ESSAYS ON THE ECONOMIC IMPLICATIONS OF CLIMATE CHANGE UNCERTAINTIES

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DECLARATION

I certify that the thesis I have presented for examination for the MPhil/PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

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

I declare that my thesis consists of 57,205 words.

STATEMENT OF CONJOINT WORK

I confirm that Chapter 2 was co-authored with Professor Simon Dietz at the London School of Economics and Political Science and Professor Christian Gollier at the Toulouse School of Economics, and I contributed 33% of this work.

I confirm that Chapter 5 was co-authored with Professor Simon Dietz and Dr. Alex Bowen of the Grantham Research Institute at LSE, and I contributed 75% of this work.

STATEMENT OF PRIOR PUBLICATION

A version of Chapter 2 is publicly available as “The climate beta”, *Journal of Environmental Economics and Management*, 2017.

A version of Chapter 3 is publicly available as “Estimating the economic impact of the permafrost carbon feedback”, *Climate Change Economics*, Vol. 08, No. 02, 1750008, 2017.

ABSTRACT

This thesis investigates the economic implications of climate change uncertainties. It seeks to contribute to the existing literature by exploring various aspects of how uncertainty can and should be integrated in economic assessments of climate impacts and what this entails for policy-making.

For several reasons, including analytical tractability and the difficulties of accommodating uncertainty in individual and social decision-making, the full scale of climate change uncertainties is often artificially reduced in economic assessments of climate change, e.g. through the use of best estimates, averages or mid-point scenarios. However, the impacts of future climate change on humankind are highly uncertain and require full investigation. The approach taken in this thesis has therefore been to ask new questions related to the economic implications of climate change uncertainties and to address each problem using innovative methods, which allow a more accurate characterization of the uncertainties at stake and of their potential interactions.

This thesis comprises four standalone chapters (Chapter 2 to 5). The first chapter (Chapter 2) investigates how uncertainty about the benefits of climate mitigation, about future economic growth and about the relationship between these uncertainties affects the rate at which we should discount the benefits of reducing greenhouse gas emissions today. The second chapter (Chapter 3) examines the impact of including the permafrost carbon feedback in the DICE Integrated Assessment Model on the social cost of carbon and on the optimal global mitigation policy. Whereas the first two chapters rely on the use of an Integrated Assessment Model, the final two chapters are based on econometric methods applied to weather and climate variables. The third chapter (Chapter 4) explores the impacts of droughts on regional economic growth in the United States. The last chapter (Chapter 5) examines the implications of temperature on inflation and central banks' policy interest rates.

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Table of Contents

Chapter 1: Uncertainty in climate change economics

"We need not only a new generation of models, but also a broader and wiser set of perspectives on how to use the models that we have, and that we may have, to examine, discuss and propose policies."

– Pr. Nicholas Stern (Stern, 2013)

"Seek simplicity but distrust it."

– Alfred North Whitehead et al. (Whitehead, Griffin, & Sherburne, 1929)

1. Introduction

The emergence of the field of climate change economics can be linked to the fact that, as soon as the scientific community reached a consensus on the anthropogenic origin of climate change, economists have wanted to know two things about climate change: 1) how big will the impacts be? 2) What is their value and how much should we be willing to pay to avoid them? Thanks to the complexity of the task, this research field has flourished: indeed, any attempt at providing a well-informed answer to this question very quickly brings up the following hard fact: that the nature and the scale of the uncertainties pervading every aspect of climate change forestall the possibility of a clear and simple answer.

Just like pulling a thread, delving into the uncertainty about the future impacts of climate change only leads to the unravelling of more uncertainties: how then can these questions be addressed? The learning journey that constitutes my PhD has included the following stages: first, getting a clear understanding of the nature, magnitude and scope of climate change uncertainties, distinguishing between the uncertainty about the drivers of climate change and the uncertainty about the impacts, and between uncertainties pertaining to the climate system, and those affecting future socioeconomic factors. Second, getting to grips with the tools and methods that economists have designed to estimate the future damage from climate change and how these incorporate and account for these uncertainties. Finally, discerning how these assessments of the future economic impacts of climate change can and should be integrated into decision-making processes and translated into policy recommendations.

This learning process led me to the overarching question of this PhD: “What are the economic implications of climate change uncertainties?” But given the immensity of the task, the four papers that comprise this PhD are merely small pieces of a big puzzle. The approach I have taken in this thesis has been to find original research questions related to the implications of climate change uncertainties for assessments of the future impacts of climate change, to use innovative ways to address each problem, and to discuss their implications for policy-making.

I have also strived to ensure that these papers reflect the findings of my four-year journey in the deeper recesses of climate change uncertainties. The first one is that the exploration of the implications of climate change uncertainties cannot be done without fully engaging with the multidisciplinarity of the topic. For that reason, I tried to make sure that each of these four papers would put in practice a multidisciplinary approach, which is why I made incursions into the fields of climate models, weather models, biophysics, geology, statistics, and micro- and macro-economics. Rather than a dispersion, I see it as a reflection of the multifacetedness of the issue.

The second one is that, more than the impact of specific uncertainties, what matters ultimately seems to be the impact of combinations of uncertainties. In each paper I have tried to consider multiple uncertainties together and to understand the extent to which the interactions between multiple uncertainties drive outcomes. For instance, Chapter 2 explores the mechanisms through which the interplay of economic and climatic uncertainties drives our results on the “climate beta”.

The third one has been that we need not only to improve the tools that already exist to represent and assess these uncertainties, but also to consider them with fresh eyes and new perspectives – this has been formulated better by Stern (Stern, 2013). Moreover, I have tried to characterize and represent climate uncertainties in ways which make them more tractable, without being unduly restrictive – this has been one of the major concerns for Chapter 3, in which I tried to add a highly uncertain feedback to an existing Integrated Assessment Model. Also, I am well aware of the fact that, given our current level of knowledge, improvements in our understanding of climate processes are likely to increase the range of uncertainties rather than reduce it.

This thesis is structured as follows. This chapter provides an overview of the overall topic of this PhD, locates my research within the broader field of climate change economics and outlines the relationship between the different research questions I have chosen to address. It starts with an outline of the different types of uncertainties pertaining to climate change, distinguishing between uncertainties on the drivers and on the impacts of climate change, and between physical and socio-economic uncertainties. Then, it presents the methods that have been used to derive economic assessments of climate change impacts and the role of Integrated Assessment Models as tools for policy analysis. The final section of this chapter briefly traces the intellectual journey that has led to my four research questions. The remainder of the thesis comprises four essays and a brief concluding chapter which summarizes my findings and provides recommendations for researchers and policymakers.

2. A survey of uncertainties about the drivers of climate change

i. *Uncertainties pertaining to socioeconomic drivers of climate change*

The wide uncertainty about the level and timing of future anthropogenic greenhouse gas (GHG) emissions pertains to the fact that these are the product of complex dynamic systems and require projections of demographic development, economic activity, lifestyle, energy use, land use patterns, technology and climate policy (IPCC, 2013; Nakicenovic et al., 2000).

Given the considerable range of factors that influence future emissions paths, a schematic approach based on the Kaya identity (Field & Raupach, 2004) is often used (Nakicenovic et al., 2000): indeed, in this equation, the global carbon dioxide (CO_2) emissions flux from fossil fuel combustion is decomposed into four driving forces:

Equation 1.1

$$F = P * \left(\frac{G}{P}\right) * \left(\frac{E}{G}\right) * \left(\frac{F}{E}\right)$$

Where:

- F is the global CO_2 emissions flux from fossil fuel combustion;
- P is global population;
- G is world gross domestic product (GDP);
- E is global primary energy consumption.

Hence CO_2e emissions can be expressed as the product of global population, world per-capita GDP, world energy intensity and the carbon intensity of energy. Thus, the uncertainty about the level of future GHG emissions can be decomposed into the uncertainty about each of these four components.

The uncertainty about world population, which is the first component of the Kaya identity, is non-negligible: according to the United Nations, the upward trend in population size is expected to continue, and the 95% confidence interval of the world's population by 2100 currently stands at 9.6 to 13.2 billion (United Nations, 2017). The uncertainty about future population growth at the global level stems from the uncertainty about the future levels of fertility and mortality.

The uncertainty about the second component of the Kaya identity, i.e. the world's GDP per capita, refers to projections of future economic growth. There are four main types of production functions in the theoretical and empirical literature: the Cobb-Douglas and the Constant Elasticity of Substitution production functions, production functions with variable elasticity of substitution and Leontief production functions. Estimates of future economic growth often rely on the use of a Cobb-Douglas production function with constant elasticity of output to factor inputs, featuring physical capital, human capital and labour as production factors, and technological progress. The uncertainty about the growth of the world's economy over the coming decades/centuries hinges on the uncertainty about the future growth of total factor productivity (TFP): indeed, two main scenarios can be found in the literature (Cette, Lecat, & Ly-Marin, 2017): the first one is referred to as "secular stagnation" (Eichengreen, 2015) and refers to the possibility that most of the economy has already benefited from the Internet and web revolution (Gordon, 2015). The second one assumes that the digital revolution will lead to a third technology shock, which will provide similar TFP gains to those that were provided by electricity during the second industrial revolution. According to Cette et al. (2017), the secular stagnation scenario would mean that the yearly rate of TFP growth in the United States over the period 2015-2100 would be around 0.6%, whereas in the technology shock scenario, TFP growth could reach 1.4% per year. These scenarios are useful in that they provide us with an order of magnitude on plausible paths of future TFP growth but should not hide the fact that the long-run average of TFP growth belongs to the realm of deep uncertainties.

The uncertainty about world energy intensity, which is the third component of the Kaya identity, refers to the future levels of energy consumption per dollar of GDP. The scale of the decoupling between energy consumption and economic growth is likely to be driven by two factors. The first one concerns structural changes such as the growing share of the service sector, the replacement of energy-intensive by energy-extensive industries and the dematerialization of the economy. The second one relates to the level of energy-saving technical progress that is achieved. The uncertainty about these factors is further amplified by the fact that they will be highly dependent on regulatory frameworks, research and development policies and societal changes.

Finally, the uncertainty about the carbon intensity of energy, which is the fourth component of the Kaya identity, will depend on the fuel mix of the world economy, which is likely to be driven by two major factors. The first one is technological progress, which could make renewable energy cost-competitive with fossil fuels. This could have considerable implications for CO_2 emissions from the power and transportation sectors. The second important one relates to the energy and climate policies which will be put in place over the coming decades. For instance, mitigation policies range from a business-as-usual scenario, which assumes that no major changes in policies will take place, to more aggressive mitigation scenarios, such as those consistent with the 1.5°C target, and which imply achieving net negative CO_2 emissions after 2050 (Rogelj et al., 2015).

The uncertainty about the socioeconomic drivers of climate change has been condensed into four scenarios of human activity called the Representative Concentration Pathways (RCPs) (R. H. Moss et al., 2010), which describe four different 21st century pathways of GHG emissions and atmospheric concentrations, air pollutant emissions, land use changes and climate policy. They include one stringent mitigation scenario (RCP2.6), two stabilization scenarios (RCP4.5 and RCP6.0) and one scenario with very high greenhouse gas emissions (RCP8.5). The uncertainty about the level of future GHG emissions appears clearly in the very wide range of cumulative CO_2 emissions for the 2012 to 2100 period in each of the four RCP scenarios: these range from 140 to 410 GtC for RCP2.6, 595 to 1,005 GtC to RCP4.5, 840 to 1,250 GtC for RCP6.0 and 1,415 to 1,910 GtC for RCP8.5 (IPCC, 2013).

ii. Uncertainties pertaining to the climate system

We consider in this section the uncertainty about the physical processes that will drive the change in the Earth's climate from anthropogenic GHG emissions. As a matter of fact, we know very little about the complex components of the Earth's climate system and their interactions.

Since Arrhenius (1896), we have known the basic physics underlying the greenhouse effect, through which greenhouse gases like carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (NO_2) trap solar radiation into the atmosphere, thus making the Earth warmer. What we do not know are the complex processes of the Earth's climate, which will determine the timing and the scale of the response of the planet to anthropogenic emissions, which is why our projections of future climate change are so imprecise. The uncertainty about the physical drivers of climate change can be segmented into four components: the carbon cycle, the equilibrium climate sensitivity, feedbacks, and potential nonlinearities including tipping points and threshold effects.

The first major uncertainty regarding the physical drivers of climate change is the carbon cycle, i.e. what happens to carbon once it is emitted into the atmosphere. Indeed, the greenhouse effect is based on the concentration of greenhouse gases into the atmosphere, and since these GHGs come from emissions, we need to know how these GHG emissions accumulate in the atmosphere. Oceans play a vital role in the carbon cycle through their uptake of CO_2 from the atmosphere and understanding these ocean processes is thus crucial. According to the IPCC, the oceans have de facto absorbed about 30% of the emitted anthropogenic CO_2, but there are huge uncertainties about the ocean's absorptive capacity and whether we should expect it to decrease as oceans undergo acidification and warming (IPCC, 2013). Similarly, carbon residence time is recognized as an important source of model uncertainty (Friend et al., 2014; Yizhao et al., 2015).

The second major uncertainty lies in the relationship between the stock of GHGs in the atmosphere and the expected change in global mean temperature, which has been embodied in the concept of equilibrium climate sensitivity (ECS), defined as the change in global mean surface temperature at equilibrium that is caused by a doubling of the atmospheric CO_2 concentration. The ECS is the result of a combination of various positive feedbacks, including the water vapour/lapse rate and the albedo and cloud feedbacks and is generally estimated from Atmosphere-Ocean General Circulation Models. The increasing complexity of our representations of these feedbacks as well as the use of enlarged model ensembles explain why the equilibrium climate sensitivity is one of the components of the climate system for which uncertainty widens as knowledge increases: indeed, whereas the IPCC's Fourth Assessment Report mentioned that the ECS was likely in the range of 2.0°C to 4.5°C with a best estimate of 3°C (IPCC, 2007), the IPCC's Fifth Assessment Report stated that the ECS was likely in the range 1.5°C to 4.5°C (IPCC, 2013). Given the reliance of humans and ecosystems on stable temperatures, the discussion on whether or not there is a non-negligible probability that the ECS is around 4.5°C or higher has long expanded outside the field of climate science and has spurred numerous discussions on the implications of "fat tails"[1] for decision-making (Calel, Stainforth, & Dietz, 2015; Pindyck, 2013; Weitzman, 2011). These "fat tails" are a direct consequence of the high uncertainty about the feedbacks underlying the ECS and explain why this parameter may well be one of those "known unknowables".

In many respects, feedback processes are a fundamental component of the uncertainty about future climate change. First, as we have seen above, short-scale feedback processes such as the cloud, albedo and aerosol feedbacks are crucial components of the ECS, i.e., the response of the climate system to an increase in atmospheric CO_2 concentration. Moreover, climate change will induce changes in the water, carbon and other biogeochemical cycles, which might trigger,

[1] "Fat tails" have been used to refer to the difference in upper tail behaviour between the fat-tailed Pareto distribution and the thin-tailed Normal distribution.

reinforce, or overturn feedbacks. These feedbacks can be positive (when they accelerate climate change), or negative (when they dampen climate change). One example of a positive feedback triggered by climate change relates to ocean warming; not only have oceans absorbed a significant share of the CO_2 emitted into the atmosphere historically, they have also absorbed part of the radiative imbalance of the climate system, and as a result, have become warmer[2]. Unfortunately, the solubility of CO_2 in seawater decreases as oceans become warmer, which means that as oceans warm, they are less able to remove CO_2 from the atmosphere. In this case, climate change triggers a new positive feedback. Other examples of positive feedbacks triggered by climate change include heat-induced releases of sequestered carbon, e.g. from permafrost or offshore methane clathrates. Another reason why feedbacks are a major cause of uncertainty pertains to the fact that positive feedbacks compound each other, meaning that the total effect of two positive feedbacks is larger than the sum of the effects of the individual feedbacks (Roe & Baker, 2007). There is also considerable uncertainty on potential negative feedbacks, such as a cooling effect from CO_2-induced increases in vegetation density (Jiang et al., 2012). Finally, it should be emphasized that, despite the advances in our understanding of the climate system, we have an idea of the biophysical processes underlying some feedback loops, but we know close to nothing as to their potential compound strength and the ways in which they might interact with each other – it is also very possible that there are other feedbacks that could be triggered by climate change that we know nothing about. This explains why the IPCC has made clear in its latest report that the Earth system sensitivity over millennial time scales would include long-term feedbacks and would therefore likely be significantly higher than the ECS (IPCC, 2013).

Feedbacks introduce nonlinearities in the response of the climate system, which can then lead to 'tipping points', i.e. switches to qualitatively different states (Lenton, 2011). For example, the continued warming of the oceans could lead to a weakening of the Atlantic Meridional Overturning Circulation (AMOC) to a point where it collapses suddenly. The possibility of a collapse of the AMOC happening by 2100 has been estimated as very unlikely by the IPCC but has not been excluded for longer time horizons (IPCC, 2013). Other examples of potential tipping points which could be triggered by human-induced climate change include the irreversible melting of the Greenland and West Antarctic ice sheets, disruptions of the West African monsoon and diebacks of the Amazon and boreal forests (Huntingford et al., 2008; IPCC, 2013).

Due to the deep uncertainty[3] that characterizes them, feedbacks and tipping points have so far received little attention in assessments of climate change impacts. We know that these processes could be triggered by climate change, but we have no idea of their potential strength or the time horizon over which they could happen – for that reason, they have been mostly (though not entirely) ignored by climate change economists. We will see further the ways in which these deep uncertainties have been treated in the economics literature, but I argue that this deep uncertainty should be fully acknowledged, brought to the fore, and made an integral part of the policy-making process. Finally, these uncertainties about the physical drivers of climate change contribute to the significant uncertainty regarding the link between temperature targets (e.g. 2°C) and the corresponding carbon budget (IPCC, 2013).

[2] According to the IPCC, ocean warming dominates the increase in energy stored in the climate system, accounting for more than 90% of the energy accumulated between 1971 and 2010 (IPCC, 2013)

[3] Deep uncertainty has been defined by Hallegatte et al. (2012) as "a situation in which analysts do not know or cannot agree on (1) models that relate key forces that shape the future, (2) probability distributions of key variables and parameters in these models, and/or (3) the value of alternative outcomes".

3. A survey of uncertainties about the impacts of climate change

The previous section concentrated on the uncertainties pertaining to the socioeconomic drivers of climate change, as well as to the features of the climate system which will determine Earth's response to the increase in forcing from human activities. This section will concentrate instead on the impacts on ecosystems and human societies.

iii. Uncertainties pertaining to the physical effects of climate change

The question of the future increase in global mean temperature, which has been used as the metric summarizing the state of the global climate, has dominated much of the discussion on climate change. The reasons for this are threefold: first, due to the greenhouse effect, we know that the increase in radiative forcing will lead to an increase in global mean temperature. Even if we do not know how much warming, we understand the basic physics behind it. The second reason pertains to the fact that paleoclimate analyses suggest that the changes that we are currently undergoing are unprecedented: not only is global temperature warmer now than it has been in the past 1,000 years, but the rate of warming is also unparalleled over the past 11,000 years (Marcott, Shakun, Clark, & Mix, 2013). The third reason pertains to the fact that most components of the climate system are extremely sensitive to temperature and that several regions display amplified responses to climate variability (Seddon, Macias-Fauria, Long, Benz, & Willis, 2016).

The increase in global mean temperature so far is estimated at 0.85°C for the period from 1880 to 2012 (IPCC, 2013). As we have discussed previously, the combination of uncertainties about the equilibrium climate sensitivity, the carbon cycle and the future level of anthropogenic GHG emissions explains why the uncertainty about future increases in global mean temperature is so wide: according to the latest Assessment Report from the IPCC, baseline scenarios (without additional mitigation) indicate that global mean surface temperature increases in 2100 could range from 3.7 to 4.8°C above the average for 1850-1900 for a median climate response; this range increases to 2.5-7.8°C when climate uncertainty is included (5th to 95th percentile range) (IPCC, 2013)[4].

Crucial components of the Earth system, notably the cryosphere and oceans, are highly sensitive to global mean temperature. Indeed, the warming of recent decades has already caused ice sheets to recede globally: the Greenland and Antarctic ice sheets have lost mass, glaciers have continued to shrink almost worldwide, Arctic sea ice and the Northern Hemisphere spring snow have continued to decrease in extent and permafrost temperatures have increased in most regions since the early 1980s (IPCC, 2013). These effects are expected to intensify as warming continues, but projections of their magnitude bear significant uncertainty: by the end of the 21st century, the global glacier volume, excluding glaciers on the periphery of Antarctica, is projected to decrease by 15% to 55% for RCP2.6, and by 35% to 85% for RCP8.5 (IPCC, 2013).

Both the increase in global mean surface temperature and the degradation of ice sheets around the globe will in turn have direct impacts on oceans. So far, oceans seem to have absorbed most of the increase in the energy stored in the climate system, as well as a non-negligible share

[4] Scenarios without additional efforts to constrain emissions ('baseline scenarios') lead to pathways ranging between RCP6.0 and RCP8.5 (IPCC, 2013).

of the emitted anthropogenic CO_2, which has led to ocean warming[5] and acidification[6] (IPCC, 2013). The global ocean is expected to continue to warm, which will likely trigger and amplify biophysical processes: the penetration of heat to the deep ocean is expected to affect ocean circulation; ocean thermal expansion and glacier loss will cause sea level rise; and ocean warming will affect sea ice dynamics. Under all RCP scenarios, global mean sea level is expected to rise during the 21st century at rates above those observed between 1971 and 2010, precisely because of ocean warming and increased loss of glacier and ice sheets volume (IPCC, 2013).

Finally, even though the increase in global mean temperature has been used as a metric to summarize the state of Earth's climate, it says nothing about future local and regional changes in weather. Changes in global mean temperature will have differentiated impacts on temperature, precipitation and wind patterns across the different regions of the world. According to the IPCC, it is virtually certain that most places will experience more hot and fewer cold temperature extremes as global temperatures increase, with the Arctic region expected to warm most (IPCC, 2013). Projections of future precipitation patterns are more hazy: according to current projections, some regions will experience increase and others will experience decreases, while the contrast between wet and dry regions and between wet and dry seasons will increase, although the uncertainties in precipitation projections are larger than for temperature (IPCC, 2013).

There is a general consensus that climate change will increase both the intensity and the frequency of extreme weather events (Herring, Hoerling, Kossin, Peterson, & Stott, 2015; IPCC, 2012). In many land regions, current 1-in-20 year maximum temperature events are expected to become annual or 1-in-2 year events by the end of the 21st century under high-emissions scenarios. Heatwaves are expected to occur with a higher frequency and longer duration (IPCC, 2013). Similarly, extreme precipitation events over wet tropical regions are likely to become more intense and more frequent by the end of the century (IPCC, 2013). There is no clear consensus on the influence of future climate change on tropical cyclones (IPCC, 2013). These co-occurring changes in frequency and intensity could have significant implications for humans and ecosystems: the possibility that changes in the interplay and succession of weather events could cause significant impacts has led to the definition of "compound events", which have been defined as "extreme impact [events] that depends on multiple statistically dependent variables or events" (Leonard et al., 2014); for instance, these would cover sequences of repeated droughts, periods of very low precipitation co-occurring with high temperatures, or conjoined occurrences of high precipitation events and storm surges.

We mentioned earlier that some components of the climate system could potentially exhibit threshold behaviour (e.g. the collapse of the Atlantic Meridional Overturning Circulation, or the Greenland or West Antarctic ice sheets), which would have potentially severe impacts on human and natural systems. According to the mainstream scientific literature, a 4°C or more increase in global mean temperature compared to pre-industrial times could bring catastrophic climate change, which would manifest itself through tsunamis, extreme sea level rise, desertification of the Sahel region, monsoon disruptions, dieback of the Amazon rainforest, large-scale wildfires in boreal regions and regions disappearing under water (Schellnhuber et al., 2013). There is little information or consensus among scientists on the likelihood of such events

[5] The upper 75m of the ocean warmed by 0.11°C per decade over the period 1971 to 2010 (IPCC, 2013).
[6] The pH of ocean surface water has decreased by 0.1 since the beginning of the industrial era (IPCC, 2013).

over the 21st century, but most assessments emphasize that the risk of abrupt or irreversible changes increases as the magnitude of the warming increases (IPCC, 2014).

iv. Uncertainties pertaining to the socioeconomic impacts of climate change

Climate change is expected to impact humans and societies through many channels, including agriculture/food, water, health, flooding, natural ecosystems, and even conflict and migration (IPCC, 2014). Both gradual changes and changes in the frequency and severity of extreme weather events will have an impact.

The monetary value of the projected global aggregate impacts of climate change remain highly uncertain: the IPCC estimated that these should remain moderate for a 1 or 2°C warming but are likely to accelerate with increasing temperature, due to the increased risk of regime shifts and biodiversity loss[7] accompanying warming of 3°C or more (IPCC, 2014). Unfortunately the majority of the studies of the global aggregate impacts of climate change that can be found in the literature (see Tol, 2009, 2014 for a review) only consider moderate warming, and only 7 studies estimate welfare impacts for warming of 3°C or more (IPCC, 2014). Losses seem to increase sharply with temperature but the uncertainty around these is very high: the most recent estimates project greater impacts than the previous ones and also significantly widened the uncertainty range (IPCC, 2014). We will provide in Section 4 below a more detailed account of the tools and methods that have been devised by economists to estimate these impacts.

These aggregate estimates say nothing about how climate change will impact different countries and populations. However, it is very likely that the impacts of climate change will be felt more strongly by developing countries, both in terms of human and economic impacts.

So far, the human impacts of climate change have been borne predominantly by developing countries: according to the World Health Organization, approximately 60 000 deaths occurred worldwide as a result of weather-related disasters in the 1990s, some 95% of which were in developing countries (World Health Organization, 2017). This is due to a combination of factors including greater exposure, the lack of early warning systems and the absence of available funds for emergency relief and recovery. Unfortunately the situation is likely to get worse in the future: not only will developing countries be the hardest hit by drought-induced food and freshwater shortages, but adverse health impacts, including heat stroke, malaria, dengue and diarrhoea, are also expected to be felt predominantly by low-income countries (UNFCCC, 2010).

Similarly, the economic impacts of extreme weather in the recent past have been incurred predominantly by developing countries: according to a report from the United Nations, the greatest economic losses caused by all weather-related disasters that occurred during the period 1995-2015 were incurred in low-income countries and represented around 5% of GDP (United Nations, 2016). In the round, developing countries are expected to be most vulnerable to future climate change (IPCC, 2014). There are several reasons for this. First, developing countries tend to be geographically located in tropical zones close to the equator, where the effects of climate change will be more negative (IPCC, 2014). For instance, the reduction in the availability of renewable surface water and groundwater is projected to be more acute for dry subtropical

[7] According to the Fourth Assessment Report of the IPCC, more than 2 or 3°C warming above preindustrial levels would cause extinction risks to 20 or 30% of present-day species (IPCC, 2007).

regions (IPCC, 2014). Second, developing countries are generally more reliant on climate-sensitive sectors (e.g. agriculture and fisheries) than developed countries. Finally, they often have a lower adaptive capacity due to low levels of human capital and technology, limited financial and material resources and unstable or weak institutions (IPCC, 2001a; Lemos et al., 2013). For these reasons climate change could be extremely detrimental to populations at risk in low-income countries, and is expected to prolong existing and create new poverty traps (IPCC, 2014).

But the discrepancy is not only between rich and poor countries: according to the IPCC (2014), the risks related to climate change are expected to be greater for disadvantaged people and communities in countries at all levels of development. Indeed, low-income households usually have a lower adaptive capacity, limited access to insurance and fewer possibilities to relocate to safer accommodation (IPCC, 2014).

The arguments and evidence presented above seem to support the hypothesis that the poor are likely to suffer disproportionate damage from climate change, which, in economic terms, means that the income elasticity of climate change-related damage[8] is between 0 and 1. This could have significant implications for the stringency of mitigation at the global level: Dennig et al. (2015) have shown that the optimal level of mitigation is considerably higher when future damage falls especially hard on the poor than when damage is proportional to income. This would also mean that development might be the best defence against climate change impacts (Anthoff & Tol, 2012).

4. What are the methods that have been used by economists to estimate the impacts of climate change?

We will see in this section the different approaches and methods that have been used by economists to estimate and quantify the impacts of climate change. In his review of the estimates of the welfare effects of climate change, Tol (2009) identified two main approaches: the enumerative method and the (traditional) statistical approach. We will add to these the methods that have been developed since, which include Computable General Equilibrium models, the subjective wellbeing approach and the "New Climate-Economy Literature" (Dell, Jones, & Olken, 2014). Integrated Assessment Models (IAMs), such as DICE (Nordhaus, 1992; Nordhaus & Sztorc, 2013), PAGE (Hope, 2011; Hope, Anderson, & Wenman, 1993), MERGE (Manne, Mendelsohn, & Richels, 1995) and FUND (Tol, 1997), have been used to estimate the impacts of climate change, but can also be considered as policy tools, and will be the topic of the next section.

The enumerative method

These are studies based on the following methodology: projections of the physical impacts of climate change are first obtained from either climate or impact models; these physical impacts are then given a monetary value, and finally added up (enumerated). Despite its apparent simplicity and ease of interpretation, this method suffers from several shortcomings: first, as noted by Fankhauser (2013), this method is based on a partial equilibrium approach, in which the sum of the total damage is the sum of the damage in individual sectors, and does not account for higher-order effects. Then, because it relies on precise sector- and location-specific

[8] Defined as the change in damage from the addition of a small amount of income (Anthoff & Tol, 2012)

projections and real market prices, it does not lend itself easily to extrapolation. Finally, because it relies on prices, it is not easily applicable to non-market types of impacts, such as health and biodiversity (Tol, 2009).

The traditional statistical approach

The second group of studies relies on cross-sectional variation in prices and expenditure and how that is associated with cross-sectional variation in climate. This method has been used notably to measure how climate in different places affects the value of farmland (Mendelsohn, Nordhaus, & Shaw, 1994) or per-capita rural income (Mendelsohn, Basist, Kurukulasuriya, & Dinar, 2007). Contrary to the enumerative approach, the statistical approach is based on real-world differences between climate and economic variables and thus it implicitly accounts for adaptation (Tol, 2009). However, cross-sectional studies are at high risk of omitted variable bias, which occurs when the control variables do not account for variables correlated with both the dependent variable and one or more independent variables. This potential bias is a serious challenge for cross-sectional studies as it significantly undermines the ability to make causal inferences, and cannot be easily fixed, as adding control variables can lead to an "over-controlling" problem (Dell et al., 2014).

Computable General Equilibrium models

A third approach to estimating the economic impacts of climate change has made use of Computable General Equilibrium (CGE) models. There were two main reasons that motivated the application of this type of model to climate impacts: the first one is that CGE modelling has enabled economists to address one of the main shortcomings of the enumerative approach, which is the lack of higher-order effects. A few studies have made use of static CGE models to analyse the impacts of climate change on multiple markets (Bosello, Roson, & Tol, 2007; Darwin & Tol, 2001) and most have found that the second-order effects increased the impacts of climate change on welfare (Bowen, Cochrane, & Fankhauser, 2012). In any case, the second-order effects are almost always significant. The second reason, which prompted the use of dynamic CGE models, was the realization of the reverse causation of climate change, i.e. the fact that climate change will be driven by the level of anthropogenic emissions but, at the same time, climate change will affect the economy and thus the level of future GHG emissions; an application of a dynamic CGE model to climate change can be found in Eboli et al. (2010). The limitations of CGE models are twofold: first, since they rely on key parameters which are often arbitrary, they have been criticized for not being sufficiently validated (IPCC, 2001b). Moreover, CGE models can only compare different states of equilibrium and therefore do not provide insight into adjustment processes (IPCC, 2001b).

The subjective wellbeing approach

A fourth approach to eliciting the monetary value of climate change has made use of the environmental valuation method based on happiness data. This approach relies on the idea that stated subjective well-being can serve as an empirical proxy for people's experienced utility, and can therefore, under the presumption of utility maximising behaviour, be used to calculate the trade-off people would be willing to make between income and environmental conditions (Welsch, 2009). The implied marginal rate of substitution between income and climate can then be used to derive the monetary value of climate (Cuñado & de Gracia, 2013; Welsch, 2009). The use of happiness data to study economic issues is relatively recent and its application to weather and climate has so far been limited (Carroll, Frijters, & Shields, 2009; Luechinger & Raschky, 2009; Rehdanz & Maddison, 2005). Some methodological issues pertaining to the use of happiness data for environmental valuation have been raised by Welsch and Kuhling (2009) but there are two other factors that limit its applicability to climate change specifically: first, the issue of the spatial and temporal matching of life satisfaction and weather data, which might become problematic in the context of climate change; and second, the substantial challenge posed by the cultural and language components of findings obtained through subjective wellbeing methods, which might significantly impede their external validity.

"The New Climate_Economy Literature" (Dell et al., 2014)

A fifth approach to the estimation of damages from climate change has focused on applying panel data methods to examine how weather variables (mainly temperature, precipitation and windstorms) influence socio-economic outcomes, including agricultural output (Auffhammer & Schlenker, 2014; Deschenes & Greenstone, 2007; Schlenker & Roberts, 2009), production (Hsiang, 2010) and productivity (Burke, Hsiang, & Miguel, 2015). Thorough reviews of this literature can be found in Dell et al. (2014) and Hsiang (2016).

Panel models are generally of the form:

Equation 1.2

$$y_{it} = \beta \boldsymbol{C}_{it} + \gamma \boldsymbol{Z}_{it} + \mu_i + \theta_{rt} + \varepsilon_{it}$$

Where:

- y_{it} is the outcome variable of interest;
- $\boldsymbol{C}_{it}$ is a vector of climate variables;
- $\boldsymbol{Z}_{it}$ is a vector of other time-varying observables;
- μ_i are fixed effects for the spatial areas;
- θ_{rt} are time fixed effects, which can enter separately by subgroups of the spatial areas to allow for different trends in subsamples of the data (Dell et al., 2014).

The advantages of using panel models are manifold: first, contrary to cross-sectional studies, which may incorporate very long-run mechanisms (e.g. the date of adoption of agriculture), panel data regression models emphasize the current impacts of weather. Most importantly, panel data models include both location- and time- fixed effects, which facilitate the identification of causal effects by presumably picking up most variation in unobserved explanatory variables. Indeed, fixed effects for the different spatial areas absorb spatial characteristics, thus preventing potential bias from omitted variables that do not change over time. Moreover, time fixed effects neutralize trends which are common to the different locations and therefore improve the credibility of the identification, as they help ensure that the observed effect is due to weather variations in the local area (Dell et al., 2014). Finally, the fact that climatic and weather variables are exogenous on all but long (i.e. centennial and longer) time-scales makes them especially suited to panel data analyses, as their exogeneity removes any concerns about reverse causation effects.

The main limitations of panel models have to do with how their result can and should be interpreted. The first limitation of panel models is that the inclusion of time fixed effects removes any global effect of weather variations. For instance, panel models such as the one described in the above equation can only provide information on the impact of local, idiosyncratic variations in weather on local outcomes. Spatial spillover effects of a weather shock in a specific region will not be captured by the regression results. One solution to this can be found by dropping the time fixed effects, but this raises the concern that results might be biased by time-varying omitted variables (Dell et al., 2014).

The second limitation of panel models is the question of their external validity in the context of climate change. One of the motivations that spurred this stream of research has been to use these findings on the effect of changes in *weather* on economic activity, to infer the effects of changes in *climate* (which can be defined as the average of weather over long time scales) on economic activity. Even supposing that we had access to reliable regional projections of future changes in weather patterns, there are serious limitations to the extrapolation of the findings from these panel models to states of the climate in which Earth's temperature will be considerably warmer: these restrictions come from the possibility of nonlinearities, potential intensification effects, the eventuality of adaptation, and general equilibrium effects (Dell et al., 2014). For these reasons, the estimates derived from these panel models cannot necessarily be applied to future climate damages: for instance, if adaptation policies are implemented on a large scale, then the effects of current weather shocks might be stronger than the future effects of climate; conversely, if the intensification of weather shocks leads to steep increases in impacts, then estimates derived from current weather shocks could be underestimating the future damages from climate change (Dell et al., 2014). Despite these shortcomings, the emergence of this literature has brought valuable insight.

5. The role of Integrated Assessment Models as policy tools

There are two factors that explain the development of Integrated Assessment Models (IAMs) as tools for conducting the assessment of different policy options in the context of climate change: first, the release of the First Assessment Report by the IPCC in 1990, the launch of the United Nations Framework Convention on Climate Change and the achievement of a consensus on the anthropogenic origin of climate change; second, the realisation that the methods that have been used to quantify the future impacts of climate change do not provide guidance for action. This has led to the emergence of IAMs, which are based on the coupling of sub-models of the climate and economic systems and which have been used to serve two purposes: first, to derive estimates of the social cost of carbon (SCC), defined as the net present value of the future climate damages caused by the emission of one additional ton of CO_2 and which should be the basis for a tax on carbon emissions; second, to balance the future costs and benefits of climate change mitigation to determine the optimal mitigation policy. Numerous IAMs have been developed over the past two decades; these include DICE (Nordhaus, 1992; Nordhaus & Sztorc, 2013), PAGE (Hope, 2011; Hope et al., 1993), MERGE (Manne et al., 1995), FUND (Tol, 1997), ENTICE-BR (Popp, 2006) and MIND (Edenhofer, Bauer, & Kriegler, 2005). Since two of the chapters in this thesis are based on the DICE-2013R model (Nordhaus & Sztorc, 2013), the following section will focus on this specific IAM.

i. Two crucial features of IAMs: the damage function and the discount rate

Because so much information on the Earth's climate, the global economy and the links between them is condensed in an extremely simple model, IAMs are fraught with structural and parameter uncertainty. This affects many relationships and parameters in IAMs but three components have come under particular scrutiny: the equilibrium climate sensitivity, the damage function and the discount rate (Farmer, Hepburn, Mealy, & Teytelboym, 2015; Stern, 2013). We have mentioned in Section 2 the uncertainty surrounding the equilibrium climate sensitivity as well as the notion of "fat tails", so we will focus here on the two key economic components of IAMs, the damage function and the discount rate.

<u>The damage function</u>

The first key economic component of IAMs is the damage function, which is a measure of the relative impact on welfare (expressed in terms of GDP) of an increase in global mean temperature, as an index of a wider set of climatic changes. Since climate change is an unprecedented phenomenon in the history of mankind, there are no historical observations available, which could inform the "shape" of this relationship; damage functions thus belong to the realm of the structural uncertainties and result from largely arbitrary choices.

The damage function in the DICE Integrated Assessment Model is quadratic in global mean temperature change. Previously, this damage function was calibrated based on the enumerative approach, involving detailed regional and sectoral estimates (Nordhaus & Boyer, 2000), but in DICE-2013R (Nordhaus & Sztorc, 2013), a most recent version of the model, the calibration of the damage function is based on the estimates of monetized damages from the Tol survey (Tol, 2009, 2014), to which a judgemental 25% adjustment is added to reflect non-monetized impacts, such as biodiversity losses, health impacts and changes in ocean circulation.

Equation 1.3

$$\Omega_{DICE}\big(TATM(t)\big) = \frac{1}{1 + \alpha_1 * TATM(t) + \alpha_2 * (TATM(t))^2}$$

Where:

- $TATM$ is the increase in global mean temperature since pre-industrial times (in °C);
- $\alpha_1 = 0$;
- $\alpha_2 = 0.002664$.

There are two important issues with this damage function. The first issue regards the choice of a quadratic specification, which is essentially arbitrary: as noted by Dietz and Asheim (2012, p. 328), "there has never been any stronger justification for the assumption of quadratic damages than the general supposition of a non-linear relationship, added to the fact that quadratic functions are of a familiar form to economists, with a tractable first derivative"[9]. The second issue concerns the calibration of this damage function: not only is it designed so that damages cannot reach 100% of output, but its calibration is only valid for temperature increases

[9] It is worth noting here that, in contrast to most IAMs, the impact function in PAGE09 has a flexible exponent that can be as high as 3.

in the range of 0 to 3°C. Indeed, the damage function used in DICE means that a 6°C increase in global mean temperature warming would result in a loss of utility equivalent to just 4.7% of output, while it would take an 18°C increase in global mean temperature to reach a loss of utility equivalent to 50% of output (Ackerman, Stanton, & Bueno, 2010; Dietz & Asheim, 2012). Hence several economists have expressed their concerns about the choice of a quadratic damage function that might significantly understate the economic impacts associated with very large increases in global mean temperature (Ackerman et al., 2010; Pindyck, 2013; Stern, 2013; Weitzman, 2011). The third issue pertains to the fact that the damage function used in DICE-2013R does not include thresholds, and therefore does not account for the possibility of tipping points, regime shifts, or the possibility of catastrophic climate change (Lemoine & Traeger, 2014).

The structural uncertainty about the specification of the damage function has been dealt with in three ways: the first one has been to keep the base relationship and to introduce a higher-order term into the damage function to capture greater non-linearity (Weitzman, 2011). To that effect, Dietz and Asheim (2012) transformed this structural uncertainty into a parametric uncertainty by proposing the use of a damage function which is such that, for different parameter values, the damage function can be equivalent either to the quadratic form of Nordhaus (2014), or that of Weitzman (2012). They interpret the parametric uncertainty as being subjective or epistemic in nature, rather than objective or aleatory.

The second approach has been to question the assumption that damages do not enter the utility function directly, which supposes that there is a strong substitutability between consumption and the costs of temperature change. Instead, Weitzman (2009a, 2011) has suggested to make the disutility of temperature change additively separable from the utility of consumption, which would reflect the fact that climate change might have impacts (e.g. on biodiversity, ecosystems and human health) which are not readily substitutable with material wealth.

The third approach has been to replace the damage function in which economic impacts of climate change hit current year GDP losses by a damage function which better reflects the scale and long-lasting effects of climate damage. To this effect, Stern (2013) has suggested alternative damage functions, where climate damage could be modelled as 1) damage to social, organizational or environmental capital; 2) damage to stocks of capital or land; 3) damage to overall factor productivity; 4) damage to learning and endogenous growth. Some of these recommendations have since been implemented: Moyer et al. (2014) integrated in the DICE model the possibility that climate change may directly affect productivity. Similarly, Moore and Diaz (2015) adapted DICE so that temperature could affect GDP through two pathways: total factor productivity growth and capital depreciation. Finally, Dietz and Stern (2015) incorporate in DICE two models of endogenous growth, in which the damage from climate change affect the drivers of long-run growth.

The discount rate

The second key economic component of IAMs is the social discount rate; indeed, any assessment of costs or benefits that are incurred at different time scales implies the use of a discount rate. In our previous discussion on the drivers and effects of climate change, we have emphasized that the uncertainty is as much about the nature as it is about the scale and the timing of future climate change. Despite the fact that the time lag between an emission of CO_2 and the maximum warming response is a decade on average (Ricke & Caldeira, 2014; Zickfeld & Herrington, 2015), CO_2 emissions are long-lived: on average 40% of a CO_2 pulse is still in the atmosphere after 100 years (Ciais et al., 2013). This means that an emission today produces a stream of impacts for centuries, and that the net present value of the total impact is heavily influenced by the choice of the discount rate. Consequently, the costs of an abatement policy would be incurred as of now, but that most of the benefits would occur at uncertain horizons and in the long distant future. Given the timescales involved, the choice of a discount rate can therefore make an immense difference in the net present value of future costs and benefits.

In the discounted utilitarian framework, which is the one used in DICE, social welfare is represented by the sum of the utility of a representative agent:

Equation 1.4

$$U\big(c(t)\big) = \int_0^\infty u[c(t)] \exp(-\rho t)\, dt$$

where the instantaneous utility function u[c(t)] is time invariant and has positive but diminishing marginal utility of consumptions (i.e. u'(.) > 0 and u''(.) ≤ 0).

Assuming that we are in a risk-free setting, that the utility function is iso-elastic and that we are in an economy where capital yields output, which can be devoted to consumption or investment, the maximisation[10] of the above equation leads to the Ramsey rule (Ramsey, 1928):

Equation 1.5

$$r_t = \rho + \theta g_t$$

Where:

- r is the social marginal productivity of capital;
- ρ is the utility discount rate or the pure rate of time preference;
- θ is the coefficient of risk aversion or the elasticity of marginal utility;
- $g = \frac{\dot{c}(t)}{c(t)}$ is defined as the growth rate of consumption.

The uncertainty about what would be the "appropriate" discount rate in the context of climate change stems from at least two factors: first, whether the components of the discount rate (namely the rate of pure time preference and the consumption elasticity of marginal utility) should be taken from a normative or a positive perspective. For instance, Ramsey (1928, p. 543) argued that putting different weights upon the utility of different generations is "ethically indefensible" while Stern (2007) defends the use of a pure rate of time preference of 0.1 to account for the small risk of extinction of the human race, but otherwise rules out impatience as a legitimate motivation for pure-time discounting. Nordhaus (2007) has taken the opposite view and has argued that discount rates should be derived from actual behaviour, which means that the ρ parameter should be inferred from empirical estimates of market rates of return.

The second factor concerns the uncertainty about future consumption growth. Assuming that that there is uncertainty about consumption growth and that the growth rate of consumption

[10] See Groom et al. (2005) for details.

is independently and identically normally distributed with mean μ and variance σ^2, a third term, called the precautionary effect, is added to Equation 1.5, which becomes the extended Ramsey rule (Equation 1.6).

Equation 1.6

$$r_t = \rho + \theta\mu - 0.5\theta^2\sigma^2$$

In the Ramsey framework, the presence of uncertainty about the future rate of growth in per capita consumption justifies a declining discount rate (Gollier, 2002), if we make the assumption that the utility function is isoelastic and that shocks in consumption are positively correlated (Cropper, Freeman, Groom, & Pizer, 2014).

It is worth emphasizing that at the core of the discounted utilitarian framework lies the assumption that the utility of future generations should be given less weight than the utility of the present generation, which becomes crucial when it comes to evaluating climate policies (Dietz & Asheim, 2012). Although they are not explored in this thesis, alternative approaches to the discounted utilitarian framework have been proposed in the literature; these include for instance sustainable discounted utilitarianism (Asheim & Mitra, 2010) and the rank-discounted utilitarian approach (Zuber & Asheim, 2012).

ii. Limitations of Integrated Assessment Models

Three issues with the representation of uncertainty in IAMs have been raised in the literature: IAMs have difficulty in accounting for the possibility of catastrophic climate change, they generally cannot provide detailed projections of regional impacts, and they present an illusion of certainty which can be misleading to some.

The first concern regarding the reliability of IAM-derived projections lies in the fact that these do not seem to reflect the findings of climate scientists regarding the range of future states of the climate, mainly due to the absence of positive feedbacks and tipping points (Kaufman, 2012; Lenton & Ciscar, 2013; Warren, Mastrandrea, Hope, & Hof, 2010). This claim has been substantiated by the work of Ackerman et al. (2010), who examined the conditions under which DICE could project forecasts of disastrous climate outcomes and found that it required a conjunction of a fat-tailed distribution for the equilibrium climate sensitivity parameter and the specification of the damage function. One of the responses to this concern has been to integrate the possibility of a climate catastrophe in IAMs through tipping points (Lemoine & Traeger, 2016; Lenton & Ciscar, 2013; Lontzek, Cai, Judd, & Lenton, 2015). A different standpoint was taken by Weitzman (2009b), who laid out the Dismal Theorem which argues that the large structural uncertainty surrounding the possibility of a climate catastrophe renders obsolete the use of standard cost-benefit analysis.

The second critique of IAMs that can be found in the literature is that most of them operate on a global scale, and therefore say nothing on the local impacts of climate change on lives and livelihoods. Some regional IAMs have been developed[11] but these suffer from two drawbacks: first, reliable projections of regional climatic changes do not in general exist, except perhaps for warming; second, these impacts will also depend very strongly on local socio-economic factors

[11] E.g. RICE (Nordhaus & Yang, 1996).

which are extremely hard to project, such as the implementation of adaptation policies and changes in vulnerability and resilience. The fact that most IAMs rely on the assumption of a representative agent (Farmer et al., 2015) also forecloses the possibility of including heterogeneous agents (Beinhocker, Farmer, & Hepburn, 2013).

The final objection that has been made is that IAMs can, if not used with care, give an illusion of knowledge to policy-makers who use their output. It is true that IA modellers have considerable freedom in choosing functional forms and parameter values, which can lead to very different estimates of the social cost of carbon and the optimal policy; this highlights the fragility of these models to the underlying specifications but is not a major issue in itself. What is wrong and dangerous is to consider the results from these models as certain, without acknowledging the wide uncertainties underlying them and the numerous assumptions that these results depends on. In the words of Pindyck (2017, p. 102) : "the use of IAMs to estimate the SCC or evaluate the alternative policies is problematic because it creates a veneer of scientific legitimacy that is misleading".

What then should be the purpose of IAMs? Integrated Assessment Models should be used as analytical devices, designed to bring a better understanding of the dynamic interactions between climate change and the economy and to compare different mitigation scenarios in relative terms. IA modellers should resist the demands of policy-makers for scientific-looking probability distributions of future climate impacts, and instead acknowledge the depth of our ignorance, and precisely use these models to explore the full range of climate and economic uncertainties, and the ways in which these combine and compound.

All in all, what matters ultimately in the context of climate change is the probability of catastrophic climate change and the scale and nature of regional impacts, for which IAMs are of limited use anyway. Alternative methods have thus been developed to address more precisely these issues.

iii. Alternative approaches to IAMs

Four approaches have been used in the field of climate change to deal with the weaknesses and shortcomings of Integrated Assessment Models: expert elicitation, aimed at facilitating the characterization of deep uncertainty; closed-form analytical solutions, meant to replicate IAMs' outputs with simple and transparent formulae; dynamic stochastic general equilibrium model, which allow for stochastic elements in the path to the steady state; and agent-based models, which answer the need to take into account the heterogeneity of agents.

Expert elicitation

The first approach, expert elicitation, has been used to tackle deep uncertainty by estimating likelihoods on the basis of expert judgments. This method has two advantages: first, it has been argued that the human brain is capable of handling more complexity than integrated assessment models, which can never hope to include all relevant factors (Morgan, 2014). Second, the elicitation of individual expert judgments may provide a better reflection of the underlying uncertainties than consensus reviews (Zickfeld et al., 2007). Most of the applications of this method in the field of climate change have concerned the threat of catastrophes; these include the collapse of the Atlantic Meridional Overturning Circulation (Zickfeld et al., 2007), future sea level rise from ice sheets (Bamber & Aspinall, 2013), the likelihood of tipping points (Lenton et al., 2008) and the strength of the permafrost carbon feedback (Schuur et al., 2013). Pindyck (2016) suggests that instead of relying on IAMs to project future economic impacts of climate change, we should rely on expert opinion to elucidate the likelihood of a catastrophe (which is, in the end, the major determinant of the economic value of mitigation). There are several limitations to this method: the first one lies in the fact that the potential pool of experts for these types of survey is extremely small; second, the likelihood assessments provided by these experts might be constructed in very different ways, from heuristic methods to model simulations; third, though representative of the range of beliefs about the likelihoods of catastrophic climate change, the aggregated results of the survey cannot be treated as a consensus probability distribution (Arnell, Tompkins, & Adger, 2005). Finally, the human brain has been shown to be prone to heuristics which can significantly influence judgments (Tversky & Kahneman, 1975).

Closed-form analytical solutions

A second approach has tried to provide similar, policy-relevant results to the ones provided by IAMs (e.g. the optimal level of mitigation or the social cost of carbon), but using closed-form analytical formulae. IAMs are often criticised for their lack of transparency and the fact that they operate as "black boxes". There are two prominent examples in the recent literature. Golosov et al. (2014) found that, under a certain set of assumptions, the calculations leading to the optimal carbon tax in a dynamic stochastic general equilibrium model could be synthetized into a closed-form analytical formula. The main advantage of this solution lies in the fact that it only depends on a few basic parameters, namely, assumptions on discounting, a measure of expected damages and how fast emitted carbon leaves the atmosphere. Moreover, it should be palatable to policy-makers, as its simplicity makes it easy to understand and its outcome does not rely on calculations happening behind the scenes. A similar approach was used by van den Bijgaart et al. (2016), who derived a closed-form analytical solution for the social cost of carbon. The authors compared the performance of their formula against the DICE IAM and found that their formula predicts the outcome from DICE without quantitatively significant systematic bias.

Dynamic stochastic general equilibrium models

A third approach has tried to improve the treatment of uncertainty by combining IAMs with Dynamic Stochastic General Equilibrium (DSGE) methods. For instance, Traeger (2014) transformed DICE into a recursive dynamic programming model, so as to be able to incorporate stochastic shocks, persistent uncertainty and Bayesian learning. The main advantage of DSGE models is that they enable a more thorough integration of uncertainty but they are usually computationally intensive and rely on the assumption of forward-looking fully-informed maximising agents (Farmer et al., 2015).

Agent-based models

The final approach has aimed at going beyond the "representative household" assumptions underlying IAMs, by enabling a more flexible and realistic characterization of socio-economic systems through the inclusion of interactions between a large number of heterogeneous agents (Farmer et al., 2015). Other advantages of agent-based models (ABMs) are that they allow a broader perspective on policy effectiveness and efficiency, the analysis of additional instruments (e.g. diffusion of information and lifestyles), and addressing Schumpeterian competition (through innovation, rather than price competition). It has been argued that the use of ABM would be especially salient in the context of climate change, as population groups are expected to be impacted differently by the opportunities and threats posed by mitigation policies (S. Moss, Pahl-Wostl, & Downing, 2001). However, the use of ABMs comes at the cost of considerable computational needs and they usually require the empirical estimation of a significant number of parameters.

6. Dissertation outline

The second chapter of my PhD, titled "The climate beta", and co-written with Pr. Simon Dietz and Pr. Christian Gollier, investigates the discount rate that should be applied to mitigation projects through the prism of the climate beta, i.e. the correlation between the returns of a mitigation project and future consumption growth. We start by exploring analytical properties of the climate beta, before estimating it numerically using the Integrated Assessment Model DICE. The fact that I had to code DICE from scratch in Matlab gave me a sound understanding of the calculations going on in the "black box" and made me aware of the considerable structural and parameter uncertainties which underlie these models. Given that our analysis examines the impact of uncertainty about the climate beta, I also had to find sensible probability distribution functions for ten key uncertainties, including the rate of CO_2 uptake by the ocean, the notion of equilibrium climate sensitivity and the curvature of the damage function, which provided me with both a wide and a precise knowledge of climate change uncertainties.

Delving into the notion of equilibrium climate sensitivity made me reflect on the crucial role played by feedbacks in the response of the Earth's climate to an increase in radiative forcing, which led me to the third chapter of my PhD: "Estimating the economic impact of the permafrost carbon feedback". In this chapter, I explore the impact of integrating the permafrost carbon feedback in the Integrated Assessment Model DICE. The complexity came from finding a simple and yet informative representation of this biogeophysical feedback, which could be incorporated in DICE so as to assess its potential impact on the social cost of carbon and the optimal climate policy.

I found that incorporating the PCF in DICE had a non-negligible impact on the social cost of carbon but I also came to the cruel realization that, although irreversible, the PCF would not matter much to policy-makers now because most of the impacts will be felt globally and in the long distant future. I also came across the literature on the "New Climate Economy" (Dell et al., 2014) and noticed that changes in weather patterns were most often analysed independently from each other. For that reason, I decided to focus instead on near-term economic impacts, to switch tools from climate models to econometrics based on historical weather data, and to change scope from the global to the local and from the very long-term to the current period. Chapter 4, titled "What are the impacts of droughts on economic growth? Evidence from U.S. states" thus applied panel data methods to historical weather data to estimate the economic impact of changes in the duration and intensity of droughts on U.S. states' economic growth. I also tried to apply the compound events framework, which I had come across in a statistics paper, to this econometric setting.

It was then only a small step to go from assessing the economic impacts of climate change to the policy impacts of climate change. The fifth chapter of my PhD, co-written with Pr. Simon Dietz and Dr. Alex Bowen, and titled "Climate shocks, inflation and monetary policy: The global experience since 1950" is indeed the only one which analyses how climate change influences human behaviour through policy-making. It employs similar econometric methods to those in Chapter 4 and makes use of panel data analysis to investigate how changes in temperature and precipitation patterns impact inflation rates, and, in turn, influence central banks' decisions to increase or decrease policy interest rates. In a sense, this paper is not only closing my PhD but is also closing the loop between the climate system, the economy and policy.

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Chapter 2: The climate beta

Abstract

How does climate-change mitigation affect the aggregate consumption risk borne by future generations? In other words, what is the 'climate beta'? In this paper we argue using a combination of theory and integrated assessment modelling that the climate beta is positive and close to unity for maturities of up to about one hundred years. This is because the positive effect on the climate beta of uncertainty about exogenous, emissions-neutral technological progress overwhelms the negative effect on the climate beta of uncertainty about the carbon-climate-response, particularly the climate sensitivity, and the damage intensity of warming. Mitigating climate change therefore has no insurance value to hedge the aggregate consumption risk borne by future generations. On the contrary, it increases that risk, which justifies a relatively high discount rate on the expected benefits of emissions reductions. However, the stream of undiscounted expected benefits is also increasing in the climate beta, and this dominates the discounting effect so that overall the net present value of carbon emissions abatement is increasing in the climate beta.

1. Introduction

Because most of the benefits of mitigating climate change arise in the distant future, the choice of the rate at which these benefits should be discounted is a crucial determinant of our collective willingness to reduce emissions of greenhouse gases. The discount rate controversy that has emerged in economics over the last two decades shows that there is still substantial disagreement about the choice of this parameter for cost-benefit analysis. One source of controversy comes from the intrinsically uncertain nature of these benefits. It is a tradition in economic theory and finance to adapt the discount rate to the risk profile of the flow of net benefits generated by the policy under scrutiny. The underlying intuition is simple. If a policy tends to raise the collective risk borne by the community of risk-averse stakeholders, this policy should be penalised by increasing the discount rate by a risk premium specific to the policy. On the contrary, if a policy tends to hedge collective risk, this insurance benefit should be acknowledged by reducing the rate at which expected net benefits are discounted, i.e. by adding a negative risk premium to the discount rate.

This simple idea can easily be implemented through the Consumption-based Capital Asset Pricing Model (CCAPM) of Lucas (1978). An investment raises intertemporal social welfare if and only if its Net Present Value (NPV) is positive, where the NPV is obtained by discounting the expected cash flow of the investment at a risk-adjusted rate. This investment-specific discount rate is written as

$$r = r_f + \beta\pi$$

Where r_f is the risk-free rate, π is the systematic risk premium and β is the CCAPM beta of the specific investment under scrutiny. It is defined as the elasticity of the net benefit of the investment with respect to a change in aggregate consumption. This means that a marginal project, whose net benefit is risky but uncorrelated with aggregate consumption, should be discounted at r_f, because implementing such a project has no effect at the margin on the risk borne by the risk-averse representative agent. A project with a positive β raises collective risk and should be penalised by discounting its flow of net benefits at a higher rate, and vice versa for a project with a negative β.

The objective of this paper is not to offer a new contribution to the debate about the choice of the risk-free rate, or of the systematic risk premium: there have been many of these in the recent past (see Kolstad et al. (2014) for a recent summary). Rather, the aim of this paper is to discuss the CCAPM β that should be used to value climate-mitigation projects. This 'climate β' should play an important role in the determination of the social cost of carbon (i.e. the present social value of damages from incremental carbon emissions), just as an asset β is known to be the main determinant of the asset price. Indeed, in the United States over the last 150 years, financial markets have exhibited a real risk-free rate of around 1.6% and a systematic risk premium of around 4.8 percentage points. Thus, assets whose CCAPM betas are respectively 0 and 2 should be discounted at very different rates of 1.6% and 11.2% respectively[12].

