bias driving agents' perceived potential benefits of technology adoption is introduced in a way such that it also affects the intensive margin consumption decisions on energy consumption. Resulting, therefore, in a negative correlation between energy consumption levels and the likelihood of technology adoption. This is what in my work I refer to as adverse selection.

In the empirical study presented in the third chapter, I provide different pieces of empirical evidence to address the question on whether selection into adoption is adverse or not. The results show that there is a strong negative correlation between pre-adoption consumption levels and the time of adoption. This suggests that households with higher energy consumption levels are likely to adopt first, perhaps responding purely to the higher potential financial savings they experience as a consequence of the adoption of energy efficiency measures. Second, I find that energy consumption drops upon adoption are larger for early adopters.

The empirical results I find, suggest that selection into energy efficiency measures adoption is dominated by heterogeneity in preferences. This correlation test, however, does not preclude that heterogeneity in energy efficiency beliefs play an important role in the technology diffusion process and on how consumers respond to incentive schemes. An interesting empirical challenge for further research is to try to separately identify the role of the different sources of heterogeneity, as this is of extreme relevance for the design of energy efficiency policy.

In Chapter 3, in addition, I provide estimates for the effect of incentives on selection into adoption studying the impact of a policy change on adopters pre-adoption consumption and energy consumption drops. I find results suggesting that households who adopt under the policy scheme do not experience significantly larger drops in energy consumption in the year of technology adoption. However, when considering the drop between 2 years before and the year after adoption, I find that those who adopt under the policy incentives experience larger consumption savings. As previously discussed this estimates should be taken with care, as they rely on a very strong identifying assumption. Providing more accurate estimates of the impact of incentives on selection into adoption is an interesting avenue for further empirical research in the field of energy efficiency policy.

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A Appendix

A.1 Appendix 1

A.1.1 Properties of $s(\tau, \eta)$, $e(\tau, \eta)$ and $v(\tau, \eta)$.

Lemma 2. *$s(\tau, \eta)$ is increasing in η and decreasing in τ.*

Proof. Implicit differentiation of the first order condition of the consumer utility maximisation problem implies, $\frac{\partial s(\tau,\eta)}{\partial \eta} = \frac{(p+\tau)\frac{\partial e(\tau,\eta)}{\partial \eta \partial s}}{g''[s(\tau,\eta)]} > 0$, since by assumption $e_{s\eta} = \frac{\partial e(\tau,\eta)}{\partial \eta \partial s} < 0$ and $g''(s) > 0$.

Likewise, by implicit differentiation again, $\frac{\partial s(\tau,\eta)}{\partial \tau} = \frac{\frac{\partial e(\tau,\eta)}{\partial \eta \partial s}}{g''[s(\tau,\eta)]-(p+\tau)\frac{\partial^2 e(\tau,\eta)}{\partial s^2}} < 0$, since $e_{s\eta} = \frac{\partial e(\tau,\eta)}{\partial \eta \partial s} < 0$ by assumption. The assumptions on $g(s)$ and $e(s, \eta)$ imply the denominator is negative, and hence, it follows that $\frac{\partial s(\tau,\eta)}{\partial \tau} < 0$ □

Let $\varepsilon_{s,\eta} = \frac{\partial s(p,\tau,\eta)}{\partial \eta} \frac{\eta}{s(p,\tau,\eta)}$ denote the energy efficiency elasticity of energy services demand.

Lemma 3. *$e(\tau, \eta)$ is decreasing in η if $0 \leqslant \varepsilon_{s,\eta} < -\frac{e_\eta \eta}{e_s s}$, and increasing when $\varepsilon_{s,\eta} > -\frac{e_\eta \eta}{e_s s}$.*

Proof. Differentiation of the production function with respect to η implies $\frac{\partial e(\tau,\eta)}{\partial \eta} = \frac{\partial e(\tau,\eta)}{\partial s}\frac{\partial s(\tau,\eta)}{\partial \eta} + \frac{\partial e(\tau,\eta)}{\partial \eta}$. Hence, $\frac{\partial e(\tau,\eta)}{\partial \eta} < 0$ if and only if $\frac{\partial e(\tau,\eta)}{\partial s}\frac{\partial s(\tau,\eta)}{\partial \eta} < -\frac{\partial e(\tau,\eta)}{\partial \eta}$. Multiplying both sides of the inequality by $\frac{\eta}{s}$ and rearranging the condition using the elasticity definition gives the condition above. □

Lemma 4. *$v(\tau, \eta)$ is increasing in η.*

Proof. By the envelope theorem, $\frac{\partial v(\tau,\eta)}{\partial \eta} = -(p + \tau)\frac{\partial e(\tau,\eta)}{\partial \eta}$. Hence, by Lemma 3 $\frac{\partial e(\tau,\eta)}{\partial \eta} < 0$, and it follows that $\frac{\partial v(\tau,\eta)}{\partial \eta} > 0$. □

A.1.2 Relaxing unbiased adopters assumption

Consider fixed new and old technology: η_0 and η_A, and suppose misperceptions remain upon adoption. Then the gap between the social value of adoption (w) and the willingness to pay (v) is given by:

$$w - v = (p + \theta) [\widehat{e}_0 - \widehat{e}_A] - (p + \tau) [e_0 - e_A] \tag{47}$$

At $\tau = \theta$:

$$w - v = (p + \theta) \{[e_0 - \widehat{e}_0] - [e_A - \widehat{e}_A]\} \tag{48}$$

The social value of adoption is above the willingness to pay for optimistic agents as long as the gap between actual energy consumption and planned energy consumption is larger at low levels of energy efficiency. Hence the condition $[e_0 - \widehat{e}_0] - [e_A - \widehat{e}_A] > 0$ must be satisfied.

Moreover, the willingness to pay remains decreasing in $\widehat{\eta}$ if the following condition is satisfied:

$$\frac{\partial v}{\partial \widehat{\eta}} = (p + \tau) \left[\frac{\partial \widehat{e}_A}{\partial \widehat{\eta}} - \frac{\partial \widehat{e}_0}{\partial \widehat{\eta}} \right] + g'(\widehat{s}_A) \frac{\partial \widehat{s}_A}{\partial \widehat{\eta}} - g'(\widehat{s}_0) \frac{\partial \widehat{s}_0}{\partial \widehat{\eta}} < 0 \tag{49}$$

Given that $\widehat{e}$ is decreasing and convex in $\widehat{\eta}$, this implies that $\frac{\partial \widehat{e}_A}{\partial \widehat{\eta}} - \frac{\partial \widehat{e}_0}{\partial \widehat{\eta}} < 0$. And $g'(\widehat{s}_A) \frac{\partial \widehat{s}_A}{\partial \widehat{\eta}} - g'(\widehat{s}_0) \frac{\partial \widehat{s}_0}{\partial \widehat{\eta}} < 0$ since $g(\cdot)$ is concave and $\widehat{s}(\tau, \widehat{\eta})$ is increasing and concave in $\widehat{\eta}$. Hence, these conditions together imply that $\frac{\partial v}{\partial \widehat{\eta}} < 0$.

Consider now the social value of adoption. The derivative of the social value of adoption with respect to $\widehat{\eta}$ is:

$$\frac{\partial w}{\partial \widehat{\eta}} = (p + \theta) \left[\frac{\partial e_A}{\partial \widehat{\eta}} - \frac{\partial e_0}{\partial \widehat{\eta}} \right] - (p + \tau) \left[\frac{\partial \widehat{e}_A}{\partial \widehat{\eta}} - \frac{\partial \widehat{e}_0}{\partial \widehat{\eta}} \right] \tag{50}$$

Hence, evaluated at $\tau = \theta$ it gives the following expression:

$$\frac{\partial w}{\partial \widehat{\eta}} = (p + \theta) \left\{ \left[\frac{\partial e_0}{\partial \widehat{\eta}} - \frac{\partial \widehat{e}_0}{\partial \widehat{\eta}} \right] - \left[\frac{\partial e_A}{\partial \widehat{\eta}} - \frac{\partial \widehat{e}_A}{\partial \widehat{\eta}} \right] \right\} \tag{51}$$

Therefore, $\frac{\partial w}{\partial \widehat{\eta}} |_{\tau=\theta} > 0$ for optimistic agents if

$$\left[\frac{\partial e_0}{\partial \widehat{\eta}} - \frac{\partial \widehat{e}_0}{\partial \widehat{\eta}} \right] - \left[\frac{\partial e_A}{\partial \widehat{\eta}} - \frac{\partial \widehat{e}_A}{\partial \widehat{\eta}} \right] > 0 \tag{52}$$

Hence, the negative correlation between the willingness to pay and the social value of adoption for optimistic agents still holds even if consumers remain biased upon adoption under some conditions. It is sufficient to assume that the difference between experienced and planned energy consumption is larger and steeper when the true energy efficiency is low. In other words, it must be that the effect of the internality is more severe, the lower the true energy efficiency.

A.2 Appendix 2

Cavity Wall Insulation	Detached	Semi detached	Mid terrace	Bungalow	Flat
Fuel bill savings (£/year)	£275	£155	£105	£110	£90
Typical installation cost	£720	£475	£370	£430	£330
Payback time	4 years of fewer				
CO2 savings (kgCO2/year)	1200	660	440	450	370

Source: Energy saving trust

Table 7: Cavity wall insulation investment cost and savings

Note: The table presents estimated fuel bill savings, installation cost, payback time and carbon dioxide savings resulting from the installation of cavity wall insulation for different types of properties. The values presented correspond to England, Scotland and Wales and the figures are based on March 2016 fuel prices.

Loft insulation (0 to 270mm)	Detached	Semi detached	Mid terrace	Bungalow
Fuel bill savings (£/year)	£240	£140	£135	£195
Typical installation cost	£395	£300	£285	£375
Carbon dioxide savings (kgCO2/year)	1000	590	560	820
Loft insulation top up (120 to 270mm)	Detached	Semi detached	Mid terrace	Bungalow
Fuel bill savings (£/year)	£25	£15	£15	£20
Typical installation cost	£290	£240	£230	£280
Carbon dioxide savings (kgCO2/year)	95	55	55	80

Source: Energy saving trust

Table 8: Loft insulation investment cost and savings

Note: The table presents estimated fuel bill savings, installation cost, payback time and carbon dioxide savings resulting from the installation of loft wall insulation for different types of properties. The table first part of the table presents the values for the installation of loft insulation in a totally uninsulated loft. The second part corresponds to topping up insulation from 120mm to 270mm. The values presented correspond to England, Scotland and Wales and the figures are based on March 2016 fuel prices.

