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Author
Jeon, Woongchan

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Essays on Climate Change and Finance

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Woongchan Jeon

Committee in charge:

Professor Peter Rupert, Chair
Professor Christopher Costello
Professor Lint Barrage

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The Dissertation of Woongchan Jeon is approved.

Professor Christopher Costello

Professor Lint Barrage

Professor Peter Rupert, Committee Chair

May 2023

Essays on Climate Change and Finance

As a first-generation college and doctoral graduate, I dedicate this dissertation to the people who have supported me throughout my education. A great debt of gratitude especially goes to my beloved parents and sister.

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Curriculum Vitæ

Woongchan Jeon

Education

2023 (expected)	Ph.D. in Economics	University of California, Santa Barbara
2018	M.A. in Economics	University of California, Santa Barbara
2017	M.A. in Agricultural & Resource Economics	Seoul National University
2015	B.A. in Agricultural Economics	Seoul National University

Areas of Specialization

Macroeconomics, Environmental and Resource Economics

Working Papers

- Pricing Externalities in the Presence of Adaptation
- Heterogeneity in the Spending Response to Stimulus: Evidence from the Pulse Survey
  (joint with Kieran J. Walsh)

Works in Progress

- Credit Ratings and the Cost of Wildfires: Evidence from California School District Finances
- Pricing Climate Risks: Evidence from Wildfires and Municipal Bonds
  (joint with Lint Barrage and Kieran J. Walsh)
- The Distributional Impacts of Wildfires on Household Balance Sheets in the Western United States

Grant, Honors, and Awards

- California Policy Lab (CPL) Seed Grant (7,500 USD) — 2021
- UCSB Department of Economics Dissertation Fellowship — Summer 2022
- UCSB Department of Economics Research Quarter Fellowship — Winter 2022
- California Policy Lab (CPL) Graduate Fellowship — Summer 2021
- UC Office of the President Diversity Initiative Research Assistantship — Winter, Spring 2021
- UCSB Department of Economics the Costas Fellowship — Winter 2020
- UCSB Department of Economics Gretler Fellowship — Summer 2019
- UCSB Department of Economics Block Grant Fellowship for Recruitment — Fall 2017

Abstract

Essays on Climate Change and Finance

by

Woongchan Jeon

This dissertation examines how unfavorable macroeconomic conditions — climate change and credit constraints — influence economic activities and its implication for social welfare. In expecting climate change, people adapt their behavior to reduce its harm. Despite its importance, the optimal interplay between individual adaptation and climate policies is understudied. The first chapter studies optimal taxation in a general equilibrium model in which households compete against final goods producers for carbon-intensive intermediate goods. I theoretically show that an increase in market demand for carbon-intensive goods increases energy producers' marginal profit, which leads to more energy production and higher carbon emissions. In a calibrated model with heat-related mortality and cooling loads as an example, I find that the mortality social costs of carbon in 2020 are underestimated by 7% if such feedback is not considered.

Many U.S. municipalities finance public projects by issuing bonds secured by taxes. But emerging climate risks can impair the ability to pay debts due to the tax base loss from property damages. Rating agencies have been considered trustworthy arbiters of creditworthiness in financial markets. The second chapter studies how much climate risks are factored into credit ratings using wildfires and school district finances in California. Using historic wildfires as a source of salience shocks, I find that school districts with 0.08% of the tax base at risk of burning over the next 30 years face 3.22% lower credit ratings. This finding implies that the integration of climate risks in credit ratings can encourage policymakers to adapt to climate change to avoid higher borrowing costs.

The third chapter, joint with Kieran Walsh, uses the U.S. Census Bureau Household Pulse Survey to study heterogeneity in the spending response to stimulus checks. We find that while the fraction of households who use the payment for spending declines in pre-COVID incomes for the 2020 payments, this pattern changes into a U-shaped one in 2021. This is because, during crises, liquidity constraints are binding for poorer households due to a tightening of lending standards, making them anxious to consume. On the other hand, in a normalized economy, many poorer households borrow to avoid the inconvenience of not meeting unexpected expenditure needs such as car repairs or medical bills. When faced with a random splash of cash, these households use it for saving as they had previously dissaved to meet their unexpected expenditure needs. The macro state-dependence of spending propensity distribution is crucial to understanding the propagation of fiscal and monetary shocks.

Contents

Chapter 1

Pricing Externalities in the Presence of Adaptation

Summary

I study optimal taxation in a general equilibrium model in which households compete against final goods producers for pollutant-emitting intermediate goods. For example, as the climate warms, households use more energy in the form of air conditioning. I show theoretically that an increase in market demand for such goods increases polluting firms' marginal profit. Firms respond by increasing their production, leading to higher pollution levels. To take these theoretical insights to reduced-form evidence, I construct a macroeconomic climate-economy model using heat-related discomfort and cooling loads as an example. In a calibrated economy, I find that the mortality social costs of carbon in 2020 are underestimated by about 7% if such feedback is not considered.

1.1 Introduction

When people anticipate an adverse change in environmental conditions, they may engage in *private adaptation*—the process of adjusting one's behavior to reduce related negative externalities. Some examples are reroofing with asphalt shingles against wildfires, building a house on concrete stilts to prevent flooding, installing air purifiers to reduce the amount of pollutants inhaled, etc. A failure to consider such behaviors may lead to the overstatement of the social cost of externality-generating activities [1, 2]. As such, the conventional wisdom in partial equilibrium analyses is that considering private adaptation in a cost-benefit analysis will lead to lower pollution taxes because they tend to focus narrowly on the role of adaptation in reducing external marginal costs. But when people increase their demand for a pollutant-intensive input—such as asphalt, cement, or energy—for adaptation, its market demand increases. Thus, polluting industries increase their production to meet rising demand. A key question is, "how should policymakers account for such adaptation-driven general equilibrium effects when pricing externalities?"

This paper studies the role of pollutant-intensive adaptation in setting optimal pollution taxes. To this end, I compare outcomes in a general equilibrium model in which households adapt relative to the benchmark case without adaptation. The essential ingredient of this comparative statics is an increase in market demand for pollutant-intensive inputs due to adaptation. I show theoretically that endogenizing pollutant-intensive adaptation in utility and resource constraint not only reduces the external marginal costs but also shifts up the marginal profit of polluting firms—such as asphalt or cement industries—which leads to a higher level of pollution. The second channel has been previously overlooked as the existing literature implicitly captures adaptation by netting out its net benefit from pollution damages. Neglecting such general equilibrium effects in a cost-benefit analysis will lead to lower-than-optimal pollution prices. As an example, I use a dynamic climate-economy model with heat-related discomfort and cooling energy to quantify the impact of general equilibrium effects on the mortality social costs of carbon.

This paper identifies a general equilibrium channel through which pollutant-intensive adaptation shifts up the "marginal benefit of pollution" (or the marginal cost of pollution abatement). While some studies balance the cost and benefit of investing in abatement projects such as scrubbers on smokestacks, I compare the cost and benefit of emitting pollutants as a byproduct of the production of intermediate goods throughout this paper. The economy's total production of a pollutant-intensive input is fixed in the short run. When environmental quality deteriorates, households demand this input more for adaptation, which crowds out the same input for output production. This scarcity raises the price of pollutant-intensive intermediate goods because manufacturers are willing to pay more due to their diminishing marginal products. As a result, the marginal profits of polluting intermediate firms increase because they can sell at a higher price. In response, forward-looking polluting industries will hire more factors to increase their production in the long run.

The magnitude of such general equilibrium effects relies on how much pollutant-intensive inputs households demand for adaptation in response to endogenously changing pollution levels. I use a dynamic climate-economy model à la [3] and [4], which is augmented with the use of energy for cooling against heat-related discomfort. The critical ingredient is the nonseparability between temperature and energy consumption in utility, which is captured by the constant elasticity of substitution (CES) between carbon abatement and cooling. Since cooling is a substitute for emissions abatement, a rise in temperature due to increasing carbon emissions will boost energy use for cooling. To pin down the magnitude of substitutability, I calibrate a quantitative climate-economy model to match some recent reduced-form evidence on the global mortality cost of climate change and electricity consumption by [5] and [6].

I first compare the competitive equilibria with endogenous cooling to the ones without adaptation to examine how fossil fuel-based energy producers react to the changes in their marginal profits. For example, when there are no carbon taxes, households use about 3.4% of the total energy produced in the economy for cooling—equivalent to 21 Giga tons of CO_2—in 2100. Because of an increase in market demand for energy, the share of capital and labor in the fossil fuel-based energy sector will rise by about 0.17 percentage points and about 0.06 percentage points in 2100 to clear the market. In response, CO_2 emissions per period (5 years) increase by about 33.3 Giga tons, equivalent to 3.2% of global carbon emissions in 2100.

To quantify the role of such general equilibrium effects on environmental policies, I next compare the optimal carbon taxes with endogenous cooling to the case in which a damage function implicitly includes the benefits and costs of cooling. Since adaptation is embedded in a damage function in the second case, the general equilibrium effects do not arise. I find that the mortality social costs of carbon in 2020 are underestimated by about 7% if such feedback is not considered.

Finally, I study whether efficiency improvements in cooling technologies can be accepted as a carbon abatement strategy without government intervention. In my model, the elasticity of substitution between abatement and adaptation measures how efficient cooling technologies are in reducing marginal climate impacts. Therefore, when the substitutability increases, households can enjoy the same level of cooling services with less energy, reducing their energy expenditure. But an increase in disposable income due to energy savings may lead to additional energy use for cooling because of income effects, which offsets the direct savings. I find that a 0.1% increase in the substitutability boosts the use of energy for cooling by about 1% in 2100, which leads to a temperature rise by 0.001°C. But the mortality social costs of carbon decrease from \$202 per ton of CO_2 to \$199 per ton of CO_2 in 2010 USD in 2100, which implies that the problem of an increase in energy consumption resulting from an efficiency improvement is not consequential in this case.

This paper offers a structural framework for reconciling the two seemingly contradictory strands of reduced-form studies on cooling energy consumption. One focuses on its role as a self-protective measure in reducing mortality sensitivities to weather variations [7, 8, 9, 5]. The other underscores the adverse effects of climate-driven cooling energy demand by showing that electricity consumption responses to heat waves are much more prominent in areas with higher levels of long-run average temperature [10, 11, 6, 12, 13]. Depending on which perspective one takes, the welfare implication of cooling will vary. This paper accounts for both private benefits and social costs of cooling by specifying household preferences for adaptation in a climate-economy model.

This paper also conducts a consistent welfare analysis of climate change and adaptation by taking a dynamic general equilibrium approach in line with other macroeconomic studies on endogenous climate such as [14], [3], and [15]. In general, it may not be innocuous to extrapolate a dose-response relation between economic outcomes and weather fluctuations using exogenously given emissions pathways, which is a common practice in reduced-form studies; see [16] for a review. For example, as much as mortality sensitivities to temperature fluctuations decline due to cooling, an ensuing increase in emissions can feed back into the economy by heightening the risks of heat-related discomfort. This vicious cycle can further elevate the use of energy for cooling, leading to a different trajectory of carbon emissions. This type of analysis will be valid if exogenously given scenarios are in line with its implied emissions, but it may not be ideal for simulating various policy counterfactuals that can endogenously change emissions pathways. The empirical literature has long highlighted the potential importance of accounting for these feedback effects [6]. In this paper, I adopt a general equilibrium framework that includes the interaction between the climate and the economy to account for such feedback effects.

This paper also contributes to our understanding of the interrelation between private and public adjustments to climate externalities. Most structural cost-benefit studies on climate change lump all the relevant welfare effects of adaptation into one stylized damage function; see [17] for a review. Specifically, each locus on this damage curve represents the least-cost combination of adaptation costs and ceteris paribus temperature effects net of adaptation benefits. But there is an emerging literature that explicitly addresses adaptation. An earlier strand of the literature decomposes the climate damage in [18] on an ad-hoc basis to model adaptation as a decision variable [19].[1] More recently, a couple of studies have used micro-data to build an empirically-grounded damage function with adaptation in a quantitative macroeconomic model such as [28], [29], [30], [31], [32], and [33]. In particular, [34] develops a climate-economy model with distortionary taxes in which climate change affects public investments in adaptation, government consumption requirements, tax revenue, and transfer payment to examine the interplay between optimal carbon taxes and the fiscal burden caused by climate change and public adaptation. But none of the previous studies discuss private adaptation using pollutant-intensive intermediate goods. Thus, general equilibrium effects in factor markets do not arise in response to an endogenously evolving climate.

The remainder of this paper proceeds as follows. In section 1.2, I illustrate how pollutant-intensive adaptation shifts up the marginal profit of polluting industries using a static model. Section 1.3 introduces a macroeconomic climate-economy model enriched with cooling against heat-related discomfort as a stylized example, which is calibrated in section 1.4. Section 1.5 presents quantitative results, and I conclude with a discussion of the implication of this paper for reduced-form environmental studies in section 1.6.

[1]See also [20], [21], [22], [23], and [24] that use climate damages from [25] or [18]. Other integrated assessment models that account for adaptation are the Climate Framework for Uncertainty, Negotiation, and Distribution (FUND) by [26] and the Policy Analysis of the Greenhouse Effect (PAGE) by [27].

1.2 Static Model with Private Adaptation

I build a static model to illustrate how pollutant-intensive adaptation shifts the marginal profit of polluters by altering factor prices. For simplicity, I consider a cutback in producing pollutant-intensive intermediate goods as emissions abatement strategies and abstract from carbon-free technologies. In section 1.3, I build a dynamic climate-economy model with carbon-free technologies, capital accumulation, and carbon dynamics for quantitative analyses.

1.2.1 Environment

Household A representative household has preferences over non-durable consumption C, pollution T, and pollutant-intensive goods for private adaptation E^H. For simplicity, I assume quasi-linearity (to be relaxed in section 1.3). The literature has not reached a consensus on how the shape of the utility function varies with health status [35]. I assume state independence of consumption with respect to pollution externalities and focus on the interdependence of private adaptation and pollution as follows

$$u(C, T, E^H) = C - h(T, E^H),$$

where $\frac{\partial h(T,E^H)}{\partial T} \geq 0$, $\frac{\partial^2 h(T,E^H)}{\partial (T)^2} \geq 0$, $\frac{\partial h(T,E^H)}{\partial E^H} \leq 0$, and $\frac{\partial^2 h(T,E^H)}{\partial (E^H)^2} \geq 0$. The household takes T as given, and thus, it is an externality. Utility damages are determined by the pollution level T and adaptation E^H. I consider heat-related discomfort from climate change T and cooling E^H as an example. Still, the framework is general enough to capture a broad set of pollutant-intensive goods for adaptation, such as cement stilts or asphalt shingles. Specifically, I model adaptation as a flow decision. I do not explicitly consider investments in durable goods—such as air conditioners—to focus on the pecuniary effects caused by using energy for cooling. Following the standard practice in the environmental macroeconomics literature, I define T as a change in the global mean surface temperature relative to the pre-industrial level. The population size is normalized to one, and the household supplies one unit of labor inelastically.

Importantly, I assume that the sign of the cross-partial derivative of utility damages with respect to climate T and household energy consumption E^H is nonpositive.

Assumption 1 For any $(T, E^H) \in \mathbb{R}^2_+$, $\frac{\partial}{\partial E^H}\left(\frac{\partial h(T,E^H)}{\partial T}\right) \leq 0$.

This assumption implies that the marginal impacts of climate are smaller when a household takes an additional self-protective measure. It is consistent with the empirical observation that the dose-response relationship between extreme heat events and mortality rates becomes less sensitive as per capita income or long-run average temperature rises, which are vital indicators of private adaptation [8, 9, 5]. As an extreme case, if the cross-partial derivative becomes zero, cooling will lessen damage to utility in level, but the slope of the marginal damage curve will remain unchanged. If the cross-partial derivative is negative, the marginal damage curve becomes flatter as a household increases its energy use for self-protection. Many empirical studies find a similar negative association between key determinants of adaptation and the marginal effect of environmental stresses such as extreme heat events or hurricanes.[2]

[2]See for example [36], [37], [38], [39], [40], [28], [31] and [32].

In other words, this assumption implies that damage reductions from adaptive responses are more substantial in magnitude with a more drastic change in the climate.[3] It is aligned with the empirical evidence that dose-response relations between extreme heat events and electricity usage become more sensitive as either per capita income or a long-run average temperature rise [6, 12]. Since abating carbon curbs global warming, this complementarity captures how much abatement can be substituted for cooling.

Production A representative firm in the final goods sector combines labor L^Y and energy E^Y to produce output Y. Its technology F^Y exhibits constant returns to scale with positive and diminishing marginal returns, satisfying the Inada condition

$$Y = F^Y(L^Y, E^Y). \tag{1.1}$$

A representative firm in the intermediate goods sector hires labor L^E to generate energy E. The production of energy is linear in labor L^E

$$E = A^E L^E \quad \text{where} \quad A^E > 0. \tag{1.2}$$

Both labor and energy are perfectly mobile across the sectors

$$L^Y + L^E = 1 \quad \text{and} \quad E^H + E^Y = E. \tag{1.3}$$

Energy can be substituted for any pollutant-intensive intermediate goods such as cement.

[3] It follows from Young's theorem that Assumption 1 can be rewritten as $\frac{\partial}{\partial T}\left(-\frac{\partial h(T,E^H)}{\partial E^H}\right) \geq 0$.

Carbon cycle Producing energy yields carbon as its byproduct. I normalize E such that it can be expressed in the same unit of its carbon content. That is, one unit of energy makes one unit of carbon. I assume a linear model of warming with respect to carbon emissions (to be discussed further in section 1.3)

$$T = \zeta E \quad \text{where} \quad \zeta > 0. \tag{1.4}$$

This can be generalized to a relationship between other pollutants and pollution, such as cement production and particulate matter levels in the atmosphere.

1.2.2 Social planner's problem

To highlight the general equilibrium effects of pollutant-intensive adaptation on the marginal profit of polluting firms, I compare the two otherwise identical economies that differ in households' ability to adapt to uncover the role of pollutant-intensive adaptation on both the external marginal costs and private marginal benefit of pollution.

To provide comparative statics for the changes in the availability of energy as adaptation, I generate an objective function with a dummy parameter $\theta \in \{0, 1\}$ as follows

$$d(T, E^H; \theta) = \theta \cdot h(T, E^H) + [1 - \theta] \cdot g(T) = \begin{cases} h(T, E^H) & \text{if } \theta = 1 \\ g(T) & \text{otherwise} \end{cases}.$$

Here, g denotes the utility damage caused by climate change without private adaptation, which is increasing and convex in T. I assume that marginal climate damages are smaller when a household adapts; $\frac{dg(T)}{dT} \geq \frac{\partial h(T,E^H)}{\partial T}$ for all $(T, E^H) \in \mathbb{R}^2_+$. This parameterization is along the lines of the monotone comparative statics [41], which allows for a discrete change in parameter space. If $\theta = 1$, households can use energy for space cooling. Otherwise, energy is unavailable as an adaptive measure (benchmark case).