Howarth (2003) was one of the first to examine this question. He pointed out that the net benefits of climate-mitigation projects should be discounted at r_f, provided those net benefits are certainty equivalents (thereby containing a risk premium). He went on to suggest that the climate β is negative, but did not offer detailed analysis to back up the suggestion[13]. Weitzman's Review of the Stern Review (2007a) also emphasised that the appropriate discount rate for climate-mitigation projects depends on the correlation between mitigation benefits and consumption, although he did not offer detailed analysis of this correlation either. He was contributing to a debate about discounting in the wake of the *Stern Review* (Stern, 2007), in which some scholars' views of what is an appropriate rate at which to discount mitigation benefits were in effect anchored against r_f, while others were anchored against r for standard investments, such as a diversified portfolio of equities. As Weitzman pointed out, there is no guarantee the features of climate mitigation match either of these cases.

Sandsmark and Vennemo (2007) provided the first explicit investigation of the climate β. They constructed a simplified climate-economy model, in which the only stochastic parameter represents the intensity of damages – the loss of GDP – associated with a particular increase in global mean temperature. Given this set-up, large damages are simultaneously associated with low aggregate consumption and a large benefit from mitigating climate change. Hence this model yields a negative climate β. Weitzman (2013) extended the idea that emissions abatement is a hedging strategy against macro-economic risk, invoking potential catastrophic climate change and its avoidance, while Daniel et al. (2016) also find a negative climate β in the more general

[12] See Shiller's dataset: http://www.econ.yale.edu/ shiller/data.htm.

[13] Aalbers (2009) situated the climate β within a broader set of theoretical conditions, according to which climate-mitigation investments might be discounted at a lower rate than other investments.

context of Epstein-Zin preferences, since their estimation of the social cost of carbon is increasing in the degree of risk aversion of the representative agent[14].

On the other hand, an alternative channel driving the climate β may exist. Nordhaus (2011) concludes from simulations with the RICE-2011 integrated assessment model (IAM) that "those states in which the global temperature increase is particularly high are also ones in which we are on average richer in the future." This conclusion implicitly signs the climate β and is compatible with the following scenario. Suppose that the only source of uncertainty is exogenous, emissions-neutral technological progress, which determines economic growth. In this context, as long as growth is in some measure carbon-intensive, rapid technological progress yields at the same time more consumption, more emissions, more warming and, under most circumstances, a larger marginal benefit from reducing emissions. This would yield a positive correlation between consumption and the benefits of mitigation, i.e. a positive climate β. This channel is present in neither Sandsmark and Vennemo (2007) nor Daniel et al. (2016), because they assume a sure growth rate of pre-climate-damage production and consumption.

In this paper, we provide an overarching analysis of the sign and size of the climate β, which encompasses the aforementioned two stories, as well as other drivers. Our analysis is in two complementary parts. First, we explore analytical properties of the climate β in a simplified model. As well as serving to develop intuition, the model allows us to explore the role of the structure of climate damages, in particular whether they are multiplicative, as standardly assumed, or additive. We then estimate the climate β numerically using a dynamic IAM with investment effects on future consumption. We perform Monte Carlo simulations of the DICE model, introducing ten key sources of uncertainty about the benefits of climate mitigation and future consumption. We use these simulations to estimate the climate β for different maturities of our immediate efforts to reduce emissions. We find that in our version of DICE the positive effect on β of uncertain technological progress dominates the negative effect on β of uncertain climate sensitivity and damages. Put another way, emissions reductions actually increase the aggregate consumption risk borne by future generations. This is in line with Nordhaus (2011), but our analysis advances the literature by quantifying the climate β explicitly. We also extend Nordhaus' analysis in several ways: we treat TFP growth as a first-order autoregressive process, consistent with historical data; we treat the income elasticity of damages as uncertain, so damages are not necessarily multiplicative; and we include the possibility of catastrophic damages.

In the next section we review β in the context of Lucas' CCAPM and clarify how it relates to the NPV of a project. Section 3 describes our analytical model and its results. Section 4 describes how we set up and run the DICE model in order to estimate the climate β. Section 5 sets out the results from our DICE simulations. The subsequent sections provide a discussion and some concluding comments.

[14] Our paper sits within a large literature on uncertainty and climate policy (see Heal and Millner (2014), for a review). Recent papers relevant to our analysis include Bansal et al. (2016) and Lemoine (2015).

2. The CCAPM beta

In this section, we derive the standard CCAPM valuation principles as in Lucas (Lucas, 1978) and obtain an important result, which means that the relationship between the climate β and the NPV of climate mitigation is very likely to be positive, the opposite of what one might have expected. Consider a Lucas-tree economy with a von Neumann-Morgenstern representative agent, whose utility function u is increasing and concave and whose rate of pure preference for the present is δ. Her intertemporal welfare at date 0 is:

Equation 2.1

$$W_0 = \sum_{t=0}^{\infty} e^{-\delta t}\, \mathbb{E}[u(c_t)]$$

where c_t measures her consumption at date t. Because c_t is uncertain from date 0, it is a random variable. We contemplate an action at date 0, which has the consequence of changing the flow of future consumption to $c_t + \varepsilon B_t$, $t = 0, 1, \ldots$, where B_t is potentially random and potentially statistically related to c_t. For small ε, the change in intertemporal welfare generated by this action is equivalent to an immediate increase in consumption by εNPV, where NPV can be measured as follows:

Equation 2.2

$$NPV = \sum_{t=0}^{\infty} e^{-\delta t} \mathbb{E} B_t \frac{u'(c_t)}{u'(c_0)} = \sum_{t=0}^{\infty} e^{-r_t t} \mathbb{E}\, B_t$$

with

Equation 2.3

$$r_t = \delta - \frac{1}{t} \ln \frac{\mathbb{E} B_t u'(c_t)}{u'(c_0) \mathbb{E} B_t}$$

The right-hand side of Eq. 2.2 can be interpreted as the NPV of the action, where, for each maturity t, the expected net benefit $\mathbb{E}B_t$ is discounted at a risk-adjusted rate r_t, which is in turn defined by Eq. 2.3. In order to simplify Eq. 2.3, we make three additional assumptions, which are in line with the classical calibration of the CCAPM model:

1. For all states of nature, the elasticity of the net conditional benefit at date t with respect to a change in consumption at t is constant, so that there exists $\beta_t \in \mathbb{R}$ such that $\mathbb{E}[B_t|c_t] = c_t^{\beta t}$

2. Consumption follows a geometric brownian motion with drift μ and volatility σ, so that $x_t = \ln c_t/c_0 \sim N(\mu t, \sigma^2 t)$.

3. The representative agent has constant relative risk aversion γ, so that $u'(c_t)=c_t^{-\gamma}$.

This allows us to rewrite Eq. 2.3 as follows:

Equation 2.4

$$r_t = \delta - \frac{1}{t}\ln\frac{\mathbb{E}\left[e^{(\beta_t-\gamma)x_t}\right]}{\mathbb{E}\left[e^{\beta_t x_t}\right]}$$

We now use the well-known property that if $x \sim N(a, b^2)$, then for all $k \in \mathbb{R}$. $[\exp(kx)] = \exp(ka + 0.5k^2b^2)$. Applying this result twice in the above equation implies that

Equation 2.5

$$r_t = \delta + (\beta_t\mu + 0.5\beta_t^2\sigma^2) - [(\beta_t-\gamma)\mu + 0.5(\beta_t-\gamma)^2\sigma^2] = r_f + \beta_t\pi$$

where the risk-free rate r_f equals

Equation 2.6

$$r_f = \delta + \gamma\mu - 0.5\gamma^2\sigma^2$$

and the systematic risk premium equals

Equation 2.7

$$\pi = \gamma\sigma^2$$

Observe that both the risk-free rate r_f and the systematic risk premium π have a flat term structure in this framework. However, the risk-adjusted discount rate r_t may have a non-constant term structure, which is homothetic in the term structure of β_t. Therefore later in the paper we shall be interested in estimating the term structure (β_1, β_2, ...) of the climate β. This can be done by observing that if $[B_t|c_t] = c_t^{\beta t}$, then β_t is nothing other than the regressor of ln B_t with respect to ln c_t:

Equation 2.8

$$\ln B_t = \beta_t \ln c_t + \xi_t$$

where c_t and ξ_t are independent random variables. We take 50,000 draws from a Monte-Carlo simulation of the DICE model to generate, for each maturity t, a series (ln $B_{it,}$ ln $c_{it,}$), i = 1, 2, ..., 50 000, from which the OLS estimate of ln B_t on ln c_t gives us the climate β associated with that maturity.

Before turning to the modelling proper, we show an important result. Although a larger β implies a higher discount rate on project benefits, a larger β also raises the expected benefit $\mathbb{E}B_t$ to be discounted. Given the assumptions just set out,

Equation 2.9

$$\mathbb{E}B_t = c_0^{\beta_t}\mathbb{E}e^{\beta_t x_t} = c_0^{\beta_t}e^{(\beta_t\mu + 0.5\beta_t^2\sigma^2)}$$

With constant β, $\mathbb{E}B_t$ is exponentially increasing in t when trend growth μ is positive. Moreover, the larger is β_t, the larger is the growth rate of the expected benefit. The intuition is as follows. The elasticity of benefits with respect to changes in consumption has two reinforcing effects on $\mathbb{E}B_t$. First, if trend growth is rapid, highly elastic investments will benefit more from economic growth. Second, the benefit is a convex function of the growth rate x_t of consumption. By Jensen's inequality, the uncertainty affecting economic growth raises the expected benefit. Because this convexity is increasing in the elasticity β_t, this effect is increasing in β_t. The combination of these two effects may dominate the discounting effect. Indeed, combining Eqs. 2.5 and 2.9 implies that

$$NPV = \sum_{t=0}^{\infty} c_0^{\beta_t} exp\left[\left(-r_f + \beta_t(\mu - \gamma\sigma^2) + 0.5\beta_t^2\sigma^2\right)t\right]$$

This is increasing in β_t if β_t is larger than $\gamma - (\mu/\sigma^2)$. This result is summarised in the following proposition:

Proposition 1. Consider an asset with maturity-specific constant betas, i.e., an asset whose future benefit $B_{t|t\geq 0}$ is related to future aggregate consumption $c_{t|t\geq 0}$ in such a way that for all t there exists $\beta_t \in \mathbb{R}$ such that $[B_t|c_t] = c_t^{\beta t}$. Under the standard assumptions of the CCAPM, the value of this asset is locally increasing in β_t if it is larger than the difference between relative risk aversion and the ratio of the mean by the variance of the growth rate of consumption.

In the United States over the last century, we observed $\mu \approx 2\%$ and $\sigma \approx 4\%$ (Kocherlakota, 1996; Mehra, 2012). If we take $\gamma = 2$, this implies that $\gamma - (\mu/\sigma^2) \approx -10.5$. Alternatively, to acknowledge the equity premium puzzle, we might take $\gamma = 10$, so that we obtain $\gamma - (\mu/\sigma^2) \approx -2.5$. Because most actions yield β_t larger than either of these two numbers, we conclude that the NPV of most investment projects is increasing in their CCAPM β. The intuition is that the mean growth rate of consumption has been so much larger than its volatility in the past that the effect of a larger β on the expected benefit is much larger than its effect on the discount rate, thereby generating a positive effect on NPV.

3. A simple analytical model of the climate beta

In this section we derive the climate β from a simple analytical model. As well as helping to formalize notions of what determines the climate β, we also use the model to make an important point about the role of the structure of climate damages, specifically what difference it makes to the climate β that damages are multiplicative in most models such as standard DICE, as opposed to additive.

Let us consider any specific future date t, and let Y represent global economic output within the period $[0, t]$ in the absence of climate damages. Over time scales from a decade to centuries, important recent papers in climate science have shown that (a) the increase in the global mean temperature T is approximately linearly proportional to cumulative carbon dioxide emissions (Allen et al., 2009; Goodwin, Williams, & Ridgwell, 2015; H. D. Matthews, Gillett, Stott, & Zickfeld, 2009; Zickfeld, Eby, Matthews, & Weaver, 2009) and (b) the warming response to an emission of carbon dioxide is virtually instantaneous, and then constant as a function of time (Eby et al., 2009; Held et al., 2010; H. D. Matthews & Caldeira, 2008; Ricke & Caldeira, 2014; Shine, Fuglestvedt, Hailemariam, & Stuber, 2005; Solomon, Plattner, Knutti, & Friedlingstein, 2009). This enables us to write:

Equation 2.10

$$T = \omega_1 E$$

where E stands for cumulative industrial CO_2 emissions from 0 to t and ω_1 is a parameter called the carbon-climate response (CCR)[15], combining the response of the carbon cycle to emissions and the temperature response to atmospheric carbon. More complex models like DICE deal with these components separately. Emissions of CO_2 are themselves proportional to pre-damage production, so that:

Equation 2.11

$$E = \omega_2 Y - I_0$$

where ω_2 parameterises the carbon intensity of production, and I_0 is an investment to reduce emissions at the margin.

We assume the damage index D is proportional to increased temperature T at some power k:

Equation 2.12

$$D = \alpha T^k$$

where α calibrates the damage function. Parameter k turns out to play an important role in the determination of the climate β in this model. It is widely believed that there is a convex relationship between climate damages and warming, i.e. $k > 1$.

At this stage, let us remain quite general about the way to model the interaction between the damage index D and the index of economic development Y:

Equation 2.13

$$Q = q(Y, D)$$

where Q is post-damage aggregate output and q is a bivariate function, which is increasing in Y and decreasing in D, with $Q(Y,0) = Y$ for all Y. If $c \in (0, 1]$ is the propensity to consume output in period t, then the model yields the following reduced form:

Equation 2.14

$$C(I_0) = cq\left[Y, \alpha\omega_1^k(\omega_2 Y - I_0)^k\right]$$

[15] The Intergovernmental Panel on Climate Change has also called it the Transient Climate Response to Cumulative Carbon Emissions or TCRE (Collins et al., 2013).

We consider the β of a marginal emissions reduction project. The benefit or cash flow of the project is:

Equation 2.15

$$B \equiv \frac{\partial C}{\partial I_0}|_{I_0=0} = -c\omega_2^{-1}hY^{k-1}q_D(Y, hY^k)$$

with $h = \alpha\omega_1^k\omega_2^k$. To sum up, our model characterises the statistical relationship between future consumption $C = C(0)$ and future benefits B as a function of a set of uncertain parameters, such as Y and ω_1. This system is given by the following two equations:

Equations 2.16

$$\ln B = \ln(c\omega h) + (k-1)\ln Y + \ln[-q_D(Y, hY^k)]$$

$$\ln C = \ln c + \ln q(Y, hY^k)$$

How does β respond to the various uncertainties in this model? We proceed one by one through each of the key sources of uncertainty[16].

<u>The climate β when the main source of uncertainty is related to exogenous economic growth</u>

Suppose the only source of uncertainty is exogenous, emissions-neutral technological progress, captured in this simplified model by pre-damage production Y. Then a local estimation of β can be obtained by differentiating the system 2.16 with respect to Y:

Equation 2.17

$$\beta = \frac{d\ln B/dY}{d\ln C/dY} \approx \frac{q}{q_D}\frac{(k-1)q_D + Yq_{YD} + Dq_{DD}}{Yq_Y + kDq_D}$$

where q and its partial derivatives appearing in this equation are evaluated at (Y, hY^k). This approximation, which is based on the Taylor expansion, is exact when the uncertainty affecting Y is small.

We calibrate this equation by considering two alternative damage models. In IAMs like standard DICE, damages are assumed to be multiplicative – proportional to Y – which implies that for instance doubling income also doubles absolute climate damages, all else being equal. We can represent this class of model with the function:

[16] It can be seen that, in fact, the CCAPM climate β is not constant in this model. In other words, log climate damages are not linear in log consumption, plus white noise (Eq. 2.8). Therefore the risk-adjusted discount rate $r = r_f + \beta\pi$ holds only as an approximation. In reality, the true climate β is stochastic and correlated with economic growth. Recent developments in the finance literature initiated by Jagannathan and Wang (1996) have focused on the impact of stochastic betas on equilibrium asset prices, however the literature is yet to reach the stage where such an extension could be implemented here. In our numerical modelling with DICE, we allow the climate β to be sensitive to maturity, and we are also able to show that at a given date t the relationship between log benefits and log consumption in DICE is linear.

$$q(Y, D) = Y(1 - D)$$

where D is expressed in percentage points of aggregate income. In this context, Eq 2.17 simplifies to:

Equation 2.18

$$\beta \approx \frac{k(1 - D)}{1 - (k + 1)D}$$

Table 2.1: Calibration of the climate β using Eq. 2.18 when the source of uncertainty is exogenous emissions-neutral technological progress.

	k = 0.5	k = 1	k= 2	k = 3
D = 1%	0.50	1.01	2.04	3.09
D = 3%	0.51	1.03	2.13	3.31
D = 5%	0.51	1.06	2.24	3.56
D = 10%	0.53	1.13	2.57	4.50
D = 20%	0.57	1.33	4.00	12.00

Notes: If instead Eq. 2.20 is used, subtract one from all cells.

In Table 2.1, we compute the climate β derived from this formula for reasonable values of k and D. It is uniformly positive. Moreover, observe that for damage of less than 5% of GDP[17], the climate β can be approximated by k. In other words, when the main source of uncertainty is emissions-neutral technological progress, the climate β is approximately equal to the elasticity of climate damage with respect to the increase in global mean temperature. The consensus in the damages literature is that $k > 1$, which implies that the climate $\beta > 1$, based on this source of uncertainty. What is the intuition behind this result? It is simply that faster technological progress serves as a positive shock to output and consumption, which in turn leads to higher emissions (assuming $\omega_2 > 0$, i.e. provided production is not carbon-free), higher total damages from climate change and higher marginal damages, thus higher benefits from emissions abatement. Future climate benefits of mitigation and future consumption are positively correlated.

Obviously, the fact that damages are assumed to be proportional to pre-damage aggregate income Y plays an important role in this calibration. It is a built-in mechanism towards a positive β. Let us therefore consider an alternative, additive damage structure with

$$q(Y, D) = Y - D$$

where D measures the absolute level of damages expressed in consumption units[18]. In other words, for given warming, doubling pre-damage income has no effect on absolute climate damage. However, the above intuition still applies: increasing income/production results in an increase in emissions as long as $\omega_2 > 0$, which in turn increases temperature and marginal climate damages, if the damage function (Eq. 2.12) is convex. So the benefit of mitigation is increased

[17] The literature on the total economic cost of climate change indicates that it might be at most 5% of GDP when T = 3°C (IPCC, 2014; Tol, 2009).

[18] The damage function (Eq 2.12) parameter α would need to be recalibrated in order to yield the same absolute damages as in the multiplicative case, for given warming.

accordingly. What difference then does the additive structure make? When the only source of uncertainty is Y,

Equation 2.19

$$\beta \approx \frac{(k-1)(Y-D)}{Y-kD}$$

It is interesting to compare Eqs. 2.18 and 2.19, i.e. our estimates of β under multiplicative and additive damages respectively. These two equations are not immediately comparable in fact, because D is expressed in percentage points in the former and in consumption units in the latter. If we express the damage in Eq. 2.19 in percentage points, $D^{\%} = D/Y$, it can be rewritten as

Equation 2.20

$$\beta \approx \frac{(k-1)(1-D^{\%})}{1-kD^{\%}}$$

Eq. 2.20 is now directly comparable with Eq. 2.18 and it is clear that the difference lies in replacing k in 2.18 with $k-1$ in 2.20. Thus, the numbers in Table 2.1 also apply in the additive case, except that all betas appearing in this table should be reduced by 1. This means that $\beta < 0$ when $k = 0.5$. We summarise these results in the following proposition:

Proposition 2. Suppose that the main source of uncertainty is emissions-neutral technological progress, and that climate damages are small ($D \leq 5\%$). Then in (a) the multiplicative case, the climate β can be approximated by k, the elasticity of climate damages with respect to warming. In (b) the additive model, the climate β can be approximated by $k - 1$.

Conversely when climate damages are large, there is no short-cut to using Eqs. (2.18) and (2.20) in the multiplicative and additive cases respectively to estimate the climate β. Either way, our analysis shows the classical multiplicative model of climate damages has a built-in mechanism towards producing a positive climate β, which is dampened in the additive model. In fact, our analysis shows that there are two independent channels that generate a positive β in the multiplicative case:

- **convexity effect**: An increase in Y results in higher cumulative emissions E. This in turn increases marginal climate damage – thus the marginal benefit of mitigation – if the damage function (Eq 2.12) is convex, i.e. if $k > 1$;
- **proportionality effect**: An increase in Y raises damages directly if damages are proportional to Y.

We believe that these two explanations for a positive β in this context have their own merit. The bottom line is that the climate β is positive in this context.

<u>The climate β when the main source of uncertainty is related to the carbon-climate-response and/or the damage intensity of warming</u>

By contrast, let us now suppose that the only source(s) of uncertainty are the CCR parameter ω_1 and/or the damage intensity of warming α. Differentiating the system (2.16) with respect to ω_1 we obtain

Equation 2.21

$$\beta \approx \frac{d \ln B \ /d\omega_1}{d \ln C \ /d\omega_1} = \frac{d \ln B \ /d\alpha}{d \ln C \ /d\alpha} = \frac{q}{q_D} \frac{q_D + Dq_{DD}}{Dq_D}$$

where q and its partial derivatives appearing in this equation are again evaluated at (Y, hY^k). The approximation is exact when the uncertainty affecting ω_1 is small. Exactly the same expression for β is obtained when assuming that α rather than ω_1 is uncertain, as examined by Sandsmark and Vennemo (2007) and Daniel et al. (2016). Therefore Eq. 2.21 shows how uncertainty about the CCR and the damage intensity of warming affect the climate β. Observe that in both the multiplicative and additive models, q_{DD} = 0, so that this equation simplifies to:

Equation 2.22

$$\beta \approx \frac{q}{Dq_D}$$

which is unambiguously negative. The intuition for this result is that a higher CCR results in more warming for given cumulative carbon emissions, which in turn yields at the same time higher marginal damage and lower aggregate consumption. Therefore, the uncertainty affecting the CCR results in a negative correlation between B and C, and a negative climate β. Similarly, a higher damage intensity of warming results in greater damages for given emissions, and so on.

Proposition 3. The climate β is unambiguously negative when the main sources of uncertainty are the carbon-climate response and/or the damage intensity of warming.

This result is independent of whether climate damages are additive or multiplicative in relation to aggregate consumption. For example, in the multiplicative case $q = Y(1 - D)$, the climate β is approximately equal to $-(1 - D)/D$. The same approximation holds in the additive case[19]. If we expect climate damage of around 5% of GDP, we should use a climate β of around –19. There is also an explanation for why the climate β is so large in absolute value in this context. Take the limiting case ω_1= 0 as a benchmark and examine the impact of a marginal increase in its value. This will have a marginal (negative) effect on log consumption, but an unbounded effect on the marginal log benefit, since the initial benefit is zero. In other words, fluctuations in ω_1 yield limited relative fluctuations in consumption, but wild relative fluctuations in marginal benefits. This yields a large β in absolute value.

Overall, this analysis illustrates that uncertainty about technological progress on the one hand and about the carbon-climate response and damage intensity of warming on the other hand most likely have contrasting effects on the climate β, the former positive, the latter two negative. This explains the contradictory conclusions that can be found in the literature. Sandsmark and Vennemo (2007) and Daniel et al. (2016) propose models, in which there is no macro-economic uncertainty independent of climate change. Sandsmark and Vennemo (2007) concluded that fighting climate change has a negative CCAPM β. Daniel et al. (2016) corroborate the result of Sandsmark and Vennemo (2007), by showing that the social cost of carbon is increasing in risk aversion in their model. But Nordhaus (2011) contradicts these conclusions by modelling benefits of mitigation that are positively correlated with aggregate consumption. We propose that

[19] Indeed, assuming $q = Y - D$, Eq. 2.21 yields $\beta \approx -(Y - D)/D$. This is equal to $-(1 - D^{\%})/D^{\%}$, where $D^{\%} = D/Y$ is the damage expressed as a fraction of Y.

this contradiction rests in the fact that the Monte-Carlo simulations in Nordhaus (2011) include a source of uncertainty about emissions-neutral technological progress, and it can also be attributed in part to the fact that DICE/RICE deploys a multiplicative damage structure.

4. Estimating beta with DICE

We now develop estimates of the β of CO_2 emissions abatement using a modified version of William Nordhaus' well-known DICE model. The advantages of using an IAM include: we can obtain more empirically grounded estimates of the climate β, albeit the empirical basis of IAMs has been criticised (e.g. Stern (2013); Pindyck (2013)); we can obtain estimates of the term structure of β; and DICE can incorporate a broader range of uncertainties than our analytical model. Another advantage is that DICE is a dynamic model, in which future consumption depends in part on current output through current savings and investment. This introduces a new set of effects on the β, which we describe below. We can also generalise the form of the damage function, so that we can consider the pure multiplicative and additive cases, as well as cases between and beyond these. Naturally the disadvantage of using an IAM is that the workings of the model are less transparent.

Table 2.2: Uncertain parameters of modified DICE-2013R

Parameter	Functional form	Mean	Standard deviation	Source	Effect on β (likely)
Initial trend growth rate of TFP (per year) g_0^A	Normal	0.016	0.009	Maddison project and other sources (see text)	+
TFP shock (per five years) ε	Normal	0	0.06	Maddison project and other sources (see text)	+
Asymptotic global population (millions)	Normal	10 854	1 368	United Nations (2013)	-
Initial rate of decarbonisation (per year)	Normal	-000102	0.0064	IEA (2013)	(+)
Price of back-stop technology in 2050 US$/tCO2 (2010 prices)	Log-normal	260	51	Edenhofer et al. (2010)	+
Uptake of atmospheric carbon by the upper ocean and biosphere (per five years)	Normal*	0.06835	0.0202	Ciais et al. (2013)	(-)
Climate sensitivity °C per doubling of atmospheric CO2	Log-logistic**	2.9	1.4	IPCC (2013)	(-)
Damage function coefficient α_2 (% GDP)	Normal	0.0025	0.0006	Tol (2009)***	(-)
Damage function coefficient α_3 (% GDP)	Normal	0.082	0.028	Dietz and Asheim (2012)	(-)
Income elasticity of damages ξ	Normal	1	0.33	Anthoff and Tol (2012)	(+)

Notes: * Truncated from above at 0.1419. **Truncated from below at 0.75. ***Including corrigenda published in 2014.

DICE couples a neo classical growth model to a simple climate model. Output of a composite good is produced using aggregate capital and labour inputs, given exogenous total factor productivity (TFP). However, production also leads to CO_2 emissions, which are an input to the climate model, resulting in an increase in the atmospheric concentration of CO_2, radiative forcing of the atmosphere and an increase in global mean temperature. The climate model is coupled back to the economy via a damage function, which is a reduced-form polynomial equation associating an increase in temperature with a loss in utility, expressed in terms of equivalent output.

Our analysis is based on the 2013 version of the model (Nordhaus & Sztorc, 2013). We randomise ten parameters to estimate the climate β (details in Table 2.2). These parameters represent key uncertainties at all stages in the (circular) chain of cause and effect that links baseline economic and population growth with CO_2 emissions, the climate response to emissions, damages and the costs of emissions abatement. Our parameter selection is informed by, but extends, past studies with DICE, which provide evidence on the most important uncertainties (Anderson, Borgonovo, Galeotti, & Roson, 2014; Dietz & Asheim, 2012; Nordhaus, 2008).

We implement a CO_2 emissions reduction project by removing one unit of industrial emissions in 2015[20]. For reasons of computational tractability, we assume that the marginal propensity to save is exogenous and we use Nordhaus'(2013) time series of values, whereby the savings rate is always c. 0.23 − 0.24. Previous research (Golosov, Hassler, Krusell, & Tsyvinski, 2014; Jensen & Traeger, 2014), as well as our results below, indicate that endogenous savings decisions would not have a major effect on the results. We take a large Latin Hypercube Sample of the parameter space, which has the advantage of sampling evenly from the domain of each probability distribution, with 50,000 draws. The parameter distributions are assumed independent.

Most of the technical details of the parameter scheme are relegated to the Supplementary Material. However, we make two changes to the structure of standard DICE that are worth detailing here.

<u>TFP growth</u>

As a neo classical growth model, DICE allocates to TFP the portion of output that cannot be explained by capital and labour inputs at their assumed elasticities (0.3 and 0.7 respectively). It follows that TFP growth plays a very significant role in determining GDP growth and therefore future consumption and CO_2 emissions (Kelly & Kolstad, 2001). As discussed in the climate beta, the effect on β of variation in TFP growth should be positive.

In DICE, the equation of motion for TFP is

$$A_t = A_t(1 + g_t^A)$$

where A is TFP and g^A is the growth rate of TFP.

We depart from standard DICE, however, in how we specify the evolution of g_t^A so that we can distinguish two sources of TFP uncertainty. In particular, we assume that g_t^A evolves according to a transformed first-order autoregressive process with an uncertain trend:

Equation 2.23

$$g_t^A = [(1 - \psi)g_0^A + \psi g_{t-1}^A + \varepsilon_t](1 + \delta^A)^{-t}$$

[20] This amounts to one gigatonne of CO_2 (Gt CO_2). Since the atmospheric concentration of CO_2 in 2015 is estimated by DICE to be c. 31.67GtCO_2, it may indeed be regarded as a marginal reduction, consistent with the definition of β given above.

Where g_0^A is the uncertain trend growth rate, ε is an independent and identically distributed (i.i.d.) normal shock and ψ is the coefficient of persistence of shocks, which is assumed certain/fixed. This AR(1) process is multiplied by the factor $(1 + \delta_A)^{-t}$, which is a feature of standard DICE. The parameter δ_A is an assumed rate of decline of TFP growth. It is several times smaller than the expected value of g_0^A [21].

We estimate g_0^A, ψ and ε using data on historical TFP growth. Since we are forecasting more than two centuries into the future, we want a very long-run series of historical TFP growth, so we use data from the US and UK over the period 1820–2010, compiled from multiple sources[22]. The coefficient of persistence in this time series is ψ = 0.42. The estimates of g_0^A and ε can be found in Table 2.2[23].

Damage function

Damages are one of the most contestable elements of IAMs. By virtue of its accessibility and simplicity in this regard, DICE has become the common means to give expression to competing views. Much of the debate stems from the inability to constrain a reduced-form damage function at warming of more than 3°C, due to the lack of underlying studies. Antipodes in the literature are given by the traditional quadratic form of Nordhaus (2008, 2013) and the damage function proposed by Weitzman (2012), in which damages are much more convex with respect to warming. However, the curvature of the damage function is not the only issue. As the previous section showed, the climate β also depends on the income elasticity of damages.

Our damage function takes the following flexible form:

$$D_t = Y_t\left[1 - \frac{1}{1 + \alpha_1 T_t + \alpha_2 T_t^2 + (\alpha_3 T_t)^7}\right]\left(\frac{Y_t}{Y_0}\right)^{\xi-1}$$

where D is damages as a percentage of GDP, Y is pre-damage output, α_i, $i \in (1, 2, 3)$, are coefficients and ξ is the income elasticity of damages (following the specification in van den Bijgaart et al. (2016). If ξ = 1 then the damage function is multiplicative like standard DICE, whereas if ξ = 0 it is additive.

We specify both α_2 and α_3 as random parameters (α_1 = 0 as usual). The former coefficient enables us to capture uncertainty about damages that is represented by the spread of existing estimates at warming of 2-3°C (summarised in Tol (2009)[24]. The coefficient α_3 may be calibrated so as to capture the difference in subjective beliefs of modellers about how substantial damages may be at higher temperatures (given there are virtually no existing estimates). We follow Dietz and Asheim (2012) in specifying a normal distribution for α_3 that spans existing suggestions: at

[21] Standard DICE simply assumes that $g_t^A = g_0^A\ (1 + \delta_A)^{-t}$. Nordhaus (2008) and Dietz and Asheim (2012) randomised g_0^A in this structure, meaning that all the uncertainty about future TFP stems from the initial trend and that this uncertainty is very large.

[22] Bolt and Van Zanden (2013); US Census Bureau; US Bureau of Economic Analysis; Feinstein and Pollard (1988); R. C. O. Matthews, Feinstein, and Odling-Smee (1982).We would like to acknowledge the help of Tom Mc Dermott and Antony Millner in collecting these data, although the resulting estimates are our responsibility.

[23] In terms of whether the historical time series conforms with an AR(1) process, we fail to reject the null hypothesis that there is no serial correlation in ε_t, using both Durbin's alternative test and the Breusch-Godfrey test. Based on the Ljung-Box portmanteau test, we reject the null hypothesis that ε_t is white noise, however further inspection of the time-series of ε_t indicates that the heteroskedasticity is caused by noisy data around World War II, rather than a secular trend.

[24] α_2 is also equivalent to the stochastic parameter in the model proposed by Sandsmark and Vennemo (2007).

three standard deviations above the mean total damages approximate Weitzman (2012), while at three standard deviations below the mean they approximately reduce to standard quadratic damages.

Empirical evidence to directly inform ξ is limited to a study by Anthoff and Tol (2012), which used the FUND IAM to estimate ξ disaggregated by region and impact type. Other IAMs like standard DICE cannot be used to estimate ξ, because of course they assume a multiplicative structure. The estimates in Anthoff and Tol (2012) suggest that ξ is normally distributed and centred around the multiplicative case ($\xi = 1$).

Since α_2 and α_3 determine the damage intensity of warming, the main effect of an increase in one or both will be a decrease in β, for a given path of output (cf. Proposition 3). However, unlike the simple model of the previous section, the path of output is not given in a dynamic economy like that of DICE. Instead, when higher damages at time t reduce output at t, there is a knock-on, negative effect on investment at t, which reduces pre-damage output at future times[25]. All else being equal, this negative effect on future pre-damage output will reduce future emissions, damages and the benefits of mitigation. Therefore the direction of the overall main effect of an increase in α_2 and α_3 on β cannot be determined a priori. Nonetheless, we might suppose the direct negative effect on β dominates. In addition to the main effect of α_2 and α_3 on β, they likely interact with other uncertainties. In particular, the previous section showed that the effect of uncertainty about emissions-neutral technological progress on β is more positive, the higher is the curvature of the damage function.

The main effect on β of variation in ξ is similar. For a given output path, an increase in ξ results in an increase in damages, hence a decrease in consumption and an increase in the benefits of mitigation. This decreases β, but again the output path is not given. The previous section showed that ξ has an important interaction effect too: we would expect the positive effect of TFP uncertainty on β to be larger, the higher is ξ.

<u>Effect on β of remaining uncertainties</u>

In addition to our treatment of TFP growth and damages, here is a brief summary of how each of the other uncertain parameters in Table 2.2 is expected to affect the climate β.

- Since DICE has a neoclassical (Cobb-Douglas) production function, an increase in population growth reduces capital intensity and hence pre-damage output per capita. But although β depends on consumption and benefits measured on a per-capita basis (see The CCAPM beta), the effect of population growth on the aggregate scale of the economy also matters. A faster-growing population means a bigger economy on aggregate, higher emissions and higher total and marginal damages. This reduces post- damage consumption per capita and raises the benefits of mitigation. Therefore, population growth should have a negative effect on β.

- While growth in CO_2 emissions is proportional to growth in GDP in IAMs like DICE, the proportion is usually assumed to decrease over time due to structural change away from carbon-intensive production sectors and decreases in emissions intensity in a given sector. These are baseline trends, i.e. achieved without the imposition by a planner of a

[25] We can be sure of this, since the marginal propensity to save is exogenous.

price/quantity constraint on emissions. A priori, variation in the rate of decarbonisation has an ambiguous effect on β. For a given path of output, an increase in the rate of decarbonisation reduces the benefits of mitigation, because it lowers emissions and hence total and marginal climate damages. But lower damages increase current income and hence they increase capital investment, future consumption, emissions and damages. So while there is no doubt that an increase in the rate of decarbonisation increases consumption, what happens to the benefits of mitigation depends in principle on the balance between the negative effect on marginal damages of a reduction in emissions intensity and the positive effect on marginal damages of an expansion in production.

- While β is a measure of the correlation of the marginal benefits of emissions abatement with consumption, and therefore abatement costs do not play a direct role in its calculation, they nonetheless play an indirect role, since the emissions scenario on which the mitigation project is undertaken may involve abatement. Variation in abatement costs increases β: an increase in abatement costs, for a given quantity of abatement, decreases income/consumption, but by decreasing income it also decreases industrial emissions in the long run, through the investment channel. This reduces the benefits of mitigation.

- There are numerous uncertainties, many of them large, about the behaviour of the climate system in response to carbon emissions (IPCC, 2013). In the structure of DICE's simple climate model, these can be grouped into two types. The first type is uncertainties about the carbon cycle, which render estimates of the atmospheric stock of CO_2 for a given emissions scenario imprecise. We focus on variation in the uptake of atmospheric carbon by the upper ocean and biosphere, which also has an ambiguous a priori effect on β. Consider a decrease in this uptake, which means that more CO_2 emissions remain in the atmosphere. Under these circumstances, if the path of pre-damage output is taken as given, then more atmospheric CO_2 means increased total damages, hence consumption is reduced, and the marginal benefits of mitigation are increased. This reduces β. However, to reiterate, the investment effect means that the path of pre-damage output is not given; reduced income at a particular date due to greater damages results in lower investment, which depresses future output. This reduces future consumption too, but because it reduces future CO_2 emissions there is a countervailing, negative effect on the benefits of mitigation. Again, we might expect the direct effect to dominate, so variation in the uptake of atmospheric carbon should reduce β.

- The second type of uncertainty about the climate system is about the relationship between the stock of atmospheric CO_2 and global mean temperature[26]. Studies that deploy stochastic versions of DICE have overwhelmingly fixed on the climate sensitivity parameter as a means of rendering uncertain the temperature response to atmospheric CO_2. Climate sensitivity is the increase in global mean temperature, in equilibrium, that results from a doubling in the atmospheric stock of CO_2 from the pre-industrial level. In simple climate models, it is indeed critical in determining how fast and how far the planet is forecast to warm in response to emissions. Variation in climate sensitivity has an ambiguous – but likely negative – effect on β, with the causal mechanisms being very similar to those at play in the carbon cycle. Higher climate sensitivity means higher damages, lower consumption and higher benefits of mitigation for given output, but with

[26] Note that together these two types of uncertainty make up the carbon-climate response in the previous section.

lower income comes lower investment, lower future output and therefore a counter-balancing negative effect on future emissions that tends to reduce the benefits of mitigation.

7. Results and discussion

Using the 50,000 draws of the Monte Carlo simulation as the source of variation, we can calculate the instantaneous consumption β of CO_2 emissions abatement. As a function of time, we can then plot its term structure.

Define the benefits of emissions abatement as its avoided damages, in particular as the difference in consumption per capita with and without removing 1GtCO_2. The benefits of abatement B are then given by:

$$B_t = c_t - c_t^{REF}$$

$$B_t = (1 - s_t)(1 - D_t)y_t - (1 - s_t)(1 - D_t^{REF})y_t^{REF}$$

where c is consumption per capita, y is pre-damage output per capita, REF denotes reference outcomes before 1GtCO_2 is removed and s is the savings rate. Note that output here is net of abatement costs.

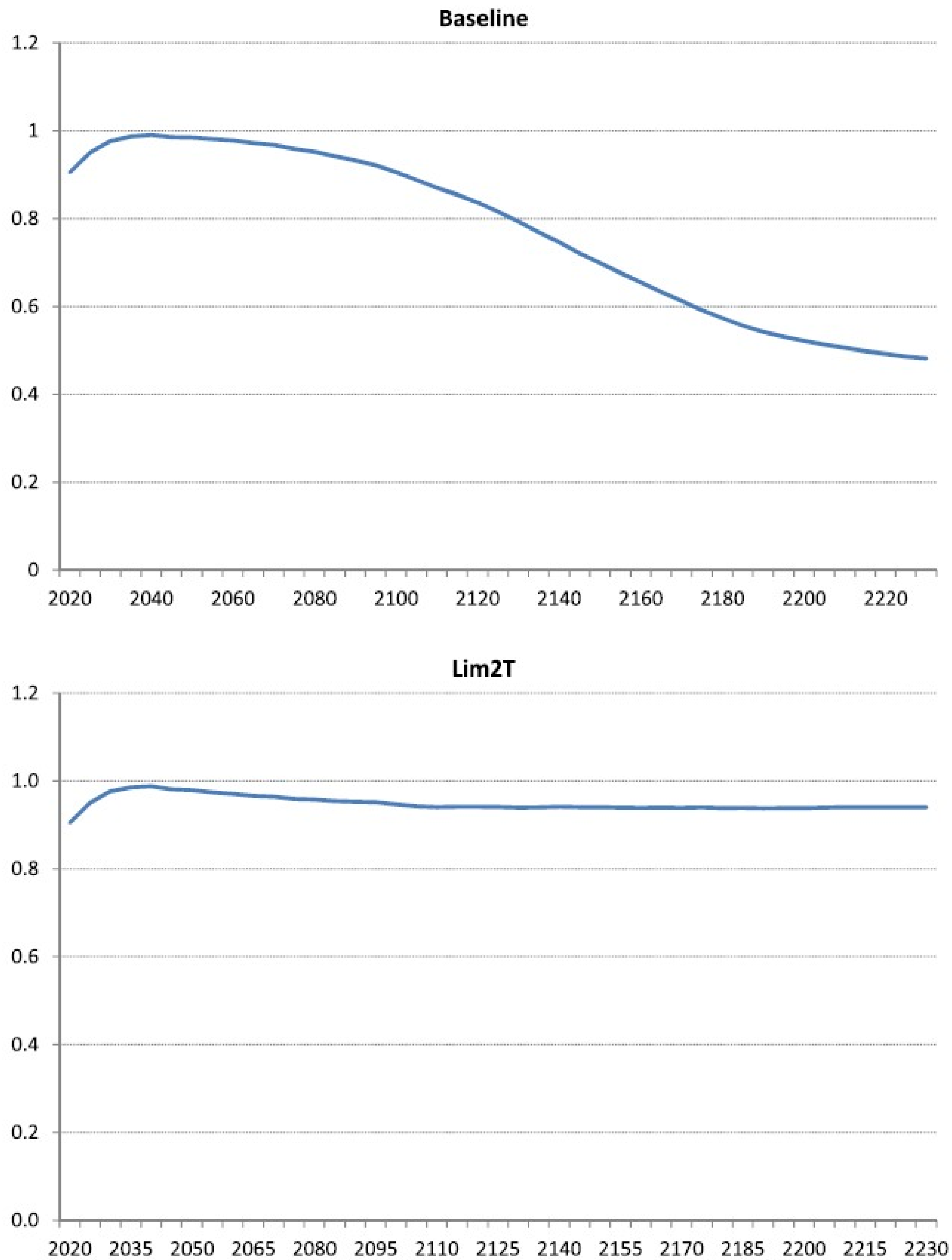
β_t is then the covariance between ln c_t^{REF} and ln B_t , divided by the variance of ln c_t^{REF}:

$$\beta = \frac{cov[\ln c_t^{REF}, \ln B_t]}{var[\ln c_t^{RE}\ \ ]}$$

The discussion above gives us reason to suppose that, in a dynamic model, the β of CO_2 emissions abatement might depend on the path of growth and emissions. Many of the parameter choices we have already described will impact on this, for instance the various determinants of TFP growth, and the initial rate of decarbonisation. But one set of exogenous variables that we must still choose is the emissions reductions imposed by the planner. Therefore, in Figure 2.1 we plot the term structure of β for two different emissions control scenarios. The first scenario corresponds to the baseline in DICE-2013R, which is a representation of 'business as usual'. According to this scenario, emissions reductions rise gradually from 4% of uncontrolled industrial emissions in 2015 to 14% in 2100 and 54% in 2200. Hence emissions abatement is non-trivial even in the baseline[27]. The second scenario is an example of a path in which emissions reductions are deep: it is the so-called 'Lim2T' scenario from DICE-2013R, in which the planner seeks to limit global warming to no more than 2°C. In Lim2T, emissions reductions are already 33% in 2015 and they hit the maximum 100% in 2060[28].

[27] Which illustrates why abatement costs might affect β even in the baseline scenario.
[28] While the changes we have made to DICE-2013R in this study mean that Lim2T is no longer guaranteed to deliver warming equal to 2°C, for the purpose of estimating β it is a perfectly good example of a stringent mitigation scenario.

Figure 2.1: The term structure of β_t for two contrasting emissions scenarios.



The headline result is that on both emissions scenarios β is positive. Overall, given the various uncertainties we specify, there is a positive correlation between consumption and the benefits of emissions abatement. Indeed, over the remainder of this century, the magnitude of β is quite similar on what are two very different emissions paths; it is between 0.9 and 1. However, the term structure of β on the two emissions paths is different and this difference starts to matter after 2100. In the baseline scenario, β falls monotonically to 0.48 in 2230. In the Lim2T scenario, β remains between 0.9 and 1 throughout.

What is behind these results? To answer this question, we perform repeated Monte Carlo simulations of the baseline scenario with subsets of the uncertain parameters and re-estimate the term structure of β. The results can be found in Table 2.3 for selected years. Where a parameter is treated as certain, it is fixed at its mean value. First, we treat all the model parameters as certain, except for the TFP shocks ε_t. Then we run through the remaining uncertain parameters, one at a time, and combine each with the TFP shocks.

Table 2.3: Estimates of βt on the baseline scenario in selected years, for different subsets of uncertain parameters

Uncertain parameters	2025	2065	2115	2165	2215
TFP shocks	1.02	1.06	1.06	1.05	1.05
TFP shocks + initial trend growth rate of TFP	1.02	1.06	1.06	1.05	1.05
TFP shocks + asymptotic global population	1.02	1.06	1.06	1.05	1.05
TFP shocks + initial rate of decarbonisation	1.02	1.06	1.06	1.05	1.05
TFP shocks + price of back-stop technology in 2050	1.02	1.06	1.06	1.05	1.05
TFP shocks + uptake of atmospheric carbon by the upper ocean and biosphere (per five years)	1.02	1.05	1.05	1.04	1.04
TFP shocks + climate sensitivity	1.00	1.01	0.93	0.85	0.78
TFP shocks + damage coefficient α_2	0.95	1.04	1.04	1.03	1.03
TFP shocks + damage coefficient α_3	1.02	1.06	1.09	1.10	1.10
TFP shocks + income elasticity of damages	1.01	1.05	1.03	0.01	1.00
TFP shocks + climate sensitivity + α_2 + α_3 + income elasticity of damage ξ	0.95	0.98	0.86	0.67	0.55
All	0.95	0.97	0.85	0.63	0.49

What emerges clearly from Table 2.3 is that the driver of positive β is uncertainty about TFP growth. Moreover, it is specifically the transitory shocks to TFP, allied with their moderate persistence, that do it, rather than uncertainty about trend TFP growth. If we run the model just with TFP shocks, β = 1.02 in 2025, 1.06 in 2115 and 1.05 in 2215. Most of the remaining uncertainties make no discernible difference to β when combined individually with TFP shocks: trend TFP growth; population growth; the rate of decarbonisation; abatement costs; and uptake of atmospheric CO_2. Including uncertainty about the damage function coefficient α_2 or the income elasticity of damages reduces β very slightly, while including uncertainty about the damage function coefficient α_3 increases it very slightly[29].

The one source of uncertainty that does have a significant effect on the β obtained with TFP shocks alone is the climate sensitivity. The effect is negative. However, this negative effect is not enough to pull β much below unity this century, so the effect of TFP shocks dominates. When the model is run with TFP shocks and uncertain climate sensitivity, β = 0.93 in 2115 and 0.78 in 2215.

At the foot of the table we reproduce the simulation in which all parameters are uncertain. In this simulation, β does fall to 0.63 in 2165 and eventually 0.49 in 2215. The penultimate simulation in the table shows that this is mostly accounted for by combining just five uncertainties: TFP shocks; climate sensitivity; α_2; α_3; and the income elasticity of damages. These

[29] This implies that when the only sources of uncertainty are TFP shocks and α_3, the positive interaction between $\alpha 3$ and the TFP shocks dominates the main, negative effect of α_3 on β.

analyses also help us explain why β has a different term structure on the Lim2T emissions scenario than it has on the baseline. On Lim2T the atmospheric concentration of CO_2 is much lower than on the baseline, so the negative effects on β of the climate sensitivity and damage parameters are lower. Consequently, β does not decline after the beginning of the next century.

Discussion of results

In this paper we have studied the sign and size of the climate β, using both a simple analytical model and an empirically grounded Monte Carlo simulation of the DICE model. Using the DICE model also enabled us to take into account the effects on the climate β of investment, as well as generalising the form of the damage function. Our results strongly suggest that the climate β is positive. In particular, our numerical modelling with DICE suggests it is positive and close to unity for maturities of up to about one hundred years. Beyond that, the climate β depends more strongly on the emissions path. On business as usual it falls to about 0.5 for maturities of two hundred years or more, while it remains close to unity on a path of deep emissions cuts that aims to limit warming to 2°C. One might think that reality will turn out to be somewhere between these two extreme cases (e.g. UNEP (2015)), hence the climate β for very long maturities is somewhere between 0.5 and 1.

The overwhelming driver of these results is uncertainty about exogenous, emissions-neutral technological progress in the shape of transitory but moderately persistent shocks to TFP. Positive TFP shocks are simultaneously associated with higher marginal benefits of emissions reductions and higher consumption. Uncertainty about climate sensitivity and the damage intensity of warming provide a countervailing effect that tends to reduce β, but it is outweighed by the effect of TFP shocks. It is important to remember that we allow for fat-tailed climate sensitivity and large convexity of the damage function, two of the principal sources of risk of catastrophic climate damages, which have been claimed to give rise to a negative β.

Naturally the validity of our numerical estimates is affected by the well-known weaknesses shared by all IAMs (e.g. Pindyck (2013) and Stern (2013)). In addition, we face the particular issue of whether and to what extent damages are proportional to output. The basic assumption embodied in a multiplicative damage structure is that damages are a constant fraction of output, for given warming and damage intensity. By contrast, in an additive structure the share of damages in output decreases as output increases, and vice versa. Therefore it is related to the so-called 'Schelling conjecture' that developing countries "best defence against climate change may be their own continued development" (Schelling, 1992, p. 6). A simple analytical model of the climate beta made clear that if climate damages are better represented by an additive structure, then the conditions required for a positive climate β are stricter. However, the empirical evidence we used to calibrate the income elasticity of damages in DICE does not support this (Anthoff & Tol, 2012). Rather, it suggests that the income elasticity of damages in most regions at most times is greater than zero and often greater than one, without strong support for a central value other than one. The worry is that the empirical evidence is currently very thin, and more research is clearly required on this issue.

Understanding the implications of our findings for climate mitigation requires understanding the dual role played by β in determining the NPV of mitigation. It is most straightforward to observe that positive β implies the future benefits of emissions abatement should be discounted at a relatively higher rate. How much higher?

Two approaches can be followed to answer this question, with radically different conclusions. Both approaches use the CCAPM rule $r = r_f + \beta\pi$. The first approach consists in using the systematic risk premium π that has been observed in markets, for instance in the United States over the last century, where it has been around 5% (see Gollier (2013, Chapter 12)). For a project with a unit β, this means the efficient discount rate for that project should be five percentage points higher than the risk-free rate. The second approach is model-based rather than market-based; one uses the CCAPM formula $\pi = \gamma\sigma^2$ to estimate the risk premium, where σ^2 is the volatility of consumption growth estimated in DICE. According to our simulations, $\sigma^2 = 0.1\%$ with respect to average growth over the period 2015-2230, so we obtain a risk premium of only 0.2 percentage points if we accept a coefficient of relative risk aversion $\gamma = 2$, which much of the existing literature would suggest (Kolstad et al., 2014). This leads to a much smaller impact of the positive climate β on the risk-adjusted climate discount rate.

The large discrepancy between these two recommendations may be seen as a manifestation of the well-known "equity premium puzzle". Three decades of research on this financial puzzle suggest that the model-based CCAPM approach fails to capture many dimensions of the real world, in particular the existence of structural uncertainties and fat tails (Weitzman, 2007b). Although including these dimensions in our model is beyond the reach of this paper – a new concept of β will need to be developed to accommodate these features – we are inclined to accept this position. We then conclude that a large positive climate β is important for discounting the future benefits of mitigating climate change.

But this is not the end of the story. The CCAPM beta showed that the NPV of climate mitigation is increasing in β if β is larger than $\gamma - (\mu/\sigma^2)$, which is at most of the order of -2.5. Since our estimates are clearly larger than that, it can be concluded that the NPV of climate mitigation is indeed increasing in β. More broadly, this shows that the implications of our work do not just concern the discount rate. It would be wrong to discount the future benefits of emissions abatement at a risk-adjusted rate with unit β, unless the undiscounted future benefits have been calculated in a way that properly factors in, implicitly or explicitly, how they scale with economic growth.

8. Conclusion and policy implications

Because a large fraction of the climate damages generated by greenhouse gases emitted today will not materialise until the distant future, the choice of the rate at which these future damages should be discounted plays a critical role in the determination of the social cost of carbon. Most of the recent literature on climate discounting implicitly assumes that these damages are uncorrelated with aggregate consumption, so that they should be discounted at the risk-free rate. This justifies using either the Ramsey rule or the observed interest rate to estimate the climate discount rate. However, we show in this paper that the climate β, i.e. the elasticity of climate damages with respect to a change in aggregate consumption, is close to one, at least for maturities of up to one hundred years. This is mainly due to the role of exogenous, emissions-neutral technological progress in raising consumption, emissions, atmospheric carbon and marginal damages. This implies that mitigating climate change raises the risk borne by future generations, which justifies using a climate discount rate that is larger than the risk-free rate. How much larger depends on our evaluation of the equity premium puzzle in finance. That the climate

β is relatively large should induce climate economists to change the focus of long-term discounting from safe to risky claims.

A large climate β not only implies a large climate discount rate. Indeed, the climate β measures the sensitivity of monetized climate damages to a change in consumption of other goods and services in the economy. In a growing economy, a large climate β also implies large expected damage in the long run. As we have shown, under the standard assumptions of the CCAPM, the value of an asset whose future benefit $B_{t|t\geq 0}$ is related to future aggregate consumption $c_{t|t\geq 0}$ in such a way that for all t there exists $\beta_t \in \mathbb{R}$ such that $[B_t|c_t] = c_t^{\beta t}$ is locally increasing in β_t if it is larger than the difference between relative risk aversion and the ratio of the mean by the variance of the growth rate of consumption. Because most actions yield a β_t which is larger than this number, this means that an increase in the climate β increases expected damages more than it reduces the discount factor, so that in fact the social cost of carbon is increasing in the climate β.

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APPENDICES

Appendix 2.1: Further details of random parameters in DICE-2013R

Asymptotic global population. In DICE population grows according to the following equation of motion:

$$L_{t+1} = L_t \left(\frac{L_\infty}{L_t}\right)^{g^N}$$

where L is the population, which converges to the asymptotic global population L_∞ according to the growth rate g^N. We use the global population projections of the United Nations (2013) to calibrate a probability distribution over L_∞. According to these projections, the world population will be at an approximate steady state of 10.85 billion in 2100 on the medium (fertility) variant, within a range of 6.75 billion on the low variant to 16.64 billion on the high variant. This is a non-probabilistic range, which can be set against an emerging – though not uncontested (Lutz, Butz, Samir, Sanderson, & Scherbov, 2014) – field of probabilistic population forecasting based on Bayesian methods (Raftery, Li, Ševčíková, Gerland, & Heilig, 2012). According to these forecasts, the UN's low and high variants are very unlikely to eventuate (i.e. they are suggested to be well outside the 95% confidence interval: Gerland et al. (2014)), because they assume fertility is systematically different to the medium scenario in all countries. Taking this perspective into account, we fit a normal distribution to the UN population projections, such that the low variant is three standard deviations away from the mean, with the result that the high variant is even further from the mean.

Initial rate of decarbonisation. In DICE, autonomous decarbonisation is achieved by virtue of a variable representing the ratio of emissions/output, which decreases over time as a function of a rate-of-decarbonisation parameter:

$$E_t^{IND} = \sigma_t(1 - \mu_t)Y_t$$

where E^{IND} represents industrial CO_2 emissions, μ is the control rate of emissions set by the planner, Y is pre-damage output and s is the ratio of uncontrolled emissions to output, given by

$$\sigma_{t+1} = \sigma_t(1 + g_t^\sigma)$$

where $g^\sigma < 0$ is the rate of decline of emissions to output, given by

$$g_t^\sigma = g_0^\sigma(1 + \delta^\sigma)^t$$

with the initial rate of decline of emissions to output being g_0^σ, subject itself to a rate of decline of $\delta^\sigma < 0$. Similar to TFP, δ^σ is around an order of magnitude smaller than g_0^σ, so the latter is key in driving long-run uncertainty about declining emissions intensity.

To calibrate a distribution over g_0^σ we use data from the International Energy Agency (IEA, 2013), which provides the ratio of global CO_2 emissions from fossil fuels to real global GDP for the period 1971-2011, a period in which planned emissions reductions (i.e. through μ) were trivially small at the global level. We partly smooth annual fluctuations by taking a five-year rolling average. The resulting data are fit best by a normal distribution with mean and standard deviation as reported in Table 2.2.

Price of the backstop technology. In DICE the total cost of abatement as a percentage of annual GDP, Λ, is determined by

$$\Lambda_t = \theta_{1,t}\mu_t^{\theta_2}$$

where θ_1 and θ_2 are coefficients. The time-path of θ_1 is set so that the marginal cost of abatement at μ_t = 1 t is equal to the backstop price at t. Hence randomising the backstop price is a way to introduce uncertainty into abatement costs. We use the findings of an inter-model comparison study by Edenhofer et al. (2010) to update and characterise uncertainty over the backstop price. Edenhofer et al. (2010) assess the cost of limiting warming to below 2°C in five global energy models. A scenario that stabilises the atmospheric stock of CO_2 at 400 ppm requires zero emissions by around 2050, so we can use the models' estimates of marginal abatement costs in 2050 as a measure of the backstop price at that time. Marginal costs range from \$150/tCO_2 to \$500, with an average of \$260, all at today's prices. Since the distribution of cost estimates is asymmetric, we use a log-normal distribution. We set the mean to \$260 and posit that the probability of the lowest and highest estimates is 1/1000. We use a comparable emissions scenario in DICE to retrieve, for each value of the backstop price in 2050, the value of the backstop price in 2010, the initial period.

Uptake of atmospheric carbon by the upper ocean and biosphere. The atmospheric stock of carbon in DICE is driven by the sum of industrial emissions from Eq. 2.25 and exogenous emissions from land-use. A system of three equations represents the cycling of carbon between three reservoirs, the atmosphere M^{AT}, a quickly mixing reservoir comprising the upper ocean and parts of the biosphere M^{UP}, and the lower ocean M^{LO}:

$$M_{t+1}^{AT} = E_{t+1} + \varphi_{11}M_t^{AT} + \varphi_{21}M_t^{UP}$$

$$M_{t+1}^{UP} = \varphi_{12}M_t^{AT} + \varphi_{22}M_t^{UP} + \varphi_{32}M_t^{LO}$$

$$M_{t+1}^{LO} = \varphi_{23}M_t^{UP} + \varphi_{33}M_t^{LO}$$

where total emissions of CO_2 to the atmosphere are E, and the cycling of CO_2 between the reservoirs is determined by a set of coefficients φ_{jk} that govern the rate of transport from reservoir j to k per unit of time. We follow Nordhaus (2008) uncertainty analysis by randomising φ_{12}, the coefficient for the transfer of carbon from M^{AT} to M^{UP}. However, we make use of the latest scientific findings from the IPCC's Fifth Assessment Report (Ciais et al., 2013) to calibrate φ_{12}. In particular, φ_{12} may be calibrated by inspecting evidence on the percentage of a pulse of CO_2 emissions that remains in the atmosphere after 100 years. According to the standard parameterisation of DICE-2013R, this would be c.36%, but the evidence from multiple climate models collected by Ciais et al. (2013) suggests a mean of 41%, with 54% at +2 standard deviations and 28% at −2 standard deviations. We calibrate φ_{12} accordingly, however to ensure the DICE carbon cycle maintains physically consistent behaviour at all values of φ_{12}, we must set the lower bound at 31% removed. Table 2.2 provides details.