Old boiler rating	Detached	Semi detached	Mid terrace	Bungalow	Flat
G ($<$ 70%)	£350	£215	£175	£180	£95
F (70–74%)	£240	£145	£120	£125	£65
E (74–78%)	£190	£115	£95	£95	£50
D (78–82%)	£140	£85	£70	£70	£35

Source: Energy saving trust

Table 9: Boiler replacement savings

Note: Estimated savings are based on installation of a new A-rated boiler. The typical installation cost is £2300. The values presented correspond to England, Scotland and Wales and the figures are based on March 2016 fuel prices.

A.3 Appendix 3

	Cavity wall insulation	Loft insulation	Boiler replacement
Year relative to cwi		0.173*** (0.00026)	0.0892*** (0.000212)
Year relative to li	0.224*** (0.00034)		0.154*** (0.000256)
Year relative to boiler	0.102*** (0.00031)	0.130*** (0.00025)	
Index of Multiple deprivation	-0.0091*** (0.00066)	0.00016 (0.00055)	0.0265*** (0.000446)
Energy 7 meter	0.0072** (0.00306)	0.0321*** (0.0025)	0.0434*** (0.00191)
Fuel poverty	0.0050*** (0.00079)	0.0187*** (0.00069)	0.0147*** (0.000496)
EPC inspection date	0.0178*** (0.0021)	-0.0151*** (0.0017)	-0.132*** (0.00135)
Main heating fuel	0.154*** (0.0077)	0.0217*** (0.0060)	-0.0221*** (0.00526)
Property age	-0.0638*** (0.00081)	-0.0144*** (0.00070)	-0.0179*** (0.00053)
Property type	-0.0009 (0.00063)	0.0420*** 0.00054	-0.0234*** (0.000438)
Floor area band	0.0218*** (0.0016)	0.0284*** (0.0013)	0.0354*** (0.00103)
Energy efficiency band	-0.179*** (0.0012)	-0.0074*** (0.00099)	-0.254*** (0.000816)
Loft depth	0.0040*** (0.000029)		0.00305*** (0.0000153)
Wall construction	-0.287*** (0.0044)	0.307*** (0.0020)	0.262*** (0.00156)
Constant	7.862*** (0.154)	-4.294*** (0.132)	3.901*** (0.0988)
Number of observations	2946680	4134864	5844936
Region FE	X	X	X

Table 10: Adoption determinants

Note: Coefficient estimates are obtained from probit model. In the regression the outcome variable is an adoption dummy that takes a value of 1 in adoption years and 0 otherwise. Regressors include all property characteristics and region-specific fixed effects. Robust standard errors are presented in parentheses.

A.4 Appendix 4

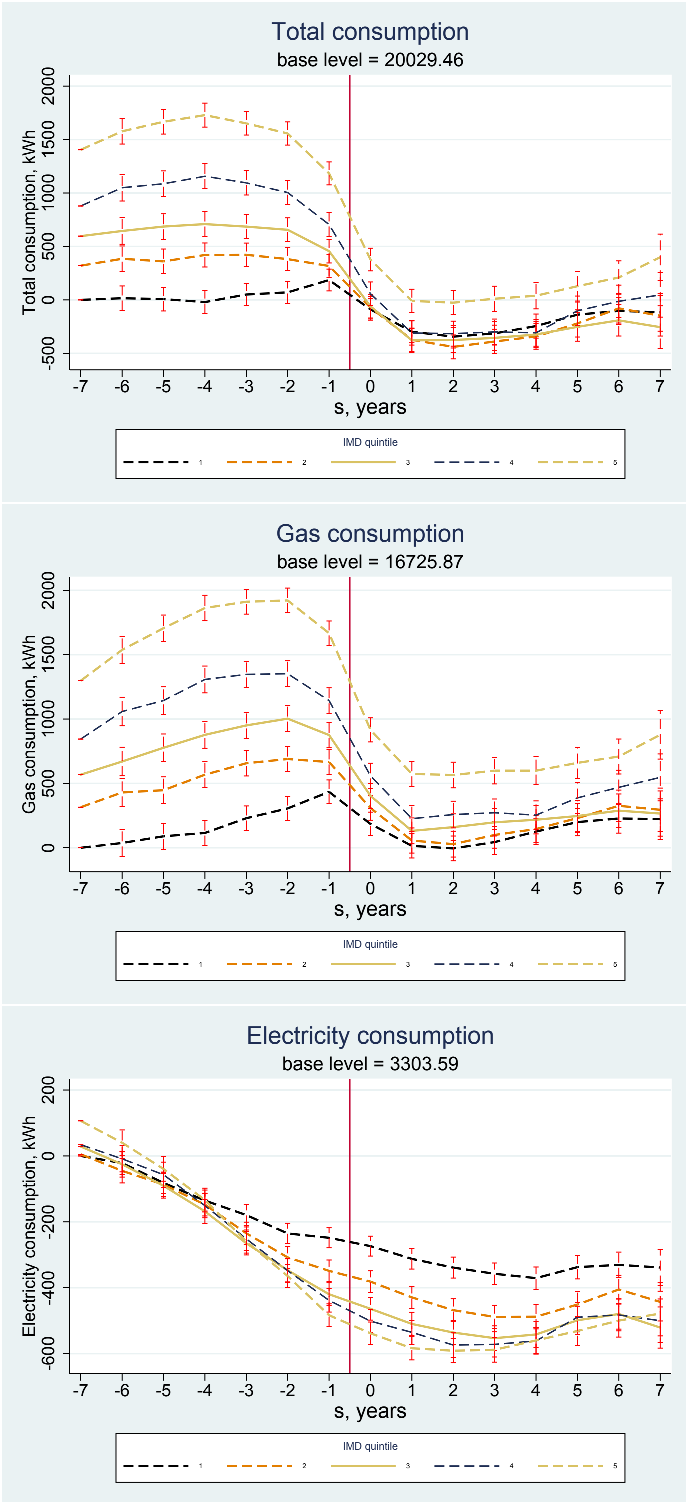

Figure 25: IMD groups (Loft insulation adoption)

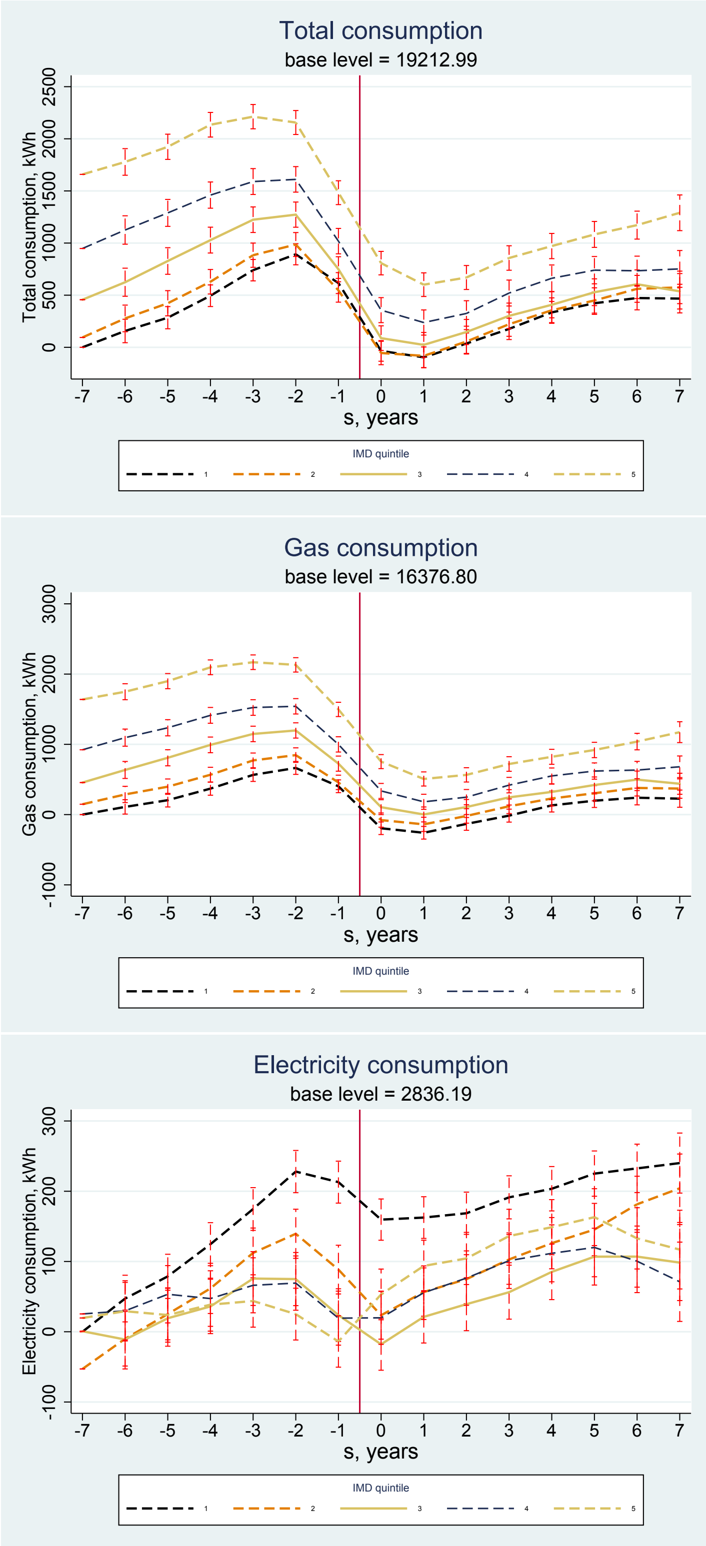

Figure 26: IMD groups (Boiler adoption)