Given $\theta \in \{0,1\}$, a planner solves the following problem: $\max_{\{C,T,E^H,L^Y,E^Y,L^E\}} \; C - d(T, E^H; \theta)$ subject to (1.1),(1.2),(1.3),(1.4), and $C = Y$, as well as nonnegativity constraints for choice variables. Substituting the constraints into the objective function, I can transform the planner's problem into an unconstrained optimization with two choice variables and one dummy parameter θ:

$$\max_{\{L^E,E^H\}} W\big(L^E, E^H; \theta\big) \;=\; F^Y\big(1 - L^E, A^E L^E - E^H\big) \;-\; d\big(\zeta A^E L^E, E^H; \theta\big).$$

The planner decides how much carbon to release into the air by adjusting labor in the energy sector L^E while protecting households from climate damages using energy E^H.

The first-order conditions are given by;

$$\underbrace{-\,\theta \cdot \frac{\partial h(T, E^H)}{\partial E^H}}_{\text{Marginal benefit of adaptation}} \;=\; \underbrace{\frac{\partial F^Y(L^Y, E^Y)}{\partial E^Y}}_{\text{Marginal cost of adaptation}}, \quad \text{and} \tag{1.5}$$

$$\underbrace{\left[\theta \cdot \frac{\partial h(T, E^H)}{\partial T} + [1-\theta] \cdot \frac{dg(T)}{dT}\right]\zeta}_{\text{Marginal external cost from carbon emissions}} \;=\; \underbrace{\left[\underbrace{\frac{\partial F^Y(L^Y, E^Y)}{\partial E^Y}}_{\text{Gains from energy}} \;-\; \underbrace{\frac{\partial F^Y(L^Y, E^Y)}{\partial L^Y} \cdot \frac{1}{A^E}}_{\text{Losses from labor reallocation}}\right]}_{\text{Marginal private profit from carbon emissions}}. \tag{1.6}$$

Without clean energy, the carbon inventory is one-to-one related to the energy production in the economy, which is determined by employment in the energy sector. Given any $L^E \in [0,1]$, the climate T is determined according to (1.4). The planner then decides how much energy to allocate for households—$E^H(L^E)$—balancing its damage reductions and the losses from foregone consumption as in (1.5). While taking as given this contingent plan $E^H(L^E)$, the planner balances the external cost and private benefit from emissions as in (1.6). If $\theta = 0$, only the condition (1.6) becomes relevant; the planner would not allocate any energy for households.

To study how efficient allocations change as adaptation becomes relevant ($\theta = 0 \to 1$), I use the monotone comparative statics method by [41].

Proposition 1 *$W(L^E, E^H; \theta)$ has increasing differences in (L^E, θ), (E^H, θ), and (L^E, E^H).*

Proof. A function has increasing differences if an incremental return from one argument is larger when the other variable is higher. For any $(L^E, E^H) \in [0,1] \times \mathbb{R}_+$,

$$\frac{\partial W(L^E, E^H; \theta = 1)}{\partial E^H} - \frac{\partial W(L^E, E^H; \theta = 0)}{\partial E^H} = -h_2(T, E^H) \geq 0 \tag{1.7}$$

$$\frac{\partial W(L^E, E^H; \theta = 1)}{\partial L^E} - \frac{\partial W(L^E, E^H; \theta = 0)}{\partial L^E} = \left[g'(T) - h_1(T, E^H)\right] \zeta A^E \geq 0 \tag{1.8}$$

$$\frac{\partial^2 W(L^E, E^H; \theta)}{\partial L^E \partial E^H} = \left[-F_{22}(L^Y, E^Y) + F_{12}(L^Y, E^Y)\frac{1}{A^E}\right] - \theta h_{12}(T, E^H)\zeta \geq 0 \tag{1.9}$$

■

Adaptation benefits are positive when it is available as in (1.7). The returns to fossil fuel use are higher with adaptation as the marginal damage curve becomes flatter with adaptation as in (1.8). Provided that the economy's total energy volume is fixed in the short run, transferring some from firms to households for cooling will crowd out energy that can be used to produce other consumption goods. This scarcity raises the marginal profit of carbon-emitting firms via general equilibrium effects on factor prices; energy price increases and wage decreases. When a factor market is competitive, the equilibrium factor price equals its marginal product because arbitrage opportunities do not exist. First, energy scarcity in the final goods sector increases energy prices because of the diminishing marginal product of energy. Second, the energy shortage in the final goods sector makes wages go down because the value of a marginal product of labor declines due to the complementarity between labor and energy. On the other hand, cooling energy modulates the marginal impacts of climate. In sum, adaptation and carbon emissions complement each other as in (1.9).

Proposition 1 establishes the sufficient condition for monotone comparative statics.

Proposition 2 *It follows from monotone comparative statics [41] that*

$$E^H(\theta = 1) \;\geq\; E^H(\theta = 0) = 0 \qquad \text{and} \qquad L^E(\theta = 1) \;\geq\; L^E(\theta = 0).$$

When $\theta = 0$, the planner would not allocate any energy for households because it decreases output without any benefits. Let $L_0^E := L^E(\theta = 0)$ be an optimal labor allocation when adaptation is unavailable. Then, by construction, given any $l \in [0, L_0^E]$, the planner prefers L_0^E to l under $\theta = 0$. That is, the incremental returns to choosing L_0^E over l is always positive under $\theta = 0$; $W(L_0^E, E^H; \theta = 0) - W(l, E^H; \theta = 0) \geq 0$. It follows from Proposition 1 that these positive incremental returns to emitting more carbon are further sustained even under $\theta = 1$. Therefore, even though self-protective measures directly contribute to negative externalities, the planner would never choose lower carbon emissions, which leads to a higher temperature.

The optimal Pigouvian tax is determined where the marginal external cost and private profit from carbon emissions intersect according to the equation (1.6).

$$\text{Pigou Tax} = \begin{cases} \frac{dg(T)}{dT} & \text{if } \; \theta = 0 \\ \frac{\partial h(T, E^H)}{\partial T} & \text{if } \; \theta = 1 \end{cases}$$

On the one hand, adaptation—$E^H(\theta = 1) \geq 0$—reduces marginal damages decreasing optimal carbon taxes. On the other hand, an increase in emissions from general equilibrium effects—$L^E(\theta = 1) \geq L^E(\theta = 0)$—offsets the direct impact of adaptation, which increases the Pigou tax. In section 1.3, I provide proof for the optimal carbon taxes that decentralize the efficient allocations in a dynamic climate-economy model with private adaptation.

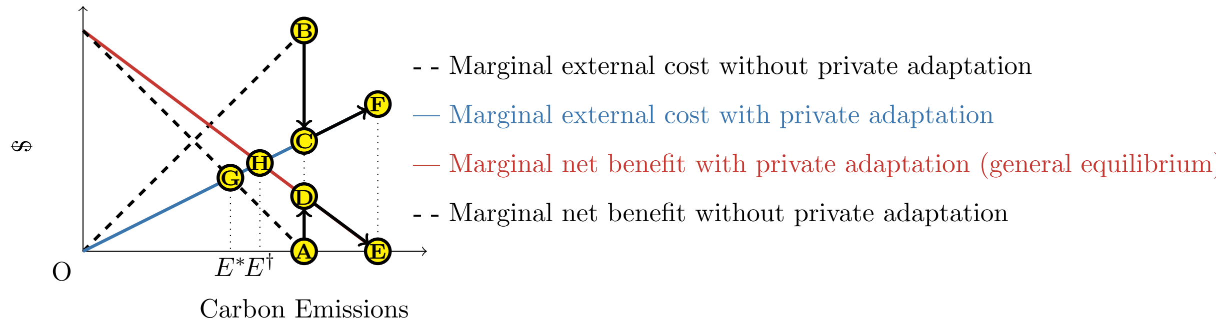


Figure 1.1: Graphical cost-benefit analysis

1.2.3 A graphical representation of cost-benefit analysis

Figure 1.1 illustrates the intuition of the model's general equilibrium effects using a graphical cost-benefit analysis. As a benchmark, consider an economy without cooling. With no carbon taxes, energy producers will increase their production until their marginal profit becomes zero (point A), which leads to external damages (point B). Now, suppose that energy is available for cooling. Private adaptation reduces the marginal impacts of climate (point C). The crowding-out of industrial energy by residential energy increases energy prices but decreases wages. Consequently, the profit of carbon-emitting firms rises in the short run (point D). With no carbon taxes, energy producers will increase their production capacity in the long run (point E), which leads to a higher external cost (point F) along the solid line since forward-looking households adapt to an endogenously evolving climate.

In principle, climate externalities can be internalized by regulating carbon emissions at the point where its private marginal net benefit equals its external marginal cost. However, such cost-benefit analyses may not be straightforward with endogenous adaptation because both curves shift. When it comes to optimal climate policies, failing to account for such effects may lead to inefficient levels of emissions. Much of the existing literature has focused on the shift in the marginal damage curve. Specifically, many Integrated

Assessment Models (IAMs) implicitly incorporate the costs and benefits of adaptation into a damage function by calibrating it to the least cost combination of residual damage and adaptation costs [17]:

$$\text{Damage}(T) := \arg\min_{E^H} \left\{ \text{Residual Damage}(T, E^H) + \text{Adaptation Cost}(T, E^H) \right\}, \quad (1.10)$$

where T is a global mean surface temperature change relative to the pre-industrial level and E^H is adaptation. But since most of the existing damage functions lump all the relevant welfare effects of adaptive responses into one stylized damage function in a reduced-form way, the previous research has overlooked the general equilibrium effects of pollutant-intensive adaptation on the marginal profit of polluting firms. In this paper, I specify endogenous adaptive decisions in households' preferences and budget constraints to shed some light on its general equilibrium effects on factor markets. In section 1.3, I construct a quantitative dynamic climate-economy model with private adaptation using the global mortality costs of climate change and electricity consumption for cooling as an example. I then recalibrate a damage function as in equation (1.10) to quantify how much of the Pigou tax with endogenous cooling is due to its general equilibrium effects on factor markets (point G to point H in Figure 1.1).

1.3 Dynamic Model with Private Adaptation

To quantify the role of adaptation in determining optimal carbon taxes, I extend the stylized framework to a dynamic climate-economy model. First, I assume that damages are inversely related to environmental quality, which is a constant elasticity of substitution aggregate of temperature and cooling energy. Second, I model the technology for producing an energy composite as a constant elasticity of substitution production function of carbon-free and fossil fuel-based energy. Third, I assume that the global mean surface temperature change is linear in the cumulative carbon emissions. I then characterize optimal carbon taxes in a setting in which the government has access to lump-sum transfers.

Household The economy is populated by an infinitely-lived representative household with the utility function

$$\sum_{t=0}^{\infty} \beta^t \left[v(C_t) \; - \; \left[\theta \cdot h(T_t, E_t^H) + [1-\theta] \cdot g(T_t)\right] \right],$$

$$\begin{aligned}
\text{where} \quad v(C_t) &= \frac{C_t^{1-\eta_c}}{1-\eta_c}, \\
h(T_t, E_t^H) &= \frac{1}{\eta_h - 1} \left(\omega \left(\frac{1}{1+\gamma_h T_t^2} \right)^{1-\rho_h} + \; [1-\omega] \left(\epsilon E_t^H\right)^{1-\rho_h} \right)^{\frac{1-\eta_h}{1-\rho_h}}, \quad \text{and} \\
g(T_t) &= \frac{\omega}{\eta_h - 1} \left(\frac{1}{1+\gamma_h T_t^2} \right)^{1-\eta_h}.
\end{aligned} \tag{1.11}$$

Here, I consider a power function with constant elasticity of marginal utility for non-durable consumption and climate impacts; $\eta_c \geq 1$ and $\eta_h \geq 1$. The parameter $\gamma_h > 0$ is used to scale gross impacts—ceteris paribus ambient temperature effects that would occur without private adaptation. The parameter $\epsilon > 0$ determines the efficiency by augmenting energy use, which reduces the severity of climate impacts. The parameter $\beta \in (0, 1)$ is the discount factor.

Climate impacts net of adaptation are inversely proportional to ingested environmental quality Q, which I model as a constant elasticity of substitution aggregate of gross impacts and cooling in line with [42] and [43]

$$Q(T, E^H) = \left(\omega \left(\frac{1}{1+\gamma_h T^2}\right)^{1-\rho_h} + [1-\omega]\left(\epsilon E^H\right)^{1-\rho_h}\right)^{\frac{1}{1-\rho_h}} \quad \text{where} \quad \rho_h \in [0, \eta_h].$$

I restrict the parameter space for ρ_h to ensure that the assumptions mentioned above on h in section 1.2 hold (see the appendix A.1 for derivations). Carbon mitigation improves ceteris paribus ambient temperature effects by curbing climate change. Therefore, $\frac{1}{\rho_h}$ measures the ease with which the planner can switch between carbon mitigation and private adaptation along an indifference curve. This functional form is general enough to nest a wide range of the climate damages in the literature (see the appendix A.2 for comparison to other studies). Note that $g(T_t)$ is a special case of $h(T_t, E_t^H)$ when $\epsilon = 0$ and $\rho_h = \eta_h$.

Let $V_t(K_t, S_t)$ denote the household's value function in period t with capital K_t and carbon stock S_t. Taking climate and prices as given, the dynastic household solves

$$V_t(K_t, S_t) = \max_{\{C_t, K_{t+1}, E_t^H\}} \left\{ v(C_t) - \left[\theta \cdot h(T_t, E_t^H) + [1-\theta] \cdot g(T_t)\right] + \beta V_{t+1}(K_{t+1}, S_{t+1}) \right\}$$
$$\text{subject to} \quad C_t + p_t^E E_t^H + K_{t+1} = w_t L_t + [1+r_t] K_t + G_t,$$

where p_t^E is energy price, w_t is wage, r_t is the rental rate of capital, and G_t is a transfer from the government.

Production I assume that the final and intermediate goods markets are complete. The economy has four types of firms: final goods producers, energy aggregators, carbon-free energy producers, and fossil fuel-based energy producers. I assume that the final goods are produced à la Cobb-Douglas and that output depends on climate change à la [4]

$$Y_t = (1 - D(T_t)) \cdot F_t(K_t^Y, L_t^Y, E_t^Y) = \frac{1}{1 + \gamma_y T_t^2} A_t^Y \left(K_t^Y\right)^{\alpha} \left(L_t^Y\right)^{1-\alpha-v} \left(E_t^Y\right)^{v}. \tag{1.12}$$

A representative firm in the final goods sector solves

$$\max_{K_t^Y, L_t^Y, E_t^Y} Y_t - p_t^E E_t^Y - w_t L_t^Y - (r_t + \delta) K_t^Y,$$

subject to non-negativity constraints, where δ is the depreciation rate of capital.

There are two types of energy in the economy: dirty (D) and carbon-free (R). Carbon-free energy is not associated with climate externalities, whereas dirty energy emits carbon into the atmosphere. Energy from a source $i \in \{D, R\}$ is produced according to the Cobb-Douglas function

$$E_t^i = G_t^i(K_t^i, L_t^i) = A_t^i \left(K_t^i\right)^{\alpha_i} \left(L_t^i\right)^{1-\alpha_i}. \tag{1.13}$$

I assume that dirty energy is in unlimited supply and its producers do not collect the Hotelling rents à la [3], in which they show that when a non-fossil alternative becomes economically profitable in the distant future, coal is not depleted even under laissez-faire equilibria. I calibrate the economy to justify this assumption in section 1.4. I normalize dirty energy production such that one unit of E^D generates one unit of carbon. Both renewable and dirty energy is expressed in the same unit.

A representative firm in the energy sector $i \in \{R, D\}$ solves

$$\max_{K_t^i, L_t^i} \; (p_t^i - \tau_t^i) E_t^i - w_t L_t^i - (r_t + \delta) K_t^i$$

subject to non-negativity constraints for choice variables, where p_t^i is the price of energy of type i and τ_t^i is its corresponding per-unit tax on output.

Energy composites are made according to the following constant elasticity of substitution production function

$$E_t = \left[\kappa_R \big(E_t^R \big)^{\frac{\sigma_e - 1}{\sigma_e}} + \kappa_D \big(E_t^D \big)^{\frac{\sigma_e - 1}{\sigma_e}} \right]^{\frac{\sigma_e}{\sigma_e - 1}} \quad \text{where} \quad \sum_{i \in \{R,D\}} \kappa_i = 1. \tag{1.14}$$

Here, $\kappa_i \in (0, 1)$ measures the relative energy-efficiency of the source $i \in \{R, D\}$, and $\sigma_e > 0$ determines the elasticity of substitution between carbon-free and dirty energy along an isoquant. A representative aggregator solves

$$\max_{E_t^R, E_t^E} \; p_t^E E_t - p_t^R E_t^R - p_t^D E_t^D.$$

Government I assume that the government redistributes carbon tax revenues to households using lump-sum transfer

$$G_t = \sum_{i \in \{R,D\}} \tau_t^i E_t^i. \tag{1.15}$$

Carbon cycle Most existing Earth System Models—a framework widely used to calculate the state of global and regional earth system responses under various environmental conditions—generate a near proportional relation between the cumulative emissions of carbon dioxide and global mean surface temperature changes over the pre-industrial level [44]. But it follows from [45] that most of the existing climate models in economics research exhibit excessive delays in temperature responses to emissions and they fail to account for carbon sinks' declining abilities to remove carbon from the atmosphere as it becomes more saturated. They argue that unless cumulative emissions are too high in the future, a linear mapping will suffice to bring climate dynamics into line with the Earth System Models predictions. Thus, I specify climate change as a linear function of carbon stock

$$T_t = \zeta S_t \quad \text{and} \quad S_{t+1} = S_t + \vartheta_t E_t^D \quad \text{where} \quad \vartheta_t = \frac{1}{1 + \exp\{-(a + 5bt)\}}. \tag{1.16}$$

The parameter ζ captures the relationship between cumulative emissions and warming, defined as the transient climate response to cumulative carbon emissions (TCRE) by [46]. Following [47], I assume a relatively short delay—5 years—for the temperature response to carbon emissions. Furthermore, I introduce an exogenously declining emissions intensity à la [3]. The parameter $\vartheta_t \in (0, 1)$ captures the fraction of carbon emitted in period t. This is also consistent with [4], in which the economy becomes less carbon-intensive even without carbon taxes because abatement costs decline over time due to technological progress. The quantitative implications of this assumption are further discussed in the calibration section.

Let $W_t(K_t, S_t)$ denote a benevolent planner's value function in period t with capital K_t and carbon stock S_t. Then each period t, the planner solves

$$W_t(K_t, S_t) = \max_{\{C_t, K_{t+1}, L_t^Y, L_t^R, L_t^D, K_t^Y, K_t^R, K_t^D, E_t^H, E_t^Y\}} \Bigg\{ v(C_t) \; - \; \Big[\theta \cdot h(T_t, E_t^H) + [1-\theta] \cdot g(T_t)\Big] + \beta W_{t+1}(K_{t+1}, S_{t+1}) \Bigg\}$$

subject to (1.11), (1.12), (1.13), (1.14), (1.16),

$$C_t + K_{t+1} = Y_t + (1-\delta)K_t, \;\; L_t^Y + L_t^R + L_t^D = 1, \;\; K_t^Y + K_t^R + K_t^D = K_t, \;\; E_t^H + E_t^Y = E_t, \tag{1.17}$$

as well as non-negativity constraints for each choice variable. The envelope and the first-order conditions are fully characterized in the appendix A.3.

I define a recursive competitive equilibrium in this economy as follows.