Climate sensitivity. The equation of motion of temperature in DICE is given by:

$$T_{t+1} = T_t + \kappa_1 \left[F_{t+1} - \frac{F_{2xC\ 2}}{S}(T_t) - \kappa_2 (T_t - T_t^{LO}) \right]$$

where F_{t+1} is radiative forcing, which depends on the atmospheric stock of CO_2, F_{2xCO2} is the radiative forcing resulting from a doubling in the atmospheric stock of CO_2 from the pre-industrial level, S is climate sensitivity, T^{LO} is the temperature of the lower ocean, κ_1 is a parameter determining speed of adjustment and κ_2 is the coefficient of heat loss from the atmosphere to the oceans. Calel et al. (2015) contains a detailed explanation of the physics behind this equation.

The latest IPCC report (IPCC, 2013) provides a subjective probability distribution for the climate sensitivity, which is the consensus of the panel's many experts. According to this distribution, S is 'likely' to be between 1.5 and 4.5°C, where likely corresponds to a subjective probability of anywhere between 0.66 and 1. It is 'extremely unlikely' to be less than 1°C, where extremely unlikely indicates a probability of ≤0.05, while it is 'very unlikely' to exceed 6°C, where this denotes a probability of ≤0.1. Dietz and Stern (2015) find that a log-logistic function has the appropriate tail shape to fit these data[30] (taking the midpoints of the IPCC ranges), and set the scale and shape parameters of the distribution such that the mean S is 2.9°C, and the standard deviation is 1.4°C. In addition, we truncate the distribution from below at 0.75°C in order to again ensure that the DICE climate model exhibits physically consistent behaviour.

[30] That is, the log-logistic function has the lowest root-mean-square error of any distribution fitted.

Chapter 3: Estimating the economic impact of the permafrost carbon feedback

Abstract

The permafrost carbon feedback is not currently taken into account in economic assessments of climate change, yet it could have important implications for the social cost of carbon and the associated choice of the optimal greenhouse gas emissions pathway. Although this feedback is still imperfectly known, there are enough estimates of its potential strength to now include it in our assessments. In this paper, I present a model of the permafrost carbon feedback and integrate this feedback in the DICE Integrated Assessment Model to examine its consequences. I find that doing so increases the social cost of carbon by 10-20% in the baseline scenario, but that this impact is much more significant in the case of a damage function which is more reactive to very high temperature changes and can reach up to 220%. It follows that setting industrial emissions targets without taking into account this feedback would lead to excessive atmospheric carbon: I find that it increases the optimal emissions control rate by circa 5 percentage points on average over the period 2015-2110 and that this difference becomes much more significant when the constraint of limiting the increase in global mean temperature to +2°C or +1.5°C is added to the model.

1. Introduction

Integrated assessment models (IAMs) are meant to be simple, tractable models which can be readily used to evaluate the costs and benefits of different climate policies. However, the absence of key factors and crucial feedback loops in these models has been highlighted (Stern, 2013), to the point where some have argued IAMs are "close to useless as tools for policy analysis" (Pindyck, 2013). Indeed, IAMs are used for evaluations of policies over several centuries, despite the fact that the main carbon-climate feedbacks included in IAMs are those which enter through the climate sensitivity parameter, and which correspond primarily to the "fast" feedbacks: namely, water vapour, temperature lapse rate, surface albedo and clouds. Many other feedback processes, such as, for instance, the thawing of permafrost carbon, changes in ocean circulation and the shift of the terrestrial biosphere from a sink to a source of carbon, are not expected to become significant by the end of the 21st century. Still, these could have non-negligible impacts on global mean temperature and climate damages over the next 200 or 300 years and should be taken into account when assessing the long-term economic implications of climate change.

Research in this area has developed along several dimensions. The first dimension corresponds to studies aimed at assessing the significance of the climate and carbon components of IAMs for climate and economic outcomes (Marten, 2011; van Vuuren et al., 2011; Warren, Mastrandrea, Hope, & Hof, 2010). These have shown that the modelling of climate dynamics could have significant impacts, especially for longer-term horizons, and that the failure to capture climate dynamics correctly could lead to underestimating the benefits of mitigation policies (Hof et al., 2012).

The second line of research has aimed at investigating the economic impact of low-probability, high-damage feedbacks, such as a sudden and significant release of methane into the atmosphere. Ceronsky et al. (2011) considered the impact of three methane release scenarios on the level of climate damages and on the social cost of carbon (SCC); Whiteman et al. (2013) superposed a pulse of 50 Gt of methane on two standard emissions scenarios in order to assess the risks associated with the potential thawing of methane hydrates from the East Siberian Arctic shelf; finally, Lemoine and Traeger (2014) considered a framework in which multiple tipping points interact and represented the possibility that large methane stores locked in permafrost and in ocean shallow clathrates are mobilized by warming by increasing the equilibrium climate sensitivity parameter from 3°C to 5°C.

The third line of research has focused on exploring economic and physical uncertainties in IAMs through the use of Monte Carlo methods: Ackerman et al. (2010) explored the implications of varying simultaneously the climate sensitivity parameter and the damage function exponent using the DICE model; Pycroft et al. (2011) conducted a similar exercise using PAGE09; Calel et al. (2013) demonstrated that the uncertainty about the effective heat capacity of the upper ocean mattered significantly for economic evaluations. Finally, there have been some attempts at improving carbon cycles representation in IAMs. For instance, Glotter et al. (2014) have proposed a modification of the carbon cycle in DICE to reflect the nonlinear CO_2 uptake of the ocean.

Finally, the realisation that the permafrost carbon feedback is potentially the most important positive feedback on policy-relevant time scales that is currently not included in Earth System Models (Prentice, Williams, & Friedlingstein, 2015) and that it will very likely act as an amplifier of human-induced climate change, and, as such, it could represent significant costs to society, has led to an increase in the attention that this topic is receiving. Indeed, several articles have been published recently that testify to the growing interest for this topic both from a physical and an economic perspective. Schuur et al. (2015) provided an overview of the existing research on the permafrost carbon feedback with the aim of refining our understanding of its sensitivity to climate. Koven et al. (2015) presented a simplified approach for estimating the strength of the permafrost carbon feedback, based on a data-constrained approach, to measure the global sensitivity of frozen soil carbon to climate change on a 100 year time scale. Hope and Schaefer (2016) linked the PAGE09 economic model with the SiBCASA land surface model to examine the economic impact of carbon emissions from thawing permafrost under the A1B scenario from the IPCC Special Report on Emission Scenarios (Nakicenovic et al., 2000) and estimated that carbon emissions from permafrost increases the mean net present value of the impacts of climate change by about 13%.

Here I propose to complement this growing literature and to provide an estimate of the economic impact of the permafrost carbon feedback in the framework of the most widely used IAM, DICE, and to explore its potential impact in terms of additional warming, damages and optimal paths. Our approach is substantially different from the one used by Hope and Schaefer (2016): rather than linking an integrated assessment model to an existing biophysical land-surface model, we represent the permafrost carbon feedback by explicit functional forms, which not only enable us to simulate different emission scenarios and to solve the model for optimality, but which can also be used by other researchers.

This paper aims at answering the following questions: given what we know (and what we don't know) about the potential strength and timing of the permafrost carbon feedback, how does it change the scale of climate-induced risks that we face? And how does it impact our estimates of the social cost of carbon? If the permafrost carbon feedback is expected to make climate change happen faster than we project on the basis of human activities alone, then it is essential to integrate it into the tools used to design and evaluate climate change mitigation policies.

This chapter is organized as follows: in Section 2, I will first briefly describe what is referred to as the "permafrost carbon feedback" and provide estimates of its projected strength. In section 3, I will introduce the methodology I used to integrate it into DICE-2013R. In Section 4, I will present some results, in terms of the impact of the permafrost carbon feedback both on the social cost of carbon and on the optimal abatement path, under different assumptions and conditions. Section 5 concludes.

2. What is the permafrost carbon feedback?

Permafrost is defined as perennially frozen ground remaining at or below 0°C for at least two consecutive years (Brown, Ferrians Jr, Heginbottom, & Melnikov, 1997). It is composed of bedrock, gravel, silt and organic material that was buried and frozen during or since the last ice age (Schaefer, Lantuit, Romanovsky, Schuur, & Witt, 2014) and it occurs in about 24% of the exposed land surface in the Northern Hemisphere (Schaefer, Lantuit, Romanovsky, & Schuur, 2012). Because organic matter does not decay once the soil is frozen, it is only when temperatures rise, thus causing permafrost to thaw, that the organic matter starts to decay, releasing carbon dioxide (CO_2) and methane (CH_4) into the atmosphere, which amplifies the warming due to greenhouse gas emissions. The permafrost carbon feedback (PCF) is the amplification of anthropogenic warming due to carbon emissions from thawing permafrost, and it is irreversible on human time scales.

One of the characteristics of the PCF is the significant time lag between the trigger (global temperature increase) and the response (CO_2 release into the atmosphere). This means that even if the amount of permafrost carbon that is expected to be released by 2100 is limited, the impact that the permafrost carbon feedback will have in the 22nd and 23rd centuries will be partly determined by the level of warming during the 21st century, and therefore, by the mitigation policies implemented in the present century. As emphasized by Schneider von Deimling et al. (2012), "even more pronounced than many other components of the Earth system, the permafrost feedback highlights the lagged and slow response to human perturbations" (p. 659).

Another attribute of the PCF is that it is very likely to be a positive feedback (i.e. it will amplify climate change): indeed, although it might trigger some negative feedbacks (e.g. enhanced plant growth) that will dampen global warming, the uncertainty on the PCF is said to be "one-sided" in the sense that it will increase future climate impacts (Schneider von Deimling et al., 2012). The PCF will therefore add to other existing positive carbon-climate feedbacks (e.g. water vapour, temperature lapse rate, surface albedo, etc.) and as a result, the total effect of these feedbacks will be larger than the sum of the individual impacts. This "compounding effect" of positive feedbacks has been demonstrated by Roe (2009), who showed that the amplitude of the additional radiative perturbation that one positive feedback produces is amplified by the enhanced system response (i.e., the increased warming) the other has created, thus making the total system response even larger.

There are many different aspects in which the inclusion of positive long-term feedbacks such as the PCF is indispensable for the economic assessment of mitigation policies. Firstly, in the context of the classical approach of marginal costs and benefits analysis, adding the PCF in a climate-economy model is likely to have an impact on estimates of the social cost of carbon, which is defined as the net present value of the marginal benefit of mitigation. Secondly, climate policies are often expressed in terms of CO_2 concentration targets, thereby rendering the inclusion of the PCF even more relevant, as accounting for its effects will almost certainly increase the emissions reductions required to reach these targets (Schuur et al., 2013). Finally, if the PCF is projected to make climate change happen faster than expected on the basis on anthropogenic emissions alone, then it will also have significant implications for the timing of adaptation strategies.

3. Methodology

i. How are climate feedbacks usually characterized?

The global temperature response to an increase in atmospheric CO_2 is usually quantified using the equilibrium climate sensitivity (ECS) parameter, which is defined as the change in global mean surface temperature at equilibrium that is caused by a doubling of the atmospheric CO_2 concentration (Matthews, Gillett, Stott, & Zickfeld, 2009). However, the ECS only comprises biogeophysical feedbacks (e.g. the water vapour/lapse rate, albedo and cloud feedbacks) and does not account for biogeochemical feedbacks such as the permafrost carbon feedback. There have been a few attempts to incorporate both types of feedback into a combined metric (Frölicher & Paynter, 2015; J. M. Gregory, Jones, Cadule, & Friedlingstein, 2009; Matthews et al., 2009) but to the extent of our knowledge, all of these are based on Earth System Models which do not account for the permafrost carbon feedback.

One of the ways which has been used to quantify individual climate feedbacks has been to express them in $GtC.K^{-1}$ (Friedlingstein et al., 2006). However due to the considerable time lag between the thawing of permafrost and its actual release, the flux of permafrost that is released into the atmosphere at time (t) does not depend on the surface temperature at time (t) but on the temperature path over the previous decades/centuries. Schneider von Deimling et al. (2012) precisely point out the limitations of the "carbon pool sensitivity" indicator in the case of the PCF, as cumulative carbon releases per degree of warming are not a scenario- or time-independent characteristic: "carbon fluxes by 2300 are not only a consequence of permafrost thaw in the 23rd century but are also affected by emissions from soil thawed earlier in the 21st and 22nd century" (p.657).

For their assessment of the impact of climate feedbacks on the optimal carbon tax, Lemoine and Traeger (2014) made the choice of a tipping point framework. This does not seem like the most relevant modelling framework for the purpose of this paper as current research

(Schuur et al., 2015) supports the idea of a gradual and prolonged release of permafrost carbon emissions in a warming climate, which would mean that carbon dioxide release from permafrost carbon pools is more likely to act as an accelerator of climate change rather than a tipping point mechanism.

ii. Proposed approach – A two-phase model

We use the DICE model as the framework for our analysis of the impacts of the PCF, as it is one of the most well-known IAMs, and one which has often been used to provide estimates of the social cost of carbon. A full description of the equations and parameters of the 2013R version is available in Nordhaus and Sztorc (2013). Here we restrict our model description to the new module we introduce that mimics the PCF.

What we need is a characterisation of permafrost carbon release which is based on an accurate representation of the processes involved, but which is also suitable for inclusion in DICE-2013R, and tractable enough to explore different types of uncertainties. The majority of the published articles that aim to quantify permafrost carbon release use a two-phase approach; permafrost degradation (or thaw), followed by decomposition of thawed (or vulnerable) permafrost and release into the atmosphere as CO_2 or CH_4 (Burke, Jones, & Koven, 2013; Schneider von Deimling et al., 2015). It is worth noting that only the first phase (permafrost thaw) is directly dependent on global mean temperature: as surface temperature rises, the active layer thickness increases and the soil carbon which is no longer permanently frozen becomes vulnerable to decomposition. The second phase (decomposition of carbon and release as CO_2 or CH_4) is principally a function of the type of permafrost soil that is vulnerable to decomposition. The proposed modelling approach described below follows this two-phase approach.

iii. Phase 1 – Permafrost thaw

<u>Proposed model</u>

Permafrost thaw occurs when surface temperature is above 0°C for part of the year. Its physical representation is based on the modelling of active layer thickening, which indicates the increasing depth of the seasonal freeze thaw cycle. As near-surface soil temperatures increase with global warming, some of the permafrost soil changes phase from ice to water, thus increasing the layer of soil at the surface that thaws seasonally. Any thorough representation of active-layer thickening via heat transfers would therefore need to take into account the variety of landscapes that compose permafrost soils, highly localized hydrological processes and fine-grid projections of climate variables such as surface temperature (including the impact of polar amplification, which is not uniform over all permafrost areas) and precipitation patterns.

Because we are de facto constrained by the limitations of DICE, which is a simple and globally aggregated model, we use a model based on existing estimates of future permafrost thaw, rather than a process-based approach[31]. Based on the work by Gregory et al. (Jonathan M Gregory

[31] The major constraints we face in the choice of a suitable representation of permafrost thaw processes are those which arise from the fact that the proposed modelling will be incorporated in DICE, a simple and globally aggregated model. These constraints are manifold: there is no possibility to introduce spatial heterogeneity; the model operates in five-year time steps; and the only climatic variables are global mean surface temperature and atmospheric CO_2 concentration. These constraints therefore eliminate de facto any modelling of thawing processes that relies on a

et al., 2002), who showed that the Northern Hemisphere ice cover decline was proportional to the global temperature change in the HadCM3 atmosphere-ocean general circulation model developed by the Hadley Centre, we take a similar approach to the one used by Winton et al. (2011) to determine the sensitivity of the Northern Hemisphere sea ice cover to global temperature change and which is based on an Ordinary Least Squares (OLS) regression of ΔI (the change in sea ice cover) on ΔT (the change in global mean temperature). We therefore assume that the intensity of near-surface permafrost degradation is a linear function of the rise in global mean temperature above an equilibrium temperature $TATM(t_0)$.

Equation 3.1

$$PF_{area}(t) = PF_{area}(t_0) * (\max(0, 1 - \beta * [TATM(t) - TATM(t_0)]))$$

The relative extent of the near-surface permafrost area at time (t), $PF_{extent}(t)$, can therefore be expressed as follows:

Equation 3.2

$$PF_{extent}(t) = \frac{PF_{area(t)}}{PF_{area(t_0)}}$$

Equation 3.3

$$PF_{extent}(t) = (1 - \beta * [TATM(t) - TATM(t_0)])$$

Where:

- $PF_{extent}(t)$ is the relative size of the permafrost area remaining at time t (in %);
- $PF_{area}(t)$ is the size of the permafrost area at time t (in millions of square kilometres);
- $TATM(t)$ is global mean surface temperature at time t (in degrees Celsius);
- t_0 corresponds to the year 2000, which is the reference point for most projections of permafrost degradation;
- *Equation 3*.1 is not only valid if $(1 - \beta * [TATM(t) - TATM(t_0)])$ is non-negative, which is why we take the maximum of 0 and $(1 - \beta * [TATM(t) - TATM(t_0)])$ in the equation.

We then make the assumption that the near-surface northern circumpolar permafrost area is homogenous in terms of carbon content, which means that the amount of carbon made vulnerable by thawing at every period depends only on the total amount of carbon contained in the entire near-surface northern circumpolar permafrost area and in the retreat of permafrost from one period to the other. The quantity of carbon in newly thawed permafrost at every period can therefore be calculated as follows:

zonation of the permafrost zone, or on climatic variables other than global mean surface temperature. Models such as the one proposed by Anisimov et al. (1997) to make projections of changes in active-layer thickness over the Northern Hemisphere for different climate change scenarios by 2050 are therefore inapplicable for the purpose of this paper.

Equation 3.4

$$C_{thawedPF}(t) = C_{PF} * [PF_{extent}(t) - PF_{extent}(t-1)]$$

Where:

- $C_{thawedPF}(t)$ is the amount of carbon in newly thawed permafrost at time t (in GtC);
- C_{PF} is the amount of carbon contained in the entire near-surface northern circumpolar permafrost region (in GtC);
- PF_{extent} (t) is the relative size of the permafrost area remaining at time at time t (in %).

Parameter estimates

β coefficient

Physical validity

The model specification we choose for permafrost degradation relies on the following physical assumptions:

- As long as $TATM(t) = TATM(t_0)$, the extent of the permafrost area does not change. The underlying assumption is that $TATM(t_0)$ corresponds to an equilibrium state, in which the extent of permafrost is stable.
- Similarly, we assume that the intensity of permafrost degradation is a linear function of the rise in global mean temperature above the equilibrium temperature $TATM(t_0)$. The linearity claim seems to be supported by the current knowledge of permafrost dynamics (Schuur et al., 2015).

Statistical validity

We estimate the β coefficient in Equation 3.3 through pooled OLS on existing projections of future permafrost thaw. These projections come from studies (detailed in Table A3.1 in Appendix 3.1) which estimate future permafrost degradation for different emissions scenarios, corresponding to the four Representative Concentration Pathways (RCP)[32]. Most of these studies represent permafrost degradation paths starting in the year 2000, up to the year 2100, 2200, or in certain cases, 2300. Aggregating these time series of permafrost degradation gives us 796 observations on which we perform our regression analysis. We use pooled OLS with a two-level cluster procedure (by RCP and by author) for standard errors, which makes them robust to correlation between error terms and to heteroscedasticity over time. This is done through the command vce() in Stata. We find a highly significant estimate of β of 0.172 with a two-way clustered robust standard error of 0.026 (Table A3.2).

Size of the permafrost carbon pool

In order to derive projections of the amount of carbon that is made vulnerable to decomposition by the thawing of permafrost, we need to make assumptions about the amount of carbon contained in the near-surface (0-3m) northern circumpolar permafrost region. Given the

[32] RCPs refer to the four possible climate outcomes which have been defined by the IPCC based on a review of the literature. They each correspond to a possible greenhouse gas emissions scenario and are defined by their total radiative forcing pathway and level by 2100.

closeness of the estimates (Table A3.3) from Tarnocai et al. (2009) and Hugelius et al. (2014), we use the latest one, of 1035 GtC with a 95% uncertainty range of ± 150 GtC.

iv. *Phase 2: Carbon decomposition and release as CO_2 or CH_4*

Proposed model

As mentioned previously, on a global basis, the dominant pathway of carbon return from terrestrial ecosystems to the atmosphere is microbial decomposition (Schuur et al., 2008). The obvious challenge to modelling these processes lies in permafrost soils across the Northern Hemisphere being highly heterogeneous in their mineral and organic content and, as such, decomposition rates are likely to vary widely. What we need to estimate future emissions of permafrost carbon is to understand the rate at which permafrost carbon will be released into the atmosphere, as well as the form that it will take (CO_2 or CH_4). Many models of permafrost carbon decomposition are based on a partitioning of vulnerable (thawed) permafrost soils into different carbon pools based on their decomposition profiles (Burke, Hartley, & Jones, 2012; Dutta, Schuur, Neff, & Zimov, 2006; Elberling et al., 2013; Schädel et al., 2014; Schaefer, Zhang, Bruhwiler, & Barrett, 2011). The simplified model that we propose here follows this approach and is based on the following assumptions:

- The vulnerable (thawed) carbon can be divided into a passive pool slow, a fast and a passive pool;
- Based on findings from the literature, we assume that the passive pool is assumed to be very stable, meaning that no carbon will be released from it over the time scale of this study (Burke et al., 2013);
- We aggregate the slow and the fast pool and assume that the decomposition and release of thawed permafrost carbon can be modelled by an exponential decomposition function (Schaefer et al., 2011). We characterize this decomposition function by the e-folding time parameter τ which refers to the timescale for a quantity to decrease to 1/e of its initial value;
- The amount of methane release represents a fixed proportion of permafrost carbon emissions (Schneider von Deimling et al., 2015; Schuur et al., 2013).

Based on the above, the amount of permafrost carbon that is released into the atmosphere at time (t) can therefore be calculated as the sum of the lagged carbon fluxes from each time-indexed "pool" of newly thawed carbon $C_{thawedPF}(s)$, for $s = [t_0, t]$. These time-indexed pools all follow the same exponential decomposition function based on the parameter τ, but the amount of carbon coming from each pool at period t depends on the time elapsed since thawing, i.e. $(t - s)$. We then multiply by the (fixed) proportion of methane emissions to calculate emissions of carbon dioxide and methane from permafrost at each period of the model.

Equation 3.5

$$\boldsymbol{CO_2em.(t) = CO2_{conv.} * (1 - propCH_4) * [\sum_{s=t_0}^{t} C_{thawedPF}(s) * \ (1 - propPassive) * \left(1 - exp^{-\frac{t-s}{\tau}}\right)]}$$

Equation 3.6

$$CH_4em.(t) = CH4_{conv}.* (propCH_4) * [\sum_{s=t_0}^{t} C_{thawedPF}(s) * (1 - propPassive) \ * \left(1 - exp^{-\frac{t-s}{\tau}}\right)]$$

Where:

- $CO_2em.(t)$ is the amount of carbon dioxide from permafrost emitted into the atmosphere at time t (in $GtCO_2$);
- $CH_4em.$(t) is the amount of methane from permafrost emitted into the atmosphere at time t (in $TgCH_4$);
- $CO_2conv.$ is the conversion factor from GtC to $GtCO_2$;
- $CH_4conv.$ is the conversion factor from GtC to $TgCH_4$;
- $propCH_4$ is the (constant) share of methane emissions (in %);
- $C_{thawedPF}(s)$ is the amount of newly thawed permafrost at time s (in GtC);
- *propPassive* is the proportion of thawed permafrost in the passive pool (in %);
- τ is the e-folding time of permafrost decomposition in the active and slow pools (i.e. not in the passive pool)

Parameter estimates

Size of the passive pool

The existing estimates of the size of the passive pool, presented in Table A3.4 present significant uncertainty ranges, which means that the passive pool could represent between 15% and 70% of the thawed carbon. For our baseline scenario, we therefore take a mid-point estimate of the size of the passive pool at 40%.

E-folding time of permafrost carbon decomposition

The decomposition time of the thawed carbon that is not in the passive pool is considered to be in the range of 0-200 years (Burke et al., 2013). We derive an estimate of the e-folding time of permafrost carbon decomposition, which is represented by the parameter τ, through existing estimates of permafrost decomposition rates, which are collected in Table A3.5. Based on these estimates, we assume a mean value for τ of 70 years.

Share of methane emissions

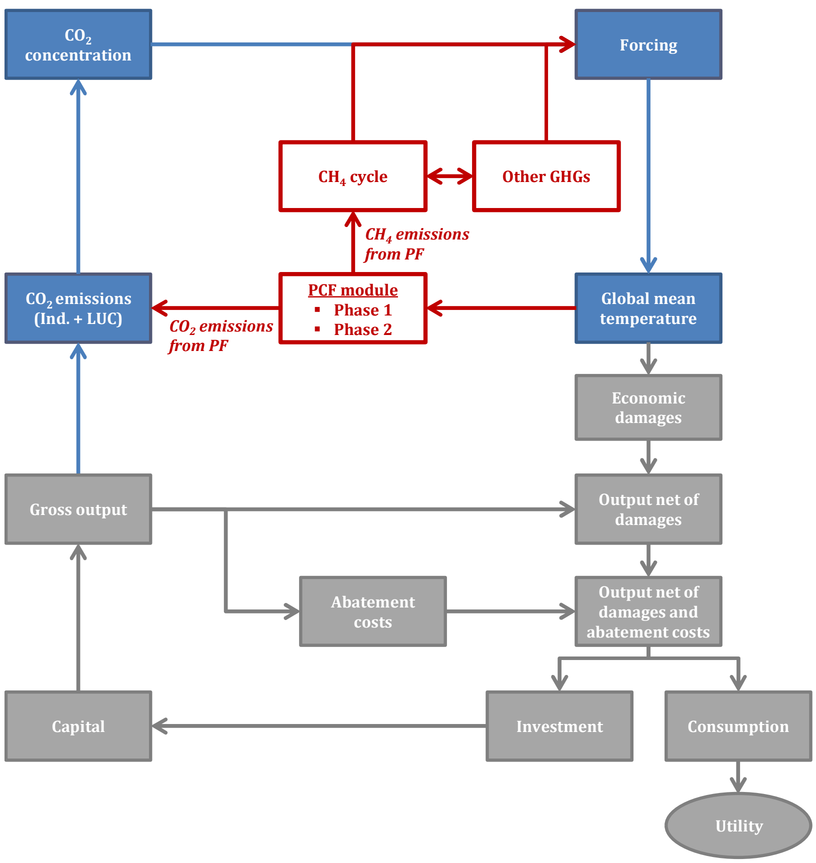
The only two studies we are aware of which provide an explicit estimate of the percentage of permafrost carbon which will be emitted into the atmosphere as methane are the one by Schuur et al. (2013), which indicates that this proportion will be around 2.3% and the one by

Schneider von Deimling et al. (2015), which indicates that this proportion will be in the range 1.5% - 3.5% (Table A3.6). We therefore assume a mean value for the proportion of methane emissions of 2.3%.

v. Integrating our PCF module in DICE-2013R

The following diagram (Fig. 3.1) presents a simplified overview of the DICE-2013R model and of our proposed permafrost carbon feedback module (in red). Grey boxes and arrows represent the economic components of the model while blue boxes and arrows represent the climate components of the model. As we described above, the permafrost carbon feedback introduces a loop in the model which amplifies anthropogenic warning: first, the increase in global mean temperature feeds into the PCF module; then, CO_2 emissions from permafrost are added to the industrial and land-use change CO_2 emissions while CH_4 emissions from permafrost go through a simplified methane cycle and add to the forcing variable in the model.

Figure 3.1: Simplified representation of the DICE-2013R model and of the proposed permafrost carbon feedback module



In DICE-2013R, the only greenhouse gas (GHG) that is subject to controls is industrial CO_2, and other GHGs are included as exogenous trends in radiative forcing. Because part of the permafrost carbon is released in the atmosphere in the form of methane, we had to add a methane cycle to the model. According to DICE-2013R's User Manual (Nordhaus & Sztorc, 2013), aggregate estimates of non-CO_2 forcings in the model are based on the RCP 6.0 W/m2 representative scenario. Therefore, we use the disaggregated estimates for methane (CH_4), nitrous oxide (N_2O), halocarbons and other GHGs from RCP6.0[33] as well as the formulae used to calculate the radiative forcings from CH_4 and N_2O taken from Myrhe et al. (1998) and listed in the Supplementary Material to Chapter 8 of the IPCC's Fifth Assessment Report (IPCC, 2013) (see Table A3.7) to include specific equations for the non-CO_2 GHGs in the model, which we link to methane emissions from permafrost.

4. Results and discussion

In this section, we calculate the projected impact of the PCF on different physical and economic variables, we estimate the absolute and relative impact of the PCF on the social cost of carbon for different discounting parameters, we solve the model for the optimal abatement paths and we compare results with and without the PCF. Unless otherwise specified, we make the assumption that damages follow the base (quadratic) damage function in DICE-2013R, represented by the following equation.

Equation 3.7

$$\Omega_{DICE}\big(TATM(t)\big) = \frac{1}{1 + \alpha_1 * TATM(t) + \alpha_2 * (TATM(t))^2}$$

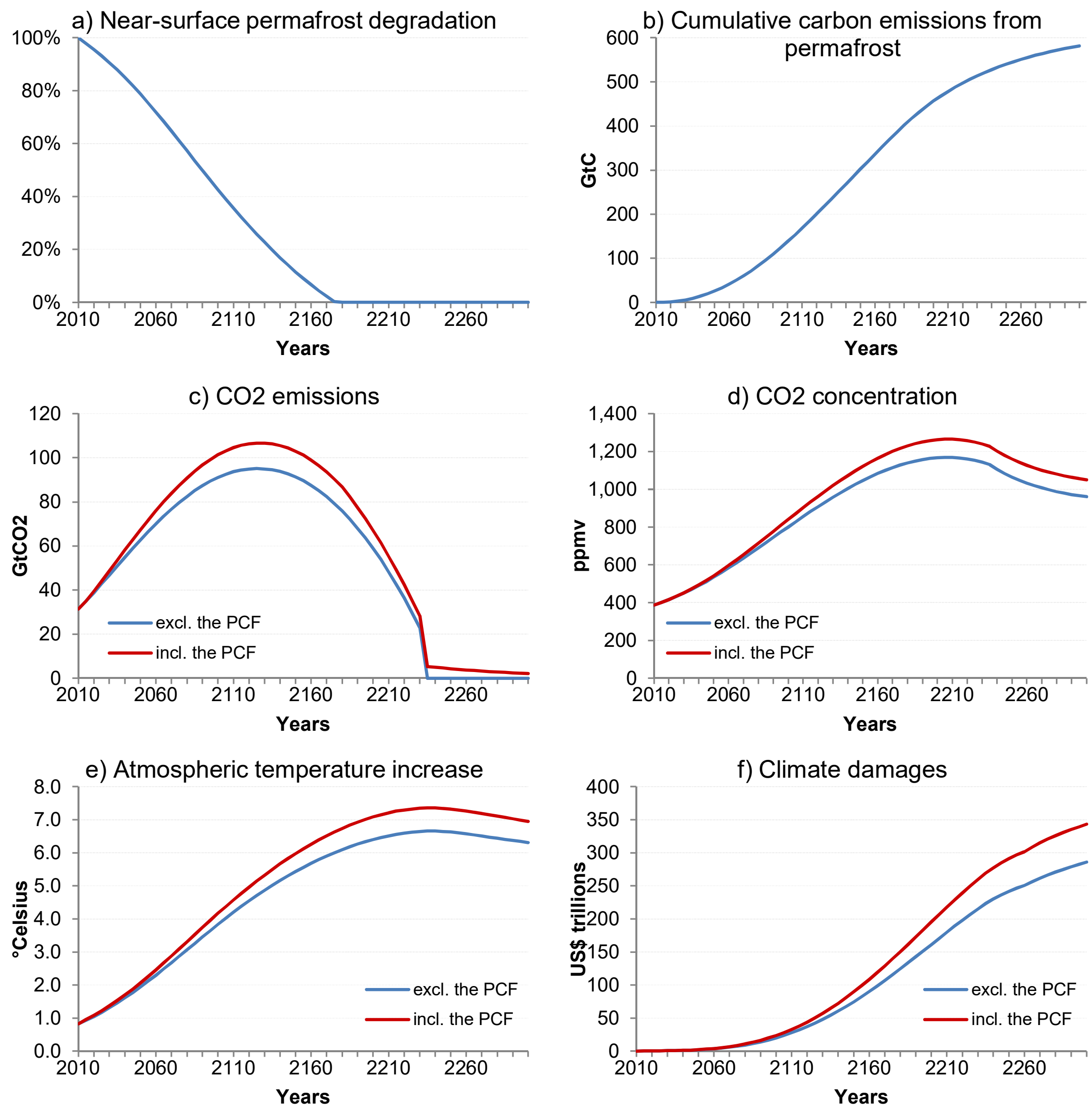
Where:

- $\alpha_1 = 0$;
- $\alpha_2 = 0.002664$.

The charts and results below are based on the baseline emissions scenario of DICE-2013R and on the mean values of the five main parameters of the PCF module (i.e. the size of the near-surface permafrost carbon pool, the β coefficient, the proportion of the passive pool, the e-folding time of permafrost carbon decomposition τ and the proportion of methane emissions).

[33] Available at https://tntcat.iiasa.ac.at/RcpDb/dsd?Action=htmlpage&page=welcome

Figure 3.2: Impact of the PCF on physical and economic outcomes of the DICE-2013R model



i. *Physical impacts of the permafrost carbon feedback*

When we add our PCF module (described above) to DICE-2013R and we run it in the base case scenario mode, we find that the near-surface permafrost area is completely thawed by 2175 (Fig. 3.2.a) and that the amount of permafrost carbon released into the atmosphere reaches 137 GtC by 2100, and 582 GtC by 2300 (Fig. 3.2.b). These estimates include both methane and carbon dioxide emissions. The estimate for 2100 is slightly higher than the mean estimate published in the meta-analysis from Schaefer et al. (2014), which predicts 120 ± 85 Gt of carbon emissions from thawing permafrost by 2100. However, only two studies (MacDougall, Avis, & Weaver, 2012; Schneider von Deimling et al., 2012) in the meta-analysis consider closed-loop estimates (i.e., include the impact of permafrost carbon released into the atmosphere on future thaw), which could explain why our estimate is slightly larger.

When we compare climate outcomes in the base case scenario of DICE-2013R with and without the PCF module, we can see (Fig. 3.2.c) that the PCF has an amplification effect on total CO_2 emissions, which starts to become significant towards the end of the 21st century and reaches its peak around 2150. We can also see from the chart that although industrial emissions start falling after 2130 to finally reach zero in 2235 (this corresponds to the base case scenario for the emissions control rate in DICE-2013R), CO_2 emissions from permafrost made vulnerable by thawing continue to be released in the atmosphere. These CO_2 emissions translate into an impact on atmospheric CO_2 concentration of roughly 97 ppmv by 2300 (Fig. 3.2.d). This is consistent with the closed-loop estimates from MacDougall et al. (2012), according to which the additional CO_2 concentration due to permafrost carbon could be in the range of 53-213 ppmv (with a best estimate of 101 ppmv) for DEP8.5[34].

We also find that the PCF will add 0.64°C to the atmospheric temperature by 2300 (Fig. 3.2.e). This is in line with estimates provided by MacDougall et al. (2012), according to which the impact of the permafrost carbon feedback on atmospheric temperature could be in the range of 0.13-1.69°C by 2300. It is higher than the impact projected by Schneider von Deimling et al. (2015) who forecast that long-term warming through the PCF could add 0.4 °C to global mean temperature. However, the authors recognize that their estimates can be considered conservative and that the impact of the PCF is likely to be stronger.

ii. Economic impacts of the permafrost carbon feedback

Impact on future climate damages

In our baseline scenario (DICE-2013R) we find that the mean annual value of the extra damages due to the PCF is about $3.6 trillion in 2100 and increases until it reaches $57.3 trillion by 2300 (Fig. 3.2.f). To our knowledge there has been only one other attempt at estimating the economic cost of the PCF through the use of an IAM, and this is the recent paper by Hope and Schaefer (2016), according to which the mean annual value of all extra impacts represents $2.8 trillion in 2100 and peaks at $30 trillion in 2200. Our estimates are significantly larger, but there are two factors which can explain this discrepancy: first, the scenario they consider is the A1B scenario from the Fourth Assessment Report of the IPCC (2007) which means that all their results are based on the assumption that there are zero anthropogenic emissions after 2100, whereas in our model, we use the baseline emissions path from DICE in which emissions only reach zero in 2235; secondly, their model only runs to 2200, whereas our model considers all impacts to 2300.

Impact on the social cost of carbon

The social cost of carbon is a measure of the long-term damage done by a ton of CO_2 emissions in a given year. In order to estimate it, we take the net present value of the difference between the business-as-usual consumption path to 2300, and the consumption path to 2300 which results from adding 1 ton of CO_2 to emissions in 2015. Based on this definition, the social cost of carbon for the current period (2015), calculated using DICE-2013R[35] without the PCF

[34] The Diagnosed Emissions Pathways (DEPs) used by MacDougall et al. (2012) are first derived from simulations of their earth system model (the UVic ESCM) driven by specific RCPs. These DEPs are then used to force the UVic ESCM, and to estimate the full impact of the PCF on the Earth's atmosphere.
[35] We assume a pure rate time of time preference ρ = 0.015 and an elasticity of marginal utility η = 1.45, as in the default settings of DICE-2013R.

module is \$20.9 per ton of CO_2. We find that accounting for the PCF raises the social cost of carbon to \$24.8 per ton of CO_2. More generally, as can be seen in the sensitivity analysis presented in Table A3.8, adding the PCF to the model raises the social cost of carbon by 10-20% depending on the choice of the discounting parameters.

We now repeat this analysis under the assumption of the Weitzman damage function (Weitzman, 2012), which is more reactive in very high temperature changes than the quadratic damage function used in DICE-2013R.

Equation 3.8

$$\Omega_{WEITZMAN}\left(TATM(t)\right) = \frac{1}{1 + \alpha_1 * TATM(t) + (\alpha_2 * \left(TATM(t)\right)^2 + (\alpha_3 * \left(TATM(t)\right)^\gamma}$$

Where:

- $\alpha_1 = 0$;
- $\alpha_2 = 1/20.46$;
- $\alpha_3 = 1/6.081$;
- $\gamma = 6.754$.

Under this new assumption for the damage function specification, the base social cost of carbon without the PCF is \$87.2 per ton of CO_2, but increases to \$135.4 when the PCF is included in the model. The relative impact of the PCF, which was 19% under the assumption of quadratic damages, now reaches 55% for Weitzman damages. Moreover, the sensitivity analysis based on the choice of discounting parameters (Table A3.9) shows that the range of the potential impact of the PCF on the social cost of carbon is significantly wider under Weitzman damages (18%-220%) than under quadratic damages (10-20%). Whereas our previous results emphasized the importance of the lagged impacts of the PCF, the results above demonstrate that the relative impact of the PCF on the social cost of carbon is extremely sensitive to the specification of the damage function used in the model.

All our previous analyses were based on the mean values of the parameters of our PCF module. We now examine the impact of parameter uncertainty about the PCF on the social cost of carbon. In order to do so, we assign distributions to the five main uncertain parameters of our PCF module:

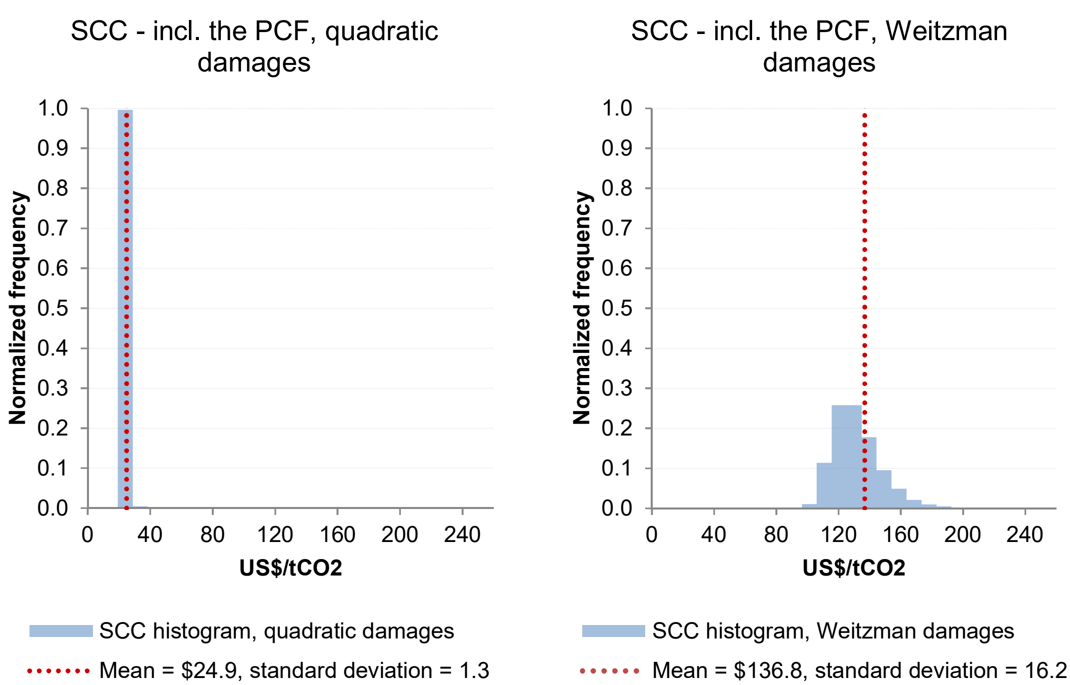
- β coefficient: based on the estimation described in Section 3, we assume that the β coefficient follows a normal distribution with a mean of 0.172 and a standard deviation of 0.026 (Table A3.2).
- Size of the permafrost carbon pool: we calibrate a normal distribution based on the 95% confidence interval provided by Hugelius et al. (2014) (Table A3.3).
- Proportion of the passive carbon pool: based on the estimates from Table A3.4 we make the assumption that the proportion of the passive pool follows a normal distribution with a mean of 40% and a two-standard deviation interval of 11%.

- E-folding time of permafrost carbon decomposition: Given the wide range of the estimates in Table A3.5 we assume that the e-folding time of permafrost carbon decomposition (in the active and slow pools, i.e. not considering the passive pool) follows a normal distribution with a mean of 70 and a standard deviation of 30.
- Share of methane emissions: based on the few estimates we have of the share of methane emissions, we consider for this parameter a normal distribution with a mean of 2.3% and a standard deviation of 0.6% (Table A3.6).

We take a large Latin Hypercube Sample of the parameter space, which has the advantage of sampling evenly from the domain of each probability distribution, with 10 000 draws, and we run the model for both the quadratic and the Weitzman damage functions. The resulting two normalized histograms for the social cost of carbon are displayed on Figure 3.3. As we can see in the chart below, accounting for the uncertainty on the PCF increases significantly the range of the social cost of carbon under Weitzman damages compared to quadratic damages. This is a direct implication of the higher reactivity of the Weitzman damage function, which amplifies the impacts of the uncertainty pertaining to the PCF on social welfare.

It should be emphasized here that this uncertainty analysis only examines the impacts of parameter uncertainty and assumes that these are revealed at the beginning of the modelling period and do not change over time. We do not here delve into the consequences of potential regime shifts, which could be explored through the use of a multiple tipping points framework such as the one developed by Lemoine and Traeger (2014).

Figure 3.3: Comparing the impact of PCF uncertainty on the social cost of carbon histogram for the quadratic and the Weitzman damage functions



Impact on the optimal abatement path

One of the most significant inputs in the DICE model is the emissions control rate, which represents the stringency of the mitigation policies in place. In all our previous analyses, we used the emissions control rate from DICE-2013R's base case, which corresponds roughly to a business-as-usual scenario.

In this section, we derive the optimal abatement path in the case with and without the PCF. In order to do so, we solve our model for the emissions control rate which maximizes a social welfare function W, which corresponds to the discounted sum of the population-weighted utility of per capita consumption:

Equation 3.9

$$W = \sum_{t=1}^{T_{max}} U[c(t), L(t)]R(t)$$

Where:

- $U[c(t), L(t)] = L(t) * \frac{c(t)^{1-\eta}}{1-\eta}$
- $R(t) = (1 + \rho)^{-t}$

For this exercise we consider that the discounting parameters are fixed with ρ = 0.015 and η = 1.45, which correspond to the default settings in DICE-2013R.

Once we have derived the optimal emissions control rate, we can use assumptions on the cost of the backstop technology to derive an estimate of the corresponding optimal carbon price. The equations for these can be found in Nordhaus and Sztorc (2013).

As we can see in Figure 3.4 below, the difference in the optimal emissions control rate between the case with the PCF and the case without the PCF is on average 5 percentage points over the period from 2015 to 2110, before the emissions control rate reaches 1, i.e. before industrial CO_2 emissions fall to zero (Fig. 3.4.a). This translates into a c. 17% difference between the average optimal carbon price in the case with the PCF and without the PCF over the same period (Fig. 3.4.b).

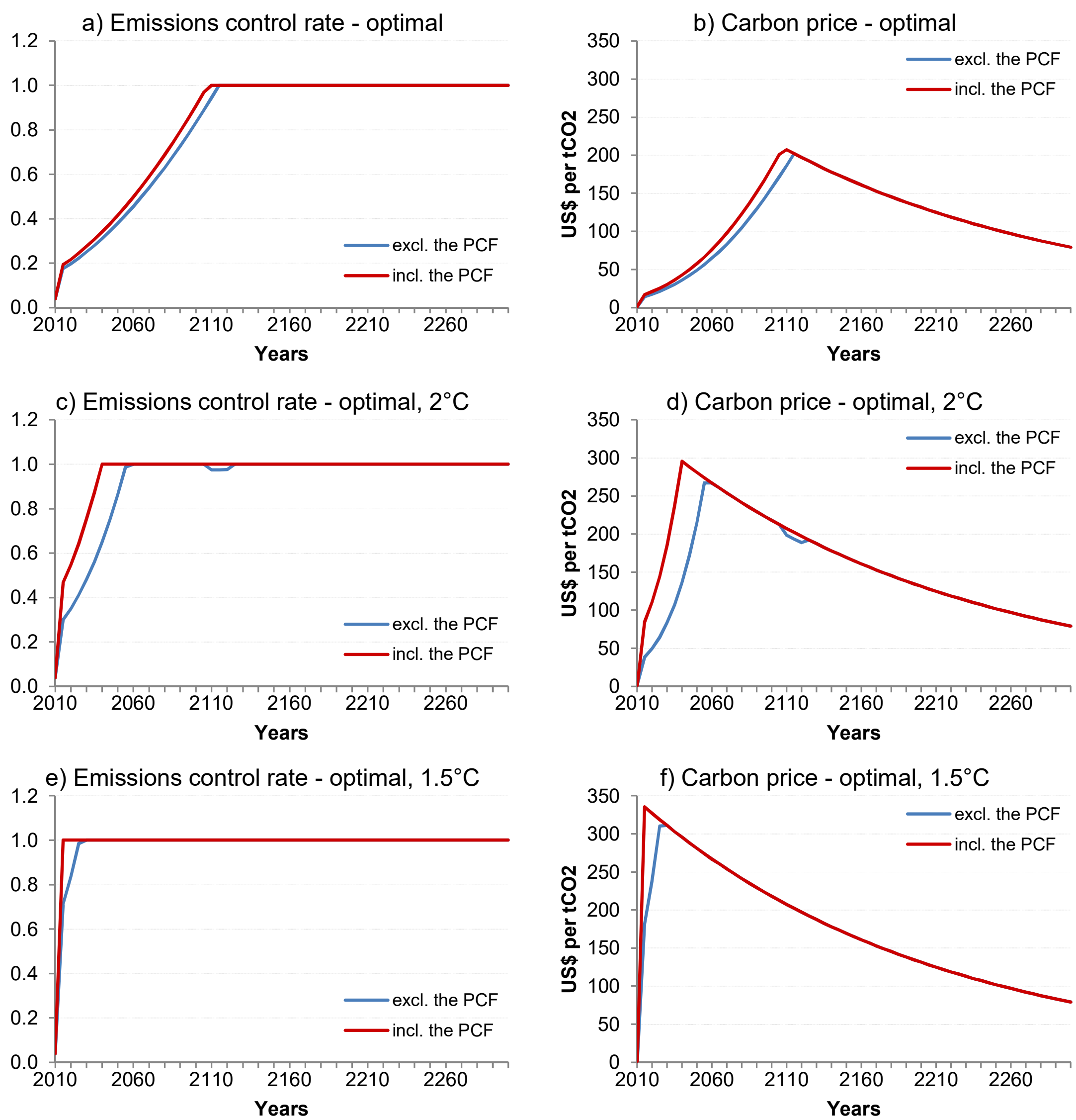
When we run the model with the additional constraint that the increase in atmospheric temperature should not exceed 2°C [36], we find that the difference in the optimal emissions control rate between the case with the PCF and the case without the PCF is on average 21 percentage points over the period 2015-2055 (Fig. 3.4.c). This translates into a c. 92% difference between the average optimal carbon price in the case with the PCF and in the case without the PCF over the same period (Fig. 3.4.d).

The recent Paris Agreement reinstated the long-term goal of keeping the increase in global mean temperature to below 2°C but also added the target of limiting this increase to 1.5°C. When we solve the model for optimality with the +1.5°C constraint on the increase in global mean temperature, we find that difference in the optimal emissions control rate between the case with

[36] Limiting atmospheric temperature increase to 2°C above pre-industrial levels has long been presented by scientists (Rijsberman & Swart, 1990) as the condition to avoid the worst impacts of climate change, and has become, since the Copenhagen Accord in 2009, the internationally accepted target for climate policy.

the PCF and the case without the PCF is on average 16 percentage points over the period 2015-2025 (Fig. 3.4.e). This translates into a c. 42% difference between the average optimal carbon price in the case with the PCF and in the case without the PCF over the same period (Fig. 3.4.f). The reason why this impact seems to be less than for the +2°C constraint is that the optimal emission control rate reaches 1 as early as 2030 even when the PCF is not taken into account. What these results show is that the optimal path compatible with the +1.5°C target and taking into account the PCF would require us to end all industrial CO_2 emissions very shortly.

Figure 3.4: Comparing the impact of the PCF on the optimal emissions control rate and carbon price when there is no constraint on the increase on global mean temperature, when the increase on global mean temperature is limited to +2°C, and when the increase in global mean temperature is limited to +1.5°C (using the quadratic damage function)



The two charts in the first row represent the impact of the PCF on the optimal emissions control rate and carbon price. The graphs in the middle row and bottom rows correspond to the case when the +2°C (respectively, +1.5°C) constraint on atmospheric temperature increase is added to the model.

5. Conclusion and policy implications

As emphasized by Prentice et al. (2015), the PCF is, on the basis of current knowledge, potentially the most important positive feedback on policy-relevant timescales that is currently not included in Earth System Models. This omission should be a concern for policy makers as it could lead to a dangerous overestimation of the level of emissions that is compatible with a given CO_2 concentration target.

A variety of ad hoc methods combining data and model results have produced a large range of estimates of the potential physical magnitude of this feedback, but its economic impact has not yet been fully investigated. Despite the complexity of the processes involved, we used these projections to build a simplified model, which we integrated in DICE-2013R and which represents the main uncertainties at stake. To our knowledge, we are the first to provide an estimate of the impact of the PCF on the social cost of carbon, and to compare optimal paths with and without the PCF.

We have shown in this paper that including a rough model of the permafrost carbon feedback adds on average between 10 and 20% to the current estimates of the social cost of carbon calculated in the baseline scenario. We have also examined the implications of the choice of a damage function on the projected impacts of the PCF., and the results presented here demonstrate that the relative impact of the PCF on the social cost of carbon is extremely sensitive to the specification of the damage function used in the model. Indeed, the sensitivity analysis based on the choice of discounting parameters shows that the range of the potential impact of the PCF on the social cost of carbon is significantly wider under Weitzman damages (18%-220%) than under quadratic damages (10-20%).

Moreover, by amplifying the economic impacts, it increases drastically the uncertainty on the projected effect on the social cost of carbon. We also showed in our sensitivity analyses that our results were highly dependent on the choice of discounting parameters. This is yet another illustration of the crucial role that discounting and damage functions play in assessments of climate change based on integrated assessment models.

There are numerous potential improvements which could help us to better assess the economic impacts of this imperfectly known feedback: these include a more extensive knowledge of the permafrost zone as well as a better understanding of the processes which lead to permafrost thaw and carbon decomposition. Markedly, the rates of permafrost thawing and decomposition, as well as the relative proportions of methane and carbon dioxide emissions will be of considerable significance.

Finally, there are two features of the PCF that underpin our model, but which do not appear explicitly in our numerical results: its long-term path dependency, which stems from the significant time lag between the trigger (global temperature increase) and the response (CO_2 release into the atmosphere), and its irreversibility, at least on human-relevant timescales. More than the figures of the projected impacts of the PCF on the social cost of carbon, what policy makers should have in mind is that the level of industrial emissions that we allow for over the next decades will have critical implications for the amount of permafrost carbon that is released in the atmosphere over the next centuries, and for the extent of future climate change.

These findings, as well as the width of uncertainties pertaining to this feedback, call not only for further research in this field, but also for an explicit consideration in the climate policy debate.

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APPENDICES

Appendix 3.1: Estimates of permafrost degradation

Table A3.1: Estimates of permafrost degradation

Study	Permafrost area degradation		
	2100	2200	2300
RCP2.6			
Burke et al. (2012)	16%	n/a	n/a
Lawrence et al. (2012)	30%	n/a	n/a
Mokhov and Eliseev (2012)	38%	33%	22%
Koven et al. (2013)	23%	n/a	n/a
Schuur et al. (2013)	15%	n/a	25%
Slater and Lawrence (2013)	37%	n/a	n/a
DEP2.6			
MacDougall et al. (2012)	38%	38%	36%
Schneider von Deimling et al. (2012) *	15%	15%	14%
Schneider von Deimling et al. (2015) *	17%	n/a	n/a
RCP4.5			
Burke et al. (2012)	24%	n/a	n/a
Harden et al. (2012)*	23%	n/a	n/a
Lawrence et al. (2012)	49%	n/a	n/a
Mokhov and Eliseev (2012)	48%	59%	59%
Koven et al. (2013)	46%	n/a	n/a
Schuur et al. (2013)	24%	n/a	39%
Slater and Lawrence (2013)	52%	n/a	n/a
DEP4.5			
MacDougall et al. (2012)	46%	53%	57%
Schneider von Deimling et al. (2012) *	26%	35%	38%
Schneider von Deimling et al. (2015) *	n/a	n/a	n/a
RCP6.0			
Burke et al. (2012)	27%	n/a	n/a
Lawrence et al. (2012)	56%	n/a	n/a
Mokhov and Eliseev (2012)	60%	81%	83%
Koven et al. (2013)	n/a	n/a	n/a
Schuur et al. (2013)	42%	n/a	56%
Slater and Lawrence (2013)	63%	n/a	n/a
DEP6.0			
MacDougall et al. (2012)	49%	58%	63%
Schneider von Deimling et al. (2012) *	33%	55%	62%
Schneider von Deimling et al. (2015) *	n/a	n/a	n/a
RCP8.5			
Burke et al. (2012)	35%	n/a	n/a
Harden et al. (2012)*	41%	n/a	n/a
Lawrence et al. (2012)	76%	n/a	n/a
Mokhov and Eliseev (2012)	84%	93%	93%
Koven et al. (2013)	76%	n/a	n/a
Schuur et al. (2013)	57%	n/a	74%
Slater and Lawrence (2013)	87%	n/a	n/a
Chadburn et al. (2015)*	50%	n/a	n/a
DEP8.5			
MacDougall et al. (2012)	52%	63%	69%
Schneider von Deimling et al. (2012) *	57%	100%	100%
Schneider von Deimling et al. (2015) *	37%	n/a	58%

Notes: The estimates marked with an asterisk (*) were not used in the regression, usually because of a lack of continuous data.

Appendix 3.2: Permafrost thaw: regression results

Table A3.2: Regression results

	(1) *PFthawed*
ΔTATM	0.172***
	(0.0261)
Adj. R-squared	0.812
Number of observations	796

Notes: Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001
Statistics robust to heteroskedasticity and clustering on RCP and author

Appendix 3.3: Estimates of the carbon content of the near-surface northern circumpolar permafrost region

Table A3.3: Published estimates of the carbon content of the near-surface (0-3m) northern circumpolar permafrost region

Study	Estimate (GtC)	Confidence Interval
Tarnocai et al. (2009)	1,024	n/a
Hugelius et al. (2014), Schuur et al. (2015)	1,035±150	95%

Appendix 3.4: Estimates of the size of the passive pool

Table A3.4: Published estimates of the relative size of the passive pool

Study	Best estimate	Uncertainty range
Falloon et al. (1998)	n/a	15%-60%
Dutta et al. (2006)	18%	n/a
Burke et al. (2012)	n/a	18%-60%
Burke et al. (2013)	n/a	15%-60%
Schneider von Deimling et al. (2015)	52.5%	40%-70%
Schädel et al. (2014)	n/a	69-93%

We take a mid-point estimate of the size of the passive pool at 40%.

Appendix 3.5: Estimates of the size of the e-folding time of permafrost carbon decomposition

The decomposition time of the thawed carbon that is not in the passive pool is considered to be in the range of 0-200 years (Burke et al., 2013). We derive an estimate of the parameter τ through existing estimates of permafrost decomposition rates, which are collected in Table A3.5.

Table A3.5: Published estimates of the e-folding time of permafrost carbon decomposition

Study	e-folding time (years)	Comments
Dutta et al. (2006)	20	Estimate based on the projection that a 10% thaw of the yedoma stock (46 GtC) would lead to a total of 40 GtC being transferred directly or indirectly to the atmosphere four decades later under a uniform temperature of 5°C.
Schaefer et al. (2011)	70	Estimate defined as the characteristic e-folding time of permafrost carbon decay.
Elberling et al. (2013)	34-361	Estimate based on a three-pool dynamic model that projects a potential C loss between 13 and 77% for 50 years of incubation at 5°C.
Knoblauch et al. (2013)	167	Estimate calculated from turnover times of 170.3 years for the stable pool and 0.26 years for the labile pool.
Schädel et al. (2014)	22-224	Estimate based on projections that between 20 and 90% of the organic C will potentially be mineralized to CO_2 within 50 incubation years at a constant temperature of 5°C.
Schneider von Deimling et al. (2015)	25 (10-40)	Estimate that corresponds to the turnover time of an aerobic slow pool at 5°C.