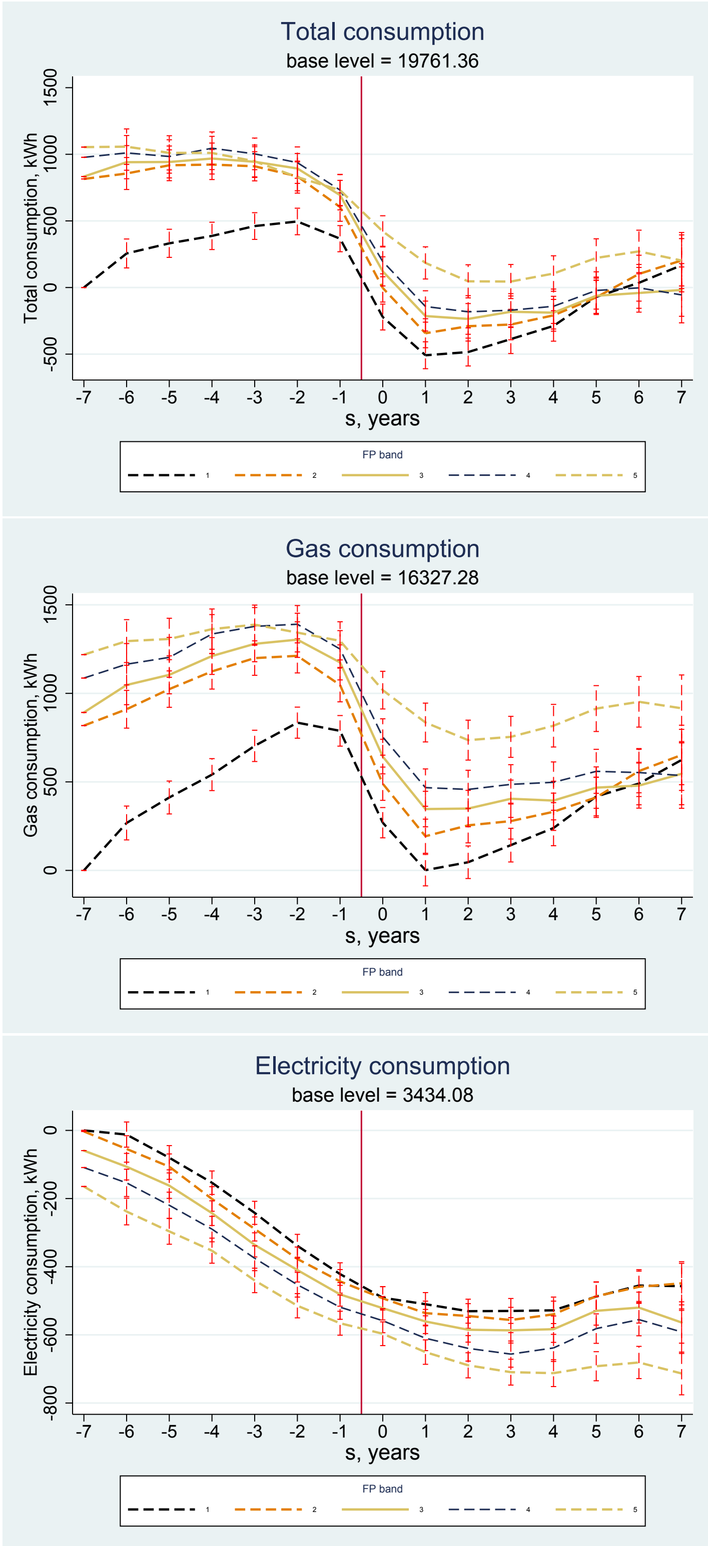

Figure 27: Fuel Poverty groups (Loft insulation adoption)

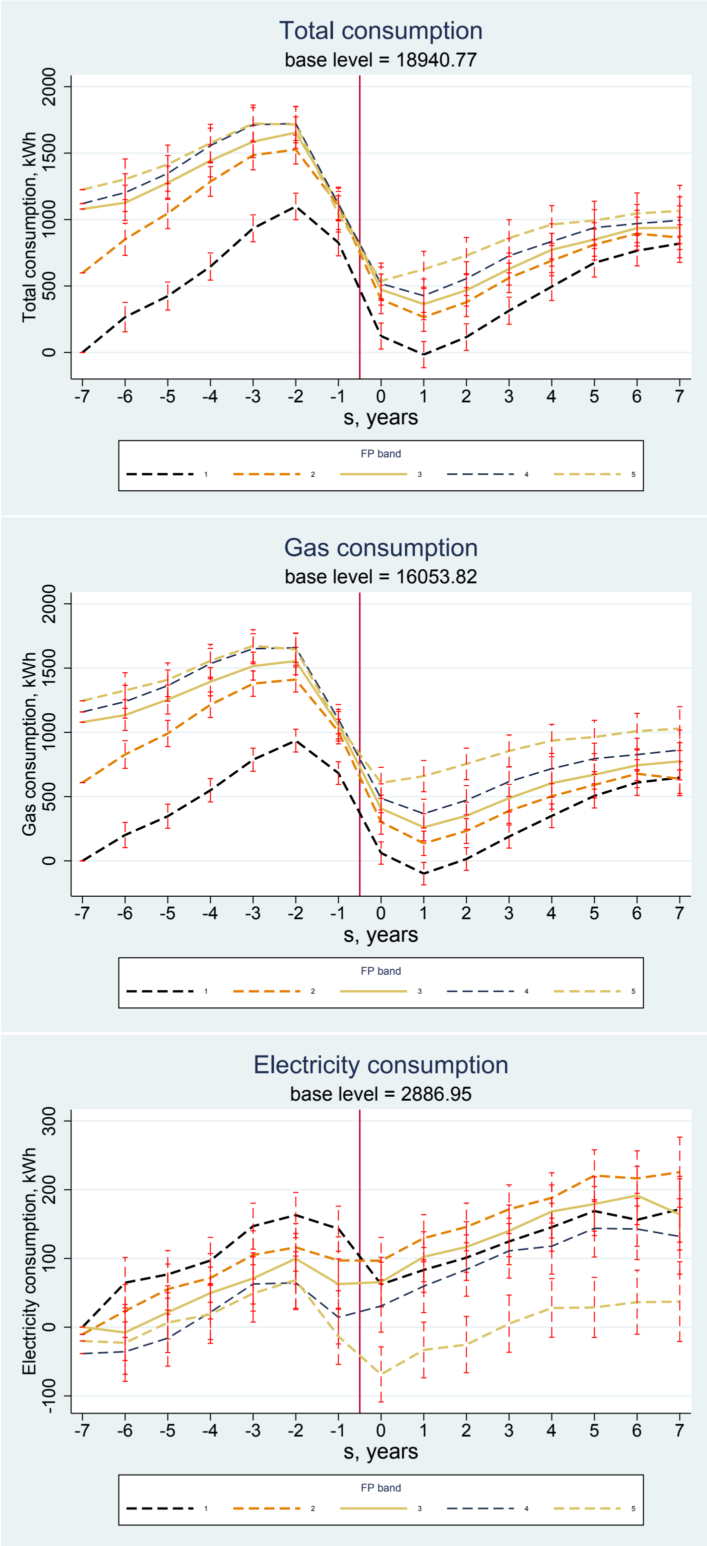

Figure 28: Fuel Poverty groups (Boiler adoption)

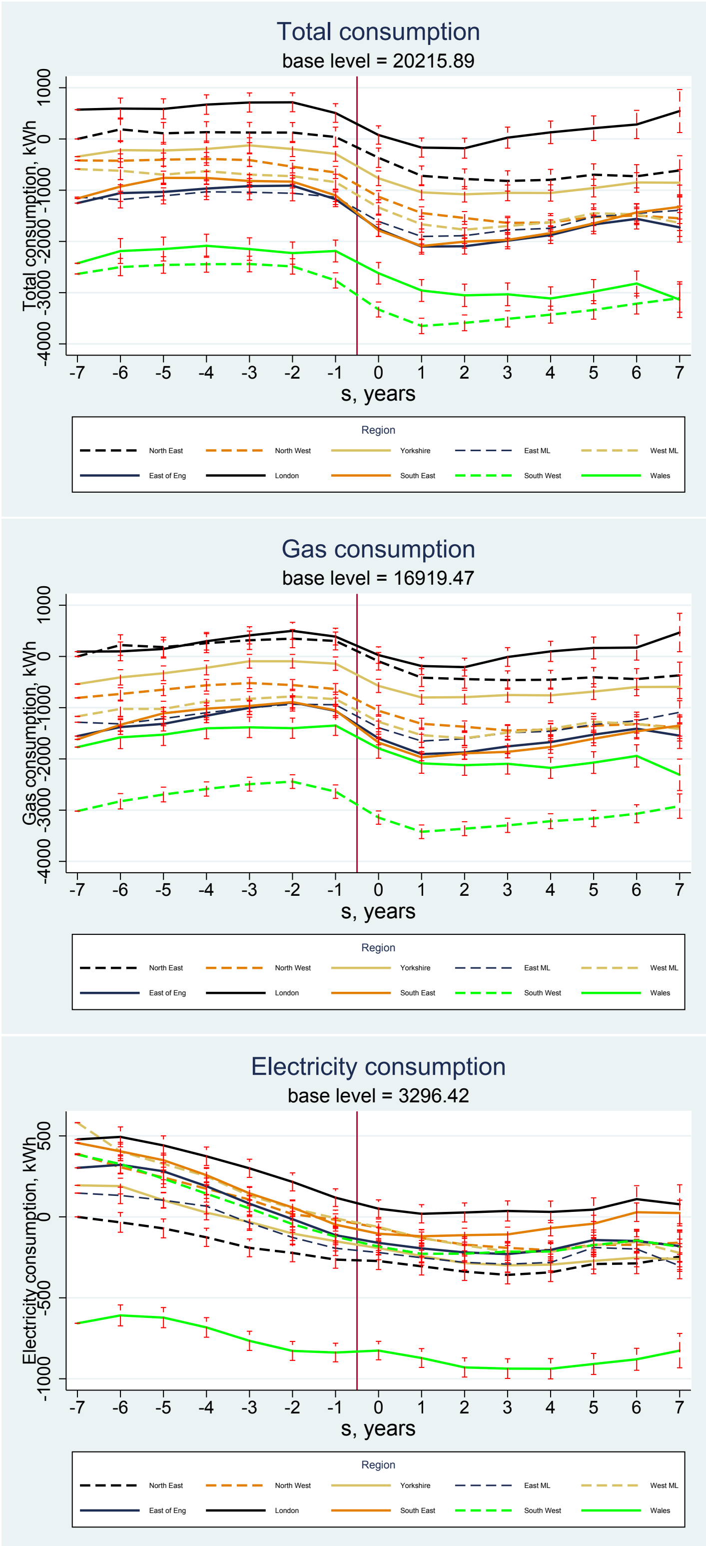

Figure 29: Region groups (Loft insulation adoption)