Definition 1 *A recursive competitive equilibrium consists of prices* $\{p_t^E, w_t, r_t, p_t^R, p_t^D\}$, *climate change* $\{T_t\}$, *tax/transfer* $\{\tau_t^R, \tau_t^D, G_t\}$, *a value function* $\{V_t\}$, *and policy functions* $\{C_t, K_{t+1}, E_t^H, E_t^Y, L_t^Y, L_t^R, L_t^D, K_t^Y, K_t^R, K_t^D\}$ *such that each period* $t = 0, 1, 2, \cdots$,

1. *taking prices, climate change, and tax/transfer as given, the policy functions and the value function solve the households' and the producers' maximization problem,*
2. *the government budget is balanced as in* (1.15),
3. *the climate change* $\{T_t\}$ *is consistent with the policy functions through* (1.16), *and*
4. *the markets clear as in* (1.17).

The envelope and the first order conditions are fully characterized in the appendix A.3.

Proposition 3 *Suppose the government plans to maximize economic efficiency using tax and transfer systems. Then the following output taxes on energy sectors decentralize the first best allocation from the planning problem*

$$\tau_t^R = 0 \text{ and } \tau_t^D = \begin{cases} \frac{1}{v'(C_t)} \sum_{s=t+1}^{\infty} \beta^{s-t} \left(\frac{dg(T_s)}{dT_s} - v'(C_s) \frac{\partial Y_s}{\partial T_s} \right) \zeta \vartheta_t & \text{if } \theta = 0 \\ \frac{1}{v'(C_t)} \sum_{s=t+1}^{\infty} \beta^{s-t} \left(\frac{\partial h(T_s, E_s^H)}{\partial T_s} - v'(C_s) \frac{\partial Y_s}{\partial T_s} \right) \zeta \vartheta_t & \text{if } \theta = 1 \end{cases} \quad \forall t = 0, \cdots$$

where policy functions are the solutions for the planning problem.

See the appendix A.3 for proof. Under the linear warming model, an additional unit of carbon emissions in period t translates into a temperature rise by $\zeta\vartheta_t$ from period $t+1$ onwards. The optimal tax on dirty energy equals the sum of the present values of all future climate impacts discounted by the marginal utility of non-durable consumption in period t. Adaptation makes the marginal damage curve flatter, lowering Pigouvian carbon taxes. On the other hand, a rise in temperature from general equilibrium effects increases optimal carbon taxes because the damage function h is convex in T.

1.4 Calibration

I calibrate the model's laissez-faire equilibrium to match the projected impacts of climate change on heat-related mortality costs and electricity consumption under a high emissions scenario (Representative Concentration Pathway [RCP] 8.5); for details of this scenario, see [48]. I choose this scenario because it does not include any carbon mitigation targets, which corresponds to the model's competitive equilibrium with no carbon taxes. I calibrate six parameters $\{\gamma_h, \epsilon, 1/\rho_h, \omega, a, b\}$ to justify some recent reduced-form evidence on the benefits and costs of the use of energy for cooling [6, 5]. I adopt other parameters directly from the existing literature. The time step is five years. The year 2015 is a base period ($t = -1$), and simulations begin in 2020 ($t = 0$).

Using the external parameters in Table 1.2, I relate my model to some observables in the base period to initialize allocations. The 2015 world gross saving rate is used to calculate the base-period consumption.[4] The 2016 world final energy consumption for space cooling is used to calculate the base-period household cooling energy, which is about 3% of the world's total primary energy use [49]. The 2014 primary global fossil fuel-based energy demand was 11.085 Giga tons of oil equivalents of coal, oil, and gas. The 2014 primary global carbon-free energy demand was 2.599 Giga tons of oil equivalents of nuclear, hydro, bioenergy, and other renewables [50]. Using the guidelines on national greenhouse gas inventories by [51], I express the energy demand in carbon units.

1.4.1 Internal parameters

Preferences [5] find that ceteris paribus effects of climate change on global heat-related mortality costs in 2100 are projected to be 221 deaths per 100,000 people under the RCP8.5, which is about 8.32% of the 2100 world gross domestic product.[5] I calibrate the parameter γ_h such that the model-simulated disutility caused by climate change from 2015 to 2100 without cooling equals the utility loss from 8.32% consumption

$$g\big(T_{2015}\big) - g\big(T_{2100}\big) = v\big(C_{2100}\big) - v\big([1 - 0.0832]C_{2100}\big).$$

In addition, [5] project that the mortality costs net of adaptation benefits are expected to be 73 deaths per 100,000 people, which is about 5.57% of the 2100 world gross domestic product. I calibrate the parameter ρ_h such that the model-simulated adaptation benefits

[4] World Bank, "Gross savings (% of GDP)." The World Bank Group, accessed July 15, 2022, https://data.worldbank.org/indicator/NY.GNS.ICTR.ZS?end=2021&start=1960&view=chart.

[5] [5] report climate damages as a percentage of global GDP only for the full mortality costs of climate change that include both the benefits and costs of adaptation. To calculate the ceteris paribus climate impacts as a percentage of global GDP, I assume that both benefits and costs of adaptation occur proportionally to all age groups.

match the empirical moments as follows

$$\frac{h^{\max}\big(T_{2100}, E_{2100}^{H}\big) - h\big(T_{2100}, E_{2100}^{H}\big)}{h^{\max}\big(T_{2100}, E_{2100}^{H}\big) - h^{\min}\big(T_{2100}, E_{2100}^{H}\big)} = \frac{v\big(C_{2100}\big) - v\big([1-0.0557]C_{2100}\big)}{v\big(C_{2100}\big) - v\big([1-0.0832]C_{2100}\big)},$$

where $h^{\max}$ equals to h when $1/\rho_h = 1/\eta_h$ and $h^{\min}$ equals to h when $1/\rho_h \to \infty$. If cooling reduces deaths by 221 per 100,000 people, then the parameter $1/\rho_h$ becomes infinity. If there are no cooling benefits, the parameter $1/\rho_h$ equals its lower bound $1/\eta_h$.

The parameter ω governs the efficiency of greenhouse gas abatement efforts relative to space cooling in determining an environmental quality Q. All else being equal, as ω increases, households need to use more energy to attain the same level of well-being. [6] project future global electricity consumption relative to 2000-2010 under the RCP8.5. Using the standard two-way fixed effects model, they first identify a causal effect of temperature fluctuations on electricity consumption. They allow their dose-response functions to become steeper as either the long-run average temperature or income per capita rises, which are two key adaptation indicators. It is worth noting that their projection does not include secular trends in energy consumption, but it just captures an increase in electricity usage attributable to climate change.[6] Therefore, I calibrate the parameter ω such that the changes in the model-simulated cooling energy net of secular trends match the changes in electricity consumption projections in [6], which is 1.21 Giga joule per capita per year by the end of this century. I multiply this estimate by the 2015 world population to derive climate-driven cooling loads, which is 3.3214 Giga ton of CO_2 per period. To derive the secular trends of household energy consumption, I simulate the competitive equilibrium without climate externalities.

[6]In projecting the impact of climate change on future energy consumption, [6] do not include time fixed effects. This is because the standard two-way fixed effects model estimates time fixed effects non-parametrically, and it is impossible to extrapolate them.

Moment	Model-simulated	Empirical	Source
Climate impacts on mortality (% of world GDP)	8.32	8.32	[5]
Mortality reduction due to cooling (% of world GDP)	5.57	5.57	[5]
Climate-driven cooling demands (giga ton of CO_2)	3.3215	3.3214	[6]
Asymptotic cumulative emissions (giga ton of carbon)	4,889	5,000	[52]

Table 1.1: Model's fit for targeted moments

$$\left[E^H_{2100} - E^H_{2015}\right] \; - \; \left[E^{H,\,\text{Secular}}_{2100} - E^H_{2015}\right] \; = \; 3.3214$$

Lastly, I calibrate the parameter ϵ such that the marginal rate of substitution between C and E^H equals its price ratio in the base year. It is worth noting that [5] identify the benefits of adaptation by estimating reduced mortalities to weather fluctuations, which result from all of the actions people take to alleviate their mortality costs. In calibration, I assume that all the benefits result from using energy for cooling.

Climate model I introduce a declining emissions intensity $\{\vartheta_t\}$ so that a temperature change can reach a steady state in the distant future à la [3]. This assumption serves to validate the linear warming model. At high cumulative emissions, the transient climate response to cumulative carbon emissions (TCRE) is no longer constant, and it starts to decline [44, 45]. I set $a = 8$ and calibrate b such that the atmospheric carbon concentration in laissez-faire converges to five trillion tons of carbon, which validates the TCRE parameter in [52]. Five trillion tons of carbon also corresponds to the lower end of the range of estimates of the total fossil fuel resource [53]. Therefore, my calibration justifies the assumption of an unlimited supply of fossil fuel-based energy since the depletion of fossil fuels does not arise.

I numerically solve for the model's laissez-faire equilibrium to match all the moments jointly. Model-simulated moments are compared to the empirical moments in Table 1.1, and the resulting parameter values are summarized in Table 1.2. In both [5] and [6], the median warming in 2100 relative to 2001-2010 under the RCP8.5 across all the climate models both studies consider is 3.7°C. A simulated temperature change in 2100 relative to 2015 is about 3.6°C in the laissez-faire equilibrium. The computational procedures are provided in the appendix A.4.

1.4.2 External parameters

Climate model The atmospheric carbon concentration in 2015 is from [4]. The transient climate response to cumulative carbon emissions (TCRE) is set to 0.00163 °C per Giga ton of carbon from [52].

Preferences I assume that the elasticity of marginal utility equals 2 for both non-durable goods and environmental qualities. The rate of pure time preference is set to be 0.015 per year, or $\beta = (0.985)^5$ in the quantitative model in line with [4].

Technology Following [3], I assume a capital share of 0.3 and an energy income share of 0.04 for the final goods sector. Based on [15], I assume a capital share of 0.597 in both fossil fuel-based and carbon-free energy sectors. Following [54], I set the elasticity of substitution between renewable and dirty energy to be 1.949 and the relative efficiency of renewable energy to be 0.442. The depreciation rate is set to 0.1 per year, or $\delta = 0.4095$ in the quantitative model in line with [4]. The path of total factor productivity is also taken from [4]. The productivity in both dirty and renewable energy sectors is set such that the labor augmenting technological progress is the same across all sectors.

	Parameter	Description	Sources and notes
Preferences			
η_c	2	Elasticity of marginal utility of consumption	[55]
η_h	2	Elasticity of marginal utility of environmental quality	
β	$(0.985)^5$	Discount factor	[4]
γ_h	8.6801e-05	Utility damage	Internally calibrated
ϵ	2.0700	Effectiveness of adaptation	Internally calibrated
$1/\rho_h$	0.5601	Substitutability between abatement and adaptation	Internally calibrated
ω	0.0214	Relative efficiency	Internally calibrated
Technology			
γ_y	0.0021	Production damage	[15]
α	0.3	Capital expenditure share in Y	[3]
ν	0.04	Energy expenditure share in Y	[3]
α_R	0.597	Capital expenditure share in R	[15]
α_D	0.597	Capital expenditure share in D	[15]
σ_e	1.949	Substitutability between R and D	[54]
κ_R	0.442	Relative energy efficiency of R	[54]
κ_D	0.558	Relative energy efficiency of D	$1 - \kappa_R$
δ	0.4095	Capital depreciation rate	[4]
gA_1^Y	0.076	Initial growth rate in output productivity	[4]
δ_A	0.005	Decline rate in productivity growth	[4]
gA_t^Y		$gA_1^Y \exp(-5\delta_A(t-1))$	[4]
gA_t^R		Growth rate in R: $((1+gA_t^Y)^{\frac{1}{1-\alpha-\nu}})^{1-\alpha_R} - 1$	
gA_t^D		Growth rate in D: $((1+gA_t^Y)^{\frac{1}{1-\alpha-\nu}})^{1-\alpha_D} - 1$	
Climate model			
S_{2015}	851	The 2015 atmospheric carbon concentration (giga ton of carbon)	[4]
ζ	1.63e-03	TCRE (°C per giga ton of carbon)	[52]
ϑ_t		$[1+\exp\{-(a+5bt)\}]^{-1}$	[3]
a	8		
b	-0.0798		Internally calibrated

Table 1.2: Calibration Summary

1.5 Quantitative Results

I use the calibrated model to quantify the economic impacts of heat-related mortalities and ensuing adjustments in cooling. First, I quantify the general equilibrium effects of cooling on factor markets in competitive equilibria. Second, I quantify the impact of adaptation-driven general equilibrium effects on the mortality social costs of carbon. Third, I compare household saving with and without cooling in the first best to quantify ex-ante adaptation to climate change. Fourth, I examine the welfare impacts of exogenous advances in cooling technology.

1.5.1 General equilibrium effects of cooling on factor markets

To isolate the general equilibrium effects of household energy consumption for cooling on the marginal profit of dirty energy producers, I compare competitive equilibrium allocations from the two otherwise identical economies that differ in household's ability to adapt. When I do not include endogenous adaptive decisions in utility and resource constraints, adaptation-driven general equilibrium effects do not arise. Therefore, I attribute an increase in factor shares in the dirty energy sector to the general equilibrium effects of cooling on factor prices.

Figure 1.2 compares the simulated paths of competitive equilibrium allocations with cooling to the ones without adaptation as output taxes on the dirty energy sector—$\{\tau_t^D\}$—change. I solve for the socially optimal allocation to derive the optimal carbon taxes—$\{\tau_t^*\}$. I then solve for competitive equilibria when $\{\tau_t^D\}$ equals to $x\%$ of $\{\tau_t^*\}$ where $x \in \{0, 25, 50, 75, 100\}$. Panel (A) shows that as output taxes on the dirty energy sector vary from optimal carbon taxes to zero taxes, the time path of cooling shifts up. For example, when there are no carbon taxes, about 21 Giga tons of CO_2—3.4% of energy— will be used for cooling in 2100. Having less regulation in dirty sectors leads

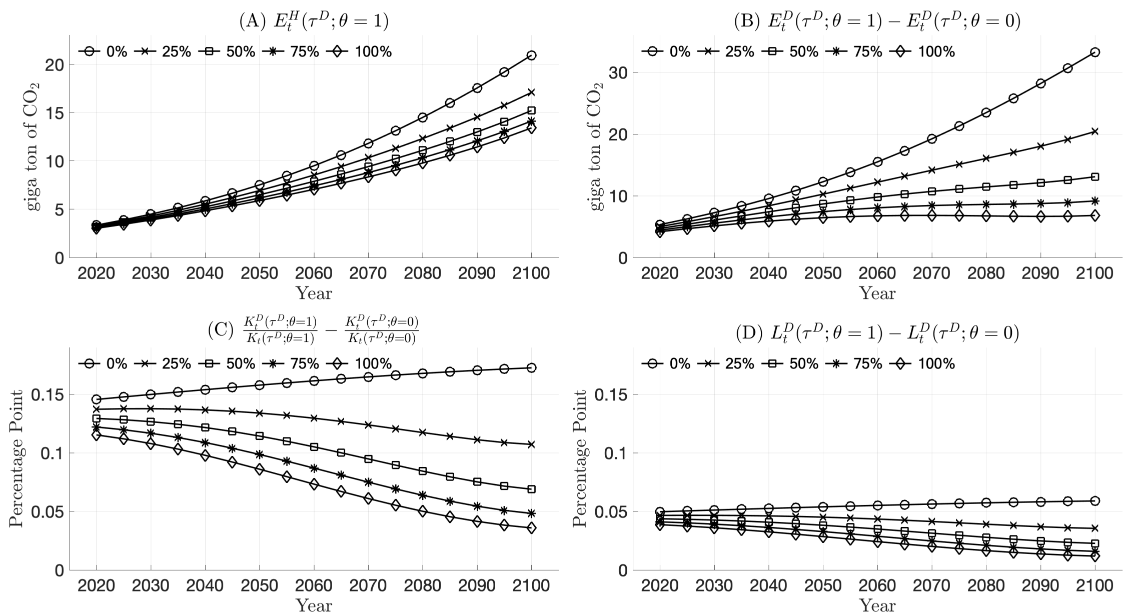


Figure 1.2: General equilibrium effects of cooling on factor markets in competitive equilibria

Each panel compares the time paths of competitive equilibrium allocations with cooling to the ones without adaptation as output taxes on the dirty energy sector (τ^D) vary. I solve for the optimal carbon taxes with endogenous adaptation (τ^*). I then solve for competitive equilibria when τ^D equals to $x\%$ of τ^* where $x \in \{0, 25, 50, 75, 100\}$. Note that I convert all the energy sources into tonnes of oil equivalent and then convert them into CO_2 for presentation. Panel (A): The use of energy for cooling. Panel (B): The difference in CO_2 emissions per period. Panel (C): The difference in capital share in the dirty energy sector. Panel (D): The difference in labor share in the dirty energy sector.

to more emissions. Because of the nonseparability between environmental quality and cooling, a higher temperature change makes household demand more energy for cooling. Note that equilibrium cooling is not zero when the government imposes optimal carbon taxes. This is because the planner reduces carbon until its private marginal benefit equals its external marginal costs, which leads to non-zero carbon emissions. Since the efficient pollution level is not zero, efficient cooling does not equal zero either.

In response to endogenous cooling, the dirty energy sector's marginal profit shifts because of an increase in market demand. If there were no shifts, factor shares between the two economies should be the same. Panels (C) and (D) show that the differences in factor shares in the dirty energy sector increase as output tax rates for the dirty sector decline. For example, when there are no carbon taxes, the share of capital and labor in the dirty energy sector will increase by about 0.17 percentage points and about 0.06 percentage points by the end of this century. This is because increases in cooling loads due to a higher temperature amplify general equilibrium effects. In response to increases in factor shares in the dirty energy sector, emissions also increase as output tax rates decline for the dirty energy sector, as in Panel (B). For example, when there are no carbon taxes, emissions per period increase by about 33.3 Giga ton of CO_2 in 2100, equivalent to 3.2% of global greenhouse gas emissions in 2100.

1.5.2 General equilibrium effects of cooling on Pigou taxes

To quantify the general equilibrium effects of cooling on optimal climate policies, I compare the Pigou tax with endogenous cooling to the case in which a damage function is recalibrated to the least cost combination of residual damage and adaptation costs (point G to point H in Figure 1.1). When adaptation is implicit in a damage function, general equilibrium effects do not arise because household energy consumption does not appear in resource constraints.

Figure 1.3 shows the global mean surface temperature change over the pre-industrial level and mortality social costs of carbon in the first-best. To compare the simulated outcomes with endogenous cooling to the ones with implicit adaptation, I use upward-pointing triangle and circle symbols, respectively. In the social optima, the equilibrium temperature change is higher with endogenous cooling (Panel A of Figure 1.3). This is because the marginal profit of fossil fuel-based energy producers shifts up. Since increased profits flow back to the households' budget constraint, the planner increases optimal carbon emissions. Equilibrium temperature keeps going up over time in both cases because it is linear in the cumulative carbon emissions.