Based on these estimates, we assume a mean value for the parameter τ of 70 years, which, combined with the assumption that the size of the passive pool stands at c. 40%, means that 31% of thawed permafrost carbon will have decomposed after 50 years. This estimate is slightly below the mean estimates from Elberling (2013) and Schädel (2014) of the percentage of total thawed carbon which has decomposed after 50 years (45% and 55%, respectively). However, their results rely on the assumption that the thawed permafrost is exposed to a constant temperature of 5°C, which is why we adjust our estimate downwards.

Appendix 3.6: Share of methane emissions

Table A3.6: Published estimates of the share of methane emissions

Study	Share of methane emissions	Comments
Schuur et al. (2013)	2.3%	Up to 2300.
Schneider von Deimling et al. (2015)	1.5-3.5%	Up to 2300.

Appendix 3.7: Formulae to calculate the radiative forcings from methane (CH_4) and nitrous oxide (N_2O)

The table below is taken from the Supplementary Material to Chapter 8 of the IPCC's Fifth Assessment Report (Myhre et al., 2013).

Table A3.7: Formulae for radiative forcing of methane and nitrous oxide

Gas	Radiative forcing (in W m^{-2})	Constant α
CH_4	$\Delta F = \alpha(\sqrt{M} - \sqrt{M_0}) - (f(M, N_0) - f(M_0, N_0))$	0.036
N_2O	$\Delta F = \alpha(\sqrt{N} - \sqrt{N_0}) - (f(M_0, N) - f(M_0, N_0))$	0.12

Notes:

- $f(M, N) = 0.47\ln(1 + 2.01 * 10^{-5}(MN)0.75 + 5.31 * 10^{-15}M(MN)^{1.52})$;
- M is CH_4 in ppb;
- N is N_2O in ppb;

The subscript 0 denotes the unperturbed molar fraction for the species being evaluated. However, note that, for the CH_4 forcing, N_0 should refer to present-day N_2O, and for the N_2O forcing, M_0 should refer to present-day CH_4.

Appendix 3.8: Sensitivity analysis for the social cost of carbon under quadratic damages

Table A3.8: Sensitivity analysis of the social cost of carbon – assuming a quadratic damage function

Social cost of carbon – without the PCF, quadratic damages									
		Elasticity of marginal utility η							
		1.0	1.45	1.5	2.0	2.5	3.0	3.5	4.0
PRTP ρ	0.000	$204.6	$83.3	$75.9	$32.6	$16.1	$9.0	$5.6	$3.8
	0.010	$60.0	$30.3	$28.3	$15.0	$8.8	$5.6	$3.8	$2.7
	0.015	$38.0	$20.9	$19.6	$11.2	$6.9	$4.6	$3.2	$2.4

Social cost of carbon – with the PCF, quadratic damages									
		Elasticity of marginal utility η							
		1.0	1.45	1.5	2.0	2.5	3.0	3.5	4.0
PRTP ρ	0.000	$239.9	$99.7	$91.0	$39.2	$19.2	$10.6	$6.4	$4.2
	0.010	$72.3	$36.4	$33.9	$17.7	$10.2	$6.3	$4.2	$3.0
	0.015	$45.6	$24.8	$23.2	$13.0	$7.9	$5.2	$3.6	$2.6

Relative impact of the PCF on the social cost of carbon, quadratic damages									
		Elasticity of marginal utility η							
		1.0	1.45	1.5	2.0	2.5	3.0	3.5	4.0
PRTP ρ	0.000	17.2%	19.7%	19.9%	20.4%	19.0%	16.7%	14.4%	12.3%
	0.010	20.5%	19.9%	19.8%	17.9%	15.7%	13.6%	11.7%	10.2%
	0.015	20.0%	18.6%	18.4%	16.3%	14.2%	12.3%	10.8%	9.5%

Appendix 3.9: Sensitivity analysis for the social cost of carbon under Weitzman damages

We recalculate previous results using an alternative damage function, which was proposed by Weitzman (2012).

$$\Omega_{WEITZMAN}(TATM(t)) = \frac{1}{1 + \left(\alpha_1 * TATM(t)\right)^2 + \left(\alpha_2 * TATM(t)\right)^{\gamma}}$$

Where parameter values are the following:

- α_1 = 1/20.46
- α_2 = 1/6.081
- γ = 6.754

Table A3.9: Sensitivity analysis of the social cost of carbon – assuming the Weitzman damage function

Social cost of carbon – without the PCF, Weitzman damages									
		Elasticity of marginal utility η							
		1.0	1.45	1.5	2.0	2.5	3.0	3.5	4.0
PRTP ρ	0.000	$1,676.5	$777.6	$714.6	$310.0	$137.2	$62.2	$29.1	$14.2
	0.010	$338.5	$165.4	$153.0	$70.9	$33.9	$17.0	$9.0	$5.1
	0.015	$173.3	$87.2	$80.9	$39.0	$19.6	$10.4	$5.9	$3.6

Social cost of carbon – without the PCF, Weitzman damages									
		Elasticity of marginal utility η							
		1.0	1.45	1.5	2.0	2.5	3.0	3.5	4.0
PRTP ρ	0.000	$1,974.5	$1,088.2	$1,019.2	$533.3	$282.8	$152.1	$82.9	$45.9
	0.010	$459.1	$252.7	$236.6	$124.0	$66.1	$36.0	$20.1	$11.5
	0.015	$245.5	$135.4	$126.9	$66.9	$36.0	$19.9	$11.4	$6.7

Relative impact of the PCF on the social cost of carbon with Weitzman damages									
		Elasticity of marginal utility η							
		1.0	1.45	1.5	2.0	2.5	3.0	3.5	4.0
PRTP ρ	0.000	17.8%	39.9%	42.6%	72.0%	106.1%	144.4%	184.7%	222.8%
	0.010	35.6%	52.7%	54.7%	74.8%	94.8%	112.2%	124.0%	127.3%
	0.015	41.6%	55.4%	56.9%	71.6%	84.0%	92.1%	94.1%	89.3%

Chapter 4: What are the impacts of droughts on economic growth? Evidence from U.S. states

Abstract

In recent years, a literature has established itself on the macroeconomic impacts of variations in temperature and precipitation, but the impacts of droughts *per se* (which can be defined roughly as periods of abnormally dry weather conditions) have been the focus of much less attention, apart from extreme drought events that are classified as natural disasters. There are several factors that could explain why droughts have been studied less extensively than other types of weather events, from the difficulty of their characterization to the insidiousness of their impacts, but there are also several compelling reasons to undertake a thorough study of their macroeconomic impacts, especially in the context of a changing climate, where rainfall patterns are expected to shift, along with warming trends. I choose the setting of the United States to examine the following questions: Do droughts have an impact on states' economic growth? Are these effects lagged and/or persistent? Are the impacts of droughts made worse when they co-occur with high temperature conditions? I outline here a framework for researching these effects, as well as some preliminary results and a discussion of the extent to which these can be relevant for societal decision-making processes.

1. Introduction

It is now generally agreed that climate change will modify the intensity and frequency of weather and climate events (Herring, Hoerling, Kossin, Peterson, & Stott, 2015; IPCC, 2012). Over the past few years, this realization has spawned two different (and seemingly unrelated) streams of research: the first has been described as the "new climate-economy literature" (Dell, Jones, & Olken, 2014) and relies on the application of advanced econometric methods to examine the socio-economic impacts of weather events; the second, which is less well-known, proposes the use of a "compound events framework" to examine how combinations of variables produce extreme impact events (Leonard et al., 2014).

The first stream of research, which applies panel data methods to examine how climate and weather (mainly temperature, precipitation and windstorms) influence socio-economic outcomes, has been growing rapidly over the past few years. Much of this body of literature has focused on quantifying the impact of year-to-year fluctuations in temperature and precipitation on various socio-economic outcomes, including: agricultural output (Auffhammer & Schlenker, 2014; Deschenes & Greenstone, 2007; Schlenker & Roberts, 2009); aggregate output (Burke, Hsiang, & Miguel, 2015; Dell, Jones, & Olken, 2012; Hsiang, 2010); labour productivity (Heal & Park, 2016; Park, 2016); labour market dynamics (Bastos, Busso, & Miller, 2013); democratic institutions (Brückner & Ciccone, 2011); migration (Bohra-Mishra, Oppenheimer, & Hsiang, 2014; Deschenes & Moretti, 2009); conflict (Hsiang, Burke, & Miguel, 2013; Maystadt & Ecker, 2014); mortality (Deschênes & Greenstone, 2011); and birth rates (Barreca, Deschenes, & Guldi, 2015). Thorough reviews of this literature have been provided by Dell et al. (2014), Hsiang (Hsiang, 2016) and Carleton and Hsiang (Carleton & Hsiang, 2016).

Some of these studies have focused explicitly on the impact of variations in weather conditions on economic growth. Dell et al. (Dell et al., 2012) found that higher temperatures reduce economic growth in poor countries, but that changes in temperature do not have a discernible effect on growth in rich countries. This finding has been challenged by Burke, Hsiang and Miguel (2015), who showed that the growth rate of output per capita is non-linear in temperature for both rich and poor countries, with economic growth peaking at an annual average temperature of 13°C and declining strongly at higher temperatures. A more recent article by Colacito et al. (2014) provides empirical evidence that temperature affects economic growth in the United States (U.S.) by focusing on the role of seasonal temperatures. Similarly, Hsiang and Jina (2014) established that tropical cyclones have long-term negative effects on economic growth in those countries affected. There is more limited evidence for precipitation: Dell et al. (2012) found that changes in precipitation have relatively mild effects on national growth in both rich and poor countries, with an extra 100mm of annual precipitation being associated with a 0.08 percentage point lower growth rate in rich countries and a statistically insignificant 0.07 percentage point higher growth rate in poor countries. Tebaldi and Beaudin (2016) found significant impacts of low and high precipitation levels on regional economic growth in Brazil but their results could come from seasonal effects which are not fully controlled for in their model.

The macro-economic consequences of droughts (which can be defined roughly as periods of abnormally dry weather) have been much less intensively explored. Naturally, the initial interest has been in studying the economic damage caused by specific drought events in the agricultural sector (Anderson, Welch, & Robinson, 2012; Leister, Paarlberg, & Lee, 2015). Agriculture should be among the most sensitive sectors of the economy to droughts. A few studies have concentrated on evaluating the impacts of droughts severe enough to be classified as natural disasters (Loayza, Olaberria, Rigolini, & Christiaensen, 2012; Raddatz, 2009). These latter studies usually take their drought data from the Emergency Disasters Database (EM-DAT[37]), and therefore only explore the impacts of the most extreme drought events.

The macro-economic impacts of droughts of all degrees of severity have been the subject of even less attention; I am only aware of a working paper by Berlemann and Wenzel (2015), which looks at how droughts affect medium and long-term growth. This gap in the literature can be linked to the fact that, unlike one-dimensional climate variables such as the level of temperature or precipitation, droughts are difficult to characterize and suppose the choice of a baseline and time frame. Also, droughts usually have an unclear onset and ending, as well as unclear spatial coverage. Unlike other types of natural hazard such as hurricanes, droughts often lack visible and structural impacts, which can sometimes make them relatively inconspicuous.

Nevertheless, there are many reasons why the socio-economic outcomes of periods of dry weather deserve to be assessed in a more thorough manner than they have been in the past. As

[37] The EM-DAT database, managed by the Centre for Research on the Epidemiology of Disasters at the Catholic University of Louvain, accounts for events that meet at least one of the following conditions: there are 10 or more people reported killed; there are 100 or more people reported affected; a state of emergency is declared; or there is a call for international assistance.

we will see in the next section, there are numerous channels through which local drought events could have ripple effects on all sectors of the economy, and there are reasons to believe that these effects could be nonlinear, lagged and/or persistent. Moreover, droughts are likely to become one of the most apparent manifestations of future climate change in many areas, including southern Europe and the Mediterranean region, central Europe, central North America and Mexico, northeast Brazil and southern Africa (IPCC, 2012). Assessing the macroeconomic impacts of dry weather should therefore help to improve our understanding of the near- and long-term threats posed by climate change.

However, given their complex nature, the study of the macroeconomic impacts of droughts raises further questions. For instance, it seems reasonable to consider the possibility that repeated droughts could have cumulative (negative) effects on growth, which would require us to look at intensification effects. Moreover, research has shown that the impact of droughts is often made worse by interactions with other types of weather events, such as heat waves, windstorms or floods. For these reasons, I believe that the assessment of the macroeconomic impacts of droughts should make use of the recently formalized compound events framework.

The emergence of the notion of compound events in the field of statistics can be linked to the recent focus on extreme weather events and to the willingness to better understand how climate variables combine to produce extreme impacts. Indeed, as emphasized by Sedlmeier et al. (2016, p. 1): "the potential impact of extreme events such as heat waves or droughts does not only depend on their number of occurrence but also on "how the extremes occur", i.e. the interplay and succession of the events". The IPCC's Special Report on Managing the Risk of Extreme Events and Disasters (SREX) (2012, p. 118) has proposed a flexible definition of compound events: "(1) two or more extreme events occurring simultaneously or successively, (2) combinations of extreme events with underlying conditions that amplify the impact of the events, or (3) combinations of events that are not themselves extremes but lead to an extreme event or impact when combined. The contributing events can be of similar (clustered multiple events) or different type(s)". A simpler and more straightforward definition of compound events has been given by Leonard et al. (2014, p. 115): "A compound event is an extreme impact that depends on multiple statistically dependent variables or events". This loose definition of compound events can therefore be used to encompass both repeated and co-occurring weather and climate events.

So far, the literature on compound events seems to have focused exclusively on exploring the statistical dependence between weather variables and assessing whether or not some types of compound events have – or will – become more frequent (AghaKouchak, Cheng, Mazdiyasni, & Farahmand, 2014; Wahl, Jain, Bender, Meyers, & Luther, 2015). To my knowledge, the other research avenue, namely the use of the compound events framework to analyse the risks and the impacts of weather and climate events, has not yet received any attention.

I am therefore proposing to contribute to the "new climate-economy literature" by thoroughly assessing the macroeconomic impacts of drought events, but also to use the compound events framework to examine intensification effects and to assess the impact of combinations of droughts and other weather variables, which to my knowledge has not yet been addressed.

The rest of the chapter is structured as follows. Section 2 will present a review of the literature. Section 3 will detail the contribution of this paper and set out research objectives.

Section 4 will present the methodology used, including the setting, data sources and the econometric model. Results will be presented in Section 5. Section 6 concludes.

2. Literature review

As our analysis will focus on the impacts of droughts on regional economic growth in the United States, the focus of the literature review below is mainly on developed countries. This literature review is organised in three parts: first, it presents the channels through which droughts can affect the economy; second, it provides an overview of the quantitative assessments that have been made of the economic impacts of droughts; finally, it introduces how the compound events framework can be used in the context of drought events.

i. On the channels through which droughts affect the economy

Despite the shortage of literature on the macroeconomic impacts of droughts, particularly droughts insufficiently extreme to be classed as natural disasters, there are compelling reasons to consider the impact of abnormally dry weather on the economy as a whole, given that there are many channels through which even local droughts could have repercussions on all sectors of the economy. Indeed, even if crop failures and agricultural losses are generally the most immediate and obvious impacts of droughts, these often translate into supply shocks on the markets for agricultural products, which in turn can lead to increases in the price of feed grain, food and timber. For instance, the FAO estimated that the 2012 drought would increase retail food prices by between 3 and 4% in the following year[38]. These price increases then affect consumer expenditure and it has even been suggested that they can cause stock market frenzies (Terazono, 2014). Droughts can also significantly lower agricultural capital, for instance through impacts on livestock; these can be strong enough to jeopardize pastoralism as a viable livelihood strategy, and thus reduce agricultural growth, particularly in low-income countries and regions (Loayza et al., 2012).

Prolonged dry conditions can also have severe consequences for other water-dependent industries, such as hydropower generation, fluvial navigation and tourism. For instance, the 2015 drought in California reduced the share of hydroelectricity production in the state's overall electricity generation to 7%, down from an average of 18% (Gleick, 2015). Because the alternatives to hydropower (natural gas, wind, solar, out-of-state sources) have higher marginal variable costs, these translate into an increase in direct electricity costs to ratepayers. According to Gleick, the reduction in hydroelectricity generation during the 2012-2015 California drought increased state-wide electricity costs by c. $2.0 billion in total. Another study by Barnett and Pierce (2008) estimated that the flow of the Colorado river is likely to decline 10-30% over the next 30-50 years; this would significantly reduce live storage and the system's hydropower production.

These sectoral effects can also lead to increased unemployment and reduced tax revenues. According to Howitt et al. (2015), the 2015 drought in California was responsible for the loss of 21,000 jobs, including 10,100 seasonal jobs in the agricultural sector.

[38] Source: http://www.fao.org/docrep/017/aq191e/aq191e.pdf

It also seems reasonable to envisage that droughts could have lagged and/or persistent impacts. As regards space-lagged impacts, as highlighted by Mishra and Singh (2010), droughts can have economic impacts in areas not directly affected by anomalously dry conditions, whether through changes in prices (e.g. food and electricity prices, insurance premiums), monetary transfers from regional or federal authorities, international trade shocks or population migration. As an illustration, the 2012 drought episode (which affected 80% of US agricultural land in the summer of 2012) led to U.S. export prices for corn soaring 128% above the 20-year historical average. As regards time-lagged impacts, research has found that the main effects of droughts are found in the years following the actual drought (Leister et al., 2015).

As regards the persistent effects of droughts, there are two opposing hypotheses: the first hypothesis is that severe droughts are likely to have persistent impacts, especially when they lead to large-scale land degradation and permanent migration (Hornbeck, 2012). The second hypothesis is supported by results from Loayza et al. (2012), which suggest that there is some reversion, in the sense that while contemporaneous droughts cause a decline in total and agricultural growth, previous droughts produce the opposite effect. One of the explanations for this beneficial delayed impact could be that droughts lead governments and institutions to undertake recovery actions and programs, which have lagged positive effects. This issue of the persistence of drought impacts raises further questions pertaining to the resilience of the economy and to potential threshold effects. For instance, the impact of a drought can be mitigated in the short-term by the use of groundwater resources, but repeated droughts could lead to the depletion of aquifers, and any subsequent droughts would have far more severe consequences.

ii. On the economic impacts of droughts

The literature on the economic impacts of droughts can be segmented into three different streams.

The first stream of this literature has focused on the impact of droughts on crop yields, agricultural production and farm income. Westcott and Jewison (2013) found that dry weather in summer had a negative impact on corn and soybean yields. Lambert (2014) quantified the weather effects on output and income for a panel of Kansas farmers and found that precipitation had asymmetric effects on crop production throughout the growing year. Craft et al. (2013) examined the impact of six severe drought episodes on corn in Kentucky and found a 47% reduction in revenue from corn during episodes of severe drought in Kentucky. Leister et al. (2015) and Countryman et al. (2016) both used dynamic partial equilibrium models to assess the long-term economic impact of U.S. drought conditions on crop and live cattle prices; both found that, in the long run, market adjustments cause a significant decrease in consumer surplus. Finally, Lott and Ross (2015) have estimated that reduced crop yields across the United States due to droughts and heat waves have resulted in losses equivalent to $145bn over the past three decades.

The second stream of this literature has focused on the economic impacts of extreme droughts. Some of these studies have focused on specific drought events. For instance, Ziolkowska (2016) used an input-output model to estimate the economic losses from the 2011 drought in Texas and found that it had caused $16.9 billion of losses to the entire Texas economy and increased unemployment by 166,895 people. Howitt et al. (2015) calculated that the economic cost of the 2015 California drought was around $2.74 billion, including direct agricultural costs of $1.84 billion, and 21,000 jobs.

Other studies, most of them based on the EM-DAT database[39], have used panel data analysis methods to examine the impacts of major droughts on macroeconomic growth, in both the agricultural and non-agricultural sectors. By applying panel data methods to an indicator of drought incidence, Raddatz (2009) found that, among climatic disasters, droughts had the largest average impact, with cumulative losses of 1 percent of gross domestic product (GDP) per capita. Similarly, Loayza et al. (2012) used a cross-country panel dataset to compare the effects of different types of disasters on economic growth and found that, overall, droughts, measured as a function of the number of people affected relative to the country's population, had a significant and negative impact on agricultural growth and a negative and insignificant impact on total GDP growth. Fomby et al. (2013) examined the impact of natural disasters on GDP growth using an intensity indicator based on the number of fatalities and the total number of people affected relative to a country's population, and found that, in advanced countries, droughts had a significant negative contemporaneous effect, but that it only applied to agricultural growth, and did not persist over time.

A slightly different approach was taken by Jenkins and Warren (2015a), who quantified the economic cost of droughts by linking the Standard Precipitation Index[40] and the reported economic cost of 34 historic drought events in the EM-DAT database; they then applied these country-damage functions to projections of drought magnitude under future scenarios of climate change and found that severe and extreme drought events were projected to cause estimated additional losses ranging between 0.04 and 9 percent of national GDP in Australia, the U.S. and Spain/Portugal.

The third stream of this literature has looked at the impact of precipitation levels (rather than drought *per se*) on economic growth. As mentioned in the Introduction, Dell et al. (2012) showed that an extra 100mm of annual precipitation was associated with lower growth rate of 0.08 percentage points in rich countries and a statistically insignificant higher growth rate of 0.07 percentage points in poor countries. Burke, Hsiang and Miguel (2015) did not find any significant effects of precipitation on country-level economic production[41].

In summary, the macroeconomic impacts of "disaster droughts" have already been the focus of some studies, as have the impacts of precipitation variations on economic growth. However, the effects of droughts of any degree of severity on economic growth do not seem to have been researched extensively. As far as I am aware, this fourth stream only comprises a study by Berlemann and Wenzel (2015), who performed panel data analysis on 135 countries over the period of 1960-2002 to examine the long-term effects of droughts (defined by a drought indicator

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[39] The EM-DAT database only accounts for events that meet at least one of the following conditions: there are 10 or more people reported killed; there are 100 or more people reported affected; a state of emergency is declared; or there is a call for international assistance.

[40] The Standard Precipitation Index is a commonly used tool to define and monitor droughts – see Section 4 for a detailed description.

[41] There is also a paper by Carroll et al. (2009) which considers the impact of droughts not on economic growth, but on the economy as a whole: they estimated the cost of droughts by matching rainfall data with individual life satisfaction in Australia over the period 2001 to 2004 and found that spring drought has a detrimental effect on life satisfaction equivalent to an annual reduction in income of A$18,000 for individuals living in rural areas. Based on these estimates, the predicted doubling of the frequency of spring droughts would lead to the equivalent loss in life satisfaction of around 1% of GDP annually.

based on the Standard Precipitation Index (SPI)) on per capita GDP and found significantly negative long-term growth effects of droughts in both highly and less developed countries. However, their study appears to suffer from several methodological shortcomings. Their drought indicator corresponds to the yearly average drought magnitude over past years (i.e. the absolute value of the sum of all negative 12-month-SPI-values over the current and the [k] preceding years), which does not correspond to the definition of drought events as proposed by McKee et al. (1993) (see the section below on data) and does not account for differences between years and seasons. Moreover, their aggregate drought indicator does not allow them to make a distinction between the duration and the intensity of drought events.

iii. On the compound impacts of droughts and high temperature events

The current context of a changing climate compels us to examine whether the effects of droughts are compounded by high temperatures. Indeed, high temperatures cause more evaporation from the ground, which, in the absence of precipitation, dries out the soil, leading to a further increase in air temperature. As Romm (2011) pointed out, this explains why the hottest summer ever recorded for a U.S. state took place in drought-stricken Texas in 2011. Therefore, assessing the impacts of dry periods without taking into account co-occurring high temperatures could lead to a significant underestimation of future impacts. However, the only research I have seen on the impact of co-occurring warm and dry conditions seems to be confined to agriculture and forestry. For instance, Urban et al. (2015) investigated the combined effects of moisture and heat on maize yields in Iowa, Indiana and Illinois and found that this interaction led to larger mean yield losses. Similarly, Allen et al. (2010) showed that climate change and especially the combination of drought and heat stress have already caused an increase in tree mortality, which poses significant risks to ecosystem services, including the loss of sequestered forest carbon, but also shrinking water reservoirs and insect infestation. Wildfires are also a result of the co-occurrence of warm and dry conditions, and are expected to increase in frequency and intensity as climates become warmer and drier, not only in the United States (Westerling, Hidalgo, Cayan, & Swetnam, 2006) but in many regions of the world (Liu, Stanturf, & Goodrick, 2010). An aerial survey conducted in 2015 by the U.S. Forest Service (2015) found that the four-year drought had killed more than 12.5 million trees, which significantly increased the risk of wildfires. These can have catastrophic consequences, not just in terms of physical damage but also in terms of human losses. Another channel through which high temperatures and lack of precipitation could have compound negative effects would be through changes in hydrological cycles: Barnett et al. (2008) showed that recent shifts in mountain precipitation and earlier snow melt in the Western United States have led to significant changes in river flows, which have exacerbated the drying induced by warmer conditions.

To my knowledge, the potential compound effects of droughts and periods of high temperature on economic growth have not been the topic of a thorough assessment. However, this approach of considering the co-occurrence of low precipitation and temperature conditions has been used by Fontes et al. (2017) in a recent paper, in which they develop a rainfall-temperature index that they apply to a panel dataset of Indian districts over the period 1966-2009 in order to estimate the marginal and total effects of drought on cereal productivity.

3. Contribution of this paper

We can draw two main insights from this review of the existing literature: (1) numerous studies have found that droughts have a short-term negative impact on agricultural crop yields, which translates into medium- and long-term price increases; and (2) there is some evidence that extreme droughts qualifying as natural disasters have a negative impact on macroeconomic growth, at least in the short-run.

From these, several gaps in the literature can be identified: first, the impacts of droughts *per se* (as opposed to precipitation) on economic growth do not seem to have been explored thoroughly. Second, the multi-faceted nature of droughts does not seem to have been the subject of many studies and I have not seen a discussion of which characteristics of drought events (intensity, duration, frequency, etc.) matter the most in terms of economic impact; nor does there appear to have been a thorough investigation of time- and space-lagged effects, or of persistent effects. Furthermore, extreme droughts seem to have been analysed only through indicators derived from the EM-DAT database, which are not truly exogenous (because they are measured in terms of the severity of their impact, for example the number of deaths). In any case, these typically binary indicators of drought (there is a drought disaster or there is not) are a coarse representation of the underlying drought data. Finally, as I have discussed above, there is some evidence to support the hypothesis that the economic impacts of dry weather could be compounded by co-occurring high temperatures; these potential compounding effects do not seem to have been examined at all.

The objective here is to use the recent advances in panel data analysis of weather variables to examine the impacts of meteorological droughts on economic growth. Since meteorological droughts can be considered as exogenous variations in weather (i.e. periods of abnormally low precipitation), they provide an ideal setting for causal inference tying weather events to socio-economic outcomes (Dell et al., 2014). Given that droughts are multi-dimensional events, I also propose to look at which features of drought events (e.g. duration, magnitude and peak intensity) cause the most damage to the economy and to examine whether successive drought events and the interplay with other weather variables has an effect on their macroeconomic impact.

This paper addresses these gaps in the literature by examining the following research questions:

1) Do droughts, defined here as periods of abnormally dry weather, have an impact on U.S. states' economic growth?
2) What are the characteristics of drought events that matter in terms of impact?
3) Are these impacts lagged and/or persistent?
4) Are these impacts compounded by co-occurring periods of high temperature?

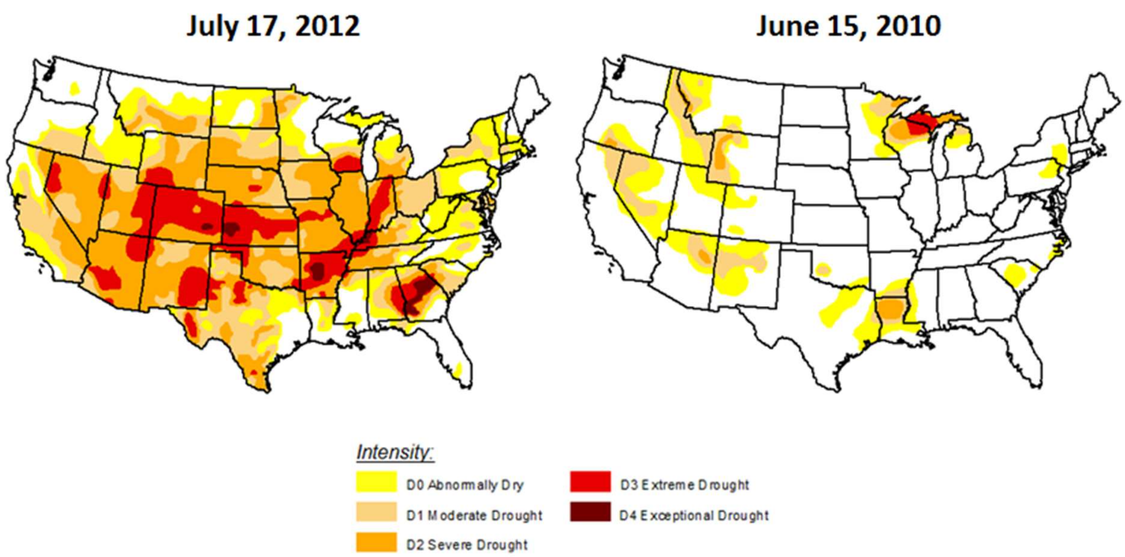
4. Methodology

i. Setting

There are several reasons why the United States provides an interesting location for the study of the impact of drought events on economic growth.

First, the U.S. territory is very often prone to droughts: according to the Environmental Protection Agency (EPA), over the period from 2000 to 2015, roughly 20 to 70% percent of the U.S. land area experienced abnormally dry conditions at any given time (EPA, 2016). As an illustration, the following figure (Fig. 4.1) shows two maps of drought conditions in the U.S.: the one on the left corresponds to the week during which the share of the U.S. territory under drought conditions (80.75%) was the largest over the period 2000-2017; the one on the right corresponds to the week during which the share of the U.S. territory under drought conditions (21.35%) was the lowest over the same period (The National Drought Mitigation Center, 2017).

Figure 4.1: Drought conditions over the United States during the weeks when the largest (and the smallest) share of the territory was affected by drought over the period 2000-2017



Source: United States Drought Monitor (The National Drought Mitigation Center, 2017)[42]

Second, the US territory seems to provide an adequate setting for the examination of the impacts of compound dry and warm conditions. We developed earlier the argument that high temperatures are likely to make dry weather conditions worse and recent drought events in the United States seem to provide evidence to support this claim. For instance, Diffenbaugh et al. (2015) showed that the increasing co-occurrence of dry years with warm years has significantly raised the risk of extreme droughts in California. Williams et al. (2015) performed a similar analysis and found that precipitation remains the main driver of drought variability, but that warmth has intensified the effects of recent precipitation shortfalls by enhancing potential evapotranspiration; according to their estimates, anthropogenic warming accounted for 8-27% of the observed drought anomaly in 2012-2014 and 5-18% in 2014. As regards wildfires, a recent study has shown that increasing trends in the number of large fires in the western U.S. over the period 1984-2011 are a reflection of long-term, global fire trends that will likely occur with

[42] The U.S. Drought Monitor is jointly produced by the National Drought Mitigation Center at the University of Nebraska-Lincoln, the United States Department of Agriculture, and the National Oceanic and Atmospheric Administration. Map courtesy of NDMC-UNL.

increased temperature and drought severity in the coming decades (Dennison, Brewer, Arnold, & Moritz, 2014).

Third, the United States is likely to be affected by an increase in the frequency and the severity of droughts over this century. According to Cook et al. (2015), the Southwest and Central Plains of Western North America are likely to experience significantly drier conditions in the second half of the 21st century compared to the 20th century and earlier paleoclimatic intervals. Strzepek et al. (2010) applied drought indices to the IPCC's 22 General Circulation Models for three greenhouse gas emissions scenarios and found that the frequency of meteorological drought (based on precipitation alone) is projected to increase in the southwestern states, while the frequency of hydrological drought (based on precipitation and temperature) is projected to increase across most of the country. Their results also exhibit a strong worsening trend along higher emissions scenarios. Several studies also project that future weather conditions will be more conducive to wildfires in the mountainous regions of the western United States (Barbero, Abatzoglou, Larkin, Kolden, & Stocks, 2015; Luo, Tang, Zhong, Bian, & Heilman, 2013).

Fourth, droughts are also among the costliest natural disasters in the United States (Riebsame, Changnon Jr, & Karl, 1991). The Federal Emergency Management Agency estimated in 1995 that droughts in the United States caused an average annual economic loss of $6-8bn (Federal Emergency Management Agency, 1995). According to NOAA[43] (NOAA National Centers for Environmental Information (NCEI)), billion-dollar drought events totalled $220.3bn of CPI-adjusted losses between 1980 and 2016, which makes them second only to tropical cyclones on the list of billion-dollar disaster events. This indicates the potential for an impact of droughts on economic growth.

Finally, from a more pragmatic standpoint, our analysis requires time series of economic and drought data on compatible spatial scales. Droughts are usually highly localized events and as such should be examined on fine spatial scales, ideally at the weather station- or county-level. Because droughts are derived from precipitation anomalies, aggregating them over larger spatial scales leads to an averaging of weather conditions, which does not reflect the fact that some areas are experiencing abnormally dry weather. On the other hand, most economic data is generally only available at state or national level. There is good data availability for both the Standard Precipitation Index (SPI) and GDP at the state level in the U.S., which is why we choose the 48 contiguous U.S. states as the framework for our analysis.

ii. Data

Drought indicators

One of the main challenges with studying droughts is that they cannot be inferred directly from weather variables. Indeed, meteorological drought is defined as a period of abnormally low precipitation, which supposes both a reference baseline and a reference time-scale. To that effect, several indicators of meteorological drought have been developed, the two most commonly used being the Palmer Drought Severity Index (Palmer, 1965) and the Standard Precipitation Index (McKee et al., 1993), both of which aim to address the intensity and the duration of droughts. For reference, other less commonly used drought indices include the Standard Runoff Index (Shukla

[43] https://www.ncdc.noaa.gov/billions/

& Wood, 2008), which is aimed at the characterisation of hydrological droughts, and the Standardized Precipitation-Evapotranspiration Index (Vicente-Serrano, Beguería, & López-Moreno, 2010) and the Supply-Demand Drought Index (Rind, Goldberg, Hansen, Rosenzweig, & Ruedy, 1990), which both rely on measures of evapotranspiration. The reasons which justify the choice of the Standard Precipitation Index for the purpose of this paper are detailed next page.

The Palmer Drought Severity Index (PDSI) is based on a simple two-layer soil moisture model which captures the basic effect of warming on drought through changes in potential evapotranspiration. In essence, it is a water balance model based on the difference between the amount of precipitation required to retain a normal water balance level and the amount of actual precipitation. Its main weakness lies in the fact that it relies on empirical constants, which limits its usefulness for spatial comparison.

The Standard Precipitation Index (SPI) is calculated from the cumulative probability of a given rainfall event occurring at a location, which is then transformed into an index, where the SPI values are given in units of standard deviation from the standardised mean, with negative values corresponding to drier periods than normal, and positive values corresponding to wetter periods than normal. The SPI is calculated on a monthly basis for a moving window of $[k]$ months, where k indicates the rainfall accumulation period, which is typically 1, 3, 6, 12, 24, or 36 months. The National Drought Mitigation Center at the University of Nebraska (National Drought Mitigation Center) provides guidelines for interpreting these different SPI indicators:

- SPI-1, based on very short rainfall accumulation periods, reflects short-term conditions and can be misleading depending on the location's climatology, as very small departures from the mean can result in large negative or positive SPI values;
- SPI-3, provides seasonal estimates of precipitation levels but can hide precipitation anomalies which take place over a longer time scale;
- SPI-6 shows precipitation anomalies over distinct seasons and can provide indications of anomalous streamflows and reservoir levels;
- SPI-12 is a comparison of precipitation for 12 consecutive months during all the previous years of available data and can reflect the impacts of rainfall (or lack thereof) on streamflows, reservoir levels and groundwater levels. The 12-month SPI for the end of December thus compares the precipitation totals for the January-December period with similar periods at the same location.

Table 4.1 below presents the 8 different bins of the SPI indicator, which range from extremely dry weather conditions (SPI ≤ -2) to extremely moist conditions (SPI ≥ 2).

Table 4.1: SPI categories (McKee et al., 1993)

SPI values	Category
≤ -2.00	Extremely dry
-1.50 to -1.99	Severely dry
-1.00 to -1.49	Moderately dry
0 to -0.99	Mildly dry
0 to 0.99	Mildly moist
1.00 to 1.49	Moderately moist
1.50 to 1.99	Severely moist
≥ 2.00	Extremely moist

The reasons which motivated the choice of the SPI as the drought indicator for this paper are manifold: first, the SPI can be easily used to describe the multiple dimensions of drought events, including intensity (peak and average), duration and spatial extent (e.g. by summing drought-affected grid cells). Second, as opposed to the Palmer Drought Severity Index and drought indicators derived from the EM-DAT database (usually a combination of fatalities and the number of people affected), drought indicators based on the SPI are solely calculated from precipitation data, which we assume to be unaffected by economic and population growth, and therefore these can be considered as purely exogenous[44]. Third, the use of the SPI to characterize meteorological droughts has been recommended by the Lincoln Declaration on Drought Indices[45] (Hayes, Svoboda, Wall, & Widhalm, 2011) and because of its ability to address drought at multiple time steps for a variety of climatic regions, it has been used extensively in hydrological studies (Dutra, Di Giuseppe, Wetterhall, & Pappenberger, 2013; Edossa, Babel, & Gupta, 2010; A. Mishra & Singh, 2009; Roudier & Mahe, 2010; Stricevic, Djurovic, & Djurovic, 2011). Finally, because the SPI represents local variations in drought conditions, it is especially well-suited to panel methods as it provides enough within-state variation to allow identification.

Based on the above discussion on the respective merits of each of the SPI indicators, as well as what has been done in the literature (Jenkins & Warren, 2015b), the 12-month SPI (SPI-12) is used as our reference drought indicator. It was downloaded for the the 48 contiguous U.S. states (i.e. excluding Alaska and Hawaii) from the NOAA's National Centers for Environmental Information (NCEI)[46].

Drought variables

To specify the dependent drought variable, we use the characterization of drought events proposed by McKee et al. (1993), according to which a drought event is defined as a period during which monthly SPI reaches a value of −1 or less. The drought start date is defined as the first month in which the SPI becomes negative and the drought ends before the SPI becomes positive again – in short, droughts are defined as periods of consecutive negative monthly SPI values, with

[44] The water balance equation underlying the PDSI requires estimates of evapotranspiration, sold recharge, runoff and moisture loss from the surface layer, which may be affected by factors such as land use change, overgrazing, deforestation, mining, poor irrigation processes and pollution.
[45] This Declaration was released at the end of an Inter-Regional Workshop on Indices and Early Warning Systems for Droughts which was held at the University of Nebraska in 2009 and whose sponsors included the World Meteorological Organisation, the U.S. NOAA, the U.S. Department of Agriculture and the United Nations Convention to Combat Desertification. Its recommendations included the use of the SPI to characterize meteorological droughts.
[46] ftp://ftp.ncdc.noaa.gov/pub/data/cirs/climdiv/

at least one monthly SPI value less than or equal to –1. We also follow McKee et al. (1993) as regards the definition of drought events' characteristics:

- the duration of a drought event corresponds to the number of months between the drought's beginning and its end;
- the magnitude (or intensity) of a drought event is calculated as the positive sum of the absolute SPI values for all the months within a drought event[47];
- the peak intensity of a drought event corresponds to the absolute value of the lowest monthly SPI over the period.

We use the above definition to identify drought events in each of the 48 contiguous states, distinguishing between moderate to extreme droughts ("moderate+"), which are defined as periods of consecutive negative SPI values, with at least one SPI value less than or equal to –1, and severe to extreme droughts ("severe+"), which are periods of consecutive negative SPI values, with at least one SPI value less than or equal to –1.5. The minimum duration of a drought event is 1 month and the maximum duration is 12 months: indeed, due to the constraints of using annual economic variables, we do not consider droughts that last more than 12 months. This is one of the limitations of our analyses which we address by also looking at time-lagged effects.

Tables 4.2 and 4.3 below presents summary statistics for drought events in each of the 48 contiguous states of the U.S. over the period 1988-2016. The first table corresponds to droughts categorized as "moderate+", while the second table only includes the droughts categorized as "severe+". The states are categorized in four regions (West, Midwest, South and Northeast) based on the U.S. Census Bureau regions[48].

[47] By definition, drought duration and magnitude are thus highly correlated.
[48] Available at https://www2.census.gov/geo/docs/maps-data/maps/reg_div.txt

Table 4.2: Drought event statistics for moderate to extreme droughts

Moderate to extreme droughts															
State name	**State code**	**Region**	**Nb. of years with drought events**	**Drought event duration (months)**				**Drought event magnitude**				**Drought event peak magnitude**			
				Average	**St. dev.**	**Min.**	**Max.**	**Average**	**St. dev.**	**Min.**	**Max.**	**Average**	**St. dev.**	**Min.**	**Max.**
Alabama	AL	South	10	9.0	4.4	1	12	10.8	7.6	1.0	22.4	1.89	0.66	1.03	2.95
Arkansas	AR	South	9	6.4	4.2	2	12	7.5	5.7	1.8	17.5	1.67	0.41	1.05	2.23
Arizona	AZ	West	11	11.1	1.6	8	12	12.9	6.3	7.6	27.8	2.11	0.63	1.05	3.09
California	CA	West	13	11.8	0.4	11	12	11.9	4.3	7.8	23.0	1.74	0.69	1.09	3.09
Colorado	CO	West	10	9.9	1.9	7	12	10.3	7.0	3.6	25.4	1.79	0.76	1.01	3.09
Connecticut	CT	Northeast	11	8.1	3.4	3	12	7.7	5.2	3.1	18.5	1.44	0.40	1.00	2.31
Delaware	DE	South	10	8.9	3.1	4	12	7.8	3.7	2.2	13.6	1.52	0.57	1.00	2.81
Florida	FL	South	11	9.1	3.7	3	12	11.0	6.0	2.4	21.5	1.77	0.42	1.15	2.35
Georgia	GA	South	15	9.0	3.7	3	12	10.7	6.5	1.2	21.7	1.63	0.36	1.01	2.12
Iowa	IA	Midwest	10	8.8	3.6	4	12	8.4	5.7	2.1	20.5	1.57	0.48	1.02	2.49
Idaho	ID	West	12	10.8	1.6	7	12	10.9	5.4	3.8	22.9	1.66	0.41	1.10	2.43
Illinois	IL	Midwest	9	9.4	2.6	4	12	7.4	2.6	2.8	11.0	1.41	0.29	1.05	1.86
Indiana	IN	Midwest	6	7.7	2.6	4	12	6.9	3.5	3.4	12.4	1.38	0.25	1.05	1.71
Kansas	KS	Midwest	9	9.1	2.1	5	12	8.2	2.6	3.3	10.6	1.50	0.31	1.10	2.02
Kentucky	KY	South	9	8.3	3.3	3	12	7.2	4.1	2.3	13.3	1.35	0.27	1.03	1.80
Louisiana	LA	South	9	8.2	4.1	3	12	9.2	8.0	2.8	22.5	1.61	0.47	1.00	2.25
Massachusetts	MA	Northeast	5	8.4	3.2	5	12	7.4	3.8	3.4	11.4	1.39	0.33	1.01	1.76
Maryland	MD	South	9	8.9	2.6	4	12	9.0	4.4	4.6	19.1	1.70	0.51	1.13	2.79
Maine	ME	Northeast	7	9.7	3.0	4	12	10.4	5.2	3.6	18.3	1.78	0.68	1.04	2.89
Michigan	MI	Midwest	5	8.2	3.9	3	12	6.1	3.1	2.7	10.2	1.23	0.12	1.03	1.35
Minnesota	MN	Midwest	5	8.0	3.7	4	12	7.6	4.9	2.7	15.5	1.39	0.49	1.05	2.23
Missouri	MO	Midwest	8	9.6	3.5	4	12	7.6	3.4	2.7	12.6	1.36	0.26	1.05	1.76
Mississippi	MS	South	7	10.1	3.5	3	12	11.2	6.2	2.8	22.2	1.81	0.34	1.45	2.49
Montana	MT	West	14	8.6	2.9	5	12	8.2	4.7	3.3	17.9	1.44	0.44	1.03	2.48
North Carolina	NC	South	10	9.4	3.1	5	12	11.3	6.6	2.5	20.4	1.85	0.70	1.02	2.93
North Dakota	ND	Midwest	11	8.3	3.3	4	12	8.3	5.1	3.4	19.0	1.47	0.46	1.01	2.60
Nebraska	NE	Midwest	9	10.0	1.6	8	12	11.4	4.1	6.1	16.8	1.92	0.57	1.27	2.97
New Hampshire	NH	Northeast	3	9.0	1.0	8	10	9.0	1.6	8.1	10.9	2.02	0.11	1.91	2.12
New Jersey	NJ	Northeast	7	9.1	3.0	4	12	10.0	5.7	3.5	20.0	1.80	0.65	1.17	3.01
New Mexico	NM	West	11	9.5	2.1	7	12	10.3	5.1	4.7	17.7	1.83	0.48	1.04	2.52
Nevada	NV	West	14	10.9	2.3	4	12	10.5	4.7	3.1	18.8	1.65	0.46	1.14	2.39
New York	NY	Northeast	8	7.9	2.7	4	12	7.7	3.1	2.5	12.8	1.65	0.47	1.00	2.53
Ohio	OH	Midwest	8	8.0	2.9	4	12	8.1	5.4	2.9	19.6	1.53	0.41	1.10	2.33
Oklahoma	OK	South	6	9.3	3.2	5	12	9.0	5.7	2.8	16.3	1.60	0.44	1.15	2.31
Oregon	OR	West	13	10.7	2.5	3	12	10.1	5.8	3.2	26.0	1.62	0.46	1.16	2.70
Pennsylvania	PA	Northeast	8	9.8	3.1	5	12	10.1	3.5	5.6	15.0	1.87	0.30	1.42	2.21
Rhode Island	RI	Northeast	6	8.2	4.0	3	12	6.1	3.2	2.2	10.7	1.27	0.24	1.08	1.65
South Carolina	SC	South	13	9.8	3.2	2	12	10.9	6.0	1.0	21.7	1.76	0.60	1.02	2.86
South Dakota	SD	Midwest	10	8.1	3.2	3	12	8.2	4.0	2.1	13.3	1.48	0.36	1.00	2.25
Tennessee	TN	South	7	10.1	3.8	2	12	11.1	6.1	1.5	20.3	1.61	0.54	1.06	2.55
Texas	TX	South	7	10.6	1.9	8	12	11.7	5.1	6.3	22.3	1.76	0.73	1.22	3.09
Utah	UT	West	12	9.7	2.8	4	12	9.5	5.4	3.0	21.5	1.55	0.50	1.04	2.83
Virginia	VA	South	12	8.0	3.5	3	12	8.1	4.8	2.7	18.2	1.55	0.44	1.01	2.47
Vermont	VT	Northeast	6	5.7	1.9	4	8	5.5	2.4	2.3	9.1	1.62	0.41	1.09	2.18
Washington	WA	West	12	8.6	4.2	2	12	8.6	6.1	1.3	22.2	1.35	0.40	1.01	2.24
Wisconsin	WI	Midwest	8	8.3	2.6	5	12	7.6	3.9	3.7	14.2	1.47	0.32	1.04	1.88
West Virginia	WV	South	11	9.6	2.5	5	12	8.5	4.7	4.2	20.5	1.41	0.36	1.10	2.00
Wyoming	WY	West	12	10.4	2.0	7	12	12.3	4.0	7.5	19.7	1.72	0.39	1.10	2.43
South			**155**	**9.0**	**3.4**	**1**	**12**	**9.7**	**5.7**	**1.0**	**22.5**	**1.65**	**0.50**	**1.00**	**3.09**
West			**134**	**10.2**	**2.5**	**2**	**12**	**10.5**	**5.3**	**1.3**	**27.8**	**1.67**	**0.53**	**1.01**	**3.09**
Midwest			**98**	**8.7**	**2.9**	**3**	**12**	**8.1**	**4.1**	**2.1**	**20.5**	**1.49**	**0.40**	**1.00**	**2.97**
Northeast			**61**	**8.4**	**3.1**	**3**	**12**	**8.2**	**4.3**	**2.2**	**20.0**	**1.63**	**0.47**	**1.00**	**3.01**
All states			**448**	**9.2**	**3.1**	**1**	**12**	**9.4**	**5.2**	**1.0**	**27.8**	**1.62**	**0.49**	**1.00**	**3.09**

Notes: The above table only includes moderate to extreme drought events which occurred in the 48 contiguous continental states during the period 1988-2016.

Table 4.3: Drought event statistics for severe to extreme droughts

Severe to extreme droughts															
State name	**State code**	**Region**	**Nb. of years with drought events**	**Drought event duration (months)**				**Drought event magnitude**				**Drought event peak magnitude**			
				Average	**St. dev.**	**Min.**	**Max.**	**Average**	**St. dev.**	**Min.**	**Max.**	**Average**	**St. dev.**	**Min.**	**Max.**
Alabama	AL	South	7	10.7	2.4	6.0	12.0	14.3	6.1	5.5	22.4	2.21	0.5	1.6	3.0
Arkansas	AR	South	6	8.2	4.1	3.0	12.0	10.0	5.5	3.2	17.5	1.90	0.3	1.6	2.2
Arizona	AZ	West	9	10.9	1.7	8.0	12.0	13.6	6.9	7.6	27.8	2.33	0.5	1.5	3.1
California	CA	West	6	12.0	0.0	12.0	12.0	15.0	4.3	10.8	23.0	2.32	0.6	1.7	3.1
Colorado	CO	West	4	11.3	1.5	9.0	12.0	17.1	6.0	11.4	25.4	2.64	0.3	2.3	3.1
Connecticut	CT	Northeast	4	11.3	1.0	10.0	12.0	12.8	5.2	6.4	18.5	1.85	0.3	1.6	2.3
Delaware	DE	South	4	10.0	1.6	8.0	12.0	11.3	2.1	8.6	13.6	2.06	0.5	1.6	2.8
Florida	FL	South	8	10.1	2.8	5.0	12.0	13.0	5.4	5.9	21.5	1.98	0.3	1.6	2.4
Georgia	GA	South	10	10.4	2.5	6.0	12.0	13.6	5.1	5.7	21.7	1.85	0.2	1.5	2.1
Iowa	IA	Midwest	5	10.2	3.0	5.0	12.0	12.0	6.1	4.7	20.5	1.93	0.4	1.5	2.5
Idaho	ID	West	6	10.5	2.0	7.0	12.0	13.8	6.4	3.8	22.9	2.01	0.3	1.8	2.4
Illinois	IL	Midwest	4	9.3	1.9	8.0	12.0	9.0	1.2	8.0	10.6	1.69	0.1	1.5	1.9
Indiana	IN	Midwest	2	10.0	2.8	8.0	12.0	10.9	2.2	9.4	12.4	1.65	0.1	1.6	1.7
Kansas	KS	Midwest	5	9.6	1.8	8.0	12.0	9.5	1.2	7.8	10.6	1.72	0.2	1.5	2.0
Kentucky	KY	South	3	10.7	2.3	8.0	12.0	10.3	3.5	6.4	13.3	1.66	0.1	1.6	1.8
Louisiana	LA	South	5	9.0	4.2	3.0	12.0	13.2	9.0	3.7	22.5	1.95	0.3	1.7	2.3
Massachusetts	MA	Northeast	2	10.0	0.0	10.0	10.0	9.5	2.7	7.5	11.4	1.71	0.1	1.7	1.8
Maryland	MD	South	5	9.0	3.0	4.0	12.0	11.0	5.2	4.6	19.1	2.01	0.5	1.7	2.8
Maine	ME	Northeast	3	12.0	0.0	12.0	12.0	15.1	3.8	10.9	18.3	2.35	0.7	1.6	2.9
Michigan	MI	Midwest	0	NA	NA	NA	NA	NA	NA	NA	0.0	NA	NA	NA	NA
Minnesota	MN	Midwest	1	12.0	NA	12.0	12.0	15.5	NA	15.5	15.5	2.23	NA	2.2	2.2
Missouri	MO	Midwest	2	10.0	2.8	8.0	12.0	10.3	3.2	8.1	12.6	1.71	0.1	1.7	1.8
Mississippi	MS	South	6	11.3	1.6	8.0	12.0	12.6	5.5	6.7	22.2	1.88	0.3	1.6	2.5
Montana	MT	West	4	10.5	3.0	6.0	12.0	13.5	5.1	7.4	17.9	2.01	0.4	1.6	2.5
North Carolina	NC	South	6	10.0	3.2	5.0	12.0	14.6	6.1	4.6	20.4	2.30	0.5	1.7	2.9
North Dakota	ND	Midwest	3	12.0	0.0	12.0	12.0	15.7	3.3	12.5	19.0	2.07	0.5	1.7	2.6
Nebraska	NE	Midwest	7	10.1	1.8	8.0	12.0	12.9	3.4	8.3	16.8	2.09	0.5	1.5	3.0
New Hampshire	NH	Northeast	3	9.0	1.0	8.0	10.0	9.0	1.6	8.1	10.9	2.02	0.1	1.9	2.1
New Jersey	NJ	Northeast	4	9.5	2.4	6.0	11.0	12.0	6.3	6.2	20.0	2.21	0.6	1.8	3.0
New Mexico	NM	West	9	10.0	2.1	7.0	12.0	11.5	4.8	4.9	17.7	2.01	0.3	1.7	2.5
Nevada	NV	West	8	11.5	1.1	9.0	12.0	12.4	4.9	6.3	18.8	1.94	0.4	1.5	2.4
New York	NY	Northeast	6	8.8	2.3	5.0	12.0	8.8	2.3	5.6	12.8	1.83	0.4	1.5	2.5
Ohio	OH	Midwest	4	8.3	3.3	4.0	12.0	10.8	6.8	2.9	19.6	1.84	0.3	1.6	2.3
Oklahoma	OK	South	3	11.0	1.7	9.0	12.0	13.3	4.3	8.4	16.3	1.96	0.3	1.8	2.3
Oregon	OR	West	6	10.2	3.5	3.0	12.0	12.5	7.9	3.2	26.0	2.02	0.4	1.7	2.7
Pennsylvania	PA	Northeast	6	10.2	2.7	5.0	12.0	10.9	3.5	5.9	15.0	2.02	0.2	1.8	2.2
Rhode Island	RI	Northeast	1	11.0	NA	11.0	11.0	10.7	NA	10.7	10.7	1.65	NA	1.7	1.7
South Carolina	SC	South	7	10.9	2.3	6.0	12.0	14.7	5.0	5.8	21.7	2.22	0.4	1.6	2.9
South Dakota	SD	Midwest	3	8.0	1.0	7.0	9.0	10.0	2.2	8.5	12.5	1.89	0.3	1.6	2.3
Tennessee	TN	South	4	12.0	0.0	12.0	12.0	14.8	4.3	9.8	20.3	1.96	0.4	1.6	2.6
Texas	TX	South	2	10.0	2.8	8.0	12.0	16.2	8.6	10.1	22.3	2.79	0.4	2.5	3.1
Utah	UT	West	5	11.4	1.3	9.0	12.0	14.7	4.2	10.8	21.5	2.00	0.5	1.6	2.8
Virginia	VA	South	7	9.3	3.6	4.0	12.0	10.6	4.7	4.8	18.2	1.84	0.3	1.6	2.5
Vermont	VT	Northeast	4	6.3	2.1	4.0	8.0	6.5	2.2	3.8	9.1	1.85	0.3	1.5	2.2
Washington	WA	West	4	11.3	1.0	10.0	12.0	14.9	4.9	12.1	22.2	1.83	0.3	1.6	2.2
Wisconsin	WI	Midwest	4	9.3	3.2	6.0	12.0	9.9	4.4	5.8	14.2	1.74	0.2	1.6	1.9
West Virginia	WV	South	4	8.8	3.3	5.0	12.0	11.5	7.0	4.2	20.5	1.83	0.2	1.6	2.0
Wyoming	WY	West	7	11.0	1.7	8.0	12.0	14.8	3.3	9.4	19.7	1.98	0.3	1.6	2.4
South			**87**	**10.1**	**2.8**	**3.0**	**12.0**	**12.8**	**5.4**	**3.2**	**22.5**	**2.00**	**0.39**	**1.54**	**3.09**
West			**68**	**10.9**	**1.9**	**3.0**	**12.0**	**13.7**	**5.3**	**3.2**	**27.8**	**2.09**	**0.42**	**1.50**	**3.09**
Midwest			**40**	**9.7**	**2.3**	**4.0**	**12.0**	**11.3**	**4.0**	**2.9**	**20.5**	**1.87**	**0.35**	**1.50**	**2.97**
Northeast			**33**	**9.6**	**2.4**	**4.0**	**12.0**	**10.5**	**4.1**	**3.8**	**20.0**	**1.97**	**0.38**	**1.50**	**3.01**
All states			**228**	**10.2**	**2.4**	**3.0**	**12.0**	**12.5**	**5.1**	**2.9**	**27.8**	**2.0**	**0.4**	**1.50**	**3.09**

Notes: The above table only includes severe to extreme drought events which occurred in the 48 contiguous continental states during the period 1988-2016.

Temperature data

We use two sets of temperature data. The first set of temperature data is used as control variables and corresponds to the yearly average temperature for each state, which we downloaded from the NOAA's National Centers for Environmental Information website[49].

The second set of temperature data is used in the part on compound drought and high temperature events. Due to the lack of standard definitions of heat waves, these are often characterized in the literature using percentile thresholds (Perkins & Alexander, 2013). However, daily temperature data at state level is not readily available, so we use cooling degree-days as an indicator of high temperature events at the state level in a given year. Cooling degree-days are a measure of the departure above a defined base temperature level during one day and correspond to every degree that the mean temperature is above 65 degrees Fahrenheit during a day: each day, the difference between the average temperature on that day and 65 degrees is computed and the sum of each day for a month gives the monthly number of cooling degree-days[50]. We downloaded monthly cooling degree-days for the period 1988-2016 from the NOAA's National Centers for Environmental Information's website[51] and summed these up over each year to obtain the annual number of cooling degree-days for each state. Since the number of cooling degree-days in a year does not distinguish between consecutive and non-consecutive hot days, it is an imperfect indicator of heatwaves; however, they provide an indication of the number of hot days (≥ 65°F) in a given year as well as of the severity of the heat during these days.

Table 4.4 includes summary statistics for the temperature data.