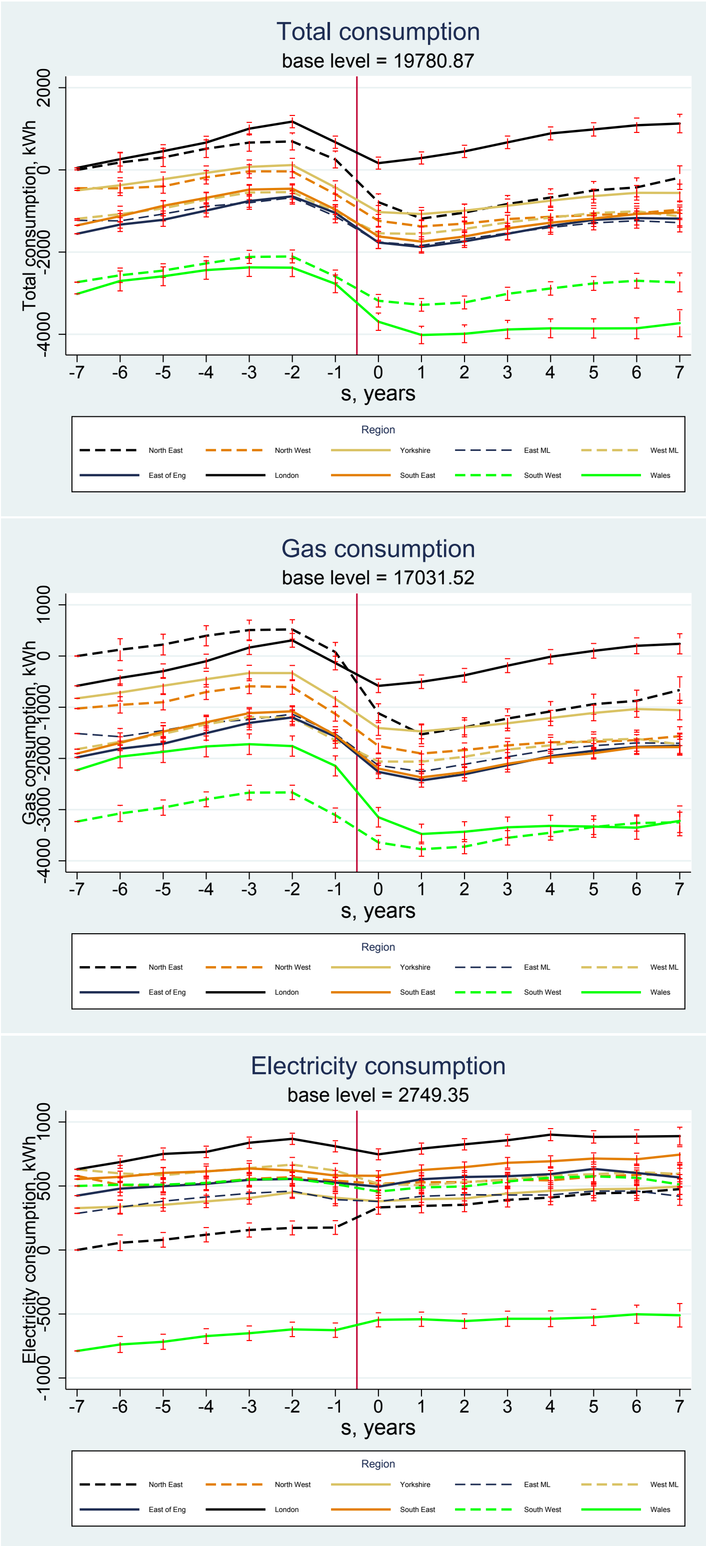

Figure 30: Region groups (Boiler adoption)

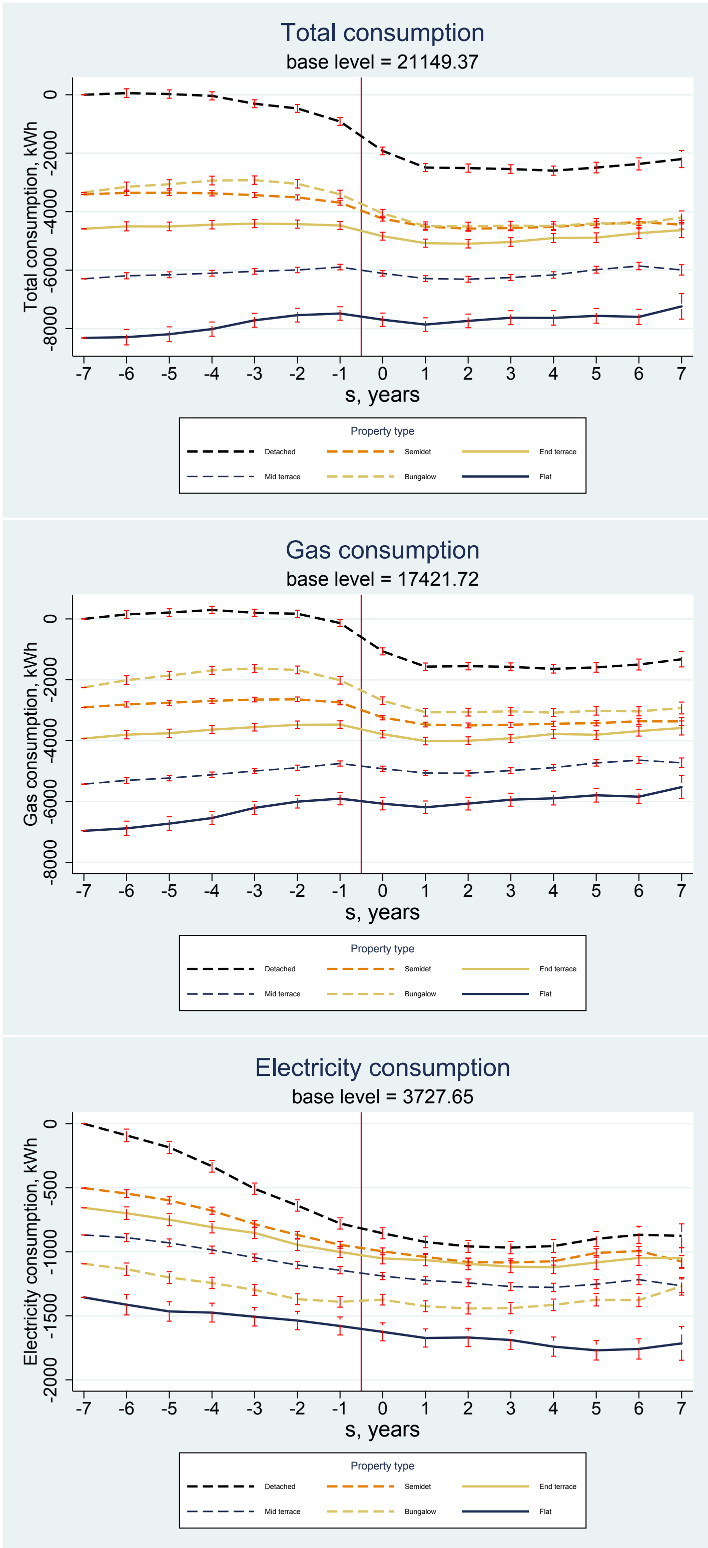

Figure 31: Property Type groups (Loft insulation adoption)

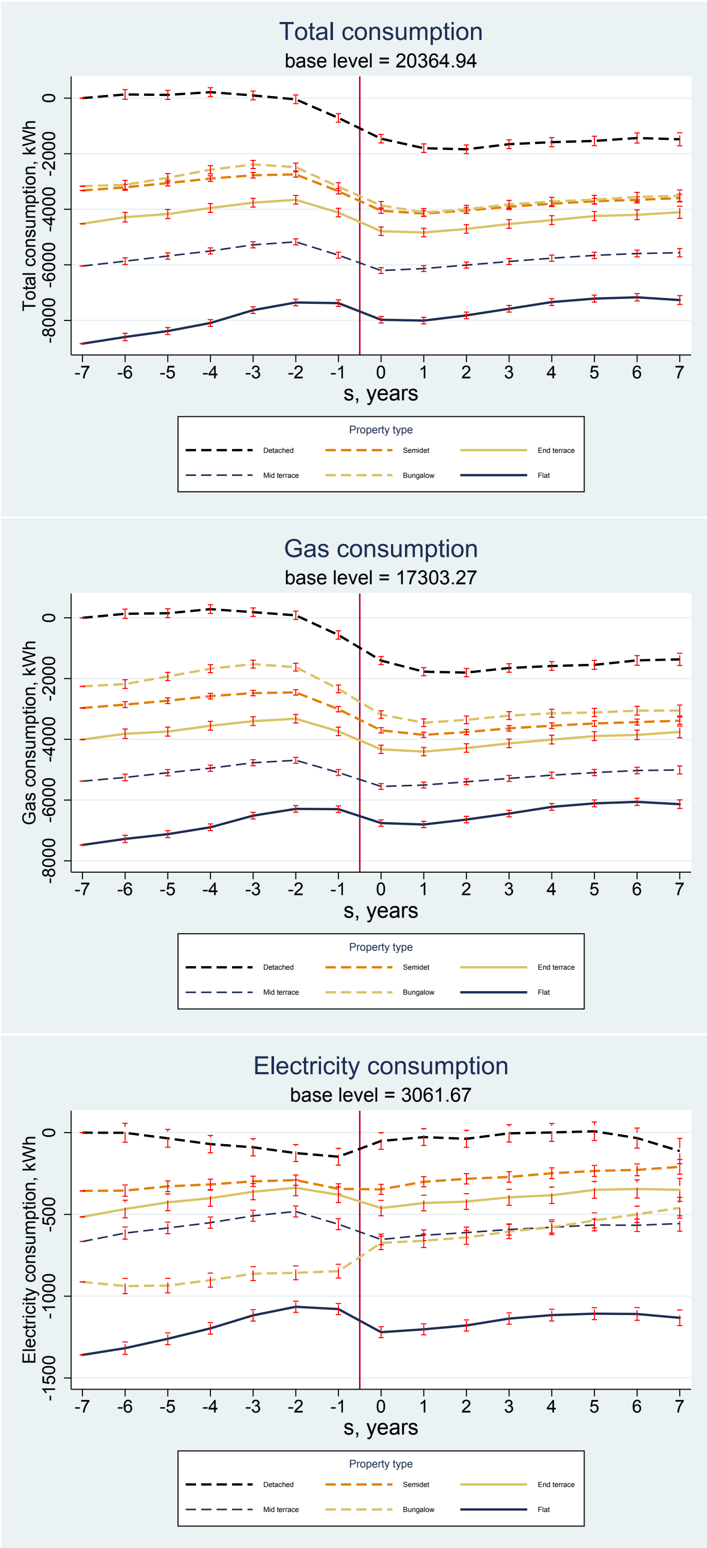

Figure 32: Property Type groups (Boiler adoption)