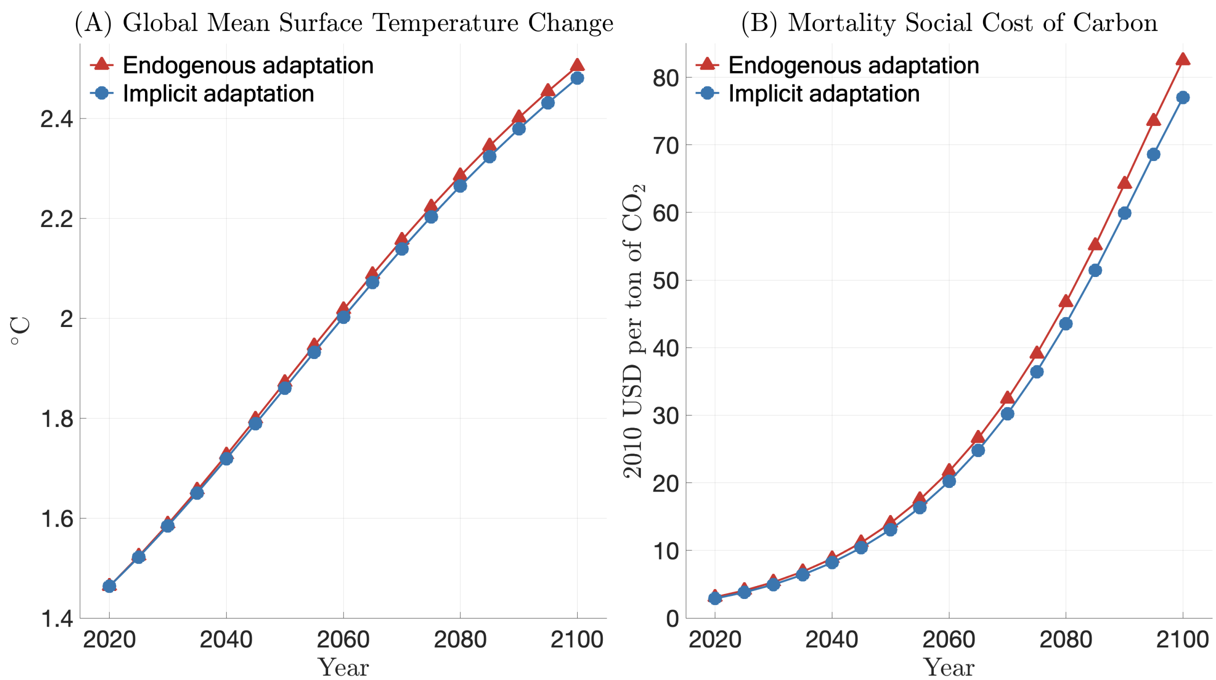


Figure 1.3: Simulated paths of climate change and Pigou tax correcting heat-related discomfort

Each panel compares the time paths of the first-best allocations with endogenous adaptation to the ones with implicit adaptation.

The social cost of carbon in this environment is defined as the present discounted sum of climate externalities that would result from emitting an additional ton of carbon dioxide. To highlight the general equilibrium effects of endogenous cooling, I isolate the mortality social costs of carbon from the social cost of carbon that additionally includes production damages. In the social optima, the mortality social cost of carbon is higher with endogenous cooling (Panel B of Figure 1.3) because of cooling-driven upward shifts in the marginal profit of dirty energy producers. It follows from Proposition 3 that efficient allocations can be fully decentralized when the government prices carbon at its social cost in the first-best solution of the model. For example, when I account for endogenous cooling, Pigou tax correcting for mortality costs increases by about 7% for the base period (2020).

1.5.3 Saving as ex-ante adaptation

[56] claim that it is crucial to distinguish between anticipatory (ex-ante) and reactive (ex-post) adaptation. In this paper, I model adaptation as an ex-post flow decision variable using residential energy for cooling. I do not explicitly consider investments in durable goods such as air conditioners. Despite my modeling assumption on adaptive measures, using energy for cooling has intertemporal implications via saving. In the social optima, the household saving in 2020 increases by 0.09% with endogenous cooling. Consequently, capital stock rises by 0.1% with endogenous cooling by the end of this century, which implies household energy expenditures due to climate change do not divert resources from productive capital accumulation. Equilibrium temperature keeps rising over time since it is proportional to the cumulative carbon emissions. As a result, as soon as cooling energy is available as a self-protective measure, households derive higher utility from converting the marginal unit of final goods to the very first unit of cooling services in the following period compared to the current period. This is because avoided damages from cooling are higher when the climate is worse, providing higher incentives to save, all else equal.

1.5.4 Welfare impacts of advances in cooling technology

Energy efficiency improvements have received attention in the global discourse on climate change as an effective greenhouse gas mitigation strategy [57]. Yet, such advances can create income from energy savings and potentially lead to increased energy use, referred to as "rebound" effects in the energy efficiency literature [58, 59]. I use the calibrated model to see if such rebound effects more than offset the energy savings from technological advances. In particular, I examine the competitive equilibria with no carbon taxes to focus on the role of energy efficiency improvements as a greenhouse gas mitigation

‡ Simulated outcomes using the parameters in Table 1.2

Competitive equilibrium without carbon taxes	Baseline‡	$(1/\rho_h) \times 1.001$
Cooling energy use in 2100 (giga ton CO_2)	20.9	21.2
Cumulative carbon dioxide emissions in 2100 (giga ton)	12,076	12,078
Mortality social cost of carbon† in 2100 (2010 US$/ton CO_2)	202	199

Table 1.3: Welfare impacts of the advances in cooling technology

strategy in the worst case. In this paper, I consider an increase in the efficacy of cooling at reducing marginal damages via the parameter $1/\rho_h$.

Table 1.3 summarizes the welfare impacts of such technological advances in cooling. A 0.1% increase in the efficacy of cooling at reducing marginal damages ($1/\rho_h$) boosts energy use by about 1% in the year 2100, which means that rebound effects reverse energy savings. Thus, related general equilibrium effects also increase, leading to higher carbon emissions. But the benefits of cooling from the enhanced efficacy dominate the unintended consequences, which decreases the mortality social cost of carbon from $202 per ton of CO_2 to $199 per ton of CO_2 in 2010 USD by the end of this century.

To convert the decrease in the mortality social cost of carbon into more interpretable units, I compute the constant consumption stream w a household must receive to attain the life-time utility à la [60]

$$\frac{1}{1-\beta}\frac{w^{1-\eta_c}}{1-\eta_c} = \sum_{t=0}^{\infty}\beta^t\Big[v(C_t) - h(T_t, E_t^H)\Big].$$

A 0.1% increase in the parameter $1/\rho_h$ provides welfare gains that are equivalent to about 1% of consumption for households. Therefore, even though rebound effects overturn the direct energy efficiency gains leading to a worse climate, the enhanced cooling services more than offset this vicious cycle effects providing welfare gains.

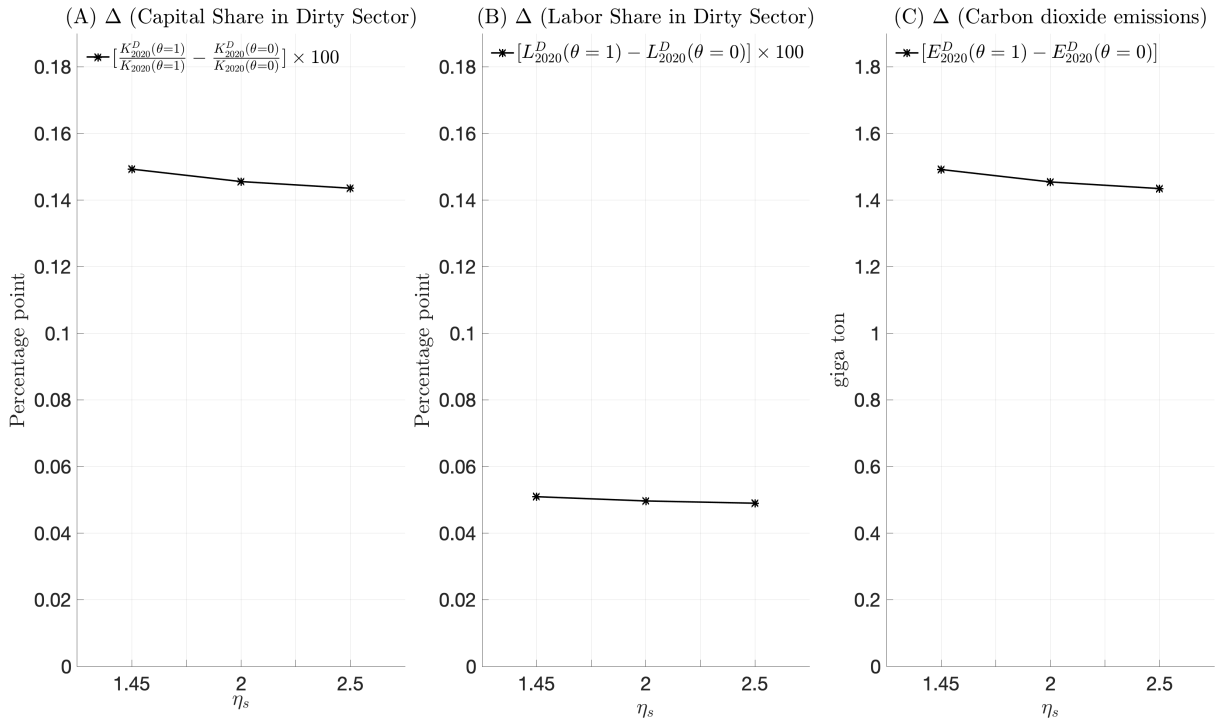


Figure 1.4: Differences of factor shares in the dirty sector and per period emissions in 2020

Each panel compares the laissez-faire allocations with cooling to the ones without adaptation in 2020 as the elasticity of marginal utility changes from 1.45 to 2.5 relative to the baseline calibration ($\eta_c = 2$).

1.5.5 Sensitivity analysis

The central theoretical insight in this paper is that cooling-driven energy scarcity increases the marginal benefit of fossil fuel use by changing factor prices, which are determined by their marginal products in a competitive factor market. Here, I examine the robustness of adaptation-driven general equilibrium effects to alternative assumptions on the elasticity of marginal utility—η_c. Figure 1.4 shows the difference of factor shares in the dirty sector between the laissez-faire with endogenous cooling and the laissez-faire without cooling across a range of parameter values. I find that the general equilibrium effects align with the baseline quantitative analysis.

1.6 Summary and Concluding Remarks

This paper develops a theory of how pollutant-intensive adaptation affects optimal Pigou taxes. The most apparent effect, highlighted previously in the literature, is that adaptation reduces the external marginal costs of pollution; this effect always decreases optimal pollution taxes. However, I show that adaptation using pollutant-intensive intermediate goods comes with unintended consequences on factor prices. An increase in demand for pollutant-intensive inputs raises the marginal profit of polluting industries. This second effect works in the opposite direction and increases the optimal pollution price. As a stylized example, I use a macroeconomic climate-economy model with heat-related discomfort and cooling energy. I find that about 7% of the Pigouvian tax for correcting heat-related mortality is due to the unintended warming caused by the use of energy for cooling for the base period.

The theoretical insight in this paper provides a guiding principle in interpreting reduced-form studies on adaptation to derive their policy implications. It is becoming more popular, in econometric analyses, to account for adaptation by allowing the dose-response relation between economic outcomes and weather fluctuations to depend on the long-run average temperature and per capita income, which are vital indicators of adaptation (see [61] for a review). Policymakers should be concerned about general equilibrium effects when potential mechanisms explaining the benefit of adaptation are from carbon-intensive intermediate goods. In such cases, a back-of-the-envelope calculation based on engineering-based or partial equilibrium pollution abatement costs could prescribe a lower-than-optimal tax rate.

Lastly, I conclude with a discussion of potential extensions of my model for future research. First, while a multi-sector growth model with various energy sources as intermediate goods elucidates the general equilibrium effects of private adaptation, additional efforts need to be undertaken to generalize the framework to a multi-sector model with input-output linkages. Adaptive behaviors that can lead to increased greenhouse gas emissions include, but are not limited to, cooling energy. The macroeconomic literature on production networks can provide a valuable framework to examine the transmission of such risks over the input-output networks. Second, future research should probe the distributional effects of climate-driven adaptation. In this paper, I focus on the wedge between potential and realized exposures to climate change, which is driven by the self-protective behaviors of a representative household. But economically disadvantaged people may not enjoy the same benefits because of their lack of resources to adapt to even worse climate conditions caused by wealthy households' adjustments to climate change. The heterogeneous agent macro model with idiosyncratic income shocks can be a helpful framework for designing climate policies that reduce both carbon emissions and inequality among households.

Chapter 2

Credit Ratings and the Cost of Wildfires: Evidence from California School District Finances

Summary

This paper examines whether and how much financial markets integrate climate risks into credit ratings using wildfires and school district finances in California. I document that countywide property tax revenues decline a year after large-scale wildfires. I then use historic wildfire events as a source of salience shocks to identify the causal relationship between future fire potentials and credit ratings. I find that when about 0.08% of the tax base in a district is at risk of burning over the next 30 years, its credit rating worsens by 3.22%. The capitalization of future climate risks into bond ratings can encourage policymakers to take measures to mitigate climate risks to avoid high borrowing costs.

2.1 Introduction

Many local governments in the United States finance their public projects — such as the construction or renovation of hospitals, schools, roads, etc. — by issuing bonds secured by tax revenues. But emerging climate risks can impair their ability to service debts because of the potential loss of tax base from property damages or out-migration. As forward-looking opinions about issuers' overall creditworthiness, credit ratings can affect the cost of borrowing and thus the allocation of capital. Given that credit rating agencies are viewed as trusted arbiters of creditworthiness in financial markets, the integration of climate risks into municipal credit ratings may potentially encourage local governments to take proactive actions in adapting to climate change.

In this paper, I examine whether and how much climate risks are factored into municipal credit ratings using wildfires and school district finances in California as an example. I first evaluate how much property tax revenue has been reduced as a result of unexpected wildfires to quantify the local fiscal cost of climate-related natural disasters. A decline in fiscal revenue from climate risks would alarm financial markets. I then leverage the arbitrariness of historic wildfire events as a source of salience shocks to estimate how much climate risks are integrated into municipal credit ratings. If financial markets are well-informed about these risks, bonds issued by municipalities with higher exposure would receive worse credit ratings and face a higher borrowing cost.

Estimating the effect of future fire risks on municipal credit ratings can be challenging due to the potential correlation between underlying future fire potentials and economic conditions that affect the creditworthiness of municipalities. The cross-sectional difference in the average credit ratings between high-risk versus low-risk municipalities can be biased because municipalities with high exposures are more likely to be located in less developed rural areas interfacing with a fire-prone grassland. Moreover, for causal interpretations, it is essential to identify the quasi-experimental variation in financial markets' awareness of future wildfire risks.

School district finances provide an ideal setup to study how much wildfire potentials are factored into municipal bond ratings. Unlike other municipal bonds that are directly connected to specific revenue-generating projects, school district bonds are secured by real property taxes or general funds. Therefore, reductions in property tax revenues due to home destruction from multiple events of unexpected wildfires can generate a random variation in the awareness of underlying future wildfire risks over time and space.

I use the structure-level damage inspection data to calculate the countywide share of housing units destroyed due to wildfires. I then apply the event study design with a continuous damage intensity to county-level panel data of property tax revenues to identify the dynamic effect of a change in the fraction of home destruction on property tax revenues. Under Proposition 13, California collects property taxes at the county level and redistributes them at the largely fixed shares that are roughly proportional to the allocation share in the 1970s. Leveraging this institutional background, I calculate the school district-wide future tax base at risk by multiplying the share of properties at the risk of burning over the next 30 years with the current-period district-wide allocation shares assuming that the shares will remain the same in the future as well. I then use the underlying future risks, combined with recent large-scale wildfire event indicators, to measure the salience shocks. I apply the event study setup with a continuous future risk intensity to bond data to identify the dynamic effect of a change in the awareness of future fire potentials on school district credit ratings.

I find that countywide tax revenues persistently decline a year after large-scale wildfires. Under Proposition 13, annual increases in the taxable value of real properties are restricted to an inflation factor but a title transfer or reconstruction can make its assessment match its market rates. The victims of wildfires can file a claim for tax relief to defer the next installment of property taxes and to retain their old assessment even after the purchase of a new house or reconstruction, which decreases property tax proceeds. On the other hand, those who sell their houses to victims and purchase a new home in the same county may face a higher taxable value because of a title transfer, which increases property tax collections. I estimate that property tax revenues decline by 1.6% a year after large-scale wildfires among counties in which 0.99% of their housing units are destroyed, which implies that the first channel dominates the latter in determining the fiscal cost of wildfires in California. I also document that increases in the awareness of future fire risks in school districts due to recent large-scale wildfires actually lead to worse credit ratings. I find that when about 0.08% of the tax base is at risk of burning over the next 30 years in a school district, its credit rating worsens by 3.22%, which implies that future fire potentials are capitalized in municipal bond ratings.

This paper brings new evidence to the question of whether and how much future climate risks are factored into municipal credit ratings. [62] empirically document that investors, in general, rely on credit rating to evaluate the creditworthiness of municipal securities, highlighting the role of credit rating agencies as information intermediaries. In the context of climate finance, [63] find that carbon-intensive firms are more likely to receive lower credit ratings when they are located in jurisdictions with stricter regulatory standards, which provides evidence in support of the integration of transition risks into credit ratings. But there is scant evidence as to whether municipal ratings depend on future climate physical risks. [64] find that both local economic conditions and municipal debt ratings deteriorate following hurricanes by comparing the exposed counties against the unaffected in the same state. They claim that the downgrades in debt ratings come from a decline in local economic conditions during disasters rather than an increase in the awareness of future risks. This is because they find statistically significant negative impacts of hurricane exposures on bond ratings by affected counties in comparison to the neighboring counties that nearly miss the exposure to the same hurricane, which should be null if rating agencies integrate future hurricane risks into credit ratings. I leverage a unique institutional setting in Proposition 13 to test whether municipal credit rating declines due to an increase in the awareness of future climate risks along the lines of several works on the causal relationship between asset prices and salience effects [65, 66].

This paper also contributes to our understanding of the local fiscal costs of climate-related natural disasters in terms of the ability of municipalities to honor their debt promises. Many existing studies on the impact of climate physical risks on municipal bond pricing typically assume a negative relationship between the source of payments and natural disasters [67, 68, 69, 70]. But empirical evidence on this link is mixed — particularly for property tax revenues, which is the main source of a school-funding system in the United States. Using a panel vector autoregression, [71] find that natural disasters cause a decline in property tax revenues, but have limited impacts on total state tax revenues. On the other hand, [64] identify a statistically significant and negative impact of hurricane exposures on total local tax revenues, but find an imprecise negative effect on property taxes using an event study setup. Furthermore, [72] rather observe null effects in the short run and positive impacts in the long run by applying an event study design to property tax revenues and wildfire data in California at the municipality level. But property taxes in California are collected at the county level and redistributed to lower-tier municipalities at the proportion largely determined in the 1970s. Their findings could therefore be affected by spillover effects in the short run. For example, if one lower-tier municipality has home destruction from a large-scale wildfire, a reduction in property taxes from disaster relief can affect other municipalities in the same county. I focus on the county-level analysis to identify the local fiscal costs of wildfires without spillover contamination.

2.2 Institutional Backgrounds and Data

In this section, I begin with an overview of California's system of property taxation under Proposition 13 to explore how wildfire-related property damages can deteriorate municipalities' ability to pay off debt. Then, I describe historic damage inspection data and property tax raw data that are used to estimate the effects of historic wildfires on property tax revenues. Finally, I describe future wildfire risk data and school district bond issuance data that are used to estimate the effect of the increased awareness of climate risks on municipal bond ratings.