[49] Available at ftp://ftp.ncdc.noaa.gov/pub/data/cirs/climdiv
[50] The name "cooling degree-days" refers to the fact that the base temperature is the temperature above which buildings are considered to need cooling.
[51] Available at ftp://ftp.ncdc.noaa.gov/pub/data/cirs/climdiv/climdiv-cddcst-v1.0.0-20170804

Table 4.4: Temperature data statistics – Average temperature and cooling degree-days

State name	State code	Region	Annual average temperature (in Fahrenheit)				Annual number of cooling degree days			
			Average	St. dev.	Min.	Max.	Average	St. dev.	Min.	Max.
Alabama	AL	South	63.4	1.0	62.0	65.3	1910	201	1534	2295
Arkansas	AR	South	60.9	1.25	58.7	63.6	1761	226	1347	2234
Arizona	AZ	West	60.9	0.86	59.3	62.3	2987	171	2585	3212
California	CA	West	58.8	0.98	56.7	61.5	893	131	699	1175
Colorado	CO	West	46.0	0.95	43.8	48.3	316	90	141	499
Connecticut	CT	Northeast	49.7	1.30	47.7	52.5	583	116	322	786
Delaware	DE	South	55.9	1.24	53.9	58.5	1105	169	744	1490
Florida	FL	South	71.2	0.90	69.2	73.4	3519	208	3184	4156
Georgia	GA	South	64.0	0.99	62.4	65.9	1703	188	1363	2107
Iowa	IA	Midwest	48.3	1.71	45.2	52.1	807	156	475	1156
Idaho	ID	West	43.8	1.10	40.9	46.4	474	108	163	646
Illinois	IL	Midwest	52.5	1.53	49.5	55.8	883	178	519	1161
Indiana	IN	Midwest	52.2	1.46	49.4	55.1	896	170	552	1172
Kansas	KS	Midwest	55.0	1.38	51.9	58.2	1448	207	1005	1825
Kentucky	KY	South	56.1	1.23	54.3	58.4	1198	181	846	1553
Louisiana	LA	South	66.9	0.99	65.1	68.7	2641	204	2279	3046
Massachusetts	MA	Northeast	48.5	1.30	46.4	51.4	495	103	261	686
Maryland	MD	South	55.1	1.21	53.2	57.5	1107	167	750	1455
Maine	ME	Northeast	41.6	1.42	39.3	44.6	230	56	107	336
Michigan	MI	Midwest	45.1	1.71	41.9	48.4	561	144	239	777
Minnesota	MN	Midwest	41.7	1.98	37.6	45.2	461	115	195	740
Missouri	MO	Midwest	55.1	1.47	52.9	58.6	1248	190	864	1608
Mississippi	MS	South	63.9	1.05	62.3	66.0	2142	199	1781	2530
Montana	MT	West	42.6	1.45	39.2	44.9	203	68	42	329
North Carolina	NC	South	59.3	1.04	57.3	61.1	1430	173	1146	1828
North Dakota	ND	Midwest	41.1	1.94	36.5	44.4	452	118	201	758
Nebraska	NE	Midwest	49.4	1.49	46.0	52.7	987	170	591	1306
New Hampshire	NH	Northeast	43.9	1.36	41.7	46.6	288	72	123	403
New Jersey	NJ	Northeast	53.3	1.32	51.2	55.9	831	152	501	1145
New Mexico	NM	West	54.2	0.90	52.5	56.0	955	137	673	1210
Nevada	NV	West	50.9	1.02	48.6	53.0	2123	176	1757	2400
New York	NY	Northeast	45.9	1.43	43.8	48.8	594	124	323	824
Ohio	OH	Midwest	51.4	1.37	49.2	54.1	765	158	453	1045
Oklahoma	OK	South	60.1	1.27	58.1	63.2	1904	252	1433	2482
Oregon	OR	West	47.8	0.99	45.5	50.4	221	63	109	371
Pennsylvania	PA	Northeast	49.3	1.30	47.4	51.8	677	135	398	904
Rhode Island	RI	Northeast	50.4	1.23	48.4	52.9	542	102	295	721
South Carolina	SC	South	63.1	1.02	61.2	65.0	1903	194	1571	2301
South Dakota	SD	Midwest	45.8	1.83	41.6	49.3	691	155	341	999
Tennessee	TN	South	58.2	1.18	56.6	60.3	1385	193	1021	1779
Texas	TX	South	65.6	1.02	63.9	67.8	2763	230	2379	3367
Utah	UT	West	49.0	1.05	46.8	50.9	511	100	233	674
Virginia	VA	South	55.7	1.10	53.9	57.6	1096	156	783	1477
Vermont	VT	Northeast	42.9	1.47	40.6	45.9	222	64	73	367
Washington	WA	West	47.3	1.05	45.5	50.0	177	54	97	311
Wisconsin	WI	Midwest	43.8	1.88	40.2	47.4	511	135	227	770
West Virginia	WV	South	52.4	1.13	50.7	54.3	779	137	541	1052
Wyoming	WY	West	42.2	1.21	38.9	44.8	275	89	79	444
South			**60.7**	**5.0**	**50.7**	**73.4**	**1772**	**730**	**541**	**4156**
West			**49.4**	**6.1**	**38.9**	**62.3**	**830**	**879**	**42**	**3212**
Midwest			**48.4**	**5.0**	**36.5**	**58.6**	**809**	**337**	**195**	**1825**
Northeast			**47.3**	**3.9**	**39.3**	**55.9**	**496**	**225**	**73**	**1145**
All states			**52.5**	**7.7**	**36.5**	**73.4**	**1076**	**805**	**42**	**4156**

Notes: The above temperature and cooling degree-days statistics only include the period 1988-2016.

Economic data

Annual data on real Gross State Product (GSP) per capita was downloaded from the Bureau of Economic Analysis (BEA) of the U.S. Department of Commerce (Bureau of Economic Analysis, 2017); it is available for each of the 48 contiguous states for the period 1988-2016.

Table 4.5: Economic data statistics – Annual rate of change of GSP per capita

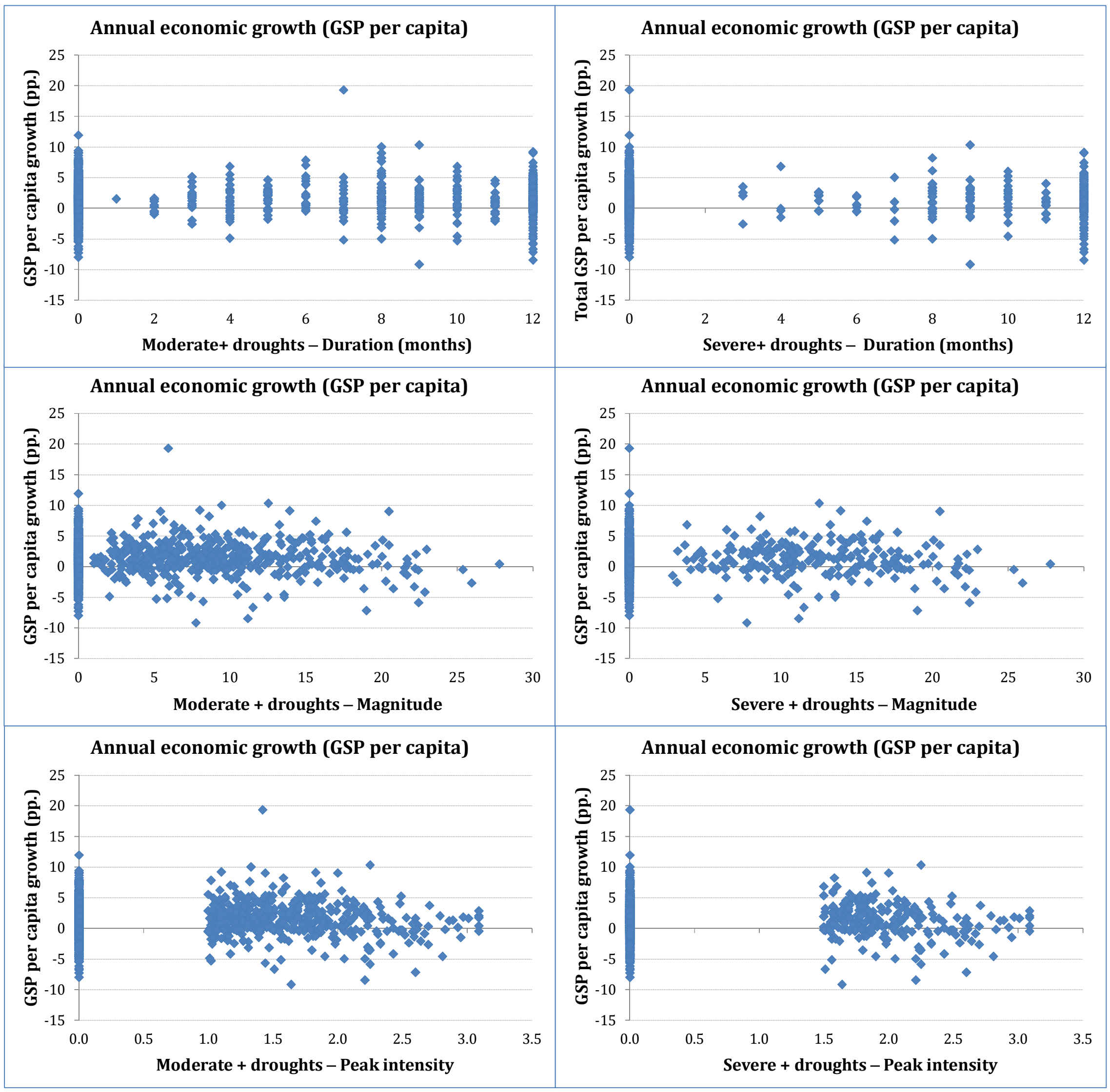
State name	State code	Region	Annual rate of change of GSP per capita (in pp.)			
			Average	St. dev.	Min.	Max.
Alabama	AL	South	1.31	1.87	-4.30	5.30
Arkansas	AR	South	1.57	1.93	-3.20	4.50
Arizona	AZ	West	1.16	3.26	-8.50	6.60
California	CA	West	1.60	2.62	-5.00	5.90
Colorado	CO	West	1.61	2.43	-3.70	7.20
Connecticut	CT	Northeast	1.27	2.85	-4.70	6.30
Delaware	DE	South	1.00	3.38	-5.70	8.20
Florida	FL	South	0.89	2.39	-6.20	4.00
Georgia	GA	South	1.10	2.39	-4.90	4.60
Iowa	IA	Midwest	2.28	2.59	-2.60	7.80
Idaho	ID	West	1.95	3.19	-5.50	9.20
Illinois	IL	Midwest	1.48	1.94	-3.00	5.60
Indiana	IN	Midwest	1.66	2.67	-6.80	6.00
Kansas	KS	Midwest	1.43	1.92	-5.00	4.60
Kentucky	KY	South	1.46	2.39	-4.40	6.80
Louisiana	LA	South	0.91	3.47	-7.30	7.60
Massachusetts	MA	Northeast	1.74	2.47	-3.10	7.40
Maryland	MD	South	1.34	1.71	-3.20	4.80
Maine	ME	Northeast	1.05	2.00	-3.30	5.80
Michigan	MI	Midwest	1.05	3.28	-8.00	8.20
Minnesota	MN	Midwest	1.62	2.31	-4.60	5.20
Missouri	MO	Midwest	1.12	1.93	-2.60	6.00
Mississippi	MS	South	1.33	2.00	-4.40	5.40
Montana	MT	West	1.51	1.72	-2.60	4.40
North Carolina	NC	South	1.23	2.25	-5.30	5.20
North Dakota	ND	Midwest	3.40	5.34	-7.20	19.30
Nebraska	NE	Midwest	2.13	1.96	-1.40	7.20
New Hampshire	NH	Northeast	1.68	2.45	-4.30	6.10
New Jersey	NJ	Northeast	1.08	1.92	-4.70	6.80
New Mexico	NM	West	1.93	3.18	-1.70	9.10
Nevada	NV	West	0.32	3.30	-9.20	6.20
New York	NY	Northeast	1.41	2.10	-3.60	5.30
Ohio	OH	Midwest	1.53	2.20	-4.50	5.50
Oklahoma	OK	South	1.79	2.18	-3.50	6.20
Oregon	OR	West	2.73	3.49	-3.60	11.90
Pennsylvania	PA	Northeast	1.71	1.44	-3.30	4.60
Rhode Island	RI	Northeast	1.33	2.32	-4.00	6.20
South Carolina	SC	South	1.10	1.93	-5.10	4.40
South Dakota	SD	Midwest	2.66	2.51	-2.10	10.30
Tennessee	TN	South	1.39	2.10	-4.50	6.00
Texas	TX	South	1.88	2.03	-2.60	5.80
Utah	UT	West	1.83	2.51	-4.20	7.00
Virginia	VA	South	1.19	1.71	-1.70	3.90
Vermont	VT	Northeast	1.74	2.22	-3.40	6.80
Washington	WA	West	1.39	2.44	-4.90	6.00
Wisconsin	WI	Midwest	1.64	1.76	-3.20	5.10
West Virginia	WV	South	1.73	2.05	-1.60	9.00
Wyoming	WY	West	1.72	3.44	-5.00	10.00
South			**1.33**	**2.27**	**-7.30**	**9.00**
West			**1.61**	**2.93**	**-9.20**	**11.90**
Midwest			**1.83**	**2.74**	**-8.00**	**19.30**
Northeast			**1.45**	**2.21**	**-4.70**	**7.40**
All states			**1.54**	**2.54**	**-9.20**	**19.30**

Notes: The above statistics are only for the period 1988-2016.

In a second stage, we repeat the analyses conducted on states' GSP growth using states' agricultural sector growth as the dependent variable instead: we use the same data source as for states' total economic growth and download real GDP by state for the agriculture, forestry, fishing and hunting industries from the Bureau of Economic Analysis at the U.S. Department of Commerce (Bureau of Economic Analysis, 2017).

<u>Scatter plots</u>

Figure 4.2: Scatter plots: U.S. states' annual GSP per capita growth vs. the duration, magnitude and peak intensity of drought events



Notes: All above graphs consider all 48 contiguous states and all drought events over the period 1988-2016. The column on the left includes moderate, severe and extreme droughts, i.e. all drought events for which at least one monthly SPI value is equal to less or less than –1. The column on the right includes only severe and extreme droughts, i.e. all drought events for which at least one monthly SPI value is equal to less or less than –1.5. As per the standard definition of drought events (McKee et al., 1993), drought magnitude and peak intensity are defined as the absolute value of the monthly SPIs.

A quick visual analysis of the above graphs does not provide immediate insight into the impacts of drought events on the economic growth of U.S. states – perhaps a very slight downward trend is noticeable for the duration and peak intensity of severe to extreme droughts.

iii. Scale of the analysis

Spatial scale

As explained above, the analyses presented in this chapter are based on state level data. This is due to constraints in terms of data availability: indeed, time series of SPI data are available at the county- or station-level in the United States, but panel datasets of economic production or economic growth variables only exist at the federal or the state-level. The (constrained) choice of the state level is likely to create aggregation biases and to impact results. For instance, Fezzi and Bateman (2015) have shown that non-linear interaction effects between temperature and precipitation at the farm level disappear when data are aggregated across countries or large regions. According to their results, which are derived from farm data in the United Kingdom, estimates of climate change impacts are far less optimistic in farm-level models than in aggregated, county level analyses. There is therefore a possibility that the use of state-level data in our analyses induces substantial aggregation biases, notably regarding the interaction effects of temperature and precipitation.

Timing

Due to data availability constraints pertaining to the economic variables, the analyses presented in this chapter are based on annual data. The drought variables considered are the duration, magnitude and peak magnitude of drought events occurring over a 12-month period, and do not consider the specific seasons or months which are covered by the drought event, even though these are likely to influence the scale of the impacts, especially when looking at the impacts of droughts on the agricultural sector. Indeed, droughts during the planting or growing phase are more likely to be detrimental than droughts which occur after harvesting. However, again, the lack of sufficient time series of economic data on a quarterly or monthly basis prevents us from including variables in our model which are on lower time scales than a year. Tebaldi and Beaudin (2016) examined the impacts of seasonal rainfall variations on the GDP growth rates of seasonal states but their analysis only includes annual fixed effects, and not seasonal fixed effects, which means that their results might be significantly biased by seasonal effects which are uncontrolled for. Here as well, the fact that the dependent variable is on an annual scale precludes the use of seasonal fixed effects and prevents us from including variables such as the month corresponding to the onset (or the peak) of the drought event.

iv. *Econometric approach*

Based on the approaches developed in the literature and which are described above, we propose to examine the impact of drought events using a panel data analysis based on the following estimation strategy:

Equation 4.1

$$y_{i,t} = \sum_{k=0}^{p} \beta_k \, D_{i,t-k} + \sum_{k=0}^{p} \gamma_k \, Z_{i,t-k} + \mu_i + \theta_{rt} + \varepsilon_{i,t}$$

Where:

- $y_{i,t}$ is economic growth in state i in year t;
- $D_{i,t}$ are drought variables;
- $Z_{i,t}$ are time-varying control variables;
- μ_i are state fixed effects;
- θ_{rt} are region-specific time fixed effects.

As regards the control variables Z_{it}, we follow the recommendations in the literature on panel data analysis in the context of weather studies and include (lags of) yearly average temperature as a control variable. Indeed, as underlined by Auffhammer et al. (2013), the fact that precipitation and temperatures are historically correlated renders necessary the inclusion of both variables in regression equations used to estimate weather impacts, in order to limit the risk of omitted variable bias.

The inclusion of state fixed effects μ_i controls for all time-invariant state characteristics, both observed and unobserved. Following the literature (Dell et al., 2012, 2014), we also include time fixed effects interacted with region dummies (θ_{rt}), which might absorb some of the variation in weather but also control for time-varying factors and these time-varying factors are furthermore allowed to differ across regions.

Standard errors are bootstrapped and are adjusted for clustering at the state level (i.e. they allow for correlation within the observations for each state)[52].

5. Results and discussion

<u>Moderate to extreme droughts</u>

We first consider all drought events from moderate to severe and examine the effect of three drought characteristics on states' GSP per capita growth: drought duration (in log; Table 4.6), drought magnitude (in log; Table 4.7) and drought peak intensity (Table 4.8). In each table, the first column considers all 48 contiguous states, while columns 2 to 5 consider each region independently. All regressions include the 0-lag of annual average temperature (removed from output tables for clarity purposes) as a control variable. Due to the strong collinearity between

[52] This is done using the *bootstrap idcluster() group(): xtreg* command in Stata

lags 0 and 1 of annual average temperature, the bootstrap procedure cannot be performed if we also include the first lag of annual average temperature in the regression.

Table 4.6: Moderate to extreme droughts – Drought duration

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)
	All	*South*	*West*	*Midwest*	*Northeast*
duration	-0.11	-0.12	$\boxed{-0.39^{***}}$	0.13	0.07
	(0.09)	(0.11)	(0.13)	(0.11)	(0.14)
L.duration	0.08	-0.01	0.07	0.20	0.19
	(0.06)	(0.10)	(0.13)	(0.15)	(0.20)
N	1392	464	319	348	261
R-sq	0.47	0.47	0.45	0.43	0.68
Drought variable	duration	duration	duration	duration	duration
Drought type	moderate+	moderate+	moderate+	moderate+	moderate+
States	All	South	West	Midwest	Northeast
Cluster obs.	48	16	11	12	9
State FE	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes

Notes: Drought magnitude in log. Above regressions include all drought events that are considered moderate to extreme. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 4.7: Moderate to extreme droughts – Drought magnitude

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)
	All	*South*	*West*	*Midwest*	*Northeast*
magnitude	-0.14	-0.12	$\boxed{-0.41^{***}}$	0.10	0.05
	(0.09)	(0.10)	(0.15)	(0.10)	(0.16)
L.magnitude	0.07	-0.05	0.08	0.24	0.22
	(0.08)	(0.11)	(0.12)	(0.16)	(0.20)
N	1392	464	319	348	261
R-sq	0.47	0.47	0.45	0.43	0.68
Drought variable	magnitude	magnitude	magnitude	magnitude	magnitude
Drought type	moderate+	moderate+	moderate+	moderate+	moderate+
States	All	South	West	Midwest	Northeast
Cluster obs.	48	16	11	12	9
State FE	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes

Notes: Drought magnitude in log. Above regressions include all drought events that are considered moderate to extreme. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 4.8: Moderate to extreme droughts – Drought peak intensity

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)
	All	*South*	*West*	*Midwest*	*Northeast*
peak intensity	-0.19*	-0.08	-0.67***	0.10	0.05
	(0.11)	(0.11)	(0.21)	(0.17)	(0.25)
L.peak intensity	0.09	-0.05	0.02	0.41*	0.36
	(0.09)	(0.16)	(0.13)	(0.21)	(0.23)
N	1392	464	319	348	261
R-sq	0.48	0.47	0.46	0.43	0.68
Drought variable	peak int.	peak int.	peak int.	peak int.	peak int.
Drought type	moderate+	moderate+	moderate+	moderate+	moderate+
States	All	South	West	Midwest	Northeast
Cluster obs.	48	16	11	12	9
State FE	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes

Notes: Drought magnitude in log. Above regressions include all drought events that are considered moderate to extreme. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

As we can see from the tables above, the magnitude and peak intensity of current-year droughts have on average a negative effect on states' economic growth but only at the 10% significance level. However, results from individual regions show reveal that these aggregate effects seem to be coming from the West region, where the duration, magnitude and peak intensity of current-year droughts have a negative and highly significant effect on states' economic growth (and despite the relative small number of observations in this region). We also find negative effects of current-year droughts on Southern states' economic growth, but these effects are insignificant. Since the predictor variables duration and magnitude are log-transformed, the results in Table 4.6 above mean that for a 30% increase in drought duration, the difference in the expected economic growth would be −0.10 percentage points in Western states. The interpretation for peak intensity is more straightforward: according to the results presented in Table 4.8, an increase in drought peak intensity of 0.5 (which corresponds to the width of drought categories) would reduce economic growth by 0.34 percentage points in Western states.

Severe to extreme droughts

Whereas in the previous section we considered all drought events, from moderate to extreme, we now consider only severe to extreme drought events. As before, drought duration (Table 4.9), magnitude (Table 4.10) and peak intensity (Table 4.11) are examined independently and all regressions include the 0-lag of annual average temperature (removed from output tables for clarity purposes) as a control variable.

Table 4.9: Severe to extreme droughts – Drought duration

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)
	All	*South*	*West*	*Midwest*	*Northeast*
duration	-0.18**	-0.09	-0.46***	-0.07	0.14
	(0.09)	(0.10)	(0.14)	(0.19)	(0.13)
L.duration	0.03	-0.08	0.02	0.30	0.04
	(0.07)	(0.12)	(0.12)	(0.22)	(0.19)
N	1392	464	319	348	261
R-sq	0.48	0.47	0.46	0.42	0.68
Drought variable	duration	duration	duration	duration	duration
Drought type	severe+	severe+	severe+	severe+	severe+
States	All	South	West	Midwest	Northeast
Cluster obs.	48	16	11	12	9
State FE	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes

Notes: Drought magnitude in log. Above regressions include all drought events that are considered moderate to extreme. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 4.10: Severe to extreme droughts – Drought magnitude

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)
	All	*South*	*West*	*Midwest*	*Northeast*
magnitude	-0.17**	-0.09	-0.42***	-0.12	0.11
	(0.09)	(0.08)	(0.13)	(0.29)	(0.11)
L.magnitude	0.03	-0.09	0.03	0.31	0.07
	(0.09)	(0.12)	(0.10)	(0.27)	(0.19)
N	1392	464	319	348	261
R-sq	0.48	0.47	0.45	0.43	0.68
Drought variable	intensity	intensity	intensity	intensity	intensity
Drought type	severe+	severe+	severe+	severe+	severe+
States	All	South	West	Midwest	Northeast
Cluster obs.	48	16	11	12	9
State FE	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes

Notes: Drought magnitude in log. Above regressions include all drought events that are considered moderate to extreme. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

Table 4.11: Severe to extreme droughts – Drought peak intensity

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)
	All	*South*	*West*	*Midwest*	*Northeast*
peak intensity	-0.22**	-0.07	-0.56***	-0.20	0.13
	(0.11)	(0.08)	(0.15)	(0.35)	(0.14)
L.peak intensity	0.04	-0.11	0.02	0.43	0.15
	(0.11)	(0.20)	(0.14)	(0.34)	(0.19)
N	1392	464	319	348	261
R-sq	0.48	0.47	0.46	0.43	0.68
Drought variable	peak int.	peak int.	peak int.	peak int.	peak int.
Drought type	severe+	severe+	severe+	severe+	severe+
States	All	South	West	Midwest	Northeast
Cluster obs.	48	16	11	12	9
State FE	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes

Notes: Above regressions include all drought events that are considered severe to extreme. All regressions include the 0-lag of of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

According to the findings presented in the three tables above, our results for severe to extreme droughts are highly consistent with the results we had found for moderate to extreme droughts, and if anything, they are somewhat stronger. We find that current-year severe and extreme droughts have a significant and negative impact on U.S. states' economic growth overall (now at the 5% significance level, including for duration), and that this effect seems to be coming predominantly from Western States. The results in Table 4.9 above mean that for a 30% increase in drought duration, the difference in the expected economic growth would be −0.12 in Western states. As regards peak intensity, the results in Table 4.11 above indicate that an increase in peak intensity of 0.5 (which corresponds to the width of drought categories) would reduce economic growth by 0.28 percentage points in Western states.

<u>Time-lagged effects</u>

The results for time-lagged effects of droughts on states' economic growth are presented in Appendix 4.1. In each table, the bottom row presents the cumulated effect of droughts[53] and its (calculated) standard error. We find that, when considering all states, droughts have a cumulated effect that is negative and highly significant, but also larger than their contemporaneous effects, which seems to indicate that droughts have time-lagged effects (Tables A4.15, A4.16 and A4.17). Again, we find that these effects seem to be coming from the Western region (Tables A4.18, A4.19 and A4.20), whereas the South and Midwest regions do not display any consistent and significant effects. Interestingly, whereas droughts do not seem to have a contemporaneous effect on

[53] For any horizon h, the cumulated lag effect is defined as $\beta_0 + \beta_1 + \beta_2 + .. + \beta_h$, which is interpreted as the change in the expected outcome h periods after a permanent, one-unit increase in the drought variable under consideration. The point estimates and standard deviations of all combinations (incl. nonlinear) of parameter estimates provided in this chapter have been estimated using the *nlcom* command in Stata which uses the delta method to compute standard errors.

Northeastern states' economic growth, the 10-year cumulated lag effect is negative and highly significant.

Compounding effects

In this part of the analysis, we only consider severe to extreme droughts (i.e. with at least one month for which the absolute value of the SPI is equal to or lower than −1.5). We use the following estimation strategy to identify compound effects:

Equation 4.2

$$y_{i,t} = \sum_{k=0}^{p} \beta_k D_{i,t-k} + \sum_{k=0}^{p} \gamma_k C_{i,t-k} + \sum_{k=0}^{p} \omega_k \left(D_{i,t-k} * C_{i,t-k}\right) + \mu_i + \theta_{rt} + \varepsilon_{i,t}$$

Where:

- $y_{i,t}$ is economic growth in state i in year t;
- $D_{i,t}$ are drought variables;
- $C_{i,t}$ are the variables indicating high temperatures (here, cooling degree-days);
- μ_i are state fixed effects;
- θ_{rt} are region-specific time fixed effects
- The ω_k coefficients on the interaction terms represent compound effects, i.e. the conjoint effect of droughts and high temperatures.

The following three tables show the effect of the interaction between the annual number of cooling degree-days and drought duration (Table 4.12); drought magnitude (Table 4.13); and drought peak intensity (Table 4.14).

Table 4.12: Severe to extreme droughts – Drought duration x cooling degree-days

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)
	All	*South*	*West*	*Midwest*	*Northeast*
duration	-0.21	-0.25	-0.44**	0.56	0.19
	(0.17)	(0.32)	(0.22)	(0.50)	(0.24)
L.duration	0.20	0.07	0.17	-0.13	0.45
	(0.12)	(0.26)	(0.16)	(0.75)	(0.44)
cdd	0.50	1.01	1.06	-0.48	0.24
	(0.60)	(0.73)	(1.66)	(2.65)	(1.40)
L.cdd	0.00	0.08	-0.07	-0.65	-0.07
	(0.08)	(0.16)	(0.20)	(0.69)	(0.40)
duration*cdd	0.00	0.08	-0.07	-0.65	-0.07
	(0.08)	(0.16)	(0.20)	(0.69)	(0.40)
L.duration*L.cdd	-0.15	-0.11	-0.18	0.45	-0.87
	(0.10)	(0.19)	(0.15)	(0.89)	(0.83)
N	1392	464	319	348	261
R-sq	0.47	0.47	0.46	0.41	0.68
Drought variable	duration	duration	duration	duration	duration
Drought type	severe+	severe+	severe+	severe+	severe+
States	All	South	West	Midwest	Northeast
Cluster obs.	48	16	11	12	9
State FE	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Drought duration in log. Above regressions include all drought events that are considered severe to extreme. The variable "cdd" corresponds to the annual number of cooling degree-days, divided by 1000. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 4.13: Severe to extreme droughts – Drought magnitude x cooling degree-days

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)
	All	*South*	*West*	*Midwest*	*Northeast*
magnitude	-0.21	-0.20	-0.39**	0.51	0.13
	(0.15)	(0.30)	(0.18)	(0.41)	(0.29)
L.magnitude	0.18	0.01	0.15	-0.13	0.47
	(0.12)	(0.25)	(0.19)	(0.64)	(0.41)
cdd	0.36	0.18	1.01	0.16	0.51
	(0.80)	(1.40)	(1.49)	(1.70)	(2.00)
L.cdd	0.48	1.02	0.91	-0.40	0.32
	(0.66)	(0.65)	(1.15)	(2.64)	(1.59)
magnitude*cdd	0.00	0.06	-0.07	-0.66	-0.01
	(0.08)	(0.16)	(0.17)	(0.45)	(0.46)
L.magnitude*L.cdd	-0.13	-0.07	-0.14	0.45	-0.82
	(0.08)	(0.18)	(0.12)	(0.66)	(0.79)
N	1392	464	319	348	261
R-sq	0.47	0.47	0.46	0.41	0.68
Drought variable	magnitude	magnitude	magnitude	magnitude	magnitude
Drought type	severe+	severe+	severe+	severe+	severe+
States	All	South	West	Midwest	Northeast
Cluster obs.	48	16	11	12	9
State FE	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Drought magnitude in log. Above regressions include all drought events that are considered severe to extreme. The variable "cdd" corresponds to the annual number of cooling degree-days, divided by 1000. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 4.14: Severe to extreme droughts – Drought peak intensity x cooling degree-days

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)
	All	*South*	*West*	*Midwest*	*Northeast*
peak intensity	-0.37**	-0.37	-0.61**	0.53	0.08
	(0.17)	(0.35)	(0.27)	(0.63)	(0.41)
L.peak intensity	0.22	0.04	0.12	-0.10	0.60
	(0.17)	(0.27)	(0.20)	(0.97)	(0.51)
cdd	0.35	0.16	0.87	0.21	0.44
	(0.89)	(1.46)	(1.87)	(1.34)	(1.76)
L.cdd	0.49	1.09	0.89	-0.39	0.37
	(0.75)	(0.87)	(1.56)	(2.93)	(1.24)
peak intensity*cdd	0.07	0.16	0.01	-0.79	0.09
	(0.10)	(0.16)	(0.35)	(0.62)	(0.44)
L.peak intensity*L.cdd	-0.15	-0.11	-0.12	0.55	-0.97
	(0.13)	(0.20)	(0.19)	(0.86)	(0.91)
N	1392	464	319	348	261
R-sq	0.47	0.47	0.46	0.41	0.68
Drought variable	peak int.	peak int.	peak int.	peak int.	peak int.
Drought type	severe+	severe+	severe+	severe+	severe+
States	All	South	West	Midwest	Northeast
Cluster obs.	48	16	11	12	9
State FE	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Above regressions include all drought events that are considered severe to extreme. The variable “cdd” corresponds to the annual number of cooling degree-days, divided by 1000. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

We find that the contemporaneous effects of the duration, magnitude and peak intensity of droughts on states economic growth remain for the Western region, even when adding the interaction term between cooling degree-days and drought characteristics. Regarding compound effects, we find no significant effects of the first lag of the interaction between drought duration/magnitude and cooling degree-days on states' economic growth.

<u>Discussion of results</u>

According to our findings, the duration, magnitude and peak intensity of droughts have negative and significant contemporaneous effects on U.S. states' economic growth on average, and these effects seem to be coming from the West region. Given that one of the most direct impacts of droughts is on the agricultural sector, we repeat the above analyses using U.S. states' agricultural sector growth as the dependent variable: we use the same data source as for states' total economic growth and download real GDP by state for the agriculture, forestry, and fishing industries from the Bureau of Economic Analysis at the U.S. Department of Commerce (Bureau of Economic Analysis, 2017).

The results of this analysis, presented in Appendix 4.2, show the following picture: when considering all states regardless of the region, the lags 0 and 1 for all drought characteristics (duration, magnitude and peak intensity) are similar in magnitude but of opposite signs, which could signal an increase in agricultural prices following hits to crop production due to droughts (Tables A4.30 to A4.32). However, these aggregate effects hide significant disparities at the region level: in the West region, the contemporaneous effects of droughts on agricultural GDP growth are significant and negative (Tables A4.33 to A4.35). In the South region, the contemporaneous effects of droughts are also negative but, for moderate to extreme droughts, the first lag of drought duration, magnitude and peak intensity has a positive and significant effect;(Tables A4.36 to A4.38). In the Midwest region, only "severe+" droughts have significant (negative) contemporaneous effects, whereas the first lag of droughts has a large and highly significant effect for both "moderate+" and "severe+" droughts (Tables A4.39 to A4.41). Finally, we find no significant effects of droughts on the agricultural sector's growth in the Northeast region (Tables A4.42 to A4.44).

As regards the channels responsible for compound effects, Tables A4.45 to A4.47 in Appendix 3 present similar regression models to the ones presented in Tables A4.12 to A4.14 above, but with agricultural GSP growth as the dependent variable. We find that the negative and highly significant effect of droughts on the agricultural sector's growth remains for all states and for the West region, despite the inclusion of the interaction term between droughts and cooling-degree-days, and that the first lag of the interaction term also has a negative and significant effect in these regions.

How can we interpret these findings? The comparison of our results on states' total GSP growth and agricultural GSP growth leads to the following considerations: it is likely that the negative effects of droughts on Western states' economic growth is linked to the negative impacts of drought on the agricultural sector. However, this does not explain why the economies of the states in the West region are sensitive to drought conditions whereas Southern states (where the agricultural sector is just as badly hit by droughts) appear to have more resilient economies[54]. An exploration of channels other than the agricultural sector through which droughts could affect the economy would be needed for Northeastern states, as the agricultural channel does not seem to explain either the negative and significant cumulated lag effect of droughts in Northeastern states.

The analyses presented above suffer from a few limitations, which may result in an underestimation of the effects: first, they are based on a relatively short time series of 29 years; as we mentioned previously, the heat measure that we use, and which is based on cooling degree-days, is an imperfect indicator of the frequency and intensity of heat spells in a given year. Second, our analysis does not consider local drought impacts and the use of state-level data is likely to be a source of aggregation biases, notably as regard the interaction effects between temperature and precipitation. Third, as mentioned previously, our dataset does not allow the examination of the impact of the timing of drought events, which is expected to be very substantial for the agricultural sector. Finally, our model does not account for financial transfers from the federal government to drought-stricken regions.

Several aspects of the preliminary findings presented in this paper warrant further exploration. For instance, the above analysis on compound effects could be redone based on a more accurate indicator of heat waves, e.g. based on the number of periods with consecutive days for which temperature is above a certain percentile threshold. Also, given the relative scarcity of the literature on the economic impacts of droughts, much remains to be done in terms of analysing the impacts of droughts: seasonal effects could be explored through the use of quarterly

[54] The share of the agricultural sector in states' GSP is on average 0.6% in the Northeast, 1.2% in the South, 1.9% in the West and 3.0% in the Midwest region.

data, while spatially-lagged or remote effects could be examined through the use of different model specifications (Hsiang, 2016). Finally, the relevance of these findings could be enhanced by a deeper exploration into the socio-economic features that make states sensitive or resilient to drought conditions.

6. Conclusion and policy implications

We have presented above a number of findings, which tend to indicate that droughts have significant and negative impacts on states' economic growth. How can these results be useful in the context of climate change? Given the pressures from policymakers to provide precise quantified estimates of future damage from weather events, the temptation has been strong for economics researchers to apply their results to the relationship between weather and socio-economic outcomes to future projections of climate change (Deschênes & Greenstone, 2011; Hsiang & Jina, 2014; Jenkins & Warren, 2015a; Urban et al., 2015). However, there are a few concerns surrounding the extrapolation of the effects of current weather to future climate.

First, finding projections of future weather to apply these findings to, is, in itself problematic. Despite recent advances in the field of climate science regarding our understanding of how global changes in climate will drive local changes in weather, there are intrinsic and significant limits to the quantification of local climate change (Chapman, Stainforth, & Watkins, 2015). Indeed, Global Circulation Models do not provide distributions of future weather events: several methods and techniques including dynamical and statistical downscaling methods have been proposed to translate GCM outputs into future distributions of local weather variables, but, as emphasized by Stainforth (2010), there are several practical and philosophical challenges to attempting to produce robust and relevant predictions on regional scales.

Then, even supposing that we had access to reliable regional projections of future changes in weather patterns, there are serious limitations to the extrapolation of the findings from these panel models to states of the climate in which Earth's temperature will be considerably warmer: these restrictions come from the possibility of nonlinearities, potential intensification effects, the eventuality of adaptation, and general equilibrium effects (Dell et al., 2014). For these reasons, the estimates derived from these panel models cannot be said conclusively to serve even as lower or upper bounds on future climate damage: for instance, if adaptation policies are implemented on a large scale, then the effects of current weather shocks might be stronger than the future effects of climate; conversely, if the intensification of weather shocks leads to steep increases in impacts, then estimates derived from current weather shocks could be underestimating the future damages from climate change (Dell et al., 2014).

Notwithstanding these stark limitations, there are two ways in which results such as those presented in this paper can be useful to inform and guide the policy debate. First, these findings can be useful to quantify current and near-term risks. Notably, estimating the socio-economic impacts of weather events will help us to more accurately assess the near-term risks posed by climate change, and to design appropriate adaptation and recovery policies.

Second, they enable us to gain a better understanding of the long-term uncertainties pertaining to future climate change. For instance, we found the co-occurrence of severe and extreme droughts and high temperature conditions had a negative and highly significant effect on the growth of the agricultural sector. Several insights can be gained from such findings on compound effects: first, in a world where both dry conditions and heat spells are expected to become more intense and more frequent, evidence of negative compound effects of dry and warm conditions could mean that, for a given global temperature increase, damage from climate change is greater than currently expected. Not only would this add another layer of complexity to the debate on the damage function (Nordhaus, 2008; Pindyck, 2013; Stern, 2013; Tol, 2014; Weitzman, 2012), but examining combinations of weather and climate events instead of each type of event separately should also fatten the tails of the distribution of potential impacts. However, far from being a step backward, the knowledge that the uncertainty we are facing is actually greater than previously expected is extremely valuable information and should be explicitly taken into account by policymakers when deciding the level of stringency of our mitigation efforts.

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APPENDICES

Appendix 4.1: Lagged effects of droughts on states' GSP per capita growth

All states

Table A4.15: All states – Lagged effects of drought duration on GSP per capita growth

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*All*	*All*	*All*	*All*	*All*	*All*	*All*	*All*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
duration	-0.11	-0.11	-0.12	-0.13	-0.17**	-0.18**	-0.19**	-0.21***
	(0.09)	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)	(0.09)	(0.07)
L.duration		0.08	0.07	0.08		0.03	0.05	0.05
		(0.07)	(0.04)	(0.07)		(0.07)	(0.08)	(0.08)
L2.duration			-0.05	-0.04			-0.14**	-0.13*
			(0.09)	(0.09)			(0.05)	(0.07)
L3.duration			-0.14***	-0.15**			-0.01	-0.01
			(0.05)	(0.07)			(0.06)	(0.07)
N	1392	1392	1392	1392	1392	1392	1392	1392
R-sq	0.47	0.47	0.48	0.49	0.48	0.48	0.48	0.48
Drought variable	duration	duration	duration	duration	duration	duration	duration	duration
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	All	All	All	All	All	All	All	All
Cluster obs.	48	48	48	48	48	48	48	48
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-0.11	-0.04	-0.30*	-0.70**	-0.17**	-0.15*	-0.31*	-0.64**
	(0.09)	(0.13)	(0.18)	(0.28)	(0.09)	(0.09)	(0.18)	(0.32)

Notes: Drought duration in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.16: All states – Lagged effects of drought magnitude on GSP per capita growth

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*All*	*All*	*All*	*All*	*All*	*All*	*All*	*All*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
magnitude	-0.13	-0.14**	-0.15*	-0.16**	-0.17***	-0.17*	-0.19**	-0.20***
	(0.09)	(0.07)	(0.08)	(0.08)	(0.06)	(0.09)	(0.08)	(0.07)
L.magnitude		0.07	0.07	0.08		0.03	0.05	0.05
		(0.07)	(0.08)	(0.08)		(0.08)	(0.08)	(0.09)
L2.magnitude			-0.07	-0.06			-0.14*	-0.14***
			(0.09)	(0.07)			(0.08)	(0.06)
L3.magnitude			-0.12**	-0.13**			-0.01	-0.01

			(0.06)	(0.06)			(0.06)	(0.07)
N	1392	1392	1392	1392	1392	1392	1392	1392
R-sq	0.47	0.47	0.48	0.49	0.48	0.48	0.48	0.48
Drought variable	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	All	All	All	All	All	All	All	All
Cluster obs.	48	48	48	48	48	48	48	48
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-0.13	-0.07	-0.32	-0.75***	-0.17***	-0.15*	-0.32	-0.61***
	(0.09)	(0.10)	(0.23)	(0.22)	(0.06)	(0.09)	(0.20)	(0.20)

Notes: Drought magnitude in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.17: All states – Lagged effects of drought peak intensity on GSP per capita growth

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*All*	*All*	*All*	*All*	*All*	*All*	*All*	*All*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
peak intensity	-0.18*	-0.19*	-0.21**	-0.21**	-0.22**	-0.22**	-0.25***	-0.26***
	(0.11)	(0.10)	(0.09)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)
L.peak intensity		0.09	0.09	0.11		0.04	0.06	0.07
		(0.10)	(0.10)	(0.10)		(0.09)	(0.10)	(0.11)
L2.peak intensity			-0.09	-0.07			-0.16*	-0.16*
			(0.10)	(0.09)			(0.09)	(0.09)
L3.peak intensity			-0.15*	-0.16**			-0.02	-0.02
			(0.08)	(0.08)			(0.07)	(0.06)
N	1392	1392	1392	1392	1392	1392	1392	1392
R-sq	0.47	0.48	0.48	0.49	0.48	0.48	0.48	0.48
Drought variable	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	All	All	All	All	All	All	All	All
Cluster obs.	48	48	48	48	48	48	48	48
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-0.18*	-0.10	-0.45**	-1.04***	-0.22**	-0.19*	-0.46*	-0.85***
	(0.11)	(0.15)	(0.21)	(0.25)	(0.10)	(0.11)	(0.25)	(0.28)

Notes: Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

West region

Table A4.18: Western states – Lagged effects of drought duration on GSP per capita growth

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*West*	*West*	*West*	*West*	*West*	*West*	*West*	*West*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
duration	-0.38**	-0.39**	-0.36**	-0.35*	-0.46***	-0.46***	-0.47***	-0.47***
	(0.18)	(0.16)	(0.17)	(0.21)	(0.14)	(0.16)	(0.17)	(0.15)
L.duration		0.07	0.06	0.08		0.02	0.04	0.10
		(0.14)	(0.11)	(0.15)		(0.11)	(0.13)	(0.14)
L2.duration			0.01	0.01			-0.19	-0.20
			(0.18)	(0.21)			(0.12)	(0.12)
L3.duration			0.00	0.00			0.08	0.10
			(0.18)	(0.14)			(0.12)	(0.12)
N	319	319	319	319	319	319	319	319
R-sq	0.45	0.45	0.45	0.47	0.46	0.46	0.46	0.47
Drought variable	duration	duration	duration	duration	duration	duration	duration	duration
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	West	West	West	West	West	West	West	West
Cluster obs.	11	11	11	11	11	11	11	11
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-0.38**	-0.32	-0.22	-0.88	-0.46***	-0.45**	-0.59	-0.95**
	(0.18)	(0.24)	(0.52)	(0.66)	(0.14)	(0.18)	(0.39)	(0.46)

Notes: Drought duration in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.19: Western states – Lagged effects of drought magnitude on GSP per capita growth

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*West*	*West*	*West*	*West*	*West*	*West*	*West*	*West*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
magnitude	-0.40***	-0.41***	-0.39**	-0.37	-0.42***	-0.42***	-0.43***	-0.43***
	(0.15)	(0.14)	(0.20)	(0.24)	(0.14)	(0.15)	(0.15)	(0.15)
L.magnitude		0.08	0.06	0.10		0.03	0.05	0.10
		(0.12)	(0.14)	(0.12)		(0.12)	(0.10)	(0.12)
L2.magnitude			-0.04	-0.02			-0.19**	-0.20
			(0.18)	(0.18)			(0.09)	(0.12)
L3.magnitude			-0.02	0.00			0.06	0.08
			(0.14)	(0.15)			(0.15)	(0.13)

N	319	319	319	319	319	319	319	319
R-sq	0.45	0.45	0.46	0.47	0.45	0.45	0.46	0.47
Drought variable	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	West	West	West	West	West	West	West	West
Cluster obs.	11	11	11	11	11	11	11	11
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-0.40***	-0.33	-0.34	-0.86	-0.42***	-0.39**	-0.55	-0.84**
	(0.15)	(0.22)	(0.51)	(0.53)	(0.14)	(0.19)	(0.40)	(0.40)

Notes: Drought magnitude in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.20: Western states – Lagged effects of drought peak intensity on GSP per capita growth

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*West*	*West*	*West*	*West*	*West*	*West*	*West*	*West*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
peak intensity	-0.67***	-0.67***	-0.66***	-0.62***	-0.55***	-0.56***	-0.57***	-0.57***
	(0.21)	(0.22)	(0.24)	(0.20)	(0.17)	(0.18)	(0.17)	(0.16)
L.peak intensity		0.02	0.01	0.08		0.02	0.04	0.10
		(0.17)	(0.13)	(0.12)		(0.16)	(0.13)	(0.14)
L2.peak intensity			-0.06	-0.03			-0.20*	(0.20)
			(0.23)	(0.25)			(0.11)	(0.13)
L3.peak intensity			-0.02	-0.01			0.08	0.09
			(0.21)	(0.22)			(0.20)	(0.13)
N	319	319	319	319	319	319	319	319
R-sq	0.46	0.46	0.46	0.47	0.46	0.46	0.46	0.47
Drought variable	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	West	West	West	West	West	West	West	West
Cluster obs.	11	11	11	11	11	11	11	11
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-0.67***	-0.65**	-0.82	-1.47**	-0.55***	-0.54***	-0.79**	-1.17**
	(0.21)	(0.27)	(0.63)	(0.63)	(0.17)	(0.21)	(0.38)	(0.49)

Notes: Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the second row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

South region

Table A4.21: Southern states – Lagged effects of drought duration on GSP per capita growth

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*South*	*South*	*South*	*South*	*South*	*South*	*South*	*South*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
duration	-0.12	-0.12	-0.13	-0.14	-0.10	-0.09	-0.10	-0.10
	(0.10)	(0.12)	(0.09)	(0.11)	(0.09)	(0.08)	(0.10)	(0.10)
L.duration		-0.01	0.00	0.00		-0.08	-0.07	-0.06
		(0.11)	(0.10)	(0.10)		(0.13)	(0.13)	(0.11)
L2.duration			-0.05	-0.04			-0.08	-0.06
			(0.12)	(0.12)			(0.10)	(0.11)
L3.duration			-0.17***	-0.19***			-0.01	-0.02
			(0.04)	(0.04)			(0.07)	(0.06)
N	464	464	464	464	464	464	464	464
R-sq	0.47	0.47	0.48	0.48	0.47	0.47	0.47	0.48
Drought variable	duration	duration	duration	duration	duration	duration	duration	duration
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	South	South	South	South	South	South	South	South
Cluster obs.	16	16	16	16	16	16	16	16
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-0.12	-0.13	-0.53***	-0.41*	-0.10	-0.18	-0.10	0.06
	(0.10)	(0.21)	(0.19)	(0.24)	(0.09)	(0.16)	(0.30)	(0.35)

Notes: Drought duration in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.22 Southern states – Lagged effects of drought magnitude on GSP per capita growth

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*South*	*South*	*South*	*South*	*South*	*South*	*South*	*South*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
magnitude	-0.13	-0.12	-0.13*	-0.14	-0.10	-0.09	-0.10	-0.09
	(0.11)	(0.10)	(0.07)	(0.13)	(0.09)	(0.07)	(0.07)	(0.08)
L.magnitude		-0.05	-0.04	-0.03		-0.09	-0.07	-0.07
		(0.12)	(0.09)	(0.10)		(0.12)	(0.12)	(0.10)
L2.magnitude			-0.09	-0.09			-0.09	-0.07
			(0.14)	(0.15)			(0.09)	(0.11)
L3.magnitude			-0.14***	-0.14***			0.00	-0.01
			(0.05)	(0.05)			(0.06)	(0.04)
N	464	464	464	464	464	464	464	464
R-sq	0.47	0.47	0.47	0.48	0.47	0.47	0.47	0.48
Drought variable	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	South	South	South	South	South	South	South	South

Cluster obs.	16	16	16	16	16	16	16	16
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-0.13	-0.17	-0.48**	-0.39	-0.10	-0.18	-0.11	0.04
	(0.11)	(0.19)	(0.20)	(0.30)	(0.09)	(0.15)	(0.27)	(0.30)

Notes: Drought magnitude in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.23: Southern states – Lagged effects of drought peak intensity on GSP per capita growth

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*South*	*South*	*South*	*South*	*South*	*South*	*South*	*South*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
peak intensity	-0.09	-0.08	-0.09	-0.09	-0.09	-0.07	-0.08	-0.08
	(0.11)	(0.11)	(0.10)	(0.10)	(0.09)	(0.09)	(0.09)	(0.09)
L.peak intensity		-0.05	-0.04	-0.03		-0.11	-0.09	-0.09
		(0.14)	(0.13)	(0.14)		(0.16)	(0.17)	(0.15)
L2.peak intensity			-0.10	-0.10			-0.10	-0.08
			(0.16)	(0.19)			(0.11)	(0.12)
L3.peak intensity			-0.13**	-0.13**			-0.01	-0.03
			(0.05)	(0.06)			(0.08)	(0.09)
N	464	464	464	464	464	464	464	464
R-sq	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47
Drought variable	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	South	South	South	South	South	South	South	South
Cluster obs.	16	16	16	16	16	16	16	16
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-0.09	-0.13	-0.45*	-0.43*	-0.09	-0.18	-0.15	-0.05
	(0.11)	(0.18)	(0.25)	(0.24)	(0.09)	(0.16)	(0.32)	(0.38)

Notes: Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Midwest region

Table A4.24: Midwestern states – Lagged effects of drought duration on GSP per capita growth

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
duration	0.15	0.13	0.10	0.12	-0.01	-0.07	-0.10	-0.13
	(0.14)	(0.11)	(0.11)	(0.13)	(0.20)	(0.27)	(0.26)	(0.25)
L.duration		0.20	0.20	0.17		0.30	0.33	0.26
		(0.17)	(0.13)	(0.18)		(0.29)	(0.25)	(0.24)
L2.duration			-0.12*	-0.13			-0.18	-0.22*
			(0.07)	(0.08)			(0.15)	(0.13)
L3.duration			-0.20	-0.13			-0.06	-0.06
			(0.16)	(0.15)			(0.14)	(0.11)
N	348	348	348	348	348	348	348	348
R-sq	0.42	0.43	0.43	0.47	0.42	0.42	0.43	0.44
Drought variable	duration	duration	duration	duration	duration	duration	duration	duration
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest
Cluster obs.	12	12	12	12	12	12	12	12
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	0.15	0.33	-0.11	-0.85**	-0.01	0.22	-0.19	-0.74
	(0.14)	(0.24)	(0.23)	(0.41)	(0.20)	(0.22)	(0.30)	(0.59)

Notes: Drought duration in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.25: Midwestern states – Lagged effects of drought magnitude on GSP per capita growth

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
magnitude	0.13	0.10	0.07	0.08	-0.05	-0.12	-0.15	-0.17
	(0.13)	(0.10)	(0.11)	(0.12)	(0.22)	(0.24)	(0.24)	(0.25)
L.magnitude		0.24	0.23	0.18		0.31	0.34	0.27
		(0.16)	(0.17)	(0.16)		(0.22)	(0.22)	(0.20)
L2.magnitude			-0.07	-0.08			-0.18	-0.22
			(0.13)	(0.09)			(0.13)	(0.15)
L3.magnitude			-0.21	-0.14			-0.06	-0.06
			(0.16)	(0.15)			(0.11)	(0.12)
N	348	348	348	348	348	348	348	348
R-sq	0.42	0.43	0.43	0.47	0.42	0.43	0.43	0.44
Drought variable	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest
Cluster obs.	12	12	12	12	12	12	12	12
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on	0.13	0.34	-0.05	-0.99*	-0.05	0.19	-0.23	-0.81
drought variables	(0.13)	(0.22)	(0.38)	(0.55)	(0.22)	(0.15)	(0.20)	(0.71)

Notes: Drought magnitude in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.26: Midwestern states – Lagged effects of drought peak intensity on GSP per capita growth#

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
peak intensity	0.16	0.10	0.05	0.06	-0.10	-0.20	-0.24	-0.24
	(0.17)	(0.22)	(0.22)	(0.17)	(0.26)	(0.38)	(0.43)	(0.29)
L.peak intensity		0.41	0.41*	0.34*		0.43	0.46	0.37
		(0.29)	(0.25)	(0.20)		(0.34)	(0.31)	(0.26)
L2.peak intensity			-0.12	-0.16			-0.19	-0.25*
			(0.17)	(0.12)			(0.23)	(0.13)
L3.peak intensity			-0.38	-0.29			-0.12	-0.13
			(0.24)	(0.20)			(0.13)	(0.14)
N	348	348	348	348	348	348	348	348
R-sq	0.42	0.43	0.44	0.48	0.42	0.43	0.43	0.45
Drought variable	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest
Cluster obs.	12	12	12	12	12	12	12	12
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on	0.16	0.51	-0.12	-1.25*	-0.10	0.23	-0.35	-1.00
drought variables	(0.17)	(0.39)	(0.56)	(0.74)	(0.26)	(0.20)	(0.22)	(0.68)

Notes: Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Northeast region

Table A4.27: Northeastern states – Lagged effects of drought duration on GSP per capita growth

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
duration	0.11	0.07	0.09	0.15	0.15	0.14	0.11	0.08
	(0.22)	(0.15)	(0.16)	(0.11)	(0.12)	(0.13)	(0.13)	(0.11)
L.duration		0.19	0.18	0.20		0.04	0.04	-0.01
		(0.17)	(0.19)	(0.14)		(0.20)	(0.18)	(0.17)
L2.duration			0.00	-0.06			0.05	-0.02
			(0.15)	(0.15)			(0.18)	(0.20)
L3.duration			-0.35	-0.41			-0.31*	-0.35**
			(0.28)	(0.29)			(0.17)	(0.15)
N	261	261	261	261	261	261	261	261
R-sq	0.68	0.68	0.69	0.70	0.68	0.68	0.69	0.70
Drought variable	duration	duration	duration	duration	duration	duration	duration	duration
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast
Cluster obs.	9	9	9	9	9	9	9	9
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	0.11	0.25	-0.46	-1.65***	0.15	0.18	-0.63	-1.35**
	(0.22)	(0.29)	(0.36)	(0.45)	(0.12)	(0.21)	(0.50)	(0.55)

Notes: Drought duration in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.28: Northeastern states – Lagged effects of drought magnitude on GSP per capita growth

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
magnitude	0.10	0.05	0.08	0.15	0.13	0.11	0.07	0.05
	(0.14)	(0.14)	(0.14)	(0.14)	(0.09)	(0.15)	(0.12)	(0.14)
L.magnitude		0.22	0.21	0.22		0.07	0.07	0.03
		(0.17)	(0.20)	(0.15)		(0.20)	(0.18)	(0.18)
L2.magnitude			-0.03	-0.10			0.00	-0.08
			(0.17)	(0.16)			(0.25)	(0.22)
L3.magnitude			-0.43	-0.51*			-0.32	-0.36**
			(0.32)	(0.26)			(0.22)	(0.17)
N	261	261	261	261	261	261	261	261
R-sq	0.68	0.68	0.70	0.71	0.68	0.68	0.69	0.70
Drought variable	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+

States	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast
Cluster obs.	9	9	9	9	9	9	9	9
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	0.10	0.28	-0.67*	-2.03***	0.13	0.18	0.72	-1.41***
	(0.14)	(0.26)	(0.40)	(0.48)	(0.09)	(0.24)	(0.45)	(0.47)

Notes: Drought magnitude in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.29: Northeastern states – Lagged effects of drought peak intensity

Dep. var. is states' GSP per capita growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
peak intensity	0.15	0.05	0.08	0.15	0.16	0.13	0.07	0.03
	(0.23)	(0.23)	(0.17)	(0.23)	(0.15)	(0.13)	(0.16)	(0.17)
L.peak intensity		0.36	0.33**	0.33		0.15	0.16	0.11
		(0.24)	(0.17)	(0.22)		(0.26)	(0.21)	(0.25)
L2.peak intensity			-0.05	-0.11			-0.03	-0.09
			(0.19)	(0.23)			(0.25)	(0.22)
L3.peak intensity			-0.53*	-0.62			-0.39	-0.41**
			(0.31)	(0.45)			(0.26)	(0.17)
N	261	261	261	261	261	261	261	261
R-sq	0.68	0.68	0.71	0.72	0.68	0.68	0.71	0.72
Drought variable	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast
Cluster obs.	9	9	9	9	9	9	9	9
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	0.15	0.40	-0.69*	-2.22***	0.16	0.27	-0.83*	-1.60***
	(0.23)	(0.38)	(0.36)	(0.63)	(0.15)	(0.25)	(0.49)	(0.47)

Notes: Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Appendix 4.2: Lagged effects of droughts on states' agricultural GSP growth

All states

Table A4.30: All states – Lagged effects of drought duration on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*All*	*All*	*All*	*All*	*All*	*All*	*All*	*All*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
duration	-0.86	-1.11*	-1.18**	-1.23***	-2.00***	-2.34***	-2.41***	-2.47***
	(0.55)	(0.59)	(0.48)	(0.47)	(0.46)	(0.48)	(0.43)	(0.58)
L.duration		2.10***	2.15***	2.26***		2.24***	2.22***	2.24***
		(0.40)	(0.47)	(0.44)		(0.47)	(0.59)	(0.62)
L2.duration			-0.87**	-0.94***			-0.28	-0.24
			(0.36)	(0.33)			(0.46)	(0.60)
L3.duration			-0.52	-0.37			-0.78*	-0.78
			(0.50)	(0.46)			(0.42)	(0.53)
N	1389	1389	1389	1389	1389	1389	1389	1389
R-sq	0.48	0.49	0.49	0.50	0.48	0.49	0.49	0.49
Drought variable	duration	duration	duration	duration	duration	duration	duration	duration
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	All	All	All	All	All	All	All	All
Cluster obs.	48	48	48	48	48	48	48	48
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on	-0.86	1.00*	-1.21*	0.21	-2.00***	-0.10	-1.67***	-0.85
drought variables	(0.55)	(0.58)	(0.70)	(0.76)	(0.46)	(0.53)	(0.59)	(0.84)

Notes: Drought duration in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.31: All states – Lagged effects of drought magnitude on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*All*	*All*	*All*	*All*	*All*	*All*	*All*	*All*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
magnitude	-1.28***	-1.61***	-1.71***	-1.74***	-2.05***	-2.39***	-2.46***	-2.54***
	(0.44)	(0.52)	(0.54)	(0.45)	(0.44)	(0.47)	(0.54)	(0.44)
L.magnitude		2.40***	2.44***	2.50***		2.21***	2.20***	2.22***
		(0.46)	(0.48)	(0.53)		(0.47)	(0.53)	(0.50)
L2.magnitude			-0.83**	-0.85**			-0.35	-0.31
			(0.39)	(0.40)			(0.50)	(0.47)
L3.magnitude			-0.56	-0.45			-0.68	-0.68*
			(0.55)	(0.48)			(0.47)	(0.41)
N	1389	1389	1389	1389	1389	1389	1389	1389