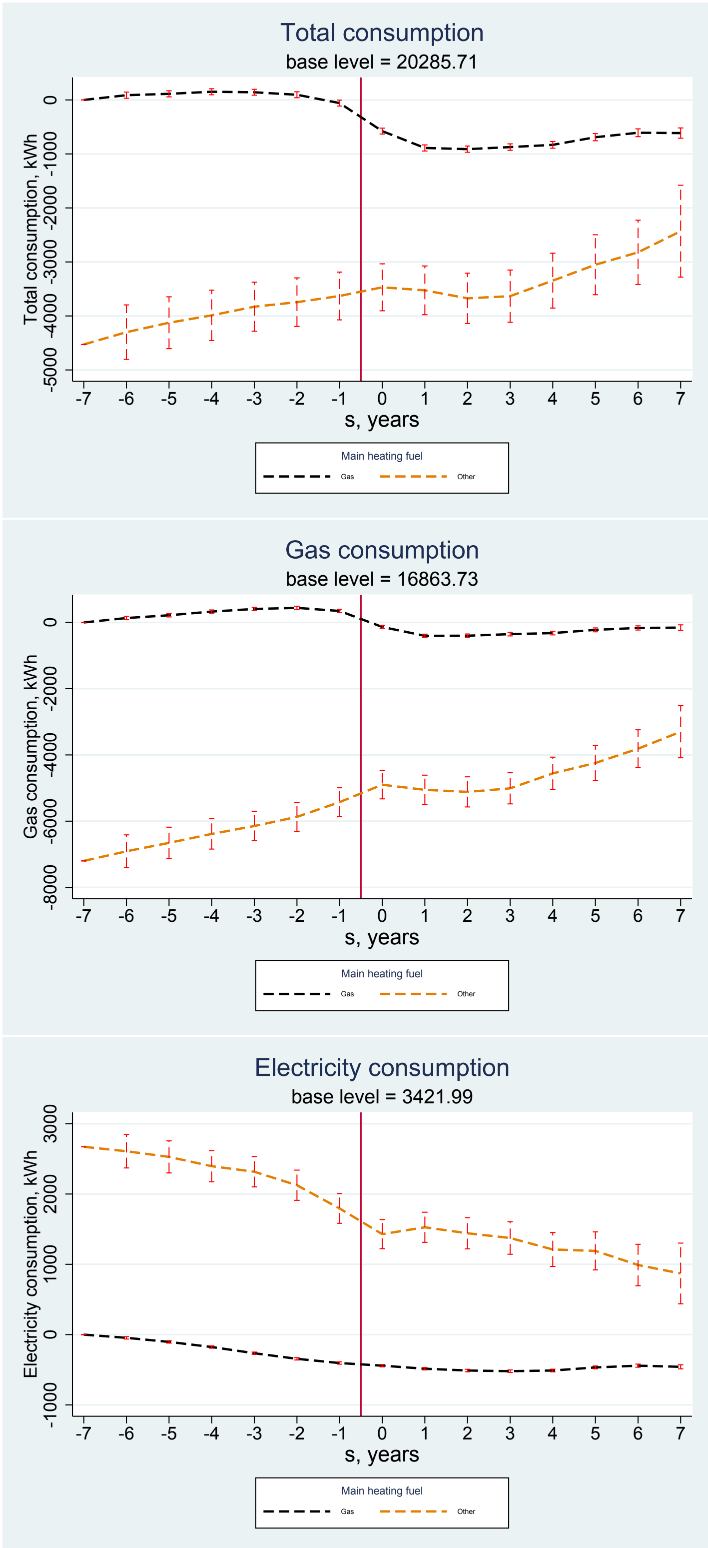

Figure 33: Main Heating Fuel groups (Loft insulation adoption)

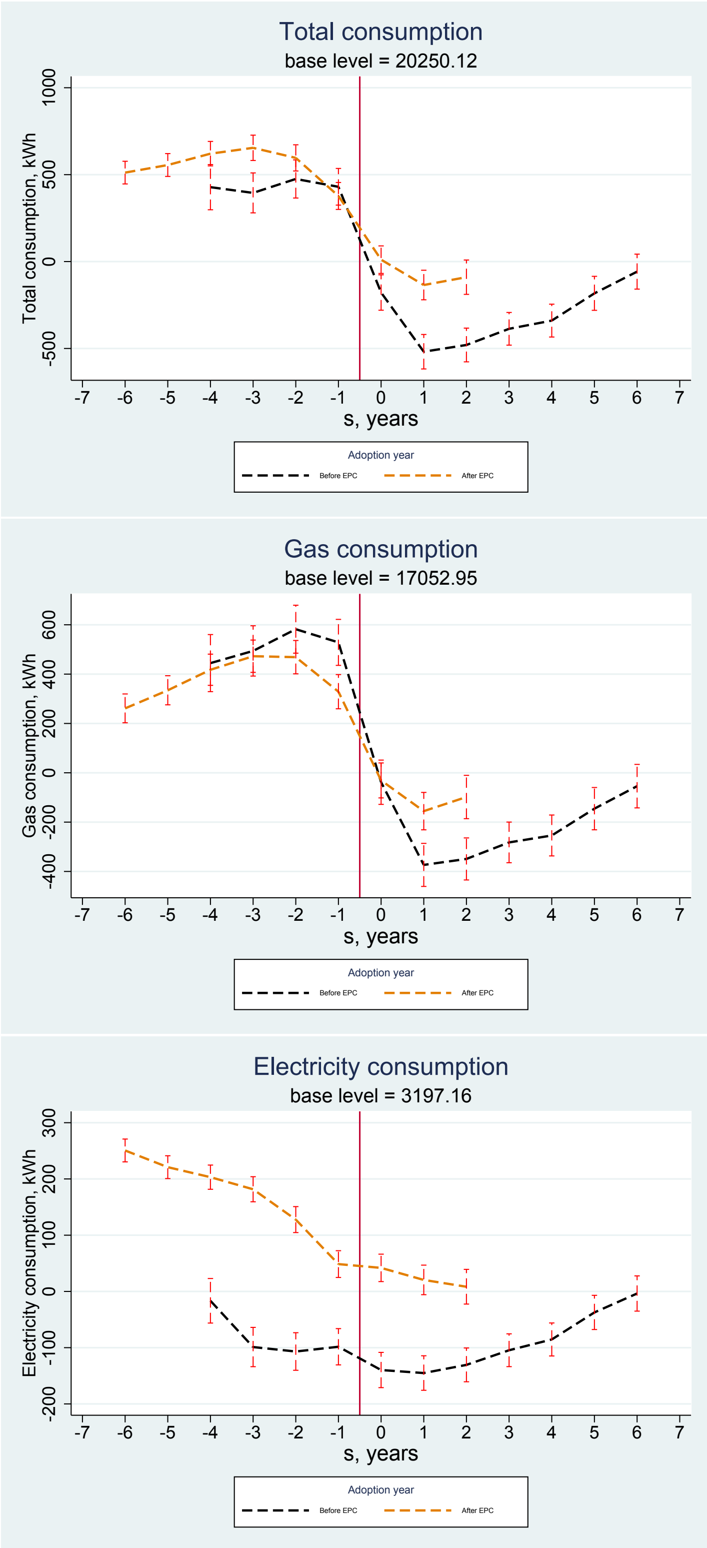

Figure 34: Adoption groups: Before EPC vs EPC period (Loft insulation adoption)

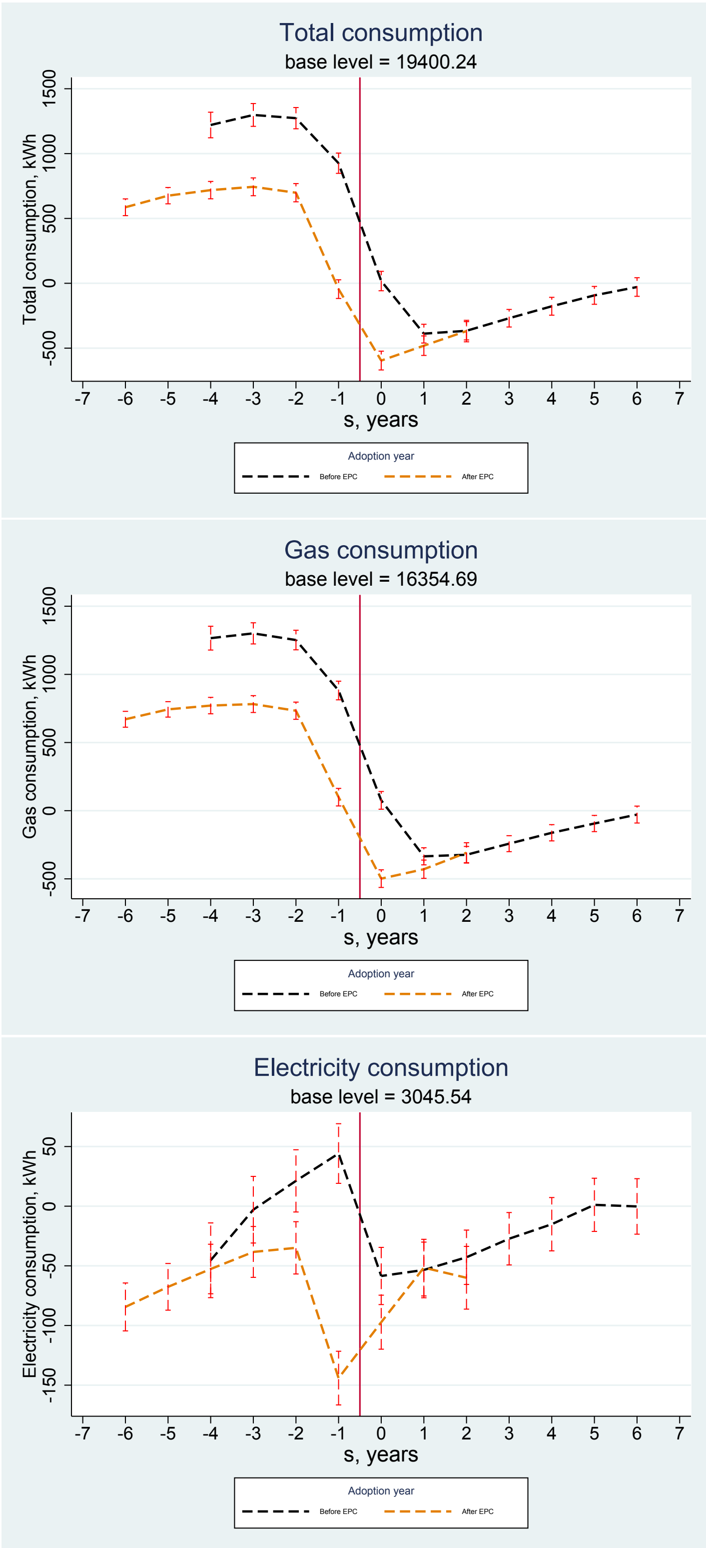

Figure 35: Adoption groups: Before EPC vs EPC period (Boiler adoption)