2.2.1 The Proposition 13 and property taxes in California

In 1978, Californian voters approved Proposition 13, which is also known as the People's Initiative to Limit Property Taxation. It establishes how property taxes are calculated in California, mainly through three channels. First, county assessors should determine a so-called "base year value" for each property, which is defined as the current market value at the time of a title transfer or new construction. When it was passed, it matched every residential and commercial property's taxable value to the 1975 fair market value level. Second, when there is no transaction or new construction in a property, the rate of annual increases in its assessed value is restricted to an inflation factor, which cannot exceed 2%. Third, the general *Ad Valorem* tax on a property cannot exceed a 1% of its assessed value, which is often called "countywide 1% property taxes."

When a property has been considerably damaged or destroyed by a wildfire, its owner may rebuild the property or purchase a new house in the same county, which could potentially trigger a reassessment of real property at its market value. But Revenue and Taxation Code section 170 provides property tax relief for victims. If property damages stem from a governor-proclaimed disaster and victims file a claim, they can defer the next property tax installment and transfer the base year value of their damaged house to a new one. The filing must be done within the time specified by their county's ordinance or twelve months from the date of property damages, whichever comes later. Therefore, wildfire victims can move to a replacement home without a potential tax penalty, which reduces property tax revenues in the short run. On the other hand, those who sell their house to wildfire victims and purchase a new one might face a higher base year value because of reassessment, which could potentially increase property tax revenues. Ultimately, it is an empirical issue as to which force dominates. To the extent that a number of victims rebuild their properties or if it takes a fair amount of time to purchase a new house, I can expect lower property tax revenues from wildfires in the short run. In the following section, I propose a research design to test if property damages from wildfires have a negative fiscal impact on municipalities.

Another important aspect of property taxation in California is that property taxes are collected at the county level and the state determines the share of revenues allocated to each government entity within the county. But the share of revenues received by each municipality is roughly proportional to the one before Proposition 13 and does not reflect the modern needs [73]. Accordingly, a reduction in revenues from property damages in one municipality can spill over to others due to the largely-fixed allocation system. Therefore, it can be misleading to analyze the fiscal impact of wildfires using entity-level data on finances and damages, which motivates my county-level analysis of the impact of historic wildfires on property tax revenues. Furthermore, I leverage the current-period allocation shares with the county-level climate risks to calculate school district-level future risks, assuming that the system for sharing revenues among governmental entities will largely remain the same in the future.

2.2.2 Data: Historic wildfires and property tax revenues

To estimate the fiscal impact of wildfires on municipal finances, I collect property tax raw data from California State Controller's Office. It contains information on how much general property tax is collected at the county level and how proceeds are allocated across governmental entities within the county each fiscal year. My sample contains the countywide 1% property tax revenues over the fiscal years 2014 (July 1, 2013 - June 30, 2014) to 2022 (July 1, 2021 - June 30, 2022) in 58 counties in California.

This countywide 1% property tax revenue data is merged with the spatial wildfire damage data at the county level. I gather the digital records of structures greater than 120 square feet that have been damaged or destroyed by wildfire events in California since 2013 from the Department of Forestry and Fire Protection (CAL FIRE).[1] I restrict the sample to residential structures that have more than 50% damage, which is classified as "destroyed (>50%)" in the data. I count the number of "destroyed" residential structures in each county during every fiscal year and then divide by the total number of housing units in the county from the American Community Survey to derive countywide historic damage as continuous treatment intensity. I focus on the fires that destroyed more than a certain amount of housing units, which I refer to as "large-scale wildfires." The threshold equals the 75th percentile of county-by-fiscal-year home destruction due to wildfire conditional on having any damages over the fiscal years 2014 - 2022.

[1] CAL FIRE does not have digital records on structures affected by wildfires prior to the calendar year 2013. Therefore, even though California State Controller's Office provides data over the fiscal years 2003 to 2022, I restrict my sample of property tax raw data to the fiscal years 2014 to 2022 to match with the damage inspection data.

2.2.3 Data: Future wildfire risks and municipal credit ratings

The future wildfire risk data in this paper comes from the First Street Foundation-Wildfire Model (FWF-WFM). It is a property-level wildfire risk model that integrates fuels, weather time series, and ignition locations into a fire behavior model, which is validated with the intensity and size of historic records. To predict wildfire risks in 2052, the model uses future weather conditions from the International Panel on Climate Change's (IPCC) Fifth Coupled Model Intercomparison Project (CMIP5) ensemble results following the Representative Concentration Pathway 4.5 (RCP 4.5). The model assigns fire factor scores to each property in the contiguous United States from 1 having no modeled exposure of being in a wildfire to 10 having more than a 36% probability of burning over 30 years.

Aggregated data is available only at the census tract, zip code, county, congressional district, and state levels for non-commercial usage. Using the county-level predictions, I compute the proportion of properties having more than a 36% chance of burning over 30 years to derive the county-level future tax base at risk. I then leverage the property tax allocation data from California State Controller's Office to calculate school district-wide future risks. Assuming that the allocation share will remain largely the same in the future, the county-level tax base at risk is disaggregated at school district levels by multiplying their revenue shares.

School district bond ratings are collected from the California State Treasurer Debt Watch database. The California Debt and Investment Advisory Commission (CDIAC) provides issuance information on all state and local outstanding debt including credit ratings, the source of payment, tax-exempt status, callable status, capital appreciation status, and maturity. I use the numerical transformations of the alphanumerical rating codes by [74], as detailed in the appendix table B.1. I select the bonds issued by K-12 school districts from the data. To use recent wildfire-related property damages from CAL FIRE Damage Inspection Data (DINS) as the source of salience shocks to credit rating agencies, I restrict my sample to bonds issued since 2013. Similar to the analysis of the relationship between tax revenues and historic wildfire events, I focus on the fires that destroyed more than the 75th percentile of county-by-calendar-year property damages conditional on having any positive home destruction over the calendar years 2013 - 2022. Because I utilize the allocation share by the school district to derive continuous treatment intensity, I drop the bonds issued by multiple counties.

2.2.4 Summary statistics

Table 2.1 reports the descriptive statistics using county-level variables (Panel A) and bond-level variables (Panel B). A large-scale wildfire destroyed, on average, about 1% of housing units per county during the event. The average countywide 1% property tax collection was $672 million (in 2012 USD) in the counties without large-scale wildfires versus $1,310 million (in 2012 USD) in the counties with large-scale wildfires. I find that credit ratings are slightly worse for the bonds issued by school districts with salience shocks due to recent large-scale wildfires, compared to the ones without an increase in the awareness of future risks. On average, the underlying future wildfire risks are higher in school districts without salience shocks. The average maturity of school district bonds in my sample is about 20 years, which supports my use of the First Street Foundation-Wildfire Model predictions on the number of properties at risk over the course of the next 30 years.

Panel A: Historic wildfires and property tax revenues

	Counties without wildfires			Counties with wildfires		
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
Countywide property tax (million in 2012 USD)	672	1,056	333	1,310	2,891	189
Share of homes destroyed	0	0	333	0.010	0.012	85

Panel B: An increase in the awareness of future fire risks and municipal credit ratings

	Bonds issued by school districts without shocks			Bonds issued by school districts with shocks		
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
Bond rating	3.345	1.126	1,035	3.588	0.911	672
Future risks	3.427e-4	0.005	1,035	3.101e-4	0.001	672
$\mathbb{I}\{$General fund-based$\}$	0.018	0.134	1,035	0.019	0.138	672
$\mathbb{I}\{$Tax-exempt$\}$	0.148	0.355	1,035	0.208	0.406	672
$\mathbb{I}\{$Callable$\}$	0.833	0.373	1,035	0.790	0.407	672
$\mathbb{I}\{$Capital appreciation$\}$	0.062	0.241	1,035	0.076	0.265	672
Maturity	20.241	8.765	1,035	19.411	9.838	672

Note: This table reports the summary statistics. In panel A, I report summary statistics for county-by-fiscal-year 1% property tax revenue collections and the shares of houses destroyed (conditional on having positive damages). In panel B, I report summary statistics for bond-issuance-level credit ratings, future risks — defined by the countywide proportion of housing units at risk in 2052 weighted by current-period district-wide revenue share, — and characteristics including the source of payment (property tax-based versus general fund-based), tax-exempt status, callable status, capital appreciation bond status, and maturity. The numerical transformation of alphanumerical bond credit ratings is available in the appendix table B.1 — the higher the number is, the worse the rating is. Callable bonds allow issuers to redeem before they reach their stated maturity. With a capital appreciation bond, issuers pay the face value plus years of compounded interest at maturity. On the other hand, with a conventional bond, interest payments are made periodically until maturity.

Table 2.1: Summary statistics

2.3 Identification Strategy

In this section, I describe two identification strategies adopted in this paper — the first is used to the countywide 1% property tax revenue data and the second is applied to the school district bond credit rating data.

2.3.1 Effects of historic wildfires on property tax revenues

My first hypothesis is that historic wildfires reduce countywide 1% property tax revenues. To estimate these effects, I adopt the following event-study research design with a continuous and staggered treatment:

$$\begin{aligned}\ln Y_{ct} &= \alpha_c + \delta_t + \sum_{l=-3,\ l\neq 0}^{2} \beta_l \times \mathbb{I}\{t - \textsc{Event Time}_c = l\} \times \textsc{Historic Damage}_c + u_{ct}, \\ &\text{where } \textsc{Historic Damage}_c = \frac{\text{Number of destruction}_{c,\textsc{Event Time}_c}}{\text{Number of housing units}_{c,\textsc{Event Time}_c - 1}}. \end{aligned} \tag{2.1}$$

Here, Y_{ct} is a countywide 1% tax revenue for county c during the fiscal year t. $\textsc{Event Time}_c$ is the fiscal year when county c initially has a large-scale wildfire, which is defined in the next paragraph. $\textsc{Historic Damage}_c$ is the treatment intensity associated with county c, which is defined as the proportion of housing units destroyed.[2] α_c and δ_t are the county and fiscal year fixed effects, respectively. The coefficients of interest are β_l, which measures the dynamic change in property tax revenues in response to a change in the fraction of home destruction in county c. The sample is trimmed around the event year, which means only observations with $l \in [-3, 2]$ are included.[3]

[2] The numerator is determined by summing the number of destroyed residential structures in county c during its event time from the CAL FIRE DINS data. The denominator equals countywide housing units in the previous year of a large-scale wildfire event from the ACS.

[3] After trimming, 443 out of 522 units are used for estimation.

I focus on the wildfires that destroyed more than a certain (large) amount of residential structures, which I refer to as "large-scale wildfires." The threshold equals the seventy-fifth percentile of county-by-fiscal-year home destruction due to wildfire conditional on having any damages over the fiscal years 2014 - 2022, which is 89 housing units per calendar year in each county. Therefore, Event Time_c is the first fiscal year when county c had home destruction of more than 89 due to wildfires in the sample.

The main identification assumption here is that absent large-scale wildfires, the countywide 1% property tax revenues of both affected and non-affected counties would have evolved similarly. Moreover, the arbitrary nature of wildfires in California makes it unlikely that the timing of wildfires is correlated with other factors that affect countywide property tax revenues. I indirectly assess the plausibility of this common trend assumption by looking at the difference in property tax revenues between the affected and unaffected counties prior to large-scale wildfires.

The coefficients of interest are estimated relative to the baseline effect in the event year — not the first lead of the event time — for two reasons. First, a wildfire incident date varies throughout the year. The State of California's fiscal year runs from July 1 to June 30. When it comes to paying secured property taxes in California, their payments are due in two biannual installments — the first installment is due on November 1 and the second installment is due on February 1. Thus, it is possible that most payments have already been made by the time a wildfire occurs. Second, property owners must file a claim with the county assessor within 12 months from the date of damage, or the time specified in their county ordinance to qualify for disaster property tax relief. Hence, even if a wildfire occurs before the due date for paying the installment of secured property taxes, a reduction in countywide property tax collections may show up later depending on how soon the affected file a claim for tax relief. Therefore, in my preferred specification, I estimate dynamic effects relative to the baseline effect in the event year.

I also employ the following difference-in-differences (DiD) setup with a continuous and staggered treatment to summarize the post-treatment dynamic effects in (2.1):

$$\ln Y_{ct} = \alpha_c + \delta_t + \beta_{\text{DiD}} \times \textsc{Post}_c \times \textsc{Historic Damage}_c + u_{ct}. \tag{2.2}$$

where $\textsc{Post}_c$ is the post-event dummy, which gets assigned the value of one during all the fiscal years "after" the first large-scale wildfire within the sample. Consistent with the regression specification (2.1), I do not include the event time in defining $\textsc{Post}_c$. The rest of the variables are defined the same as (2.1).

2.3.2 Effects of the increased salience of future wildfire risks on municipal bond ratings

My second hypothesis is that the increased salience of future wildfire risks triggered by a reduction of property tax revenues due to a large-scale wildfire has a negative effect on credit ratings. To estimate these effects, I use the following event-study research design with a continuous and staggered treatment:

$$\ln Y_{bdct} = \alpha_d + \delta_t + \sum_{\substack{l=-3,\\ l\neq -1}}^{2} \beta_l \times \mathbb{I}\{t - \textsc{Event Time}_c = l\} \times \textsc{Future Risk}_d + \boldsymbol{X}'_{bdct}\gamma + u_{bdct},$$

where

$$\textsc{Future Risk}_d = \frac{\text{Number of properties at risk}_{c,\text{Mid-Century}}}{\text{Number of properties}_{c,\text{Base Year}}} \times \frac{\text{Tax Revenues}_{d,\textsc{Event Time}_c-1}}{\text{Tax Revenues}_{c,\textsc{Event Time}_c-1}}. \tag{2.3}$$

Here, Y_{bdct} is a credit rating for bond b associated with school district d in county c during the calendar year t. I use the numerical transformations of the alphanumerical rating codes by [74], as detailed in the appendix table B.1. $\textsc{Event Time}_c$ is the calendar year when county c initially has a large-scale wildfire. $\textsc{Future Risk}_d$ is the treatment intensity associated with school district d, which is comprised of (i) a countywide tax base at risks in the future and (ii) the last annual share of revenues before a large-scale wildfire. Note that, in California, property taxes are collected at the county level and redistributed to many local governments within the county at the proportion that was determined during the mid-1970s. Therefore, for (i), I use the First Street Foundation US Climate Wildfire Risk Data to calculate the proportion of properties at risk — with more than a 36% probability of burning over 30 years — by county. For (ii), I use the share of 1% tax revenues distributed to district d in the previous year of its event time from the California State Controller's Office Property Tax raw data, assuming that the share will remain approximately the same in the future as well.[4]

α_d and δ_t are the school district and calendar year fixed effects, respectively. I exclude the first lead of the event year as normalization. The coefficients of interest are β_l, which measures the dynamic change in school district bond ratings in response to a change in the salience of future wildfire risks in district d. I control for other bond characteristics, $\boldsymbol{X}_{bdct}$, which includes the source of payment, tax-exempt status, callable status, capital appreciation status, and maturity. Only observations with $l \in [-3, 2]$ are included in the estimation.[5]

Similar to the regression analysis of property tax revenues, I focus on large-scale wildfires and its threshold equals the seventy-fifth percentile of county-by-calendar-year home destruction due to wildfire conditional on having any damages over the calendar years 2013 - 2022, which is 99 housing units per calendar year in each county. Therefore, $\textsc{Event Time}_c$ is the first calendar year when county c had home destruction of more than 99 due to wildfires in the sample.

[4]The share of revenues received by each municipality is roughly proportional to the one before Proposition 13 [73].

[5]After trimming, 1,351 out of 1,707 units are used for estimation.

The key identification assumption here is that absent the increased salience of future wildfire risks, the credit ratings of newly-issued school district bonds in the counties with recent large-scale wildfires would have evolved similarly to those without such events. In addition, due to the randomness of wildfires, it is unlikely for the timing of wildfires to be correlated with other confounders conditional on observable bond characteristics. I estimate the suggestive evidence of parallel trends by looking at the difference in credit ratings between the affected and unaffected municipal bonds prior to salience shocks.

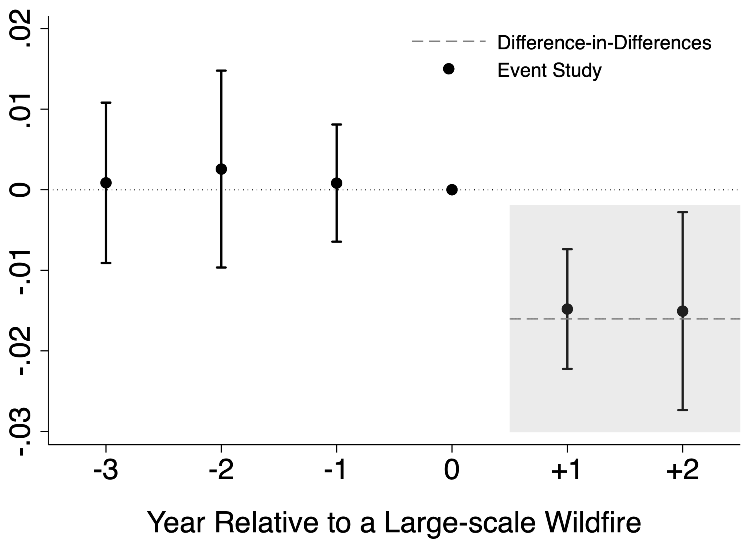
I also employ the following difference-in-differences (DiD) setup with a continuous and staggered treatment to summarize the post-treatment dynamic effects in (2.3):

$$\ln Y_{bdct} = \alpha_d + \delta_t + \beta_{\text{DiD}} \times \textsc{Post}_c \times \textsc{Future Risk}_d + \boldsymbol{X}'_{bdct}\boldsymbol{\gamma} + u_{bdct}. \tag{2.4}$$

where $\textsc{Post}_c$ is the post-event dummy, which gets assigned the value of one during all the calendar years after the first large-scale wildfire within the sample. The rest of the variables are defined the same as (2.1).

2.4 Results

In this section, I explore the fiscal impact of climate-related natural disasters on municipalities and the extent to which capital markets perceive the unfolding future climate risks due to salience shocks using wildfires and school district finance data detailed in section 2.2 and the identification strategies specified in section 2.3.



Note: This figure plots the event study coefficients from the regression specified in equation (2.1) using the county-level panel over the fiscal years 2014-2022. The regression includes the county and fiscal year fixed effects. I summarize the dynamic effects using the difference-in-differences coefficient from the regression specified in equation (2.4). Vertical bars and a shaded area represent 95% confidence intervals based on the standard errors clustered at the county level. Since the regression specifications include a continuous treatment, I rescale the estimate using the average historic damage conditional on having positive damages.