R-sq	0.48	0.49	0.49	0.50	0.48	0.49	0.49	0.50
Drought variable	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	All	All	All	All	All	All	All	All
Cluster obs.	48	48	48	48	48	48	48	48
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-1.28***	0.79	-1.37**	0.03	-2.05***	-0.18	-1.71**	-0.94
	(0.44)	(0.56)	(0.65)	(0.82)	(0.44)	(0.47)	(0.69)	(0.69)

Notes: Drought magnitude in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.32: All states – Lagged effects of drought peak intensity on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*All*	*All*	*All*	*All*	*All*	*All*	*All*	*All*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
peak intensity	-2.05***	-2.50***	-2.64***	-2.72***	-2.66***	-3.08***	-3.17***	-3.26***
	(0.50)	(0.58)	(0.73)	(0.65)	(0.53)	(0.58)	(0.57)	(0.46)
L.peak intensity		2.98***	3.02***	3.08***		2.65***	2.64***	2.65***
		(0.59)	(0.62)	(0.49)		(0.67)	(0.74)	(0.66)
L2.peak intensity			-0.81*	-0.79			-0.38	-0.33
			(0.47)	(0.55)			(0.59)	(0.59)
L3.peak intensity			-0.78	-0.68			-0.82*	-0.82
			(0.52)	(0.66)			(0.45)	(0.59)
N	1389	1389	1389	1389	1389	1389	1389	1389
R-sq	0.48	0.49	0.49	0.50	0.49	0.49	0.50	0.50
Drought variable	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	All	All	All	All	All	All	All	All
Cluster obs.	48	48	48	48	48	48	48	48
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-2.05***	0.48	-2.38***	-0.66	-2.66***	-0.42	-2.35***	-1.63*
	(0.50)	(0.67)	(0.84)	(0.85)	(0.53)	(0.54)	(0.69)	(0.84)

Notes: Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

West region

Table A4.33: Western states – Lagged effects of drought duration on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*West*	*West*	*West*	*West*	*West*	*West*	*West*	*West*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
duration	-0.77	-0.89	-1.09	-1.18	-1.68**	-1.93**	-2.08***	-2.17**
	(0.67)	(0.84)	(0.74)	(0.81)	(0.73)	(0.84)	(0.59)	(0.97)
L.duration		1.10*	1.13*	1.14		1.56*	1.57*	1.38
		(0.65)	(0.63)	(0.84)		(0.89)	(0.83)	(0.92)
L2.duration			-0.51	-0.48			-0.11	-0.03
			(0.60)	(0.81)			(0.96)	(1.12)
L3.duration			-0.47	-0.39			-1.30**	-1.28
			(0.75)	(0.70)			(0.63)	(0.78)
N	319	319	319	319	319	319	319	319
R-sq	0.34	0.35	0.35	0.36	0.35	0.36	0.37	0.38
Drought variable	duration	duration	duration	duration	duration	duration	duration	duration
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	West	West	West	West	West	West	West	West
Cluster obs.	11	11	11	11	11	11	11	11
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-0.77	0.21	-0.97	-0.83	-1.68**	-0.37	-2.32***	-1.42
	(0.67)	(1.08)	(1.44)	(1.46)	(0.73)	(0.67)	(0.61)	(1.08)

Notes: Drought duration in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.34: Western states – Lagged effects of drought magnitude on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*West*	*West*	*West*	*West*	*West*	*West*	*West*	*West*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
magnitude	-1.32*	-1.51**	-1.72**	-1.93**	-1.89***	-2.14***	-2.27***	-2.38***
	(0.68)	(0.59)	(0.76)	(0.79)	(0.69)	(0.70)	(0.70)	(0.77)
L.magnitude		1.49**	1.51**	1.60**		1.65**	1.63	1.51*
		(0.74)	(0.73)	(0.70)		(0.82)	(1.02)	(0.77)
L2.magnitude			-0.38	-0.41			-0.03	0.01
			(0.67)	(0.63)			(0.94)	(0.95)
L3.magnitude			-0.71	-0.63			-1.25*	-1.23*
			(0.60)	(0.68)			(0.74)	(0.70)
N	319	319	319	319	319	319	319	319
R-sq	0.35	0.36	0.36	0.37	0.36	0.37	0.38	0.38
Drought variable	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	West	South	West	West	West	West	West	West
Cluster obs.	11	11	11	11	11	11	11	11

State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-1.32*	-0.02	-1.44	-1.38	1.89***	-0.48	-2.42***	-1.64
	(0.68)	(1.00)	(1.48)	(1.41)	(0.69)	(0.63)	(0.91)	(1.21)

Notes: Drought magnitude in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table A4.35: Western states – Lagged effects of drought peak intensity on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*West*	*West*	*West*	*West*	*West*	*West*	*West*	*West*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
peak intensity	-2.40***	-2.62***	-2.92***	-3.19***	-2.54***	-2.82***	-2.98***	-3.05***
	(0.87)	(0.86)	(1.08)	(0.75)	(0.78)	(0.65)	(0.70)	(0.93)
L.peak intensity		1.76**	1.76**	1.88**		2.02**	2.00	1.78
		(0.70)	(0.81)	(0.77)		(0.95)	(1.23)	(1.55)
L2.peak intensity			-0.23	-0.18			-0.14	-0.03
			(0.81)	(0.84)			(1.12)	(1.42)
L3.peak intensity			-0.99	-0.92			-1.35*	-1.36
			(1.09)	(1.02)			(0.80)	(0.88)
N	319	319	319	319	319	319	319	319
R-sq	0.35	0.36	0.37	0.37	0.36	0.37	0.38	0.38
Drought variable	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	West	West	West	West	West	West	West	West
Cluster obs.	11	11	11	11	11	11	11	11
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-2.40***	-0.86	-2.94	-2.56*	-2.54***	-0.81	-3.02***	-2.16*
	(0.87)	(0.88)	(1.83)	(1.35)	(0.78)	(0.65)	(0.84)	(1.24)

Notes: Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

South region

Table A4.36: Southern states – Lagged effects of drought duration on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*South*	*South*	*South*	*South*	*South*	*South*	*South*	*South*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
duration	-2.15***	-2.33***	-2.35***	-2.50***	-2.40***	-2.56***	-2.60***	-2.69***
	(0.62)	(0.58)	(0.64)	(0.65)	(0.67)	(0.58)	(0.74)	(0.70)
L.duration		1.59***	1.76***	2.11***		1.38*	1.37	1.31
		(0.45)	(0.49)	(0.47)		(0.77)	(0.95)	(0.91)
L2.duration			-1.15**	-1.23***			-0.36	-0.25
			(0.46)	(0.47)			(0.73)	(0.87)
L3.duration			0.52	0.53			-0.43	-0.44
			(0.85)	(0.79)			(0.93)	(0.93)
N	463	463	463	463	463	463	463	463
R-sq	0.49	0.49	0.50	0.51	0.49	0.49	0.49	0.50
Drought variable	duration	duration	duration	duration	duration	duration	duration	duration
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	South	South	South	South	South	South	South	South
Cluster obs.	16	16	16	16	16	16	16	16
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-2.15***	-0.74	-2.34***	-0.76	-2.40***	-1.18	-2.11*	-0.90
	(0.62)	(0.57)	(0.82)	(1.66)	(0.67)	(0.76)	(1.11)	(1.16)

Notes: Drought duration in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.37: Southern states – Lagged effects of drought magnitude on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*South*	*South*	*South*	*South*	*South*	*South*	*South*	*South*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
magnitude	-2.29***	-2.54***	-2.65***	-2.80***	-2.30***	-2.48***	-2.56***	-2.65***
	(0.62)	(0.61)	(0.73)	(0.73)	(0.53)	(0.62)	(0.68)	(0.57)
L.magnitude		1.78***	2.02***	2.30***		1.39**	1.41*	1.37*
		(0.39)	(0.44)	(0.57)		(0.65)	(0.76)	(0.78)
L2.magnitude			-1.33*	-1.28**			-0.50	-0.40
			(0.70)	(0.51)			(0.71)	(0.67)
L3.magnitude			0.50	0.46			-0.34	-0.34
			(0.81)	(0.70)			(0.66)	(0.81)
N	463	463	463	463	463	463	463	463
R-sq	0.49	0.49	0.50	0.51	0.49	0.49	0.49	0.50
Drought variable	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	South	South	South	South	South	South	South	South

Cluster obs.	16	16	16	16	16	16	16	16
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-2.29***	-0.76	-2.39**	-0.47	-2.30***	-1.10*	-2.10**	-0.72
	(0.62)	(0.50)	(1.02)	(1.26)	(0.53)	(0.65)	(0.96)	(1.04)

Notes: Drought magnitude in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table A4.38: Southern states – Lagged effects of drought peak intensity on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*South*	*South*	*South*	*South*	*South*	*South*	*South*	*South*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
peak intensity	-2.96***	-3.31***	-3.45***	-3.69***	-2.73***	-3.01***	-3.09***	-3.17***
	(0.71)	(0.83)	(0.78)	(0.68)	(0.70)	(0.74)	(0.87)	(0.57)
L.peak intensity		2.15***	2.37***	2.61***		1.77**	1.76**	1.69**
		(0.55)	(0.51)	(0.59)		(0.72)	(0.86)	(0.73)
L2.peak intensity			-1.18*	-1.01*			-0.49	-0.35
			(0.68)	(0.57)			(0.78)	(0.84)
L3.peak intensity			0.61	0.54			-0.46	-0.45
			(0.99)	(0.81)			(0.97)	(1.01)
N	463	463	463	463	463	463	463	463
R-sq	0.49	0.50	0.50	0.51	0.49	0.49	0.49	0.50
Drought variable	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	South	South	South	South	South	South	South	South
Cluster obs.	16	16	16	16	16	16	16	16
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-2.96***	-1.16*	-3.07***	-0.70	-2.73***	-1.24*	-2.66**	-1.50
	(0.71)	(0.62)	(1.17)	(1.72)	(0.70)	(0.71)	(1.10)	(1.78)

Notes: Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table A4.39: Midwestern states – Lagged effects of drought duration on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
duration	1.33	0.87	0.56	0.46	-2.26	-3.48*	-3.70**	-3.59**
	(1.26)	(1.52)	(1.78)	(1.61)	(1.89)	(1.91)	(1.80)	(1.55)
L.duration		4.37***	4.05**	4.39***		5.63***	5.73***	5.65***
		(1.27)	(1.75)	(1.26)		(1.40)	(1.48)	(1.38)
L2.duration			-0.70	-1.07			-1.03	-1.10
			(1.48)	(1.26)			(1.61)	(1.48)
L3.duration			-2.21*	-1.97			-0.57	-0.44
			(1.20)	(1.23)			(1.46)	(1.19)
N	347	347	347	347	347	347	347	347
R-sq	0.53	0.55	0.56	0.58	0.53	0.55	0.55	0.56
Drought variable	duration	duration	duration	duration	duration	duration	duration	duration
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest
Cluster obs.	12	12	12	12	12	12	12	12
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	1.33	5.24***	0.98	2.67	-2.26	2.15	-0.17	0.68
	(1.26)	(1.69)	(2.49)	(2.71)	(1.89)	(1.59)	(2.36)	(2.58)

Notes: Drought duration in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the second row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.40: Midwestern states – Lagged effects of drought magnitude on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
magnitude	0.73	0.06	-0.28	-0.32	-2.36	-3.57*	-3.78**	-3.67*
	(1.47)	(1.65)	(1.78)	(1.96)	(1.50)	(1.84)	(1.75)	(2.01)
L.magnitude		5.03***	4.69***	4.93***		5.55***	5.72***	5.65***
		(1.27)	(1.39)	(1.82)		(1.30)	(1.51)	(1.81)
L2.magnitude			-0.66	-0.95			-1.25	-1.33
			(1.27)	(1.67)			(1.57)	(1.69)
L3.magnitude			-2.29*	-2.12			-0.32	-0.19
			(1.22)	(1.53)			(1.14)	(1.29)
N	347	347	347	347	347	347	347	347
R-sq	0.53	0.55	0.56	0.57	0.53	0.55	0.55	0.56
Drought variable	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest
Cluster obs.	12	12	12	12	12	12	12	12
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	0.73	5.09***	0.92	2.38	-2.36	1.97	-0.16	0.82
	(1.47)	(1.59)	(2.96)	(3.57)	(1.50)	(1.42)	(2.52)	(2.98)

Notes: Drought magnitude in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the second row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.41: Midwestern states – Lagged effects of drought peak intensity on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*	*Midwest*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
peak intensity	0.47	-0.48	-0.99	-1.19	-3.36	-4.74**	-4.98**	-4.78*
	(2.10)	(2.30)	(2.31)	(2.47)	(2.28)	(2.08)	(2.35)	(2.70)
L.peak intensity		6.62***	6.32***	6.60***		6.68***	6.76***	6.70***
		(1.94)	(1.70)	(1.84)		(1.84)	(2.07)	(2.07)
L2.peak intensity			-0.74	-1.20			-1.02	-1.23
			(1.51)	(1.63)			(2.18)	(1.85)
L3.peak intensity			-3.89**	-3.54**			-1.12	-0.92
			(1.68)	(1.55)			(1.27)	(1.41)
N	347	347	347	347	347	347	347	347
R-sq	0.53	0.55	0.56	0.57	0.53	0.55	0.55	0.56
Drought variable	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.
Drought type	moderate +	moderate +	moderate +	moderate +	severe+	severe+	severe+	severe+
States	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest	Midwest
Cluster obs.	12	12	12	12	12	12	12	12
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	0.47	6.14***	-0.19	2.15	-3.36	1.94	-1.35	0.50
	(2.10)	(2.32)	(2.43)	(3.62)	(2.28)	(1.54)	(3.61)	(2.90)

Notes: Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Northeast region

Table A4.42: Northeastern states – Lagged effects of drought duration on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
duration	-0.29	-0.52	-0.48	-0.63	-0.41	-0.58	-0.66	-0.74
	(1.08)	(0.79)	(1.05)	(1.16)	(1.32)	(1.31)	(1.57)	(1.48)
L.duration		0.99	1.10	0.86		0.82	0.91	0.46
		(1.08)	(1.42)	(1.32)		(0.80)	(1.00)	(1.29)
L2.duration			-1.28	-1.28			-0.71	-0.45
			(0.93)	(0.89)			(1.12)	(1.15)
L3.duration			0.20	0.10			-0.04	0.37
			(0.73)	(0.89)			(1.14)	(1.48)
N	260	260	260	260	260	260	260	260
R-sq	0.47	0.47	0.47	0.48	0.47	0.47	0.47	0.50
Drought variable	duration	duration	duration	duration	duration	duration	duration	duration
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast
Cluster obs.	9	9	9	9	9	9	9	9
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-0.29	0.47	-1.65	-0.66	-0.41	0.23	-1.43	-0.14
	(1.08)	(0.57)	(1.44)	(2.93)	(1.32)	(1.17)	(1.31)	(4.37)

Notes: Drought duration in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.43: Northeastern states – Lagged effects of drought magnitude on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
magnitude	-0.20	-0.42	-0.42	-0.57	-0.17	-0.27	-0.34	-0.32
	(0.60)	(0.73)	(0.82)	(1.07)	(1.23)	(1.38)	(1.21)	(1.36)
L.magnitude		0.97	1.05	0.87		0.49	0.58	0.09
		(1.07)	(1.33)	(1.21)		(0.86)	(0.87)	(0.72)
L2.magnitude			-1.30	-1.39			-0.74	-0.53
			(1.04)	(1.23)			(0.80)	(1.38)
L3.magnitude			0.35	0.23			-0.03	0.21
			(1.08)	(1.28)			(1.04)	(0.69)
N	260	260	260	260	260	260	260	260
R-sq	0.47	0.47	0.47	0.48	0.47	0.47	0.47	0.49

Drought variable	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude	magnitude
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast
Cluster obs.	9	9	9	9	9	9	9	9
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-0.20	0.54	-1.72	-1.51	-0.17	0.22	-1.60	-0.67
	(0.60)	(0.75)	(1.39)	(3.33)	(1.23)	(1.17)	(1.42)	(3.32)

Notes: Drought magnitude in log. Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A4.44: Northeastern states – Lagged effects of drought peak intensity on Agr. GSP growth

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
States	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*	*Northeast*
Droughts	*Moderate+*	*Moderate+*	*Moderate+*	*Moderate+*	*Severe+*	*Severe+*	*Severe+*	*Severe+*
Lags	*0 lag*	*1 lag*	*5 lags*	*10 lags*	*0 lag*	*1 lag*	*5 lags*	*10 lags*
peak intensity	-0.66	-1.07	-1.30	-1.28	-0.57	-0.73	-0.86	-0.71
	(0.88)	(1.00)	(1.12)	(1.05)	(1.30)	(1.34)	(1.21)	(1.45)
L.peak intensity		1.48	1.98	1.65		0.80	1.00	0.71
		(1.14)	(1.75)	(1.20)		(0.87)	(1.00)	(1.20)
L2.peak intensity			$\boxed{-2.55^{**}}$	-2.74			-1.32	-1.20
			(1.29)	(1.71)			(1.29)	(1.45)
L3.peak intensity			1.35	1.35			0.33	0.54
			(2.05)	(1.51)			(1.37)	(1.00)
N	260	260	260	260	260	260	260	260
R-sq	0.47	0.47	0.48	0.49	0.47	0.47	0.47	0.49
Drought variable	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.	peak int.
Drought type	moderate+	moderate+	moderate+	moderate+	severe+	severe+	severe+	severe+
States	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast	Northeast
Cluster obs.	9	9	9	9	9	9	9	9
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temp. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum of all lagged coefficients on drought variables	-0.66	0.40	-2.70	-2.50	-0.57	0.07	-2.34	-1.47
	(0.88)	(1.09)	(1.73)	(4.69)	(1.30)	(1.33)	(1.78)	(4.28)

Notes: Columns 1-4 include all moderate to extreme drought events while columns 5-8 include only severe to extreme drought events. The lags of drought characteristics included in each model are indicated in the fourth row of the table, but, for clarity purposes, only lags 0-3 are included in the output table. The last row shows the sum (and calculated standard error) of all drought coefficients. All

regressions include the 0-lag of yearly average temperature. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Appendix 4.3: Compound effects of weather on states' agricultural GSP growth

Table A4.45: Compound effects of weather on Agr. GSP growth – Drought duration x cooling degree-days

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)
	All	*South*	*West*	*Midwest*	*Northeast*
duration	-2.21**	-0.71	-2.84**	-3.71	2.14
	(0.96)	(1.78)	(1.22)	(4.11)	(4.66)
L.duration	3.36***	1.46	3.20**	6.66***	-0.69
	(0.80)	(1.90)	(1.39)	(2.56)	(2.09)
cdd	15.61***	20.40***	13.08***	8.74	-9.35
	(3.40)	(4.98)	(4.49)	(10.89)	(12.60)
L.cdd	0.10	-0.63	0.50	0.66	-4.32
	(0.54)	(1.02)	(1.28)	(3.89)	(6.49)
duration*cdd	0.10	-0.63	0.50	0.66	-4.32
	(0.54)	(1.02)	(1.28)	(3.89)	(6.49)
L.duration*L.cdd	-1.21***	-0.28	-1.83	-1.42	2.66
	(0.44)	(0.90)	(1.31)	(3.00)	(3.08)
N	1389	463	319	347	260
R-sq	0.50	0.51	0.37	0.56	0.47
Drought variable	duration	duration	duration	duration	duration
Drought type	severe+	severe+	severe+	severe+	severe+
States	All	South	West	Midwest	Northeast
Cluster obs.	48	16	11	12	9
State FE	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Drought magnitude in log. Above regressions include all drought events that are considered severe to extreme. The variable "cdd" corresponds to the annual number of cooling degree-days, divided by 1000. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 4.46: Compound effects of weather on agricultural GSP growth – Drought magnitude x cooling degree-days

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)
	All	*South*	*West*	*Midwest*	*Northeast*
magnitude	-2.32***	-1.22	-2.86***	-3.63	1.60
	(0.87)	(2.42)	(1.09)	(5.30)	(4.60)
L.magnitude	3.28***	1.82	3.09**	5.98*	-0.53
	(0.95)	(2.09)	(1.27)	(3.10)	(2.33)
cdd	-23.23***	-25.55***	-12.03**	-32.24**	-15.82
	(4.68)	(5.75)	(5.81)	(14.24)	(17.42)
L.cdd	15.42***	20.13***	12.70**	9.27	-8.43
	(3.63)	(4.34)	(5.57)	(10.87)	(13.71)
magnitude*cdd	0.15	-0.32	0.38	0.46	-2.85
	(0.50)	(1.56)	(0.65)	(5.22)	(6.68)
L.magnitude*L.cdd	-1.15**	-0.48	-1.62*	-0.70	1.74
	(0.49)	(1.07)	(0.91)	(3.73)	(3.42)
N	1389	463	319	347	260
R-sq	0.51	0.51	0.38	0.56	0.47
Drought variable	magnitude	magnitude	magnitude	magnitude	magnitude
Drought type	severe+	severe+	severe+	severe+	severe+
States	All	South	West	Midwest	Northeast
Cluster obs.	48	16	11	12	9
State FE	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Drought duration in log. Above regressions include all drought events that are considered severe to extreme. The variable "cdd" corresponds to the annual number of cooling degree-days, divided by 1000. Robust, bootstrapped standard errors are in parentheses, adjusted for clustering at state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 4.47: Compound effects of weather on agricultural GSP growth – Drought peak intensity x cooling degree-days

Dep. var. is states' AgrGSP growth	(1)	(2)	(3)	(4)	(5)
	All	*South*	*West*	*Midwest*	*Northeast*
peak intensity	-3.19***	-1.57	-3.89***	-5.23	0.36
	(1.18)	(2.76)	(1.49)	(5.89)	(3.74)
L.peak intensity	4.08***	2.59	3.85**	6.92*	-0.12
	(1.08)	(2.26)	(1.83)	(3.76)	(2.21)
cdd	-22.97***	-25.34***	-11.84	-32.42**	-15.77
	(4.35)	(6.51)	(7.40)	(13.39)	(14.04)
L.cdd	15.32***	20.00***	12.39***	9.42	-7.16
	(3.78)	(5.27)	(4.58)	(11.60)	(14.39)
peak intensity*cdd	0.35	-0.33	0.59	1.08	-1.49
	(0.72)	(1.78)	(1.77)	(5.17)	(6.06)
L.peak intensity*L.cdd	-1.44**	-0.76	-1.89	-0.42	1.62
	(0.65)	(1.20)	(2.21)	(3.67)	(3.63)
N	1389	463	319	347	260
R-sq	0.51	0.51	0.38	0.56	0.47
Drought variable	peak int.	peak int.	peak int.	peak int.	peak int.
Drought type	severe+	severe+	severe+	severe+	severe+
States	All	South	West	Midwest	Northeast
Cluster obs.	48	16	11	12	9
State FE	Yes	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Above regressions include all drought events that are considered severe to extreme. The variable "cdd" corresponds to the annual number of cooling degree-days, divided by 1000. Robust bootstrapped standard errors are in parentheses, adjusted for clustering at state level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Chapter 5: Climate shocks, inflation and monetary policy: the global experience since 1950

Abstract

The uncertainty surrounding future climate change damages has led some economists to assess empirically the socio-economic impacts of changes in observed temperature and precipitation in the recent past. We apply panel data methods to a global data set of climate/weather fluctuations, inflation and policy interest rates for the last half century or more. We find that past increases in annual average temperature led to increases in inflation, predominantly in low-income countries. We find that the cumulative effect of temperature on inflation increases as we add lagged annual average temperatures, indicating these inflationary effects were persistent. At the global level, we find a statistically significant, U-shaped relationship between temperature and inflation, which appears to be the inverse of the relationship found between temperature and growth by Burke et al. (2015), using similar methods. We find a negative effect of temperature on the annual policy interest rate in low-income countries only, and we find that precipitation had a negative effect on interest rates more widely. There is again evidence from employing lagged climate variables that these effects were persistent, particularly in relation to precipitation. Our findings that climate/weather fluctuations had differential effects according to the level of development of a country is in line with previous studies and we show that it is robust to controlling for countries' long-run average climatic conditions, for example the effect of temperature on inflation in poor countries persists having controlled for whether they are hot.

1. Introduction

A rapidly growing body of evidence suggests that weather and climate fluctuations in the past, present and future have had, are having and will have a variety of impacts on the economy (IPCC, 2014). This evidence comes from several different lines, traditionally including integrated assessment models and computable general equilibrium models, as well as cross-sectional regressions of economic variables on prevailing climatic conditions (see Tol, 2009 and 2014 for a review of the results from these studies). There is also a large body of case studies of the impacts of weather disasters, such as droughts, floods and windstorms (see Bowen et al. (2012) and Cavallo and Noy (2011) for reviews).

More recently, panel data methods have been applied to cross-sectional time-series of data on economic outcomes and climate/weather fluctuations[55], giving rise to the so-called "New

[55] Climate is standardly defined as the distribution of weather conditions, estimated over a long period of time, often thirty years. Whether 'climate' or 'weather' fluctuations are a more appropriate description of the variations measured

Climate-Economy" literature (Dell et al., 2014; hereafter NCE literature). The major advantage of panel methods is that genuine randomness in the climate system means that variation in climate/weather is plausibly exogenous on timescales ranging from hours and days to a few decades (Hawkins & Sutton, 2009; Smith, 2007). Therefore, cause and effect can be identified relatively convincingly, for climate/weather variation over time within a given spatial unit.

Application of the resulting estimates to simulation of future climate change is not straightforward, however. Doing so would require extrapolating beyond the conditions that the system was in during the estimation period (e.g. the concentration of greenhouse gases in the atmosphere, but also national development levels). Depending on the particular estimates being used, it might also require using short-term elasticities of economic variables with respect to climate variables as estimates of longer-term elasticities. Lastly, the effects of idiosyncratic local climate/weather variation are not necessarily informative on the effects of climate/weather variation on larger scales. Nevertheless, most would agree that these panel studies significantly enhance the empirical basis of our understanding of climate impacts on the economy.

Within the NCE literature, the very well-known study by Dell et al. (2012) found that positive temperature shocks reduce income per capita growth in poor countries, while they do not have a statistically significant effect on growth elsewhere[56]. Furthermore, the effect persists once lagged temperature effects are included, which is consistent with the idea that temperature shocks depress the growth rate rather than just the level of income per capita. A more recent study by Burke et al. (2015) confirms what Dell et al. (2012) found for poor countries, but suggests that the finding of no effect in higher-income countries may stem from the inappropriate specification of a linear relationship between temperature and growth. Estimating a nonlinear (specifically quadratic) relationship, Burke et al. (2015) find that temperature shocks significantly affect the growth rate of income per capita in rich and poor countries alike, and that the global relationship is inverse U-shaped (consistent with earlier cross-sectional work by Mendelsohn et al., e.g. 2006), such that cold countries benefit from positive temperature shocks, while hot countries see their growth rate reduced, and there exists an optimum temperature for growth, close to where some of the large, mid-latitude industrialised countries are located. The slope of the inverse-U function is found to be steeper for poor countries, indicating they are more sensitive to temperature fluctuations.

The NCE literature has also addressed a number of other economic outcomes, as well as social outcomes including conflict, migration and violence. Dell et al. (2014) and Carleton and Hsiang (2016) review the evidence. Of particular interest to us is the effect of climate/weather fluctuations on the output (and therefore indirectly on the prices) of commodities that are likely to feature importantly in the typical basket of goods. Several studies have shown that temperature fluctuations reduce agricultural output, both in developing countries (e.g. Schlenker and Lobell, 2010) and developed countries (Fisher, Hanemann, Roberts, & Schlenker, 2012), particularly beyond a threshold temperature (Lobell, Schlenker, & Costa-Roberts, 2011; Schlenker & Roberts, 2009), while other studies have shown that low precipitation reduces agricultural output in developing countries (see Dell et al., 2014, for a review of these).

in a particular NCE study therefore depends on the unit of time that is used. The shorter that unit, the more likely it is that weather variation is what is being measured.

[56] This was established controlling for precipitation, which was not found to have a statistically significant effect on income per capita in their global sample. Barrios et al. (2010) found that low precipitation reduced growth in sub-Saharan African countries in the second half of the 20th century, however.

Temperature and precipitation affect energy supply, because some generation technologies are sensitive to temperature and water availability, for example hydroelectric and nuclear power (Carleton and Hsiang, 2016, summarise the evidence). Various studies also confirm that energy demand is responsive to temperature and that the relationship is U-shaped in developed countries at least, so that temperature fluctuations reduce energy demand in cold places (reduced space-heating), but conversely increase them in hot places (increased air conditioning) (Aroonruengsawat & Auffhammer, 2011; Deschênes & Greenstone, 2011). Jones and Olken (2010) use a global panel of trade data to establish that temperature fluctuations lead to a reduction in the output of a range of manufactured goods, including various kinds of consumer good (also see Somanathan et al., 2015)[57].

Somewhat distinct from the NCE literature, panel data methods have also been applied to study the economic impacts of the class of weather fluctuations large enough in impact to be classed as natural disasters. Noy (2009), Raddatz (2009), Loayza et al. (2012) and Fomby et al. (2013) perform panel regressions using disaster data derived from the EM-DAT database. These studies provide some at times contradictory evidence, which may partly derive from the fact that the impacts of disasters on economic growth and related variables could conceptually be negative or positive in the medium to long run[58], but common findings include that weather disasters are more likely to have a negative impact on economic growth in developing countries (also see the meta-analysis by Klomp and Valckx, 2014), and that impacts vary with disaster type, with droughts appearing to have a negative effect, but floods having perhaps a positive effect.

Despite the proliferation of empirical studies into the consequences of climate/weather fluctuations, a pair of economic variables that have been very little studied so far are inflation and interest rates. Yet the evidence just set out suggests plausible effects of climate/weather fluctuations on inflation, either through aggregate supply and demand, or through the supply of and demand for individual commodities. These inflationary (or deflationary) effects, together with wider effects of climate/weather on output, could in turn stimulate a monetary-policy response.

Inflation is a monetary phenomenon defined as a continuous and persistent rise in the general price levels, and there is a general agreement amongst economists that economic inflation can be caused by either an increase in the money supply or a decrease in the quantities of goods supplied (Lim & Sek, 2015), while the standard basic workhorse model used for macroeconomics and monetary policy is the Clarida-Gali-Gertler "New Keynesian" model (Clarida, Galı, & Gertler, 2002) in which countries face a trade-off between using interest rates as a stimulus of economic activity and using them to curb inflation. As indicated above in the discussion of supply-side inflation, this trade-off also depends on the monetary policy regime in place: there are inflation-targeting regimes, such as the UK's, regimes targeting an absolute price level, and regimes targeting both inflation and full employment, such as the US Federal Reserve. Moreover, the independence of the central bank and the credibility of the monetary policy framework put in place by the central bank are also expected to play a role: according to Batten et al., "central banks

[57] The explanation for this effect may in turn lie with studies that have estimated a negative effect of temperature fluctuations on labour productivity.
[58] There is on the one hand a 'creative destruction' hypothesis, whereby it is argued that replacement of damaged capital increases medium- and long-run productivity. On the other hand, some studies such as Hornbeck (2012) have pointed to a negative long-run effect on output through mechanisms like out-migration and long-term disruption to capital markets.

in those countries with a credible monetary policy framework and well-anchored inflation expectations are less likely to face the need to react to sectoral price shocks, although such volatility could complicate the communication of the monetary policy strategy at times." (Batten, Sowerbutts, & Tanaka, 2016, p. 26).

Because climate/weather fluctuations can translate into both supply and demand shocks, the overall effect of climate/weather fluctuations on inflation is ambiguous, as is the effect on interest rates in turn.

Studies of industrial and aggregate economic output imply that temperature fluctuations, and in some instances fluctuations in precipitation, act as a supply-side shock, reducing output[59]. This could result in supply-side inflation, if other prices in the economy, such as wages, are slow to adjust to the shock. The inflationary effect may be particularly severe in the case of extreme weather events (also including windstorms), where outright shortages of goods are conceivable. If a particular country is disproportionately affected by climate/weather fluctuations, an inflationary effect may also occur via a falling exchange rate and higher import prices.

In these circumstances, the monetary-policy authority, if it targets inflation, will want to raise the expected real rate of interest (and *a fortiori* the nominal rate) for a period, in order to bring inflation back to target. Alternatively, if the monetary authority is not solely an inflation targeter, the increase in prices may be followed by an expansionary monetary-policy response – an increase in the money supply – if the monetary policy authority is concerned to manage the shock to the level of employment and output[60]. This would result in an increase in aggregate demand and a further rise in inflation. The problem would be exacerbated if inflation expectations in the country concerned were not well anchored.

It is worth noting that due to the uncertainty faced by central banks regarding current levels of prices and output (aggregate statistics such as industrial production and GDP take months to be compiled and published), central banks can be brought to make decisions based on projections of *future* shortages and price increases which may affect the economy. This could be case for weather events that qualify as natural disasters: and in these circumstances, the change in the policy interest rate would precede and/or limit the impact of the weather event on the inflation rate.

On the other hand, it is conceivable that climate/weather fluctuations lead to demand-side deflationary pressure, particularly in the case of extreme weather events. Financial systems may be disrupted, impairing lending and hence spending. Consumers may also save more to compensate for losses of wealth. Some of them may not be able to maintain consumption in the face of adverse shocks to their income, even if the shocks are expected to be temporary, because of liquidity and borrowing constraints. If these effects dominate the supply-side effects, there will be downward pressure on the aggregate price level and hence on inflation in the short run, tending to encourage the monetary authority to lower interest rates temporarily. During the reconstruction phase after a natural disaster, rising prices might be witnessed.

[59] The opposite supply-side effect is clearly possible where climate/weather fluctuations increase output.
[60] The monetary policy authority may also increase the money supply if an extreme weather event increases government indebtedness via for instance reconstruction costs.

We are only aware of two papers, which investigate the impact of climate/weather on inflation using panel data methods[61]. Both these papers focus on extreme weather events, as a subset of natural disasters, rather than broader climate/weather fluctuations. Heinen et al. (2016) regress monthly inflation, measured by the increase in the consumer price index or CPI, on hurricane and flood destruction indices for a sample of 15 Caribbean islands and find that these extreme weather events have a large, contemporaneous inflationary impact. This appears to mainly come through higher food prices, although the strongest hurricanes appear to also affect housing and utilities prices. Parker (2016) regresses quarterly CPI inflation on a disaster intensity index, which is constructed from data in EM-DAT, for a sample of 223 countries or territories between 1980 and 2012. Parker's disaster intensity index is a function of the number of fatalities and the total number of affected people, as recorded in EM-DAT. Similar to Heinen et al. (2016), he finds that natural disasters have a statistically significant and positive contemporaneous effect on headline inflation (i.e. in the same quarter in which they occur, and to some extent in the following quarter). Again, these inflationary effects appear to come through food prices. There is a statistically significant, negative effect on housing prices with a lag of 2-4 quarters, and no effect on energy prices. Parker (2016) also finds that the headline effects are strongest for droughts and floods, and in developing as opposed to developed countries.

The purpose of this paper is to advance our understanding of the possible effects of climate/weather fluctuations on inflation and interest rates, using panel data methods to ensure a strong empirical basis. We regress annual inflation rates and annual policy interest rates on fluctuations in annual temperature and precipitation for an unbalanced panel of 176 countries over the period 1950-2015.

Thus, we extend the existing literature by firstly considering interest rates, not just inflation, and secondly considering general fluctuations in annual climatic conditions, rather than just weather events extreme enough to quality as natural disasters. The NCE literature strongly suggests extending the frame of reference in this way. As well as simply adding to the knowledge base on the economic impacts of climate/weather variations, our analysis is intended to be helpful to monetary and macro-economic policy makers looking for guidance on the likely path of prices under weather variation and possibly climate change.

This chapter is organized as follows: section 2 will provide an overview of the methodology, including data sources, scatter plots and the estimation strategy. Results for both the inflation rate and the policy interest rate are presented and discussed in Section 3. Section 4 concludes.

2. Methodology

i. Data

Country classification

[61] There is also some case study evidence. For example, Laframboise and Loko (2012) found that the 2010 Pakistan floods increased headline inflation by 2 per cent, while Kamber et al. (2013) found that droughts in New Zealand increased food and electricity price inflation, but that there was no increase in headline inflation due to falling prices in other sectors.

For some of our analyses, we divide countries into different subgroups based on their level of income. To do so, we use the World Bank's classification by income, which is based on Gross National Income (GNI) per capita and distinguishes between four categories: low income, lower-middle income, upper-middle income and high income (World Bank, 2017). In order to assign each country to an income group for the period considered, we counted every time each country was classified as being low/lower-middle/upper-middle or high income, and assigned to each the class which came out most frequently. The list of countries in each of the income groups is available in Appendix 5.1[62]. In the rest of the analysis, we designate countries in the low and lower-middle income groups as "poor", while we call "rich" those countries in the upper-middle and high-income groups.

Inflation

We use the dataset on countries' annual inflation rates provided by the World Bank[63] and which is based on the CPI. It is available for the period 1960-2016, but there are no data for some countries and the panel is highly unbalanced. All in all, there are 174 countries, for which we have both weather and inflation data: 51 of these countries are in the low-income group, 52 are in the lower-middle-income group, 36 are in the upper-middle-income group and 35 are in the high-income group (see Appendix 5.2).

A key feature of the inflation dataset is that it contains major outliers (e.g. an annual inflation rate of 24,411% in Zimbabwe in 2007). In order to explore the effect of these outliers on our results, we impose five cut-off inflation rates (i.e. beyond which data points are omitted): no cut-off rate (i.e. the original dataset), 100% per annum, 75%, 50% and 25%. It is possible that the effects of climate fluctuations on a country's inflation rate could be "masked" by other idiosyncratic shocks, which are unrelated to weather (e.g. wars and other political events, or non-climatic natural disasters, such as earthquakes and tsunamis). Applying cut-off rates to the inflation rate is equivalent to removing the years for which we have very large inflation rates, which might remove these shocks from the data and enable us to better discern the potential effects of climate/weather.

Table 5.1 shows summary statistics for the inflation data.[64] The effect of a small number of outliers is clear to see. For the full dataset, the mean inflation rate is 34%, but removing just 165 observations with an inflation rate of more than 100% (out of 7,247 observations in grand total) reduces the mean inflation rate to just 9% per annum. The effect is particularly marked outside high-income countries. In low-income countries, excluding 43 observations with an inflation rate of more than 100% reduces mean inflation from almost 46% to just 11%. In lower-middle income countries the mean falls from 51% to 10%, and even in upper-middle income countries it falls from 28% to 11%. Occasional bouts of hyperinflation are evidently a phenomenon largely confined to low and middle-income countries.

Notice that further reductions in the cut-off inflation rate below 100% have a smaller effect on mean inflation. Notice also that all countries observed inflation rates of less than 25% at some point between 1960 and 2016. The far right-hand column shows Pearson's kurtosis

[62] This list only includes the 176 countries which are part of the analysis (i.e. for which we have weather data and either inflation rate or policy interest rate data.
[63] Available at https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG
[64] These statistics only include the 174 countries for which we have both weather and inflation data.

statistic[65], which is a measure of the presence of outliers (Westfall, 2014), for the different sub-samples. As these numbers show, the coefficients of kurtosis of the samples with no cut-off rate and of the sample with a 100% cut-off rate are very large, which could be problematic for statistical inference.

Table 5.1: Summary statistics for annual inflation rate data

Inflation rate variable	Unit	Mean	Std. Dev.	Min.	Max.	Obs.	Nb. of countries	Kurtosis
Inflation rate - *no cut-off rate*								
All countries	%	34.2	485.2	-35.8	24411.0	7,247	174	1,761.48
Low income countries	%	45.9	784.6	-35.8	24411.0	1,935	51	
Lower middle income countries	%	50.8	473.3	-23.8	11749.6	2,113	52	
Upper middle income countries	%	28.3	165.2	-11.7	3079.8	1,455	36	
High income countries	%	5.8	14.4	-4.9	373.8	1,744	35	
Inflation rate *-100% cut-off rate*								
All countries	%	9.1	12.5	-35.8	99.9	7,082	174	13.71
Low income countries	%	11.2	13.5	-35.8	97.6	1,892	51	
Lower middle income countries	%	9.7	12.0	-23.8	98.8	2,048	52	
Upper middle income countries	%	10.5	15.7	-11.7	99.9	1,404	36	
High income countries	%	5.1	6.6	-4.9	84.2	1,738	35	
Inflation rate *-75% cut-off rate*								
All countries	%	8.6	10.6	-35.8	73.7	7,030	174	9.02
Low income countries	%	10.7	12.2	-35.8	73.1	1,880	51	
Lower middle income countries	%	9.1	10.1	-23.8	73.5	2,033	52	
Upper middle income countries	%	9.2	12.3	-11.7	73.7	1,381	36	
High income countries	%	5.1	6.1	-4.9	58.5	1,736	35	
Inflation rate *-50% cut-off rate*								
All countries	%	7.8	8.5	-35.8	49.7	6,923	174	4.61
Low income countries	%	9.6	9.9	-35.8	49.4	1,838	51	
Lower middle income countries	%	8.5	8.4	-23.8	49.7	2,007	52	
Upper middle income countries	%	7.9	9.0	-11.7	49.2	1,346	36	
High income countries	%	4.9	5.7	-4.9	49.4	1,732	35	
Inflation rate *-25% cut-off rate*								
All countries	%	6.3	5.8	-23.8	25.0	6,550	174	0.98
Low income countries	%	7.4	6.4	-18.1	25.0	1,679	51	
Lower middle income countries	%	7.1	5.9	-23.8	25.0	1,903	52	
Upper middle income countries	%	6.0	5.7	-11.7	25.0	1,258	36	
High income countries	%	4.6	4.6	-4.9	24.9	1,710	35	

Policy interest rates

We obtained data on countries' annual policy interest rates from Bloomberg, which is in turn sourced from countries' monetary policy updates. For some countries (e.g. the United Kingdom), we have data since 1950, but for some other countries, the time series available is very short and there are no data at all for some countries. Some countries are de facto excluded from the analysis, as their central banks do not set policy interest rates (e.g. the UAE, Saudi Arabia, Qatar, Bahrain and Oman, which all have a fixed peg to the U.S. dollar). Finally, because we are looking at the impact of local climate fluctuations on local changes in policy rates, we exclude countries that belong to currency unions and have therefore given up their monetary policy to a supra-national central bank, which has to accommodate the interests of the other countries in the currency union. There are four currency unions in the world today: the Eurozone, the Central Africa Economic and Monetary Community (CEMAC), the West African Economic and Monetary

[65] Where a kurtosis of 0 indicates a normal distribution; a kurtosis greater than 10 is considered problematic (Acock, 2008).

Union (WAEMU) and the Eastern Caribbean Currency Union (ECCU). Unfortunately, records of countries' policy interest rates before they joined a currency union do not seem to be readily available on Bloomberg.

All in all, there are 75 countries for which we have both weather data and data on policy interest rates: 14 of these countries are in the low-income group, 29 are in the lower-middle-income group, 13 are in the upper-middle-income group and 19 are in the high-income group (see Appendix 2 for details).

The range of countries' annual policy interest rates (-0.3% to 105%) is not as large as the range of inflation rates (Table 5.2), consequently applying the same cut-off rates results in far fewer observations being removed. The column on the far right provides the kurtosis statistic for each of the sub-samples corresponding to different cut-off rates. As these show, there are large numbers of outliers in the samples with no cut-off rate, and 100% and 75% cut-off rates.

Table 5.2: Summary statistics for annual policy interest rate data

Policy interest rate variable	Unit	Mean	Std. Dev.	Min.	Max.	Obs.	Nb. of countries	Kurtosis
Pol. interest rate - *no cut-off rate*								
All countries	%	7.8	7.7	-0.3	105.8	1,441	75	38.04
Low income countries	%	11.2	8.4	2.2	55.0	280	14	
Lower middle income countries	%	8.9	7.9	0.2	105.8	471	29	
Upper middle income countries	%	7.2	10.7	0.0	92.0	180	13	
High income countries	%	5.0	3.7	-0.3	17.2	510	19	
Pol. interest rate -*100% cut-off rate*								
All countries	%	7.7	7.2	-0.3	92.0	1,440	75	25.67
Low income countries	%	11.2	8.4	2.2	55.0	280	14	
Lower middle income countries	%	8.7	6.6	0.2	57.5	470	29	
Upper middle income countries	%	7.2	10.7	0.0	92.0	180	13	
High income countries	%	5.0	3.7	-0.3	17.2	510	19	
Pol. interest rate -*75% cut-off rate*								
All countries	%	7.6	6.9	-0.3	69.8	1,439	75	16.32
Low income countries	%	11.2	8.4	2.2	55.0	280	14	
Lower middle income countries	%	8.7	6.6	0.2	57.5	470	29	
Upper middle income countries	%	6.7	8.7	0.0	69.8	179	13	
High income countries	%	5.0	3.7	-0.3	17.2	510	19	
Pol. interest rate -*50% cut-off rate*								
All countries	%	7.5	6.2	-0.3	49.5	1,434	75	9.25
Low income countries	%	10.9	7.6	2.2	45.3	278	14	
Lower middle income countries	%	8.6	6.2	0.2	46.3	469	29	
Upper middle income countries	%	6.0	6.2	0.0	49.5	177	13	
High income countries	%	5.0	3.7	-0.3	17.2	510	19	
Pol. interest rate -*25% cut-off rate*								
All countries	%	6.8	4.6	-0.3	25.0	1,400	75	1.13
Low income countries	%	9.3	4.6	2.2	24.9	260	14	
Lower middle income countries	%	7.9	4.5	0.2	25.0	455	29	
Upper middle income countries	%	5.6	4.8	0.0	23.1	175	13	
High income countries	%	5.0	3.7	-0.3	17.2	510	19	

Tables summarising the inflation and policy interest rate data we have collected for each country can be found in Appendix 5.2.

Climate fluctuations

We collected monthly temperature and precipitation data for the period 1950-2015 from the World Bank's Climate Change Knowledge Portal[66], which we then transformed into annual data. This dataset was originally produced by the Climatic Research Unit (CRU) of the University of East Anglia and reformatted by the International Water Management Institute (IWMI). The original CRU dataset is a gridded time-series dataset which covers all land areas (except Antarctica) at a 0.5x0.5 degrees resolution (see Harris et al., 2014, for details). The advantages of using gridded datasets such as the CRU one is that they provide balanced panels of temperature and precipitation data for every point on a grid. The downside is that these rely on interpolation techniques, which can put into question the reliability of the estimates, especially for precipitation, which has a higher spatial variability than temperature and for which ground station data can be sparse in some countries. The weather data we use are unweighted by population size, but these estimates have been found to be broadly similar to population-weighted ones (Dell et al., 2012). Despite these issues, gridded datasets produced by the CRU are commonly used in economic studies of weather impacts.

Table 5.3 below shows summary statistics for the temperature and precipitation variables[67].

Table 5.3: Summary statistics for temperature and precipitation data

Weather variable	Unit	Mean	Std. Dev.	Std. Dev.*	Min.	Max.	Obs.	Nb. of countries
Average annual temperature								
All countries	°Celsius	19.0	8.2	3.9	-8.9	29.7	11,616	176
Low income countries	°Celsius	22.3	6.7		-1.9	29.7	3,366	51
Lower middle income countries	°Celsius	20.0	7.4		-7.8	28.9	3,432	52
Upper middle income countries	°Celsius	18.5	7.7		3.3	27.7	2,376	36
High income countries	°Celsius	13.7	8.9		-8.9	29.0	2,442	37
Total annual rainfall								
All countries	mm.	1196.5	835.0	456.8	9.7	4370.8	11,616	176
Low income countries	mm.	1175.4	704.0		49.3	3798.2	3,366	51
Lower middle income countries	mm.	1325.1	945.5		18.6	4234.2	3,432	52
Upper middle income countries	mm.	1292.0	921.7		23.9	4251.3	2,376	36
High income countries	mm.	951.6	676.9		9.7	4370.8	2,442	37

Notes: * indicates standard deviation after removal of country- and region*year fixed effects.

ii. *Scatter plots*

Scatter plots: annual inflation vs. temperature and precipitation

Figure 5.1 simply plots observations of annual inflation vs. annual average temperature (left-hand side) and annual inflation vs. total annual rainfall (right-hand side) for all countries and years. Inflation rates above 50% have been removed to improve the visual resolution on the majority of the observations. A slight positive relationship may be visible between annual

[66] Available at: http://sdwebx.worldbank.org/climateportal/. This dataset was originally produced by the Climatic Research Unit of the University of East Anglia and reformatted by the IWMI.
[67] These statistics only include the 176 countries for which we have either data either on the inflation rate or on the policy interest rate.

inflation and annual average temperature, but there is no relationship with precipitation visible to the naked eye.

Figure 5.1: Annual inflation rate vs. annual temperature and precipitation, all countries

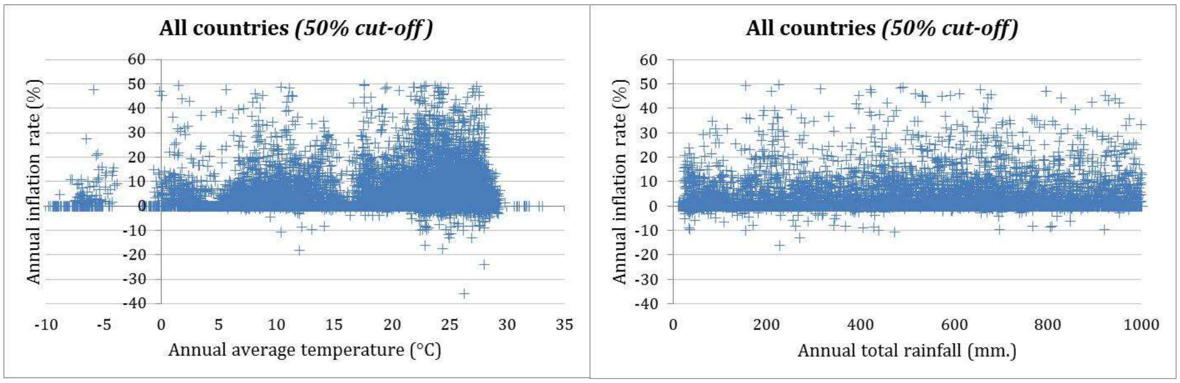


Figure 5.2 shows scatter plots of annual inflation vs. annual average temperature, this time for each of the four country-income groups (again applying the 50% cut-off rate). From visual analysis of the four plots, there does not seem to be any discernible relationship between average temperature and annual inflation in high- and upper-middle-income countries, but it seems that high inflation might be associated with high average temperatures in low- and lower-middle-income countries.

Figure 5.2: Annual inflation rate vs. annual temperature – Countries by income group

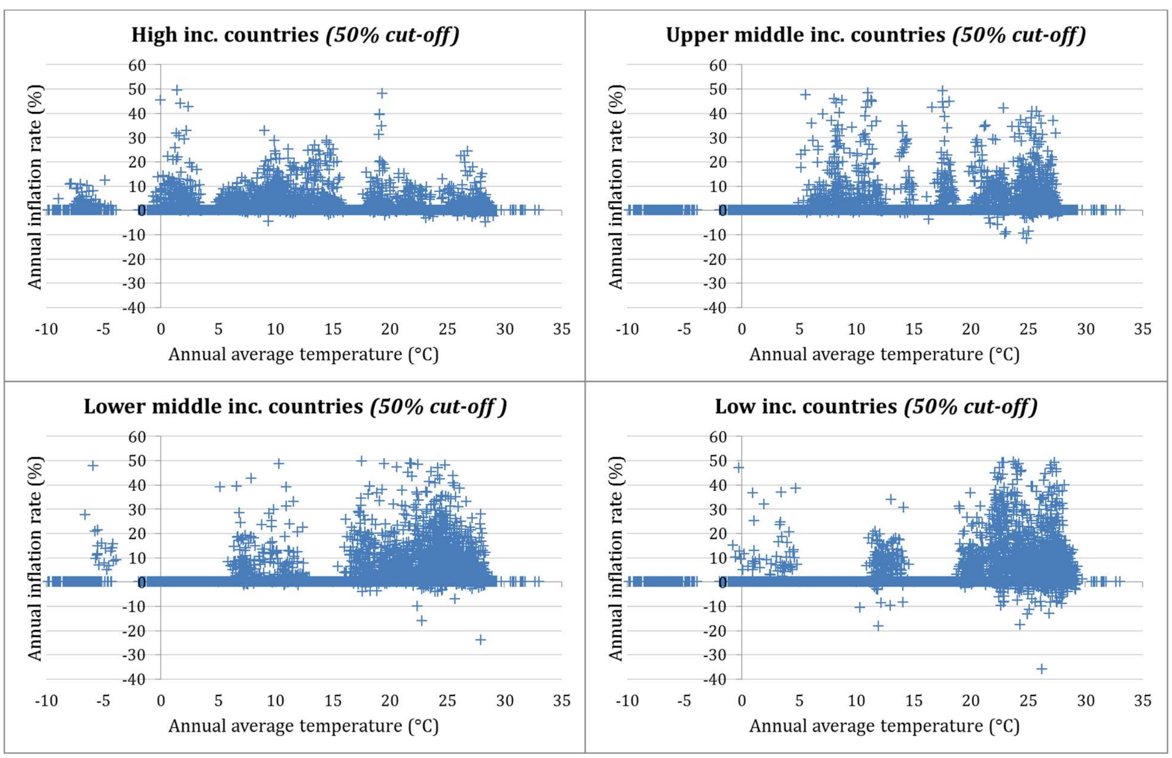
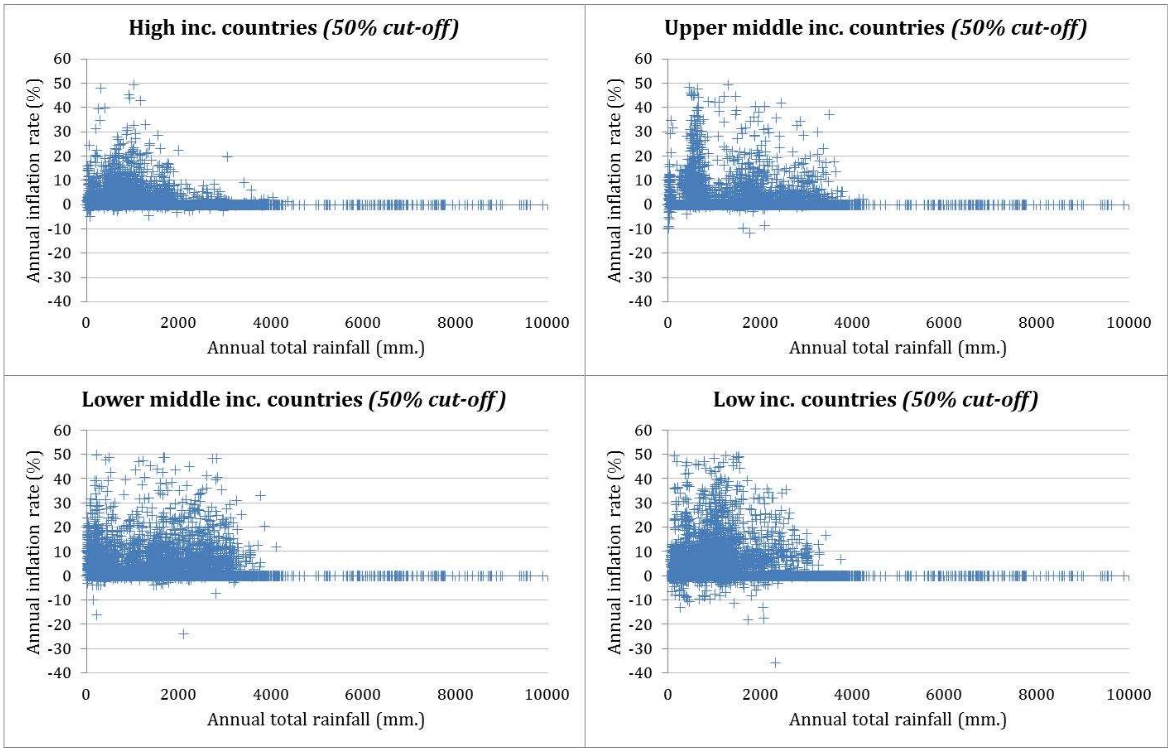


Figure 5.3 shows scatter plots of the annual inflation rate vs. annual precipitation for each of the four country-income groups. To the naked eye, there are no clear relationships between a

country's inflation rate in a given year and the total amount of rainfall it receives in that same year.

Figure 5.3: Annual inflation rate vs. annual precipitation– Countries by income group



<u>Scatter plots: annual policy interest rates vs. temperature and precipitation</u>

Figure 5.4 shows scatter plots of the annual policy interest rate vs. annual temperature (left) and precipitation (right). For visual clarity, we apply a 25% cut-off rate to the policy interest rate data showed in these scatter plots. There is no obvious relationship between interest rates and temperature, but there could be a slight negative correlation between precipitation and policy interest rates.