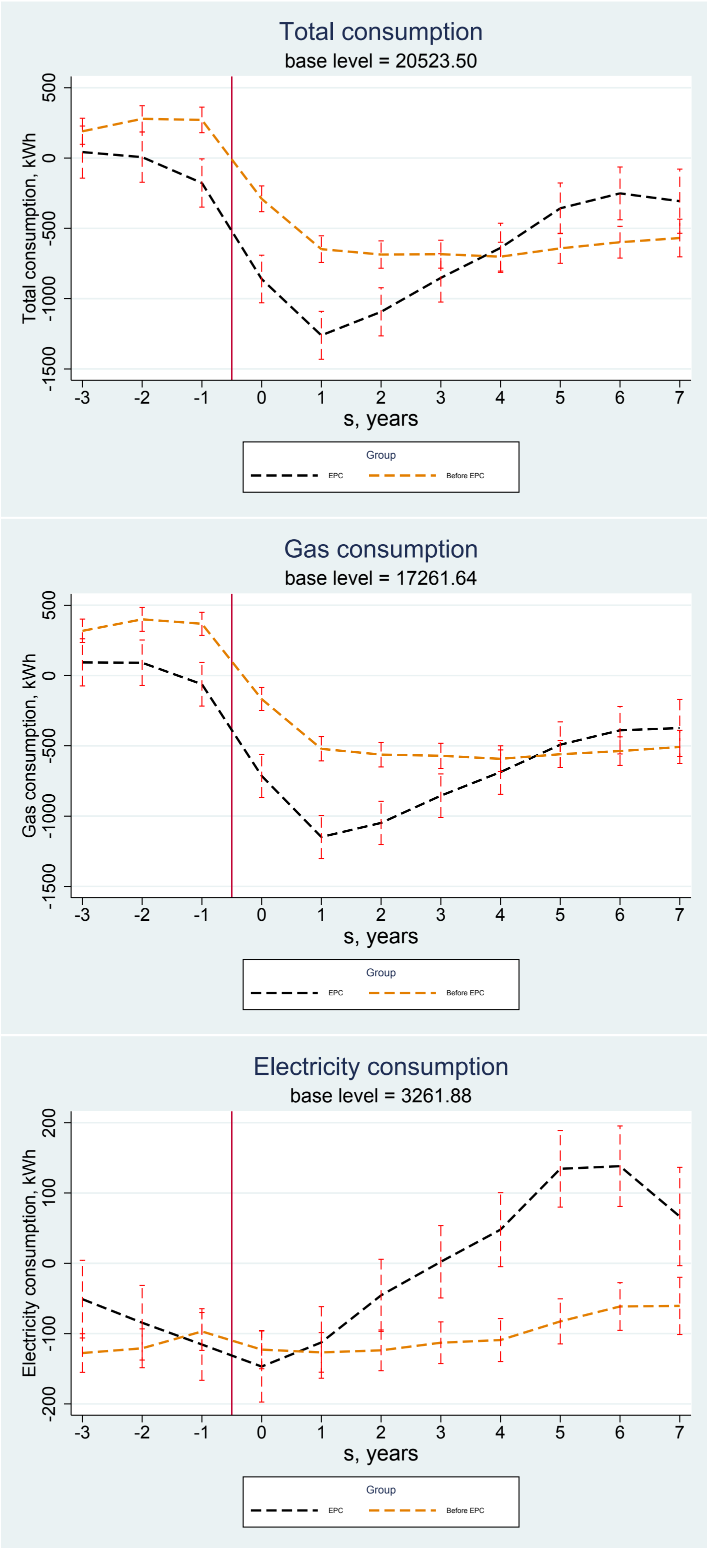

Figure 36: Early adopters (2005-2009): EPC vs Before EPC (Loft insulation adoption)

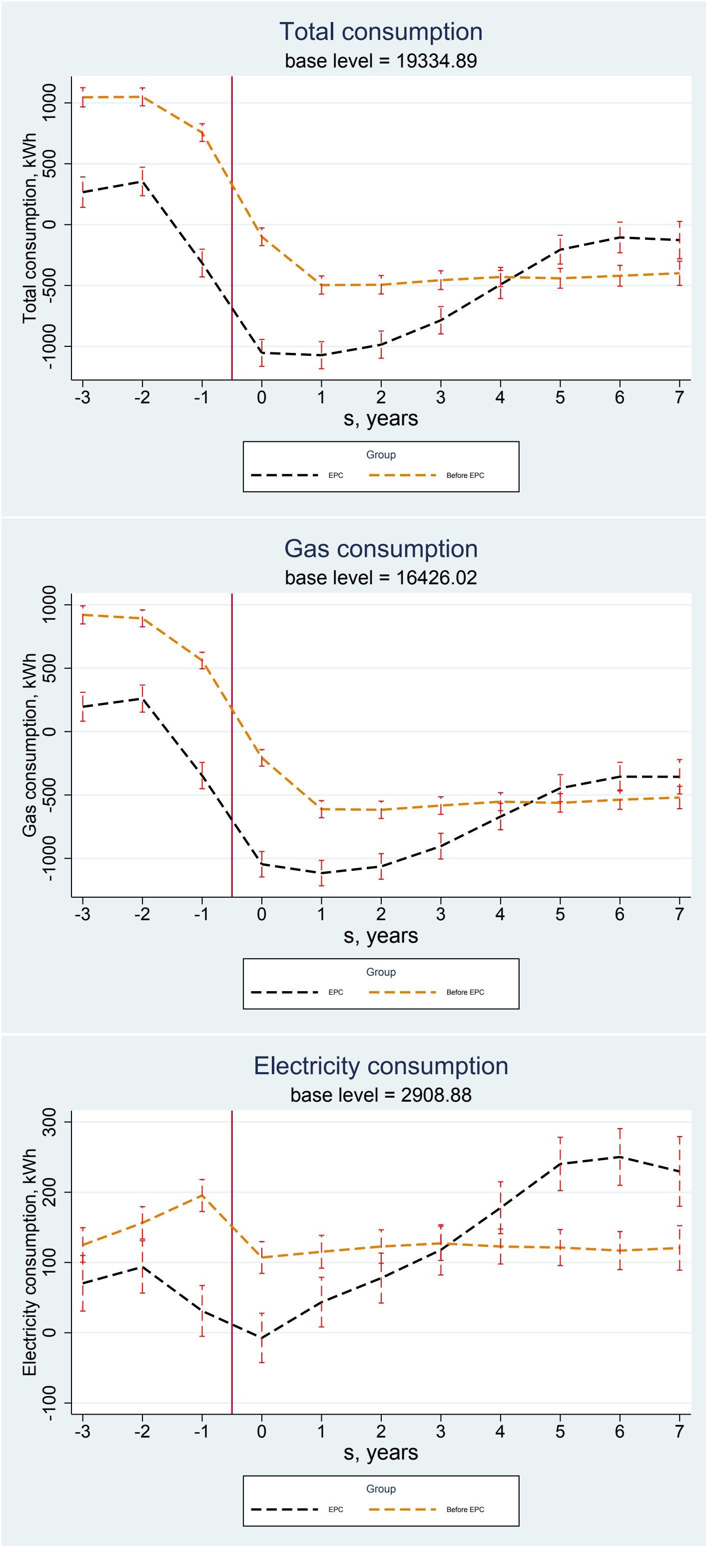

Figure 37: Early adopters (2005-2009): EPC vs Before EPC (Boiler adoption)

A.5 Appendix 5

	Pre-adoption consumption		
Cavity wall insulation year	Total	Gas	Electricity
2006	1577***	1565***	12.40
	(41.91)	(37.59)	(12.87)
2007	1832***	1803***	28.78***
	(36.97)	(33.22)	(11.00)
2008	1687***	1703***	-15.87*
	(28.14)	(25.22)	(8.40)
2009	1377***	1371***	6.469
	(25.84)	(22.92)	(8.01)
2010	1174***	1126***	47.54***
	(26.88)	(23.72)	(8.40)
2011	1386***	1329***	57.56***
	(26.21)	(22.94)	(8.39)
2012	1302***	1161***	141.6***
	(28.48)	(24.86)	(9.14)
Constant	20321***	16959***	3363***
	(58.99)	(52.48)	(17.86)
Sample size		2695520	
R^2	0.374	0.372	0.125
Property characteristics	X	X	X
Year FE	X	X	X
Region FE	X	X	X

Table 11: Pre-adoption consumption by adoption year (Cavity wall insulation)

Notes: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. Outcomes variables are total energy consumption, gas consumption and electricity consumption, measured in kWh. The table presents in each column the coefficient estimates on the before adoption calendar year of adoption specific effect in a linear regression model where the independent variables are calendar year of adoption, before adoption indicator, control variables including property characteristics, year fixed effects and region fixed effects. Robust standard errors are presented in parentheses.