Figure 2.1: Effects of historic wildfires on countywide property tax revenues

2.4.1 Effects of historic wildfires on property tax revenues

To the extent that the victims of wildfires undergo financial hardships from home destruction, I would expect to observe a decline in property tax revenues because (i) homeowners may be delinquent on their taxes or (ii) they may file a claim for tax relief. Figure 2.1 plots the event study coefficients from the regression specified in equation (2.1) and their 95% confidence intervals using the county-level panel over the fiscal years 2014-2022. Since my specification includes a continuous treatment, I rescale the regression estimates using the average treatment intensity conditional on having positive damages. The coefficients measure how property tax revenues dynamically respond to a change in the fraction of home destruction in counties due to large-scale wildfires.

	ln(Property tax revenues)
$\textsc{Post}_c \times \textsc{Historic Damage}_c$	-1.6161
	(0.7100)
%Change	1.6
Observations	443
R^2	0.9996
County Fixed Effects	Yes
Fiscal Year Fixed Effects	Yes

Note: This table reports the estimates of equation (2.2) using the county-level panel over the fiscal years 2014-2022. The regression includes the county and fiscal year fixed effects. Standard errors are clustered at the county level. Since my research design is a difference-in-differences setup with continuous treatment, I rescale the estimate using the average historic damage conditional on having positive damages and calculate the implied percentage change in property tax revenues.

Table 2.2: Effect of historic wildfires on property tax revenues

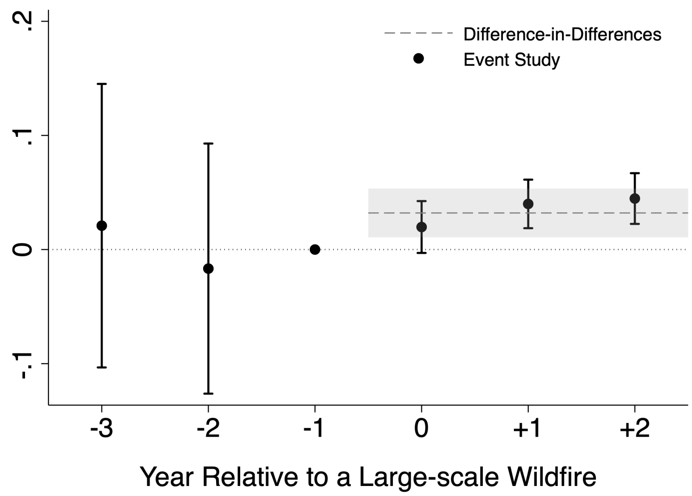
Results show a relatively flat trend of property tax revenues prior to large-scale wildfires relative to the baseline effect during the event year, which indirectly supports my identification assumption. Indeed, the baseline effect during the event year is not statistically discernible from prior effects. As discussed in section 2.3, this could be because wildfires do not necessarily happen at the beginning of the fiscal year (July 1), but rather occur throughout the fiscal year. Moreover, according to Section 170 of the California Revenue and Taxation Code, an application to reassess properties after the damage needs to be submitted within a year. Therefore, depending on when wildfires occur and the associated victims file a claim for tax relief, the fiscal impact of wildfires on municipalities may take a while to show up.

A year after the event time, the regression estimates become persistently negative, which implies that countywide 1% property tax revenues in California start to decline in counties with large-scale wildfires relative to unaffected ones, compared to the fiscal year when fires occur. Table 2.2 reports the DiD estimate, which represents the average of dynamic effects. The coefficient is statistically significant and I see a reduction in property tax revenues by 1.6% among counties in which about 0.99% of housing units are destroyed by wildfires.[6] As discussed in section 2.2, this could be because the victims of wildfires can file a disaster relief to reduce property taxes or postpone their next installment. In addition, even if they purchase a new property, a title transfer may not trigger reassessment and they can retain or transfer the base year value under some conditions. Therefore, these estimates suggest that a reduction in property taxes from affected homeowners dominates a potential increase in the tax base due to the inadvertent reassessment of "locked-in" assessment values from those who sell properties to victims but purchase a new one in the county.

2.4.2 Effects of the increased salience of future wildfire risks on municipal bond ratings

To the extent that credit rating agencies become aware of future wildfire risks due to a recent decline in tax revenues from historic large-scale wildfires, I would expect school districts' credit ratings to decrease. Figure 2.2 plots the event study coefficients from the regression specified in equation (2.3) and their 95% confidence intervals using the bond-level data over the calendar years 2013-2022. Since my specification includes a continuous treatment, I rescale the regression estimates using the average treatment intensity conditional on having positive salience shocks due to recent historic wildfires. The coefficients capture how the credit ratings of school district bonds in California dynamically evolve in response to a change in the salience of future tax base at risks, which is triggered by large-scale wildfires.

[6]Conditional on having positive damages, about 0.99% of housing units in affected counties are destroyed by large-scale wildfires in the sample.



Note: This figure plots the event study coefficients from the regression specified in equation (2.3) using the bond-level data over the calendar years 2013-2022. In addition to the county and fiscal year fixed effects, I control for bond characteristics, including the source of payment, tax-exempt status, callable status, capital appreciation status, and maturity. I summarize the dynamic effects using the difference-in-differences coefficient from the regression specified in equation (2.4). Vertical bars and a shaded area represent 95% confidence intervals based on the standard errors clustered at the county level.

Figure 2.2: Effects of the increased salience of future wildfire risks on municipal bond ratings

I find little evidence that there exist differences in trends of credit ratings prior to salience shocks before the event time. Beginning in the event time, the coefficients become persistently positive, which means that rating agencies lower the credit ratings of affected school districts relative to unaffected ones. I leverage the countywide mid-century tax base at risk with the share of revenues redistributed to each municipality as a source of identifying variation. In table 2.3, I summarize the dynamic effects using the DiD estimate. It is statistically significant and I see an increase in the numeric transformation of alphanumeric ratings by 3.22% among school districts in which about 0.08% of the tax base is at risk of burning over the next 30 years.[7] Note that the higher the number is, the lower the creditworthiness of a newly-issued bond is. Most municipal bonds are

[7]Conditional on having positive damages, about 0.08% of the tax base is exposed to future wildfire risks over the next 30 years in the sample.

	ln(Credit ratings)
$\textsc{Post}_c \times \textsc{Future Risk}_d$	41.5718
	(13.4386)
%Change	3.22
(Reference: Property tax based)	
$\mathbb{I}$\{General fund based\}	0.2158
	(0.0556)
(Reference: Taxable)	
$\mathbb{I}$\{Tax exempt\}	-0.0351
	(0.0219)
(Reference: Not callable)	
$\mathbb{I}$\{Callable\}	-0.0206
	(0.0273)
(Reference: Current interest bond)	
$\mathbb{I}$\{Capital appreciation bond\}	-0.0061
	(0.0176)
Maturity	0.0008
	(0.0009)
Observations	1,351
R^2	0.8454
County Fixed Effects	Yes
Calendar Year Fixed Effects	Yes

Note: This table reports the estimates of equation (2.4) using the county-level panel over the fiscal years 2014-2022. The regression includes the county and fiscal year fixed effects. Standard errors are clustered at the county level. Since my research design is a difference-in-differences setup with continuous treatment, I rescale the estimate using the average future risk conditional on having positive salience shocks due to historic damages and calculate the implied percentage change in credit ratings.

Table 2.3: Effect of historic wildfires on property tax revenues

secured by the taxing authority of issuing municipalities. In addition, school district finances are heavily dependent on local sources including property tax revenue. Thus, recent unprecedented and consecutive large-scale wildfires in California can make rating agencies to become aware of the future wildfire risks of school district bonds, especially for those who are subject to a bigger aggregate countywide risk or for those who receive a larger share of the countywide property tax revenues. Other coefficients on covariates are statistically indistinguishable from zero.

2.5 Conclusion

In this paper, I use municipal finances in California to study the fiscal impact of natural disasters on local governments and the extent to which future climate risks are factored into municipal credit ratings. First, I find that a year after large-scale wildfires, property tax proceeds start to decrease by 1.6% among counties in which about 0.99% of residential structures are destroyed. Second, I uncover that after recent wildfire events, credit ratings worsen by 3.22% among school districts in which about 0.08% of the tax base is at risk of burning over the next 30 years.

These findings imply that municipalities with more climate exposures receive worse credit ratings. Especially in the context of California, municipalities with higher future wildfire risks — usually located in less developed rural areas interfacing fire-prone grasslands — will find it more difficult to finance their projects, leading to a vicious cycle of lower public goods provision. To the extent that climate-related risks are materialized in credit ratings, financial markets can encourage policymakers to take proactive measures in mitigating climate risks to reduce borrowing costs. These findings can be used for prioritizing the allocation of state resources for public adaptation to future climate risks.

Chapter 3

Heterogeneity in the Spending Response to Stimulus: Evidence from the Pulse Survey

Coauthored with Kieran J. Walsh

Summary

The US Census Bureau asked households how they spent stimulus payments over 2020 and 2021. Controlling for many demographic variables, we find that while for the 2020 payments the fraction of mostly-spending households was declining in pre-COVID income, in 2021 this stimulus spending distribution was U-shaped. The theory of [75, 76] offers an explanation for these results: in crisis times, such as 2020, liquidity constraints are binding for poorer households, rendering them anxious to consume, whereas in a normalized economy (2021) many poorer households are anxious to save or service debt due to expenditure shocks.

3.1 Introduction

In response to economic disruptions caused by COVID-19, the US government distributed three Economic Impact Payments (EIPs) to American households over 2020 and 2021. Concurrently, the US Census administered its new Household Pulse Survey (HPS), which contains detailed information on how the pandemic affected the socioeconomic status of households across the nation. The HPS asked households how they used their EIP stimulus checks, and in this paper, we study the heterogeneity in the responses. In 2020 the rate of mostly spending (vs. saving or paying off debt) from an EIP was declining in household income. But in 2021, after the economy had largely recovered, the relationship between spending and income became much flatter and U-shaped, with spending increasing in income over much of the distribution. We explain how the recent expenditure shock theory of [75] offers a simple explanation for both this macro state-dependence of the spending propensity distribution and the exotic shape of the distribution in 2021.

An intuitive idea from consumer theory is the consumption function that is concave and increasing in wealth or income, concavity resulting from borrowing constraints or precautionary saving. As current resources fall, the consumer becomes either less able or less willing to consume more presently. The marginal propensity to consume (MPC) is the derivative of the consumption function, and when consumption is concave, it follows that the MPC is decreasing in wealth or income. Poorer households are more likely to be borrowing-constrained or more concerned about future income fluctuations, leading them to disproportionately reduce current consumption. Hence, poorer households are relatively desperate to consume immediately out of new income. In this world, when faced with a random splash of money (e.g., a government stimulus check), richer households mostly save (in line with the Permanent Income Hypothesis (PIH)). Poorer households were already constrained in their ability to consume and thus consume a higher fraction of the same splash of income. See the top row of Figure 3.1 for a numerical example of this intuitive phenomenon (the full details of this two period model are presented in Section 3.3). With constant relative risk aversion (CRRA) utility and random income in the second period, first period consumption is concave in present income, and the MPC is decreasing in present income (solid lines). With a tight borrowing constraint (dotted lines), consumption concavity and the declining MPC become more pronounced.

Interestingly, a number of recent papers (referenced below) have uncovered evidence seemingly at odds with this standard theoretical MPC distribution in which MPCs decline monotonically with wealth or income. These papers observe MPCs *increasing* in income and, combined with existing evidence on higher MPCs amongst the poor, suggest the potential for a non-monotonic relationship in which higher MPCs come from richer households and the very poor. Looking across papers, it seems possible that "moderately-low-income" households, using the parlance of [76], have the MPCs closest to zero.

We show that this U-shaped cross-household spending propensity distribution arises in the recent HPS. The HPS has surveyed adults across all 50 states and the District of Columbia in weekly or biweekly cross-sectional samples drawn from the Census Bureau's Master Address File to track socioeconomic developments, including consumption/saving/debt behavior, over the course of the COVID pandemic. Central to our paper, many of the survey weeks have contained questions about the use of stimulus checks. However, the U-shape appears only later in the sample, in 2021, after the US economy had substantially recovered. In contrast, during the throes of the COVID economy in 2020, spending propensities are declining in income.[1]

More specifically, for both June-July 2020 and January-July 2021, we first plot the

[1]See [77], [78], and [79] for general analyses of the HPS. [77] and [78] look at 2020 and highlight stimulus spending rates declining in income. In contemporaneous work, [79] examine 2021. Their Table 6 logit regressions reveal the U-shape, but they do not emphasize it, instead stating that "households with higher income are more likely [to] 'mostly spend' the stimulus payment."

fraction of US households reporting "mostly spend" by the 2019 income bin. Spending rates in 2020 are high and decline in income. Spending rates in 2021, in contrast, are much lower, and the distribution is much flatter with a slight U-shape. To control for confounding factors that may explain these patterns, we use the HPS microdata to estimate a linear probability model for the outcome "mostly spend." With numerous demographic controls and state-by-week fixed effects, the same patterns emerge as in the US aggregate plot without controls. For both 2019 and 2020, we reject the hypothesis that the spending rate does not vary by income, and the spending rate is clearly downward sloping in income in 2020. Moreover, in 2021 both the lowest income coefficient and highest income coefficients are statistically significantly higher compared to the reference group of $\$25,000$ to $\$34,999$. Coefficients related to the effect of job loss on spending also flip signs between 2020 and 2021. In short, the effects of demographics on spending out of stimulus did not just change in magnitude going from 2020 to 2021. They also changed qualitatively.

The odd U-shaped spending distribution is a key feature of the consumption theories established in [75] and [76].[2] In the models of these two papers, households face consumption thresholds, which, if violated, yield a utility cost. The idea is that households face a variety of expenditure shocks – education expenses, medical bills, home or car repairs, for example – that impose substantial costs if not serviced. These consumption thresholds, modeled as a kink in the utility function, create a flat portion of the consumption function where the MPC is zero. Households for which consumption thresholds are binding are "saving-constrained" and use additional income to save or delever, as they had previously borrowed or dissaved simply to meet the threshold. At the same time,

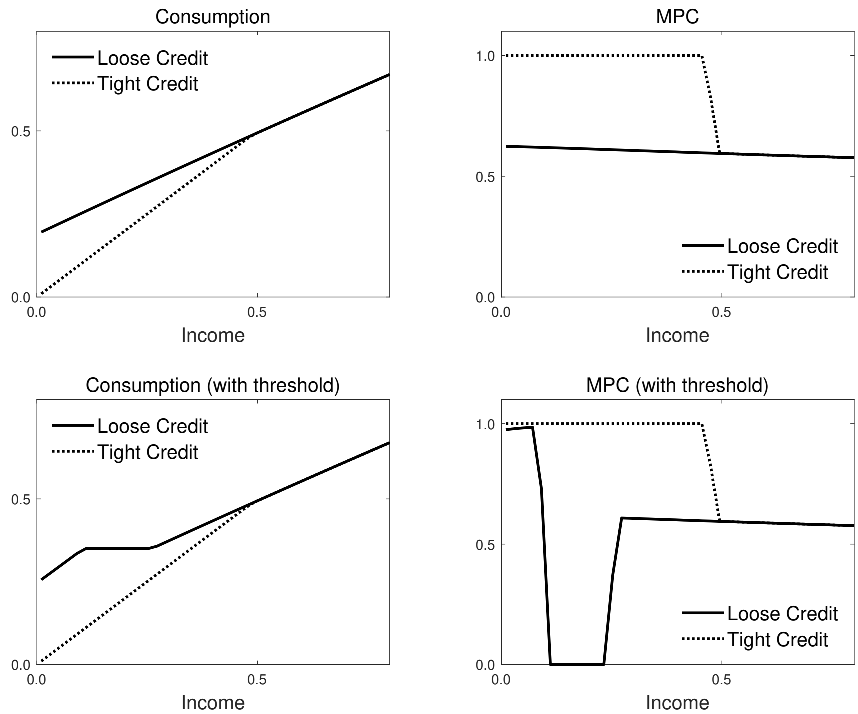
[2]While we use the model of [75] and [76] to interpret the HPS, the present analysis is distinct from those papers. The former is a quantitative, infinite horizon model used to match the joint dynamics of consumption and income in the Panel Study of Income Dynamics, and the latter is about the cross-country relationship between inequality and the interest rate response to fiscal stimulus.

very poor households are borrowing constrained, meaning they have high MPCs, while rich households have moderate MPCs, consistent with the PIH. Thus, the consumption threshold model generates a U-shaped MPC distribution. The bottom row of Figure 3.1 illustrates these cases when credit is loose (solid lines). But in recessions with tight credit, the COVID crisis for example, more households are in the borrowing-constrained portion of the consumption function and tighter borrowing constraints make consumption thresholds harder to meet (bottom row of Figure 3.1 with dotted lines). So in deep recessions the MPC distribution becomes more like the monotonic one from standard consumption theory. Section 3.3 presents a simple two period version of [75] that illustrates these mechanisms.[3]

Our paper relates to the existing literature by presenting new evidence on the spending propensity distribution. Our results indicate a U-shape with respect to income, consistent with the theory of [75]. The potential for this U-shape is discussed in some previous papers. [81] write, in their MPC literature review, "...at least some of the papers document a U-shaped response of consumption to transitory changes both in income and assets. Hence, both the very poor (in terms of income and assets) and the very rich seem to have large consumption responses." Citing the 2001/2008 tax rebate studies of [82] and [83], [84] emphasize that the mostly-spend-rebate fraction of households is U-shaped in stock wealth. And the U-shape is mentioned in footnote 11 of [85]. But all of these authors note the large standard errors in this literature and none takes a firm stance on the U-shape. In contrast, in our 2021 sample with over 205,000 households and a rich set of control variables, our linear probability model regression reveals a

[3]Relatedly, [76] argue that this tension between saving constraints (from their expenditure shock model) and borrowing constraints has important general equilibrium implications at the macro level: in normal times, saving-constrained agents dominate the distribution of households and fiscal stimulus has a muted effect on interest rates. In crises, borrowing-constrained households dominate and fiscal stimulus pushes interest rates up. See also [80] for recent work on the state-dependence of the effects of fiscal policy.

Figure 3.1: See Footnote 12 for parameter values.



statistically significant U-shape in the "mostly spend" fraction by income (in the sense that we reject no difference in spending rates, and the lowest and highest income groups have a significantly larger spend fraction relative to the reference group). Since we are using new data from a new time period and generating precise estimates, our findings lend credence to the hypothetical U-shape only hinted at in previous papers.

While only a few papers directly discuss the U-shape, arguably it also emerges from a general reading of the literature. On one hand, an abundance of papers finds that lower income or lower wealth households have higher spending propensities. See, for example, [86] and [87]. On the other hand, [88] and [89] show MPCs increasing with income, and [90] find both the highest and lowest MPCs concentrated amongst richer households (so moderate MPCs come from the poor). Other papers, [82] and [91] for example, show higher point estimates for higher income households but fail to reject that spending propensities do not differ by income. A theory with a macro state-dependent spending propensity distribution that sometimes has a U-shape – in which moderately-low-income households have low MPCs, very poor households have high MPCs, and wealthy households have moderate MPCs on average – provides a simple explanation for the seemingly contradictory evidence in the literature: the *empirical* shape of the MPC distribution is sensitive to (1) the state of the economy (boom vs. bust) in the particular sample, (2) the part of the income/wealth distribution sampled, and (3) as [90] observe, the exogenous cutoffs used by the researcher to group households.