Figure 5.4: Annual policy interest rate vs. annual temperature and precipitation, all countries

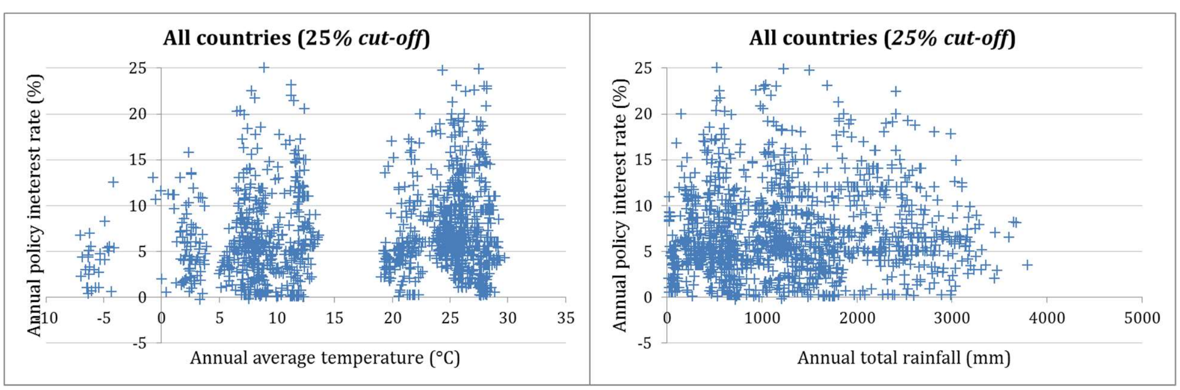
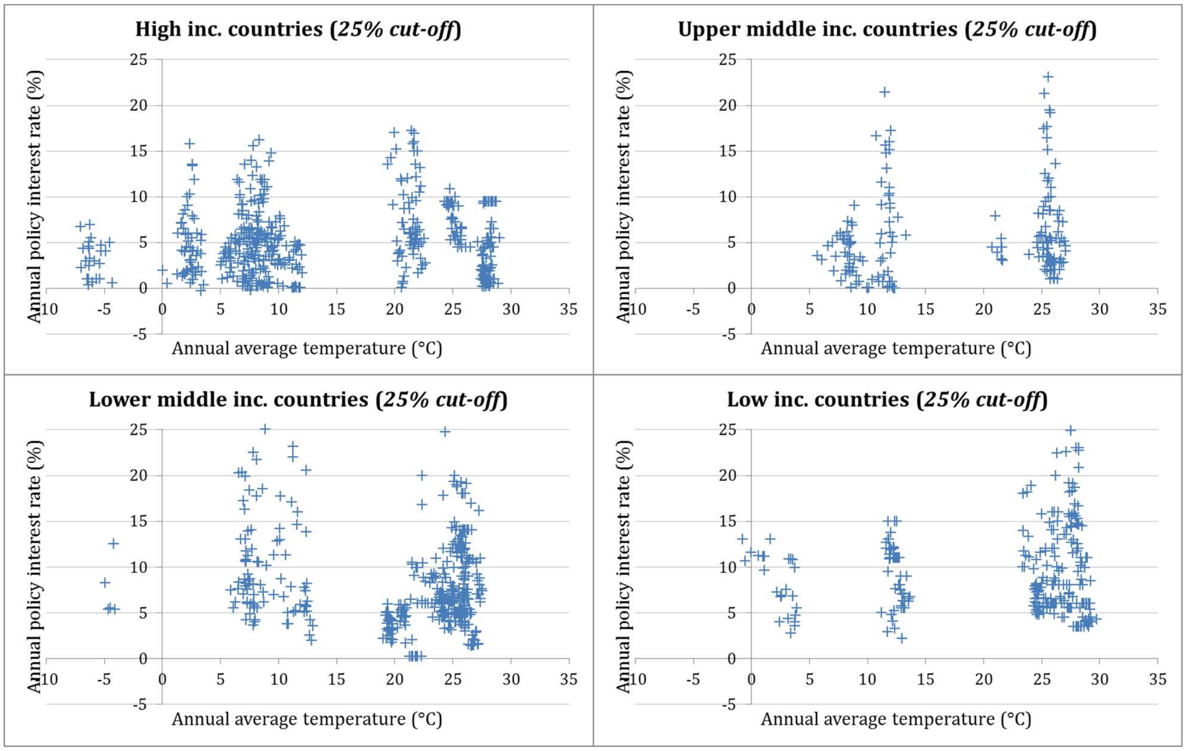


Figure 5.5 shows scatter plots of the annual policy interest rate vs. annual average temperature for each of the four country-income groups. From visual inspection, there does not

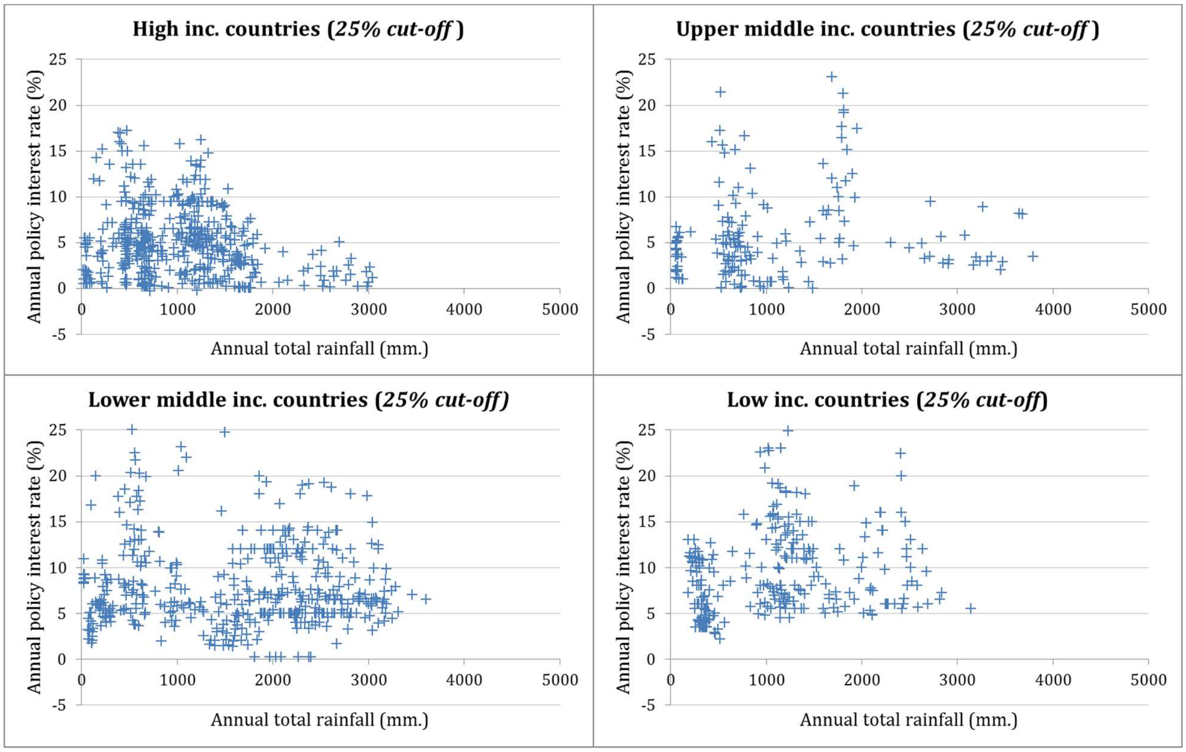
seem to be any discernible relationship between average temperature and interest rates, except for lower-middle-income countries, where higher temperatures seem to be associated with relatively lower policy rates.

Figure 5.5: Annual policy interest rate vs. annual temperature – Countries by income group



Finally, Figure 5.6 below shows scatter plots of the annual policy interest rate vs. annual precipitation for each of the four country-income groups. There does again seem to be a slight correlation between high levels of precipitation and low policy interest rates.

Figure 5.6: Annual policy interest rate vs. annual precipitation – Countries by income group



iii. Econometric approach

We propose to examine the impact of annual temperature and precipitation fluctuations on annual inflation and interest rates using the following estimation strategy:

Equation 5.1

$$y_{i,t} = \sum_{k=0}^{p} \beta_k \boldsymbol{C}_{i,t-k} + \mu_i + \theta_{rt} + \varepsilon_{i,t}$$

Where:

- $y_{i,t}$ represents the rate of inflation or the policy interest rate in country i in year t;
- $\boldsymbol{C}_{i,t}$ is a vector of annual average temperature and precipitation with up to p lags included;
- μ_i are country fixed effects;
- θ_{rt} are region-specific time fixed effects.

The inclusion of country fixed effects μ_i constitutes a relatively powerful control for time-invariant country characteristics, both observed and unobserved. Following the literature (Dell et al., 2012, 2014), we also include time fixed effects interacted with region dummies (θ_{rt}), which serve the important purpose of controlling for time-varying factors that may have different impacts across geographical regions.[68] This does come at the cost of absorbing some of the variation in weather, however. The inclusion of μ_i and θ_{rt}, together with the fact that variation in temperature and precipitation on an annual basis is undoubtedly random and exogenous, has strong identification properties. Hence, we follow the literature by not including further, explicit control variables, so as to avoid the problem of 'over-controlling', whereby the controls are potentially endogenous to the weather variation (Dell et al., 2014). Standard errors are calculated allowing for correlation within the observations of each country.[69]

The first part of our analysis considers the annual inflation rate as the dependent variable. Following Dell et al. (2012), we begin by estimating Equation 5.1 with no lags, focusing on the null hypothesis that temperature and precipitation do not affect the contemporaneous annual rate of inflation. If we can reject this null hypothesis, we will consider more flexible models with up to 10 lags of temperature and precipitation, as well as non-linear models, which include squared terms of the climate variables (Burke et al., 2015). The second part of our analysis will consider the annual policy interest rate as the dependent variable and will follow the same sequence.

3. Results and discussion

i. The effects of temperature and precipitation on annual inflation

Annual inflation – Linear models without lags

In the following three tables (Tables 5.4 to 5.6), we examine the contemporaneous effects of temperature and precipitation on annual inflation in: all countries (Table 5.4); poor vs. rich countries (Table 5.5); and countries by income groups (Table 5.6). We explore differences in country class using interaction effects. In each table, we also examine the influence of outliers by applying different cut-off rates of inflation (in Columns 1 and 2, no cut-off rate is applied; in Columns 3 and 4 a 100% cut-off rate is applied; in Columns 5 and 6 a 75% cut-off rate is applied; in Columns 7 and 8 a 50% cut-off rate is applied and in Columns 9 and 10 a 25% cut-off rate is applied).

[68] These region dummies correspond to the following six geographical regions: Middle-East and North Africa; Sub-Saharan Africa; Latin America and the Caribbean; Western Europe and Offshoots; Eastern Europe and Central Asia; and South-East Asia and Pacific Islands.
[69] Using the vce(cluster id) command in Stata.

Table 5.4: Effects of temperature and precipitation on annual inflation – linear model without lags, all countries

Dep. Var. is the annual inflation rate	(1) *No cut*	(2) *No cut*	(3) *100%*	(4) *100%*	(5) *75%*	(6) *75%*	(7) *50%*	(8) *50%*	(9) *25%*	(10) *25%*
Temp.	-7.37	-8.36	-0.02	-0.04	0.10	0.09	0.41	0.40	0.36*	0.35*
	(10.72)	(10.90)	(0.40)	(0.41)	(0.34)	(0.34)	(0.28)	(0.29)	(0.20)	(0.20)
Prec.		-30.98		-0.58		-0.43		-0.37		-0.33
		(26.42)		(0.54)		(0.48)		(0.43)		(0.29)
N	7247	7247	7082	7082	7030	7030	6923	6923	6550	6550
R-sq	0.043	0.043	0.265	0.265	0.288	0.288	0.325	0.325	0.374	0.374
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Infl. rate cut	None	None	100%	100%	75%	75%	50%	50%	25%	25%
Prec. variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Temperature is in °Celsius and precipitation in meters. Columns 1-2 include all inflation rate data. Columns 3-4 apply a 100% cut-off to the annual inflation rate. Columns 5-6 apply a 75% cut-off to the annual inflation rate. Columns 7-8 apply a 50% cut-off to the annual inflation rate. Columns 9-10 apply a 25% cut-off to the annual inflation rate. Columns 1, 3, 5, 7, 8 and 9 do not control for precipitation, whereas regressions presented in columns 2, 4, 6, 8 and 10 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 5.5: Effects of temperature and precipitation on the annual inflation rate – linear model without lags, Poor vs Rich countries

Dep. Var. is the annual inflation rate	(1) *No cut*	(2) *No cut*	(3) *100%*	(4) *100%*	(5) *75%*	(6) *75%*	(7) *50%*	(8) *50%*	(9) *25%*	(10) *25%*
Temp.*Poor	-14.54	-17.11	0.87	0.84	1.04*	1.03*	1.39***	1.37***	1.13***	1.11***
	(15.20)	(15.67)	(0.62)	(0.63)	(0.55)	(0.56)	(0.48)	(0.49)	(0.30)	(0.30)
Temp.*Rich	-1.84	-2.30	-0.66	-0.67	-0.57	-0.58	-0.29	-0.29	-0.17	-0.17
	(9.17)	(9.26)	(0.46)	(0.46)	(0.41)	(0.41)	(0.34)	(0.34)	(0.25)	(0.25)
Prec.*Poor		-50.67		-0.52		-0.17		-0.41		-0.34
		(39.68)		(0.73)		(0.66)		(0.58)		(0.43)
Prec.*Rich		-2.05		-0.40		-0.55		-0.01		-0.09
		(11.34)		(0.63)		(0.58)		(0.49)		(0.33)
N	7247	7247	7082	7082	7030	7030	6923	6923	6550	6550
R-sq	0.043	0.044	0.266	0.267	0.289	0.289	0.327	0.327	0.377	0.377
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Infl. rate cut	None	None	100%	100%	75%	75%	50%	50%	25%	25%
Prec. variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Temperature is in °Celsius and precipitation in meters. Columns 1-2 include all inflation rate data. Columns 3-4 apply a 100% cut-off to the annual inflation rate. Columns 5-6 apply a 75% cut-off to the annual inflation rate. Columns 7-8 apply a 50% cut-off to the annual inflation rate. Columns 9-10 apply a 25% cut-off to the annual inflation rate. Columns 1, 3, 5, 7, 8 and 9 do not control for precipitation, whereas regressions presented in columns 2, 4, 6, 8 and 10 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 5.6: Effects of temperature and precipitation on the annual inflation rate – linear model without lags, countries by income groups

Dep. var. is the annual inflation rate	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	No cut	*No cut*	*100%*	*100%*	*75%*	*75%*	*50%*	*50%*	*25%*	*25%*
Temp.*Low inc.	-6.62	-10.81	1.13	1.01	1.01	0.92	1.46**	1.39**	1.49***	1.43***
	(14.46)	(14.73)	(0.72)	(0.73)	(0.74)	(0.75)	(0.68)	(0.68)	(0.43)	(0.43)
Temp.*Lower mid. inc.	-23.73	-25.54	0.40	0.39	0.85	0.86	1.22*	1.22*	0.78**	0.78*
	(23.37)	(24.04)	(0.93)	(0.94)	(0.79)	(0.80)	(0.66)	(0.66)	(0.39)	(0.40)
Temp.*Upper mid. inc.	-9.99	-10.70	-1.59*	-1.60*	-1.30	-1.31	-0.69	-0.69	-0.31	-0.31
	(20.08)	(20.32)	(0.93)	(0.93)	(0.86)	(0.86)	(0.64)	(0.64)	(0.42)	(0.43)
Temp.*High inc.	0.94	0.84	-0.24	-0.24	-0.20	-0.20	-0.10	-0.10	-0.17	-0.17
	(5.42)	(5.45)	(0.51)	(0.51)	(0.44)	(0.44)	(0.41)	(0.41)	(0.31)	(0.31)
Prec.*Low inc.		-70.52		-1.99		-1.52		-1.27*		-1.11*
		(76.30)		(1.42)		(1.06)		(0.76)		(0.57)
Prec.*Lower mid. inc.		-41.92		0.09		0.38		-0.05		-0.01
		(48.44)		(0.82)		(0.78)		(0.74)		(0.56)
Prec.*Upper mid. inc.		3.2		-0.34		-0.43		0.15		-0.05
		(16.69)		(0.86)		(0.71)		(0.65)		(0.39)
Prec.*High inc.		-9.47		-0.47		-0.70		-0.24		-0.09
		(9.29)		(0.82)		(0.90)		(0.75)		(0.56)
N	7247	7247	7082	7082	7030	7030	6923	6923	6550	6550
R-sq	0.043	0.044	0.267	0.267	0.29	0.29	0.328	0.328	0.377	0.378
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Infl. rate cut	None	None	100%	100%	75%	75%	50%	50%	25%	25%
Prec. variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Temperature is in °Celsius and precipitation in meters. Columns 1-2 include all inflation rate data. Columns 3-4 apply a 100% cut-off to the annual inflation rate. Columns 5-6 apply a 75% cut-off to the annual inflation rate. Columns 7-8 apply a 50% cut-off to the annual inflation rate. Columns 9-10 apply a 25% cut-off to the annual inflation rate. Columns 1, 3, 5, 7, 8 and 9 do not control for precipitation, whereas regressions presented in columns 2, 4, 6, 8 and 10 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

When all countries are pooled (Table 5.4), we find a positive but only weakly significant effect of temperature on the annual inflation rate (at the 10% significance level), and only when we apply a 25% cut-off rate of inflation. However, the positive effect of temperature on inflation is stronger in some types of country. In particular, we find a positive and significant effect of temperature on annual inflation in poor countries (i.e. low income and lower-middle income), when we omit inflation rates in excess of 75%. For a 25-50% cut-off rate, the effect is significant at the 1% level. Table 5.6 shows that this effect on poor countries comes predominantly from low-income countries: omitting inflation rates in excess of 50%, the net effect of a 1°C rise in temperature is to increase the inflation rate in low-income countries by 1.39 percentage points (Column 8). Since the standard deviation of annual temperature once country- and region-year fixed effects are removed is 3.9 degrees (see Table 5.3), the estimates in Table 5.6 imply that a one standard deviation increase in annual temperature is associated with an increase in inflation of about 5.4 percentage points in low-income countries. We do not find that precipitation has a significant effect on annual inflation when all countries are pooled, or in poor/rich countries, but we find a negative and weakly significant (at the 10% level) effect of precipitation on inflation in low-income countries (Table 5.6).

<u>Annual inflation– Linear models with lags</u>

The above results, based on the simple model with no lags, lead us to reject the null hypothesis that temperature has no effect on inflation in poor countries (i.e. low- and lower-middle-income countries). There is also some weak evidence that precipitation fluctuations affect inflation in low-income countries (excluding outliers). This section considers more flexible models with up to 10 annual lags of the level of average temperature and the level of precipitation, to better understand the dynamics of these weather effects. Table 5.7 presents results from estimating Equation 5.1 with no lag, one lag, five lags, or ten lags of the climate variables. In columns 1-4, temperature and its lags are the only climate variables included. Columns 5-8 present results including precipitation and its lags. In Table 5.7, all temperature and precipitation variables are interacted with income subgroup dummies; results for all countries and for poor vs. rich countries can be found in Appendix 5.3. The rows at the bottom of the table present the cumulated effects of temperature and precipitation for countries in each of the income subgroups[70]. Due to space constraints, only the coefficients for lags 0-2 are reported. Based on the results we obtained above, we omit outlying inflation rates of more than 50%.

[70] The point estimates and standard deviations of all combinations (incl. nonlinear) of parameter estimates provided in this chapter have been estimated using the *nlcom* command in Stata which uses the delta method to compute standard errors.

Table 5.7: Effects of temperature and precipitation on the annual inflation rate – linear model with lags, Countries by income group

Dep. var. is the annual inflation rate – *50% cut-off rate*	(1) *No lags*	(2) *1 lag*	(3) *5 lags*	(4) *10 lags*	(5) *No lags*	(6) *1 lag*	(7) *5 lags*	(8) *10 lags*
Temp. * Low inc.	1.46**	1.34**	1.17*	1.09*	1.39**	1.25**	1.12*	1.05*
	(0.68)	(0.62)	(0.60)	(0.62)	(0.68)	(0.62)	(0.60)	(0.63)
L.Temp. * Low inc.		0.42	-0.01	-0.13		0.42	-0.04	-0.17
		(0.52)	(0.47)	(0.48)		(0.52)	(0.46)	(0.47)
L2.Temp. * Low inc.			0.32	0.24			0.24	0.15
			(0.52)	(0.52)			(0.52)	(0.51)
Temp. * Lower mid. inc.	1.22*	0.86	0.73	0.72	1.22*	0.87	0.75	0.72
	(0.66)	(0.52)	(0.46)	(0.46)	(0.66)	(0.53)	(0.47)	(0.46)
L.Temp. * Lower mid. inc.		1.03*	0.88**	0.90**		1.06*	0.90**	0.90**
		(0.55)	(0.43)	(0.42)		(0.55)	(0.42)	(0.42)
L2.Temp. * Lower mid. inc.			-0.01	-0.05			-0.06	-0.14
			(0.48)	(0.49)			(0.48)	(0.48)
Temp. * Upper mid. inc.	-0.69	-0.78	-0.78*	-0.51	-0.69	-0.77	-0.77	-0.49
	(0.64)	(0.55)	(0.47)	(0.53)	(0.64)	(0.56)	(0.48)	(0.56)
L.Temp. * Upper mid. inc.		0.44	0.51	0.46		0.44	0.50	0.42
		(0.53)	(0.47)	(0.52)		(0.53)	(0.48)	(0.54)
L2.Temp. * Upper mid. inc.			-0.70*	-0.55			-0.75*	-0.61
			(0.41)	(0.40)			(0.41)	(0.42)
Temp. * High inc.	-0.10	-0.14	-0.10	-0.17	-0.10	-0.12	-0.08	-0.16
	(0.41)	(0.31)	(0.24)	(0.23)	(0.41)	(0.31)	(0.24)	(0.24)
L.Temp. * High inc.		0.29	0.30	0.25		0.29	0.32	0.27
		(0.32)	(0.22)	(0.21)		(0.32)	(0.22)	(0.22)
L2.Temp. * High inc.			0.00	-0.04			0.00	-0.05
			(0.21)	(0.20)			(0.21)	(0.21)
Prec. * Low inc.					-1.27*	-1.24	-0.64	-0.73
					(0.76)	(0.75)	(0.70)	(0.71)
L.Prec. * Low inc.						-0.61	-0.09	-0.17
						(0.95)	(1.01)	(1.04)
L2.Prec. * Low inc.							-0.49	-0.63
							(0.99)	(0.97)
Prec. * Lower mid. inc.					-0.05	-0.19	-0.24	-0.35
					(0.74)	(0.73)	(0.77)	(0.79)
L.Prec. * Lower mid. inc.						0.69	0.62	0.55
						(0.56)	(0.50)	(0.53)
L2.Prec. * Lower mid. inc.							0.08	-0.06
							(0.93)	(0.90)
Prec. * Upper mid. inc.					0.15	0.09	0.06	0.20
					(0.65)	(0.62)	(0.61)	(0.63)
L.Prec. * Upper mid. inc.						0.38	0.49	0.60
						(0.91)	(0.90)	(0.88)
L2.Prec. * Upper mid. inc.							-0.36	-0.27
							(0.60)	(0.71)
Prec. * High inc.					-0.24	-0.20	-0.22	-0.23
					(0.75)	(0.73)	(0.72)	(0.76)
L.Prec. * High inc.						-0.61	-0.53	-0.52
						(0.57)	(0.61)	(0.61)
L2.Prec. * High inc.							-0.88	-0.92*
							(0.55)	(0.55)
R-sq	0.328	0.328	0.330	0.334	0.328	0.329	0.333	0.338
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Infl. rate cut	50%	50%	50%	50%	50%	50%	50%	50%
Prec. variables	No	No	No	No	Yes	Yes	Yes	Yes
Sum of all temp. coeff. in Low	1.46**	1.76**	3.01***	4.27***	1.39**	1.67**	2.63**	3.97**
inc. countries	(0.68)	(0.85)	(1.15)	(1.65)	(0.68)	(0.85)	(1.12)	(1.64)
Sum of all temp. coeff. in	1.22*	1.89**	2.66*	3.08*	1.22*	1.93**	2.61*	2.90*
Lower mid. inc. countries	(0.66)	(0.92)	(1.39)	(1.69)	(0.66)	(0.93)	(1.36)	(1.65)
Sum of all temp. coeff. in	-0.69	-0.34	0.45	0.60	-0.69	-0.33	0.39	0.47
Upper mid. inc. countries	(0.64)	(0.82)	(1.24)	(1.52)	(0.64)	(0.82)	(1.23)	(1.47)
Sum of all temp. coeff. in High	-0.69	-0.34	0.45	0.60	-0.69	-0.33	0.39	0.47
inc. countries	(0.64)	(0.82)	(1.24)	(1.52)	(0.64)	(0.82)	(1.23)	(1.47)
Sum of all prec. coeff. in Low					-1.27*	-1.84	-5.94**	-5.37
inc. countries					(0.76)	(1.18)	(2.44)	(4.37)
Sum of all prec. coeff. in Lower					-0.05	0.50	-1.04	-4.31
mid. inc. countries					(0.74)	(0.93)	(2.37)	(4.19)
Sum of all prec. coeff. in Upper					0.15	0.47	-0.45	-1.45
mid. inc. countries					(0.65)	(1.22)	(3.36)	(5.41)
Sum of all prec. coeff. in High					0.15	0.47	-0.45	-1.45
inc. countries					(0.65)	(1.22)	(3.36)	(5.41)

Notes: Temperature is in °Celsius and precipitation in meters. In all columns, a 50% cut=off is applied to the inflation rate. Columns 1-4 do not control for precipitation, whereas regressions presented in columns 5-8 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 5.7 shows that the cumulative effect of temperature in low- and lower-middle income countries remains substantially positive and increases as we add more lags, which indicates that the effects of above-average temperature appear to persist in the medium run. With no lags (columns 1 and 5), a one-off, 1°C temperature increase in a low-income country increases inflation by 1.39-1.46 percentage points. With five lags included (columns 3 and 7), the cumulative effect of a 1°C temperature increase in low-income countries is an increase in the rate of inflation of 2.63-3.01 percentage points.

The cumulative effect of precipitation is significant (and negative) only for low-income countries. With no lags (Table 5.6, column 8 and Table 5.7, column 5), a one standard deviation increase in annual rainfall is associated with a reduction in inflation of about 0.58 percentage points in low-income countries. With five lags included (Table 5.7, column 7), the cumulative effect in low-income countries is a decrease in inflation of 2.71 percentage points. The cumulated lag effect is negative but insignificant for lags 5 and 10.

Annual inflation rate – Nonlinear models

We now consider whether temperature or precipitation have a nonlinear effect on the annual inflation rate, by adding the squared term of temperature and precipitation to the vector of climate variables in Equation 5.1. Burke et al. (2015) showed that the finding of no statistically significant effect of temperature on growth in rich countries, delivered by Dell et al. (2012), could be simply due to fitting a linear model on a set of observations that are in fact well fit by a parabola. We estimate the non-linear model on the pooled set of all countries' data.

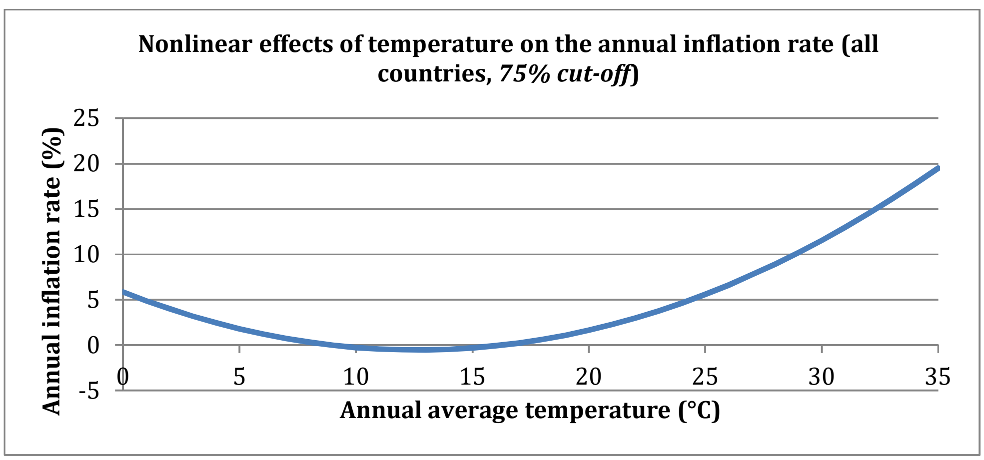
From the results presented in Table 5.8, we now find that the linear effect of temperature on inflation is negative and significant, while the effect of the square of temperature on inflation is positive and significant, albeit this result is strongest when the inflation cut-off rate is between 75% and 100%, suggesting outliers play a role in its determination. When a 50% cut-off rate is applied to the inflation rate data, an increase in annual average temperature from 19°C (which corresponds to the mean in the pooled sample) to 20°C would increase inflation by 0.70 percentage points (with a standard error of 0.36) in all countries. Figure 5.7, which plots the results for a 75% cut-off rate (Column 5), shows that our results seem to indicate inflation is low for an annual average temperature of around 13°C, but increases at lower and higher temperatures. This result appears to be the inverse of what Burke et al. (2015) found was the relationship between temperature and the growth rate of output per capita.

Table 5.8: Effects of temperature and precipitation on the annual inflation rate – linear model without lags, all countries

Dep. var.is the annual inflation rate	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	No cut	*No cut*	*100%*	*100%*	*75%*	*75%*	*50%*	*50%*	*25%*	*25%*
Temp.	-14.48	-14.32	-1.58**	-1.58**	-1.01*	-1.00*	-0.50	-0.50	-0.11	-0.11
	(9.06)	(9.07)	(0.76)	(0.76)	(0.57)	(0.57)	(0.42)	(0.42)	(0.29)	(0.29)
Temp.^2	0.24	0.21	0.05**	0.05**	0.04**	0.04**	0.03**	0.03**	0.02*	0.02
	(0.49)	(0.49)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Prec.		-28.92		-1.09		-2.35		-1.64		-1.24
		(47.34)		(1.76)		(1.46)		(1.10)		(0.85)
Prec.^2		-0.38		0.15		0.48		0.32		0.22
		(11.23)		(0.35)		(0.31)		(0.24)		(0.20)
Constant	192.41	240.05	10.24	11.55	5.85	8.22	-1.45	0.24	-2.68	-1.32
	(174.43)	(189.78)	(8.46)	(8.93)	(6.91)	(7.33)	(5.49)	(5.62)	(3.91)	(4.02)
N	7247	7247	7082	7082	7030	7030	6923	6923	6550	6550
R-sq	0.043	0.044	0.267	0.267	0.289	0.289	0.326	0.326	0.374	0.375
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Infl. rate cut	None	None	100%	100%	75%	75%	75%	75%	25%	25%
Prec. variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Temperature is in °Celsius and precipitation in meters. Columns 1-2 include all inflation rate data. Columns 3-4 apply a 100% cut-off to the annual inflation rate. Columns 5-6 apply a 75% cut-off to the annual inflation rate. Columns 7-8 apply a 50% cut-off to the annual inflation rate. Columns 9-10 apply a 25% cut-off to the annual inflation rate. Columns 1, 3, 5, 7, 8 and 9 do not control for precipitation, whereas regressions presented in columns 2, 4, 6, 8 and 10 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure 5.7: Nonlinear relationship between average temperature and the annual inflation rate, for a 75% cut-off rate



ii. The effects of temperature and precipitation on the annual policy interest rate

Annual policy interest rate – Linear models, no lags

In the following three tables (Tables 5.9 to 5.11), we examine the contemporaneous effects of temperature and precipitation on the annual policy interest rate in: all countries (Table 5.9); poor vs. rich countries (Table 5.10); and countries by income groups (Table 5.11). As explained above, outliers are a less pressing issue in the interest rate data, so, with a view to brevity, the results presented below exclude policy interest rates in excess of 50%, but sensitivity analyses for different cut-off rates can nonetheless be found in Appendix 5.4.

Table 5.9: Effects of temperature and precipitation on the annual policy interest rate – linear model without lags, all countries

Dep. var. is the annual policy interest rate *– 50% cut-off rate*	(1)	(2)
Temp.	-0.42	-0.46
	(0.36)	(0.36)
Prec.		-1.20***
		(0.38)
N	1434	1434
R-sq	0.518	0.519
Country FE	Yes	Yes
Region*Year FE	Yes	Yes
Pol. int. rate cut	50%	50%
Prec. variables	No	Yes

Notes: Temperature in °Celsius and precipitation in meters. A 50% cut-off is applied to the annual policy interest rate. Column 1 does not control for precipitation, whereas the regression presented in column 2 includes precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 5.10: Effects of temperature and precipitation on the annual policy interest rate – linear model without lags, Poor vs Rich countries

Dep. var. is the annual policy interest rate *- 50% cut-off*	(1)	(2)
Temp. * Poor	-0.39	-0.48
	(0.47)	(0.47)
Temp. * Rich	-0.44	-0.43
	(0.54)	(0.54)
Prec.* Poor		-1.59***
		(0.52)
Prec.* Rich		-0.63
		(0.53)
N	1434	1434
R-sq	0.518	0.52
Country FE	Yes	Yes
Region*Year FE	Yes	Yes
Pol. int. rate cut	50%	50%
Prec. variables	No	Yes

Notes: Temperature in °Celsius and precipitation in meters. A 50% cut-off is applied to the annual policy interest rate. Column 1 does not control for precipitation, whereas the regression presented in column 2 includes precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 5.11: Effects of temperature and precipitation on the annual policy interest rate – linear model without lags, countries by income groups

Dep. var. is the annual policy interest rate *- 50% cut-off*	(1)	(2)
Temp. * Low income	-1.69**	-1.81**
	(0.68)	(0.72)
Temp. * Lower middle income	0.25	0.16
	(0.62)	(0.60)
Temp. * Upper middle income	-1.68	-1.62
	(1.39)	(1.44)
Temp. * High income	-0.08	-0.10
	(0.53)	(0.52)
Prec. * Low income		-2.51
		(1.57)
Prec. * Lower middle income		-1.20**
		(0.46)
Prec. * Upper middle income		0.11
		(1.21)
Prec. * High income		-1.03**
		(0.50)
N	1434	1434
R-sq	0.522	0.524
Country FE	Yes	Yes
Region*Year FE	Yes	Yes
Pol. int. rate cut	50%	50%
Prec. variables	No	Yes

Notes: Temperature in °Celsius and precipitation in meters. A 50% cut-off is applied to the annual policy interest rate. Column 1 does not control for precipitation, whereas the regression presented in column 2 includes precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

In the pooled sample of all countries, we find no significant effect of temperature on the annual policy interest rate, but we find a negative and highly significant (at the 1% level) effect of precipitation on the annual policy interest rate (Table 5.9): a 1m increase in annual rainfall is associated with a reduction in the annual policy interest rate of 1.20 percentage points; put another way, since the standard deviation of annual precipitation once country- and region-year fixed effects are removed is 0.46 meters (see Table 5.3), the estimates in Table 5.9 imply that a one standard deviation increase in annual precipitation is associated with a reduction in the policy interest rate of 0.55 percentage points.

When considering poor vs. rich countries, we find no significant effect of temperature on the annual policy interest rate in either class of country, but precipitation does have a negative and highly significant effect on interest rates in poor countries (Table 5.10). In particular, a 1m increase in annual rainfall in poor countries is associated with a reduction of the annual policy interest rate of 1.59 percentage points; this is equivalent to saying that the effect of a one standard deviation increase in annual precipitation is a reduction in the policy interest rate of 0.73 percentage points. When dividing our sample into income groups, we find a negative and significant effect of temperature on the annual policy interest rate, but only for low-income countries (Table 5.11), while the negative effect of precipitation on interest rates appears to be concentrated in lower-middle and high-income countries. These are the country-income subgroups with the most data on interest rates (29 countries in the lower-middle-income class and 19 countries in the high-income class, compared to 14 and 13 countries in the low- and upper-middle-income groups respectively). Therefore, the fact that we find negative but insignificant effects for the low-income group could be due to the small sample size. We also find that results are consistent across cut-off rates (see Appendix 5.4 for details).

Annual policy interest rate – Linear models, with lags

Given the above results, based on the simple model with no lags, we can reject the null hypothesis that temperature has no effect on the policy interest rate in low-income countries and that precipitation has no effect in lower-middle and high-income countries. This section considers more flexible models with up to 10 lags of temperature and precipitation to better understand the dynamics of these weather effects. Table 5.12 presents results from estimating Equation 5.1 with no lag, one lag, five lags, or ten lags of the climate variables. In column 1, temperature and its lags are the only climate variables included. Column 2 presents results where precipitation and its lags are also included. All temperature and precipitation variables are interacted with income subgroup dummies, but results for all countries and for poor vs. rich countries are relegated to Appendix 5. The rows at the bottom of the table present the cumulated effects of temperature and precipitation for countries in each of the income subgroups. Due to space constraints, only the coefficients for lags 0-2 are reported. Based on the results we obtained above, policy interest rates above 50% have been omitted.

Table 5.12: Effects of temperature and precipitation on the annual policy interest rate – linear model with lags, countries by income group

Dependent variable is the annual policy interest rate – *50% cut-off*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No lags	*1 lag*	*5 lags*	*10 lags*	*No lags*	*1 lag*	*5 lags*	*10 lags*
Temp. * Low inc.	-1.69**	-1.52**	-1.57***	-1.69**	-1.81**	-1.59**	-1.62***	-1.68***
	(0.68)	(0.61)	(0.57)	(0.73)	(0.72)	(0.64)	(0.57)	(0.60)
L.Temp. * Low inc.		-0.71*	-0.58*	-0.88**		-0.75*	-0.47	-0.73**
		(0.42)	(0.33)	(0.41)		(0.39)	(0.37)	(0.35)
L2.Temp. * Low inc.			(0.28)	(0.49)			(0.32)	(0.49)
			(0.46)	(0.55)			(0.48)	(0.54)
Temp. * Lower mid. inc.	0.25	0.25	0.27	0.50	0.16	0.13	0.09	0.32
	(0.62)	(0.59)	(0.53)	(0.57)	(0.60)	(0.57)	(0.49)	(0.59)
L.Temp. * Lower mid. inc.		0.52	0.42	0.45		0.48	0.32	0.21
		(0.46)	(0.39)	(0.41)		(0.45)	(0.34)	(0.39)
L2.Temp. * Lower mid. inc.			0.94*	0.81*			0.89*	0.52
			(0.47)	(0.48)			(0.46)	(0.49)
Temp. * Upper mid. inc.	-1.68	-1.67	-1.60	-2.02	-1.62	-1.61	-1.57	-2.20
	(1.39)	(1.35)	(1.22)	(1.41)	(1.44)	(1.39)	(1.29)	(1.45)
L.Temp. * Upper mid. inc.		0.20	0.09	1.07		0.19	0.07	1.02*
		(0.79)	(0.78)	(0.67)		(0.78)	(0.76)	(0.60)
L2.Temp. * Upper mid. inc.			1.01	1.74**			1.00	1.87**
			(0.94)	(0.74)			(0.98)	(0.81)
Temp. * High inc.	-0.08	-0.04	0.06	0.14	-0.10	-0.05	0.03	0.09
	(0.53)	(0.43)	(0.30)	(0.25)	(0.52)	(0.43)	(0.29)	(0.27)
L.Temp. * High inc.		-0.15	-0.05	-0.01		-0.15	-0.03	0.02
		(0.48)	(0.34)	(0.29)		(0.47)	(0.33)	(0.28)
L2.Temp. * High inc.			0.10	0.11			0.07	0.09
			(0.27)	(0.22)			(0.27)	(0.23)
Prec. * Low inc.					-2.51	-2.11	-2.62**	-3.77**
					(1.57)	(1.49)	(1.24)	(1.71)
L.Prec. * Low inc.						-2.07	-2.44	-2.91
						(1.78)	(2.18)	(2.72)
L2.Prec. * Low inc.							-3.55	-4.51*
							(2.45)	(2.60)
Prec. * Lower mid. inc.					-1.20**	-1.21**	-1.16**	-2.08***
					(0.46)	(0.46)	(0.56)	(0.64)
L.Prec. * Lower mid. inc.						-0.77	-0.74	-1.53*
						(0.84)	(0.79)	(0.87)
L2.Prec. * Lower mid. inc.							-0.45	-1.37*
							(0.81)	(0.69)
Prec. * Upper mid. inc.					0.11	0.05	0.22	-1.16
					(1.21)	(1.15)	(0.90)	(1.70)
L.Prec. * Upper mid. inc.						-0.02	-0.32	-2.51
						(0.97)	(1.06)	(1.96)
L2.Prec. * Upper mid. inc.							-0.55	0.16
							(1.16)	(1.07)
Prec. * High inc.					-1.03**	-1.00**	-1.29**	-1.46**
					(0.50)	(0.49)	(0.62)	(0.62)
L.Prec. * High inc.						-1.25**	-1.30*	-1.37*
						(0.53)	(0.67)	(0.69)
L2.Prec. * High inc.							-0.83	-0.73
							(0.77)	(0.85)
R-sq	0.522	0.522	0.531	0.547	0.524	0.526	0.551	0.582
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pol. Int. rate cut	50%	50%	50%	50%	50%	50%	50%	50%
Prec. variables	No	No	No	No	Yes	Yes	Yes	Yes
Sum of all temp. coeff. in Low	-1.69**	-2.23**	-3.30*	-1.07	-1.81**	-2.35**	-3.79*	-3.61
inc. countries	(0.68)	(0.92)	(1.90)	(2.21)	(0.72)	(0.96)	(2.10)	(2.92)
Sum of all temp. coeff. in	0.25	0.77	4.50**	6.43**	0.16	0.62	3.93**	3.91
Lower mid. inc. countries	(0.62)	(0.98)	(2.04)	(2.81)	(0.60)	(0.93)	(2.01)	(2.91)
Sum of all temp. coeff. in	-1.68	-1.47	1.24	0.86	-1.62	-1.41	1.22	-3.76
Upper mid. inc. countries	(1.39)	(1.97)	(4.74)	(6.86)	(1.44)	(1.98)	(4.77)	(6.89)
Sum of all temp. coeff. in High	-0.08	-0.19	0.23	0.54	-0.10	-0.21	0.23	0.20
inc. countries	(0.53)	(0.90)	(1.52)	(2.07)	(0.52)	(0.88)	(1.49)	(2.05)
Sum of all prec. coeff. in Low					-2.51	-4.18*	-26.63***	-45.86**
inc. countries					(1.57)	(2.50)	(10.31)	(19.18)
Sum of all prec. coeff. in Lower					-1.20***	-1.98*	-4.78	-17.99***
mid. inc. countries					(0.46)	(1.06)	(3.33)	(5.15)
Sum of all prec. coeff. in Upper					0.11	0.02	-2.87	-17.05
mid. inc. countries					(1.21)	(1.64)	(3.02)	(15.72)
Sum of all prec. coeff. in High					-1.03**	-2.26**	-5.88*	-9.23*
inc. countries					(0.50)	(0.90)	(3.54)	(4.94)

Notes: Temperature in °Celsius and precipitation in meters. In all columns, a 100% cut-off is applied to the policy interest rate. Columns 1-4 do not control for precipitation, whereas regressions presented in columns 5-8 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

The results show that the cumulative effects of temperature in low-income countries remain substantially negative and increase as we add more lags, but become insignificant at the 10th lag. With no lags (columns 1 and 5), a 1°C increase in annual temperature is associated with a reduction in the policy interest rate of 1.69-1.81 percentage points in low-income countries. When we include one lag, we find that a 1°C increase in temperature produces a 2.23-2.35 percentage point reduction in the policy interest rate. The cumulated effect becomes less significant (only at the 10% level) when we include the first five lags and insignificant when ten lags are included. They are opposite in sign to the effects we had found for inflation (Table 5.7), but they seem to increase at roughly the same rate, at least until the 5th lag. The cumulated lag effects of temperature are insignificant for the three other income subgroups.

In lower-middle income countries, we find significant and positive lagged effects of temperature on the annual policy interest rate, which only become significant at the 5th and 10th lag. When we include 5 lags, a 1°C temperature increase produces a 3.93 percentage point increase in the policy interest rate. We had found similar results for inflation, but the first lags were also significant (Table 5.7). This seems consistent with the hypothesis that there are delays between changes in the inflation rate and the corresponding monetary policy response.

As regards precipitation, we find significant and negative cumulated lag effects for the low-income group, which is similar to what we had found for inflation (Table 5.7). When one lag is included (column 6), the effect of a one standard deviation increase in precipitation is a reduction of the policy interest rate by 1.91 percentage points. When five lags are included (column 7), a one standard deviation increase in annual rainfall produces a reduction in the policy rate of 12.16 percentage points. We also find significant and negative cumulated lag effects of precipitation in the lower-middle and high-income groups, whereas we had found no significant effects for inflation (Table 5.7). We find that, with five lags included (column 7), the cumulative effect of a one standard deviation increase in annual rainfall produces a reduction of the policy interest rate of 2.69 percentage points in high-income countries. With ten lags of precipitation included (column 8), the effect of a one standard deviation increase in annual precipitation is a reduction of 4.22 percentage points.

<u>Annual policy interest rate – Nonlinear models</u>

We now consider the nonlinear effects of temperature and precipitation on the annual inflation rate by adding the squared term of temperature and precipitation to the model presented in Equation 5.1. Table 5.13 shows that we find no significant effects of squared temperature or precipitation on interest rates.

Table 5.13: Effects of temperature and precipitation on the annual inflation rate – linear model without lags, all countries

Dep. Var. is the annual policy interest rate *- 50% cut-off*	(1)	(2)
Temp.	0.05	0.06
	(0.47)	(0.47)
Temp.^2	(0.02)	-0.03*
	(0.02)	(0.02)
Prec.		-2.97***
		(1.05)
Prec.^2		0.41
		(0.25)
Constant	18.62***	22.80***
	(6.22)	(6.57)
N	1434	1434
R-sq	0.519	0.521
Country FE	Yes	Yes
Region*Year FE	Yes	Yes
Pol. int. rate cut	50%	50%
Prec. variables	No	Yes

Notes: Temperature in °Celsius and precipitation in meters. A 50% cut-off is applied to the annual policy interest rate. Column 1 does not control for precipitation, whereas the regression presented in column 2 includes precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

iii. Robustness checks

Since poorer countries tend to be hotter and drier, we examine whether the effects of temperature on inflation in poor countries come from being hot. In Table 5.14 below, we compare models which include proxies for countries being hot and/or dry. We define "hot" as countries that had above-median average temperature in the period 1950-1959. Similarly, we define dry as countries that had below-median precipitation in the same period. We use a slightly different but equivalent specification to the models presented in Table 5.5: since we regress the inflation rate on Temperature and Temperature*Poor, the overall effect of temperature on poor countries corresponds to the sum of the coefficients: the overall effect of temperature on poor countries can be read in the penultimate row of the table[71]. As we can see from columns 3 and 4, adding the interaction between temperature and "hot" does not affect the coefficient on "poor". Similarly, adding the interaction between temperature and "dry" leaves the coefficient on "poor" unchanged (columns 3 and 5). These results signal that the positive effects of temperature on inflation are attached to the "poor" characteristic.

[71] Standard errors are computed with the *nlcom* command in Stata.

Table 5.14: Effects of temperature and precipitation on inflation in poor countries – controlling for "hot" and "dry" characteristics

Dep. var. is the annual inflation rate - *50% cut-off*	(1)	(2)	(3)	(4)	(5)
Temperature	0.41	-0.29	-0.29	-0.33	-0.24
	(0.28)	(0.34)	(0.34)	(0.36)	(0.55)
Temperature interacted with…					
Poor country dummy		1.68***	1.66***	1.63***	1.64***
		(0.57)	(0.58)	(0.59)	(0.58)
Hot country dummy				0.18	
				(0.66)	
Dry country dummy					-0.09
					(0.54)
Precipitation			-0.01	-0.57	0.22
			(0.49)	(0.93)	(0.52)
Precipitation interacted with…					
Poor country dummy			-0.39	-0.55	-0.54
			(0.73)	(0.75)	(0.73)
Hot country dummy				0.83	
				(1.06)	
Dry country dummy					-1.39
					(1.35)
N	6923	6923	6923	6923	6923
R-sq	0.325	0.327	0.327	0.327	0.328
Country FE	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes
Infl. rate cut	50%	50%	50%	50%	50%
Prec. variables	No	No	Yes	Yes	Yes
Temp. effect in poor countries		1.39***	1.37***	1.30**	1.40**
		(0.48)	(0.49)	(0.55)	(0.60)
Prec. effect in poor countries			-0.41	-1.12	-0.32
			(0.58)	(1.10)	(0.59)

Notes: Temperature in °Celsius and precipitation in meters. A 50% cut-off is applied to the annual policy interest rate. Columns 1 and 2 do not control for precipitation, whereas columns 3 to 5 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

We repeat the above analysis with the policy interest rate as the dependent variable. The model in column 3 is equivalent to the one we used in Table 5.10 (column 2) to assess the linear effects of temperature and precipitation in poor countries[72]. According to the results in columns 3, 4 and 5 below, the negative effects of precipitation on the policy interest rate appear through being poor.

[72] The only difference in that in this table (Table 5.15), the effects of temperature and precipitation on poor countries should be read in the last rows of the table.

Table 5.15: Effects of temperature and precipitation on the policy interest rate in poor countries – controlling for "hot" and "dry" characteristics

Dep. var. is the annual policy interest rate - *50% cut-off*	(1)	(2)	(3)	(4)	(5)
Temperature	-0.42	-0.44	-0.43	-0.41	0.79
	(0.36)	(0.54)	(0.54)	(0.55)	(0.76)
Temperature interacted with…					
Poor country dummy		0.05	-0.05	-0.04	-0.02
		(0.77)	(0.75)	(0.75)	(0.76)
Hot country dummy				-0.23	
				(0.89)	
Dry country dummy					-1.93**
					(0.95)
Precipitation			-0.63	-1.30	-0.19
			(0.53)	(0.90)	(0.59)
Precipitation interacted with…					
Poor country dummy			-0.96	-1.13	-1.21
			(0.73)	(0.75)	(0.80)
Hot country dummy				0.95	
				(0.99)	
Dry country dummy					-1.24
					(1.23)
N	1434	1434	1434	1434	1434
R-sq	0.518	0.518	0.52	0.52	0.526
Country FE	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes
Pol. rate cut	50%	50%	50%	50%	50%
Prec. variables	No	No	Yes	Yes	Yes
Temp. effect in poor countries		-0.39	-0.48	-0.45	0.77
		(0.47)	(0.47)	(0.52)	(0.69)
Prec. effect in poor countries			-1.59***	-2.42**	-1.40***
			(0.52)	(0.99)	(0.47)

Given the fact that we find in some cases opposite signs for the effects of weather on inflation and on the policy interest rate, we verify that there is a relationship between the inflation rate and the policy interest rate. There seems to be a positive effect of the inflation rate on the policy interest rate for all income groups and the cumulated lag effects increase as lags are added to the regression. However, we are well aware of the reverse causality problem at stake here and of the limitations that it sets on any quantitative interpretation of the coefficients.

Table 5.16: Inflation rate vs. policy interest rate – linear model with lags, countries by income group

Dependent variable is the annual policy interest rate	(1)	(2)	(3)	(4)
	No lags	*1 lag*	*5 lags*	*10 lags*
Inf. * Low inc.	0.37***	0.25***	0.27***	0.29***
	(0.06)	(0.04)	(0.05)	(0.07)
L.Infl * Low inc.		0.33***	0.25***	0.25***
		(0.05)	(0.05)	(0.05)
L2.Infl. * Low inc.			-0.03	-0.03
			(0.05)	(0.06)
L3.Infl. * Low inc.			-0.03	-0.04
			(0.03)	(0.03)
Infl. * Lower mid. inc.	0.28**	0.08	0.14*	0.25***
	(0.12)	(0.07)	(0.08)	(0.05)
L.Infl. * Lower mid. inc.		0.23***	0.17***	0.22***
		(0.07)	(0.05)	(0.05)
L2.Infl. * Lower mid. inc.			-0.01	0.08***
			(0.04)	(0.03)
L3.Infl. * Lower mid. inc.			0.03	0.03
			(0.03)	(0.03)
Infl. * Upper mid. inc.	0.79***	0.24*	0.35***	0.23***
	(0.20)	(0.13)	(0.09)	(0.07)
L.Infl. * Upper mid. inc.		0.44***	0.12**	0.13*
		(0.13)	(0.05)	(0.07)
L2.Infl. * Upper mid. inc.			0.00	-0.02
			(0.09)	(0.07)
L3.Infl. * Upper mid. inc.			-0.03	0.00
			(0.06)	(0.05)
Infl. * High inc.	0.39**	0.21	0.26**	0.23*
	(0.16)	(0.14)	(0.11)	(0.12)
L.Infl. * High inc.		0.25***	0.14***	0.13***
		(0.07)	(0.04)	(0.04)
L2.Infl. * High inc.			0.06	0.08*
			(0.05)	(0.04)
L3.Infl. * High inc.			0.11***	0.08**
			(0.03)	(0.03)
N	1316	1296	1214	1069
R-sq	0.689	0.727	0.718	0.735
Country FE	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes
Pol. int. rate cut	50%	50%	50%	50%
Temp. variables	No	No	No	No
Prec. variables	No	No	No	No
Sum of all infl. coeff. in Low inc. countries	0.37***	0.58***	0.49***	0.46**
	(0.06)	(0.06)	(0.11)	(0.21)
Sum of all infl. coeff. in Lower mid. inc. countries	0.28**	0.31***	0.40***	0.68***
	(0.12)	(0.11)	(0.15)	(0.12)
Sum of all infl. coeff. in Upper mid. inc. countries	0.79***	0.68***	0.50**	0.29*
	(0.20)	(0.15)	(0.20)	(0.17)
Sum of all infl. coeff. in High inc. countries	0.39**	0.46**	0.75***	0.88***
	(0.16)	(0.19)	(0.12)	(0.12)

iv. Discussion of results

<u>Inflation</u>

We find that higher-than-average temperatures increase inflation, but only in low-income countries (Table 5.6). We find no effects of precipitation on inflation, apart from weakly significant negative effects in low-income countries (Table 5.6). Our reduced-form econometric approach does not allow us to explore the precise channels through which temperature affects the price level, but the comparison of our results with previous findings from the NCE literature provides us with some insight.

In particular, there is an obvious symmetry between our results and the findings of empirical studies into the relationship between climate/weather fluctuations and economic growth that has prevailed in recent decades. These studies have shown that temperature fluctuations have a negative, linear effect on growth in poor countries (Dell et al., 2012) and that this is in line with an inverse-U-shaped relationship between temperature and growth at the global level, holding for countries of all income levels (Burke et al., 2015). In comparison, we find that temperature fluctuations increased inflation in poor countries and that this was happening in the context of a U-shaped relationship between temperature and inflation for countries of all income levels. In addition, Dell et al. (2012) found that the negative effects of temperature on output have been persistent, i.e. they work on the growth rate rather than the level of output. We also find persistent effects of temperature on inflation. Therefore, the comparison between our findings and these previous studies strongly supports the idea that temperature effects on inflation come from a supply-side shock to aggregate output. The fact that the inflationary effects are stronger in poor countries is consistent with the finding that the effects of temperature on aggregate output are stronger in poor countries. This may in itself be partly attributable to the effect of temperature on agricultural output (Dell et al., 2012; Feng et al., 2012; Guiteras, 2009; Schlenker and Lobell, 2010), which is typically a larger share of aggregate output in poor countries. But effects of temperature on agricultural output can also affect inflation more in poor countries, because the basket of goods has a higher weighting on agricultural products.

Policy interest rate

We find that precipitation has a negative and significant effect on the policy interest rate in all countries, with heterogeneous effects in countries in different income classes (Table 5.11). We do not find a corresponding effect on inflation in the pooled sample, but we do find that precipitation has a significant and negative effect on inflation in low-income countries. One explanation for this could be that high precipitation increases agricultural output in developing countries (Levine & Yang, 2006): this would likely cause a decrease in prices, which may in turn lead central banks in low-income countries to decrease the policy interest rate. The fact that precipitation does not have a significant effect on interest rates in low-income countries could simply be due to the small number of low-income countries with interest rate data.

As regards the other income subgroups, the effect of precipitation on the policy rate is not matched by a corresponding effect on the inflation rate. One explanation for this could come from high precipitation events causing the destruction of physical capital and/or labour (e.g. stronger than average monsoons, intense hurricane seasons), which would prompt central banks to take rapid action by decreasing the policy interest rate to spur the economy, even before the effects of output contraction could be reflected in prices. Indeed, precipitation has the advantage of being much more visible than temperature, and high precipitation events can thus induce rapid reaction. For instance, at the time of Hurricane Katrina in 2005, there was a widespread perception that the economic devastation of the storm would lead the Federal Reserve to prevent rate hikes or even to cut rates (E. S. Harris, 2008). This would also be consistent with the findings of Dell et al. (2012), whose results suggest that the negative effects of precipitation on growth in rich countries were driven by very large outlier events, such as floods. Another explanation for this negative correlation between precipitation and policy interest rates could be that low precipitation (e.g. droughts) leads to higher inflation, and in turn to policy interest rate increases; there would therefore be a negative correlation between precipitation and inflation, and a negative relationship between precipitation and the policy interest rate. It is also possible that these effects are at play in different groups of countries. An obvious extension would be to distinguish between floods and droughts (as in Parker, 2016) and examine how each affects the policy interest rate.

We also find a significant and negative effect of temperature on the policy interest rate, but only for low-income countries (Table 5.11). This may seem counter-intuitive, as we find that temperature has a significant and positive effect on inflation in these countries, which would justify an increase, rather than a decrease, in the policy interest rate. However, it is possible that despite the inflationary effect of a supply-side shock due to temperature, monetary policy-makers reduce the policy interest rate in order to manage the effects of the output contraction on employment. Another effect of reducing the policy interest rate is that it causes a fall in the value of the currency and therefore makes exports more competitive. In countries which are highly reliant on international markets for their products (e.g. agricultural commodities), reducing the policy interest rate may thus counterbalance the effects of temperature on the price of these products. Again, these are only hypotheses and would need to be tested empirically.

4. Conclusion and policy recommendations

The aim of the research presented in this chapter has been to bring two innovations to the field of weather and climate economics: first, to extend the question of the drivers of inflation beyond natural disasters by assessing whether non-catastrophic weather fluctuations have also had noticeable effects; second, to examine the effects of temperature and precipitation on central banks' monetary policy decisions; to our knowledge, this is the first foray into the links between weather/climate and monetary policy.

Our exploration of the effects of temperature and precipitation on inflation and the policy interest rate complements previous findings from the NCE and from the literature on the macroeconomic impacts of disasters: we find that annual weather fluctuations have non-negligible impacts on overall inflation and central bank's monetary policies, at least for some groups of countries.

We have already discussed in Chapters 1 and 4 the opportunities and limitations provided by the "weather economics" approach, insofar as that is an appropriate term, as well as the usefulness of these results. It is true that the extrapolation of these results to long time horizons is problematic; nevertheless, there are several reasons why this research area can be expected to expand. First, we are in a unique position where we have already started to experience warming and there is good data availability for various weather and socio-economic variables. Second, these results can be extremely useful to estimate near- and medium-term impacts of changes in climate and weather patterns, and to assess our adaptive capacity. Finally, by providing flexibility in the choice of econometric model, they enable us to explore non-linear and cumulated lag impacts, which can be used to inform the choice of functional forms in climate impact models.

Our results do not translate readily into general policy recommendations but they warrant further study: obvious extensions to our work would be to consider sub-indices of the consumer price index as dependent variables and test if temperature fluctuations have differentiated impacts on overall inflation, food prices, housing prices and wages; another line of research would be to explore the effects of weather fluctuations on the labour market and consider unemployment and wages as our dependent variables. Such research questions will help us get a better understanding of how we are affected by our environment, and what this implies for future climate change.

Finally, given our results, and the intricate links between the inflation rate and the interest rate, which are especially salient in the context of weather events, further research could also consider the use of a panel VAR model to estimate both rates simultaneously, and to assess the extent to which these two variables are dependent on one another.

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APPENDICES

Appendix 5.1: List of countries by income groups

Table A5.1: Countries by income group

Low income countries (N = 51)	Afghanistan, Azerbaijan, Bangladesh, Benin, Bhutan, Burkina Faso, Burundi, Cambodia, Central African Republic, Chad, Comoros, Democratic Republic of Congo, Cote d'Ivoire, Equatorial Guinea, Ethiopia, the Gambia, Ghana, Guinea, Guinea-Bissau, Haiti, India, Kenya, Kyrgyz Republic, Lao PDR, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mongolia, Mozambique, Myanmar, Nepal, Niger, Nigeria, Pakistan, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Solomon Islands, Sudan, Tajikistan, Tanzania, Togo, Uganda, Vietnam, Republic of Yemen, Zambia, Zimbabwe
Lower middle income countries (N=52)	Albania, Algeria, Angola, Armenia, Belarus, Belize, Bolivia, Bulgaria, Cabo Verde, Cameroon, China, Colombia, Republic of Congo, Djibouti, Dominican Republic, Ecuador, Arab Republic of Egypt, El Salvador, Fiji, Georgia, Guatemala, Guyana, Honduras, Indonesia, Islamic Rep. of Iran, Iraq, Jamaica, Jordan, Kazakhstan, Macedonia, Maldives, Moldova, Morocco, Namibia, Nicaragua, Papua New Guinea, Paraguay, Peru, Philippines, Romania, Russian Federation, Samoa, Sri Lanka, St. Vincent and the Grenadines, Suriname, Swaziland, Syrian Arab Republic, Thailand, Timor-Leste, Tonga, Tunisia, Ukraine, Vanuatu
Upper middle income countries (N = 36)	Antigua and Barbuda, Argentina, Barbados, Botswana, Brazil, Chile, Costa Rica, Croatia, Czech Republic, Dominica, Estonia, Gabon, Grenada, Hungary, Latvia, Lebanon, Libya, Lithuania, Malaysia, Mauritius, Mexico, Montenegro, Oman, Panama, Poland, Saudi Arabia, Serbia, Seychelles, Slovak Republic, South Africa, St. Kitts and Nevis, St. Lucia, Trinidad and Tobago, Turkey, Uruguay, Venezuela
High income countries (N = 37)	Aruba, Australia, Austria, Bahrain, Belgium, Brunei Darussalam, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Hong Kong, Iceland, Ireland, Israel, Italy, Japan, Republic of Korea, Kuwait, Luxembourg, Macao SAR, Malta, the Netherlands, New Zealand, Norway, Portugal, Qatar, Singapore, Slovenia, Spain, Sweden, Switzerland, United Arab Emirates, United Kingdom, United States
Total	176 countries.