Pre-adoption consumption			
Loft insulation year	Total	Gas	Electricity
2006	737.4***	800.4***	62.97***
	(40.48)	(36.78)	(12.11)
2007	1048***	1061***	-13.30
	(34.74)	(31.56)	(10.15)
2008	956.3***	999.4***	-43.04***
	(24.43)	(22.07)	(7.10)
2009	592.7***	640.1***	-47.42***
	(23.55)	(21.11)	(7.02)
2010	636.3***	616.1***	20.24***
	(23.30)	(20.74)	(7.14)
2011	646.6***	564.1***	82.53***
	(21.98)	(19.46)	(6.80)
2012	674.7***	481.4***	193.3***
	(22.57)	(19.90)	(7.05)
Constant	19518***	16330***	3188***
	(48.26)	(43.08)	(14.47)
Sample size		3908756	
R^2	0.337	0.335	0.111
Property characteristics	X	X	X
Year FE	X	X	X
Region FE	X	X	X

Table 12: Pre-adoption consumption by adoption year (Loft insulation)

Notes: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. Outcomes variables are total energy consumption, gas consumption and electricity consumption, measured in kWh. The table presents in each column the coefficient estimates on the before adoption calendar year of adoption specific effect in a linear regression model where the independent variables are calendar year of adoption, before adoption indicator, control variables including property characteristics, year fixed effects and region fixed effects. Robust standard errors are presented in parentheses.

Pre-adoption consumption			
Boiler replacement	Total	Gas	Electricity
2006	893.6***	732.1***	161.5***
	(31.47)	(28.32)	(10.26)
2007	1097***	1008***	88.09***
	(22.35)	(20.23)	(6.89)
2008	1168***	1120***	47.82***
	(21.26)	(19.24)	(6.47)
2009	1090***	1080***	10.03**
	(15.31)	(13.82)	(4.66)
2010	830.0***	843.8***	-13.80***
	(13.01)	(11.67)	(4.00)
2011	744.9***	762.6***	-17.73***
	(11.65)	(10.38)	(3.61)
2012	749.8***	758.3***	-8.55***
	(10.44)	(9.27)	(3.23)
Constant	18929***	15982***	2947***
	(38.52)	(34.33)	(11.81)
Sample size		5415255	
R^2	0.379	0.368	0.135
Property characteristics	X	X	X
Year FE	X	X	X
Region FE	X	X	X

Table 13: Pre-adoption consumption by adoption year (Boiler)

Notes: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. Outcomes variables are total energy consumption, gas consumption and electricity consumption, measured in kWh. The table presents in each column the coefficient estimates on the before adoption calendar year of adoption specific effect in a linear regression model where the independent variables are calendar year of adoption, before adoption indicator, control variables including property characteristics, year fixed effects and region fixed effects. Robust standard errors are presented in parentheses.

Consumption drop on adoption

	At adoption year			$s=-2$ and $s=+1$		
Cavity wall insulation year	Total	Gas	Electricity	Total	Gas	Electricity
2006	1359***	1292***	67.49***			
	(26.63)	(24.14)	(9.91)			
2007	1288***	1201***	86.88***			
	(31.38)	(28.85)	(10.67)			
2008	1086***	1001***	85.23***	2362***	2290***	71.22***
	(25.81)	(23.65)	(8.78)	(46.55)	(42.34)	(15.23)
2009	949.1***	947.9***	1.236	896.4***	848.4***	47.97***
	(26.20)	(23.61)	(9.30)	(39.18)	(35.59)	(12.53)
2010	652.2***	699.1***	-46.88***	470.0***	504.6***	-34.61***
	(29.54)	(26.24)	(10.86)	(39.68)	(35.77)	(13.10)
2011	946.9***	988.7***	-41.85***	565.8***	537.6***	28.25**
	(27.36)	(24.20)	(9.88)	(44.06)	(39.44)	(14.28)
2012	1146***	1136***	9.539			
	(22.59)	(19.88)	(8.28)			
Constant	877.2***	797.8***	79.41***	2618***	2386***	231.4***
	(41.88)	(37.48)	(6.55)	(84.80)	(77.03)	(27.28)
Sample size		2358580			1,089,285	
R^2	0.020	0.024	0.002	0.036	0.041	0.008
Property characteristics	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Region FE	X	X	X	X	X	X

Table 14: Impact of adoption year on consumption drop (Cavity wall insulation)

Notes: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. Outcomes variables are energy consumption drops in total energy consumption, gas consumption and electricity consumption, measured in kWh. The table presents in each column the coefficient estimates on the calendar year of adoption specific effect at the time of adoption in a linear regression model where the independent variables are calendar year of adoption, control variables including property characteristics, year fixed effects and region fixed effects. Robust standard errors are presented in parentheses.

	Consumption drop on adoption					
	At adoption year			$s=-2$ and $s=+1$		
Loft insulation year	Total	Gas	Electricity	Total	Gas	Electricity
2006	752.1***	697.1***	54.99***			
	(26.46)	(24.15)	(9.56)			
2007	729.3***	650.0***	79.33***			
	(30.33)	(27.97)	(10.18)			
2008	591.0***	530.4***	60.67***	1095***	1047***	48.46***
	(22.55)	(20.68)	(7.67)	(40.40)	(37.16)	(12.95)
2009	404.8***	389.7***	15.07*	558.1***	581.8***	-23.59**
	(24.36)	(22.06)	(8.41)	(30.54)	(27.86)	(9.60)
2010	196.0***	254.5***	-58.53***	197.8***	250.7***	-52.93***
	(25.68)	(22.81)	(9.25)	(32.92)	(29.90)	(10.49)
2011	275.6***	328.4***	-52.78***	415.3***	362.5***	52.81***
	(22.96)	(20.42)	(8.07)	(34.78)	(31.29)	(10.92)
2012	507.1***	496.5***	10.59*			
	(17.73)	(15.66)	(6.37)			
Constant	873.4***	794.0***	79.38***	2551***	2349***	201.5***
	(33.65)	(30.25)	(12.32)	(68.00)	(62.17)	(22.04)
Sample size		3420161			1480071	
R^2	0.013	0.015	0.002	0.023	0.026	0.009
Property characteristics	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Region FE	X	X	X	X	X	X

Table 15: Impact of adoption year on consumption drop (Loft insulation)

Notes: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. Outcomes variables are energy consumption drops in total energy consumption, gas consumption and electricity consumption, measured in kWh. The table presents in each column the coefficient estimates on the calendar year of adoption specific effect at the time of adoption in a linear regression model where the independent variables are calendar year of adoption, control variables including property characteristics, year fixed effects and region fixed effects. Robust standard errors are presented in parentheses.

Consumption drop on adoption

	At adoption year			$s = -2$ and $s = +1$		
Boiler year	Total	Gas	Electricity	Total	Gas	Electricity
2006	1061***	867.6***	193.8***			
	(22.53)	(20.34)	(9.13)			
2007	819.7***	746.4***	73.31***			
	(22.04)	(20.21)	(8.12)			
2008	741.5***	673.0***	68.53***	1911***	1756***	154.5***
	(25.59)	(23.31)	(9.54)	(30.61)	(28.20)	(10.52)
2009	632.5***	576.6***	55.93***	706.4***	694.8***	11.59
	(21.39)	(19.37)	(7.91)	(35.50)	(32.54)	(11.90)
2010	461.9***	480.2***	-18.27**	390.7***	398.0***	-7.247
	(21.07)	(18.79)	(7.97)	(30.12)	(27.51)	(10.06)
2011	371.5***	431.3***	-59.80***	571.0***	550.1***	20.83**
	(21.44)	(19.02)	(7.89)	(29.73)	(26.95)	(9.90)
2012	653.7***	701.6***	-47.94***			
	(19.94)	(17.54)	(7.44)			
Constant	779.1***	746.6***	32.44***	1935***	1891***	44.23**
	(28.42)	(25.52)	(10.49)	(55.02)	(50.05)	(18.19)
Sample size		4738347			2352625	
R^2	0.013	0.016	0.002	0.025	0.029	0.010
Property characteristics	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Region FE	X	X	X	X	X	X

Table 16: Impact of adoption year on consumption drop (Boiler)

Notes: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. Outcomes variables are energy consumption drops in total energy consumption, gas consumption and electricity consumption, measured in kWh. The table presents in each column the coefficient estimates on the calendar year of adoption specific effect at the time of adoption in a linear regression model where the independent variables are calendar year of adoption, control variables including property characteristics, year fixed effects and region fixed effects. Robust standard errors are presented in parentheses.