The expenditure shock model of [75] gives a clear explanation for both what we observe in the HPS as well as the conflicting findings in the previous literature. Additionally, the quantitative analysis of [75] shows that their model performs better than a standard Bewley model (with or without measurement error) in matching the joint dynamics of consumption and income in the post-1999 Panel Study of Income Dynamics (PSID). But there are at least two other possible theoretical explanations for the U-shape. In the model of [84], households face a borrowing constraint and need to save for large periodic expenses on a second good. In their quantitative assessment of the model, the MPC distribution is U-shaped in wealth (they do not show MPCs by income): the poor and rich have the highest MPCs, the former because of the borrowing constraint and the latter because their wealth is tied-up in anticipation of the major expense. Similarly, the model [92] exhibits "wealthy hand-to-mouth" agents, whose wealth is tied-up in an illiquid asset. This setting could in principle generate the U-shape, although its presence is not clear in the calibration of [93] (and they do not show MPCs by income).

Section 3.2 describes the HPS and presents our empirical results. Section 3.3 draws on [75, 76] to offer a simple theoretical explanation for our empirical observations. Section 3.4 links the theory and empirics and discusses the takeaways and limitations of our study.

3.2 Data and Results

The recession caused by COVID-19 led the US government to distribute the three EIPs to American households over 2020 and 2021. Under the Coronavirus, Aid, Relief, and Economic Security (CARES) Act of 2020, tax filers with adjusted gross income (AGI)[4] up to $75,000 for individuals and up to $150,000 for married couples typically received $1,200 and $2,400, respectively. The payment amount decreased by $5 for every $100 above this threshold. Therefore, without qualifying child dependents, the check amount was completely phased out above $99,000 for single filers and $198,000 for joint filers. They could additionally receive $500 for each child dependent; thus, the total phaseout amount increased by $10,000 for each qualifying child dependent.[5] The Internal Revenue Service used the 2018 or 2019 tax returns information to issue payments. The CARES Act was followed by the Consolidated Appropriations Act of 2021 and the American Rescue Plan Act of 2021.[6]

The HPS microdata contains many socioeconomic variables (employment, housing security, household spending, food sufficiency, etc.) that reveal how the pandemic affected the US households. The HPS is designed to construct estimates at three geographical levels—the 15 largest Metropolitan Statistical Areas, the 50 states plus the District of Columbia, and the nation—using the Bureau's Master Address File as the source of sampled housing units. Approximately one million housing units were selected for each wave out of 145 million addresses. About 68,000-108,000 respondents answered questionnaires in the waves used in our study. To generate estimates representative of the US

[4]AGI is the total income that is subject to income tax and is defined as gross income minus specific deductions that each filer is eligible to take. Some examples of deductions include alimony payments, 401k contributions, health savings accounts, and education expenses. In general, AGI is lower than or equal to total gross income.

[5]For example, for joint filers with 3 qualifying child dependents, the phaseout amount was $228,000.

[6]The second check was $600 for individuals and $1,200 for married couples with $600 for each qualifying child dependent. The third check was $1,400 for single filers and $2,800 for joint filers with $1,400 for each qualifying child dependent.

households at the state level, the HPS also provides sampling weights that account for nonresponse and sampling stratification. In interviews conducted from June 11, 2020 to July 21, 2020 (wave 7 to 12) and from January 6, 2021 to July 5, 2021 (wave 22 to 33), the Bureau asked respondents to report how the EIPs changed their consumption and borrowing behavior. We utilize these two sets of pooled cross-sectional waves to examine the evolution of consumer spending responses over time.[7] The main goal of our empirical exercise is to test heterogeneity in consumer spending behavior across various income groups after receiving stimulus payments. Thus, we restrict our sample to respondents who said someone in their household received or were expected to receive a payment. Summary statistics for our sample are in Table 3.1.

The main outcome of interest is reported changes in recipients' consumption behavior. Specifically, the Bureau asked whether a household that received or expected to receive a payment mostly used the stimulus (1) to pay for expenses, (2) to pay off debt or (3) to add to savings. To see how the HPS responses align with consumption theory, we look at a fraction of households in different pre-2020 income groups reporting mostly paying for expenses ("mostly spend"), which we call the average spending rate.

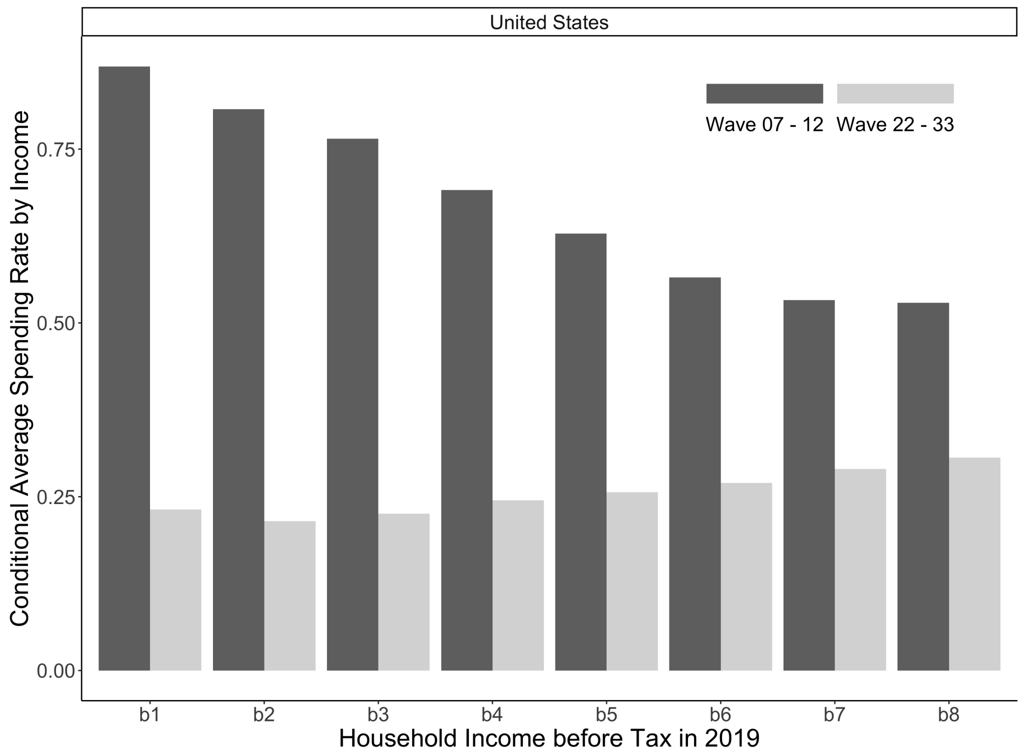
Before turning to our main results, we first plot raw spending rates by income, calculated using the HPS household weights (Figure 3.2). In the summer 2020 interviews (wave 7 to 12), the fraction of households reporting "mostly spend" is decreasing in income. Over 80% of the $< \$25,000$ income group reported "mostly spend," whereas the fraction was less than 60% for the $> \$100,000$ groups. The relationship is monotonic. The 2021 interviews (wave 22 to 33) reveal a completely different distribution of spending by income. In 2021, the spending rates are much lower (all groups less than 40%), the relationship is much flatter, and there is a slight U-shape, with the minimum

[7] A small fraction of respondents repeated surveys for one or two additional weeks from the 7th to 12th waves. Therefore, we only include each respondent's first survey.

	Wave 7 - 12	Wave 22 - 33
	Fraction / Mean	Fraction / Mean
Use of economic impact payments		
Mostly to pay for expenses	0.7168	0.2432
Mostly to pay off debt	0.1558	0.2511
Mostly to add savings	0.1273	0.5058
Household income before taxes in 2019		
Less than $25,000	0.1906	0.1784
$25,000 - $34,999	0.1379	0.1392
$35,000 - $49,999	0.1474	0.1528
$50,000 - $74,999	0.1958	0.2038
$75,000 - $99,999	0.1329	0.1314
$100,000 - $149,999	0.1298	0.1354
$150,000 - $199,999	0.0468	0.0417
$200,000 and above	0.0188	0.0173
Job loss status/expectation		
Had job losses in the last 4 weeks	0.4841	0.410
Expect job losses in the next 4 weeks	0.3343	0.2065
Education		
Less than high school	0.4072	0.3962
Some college/Associate's	0.3150	0.3067
Bachelor's	0.1640	0.1770
Graduate	0.1138	0.1202
Housing tenure		
Owner/occupied without rent	0.2019	0.2385
Mortgage	0.4304	0.4258
Rent	0.3678	0.3357
Currently married	0.4942	0.5128
Hispanic origin	0.1551	0.1656
Race		
White	0.7423	0.7544
Black	0.1507	0.1363
Asian	0.0463	0.0534
Other	0.0607	0.0559
Female	0.5293	0.5395
Age	47.4882	50.2475
Household size	2.9748	2.8702
Number of children in households	0.7426	0.6872
Observations	316,343	205,369

Note: This table reports the summary statistics for the variables used in the regression analysis. Age, household size, and the number of children in households are continuous variables, but the rest are discrete variables.

Table 3.1: Sample summary statistics



Note: b1 = (less than \$25,000), b2 = (\$25,000 - \$34,999), b3 = (\$35,000 - \$49,999), b4 = (\$50,000 - \$74,999), b5 = (\$75,000 - \$99,999), b6 = (\$100,000 - \$149,999), b7 = (\$150,000 - \$199,999), b8 = (\$200,000 and above). This figure plots the proportion of the respondents reporting "mostly spend" by income among households who received or were expected to receive a payment.

Figure 3.2: Average Spending Rate (Fraction Reporting Mostly Spend) Conditional on the 2019 Household Income before Tax

at $\$25,000 - \$34,999$.[8]

But it is difficult to interpret Figure 3.2 due to omitted variables. Pre-2020 income could easily be correlated with many factors affecting subsequent MPCs, such as other demographic variables, exposure to different regional economic developments and government policies, and job loss. This motivates us to account for time-varying state characteristics and other demographics to isolate the association between income and consumption responses.

[8]Online Appendix Figure C.1 shows the same graph for the 50 states and the District of Columbia individually. Many states, Texas and Illinois for example, have figures almost identical to the national one, and nearly all places exhibit the general pattern described.

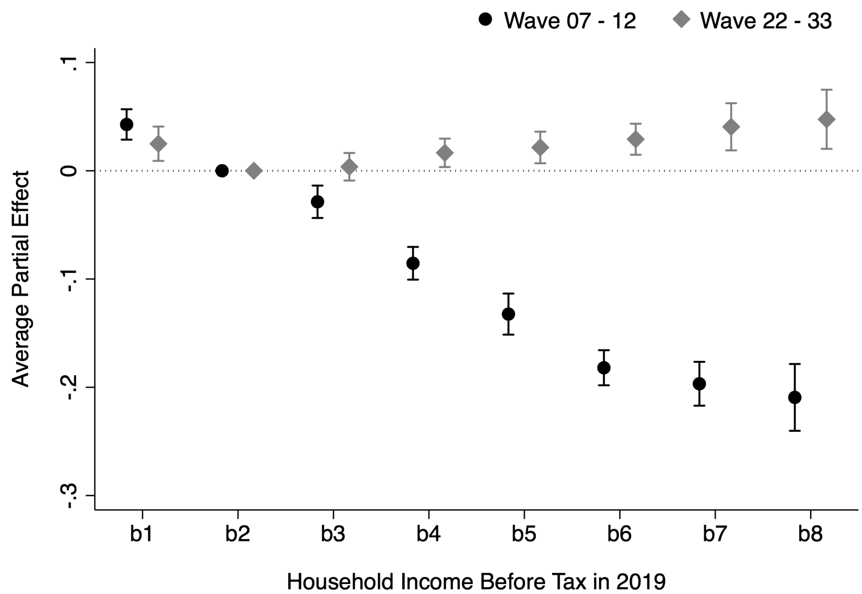
Using the ordinary least squares (OLS) method,[9] we estimate a linear probability model where the dependent variable is one for households that mostly used the stimulus to pay for expenses and zero otherwise:

$$\mathbb{I}\{\text{Mostly Spend}\}_{it} = \alpha + \sum_{g} \beta_g \, \mathbb{I}\{\text{Income Bin} = g\}_{it} + \boldsymbol{\gamma}'\mathbf{X}_{it} + \delta_{s(i)t} + u_{it}, \tag{3.1}$$

where i indexes survey respondents, t refers to the week, and u_{it} is the error term. Our main interest is in using the HPS microdata to uncover how households' consumption responses to fiscal stimulus vary with pre-2020 income (β_g coefficients). Other demographics (X_{it}) include indicators for labor force status, education, housing tenure, marital status, Hispanic origin, race, gender, age, household size, and the number of children in the household.[10] Our specification includes state-by-week fixed effects $\delta_{s(i)t}$ as controls to account for time-varying state-level macroeconomic conditions, COVID-related policies, and other unobservable characteristics. The regression coefficient associated with each covariate measures its average partial effect. All regressions use standard errors clustered at the state level to account for within-state interdependence and are weighted by household weights to be representative at the household level. Table 3.2 presents the OLS estimates.

Figure 3.3 shows the average partial effect of income, along with the 95% confidence interval. We use the second income bin, $\$25,000 - \$34,999$, as a reference. Wave 7 to 12 shows a declining spending propensity with respect to income. The F-test rejects that all income coefficients are equal (p-value = 0.000), and the average partial effects are statistically significant.

[9] The logit regressions yield very similar results.
[10] Summary statistics are in Table 3.1.



Note: b1 = (less than \$25,000), b2 = (\$25,000 - \$34,999), b3 = (\$35,000 - \$49,999), b4 = (\$50,000 - \$74,999), b5 = (\$75,000 - \$99,999), b6 = (\$100,000 - \$149,999), b7 = (\$150,000 - \$199,999), b8 = (\$200,000 and above). This figure plots the average partial effect of an income bin b_i on the probability of reporting "mostly spend." The baseline income category is b_2. Each point corresponds to a coefficient from the regression specification in equation (1). Vertical bars represent 95% confidence intervals based on the standard errors clustered at the state level. The regression includes demographics and state-by-week fixed effects.

Figure 3.3: Average Partial Effect on Spending Rate by 2019 Household Income before Tax

In contrast, wave 22 - 33 exhibits a U-shaped pattern. Again, the F-test rejects that all income coefficients are equal (p-value = 0.000), and the average partial effects are statistically significant (except for the income bin just above the reference). Compared to the households with income between \$25,000 and \$ 34,999, the households with income less than \$25,000 have a spending rate 2 percentage points higher, and the two highest income groups have a spending rate over 4 percentage points higher.

The pattern with respect to household labor force status is also striking. The survey asks respondents whether they had job losses in their household in the past 4 weeks and whether they expect to have job losses in their household in the next 4 weeks. In 2020, among the households that did not expect any job losses in the future, those who indeed had job losses in the past are about 14 percentage points more likely to spend. Moreover, among the households that did not have job losses in the past, those who expect job losses in the future are about 13 percentage points more likely to spend. The average spending rate increases by about 21 percentage points when households both had job losses in the past and expect losses in the future. In 2021, however, the spending rate decreases when households had job losses, while the expectation of job losses in the future and the interaction term are statistically not discernible from zero. This seemingly puzzling evolution in reported consumption behavior also holds for other potential indicators of financial hardship such as education and housing tenure. While the theories of [75, 76] do not explicitly address labor markets or housing, these patterns may also be explained by the tension between borrowing constraints and saving constraints: in crisis times when borrowing constraints are binding, financial hardship leads to higher spending out of stimulus, while in normal times, many struggling households have borrowed to meet consumption thresholds and are anxious to save or repay debt.

	Wave 7 - 12	Wave 22 - 33
	Mostly spend	Mostly spend
Household income before taxes in 2019		
(Reference: \$25,000 - \$34,999)		
Less than \$25,000	0.0428	0.0250
	(0.0071)	(0.0081)
\$35,000 - \$49,999	-0.0286	0.0037
	(0.0076)	(0.0065)
\$50,000 - \$74,999	-0.0855	0.0166
	(0.0077)	(0.0067)
\$75,000 - \$99,999	-0.1324	0.0215
	(0.0096)	(0.0074)
\$100,000 - \$149,999	-0.1820	0.0291
	(0.0082)	(0.0073)
\$150,000 - \$199,999	-0.1968	0.0406
	(0.0103)	(0.0111)
\$200,000 and above	-0.2093	0.0476
	(0.0157)	(0.0139)
Job loss status/expectation in households		
(Reference: Had none and expect none)		
Had losses in the past 4 weeks	0.1417	-0.0185
	(0.0052)	(0.0047)
Expect losses in the next 4 weeks	0.1373	-0.0068
	(0.0102)	(0.0136)
Had losses and expect losses	-0.0736	0.0085
	(0.0117)	(0.0139)
Education		
(Reference: Graduate)		
Less than high school	0.0914	-0.0589
	(0.0058)	(0.0055)
Some college/Associate's	0.0700	-0.0496
	(0.0058)	(0.0051)
Bachelor's	0.0066	-0.0177
	(0.0068)	(0.0053)
Housing tenure		
(Reference: Owner/occupied without rent)		
Mortgage	0.0243	-0.0256
	(0.0050)	(0.0039)
Rent	0.0400	-0.0204
	(0.0060)	(0.0050)

(table continued on next page)

	Wave 7 - 12	Wave 22 - 33
	Mostly spend	Mostly spend
Marital status		
(Reference: Not married)		
Currently married	-0.0049	-0.0006
	(0.0043)	(0.0038)
Hispanic origin		
(Reference: Not hispanic)		
Hispanic	0.0163	-0.0348
	(0.0063)	(0.0061)
Race		
(Reference: White)		
Black	0.0345	-0.0230
	(0.0066)	(0.0053)
Asian	0.0454	0.0637
	(0.0116)	(0.0079)
Other	0.0106	-0.0060
	(0.0076)	(0.0072)
Gender		
(Reference: Male)		
Female	0.0019	-0.0533
	(0.0034)	(0.0039)
Other demographic status		
Age	0.0084	-0.0017
	(0.0007)	(0.0007)
Age^2	-0.0001	3.49e-5
	(7.24e-06)	(7.08e-06)
Household size	0.0051	0.0041
	(0.0016)	(0.0018)
Number of children in households	0.0199	0.0023
	(0.0023)	(0.0026)
State × Week fixed effects	Yes	Yes
Observations	316,343	205,369
R-squared	0.1323	0.0313

Note: This table reports the ordinary least squares estimates of equation (1). The dependent variable is the indicator of individual respondents reporting "mostly spend." The baseline category for each discrete covariate is in parenthesis. Standard errors (in parentheses) are clustered at the state level.

Table 3.2: Pooled regression of economic impact payment usage

3.3 Theory

The evidence in Section 3.2 seems puzzling from the perspective of standard consumption theory. But it turns out a minor and intuitive extension to the standard model generates precisely the patterns we observe in the Pulse Survey. This extension is fully studied in the saving constraint model of [75, 76]. Here we briefly describe and solve a simple numerical example based on this framework.