Notes: only includes country for which we have temperature and precipitation and either inflation data or policy interest rate data.

Appendix 5.2: Data summary

Table A5.2.1: Data summary – Low income countries

Country name	Geographical region	Income group	Poor/Rich	Temperature data	Precipitation data	Inflation rate data	Policy interest rate data
Afghanistan	EECA	L	Poor	1950-2015	1950-2015	2005 - 2016	n/a
Azerbaijan	EECA	L	Poor	1950-2015	1950-2015	1992 - 2016	2006 - 2016
Bangladesh	SEAS	L	Poor	1950-2015	1950-2015	1987 - 2016	2009 - 2016
Benin	SSAF	L	Poor	1950-2015	1950-2015	1993 - 2016	n/a
Bhutan	SEAS	L	Poor	1950-2015	1950-2015	1981 - 2016	n/a
Burkina Faso	SSAF	L	Poor	1950-2015	1950-2015	1960 - 2015	n/a
Burundi	SSAF	L	Poor	1950-2015	1950-2015	1966 - 2016	n/a
Cambodia	SEAS	L	Poor	1950-2015	1950-2015	1995 - 2016	n/a
Central African Republic	SSAF	L	Poor	1950-2015	1950-2015	1981 - 2015	n/a
Chad	SSAF	L	Poor	1950-2015	1950-2015	1984 - 2015	n/a
Comoros	SSAF	L	Poor	1950-2015	1950-2015	2001 - 2015	n/a
Congo, Dem. Rep.	SSAF	L	Poor	1950-2015	1950-2015	1964 - 2013	n/a
Côte d'Ivoire	SSAF	L	Poor	1950-2015	1950-2015	1961 - 2016	n/a
Equatorial Guinea	SSAF	L	Poor	1950-2015	1950-2015	1986 - 2015	n/a
Ethiopia	SSAF	L	Poor	1950-2015	1950-2015	1966 - 2016	n/a
Ghana	SSAF	L	Poor	1950-2015	1950-2015	1965 - 2016	1964 - 2016
Guinea	SSAF	L	Poor	1950-2015	1950-2015	2005 - 2016	n/a
Guinea-Bissau	SSAF	L	Poor	1950-2015	1950-2015	1988 - 2016	n/a
Haiti	LAC	L	Poor	1950-2015	1950-2015	1960 - 2016	n/a
India	SEAS	L	Poor	1950-2015	1950-2015	1960 - 2016	2001 - 2016
Kenya	SSAF	L	Poor	1950-2015	1950-2015	1960 - 2016	2011 - 2016
Kyrgyz Republic	EECA	L	Poor	1950-2015	1950-2015	1996 - 2016	2000 - 2016
Lao PDR	SEAS	L	Poor	1950-2015	1950-2015	1989 - 2016	n/a
Lesotho	SSAF	L	Poor	1950-2015	1950-2015	1974 - 1996	n/a
Liberia	SSAF	L	Poor	1950-2015	1950-2015	2002 - 2015	n/a
Madagascar	SSAF	L	Poor	1950-2015	1950-2015	1965 - 2015	n/a
Malawi	SSAF	L	Poor	1950-2015	1950-2015	1981 - 2015	n/a
Mali	SSAF	L	Poor	1950-2015	1950-2015	1989 - 2015	1964 - 2016
Mauritania	SSAF	L	Poor	1950-2015	1950-2015	1986 - 2015	n/a
Mongolia	SEAS	L	Poor	1950-2015	1950-2015	1993 - 2016	2007 - 2016
Mozambique	SSAF	L	Poor	1950-2015	1950-2015	1988 - 2016	n/a
Myanmar	SEAS	L	Poor	1950-2015	1950-2015	1960 - 2015	2012 - 2016
Nepal	SEAS	L	Poor	1950-2015	1950-2015	1965 - 2015	1976 - 2016
Niger	SSAF	L	Poor	1950-2015	1950-2015	1964 - 2015	n/a
Nigeria	SSAF	L	Poor	1950-2015	1950-2015	1960 - 2016	n/a
Pakistan	SEAS	L	Poor	1950-2015	1950-2015	1960 - 2016	n/a
Rwanda	SSAF	L	Poor	1950-2015	1950-2015	1967 - 1993	n/a
São Tomé and Principe	SSAF	L	Poor	1950-2015	1950-2015	1997 - 2016	n/a
Senegal	SSAF	L	Poor	1950-2015	1950-2015	1968 - 2016	n/a
Sierra Leone	SSAF	L	Poor	1950-2015	1950-2015	1960 - 2015	1965 - 1992
Solomon Islands	SEAS	L	Poor	1950-2015	1950-2015	1972 - 2015	n/a
Sudan	SSAF	L	Poor	1950-2015	1950-2015	1960 - 2015	n/a
Tajikistan	EECA	L	Poor	1950-2015	1950-2015	2001 - 2016	n/a
Tanzania	SSAF	L	Poor	1950-2015	1950-2015	1966 - 2015	n/a
Gambia, The	SSAF	L	Poor	1950-2015	1950-2015	1962 - 2015	2004 - 2016
Togo	SSAF	L	Poor	1950-2015	1950-2015	1967 - 2016	n/a
Uganda	SSAF	L	Poor	1950-2015	1950-2015	1981 - 2015	2011 - 2016
Vietnam	SEAS	L	Poor	1950-2015	1950-2015	1996 - 2015	1996 - 2016
Yemen, Rep.	MENA	L	Poor	1950-2015	1950-2015	1991 - 2014	n/a
Zambia	SSAF	L	Poor	1950-2015	1950-2015	1986 - 2015	n/a
Zimbabwe	SSAF	L	Poor	1950-2015	1950-2015	1965 - 2007	n/a
Total	51					51	14

Notes: Region: LAC refers to Latin America and the Caribbean; MENA refers to Middle-East and North Africa; SSAF refers to Sub-Saharan Africa; WEOFF refers to Western Europe and Offshoots; EECA refers to Eastern Europe and Central Asia; SEAS refers to South-East Asia and Pacific Islands.

Table A5.2.2: Data summary – Lower middle income countries

Country name	Geographical region	Income group	Poor/ Rich	Temperature data	Precipitation data	Inflation rate data	Policy interest rate data
Albania	EECA	LM	Poor	1950-2015	1950-2015	1992 - 2016	1992 - 2016
Algeria	MENA	LM	Poor	1950-2015	1950-2015	1970 - 2015	n/a
Angola	SSAF	LM	Poor	1950-2015	1950-2015	1991 - 2016	2011 - 2016
Armenia	EECA	LM	Poor	1950-2015	1950-2015	1994 - 2016	2000 - 2016
Belarus	EECA	LM	Poor	1950-2015	1950-2015	1993 - 2016	2000 - 2016
Belize	LAC	LM	Poor	1950-2015	1950-2015	1981 - 2015	1977 - 2016
Bolivia	LAC	LM	Poor	1950-2015	1950-2015	1960 - 2016	n/a
Bulgaria	EECA	LM	Poor	1950-2015	1950-2015	1986 - 2016	n/a
Cameroon	SSAF	LM	Poor	1950-2015	1950-2015	1969 - 2015	n/a
Cabo Verde	SSAF	LM	Poor	1950-2015	1950-2015	1984 - 2015	n/a
China	SEAS	LM	Poor	1950-2015	1950-2015	1987 - 2016	1988 - 1988
Colombia	LAC	LM	Poor	1950-2015	1950-2015	1960 - 2016	1998 - 2016
Congo, Rep.	SSAF	LM	Poor	1950-2015	1950-2015	1986 - 1996	n/a
Djibouti	MENA	LM	Poor	1950-2015	1950-2015	1980 - 1987	n/a
Dominican Republic	LAC	LM	Poor	1950-2015	1950-2015	1960 - 2016	2004 - 2016
Ecuador	LAC	LM	Poor	1950-2015	1950-2015	1960 - 2016	2008 - 2016
Egypt, Arab Rep.	MENA	LM	Poor	1950-2015	1950-2015	1960 - 2016	2006 - 2016
El Salvador	LAC	LM	Poor	1950-2015	1950-2015	1960 - 2013	n/a
Fiji	SEAS	LM	Poor	1950-2015	1950-2015	1970 - 2016	n/a
Georgia	EECA	LM	Poor	1950-2015	1950-2015	1995 - 2016	2008 - 2016
Guatemala	LAC	LM	Poor	1950-2015	1950-2015	1960 - 2016	2005 - 2016
Guyana	LAC	LM	Poor	1950-2015	1950-2015	1995 - 2015	1966 - 2016
Honduras	LAC	LM	Poor	1950-2015	1950-2015	1960 - 2016	2005 - 2016
Indonesia	SEAS	LM	Poor	1950-2015	1950-2015	1960 - 2016	2005 - 2016
Iran, Islamic Rep.	MENA	LM	Poor	1950-2015	1950-2015	1960 - 2016	n/a
Iraq	MENA	LM	Poor	1950-2015	1950-2015	1960 - 1978	2004 - 2016
Jamaica	LAC	LM	Poor	1950-2015	1950-2015	1960 - 2016	n/a
Jordan	MENA	LM	Poor	1950-2015	1950-2015	1970 - 2016	2001 - 2016
Kazakhstan	EECA	LM	Poor	1950-2015	1950-2015	1994 - 2015	2005 - 2016
Macedonia, FYR	EECA	LM	Poor	1950-2015	1950-2015	1994 - 2016	n/a
Maldives	SEAS	LM	Poor	1950-2015	1950-2015	1978 - 1982	n/a
Moldova	EECA	LM	Poor	1950-2015	1950-2015	1995 - 2015	2000 - 2016
Morocco	MENA	LM	Poor	1950-2015	1950-2015	1960 - 2016	n/a
Namibia	SSAF	LM	Poor	1950-2015	1950-2015	2003 - 2015	2012 - 2016
Nicaragua	LAC	LM	Poor	1950-2015	1950-2015	1973 - 2016	n/a
Papua New Guinea	SEAS	LM	Poor	1950-2015	1950-2015	1972 - 2015	2001 - 2016
Paraguay	LAC	LM	Poor	1950-2015	1950-2015	1960 - 2016	2010 - 2016
Peru	LAC	LM	Poor	1950-2015	1950-2015	1960 - 2016	2001 - 2016
Philippines	SEAS	LM	Poor	1950-2015	1950-2015	1960 - 2016	2001 - 2016
Russian Federation	EECA	LM	Poor	1950-2015	1950-2015	1993 - 2016	2011 - 2016
Samoa	SEAS	LM	Poor	1950-2015	1950-2015	1962 - 2016	n/a
Sri Lanka	SEAS	LM	Poor	1950-2015	1950-2015	1960 - 2016	2001 - 2016
St. Vincent and the Grenadines	LAC	LM	Poor	1950-2015	1950-2015	1975 - 2015	n/a
Suriname	LAC	LM	Poor	1950-2015	1950-2015	1960 - 2016	1957 - 2016
Swaziland	SSAF	LM	Poor	1950-2015	1950-2015	1966 - 2016	n/a
Syrian Arab Republic	MENA	LM	Poor	1950-2015	1950-2015	1960 - 2012	n/a
Thailand	SEAS	LM	Poor	1950-2015	1950-2015	1960 - 2016	2000 - 2016
Timor-Leste	SEAS	LM	Poor	1950-2015	1950-2015	2003 - 2016	n/a
Tonga	SEAS	LM	Poor	1950-2015	1950-2015	1976 - 2015	n/a
Tunisia	MENA	LM	Poor	1950-2015	1950-2015	1984 - 2016	2000 - 2016
Ukraine	EECA	LM	Poor	1950-2015	1950-2015	1993 - 2016	n/a
Vanuatu	SEAS	LM	Poor	1950-2015	1950-2015	1977 - 2015	n/a
Total	52					52	29

Notes: Region: LAC refers to Latin America and the Caribbean; MENA refers to Middle-East and North Africa; SSAF refers to Sub-Saharan Africa; WEOFF refers to Western Europe and Offshoots; EECA refers to Eastern Europe and Central Asia; SEAS refers to South-East Asia and Pacific Islands.

Table A5.2.3: Data summary – Upper middle income countries

Country name	Geographical region	Income group	Poor/Rich	Temperature data	Precipitation data	Inflation rate data	Policy interest rate data
Antigua and Barbuda	LAC	UM	Rich	1950-2015	1950-2015	1999 - 2015	n/a
Argentina	LAC	UM	Rich	1950-2015	1950-2015	1960 - 2013	n/a
Barbados	LAC	UM	Rich	1950-2015	1950-2015	1967 - 2015	n/a
Botswana	SSAF	UM	Rich	1950-2015	1950-2015	1975 - 2016	n/a
Brazil	LAC	UM	Rich	1950-2015	1950-2015	1981 - 2016	1999 - 2016
Chile	LAC	UM	Rich	1950-2015	1950-2015	1960 - 2016	1995 - 2016
Costa Rica	LAC	UM	Rich	1950-2015	1950-2015	1960 - 2016	2006 - 2016
Croatia	EECA	UM	Rich	1950-2015	1950-2015	1993 - 2016	1998 - 2016
Czech Republic	EECA	UM	Rich	1950-2015	1950-2015	1994 - 2016	2004 - 2016
Dominica	LAC	UM	Rich	1950-2015	1950-2015	1967 - 1978	n/a
Estonia	EECA	UM	Rich	1950-2015	1950-2015	1993 - 2016	n/a
Gabon	SSAF	UM	Rich	1950-2015	1950-2015	1963 - 2015	n/a
Grenada	LAC	UM	Rich	1950-2015	1950-2015	1977 - 2015	n/a
Hungary	EECA	UM	Rich	1950-2015	1950-2015	1973 - 2016	n/a
Latvia	EECA	UM	Rich	1950-2015	1950-2015	1992 - 2016	2006 - 2013
Lebanon	MENA	UM	Rich	1950-2015	1950-2015	2009 - 2010	n/a
Libya	MENA	UM	Rich	1950-2015	1950-2015	1965 - 2013	n/a
Lithuania	EECA	UM	Rich	1950-2015	1950-2015	1993 - 2016	n/a
Malaysia	SEAS	UM	Rich	1950-2015	1950-2015	1960 - 2016	2004 - 2016
Mauritius	SSAF	UM	Rich	1950-2015	1950-2015	1964 - 2016	n/a
Mexico	LAC	UM	Rich	1950-2015	1950-2015	1960 - 2016	2008 - 2016
Montenegro	EECA	UM	Rich	1950-2015	1950-2015	2006 - 2015	n/a
Oman	MENA	UM	Rich	1950-2015	1950-2015	2001 - 2015	2007 - 2016
Panama	LAC	UM	Rich	1950-2015	1950-2015	1960 - 2016	n/a
Poland	EECA	UM	Rich	1950-2015	1950-2015	1971 - 2016	n/a
Saudi Arabia	MENA	UM	Rich	1950-2015	1950-2015	1964 - 2016	1992 - 2016
Serbia	EECA	UM	Rich	1950-2015	1950-2015	1995 - 2016	2006 - 2016
Seychelles	SEAS	UM	Rich	1950-2015	1950-2015	1971 - 2016	n/a
Slovak Republic	EECA	UM	Rich	1950-2015	1950-2015	1994 - 2016	n/a
South Africa	SSAF	UM	Rich	1950-2015	1950-2015	1960 - 2016	n/a
St. Kitts and Nevis	LAC	UM	Rich	1950-2015	1950-2015	1980 - 2015	n/a
St. Lucia	LAC	UM	Rich	1950-2015	1950-2015	1966 - 2015	n/a
Trinidad and Tobago	LAC	UM	Rich	1950-2015	1950-2015	1960 - 2015	2002 - 2016
Turkey	MENA	UM	Rich	1950-2015	1950-2015	1960 - 2016	1999 - 2016
Uruguay	LAC	UM	Rich	1950-2015	1950-2015	1960 - 2016	n/a
Venezuela, RB	LAC	UM	Rich	1950-2015	1950-2015	1960 - 2015	n/a
Total	36					36	13

Notes: Region: LAC refers to Latin America and the Caribbean; MENA refers to Middle-East and North Africa; SSAF refers to Sub-Saharan Africa; WEOFF refers to Western Europe and Offshoots; EECA refers to Eastern Europe and Central Asia; SEAS refers to South-East Asia and Pacific Islands.

Table A5.2.4: Data summary – High income countries

Country name	Geographical region	Income group	Poor/Rich	Temperature data	Precipitation data	Inflation rate data	Policy interest rate data
Aruba	LAC	H	Rich	1950-2015	1950-2015	1985 - 2016	1986 - 2013
Australia	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	1969 - 2016
Austria	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	n/a
Bahrain	MENA	H	Rich	1950-2015	1950-2015	1966 - 2015	2007 - 2016
Belgium	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	n/a
Brunei Darussalam	SEAS	H	Rich	1950-2015	1950-2015	1981 - 2016	n/a
Canada	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	1992 - 2016
Cyprus	EECA	H	Rich	1950-2015	1950-2015	1960 - 2016	n/a
Denmark	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	1992 - 2016
Finland	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	n/a
France	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	n/a
Germany	WEOFF	H	Rich	1950-2015	1950-2015	1992 - 2016	n/a
Greece	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	n/a
Iceland	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	1998 - 2016
Ireland	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	n/a
Israel	MENA	H	Rich	1950-2015	1950-2015	1960 - 2016	1994 - 2016
Italy	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	n/a
Japan	SEAS	H	Rich	1950-2015	1950-2015	1960 - 2016	2008 - 2016
Kuwait	MENA	H	Rich	1950-2015	1950-2015	1973 - 2016	n/a
Luxembourg	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	n/a
Macao SAR, China	SEAS	H	Rich	1950-2015	1950-2015	1989 - 2016	n/a
Malta	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	n/a
Netherlands	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	n/a
New Zealand	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	1999 - 2016
Norway	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	2002 - 2016
Portugal	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	n/a
Qatar	MENA	H	Rich	1950-2015	1950-2015	1980 - 2016	2002 - 2016
Singapore	SEAS	H	Rich	1950-2015	1950-2015	1961 - 2016	1987 - 2016
Slovenia	EECA	H	Rich	1950-2015	1950-2015	1993 - 2016	n/a
Korea, Rep.	SEAS	H	Rich	1950-2015	1950-2015	1967 - 2016	1999 - 2016
Spain	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	n/a
Sweden	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	1994 - 2016
Switzerland	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	1964 - 2016
Bahamas, The	LAC	H	Rich	1950-2015	1950-2015	n/a	1970 - 2016
United Arab Emirates	MENA	H	Rich	1950-2015	1950-2015	n/a	2008 - 2016
United Kingdom	WEOFF	H	Rich	1950-2015	1950-2015	1989 - 2016	1950 - 2016
United States	WEOFF	H	Rich	1950-2015	1950-2015	1960 - 2016	1971 - 2016
Total	37					35	19

Notes: Region: LAC refers to Latin America and the Caribbean; MENA refers to Middle-East and North Africa; SSAF refers to Sub-Saharan Africa; WEOFF refers to Western Europe and Offshoots; EECA refers to Eastern Europe and Central Asia; SEAS refers to South-East Asia and Pacific Islands.

Appendix 5.3: Lagged effects of weather on the inflation rate

Table A5.3.1: Effects of temperature and precipitation on the annual inflation rate – linear model with lags, all countries

Dep. var. is the annual inflation rate	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No lags	*1 lag*	*5 lags*	*10 lags*	*No lags*	*1 lag*	*5 lags*	*10 lags*
Temp.	0.41	0.28	0.23	0.21	0.40	0.26	0.20	0.19
	(0.28)	(0.24)	(0.23)	(0.23)	(0.29)	(0.25)	(0.23)	(0.24)
L.Temp.		0.49*	0.39*	0.33		0.50*	0.38*	0.33
		(0.26)	(0.22)	(0.22)		(0.26)	(0.22)	(0.22)
L2.Temp.			-0.06	-0.08			-0.08	-0.11
			(0.20)	(0.20)			(0.20)	(0.20)
L3.Temp.			0.31	0.28			0.31	0.26
			(0.21)	(0.21)			(0.21)	(0.21)
Prec.					-0.37	-0.40	-0.40	-0.47
					(0.43)	(0.42)	(0.41)	(0.41)
L.Prec.						0.06	0.13	0.13
						(0.42)	(0.38)	(0.38)
L2.Prec.							-0.42	-0.46
							(0.48)	(0.47)
L3.Prec.							-0.22	-0.20
							(0.36)	(0.37)
N	6923	6923	6923	6923	6923	6923	6923	6923
R-sq	0.325	0.325	0.326	0.327	0.325	0.325	0.327	0.329
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Infl. rate cut	50%	50%	50%	50%	50%	50%	50%	50%
Prec. variables	No	No	No	No	Yes	Yes	Yes	Yes
Sum of all temp. coefficients	0.41	0.77*	1.55**	2.13**	0.40	0.77*	1.46**	2.04**
	(0.28)	(0.43)	(0.74)	(1.01)	(0.29)	(0.43)	(0.73)	(0.99)
Sum of all prec. coefficients					-0.37	-0.34	-2.67*	-4.61**
					(0.43)	(0.63)	(1.39)	(2.29)

Notes: Temperature is in °Celsius and precipitation in meters. In all columns, a 50% cut=off is applied to the inflation rate. Columns 1-4 do not control for precipitation, whereas regressions presented in columns 5-8 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A5.3.2: Effects of temperature and precipitation on the annual inflation rate – linear model with lags, Poor vs Rich countries

Dep. var. is the annual inflation rate	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No lags	*1 lag*	*5 lags*	*10 lags*	*No lags*	*1 lag*	*5 lags*	*10 lags*
Temp. * Poor	1.39***	1.12***	0.94**	0.90**	1.37***	1.10**	0.90**	0.87**
	(0.48)	(0.42)	(0.40)	(0.40)	(0.49)	(0.42)	(0.40)	(0.41)
L.Temp. * Poor		0.76*	0.49	0.40		0.79*	0.48	0.38
		(0.40)	(0.36)	(0.36)		(0.40)	(0.35)	(0.36)
L2.Temp. * Poor			0.14	0.07			0.11	0.00
			(0.36)	(0.36)			(0.36)	(0.36)
L3.Temp. * Poor			0.12	0.01			0.11	-0.02
			(0.37)	(0.38)			(0.36)	(0.37)
Temp. * Rich	-0.29	-0.33	-0.28	-0.23	-0.29	-0.33	-0.29	-0.23
	(0.34)	(0.27)	(0.23)	(0.23)	(0.34)	(0.28)	(0.23)	(0.24)
L.Temp. * Rich		0.29	0.31	0.27		0.29	0.30	0.25
		(0.28)	(0.22)	(0.22)		(0.28)	(0.22)	(0.22)
L2.Temp. * Rich			-0.20	-0.20			-0.22	-0.21
			(0.20)	(0.19)			(0.20)	(0.20)
L3.Temp. * Rich			0.38*	0.39*			0.39*	0.40*
			(0.21)	(0.21)			(0.21)	(0.21)
Prec. * Poor					-0.41	-0.48	-0.51	-0.54
					(0.58)	(0.58)	(0.57)	(0.58)
L.Prec. * Poor						0.30	0.31	0.23
						(0.49)	(0.43)	(0.45)
L2.Prec. * Poor							-0.19	-0.25
							(0.72)	(0.70)
L3.Prec. * Poor							-0.08	0.01
							(0.47)	(0.49)
Prec. * Rich					-0.01	-0.02	0.01	0.04
					(0.49)	(0.47)	(0.47)	(0.49)
L.Prec. * Rich						-0.02	0.06	0.08
						(0.61)	(0.60)	(0.59)
L2.Prec. * Rich							-0.51	-0.50
							(0.43)	(0.45)
L3.Prec. * Rich							-0.14	-0.20
							(0.58)	(0.58)
N	6923	6923	6923	6923	6923	6923	6923	6923
R-sq	0.327	0.328	0.329	0.331	0.327	0.328	0.331	0.334
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Infl. rate cut	50%	50%	50%	50%	50%	50%	50%	50%
Prec. variables	No	No	No	No	Yes	Yes	Yes	Yes
Sum of all temp. coeff. in Poor countries	1.39***	1.89***	2.83***	3.67***	1.37***	1.89***	2.66***	3.43***
	(0.48)	(0.66)	(0.97)	(1.32)	(0.49)	(0.67)	(0.95)	(1.31)
Sum of all temp. coeff. in Rich countries	-0.29	-0.04	0.45	1.60	-0.29	-0.04	0.40	0.82
	(0.34)	(0.50)	(0.86)	(1.42)	(0.34)	(0.50)	(0.85)	(1.02)
Sum of all prec. coeff. in Poor countries					-0.41	-0.18	-3.03*	-5.16*
					(0.58)	(0.76)	(1.61)	(2.85)
Sum of all prec. coeff. in Rich countries					-0.01	-0.04	-0.58	-0.66
					(0.49)	(0.89)	(2.32)	(3.73)

Notes: Temperature is in °Celsius and precipitation in meters. In all columns, a 50% cut-off is applied to the inflation rate. Columns 1-4 do not control for precipitation, whereas regressions presented in columns 5-8 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Appendix 5.4: Effects of the weather on the policy interest rate for different cut-off rates

Table A5.4.1: Effects of temperature and precipitation on the annual policy interest rate – linear model without lags, all countries

Dep. var. is the annual policy interest rate	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	No cut	*No cut*	*100%*	*100%*	*75%*	*75%*	*50%*	*50%*	*25%*	*25%*
Temp.	-0.12	-0.15	-0.22	-0.26	-0.37	-0.41	-0.42	-0.46	-0.17	-0.21
	(0.31)	(0.31)	(0.31)	(0.31)	(0.34)	(0.34)	(0.36)	(0.36)	(0.30)	(0.30)
Prec.		-0.87*		-1.08***		-1.17***		-1.20***		-1.14***
		(0.46)		(0.39)		(0.41)		(0.38)		(0.32)
N	1441	1441	1440	1440	1439	1439	1434	1434	1400	1400
R-sq	0.47	0.47	0.478	0.478	0.511	0.512	0.518	0.519	0.512	0.515
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pol. int. rate cut	None	None	100%	100%	75%	75%	50%	50%	25%	25%
Prec. variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Temperature in °Celsius and precipitation in meters. Columns 1-2 include all annual policy interest rate data. Columns 3-4 apply a 100% cut-off to the annual policy interest rate. Columns 5-6 apply a 75% cut-off to the annual policy interest rate. Columns 7-8 apply a 50% cut-off to the annual policy interest rate. Columns 9-10 apply a 25% cut-off to the policy interest rate. Columns 1, 3, 5, 7, 8 and 9 do not control for precipitation, whereas regressions presented in columns 2, 4, 6, 8 and 10 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A5.4.2 Effects of temperature and precipitation on the annual policy interest rate – linear model without lags, Poor vs Rich countries

Dep. var. is the annual policy interest rate	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	No cut	*No cut*	*100%*	*100%*	*75%*	*75%*	*50%*	*50%*	*25%*	*25%*
Temp. * Poor	-0.11	-0.18	-0.42	-0.51	-0.38	-0.47	-0.39	-0.48	-0.17	-0.27
	(0.48)	(0.49)	(0.46)	(0.45)	(0.46)	(0.45)	(0.47)	(0.47)	(0.46)	(0.45)
Temp. * Rich	-0.12	-0.12	-0.10	-0.10	-0.36	-0.36	-0.44	-0.43	-0.17	-0.17
	(0.46)	(0.45)	(0.46)	(0.45)	(0.52)	(0.52)	(0.54)	(0.54)	(0.44)	(0.43)
Prec.* Poor		-1.15*		-1.45***		-1.45***		-1.59***		-1.35***
		(0.62)		(0.55)		(0.54)		(0.52)		(0.37)
Prec.* Rich		-0.47		-0.63		-0.77		-0.63		-0.85
		(0.61)		(0.53)		(0.60)		(0.53)		(0.54)
N	1441	1441	1440	1440	1439	1439	1434	1434	1400	1400
R-sq	0.47	0.47	0.478	0.479	0.511	0.512	0.518	0.52	0.512	0.515
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pol. int. rate cut	None	None	100%	100%	75%	75%	50%	50%	25%	25%
Prec. variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Temperature in °Celsius and precipitation in meters. Columns 1-2 include all annual policy interest rate data. Columns 3-4, 5-6, 7-8 and 9-10 apply a 100%, 75%, 50% and 25% cut-off to the annual policy interest, respectively. Columns 1, 3, 5, 7, 8 and 9 do not control for precipitation, whereas regressions presented in columns 2, 4, 6, 8 and 10 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A5.4.3: Effects of temperature and precipitation on the annual policy interest rate – linear model without lags, countries by income groups

Dep. var. is the annual policy interest rate	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	No cut	*No cut*	*100%*	*100%*	*75%*	*75%*	*50%*	*50%*	*25%*	*25%*
Temp. * Low inc.	-1.49***	-1.59***	-1.44***	-1.55***	-1.43***	-1.53***	-1.69**	-1.81**	-1.79***	-1.86***
	(0.46)	(0.51)	(0.47)	(0.51)	(0.46)	(0.51)	(0.68)	(0.72)	(0.53)	(0.57)
Temp. * Low. mid. inc.	0.63	0.58	0.12	0.04	0.10	0.02	0.25	0.16	0.71	0.59
	(0.63)	(0.63)	(0.65)	(0.63)	(0.66)	(0.64)	(0.62)	(0.60)	(0.55)	(0.54)
Temp. * Up. mid. inc.	-0.44	-0.39	-0.29	-0.24	-1.70	-1.70	-1.68	-1.62	-0.40	-0.36
	(0.82)	(0.81)	(0.75)	(0.77)	(1.49)	(1.56)	(1.39)	(1.44)	(0.60)	(0.63)
Temp. * High inc.	0.05	0.03	0.01	0.00	0.00	-0.01	-0.08	-0.10	-0.01	-0.02
	(0.51)	(0.51)	(0.53)	(0.52)	(0.53)	(0.52)	(0.53)	(0.52)	(0.48)	(0.48)
Prec. * Low inc.		-2.30		-2.38		-2.35		-2.51		-1.05
		(1.74)		(1.75)		(1.75)		(1.57)		(0.74)
Prec. * Low. mid. inc.		-0.71		-1.10**		-1.10**		-1.20**		-1.29***
		(0.62)		(0.48)		(0.47)		(0.46)		(0.43)
Prec. * Up. mid. inc.		0.39		-0.04		-0.73		0.11		-0.07
		(1.48)		(1.26)		(1.86)		(1.21)		(0.99)
Prec. * High inc.		-0.85		-0.89*		-0.87*		-1.03**		-1.27**
		(0.51)		(0.52)		(0.52)		(0.50)		(0.54)
N	1441	1441	1440	1440	1439	1439	1434	1434	1400	1400
R-sq	0.471	0.472	0.479	0.48	0.514	0.515	0.522	0.524	0.519	0.523
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pol. int. rate cut	None	None	100%	100%	75%	75%	50%	50%	25%	25%
Prec. variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Temperature in °Celsius and precipitation in meters. Columns 1-2 include all annual policy interest rate data. Columns 3-4, 5-6, 7-8 and 9-10 apply a 100%, 75%, 50% and 25% cut-off to the annual policy interest, respectively. Columns 1, 3, 5, 7, 8 and 9 do not control for precipitation, whereas regressions presented in columns 2, 4, 6, 8 and 10 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Appendix 5.5: Lagged effects of the weather on the policy interest rate

Table A5.5.1: Effects of temperature and precipitation on the annual policy interest rate – linear model with lags, all countries

Dep. var. is the annual policy interest rate – *100% cut-off*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No lags	*1 lag*	*5 lags*	*10 lags*	*No lags*	*1 lag*	*5 lags*	*10 lags*
Temp.	-0.22	-0.22	-0.26	-0.21	-0.26	-0.26	-0.31	-0.22
	(0.31)	(0.29)	(0.27)	(0.26)	(0.31)	(0.30)	(0.28)	(0.28)
L.Temp.		-0.01	-0.06	-0.11		-0.03	-0.12	-0.15
		(0.28)	(0.25)	(0.22)		(0.29)	(0.26)	(0.24)
L2.Temp.			0.34	0.32			0.30	0.22
			(0.27)	(0.25)			(0.27)	(0.26)
L3.Temp.			0.31	0.29			0.30	0.21
			(0.24)	(0.23)			(0.24)	(0.25)
Prec.					-1.08***	-1.00**	-1.16**	-1.91***
					(0.39)	(0.38)	(0.44)	(0.53)
L.Prec.						-1.44**	-1.66**	-1.90***
						(0.67)	(0.69)	(0.67)
L2.Prec.							-1.36*	-1.70**
							(0.71)	(0.72)
L3.Prec.							-1.78**	-2.07**
							(0.76)	(0.80)
N	1440	1439	1435	1427	1440	1439	1435	1427
R-sq	0.478	0.477	0.477	0.478	0.478	0.480	0.487	0.503
Countries	All	All	All	All	All	All	All	All
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pol. int. rate cut	100%	100%	100%	100%	100%	100%	100%	100%
Prec. variables	No	No	No	No	Yes	Yes	Yes	Yes
Sum of all temp. coeff.	-0.22	-0.23	0.27	0.51	-0.26	-0.30	-0.03	-0.40
	(0.31)	(0.53)	(1.23)	(1.97)	(0.31)	(0.54)	(1.29)	(2.05)
Sum of all prec. coeff.					-1.08***	-2.43***	-9.52***	-22.15***
					(0.39)	(0.92)	(3.58)	(5.74)

Notes: Temperature is in °Celsius and precipitation in meters. In all columns, a 100% cut-off is applied to the policy interest rate. Columns 1-4 do not control for precipitation, whereas regressions presented in columns 5-8 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A5.5.2: Effects of temperature and precipitation on the annual inflation rate – linear model with lags, Poor vs Rich countries

Dependent variable is the annual policy interest rate	(1) *No lags*	(2) *1 lag*	(3) *5 lags*	(4) *10 lags*	(5) *No lags*	(6) *1 lag*	(7) *5 lags*	(8) *10 lags*
Temp. * Poor	-0.42	-0.49	-0.47	-0.41	-0.51	-0.61	-0.64*	-0.57
	(0.46)	(0.42)	(0.41)	(0.41)	(0.45)	(0.41)	(0.38)	(0.39)
L.Temp. * Poor		0.33	0.28	-0.06		0.28	0.14	-0.29
		(0.45)	(0.42)	(0.40)		(0.45)	(0.42)	(0.35)
L2.Temp. * Poor			0.29	0.13			0.23	-0.19
			(0.43)	(0.44)			(0.41)	(0.42)
L3.Temp. * Poor			0.40	0.34			0.29	0.06
			(0.47)	(0.51)			(0.47)	(0.51)
Temp. * Rich	-0.10	-0.05	-0.09	0.11	-0.10	-0.04	-0.11	0.07
	(0.46)	(0.39)	(0.33)	(0.31)	(0.45)	(0.38)	(0.32)	(0.33)
L.Temp. * Rich		-0.23	-0.26	0.05		-0.24	-0.27	0.08
		(0.45)	(0.36)	(0.30)		(0.44)	(0.36)	(0.31)
L2.Temp. * Rich			0.40	0.59			0.40	0.59
			(0.34)	(0.38)			(0.34)	(0.39)
L3.Temp. * Rich			0.24	0.39			0.26	0.36
			(0.29)	(0.28)			(0.29)	(0.30)
Prec. * Poor					-1.45***	-1.37**	-1.55**	-3.01***
					(0.55)	(0.52)	(0.60)	(0.79)
L.Prec. * Poor						-1.68*	-1.85*	-2.74***
						(0.97)	(0.97)	(0.94)
L2.Prec. * Poor							-1.65*	-2.68***
							(0.97)	(0.95)
L3.Prec. * Poor							-2.24**	-2.70**
							(1.02)	(1.03)
Prec. * Rich					-0.63	-0.49	-0.49	-0.75
					(0.53)	(0.52)	(0.64)	(0.64)
L.Prec. * Rich						-1.08*	-1.13*	-0.95
						(0.60)	(0.67)	(0.64)
L2.Prec. * Rich							-0.66	-0.43
							(0.76)	(0.81)
L3.Prec. * Rich							-0.83	-0.93
							(0.80)	(0.82)
N	1440	1439	1435	1427	1440	1439	1435	1427
R-sq	0.478	0.478	0.478	0.489	0.479	0.480	0.489	0.517
Countries	Poor/Rich	Poor/Rich	Poor/Rich	Poor/Rich	Poor/Rich	Poor/Rich	Poor/Rich	Poor/Rich
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pol. int. rate cut	100%	100%	100%	100%	100%	100%	100%	100%
Prec. variables	No	No	No	No	Yes	Yes	Yes	Yes
Sum of all temp. coeff. in Poor inc. countries	-0.42	-0.16	0.87	3.33	-0.51	-0.33	0.07	0.66
	(0.46)	(0.72)	(1.90)	(3.39)	(0.45)	(0.71)	(1.94)	(3.48)
Sum of all temp. coeff. in Rich inc. countries	-0.10	-0.29	-0.01	3.67	-0.10	-0.27	-0.03	-0.66
	(0.46)	(0.81)	(1.65)	(3.08)	(0.45)	(0.80)	(1.60)	(2.28)
Sum of all prec. coeff. in Poor inc. countries					-1.45***	-3.05**	-11.99**	-28.75***
					(0.55)	(1.30)	(5.05)	(7.15)
Sum of all prec. coeff. in Rich inc. countries					-0.63	-1.56	-4.36	-10.77*
					(0.53)	(1.01)	(3.30)	(5.96)

Notes: Temperature is in °Celsius and precipitation in meters. In all columns, a 100% cut-off is applied to the policy interest rate. Columns 1-4 do not control for precipitation, whereas regressions presented in columns 5-8 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A5.5.3: Effects of temperature and precipitation on the annual policy interest rate – linear model with lags, Countries by income group

Dependent variable is the annual policy interest rate – *100% cut-off*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No lags	*1 lag*	*5 lags*	*10 lags*	*No lags*	*1 lag*	*5 lags*	*10 lags*
Temp. * Low inc.	-1.44***	-1.23***	-1.33***	-1.34**	-1.55***	-1.27***	-1.39***	-1.36***
	(0.47)	(0.43)	(0.38)	(0.62)	(0.51)	(0.47)	(0.35)	(0.46)
L.Temp. * Low inc.		-0.89	-0.57	-1.04*		-1.00*	-0.48	-0.96**
		(0.57)	(0.44)	(0.60)		(0.55)	(0.51)	(0.47)
L2.Temp. * Low inc.			(0.69)	(1.04)			(0.60)	(0.87)
			(0.64)	(0.79)			(0.58)	(0.70)
Temp. * Lower mid. inc.	0.12	0.06	0.11	0.23	0.04	-0.01	-0.03	-0.01
	(0.65)	(0.64)	(0.58)	(0.57)	(0.63)	(0.61)	(0.53)	(0.57)
L.Temp. * Lower mid. inc.		1.02*	1.05*	0.79*		1.00*	0.94*	0.47
		(0.53)	(0.53)	(0.44)		(0.53)	(0.52)	(0.42)
L2.Temp. * Lower mid. inc.			1.09*	1.00*			1.05*	0.69
			(0.57)	(0.53)			(0.58)	(0.55)
Temp. * Upper mid. inc.	-0.29	-0.17	-0.20	1.92	-0.24	-0.05	-0.11	1.70
	(0.75)	(0.71)	(0.68)	(1.46)	(0.77)	(0.70)	(0.68)	(1.52)
L.Temp. * Upper mid. inc.		-0.83	-1.04	1.77		-0.86	-1.09	1.85
		(1.22)	(1.35)	(1.27)		(1.22)	(1.35)	(1.23)
L2.Temp. * Upper mid. inc.			1.18	2.68***			1.22	3.19***
			(0.91)	(0.80)			(0.94)	(1.03)
Prec. * Low inc.					-2.38	-1.39	-2.03	-3.97**
					(1.75)	(1.48)	(1.39)	(1.71)
L.Prec. * Low inc.						-5.54**	-5.34**	-5.48**
						(2.45)	(2.14)	(2.39)
L2.Prec. * Low inc.							-5.22*	-6.13**
							(2.64)	(2.42)
Prec. * Lower mid. inc.					-1.10**	-1.17**	-1.01*	-2.23***
					(0.48)	(0.47)	(0.56)	(0.67)
L.Prec. * Lower mid. inc.						-0.63	-0.56	-1.62*
						(0.83)	(0.80)	(0.86)
L2.Prec. * Lower mid. inc.							-0.63	-1.79**
							(0.81)	(0.79)
Prec. * Upper mid. inc.					-0.04	0.25	0.24	-5.33
					(1.26)	(1.07)	(1.13)	(4.39)
L.Prec. * Upper mid. inc.						-0.95	-1.60	-2.26
						(1.55)	(1.48)	(2.58)
L2.Prec. * Upper mid. inc.							-0.62	1.06
							(1.24)	(1.87)
Prec. * High inc.					-0.89*	-0.88*	-1.18*	-1.43**
					(0.52)	(0.49)	(0.63)	(0.64)
L.Prec. * High inc.						-1.09**	-1.14*	-1.31*
						(0.54)	(0.67)	(0.70)
L2.Prec. * High inc.							-0.74	-0.91
							(0.82)	(0.88)
N	1440	1439	1435	1427	1440	1439	1435	1427
R-sq	0.479	0.481	0.488	0.524	0.480	0.485	0.513	0.569
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pol. int. rate cut	100%	100%	100%	100%	100%	100%	100%	100%
Prec. variables	No	No	No	No	Yes	Yes	Yes	Yes
Sum of all temp. coeff. in Low inc. countries	-1.44***	-2.12***	-4.27**	-2.23	-1.55***	-2.26***	-4.47**	-4.89
	(0.47)	(0.82)	(2.16)	(2.46)	(0.51)	(0.87)	(2.17)	(3.26)
Sum of all temp. coeff. in Lower mid. inc. countries	0.12	1.08	4.35**	6.29**	0.04	0.99	3.86*	3.48
	(0.65)	(0.96)	(2.07)	(3.07)	(0.63)	(0.91)	(2.02)	(3.20)
Sum of all temp. coeff. in Upper mid. inc. countries	-0.29	-1.00	-1.64	-8.66	-2.44	-0.91	-1.56	-9.68
	(0.75)	(1.73)	(7.18)	(14.13)	(0.77)	(1.75)	(7.21)	(14.01)
Sum of all temp. coeff. in High inc. countries	0.01	0.02	0.54	0.60	0.00	0.02	0.58	0.32
	(0.53)	(0.89)	(1.54)	(2.10)	(0.52)	(0.88)	(1.52)	(2.05)
Sum of all prec. coeff. in Low inc. countries					-2.38	-6.93*	-37.12***	-67.71***
					(1.75)	(3.58)	(11.86)	(19.21)
Sum of all prec. coeff. in Lower mid. inc. countries					-1.10**	-1.80*	-4.49	-20.03***
					(0.48)	(1.05)	(3.35)	(5.67)
Sum of all prec. coeff. in Upper mid. inc. countries					-0.04	-0.70	-3.42	-46.08
					(1.24)	(2.33)	(3.52)	(32.70)
					-0.89*	-1.98**	-5.57	-10.40**

Sum of all prec. coeff. in High inc. countries	(0.52)	(0.92)	(3.59)	(5.25)

Notes: Temperature in °Celsius and precipitation in meters. In all columns, a 100% cut-off is applied to the policy interest rate. Columns 1-4 do not control for precipitation, whereas regressions presented in columns 5-8 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Appendix 5.6: Nonlinear effects of the weather on the policy interest rate

Table A5.6.1: Effects of temperature and precipitation on the annual inflation rate – linear model without lags, all countries

Dep. Var. is the annual policy interest rate	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	No cut	*No cut*	*100%*	*100%*	*75%*	*75%*	*50%*	*50%*	*25%*	*25%*
Temp.	0.21	0.23	0.06	0.07	-0.10	-0.09	0.05	0.06	0.19	0.21
	(0.41)	(0.41)	(0.41)	(0.41)	(0.48)	(0.48)	(0.47)	(0.47)	(0.40)	(0.40)
Temp.^2	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	-0.03*	(0.02)	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Prec.		-0.85		-1.95*		-2.41**		-2.97***		-2.47**
		(1.58)		(1.04)		(1.17)		(1.05)		(0.94)
Prec.^2		-0.02		0.19		0.29		0.41		0.30
		(0.35)		(0.26)		(0.28)		(0.25)		(0.22)
Constant	12.73**	14.47**	14.49**	17.51***	17.12***	20.68***	18.62***	22.80***	11.48**	15.25***
	(5.53)	(5.97)	(5.67)	(5.73)	(5.91)	(6.23)	(6.22)	(6.57)	(5.25)	(5.24)
N	1441	1441	1440	1440	1439	1439	1434	1434	1400	1400
R-sq	0.47	0.47	0.478	0.479	0.511	0.513	0.519	0.521	0.513	0.517
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pol. int. rate cut	None	None	100%	100%	75%	75%	50%	50%	25%	25%
Prec. variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Temperature is in °Celsius and precipitation in meters. Columns 1-2 include all policy interest rate data. Columns 3-4 apply a 100% cut-off to the annual policy interest rate. Columns 5-6 apply a 75% cut-off to the annual policy interest rate. Columns 7-8 apply a 50% cut-off to the annual policy interest rate. Columns 9-10 apply a 25% cut-off to the annual policy interest rate. Columns 1, 3, 5, 7, 8 and 9 do not control for precipitation, whereas regressions presented in columns 2, 4, 6, 8 and 10 include precipitation variables. Robust standard errors are in parentheses, adjusted for clustering at country level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Chapter 6: Concluding thoughts

The focus of this thesis has been to examine the economic implications of climate uncertainties through the prism of four individual research questions. What exactly do these results tell us and how can these be used to inform the climate policy debate? In this chapter we provide a brief overview of the insights that can be gathered from our results and a discussion of how findings, such as those presented in this thesis, and which have to accommodate deep uncertainty, can be used to inform policy making.

1. Insights from previous chapters

In Chapter 2 ("The climate beta") we showed, based on an analytical model and IAM-based simulations, that the elasticity of climate damages with respect to a change in aggregate consumption was positive and close to unity, which implies that mitigation projects should be discounted at a higher rate than the risk-free rate. But we also found that a large climate beta increased the net present value of emissions abatement and hence as the social cost of carbon.

The results presented in Chapter 3 ("Estimating the economic impact of the permafrost carbon feedback") showed that the inclusion of a highly uncertain yet potentially large carbon-climate feedback in DICE – melting of permafrost – significantly raises the social cost of carbon and the stringency of the optimal mitigation policy, even under conservative assumptions. The sensitivity analyses conducted in this chapter also underscored that our findings were highly dependent on the choice of structural forms and parameter values.

The final two chapters used panels of historical data to examine the macroeconomic impacts of climate/weather fluctuations. In Chapter 4 ("What are the impacts of droughts on economic growth? Evidence from U.S. states"), we found that droughts had significant and negative impacts on economic growth in Western U.S. states. In Chapter 5 ("Chapter 5: Climate shocks, inflation and monetary policy: the global experience since 1950"), we found that temperature fluctuations increased inflation in poor countries and that precipitation affected the policy interest rate in most countries.

This thesis thus contributes to the growing literature on the implications of climate uncertainties for the economic costs of climate change, which we discussed in the Introduction. Chapters 2 and 3 can be thought of as exercises in quantifying the uncertainties and estimating their economic implications. Chapters 4 and 5 can be thought of rather as efforts to improve our understanding of the economic impacts of climate change. Some of the results in this thesis could be used directly by policy-makers: e.g. in terms of the risk premium which should be applied to mitigation projects, or regarding the social cost of carbon that we should use to tax CO_2 emissions. However, as we have discussed already, these findings rely on numerous assumptions, some of which are subject to deep uncertainty, and whether they increase or reduce our uncertainty about future climate change is a different matter: learning can be both positive and negative in that sense. Given that the red thread of the research undertaken for this PhD was the exploration of climate change uncertainties, I will use this chapter to discuss in a more general manner the implications of these climate change uncertainties for the translation of research findings into policy.

2. How can these findings be used to inform policy-making?

From a policy perspective, these climate change uncertainties put us in a paradoxical situation: on the one hand, the research shows that the full range of uncertainties should be explicitly taken into account when assessing future climate damage; on the other hand, the sheer scale of climate change uncertainties partly explains why effective mitigation policies have not been implemented yet. Indeed, the uncertainty surrounding climate change has been used as an excuse for inaction: policy-makers are reluctant to take decisive steps to reduce anthropogenic emissions without clear-cut forecasts of the future states of the climate and precise estimates of the social cost of carbon, which climate models and IAMs are unable to provide with the required confidence level. This "wait and see approach" leads to delaying action, which in turn causes a further widening of uncertainties. Therefore, the only solution seems to be to change how climate change uncertainties are integrated in decision-making processes. The section below presents the suggestions and recommendations which can be found in the literature.

<u>Embracing uncertainty in a multi-disciplinary framework</u>

So far, it seems that often, and with some notable exceptions, climate scientists and economists have taken for granted that they need to provide point estimates to policy-makers, and have devoted their efforts towards reducing the uncertainty about their results. This belief that the systematic reduction of uncertainty in climate projections is required in order for the projections to be used by decision makers has been termed the "uncertainty fallacy" by Lemos and Rood (2010). On the contrary, researchers should take up this uncertainty[73]. This would entail several things: fully acknowledging the scale of uncertainties that we are facing, integrating processes which are imperfectly known, and assessing the wildest possible range of potential impacts including those with low probability but large consequences (Stern, 2013), as well as making use of the full range of plausible climate variation projected by climate models (Burke et al., 2015). Researchers should also own up to the fact that improvements in our understanding of the climate system, and of its links with the economy, will expand the universe of potential unknowns before reducing uncertainty (Knutti & Sedlacek, 2013).

As well as being forthright about climate change uncertainties, climate scientists and economists should also make sure that policy-makers do not misuse their results. Special efforts should be made to improve disclosure of the limitations of these models and to increase the transparency of the assumptions underlying the results. It should be emphasized that, given the uncertainties we are facing, results are at most illustrative, and should be considered in terms of orders of magnitude or relative effects. Above all, researchers should avoid "central" scenarios or

[73] A recent survey (Burke, Dykema, Lobell, Miguel, & Satyanath, 2015) of the existing literature on quantitative assessments of future climate impacts found that very few studies explore the full ensemble of the twenty or so climate models which have been validated by the scientific community.

best-guess estimates (Burke et al., 2015), and be very cautious when assigning probabilities or likelihoods to forecasts or projections, in order to avoid the "fallacy of misplaced concreteness" (Whitehead, Griffin, & Sherburne, 1929), which refers to the tendency of decision makers to look on any probability distribution as a true indicator of the likelihood of a future set of events.

Adapting the tools to analyse and communicate deep uncertainty

Furthering our exploration of the deep uncertainties of climate change will only be useful if the insights that they generate can be characterized in a systematic way and effectively communicated to policy makers. The question of how to characterize and represent deep uncertainty raises complex epistemological issues. One of the core tasks of the IPCC is precisely to assess the state of knowledge on climate change and to characterize uncertainties in a clear and coherent manner. Two metrics have been used in the latest Assessment Report to characterize the degree of uncertainty in key findings: a qualitative assessment of the confidence in the validity of a finding[74], and a quantified (probabilistic) measure of the uncertainty in a finding[75] (Mastrandrea et al., 2010). However, this approach has come under criticism for suffering from a lack of precision and for not addressing the risk-uncertainty dichotomy (Aven & Renn, 2015).

Several alternative approaches for characterizing uncertainty have been proposed in the literature. For instance, Kandlikar et al. (2005) proposed a method to represent deep uncertainty, which allows for the expression of qualitative evaluations of uncertainty in situations in which quantitative evaluations are not possible. This method relies on a series of steps, which each correspond to an additional degree of ignorance: the first step asks whether the variable or the outcome can be described by a probability distribution function; then, whether bounds can be specified; whether an order of magnitude can be provided; and whether qualitative estimates of its sign or trend can be made. The lowest level of precision corresponds to "effective ignorance" when not enough is known about a quantity. The authors argue that such qualitative statements would be more useful and less misleading from a policy perspective than low-confidence likelihoods or falsely precise results. Aven and Renn (Aven & Renn, 2015) also suggested improvements to the treatment of uncertainty by the IPCC; these include expressing clearly the strength of knowledge on which uncertainties are based; making explicit the possibility of surprises relative to the knowledge ("black swans") and making a clear distinction between the uncertainty surrounding the models/parameters and the uncertainty surrounding the outputs.

Effectively communicating deep uncertainty to decision-makers in a concise yet accurate way is likely to be a challenge. Busch et al. (2015) proposed a strategy for the communication of the likelihood and consequences of different outcomes which relies on the following principles: the characterization of the changing physical hazards; the identification of the species, ecosystems and societies exposed to those changes; and the description of their vulnerabilities and sensitivities, including their adaptation capacity. Van Pelt et al. (2015) explored the potential role of simulation games whereas Berkhout et al. (2014) advocated the use of scenarios that match the frames of the stakeholders who are situated in specific decision making contexts. As regards potential ways to improve public perceptions of these uncertainties, Maslin and Austin

[74] The level of confidence is expressed using five qualifiers: "very low", "low", "medium", "high" and "very high".
[75] Quantified measures of uncertainty are: virtually certain (>99%), very likely (>90%), likely (>66%); about as likely as not (33% to 66%); unlikely (<33%); very unlikely (<10%); extremely unlikely (<1%).

(2012) recommended using a 'when' not 'if' approach, which is tantamount to placing the uncertainty on the date by which things will happen, rather than onto whether they will happen at all[76].

Devising uncertainty-robust policy recommendations

Acknowledging the full range of uncertainties in assessments of climate change impacts means that decision makers will not be able to base their decisions on a precise forecast but rather on a large range of outcomes, which include very uncertain and highly consequential events. These considerable uncertainties significantly complicate the task of decision makers and it has even been argued that the presence of deep uncertainty prevents the use of the expected-utility framework to inform decision-making in the context of climate policy (Heal & Millner, 2014). Several other frameworks have been developed and can be found in the literature on decision-making under uncertainty (see Heal and Millner, 2014 for a review) but an alternative view has been to focus on robust, rather than optimal strategies. Indeed, research has found that, when the uncertainty is sufficiently deep[77], and the set of alternative options is sufficiently large, robust strategies may be preferable to optimal strategies (Lempert & Collins, 2007).

A few approaches for identifying uncertainty-robust strategies, i.e. which perform well compared with alternative strategies over a wide range of assumptions about the future (Dessai & Wilby, 2011), have been proposed in the literature. However, the challenges of identifying and implementing robust policies are actually very different at the local and at the global level.

At the individual country level, the main challenge comes from the identification of uncertainty-robust strategies. Indeed, due to several factors, including the greater influence of natural variability on uncertainty at local scales (IPCC, 2013), the lack of reliable projections of future changes in local weather patterns, and the difficulty of predicting a countries' future socio-economic developments, policy-makers face arcane mitigation and adaptation choices. This uncertainty is further increased when we add the uncertainty about other countries' behaviour (e.g. trade considerations, spillover effects, etc.). Nevertheless, recommendations have been made that overcome these difficulties. For instance, Lempert et al. (2004) recommended that policy-makers identify the sources of vulnerabilities to lives and livelihoods and implement the technical and political actions that will reduce these vulnerabilities. Other methods have focused on retaining the flexibility to change course when new insights are uncovered (Haasnoot et al., 2013) . In practice, there is an increased focus at the national and sub-national levels on mitigation plans which integrate co-benefits, which gives these policies greater political feasibility and durability (IPCC, 2014).

At the global level, the question is of what would be a robust mitigation policy is a less tricky one. Indeed, despite the situation of deep uncertainty that we are facing, there are things that we know with certainty about the future state of the climate, and about future impacts. For instance, due to the inertia in the Earth's climate system, we know that the changes which we will experience over the 21st century will surpass those observed over the past century (IPCC, 2013,

[76] This has been the approach used by Joshi et al. (2011) who stated that "the 2°C limit will be reached between 2040 and 2100, depending on our emission pathway and the model used".
[77] The authors define "sufficiently deep" as the "condition where decision-makers do not know or cannot agree upon the system model relating actions to consequences or the prior probabilities on key parameters of the system model" (Lempert & Collins, 2007).

2014). As regards the future impacts of climate change, we lack precise quantitative assessments of the risk of catastrophe, but we know that the risks associated with crossing critical thresholds increase with rising temperatures (IPCC, 2014; Lenton et al., 2008). For instance, we do not know the precise temperature threshold that will trigger these effects; however, we know that in a business-as-usual scenario, further warming will, at some point over the 200 years, cause irreversible dry-season rainfall reductions in several regions, inexorable sea level rise (Solomon, Plattner, Knutti, & Friedlingstein, 2009) and will accelerate Earth's sixth mass extinction of species (Barnosky et al., 2011; Tilman et al., 2017). As regards the estimation of the future economic impacts of climate change, the uncertainty is not on the sign but on the scale of the damage: indeed, all the estimates of global aggregate impacts provided in the latest IPCC Assessment Report (IPCC, 2014) project negative effects for a warming larger than 1°C, which we have already passed.

We also know a few things about the benefits of mitigation. Because the likelihood of triggering tipping points and accelerating feedbacks increases with global mean temperature, the implementation of mitigation policies would reduce the risk of triggering these effects (Yohe, Schelsinger, & Andronova, 2006; Zickfeld & Bruckner, 2008), and of more "unknown unknowns" becoming known. A direct consequence of this is that mitigation would reduce both expected damages and the variance of output (Lontzek, Cai, Judd, & Lenton, 2015). Moreover, we know that the cost of remaining under the 2°C target increases as action is delayed, due to lock-in effects and the reduction of options for climate-resilient pathways (IPCC, 2014; Stern, 2007). Finally, accounting for our aversion to ambiguity aversion gives a higher value to emissions abatement (Millner, Dietz, & Heal, 2013).

For the reasons exposed above, the deep uncertainties that we are facing should be enough to make stringent mitigation at the global scale a robust policy[78]. Unfortunately, the lack of strong global governance significantly jeopardizes the implementation of adequate mitigation policies. Ironically, the answer to the question that motivated this PhD ("What are the economic implications of climate change uncertainties?") seems to ultimately point to political economy considerations. Indeed, the implications of climate change uncertainties are as much political as economic: they increase the uncertainty and the severity of projected global welfare impacts and warrant the implementation of effective multi-level governance.

[78] Other criteria for robust policies at the global level can be found in the literature. For instance Rockström et al. (2009) proposed the use of planetary boundaries to represent the safe limits within which the Earth system can continue to function in a stable manner. According to the authors three of these nine planetary boundaries have already been overstepped.

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