Drop on adoption year **Drop between $s = -2$ and $s = +1$**

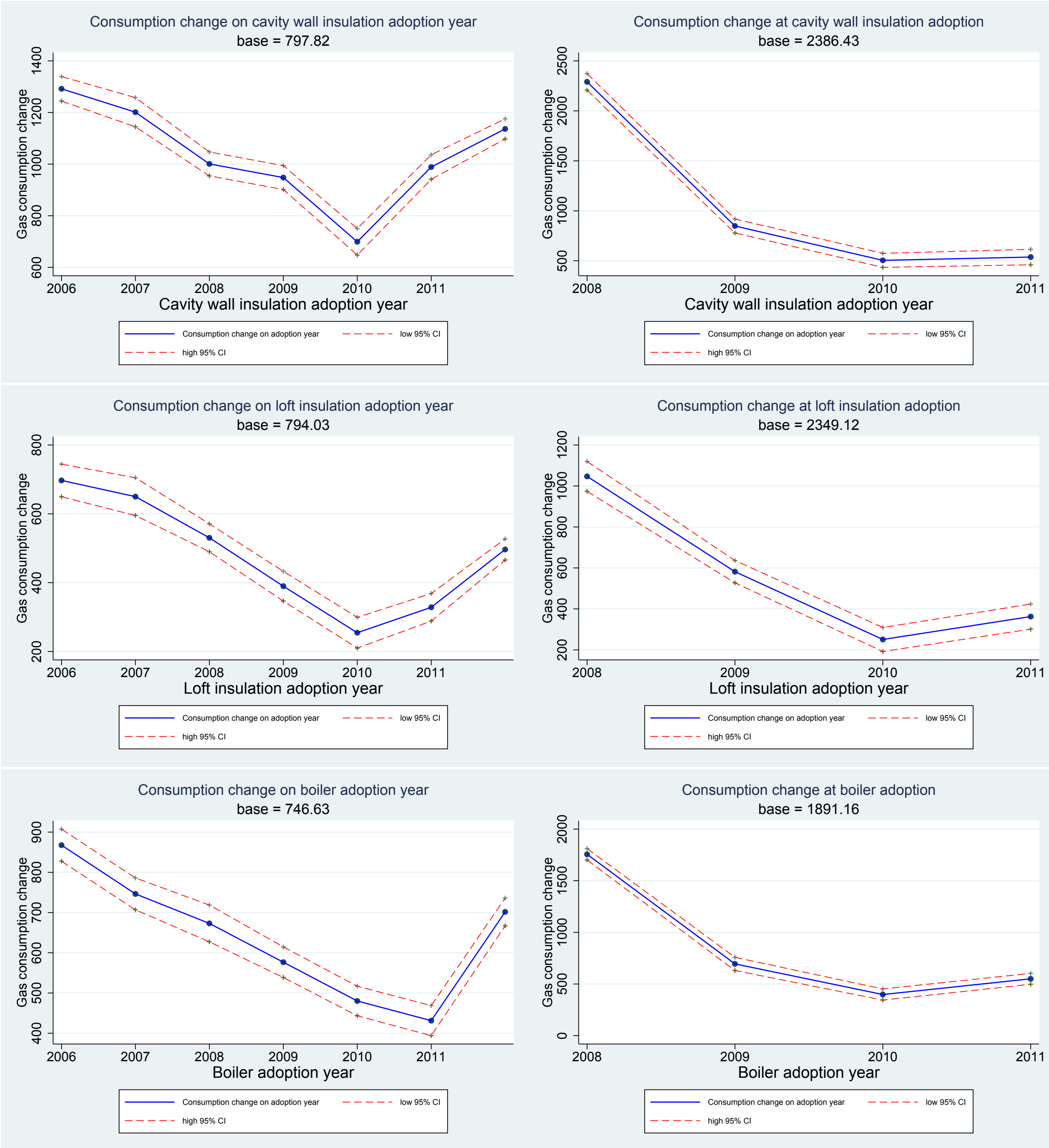

Figure 38: Gas consumption change upon adoption

Note: The graphs show the coefficient estimates and 95 % confidence intervals for the year of adoption specific effect obtained by regressing changes in energy consumption upon adoption on the interaction of a year of adoption indicator and the time of adoption indicator. The regression model includes year fixed effects, region fixed effects and property characteristics.

Drop on adoption year **Drop between $s = -2$ and $s = +1$**

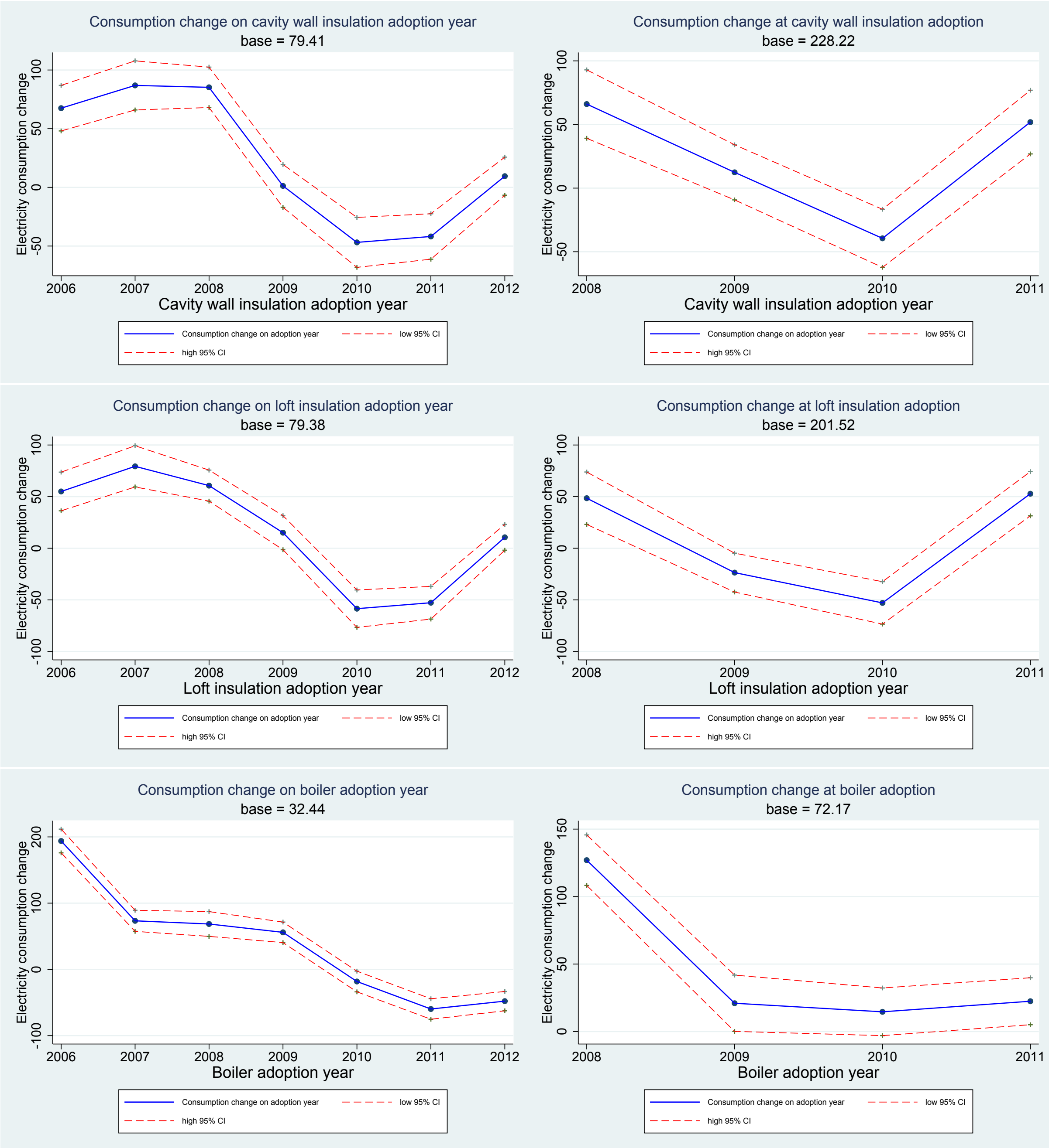

Figure 39: Electricity consumption change upon adoption

Note: The graphs show the coefficient estimates and 95 % confidence intervals for the year of adoption specific effect obtained by regressing changes in energy consumption upon adoption on the interaction of a year of adoption indicator and the time of adoption indicator. The regression model includes year fixed effects, region fixed effects and property characteristics.

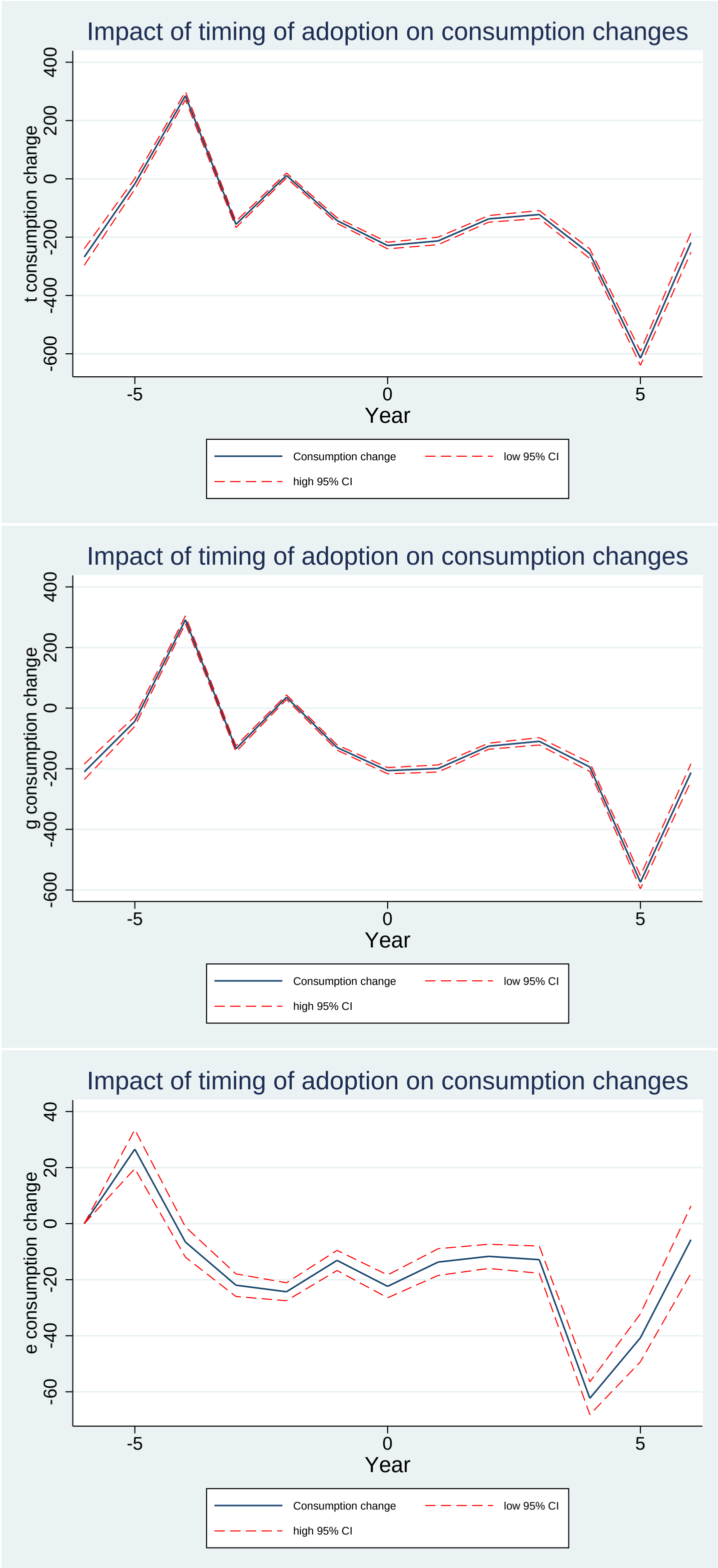

Figure 40: Impact of timing of loft insulation adoption on energy consumption change

Note: The graphs present the values of the coefficient estimates and 95% confidence intervals for calendar year in a linear regression model. The coefficient corresponding to year s is the result of a regression considering all observations for which the year relative to event time is s. In each of the regressions, the outcome variable is the consumption change in first differences and the regressors include property characteristics control variables, year dummies and region fixed effects. The confidence interval is constructed based on robust standard errors.