Suppose households solve the following two-period consumption/saving problem:

$$\max_{c_1, c_{2s}, a'} \left\{ \frac{c_1^{1-\gamma}}{1-\gamma} - \lambda \max(\underline{c} - c_1, 0) + \sum_{s=1}^{S} \pi_s \frac{c_{2s}^{1-\gamma}}{1-\gamma} \right\} \quad \text{subject to} \tag{3.2}$$

$$c_1 + a' = y_1 \tag{3.3}$$

$$c_{2s} = y_{2s} + a' \tag{3.4}$$

$$a' \geq \underline{a}, \tag{3.5}$$

where c_1 and y_1 are first period consumption and income, c_{2s} and y_{2s} are (state-dependent) second period consumption and income, and a' is saving (negative values of a' mean borrowing). There are S possible states in the second period, which correspond to different realizations of income, and π_s is the probability of state $s \in S$. The household chooses initial consumption, state-dependent second period consumption, and saving to maximize expected utility over consumption, subject to the budget constraints (Equations 3.3 and 3.4) and a borrowing constraint (3.5), where $\underline{a} \leq 0$ is the lower bound on a'. Second period flow utility has the CRRA form with risk aversion γ. First period flow utility is the sum of two terms, CRRA utility with risk aversion γ and a proportional cost of consuming below a threshold $\underline{c} \geq 0$: $c_1^{1-\gamma}/(1-\gamma) - \lambda \max(\underline{c} - c_1, 0)$, where $\lambda \geq 0$ governs the strength of the cost.

[75, 76] argue we can think of the consumption threshold as a reduced-form for expenditures on necessities. Car repairs, education expenses, medical bills, home repairs, and family emergencies require the consumption of goods and services and put a lower bound on household spending. Of course, households are not forced to meet these expenses, but ignoring them entails substantial costs (e.g., poor health, inconvenience, car/house depreciation). Moderately-low-income households facing the threshold borrow or dissave just enough to meet the expenditure necessity. These households, in the parlance of [75, 76], are saving-constrained in the sense that (1) without the threshold, they would have consumed less presently and (2) on the margin they entirely save or delever out of additional income. On the other hand, the poorest households need to pay the cost from violating the threshold and thus have very high MPCs. Richer households have lower but non-zero MPCs in line with standard theory.[11]

Figure 3.1 shows the relationship between current income (y_1) and either consumption (c_1) or the MPC ($\Delta c_1/\Delta y_1$) implied by household optimization.[12] Note that in this partial equilibrium framework, there is a one-to-one mapping between current income and liquid wealth, so varying y_1 can be interpreted as varying liquid wealth.

As described in the introduction, the top row of Figure 3.1 shows the solution to Problem 3.2 without consumption thresholds ($\underline{c} = 0$). The solid lines correspond to the case with a loose borrowing constraint ($\underline{a} = -1$), while for the dotted lines we have a tight constraint ($\underline{a} = 0$). Even without a binding borrowing constraint, we see concave consumption and a declining MPC with respect to current income, stemming

[11] Here, we are using the saving constraint model to understand the MPC distribution. While the model is taken from [75, 76], the applications in those papers are quite different, and the present theory is much simpler. [75] calibrate and solve an infinite horizon version of the model with stochastic thresholds in order to explain the joint dynamics of income and consumption in micro panel data. [76] solve a general equilibrium version of the model to explain cross-country heterogeneity in the interest rate response to fiscal stimulus.

[12] For our numerical example, we set $\gamma = 2$, $\lambda = 100$, $\underline{c} \in \{0, 0.35\}$, and $\underline{a} \in \{-1, 0\}$. y_{2s} is equally likely to be 0.3, 1, or 1.3, and we consider 50 different values for y_1, equally-spaced between 0.01 and 1. Therefore, in calculating the MPC, $\Delta y_1 \approx 0.02$.

from precautionary saving. With the tight borrowing constraint, consumption concavity is more pronounced and the MPC rises to one below the income level where borrowing would have begun (≈ 0.5). The bottom row of Figure 3.1 uses the same parameters as the top row, except with $\underline{c}$ pushed up from 0 to 0.35. With the loose borrowing constraint (solid lines), the MPC by income follows a U-shape, and there is a flat portion of the consumption corresponding to moderately-low-income. But now, when the borrowing constraint tightens, the shapes of consumption and the MPC drastically change. The saving-constrained households become borrowing-constrained (they are unable to borrow enough to get above the consumption threshold), consumption becomes concave again, and the MPC is declining in income.

3.4 Discussion

Our model, the bottom row of Figure 3.1, sheds light on two features of the Pulse Survey. The first is the U-shaped spending propensity distribution post-2020. The second is the contrast of this pattern with the spending propensity distribution in the middle of 2020. There was a deep recession in 2020, with a dramatic spike in unemployment and a fall in real GDP in the first half of the year. And as Online Appendix Figure C.2 shows, there was an extremely large decline in consumer credit over March-May 2020. While it is difficult to precisely decompose the collapse of credit into supply and demand effects, economists within the Federal Reserve System have argued there was a tightening of consumer lending standards.[13] And in the Federal Reserve Board's July 2020 Senior Loan Officer Opinion Survey on Bank Lending Practices, banks on net reported tightening lending standards for all categories of household credit in the second quarter of 2020.[14] The general decline in incomes pushes more households left along their consumption

[13] See, for example, [94], [95], and [96].

[14] https://www.federalreserve.gov/data/sloos/sloos-202007.htm

functions (although recall that in the Pulse Survey household income is pre-pandemic), moving households into the credit-constrained region with high MPCs. The lower supply of credit renders more households credit-constrained vs. saving-constrained, as borrowing to meet the consumption threshold becomes more difficult. The result is a cross-household pattern of spending propensities declining with income, as in the standard model. But by 2021, the economy had substantially normalized, with a rapid fall in unemployment and a quick recovery of real GDP. The non-crisis economy with recovered incomes moves households away from credit constraints, allowing them to once again meet consumption thresholds. The result is the normal-times U-shaped MPC distribution.

In summary, our analysis, which is based on the large and nationally representative HPS, reveals that heterogeneity in the response to the stimulus was strikingly different in 2021 vs. 2020. While the 2020 response was roughly consistent with standard theory, with spending clearly declining in income, the distribution of spending propensities in 2021 was much flatter and slightly U-shaped. We argue that the U-shape is explained by the recent theories of [75, 76], in which many lower income households are eager to repair their balance sheets that are damaged by spending on necessities. And we suggest there was no U-shape in 2020 because the deep recession made it difficult to satisfy necessities, rendering households anxious to spend.

The MPC distribution is central to the propagation of fiscal and monetary shocks, and it informs policymakers about the needs and challenges of households. Our results lend support to a growing literature suggesting that spending out of stimulus is not always monotonically decreasing in income, and we show that the distribution of household spending behavior can vary greatly with the state of the macroeconomy. We have emphasized one particular new theory, but our broader point is that theorists and policymakers should take seriously the possibility of both the low-MPC poor and a strongly state-dependent MPC distribution.

Appendix A

Appendix for Chapter 1

A.1 Regularity conditions on damage function

Given any $(T, E^H) \in \mathbb{R}^2_+$, if $\eta_h \geq 1$, $\rho_h \in [0, \eta_h]$, and γ_h is small enough,

$$
\begin{aligned}
\frac{\partial h(T,E^H)}{\partial T} &= \omega \cdot \frac{2\gamma_h T}{(1+\gamma_h T^2)^{2-\rho_h}} \left(\omega \cdot \left(\frac{1}{1+\gamma_h T^2}\right)^{1-\rho_h} + [1-\omega] \cdot \left(\epsilon E^H\right)^{1-\rho_h}\right)^{\frac{1-\eta_h}{1-\rho_h}-1} \\
&> 0 \\
\frac{\partial^2 h(T,E^H)}{\partial (T)^2} &= 2\omega\gamma_h \left(\omega \cdot \left(\frac{1}{1+\gamma_h T^2}\right)^{1-\rho_h} + [1-\omega] \cdot \left(\epsilon E^H\right)^{1-\rho_h}\right)^{\frac{1-\eta_h}{1-\rho_h}-2} \\
&\quad \times \left[\frac{1+\omega\gamma_h T^2\,(2\eta_h - 3)}{(1+\gamma_h T^2)^{4-2\rho_h}} + [1-\omega] \cdot \frac{1+\gamma_h T^2(-3+2\rho_h)}{(1+\gamma_h T^2)^{1+\rho_h}} \cdot (\epsilon E^H)^{1-\rho_h}\right] \\
&> 0 \\
\frac{\partial h(T,E^H)}{\partial E^H} &= -[1-\omega] \cdot \frac{\epsilon}{(\epsilon E^H)^{\rho_h}} \left(\omega \cdot \left(\frac{1}{1+\gamma_h T^2}\right)^{1-\rho_h} + [1-\omega] \cdot \left(\epsilon E^H\right)^{1-\rho_h}\right)^{\frac{1-\eta_h}{1-\rho_h}-1} \\
&< 0 \\
\frac{\partial^2 h(T,E^H)}{\partial (E^H)^2} &= [1-\omega] \cdot \frac{\epsilon^2}{(\epsilon E^H)^{1+\rho_h}} \left(\omega \cdot \left(\frac{1}{1+\gamma_h T^2}\right)^{1-\rho_h} + [1-\omega] \cdot \left(\epsilon E^H\right)^{1-\rho_h}\right)^{\frac{1-\eta_h}{1-\rho_h}-2} \\
&\quad \times \left[\rho_h \cdot \omega \cdot \left(\frac{1}{1+\gamma_h T^2}\right)^{1-\rho_h} + \eta_s [1-\omega] \cdot \left(\epsilon E^H\right)^{1-\rho_h}\right] \\
&> 0 \\
\frac{\partial^2 h(T,E^H)}{\partial T \partial E^H} &= -[\eta_h - \rho_h] \cdot \omega \cdot [1-\omega] \cdot \frac{2\gamma_h T}{(1+\gamma_h T^2)^{2-\rho_h}} \cdot \frac{\epsilon}{(\epsilon E^H)^{\rho_h}} \\
&\quad \times \left(\omega \cdot \left(\frac{1}{1+\gamma_h T^2}\right)^{1-\rho_h} + [1-\omega] \cdot \left(\epsilon E^H\right)^{1-\rho_h}\right)^{\frac{1-\eta_h}{1-\rho_h}-2} \\
&< 0
\end{aligned}
$$

A.2 Climate damage functions in the literature

The specification in section 1.3 nests a wide range of damage functions that have been used to study the role of adaptation in the literature.

1. When $\rho_h \to 1$, the environmental quality Q becomes multiplicative [19, 21, 22, 97, 24, 34, 28];

$$h(T, E^H) = \frac{1}{\eta_h - 1}\left(\left(\frac{1}{1+\gamma_h T^2}\right)^{\omega}\left(\epsilon E^H\right)^{1-\omega}\right)^{1-\eta_h}.$$

2. When $\rho_h \downarrow 0$, the environmental quality Q becomes additive [98, 99]:

$$h(T, E^H) = \frac{1}{\eta_h - 1}\left(\omega\left(\frac{1}{1+\gamma_h T^2}\right) + [1-\omega]\left(\epsilon E^H\right)\right)^{1-\eta_h}.$$

3. When $\rho_h \uparrow \eta_h$, the climate impacts h become separable in T and E^H;

$$h(T, E^H) = \frac{\omega}{\eta_h - 1}\left(\frac{1}{1+\gamma_h T^2}\right)^{1-\eta_h} + \frac{1-\omega}{\eta_h - 1}\left(\epsilon E^H\right)^{1-\eta_h}.$$

A.3 Proof for proposition 3

Consider the planner's problem in Section 1.3. It follows from the Envelope theorem that

$$\frac{\partial W_t}{\partial K_t} = v'(C_t)\left[1-\delta+\frac{\partial Y_t}{\partial K_t^Y}\right], \quad \text{and} \qquad \text{(Envelope condition for } K_t\text{)}$$

$$\frac{\partial W_t}{\partial S_t} = -\left[\theta\cdot\frac{\partial h(T_t,E_t^H)}{\partial T_t}+[1-\theta]\cdot\frac{dg(T_t)}{dT_t}\right]\zeta+v'(C_t)\frac{\partial Y_t}{\partial T_t}\zeta+\beta\frac{\partial W_{t+1}}{\partial S_{t+1}}. \qquad \text{(Envelope condition for } S_t\text{)}$$

Given $i\in\{R,D\}$, let $\mathcal{S}_i := \kappa_i(E_t^i)^{\frac{\sigma_e-1}{\sigma_e}} / \left[\kappa_R(E_t^R)^{\frac{\sigma_e-1}{\sigma_e}}+\kappa_D(E_t^D)^{\frac{\sigma_e-1}{\sigma_e}}\right]$. Using the envelope condition for K_t, the first order conditions can be written as follows;

$$\begin{aligned}
v'(C_t) &= \beta v'(C_{t+1})\left[1-\delta+\frac{\partial Y_{t+1}}{\partial K_{t+1}^Y}\right],\\
-\frac{\partial Y_t}{\partial L_t^Y}+\frac{\partial Y_t}{\partial E_t^Y}E_t\mathcal{S}_D\frac{1}{E_t^D}\frac{\partial E_t^D}{\partial L_t^D} &= -\beta\frac{1}{v'(C_t)}\frac{\partial W_{t+1}}{\partial S_{t+1}}\vartheta_t\frac{\partial E_t^D}{\partial L_t^D},\\
-\frac{\partial Y_t}{\partial L_t^Y}+\frac{\partial Y_t}{\partial E_t^Y}E_t\mathcal{S}_R\frac{1}{E_t^R}\frac{\partial E_t^R}{\partial L_t^R} &= 0,\\
-\frac{\partial Y_t}{\partial K_t^Y}+\frac{\partial Y_t}{\partial E_t^Y}E_t\mathcal{S}_D\frac{1}{E_t^D}\frac{\partial E_t^D}{\partial K_t^D} &= -\beta\frac{1}{v'(C_t)}\frac{\partial W_{t+1}}{\partial S_{t+1}}\vartheta_t\frac{\partial E_t^D}{\partial K_t^D},\\
-\frac{\partial Y_t}{\partial K_t^Y}+\frac{\partial Y_t}{\partial E_t^Y}E_t\mathcal{S}_R\frac{1}{E_t^R}\frac{\partial E_t^R}{\partial K_t^R} &= 0, \qquad \text{and}\\
-\frac{\partial h(T_t,E_t^H)}{\partial E_t} &= v'(C_t)\frac{\partial Y_t}{\partial E_t^Y}.
\end{aligned}$$

Now, consider the competitive equilibrium. It follows from the Envelope theorem that

$$\frac{\partial V_t}{\partial K_t} = v'(C_t)[1+r_t]. \qquad \text{(Envelope condition for } K_t\text{)}$$

Using the envelope condition for K_t, the first order conditions can be written as follows;

$$
\begin{aligned}
[p_t^i - \tau_t^i]\,\frac{\partial E_t^i}{\partial K_t^i} &= r_t + \delta \quad \forall i \in \{R, D\},\\
[p_t^i - \tau_t^i]\,\frac{\partial E_t^i}{\partial L_t^i} &= w_t \quad \forall i \in \{R, D\},\\
p_t E_t \mathcal{S}_i \frac{1}{E_t^i} &= p_t^i \quad \forall i \in \{R, D\},\\
\frac{\partial Y_t}{\partial K_t^Y} &= r_t + \delta,\\
\frac{\partial Y_t}{\partial L_t^Y} &= w_t,\\
\frac{\partial Y_t}{\partial E_t^Y} &= p_t,\\
v'(C_t) &= \beta v'(C_{t+1})[1 + r_{t+1}], \qquad \text{and}\\
-\frac{\partial h(T_t, E_t^H)}{\partial E_t} &= v'(C_t) p_t.
\end{aligned}
$$

By substituting prices, the first order conditions can be rewritten as follows:

$$
\begin{aligned}
v'(C_t) &= \beta v'(C_{t+1}) \left[1 - \delta + \frac{\partial Y_{t+1}}{\partial K_{t+1}^Y}\right],\\
-\frac{\partial Y_t}{\partial L_t^Y} + \frac{\partial Y_t}{\partial E_t^Y} E_t \mathcal{S}_D \frac{1}{E_t^D}\frac{\partial E_t^D}{\partial L_t^D} &= \tau_t^D \frac{\partial E_t^D}{\partial L_t^D},\\
-\frac{\partial Y_t}{\partial L_t^Y} + \frac{\partial Y_t}{\partial E_t^Y} E_t \mathcal{S}_R \frac{1}{E_t^R}\frac{\partial E_t^R}{\partial L_t^R} &= \tau_t^R \frac{\partial E_t^R}{\partial L_t^R},\\
-\frac{\partial Y_t}{\partial K_t^Y} + \frac{\partial Y_t}{\partial E_t^Y} E_t \mathcal{S}_D \frac{1}{E_t^D}\frac{\partial E_t^D}{\partial K_t^D} &= \tau_t^D \frac{\partial E_t^D}{\partial K_t^D},\\
-\frac{\partial Y_t}{\partial K_t^Y} + \frac{\partial Y_t}{\partial E_t^Y} E_t \mathcal{S}_R \frac{1}{E_t^R}\frac{\partial E_t^R}{\partial K_t^R} &= \tau_t^R \frac{\partial E_t^R}{\partial K_t^R}, \qquad \text{and}\\
-\frac{\partial h(T_t, E_t^H)}{\partial E_t} &= v'(C_t) \frac{\partial Y_t}{\partial E_t^Y}.
\end{aligned}
$$

Two sets of the first order conditions from planning problem and competitive equilibriums are equivalent if and only if

$$\tau_t^R = 0 \quad \text{and} \quad \tau_t^D = -\,\beta \frac{1}{v'(C_t)} \frac{\partial W_{t+1}}{\partial S_{t+1}} \vartheta_t.$$

Using the envelope condition for S_t and iteration, τ_t^D can be rewritten as follows:

$$\tau_t^D = \begin{cases} \frac{1}{v'(C_t)} \sum_{s=t+1}^{\infty} \beta^{s-t} \left(\frac{dg(T_s)}{dT_s} - v'(C_s) \frac{\partial Y_s}{\partial T_s} \right) \zeta \vartheta_t & \text{if } \theta = 0 \\ \frac{1}{v'(C_t)} \sum_{s=t+1}^{\infty} \beta^{s-t} \left(\frac{\partial h(T_s, E_s^H)}{\partial T_s} - v'(C_s) \frac{\partial Y_s}{\partial T_s} \right) \zeta \vartheta_t & \text{if } \theta = 1 \end{cases} \qquad \forall t = 0, 1, \cdots$$

■

A.4 Computation

The main computational challenge in my setting is that atmospheric carbon concentrations do not stabilize over time because carbon stock does not depreciate in a linear warming model. Furthermore, productivities systematically evolve over time. Therefore, associated value and policy functions depend on state and time. Moreover, it is impossible to convert this environment into a stationary one using labor augmenting technological progress because climate change is inversely related to utility in a quadratic fashion. To solve this problem, I combine the Extended Function Path approach by [100] with the Envelope Condition Method by [101] and [102]. [100] show that if we are interested in the evolution of an infinite-horizon nonstationary economy during the first t_0 periods, we can approximate its solution by solving a truncated problem. This method relies on the turnpike theorem that the convergence of a truncated economy to the corresponding infinite-horizon one is insensitive to a large enough terminal date (T) and specific terminal conditions.

In this paper, I derive the optimal Pigouvian carbon taxes with adaptation towards the end of this century ($t_0 = 17$). I set a large enough terminal period $T = 100$ (500 years) to reduce approximation errors. I assume technological progress becomes stationary in the terminal period T and constructs a stationary solution. Given the terminal conditions, I solve the Bellman equations by backward inductions and construct a sequence of time-inhomogeneous policy functions. Starting from an observable initial state, I simulate the economy forward and derive the optimal carbon taxes with adaptation.

Appendix B

Appendix for Chapter 2

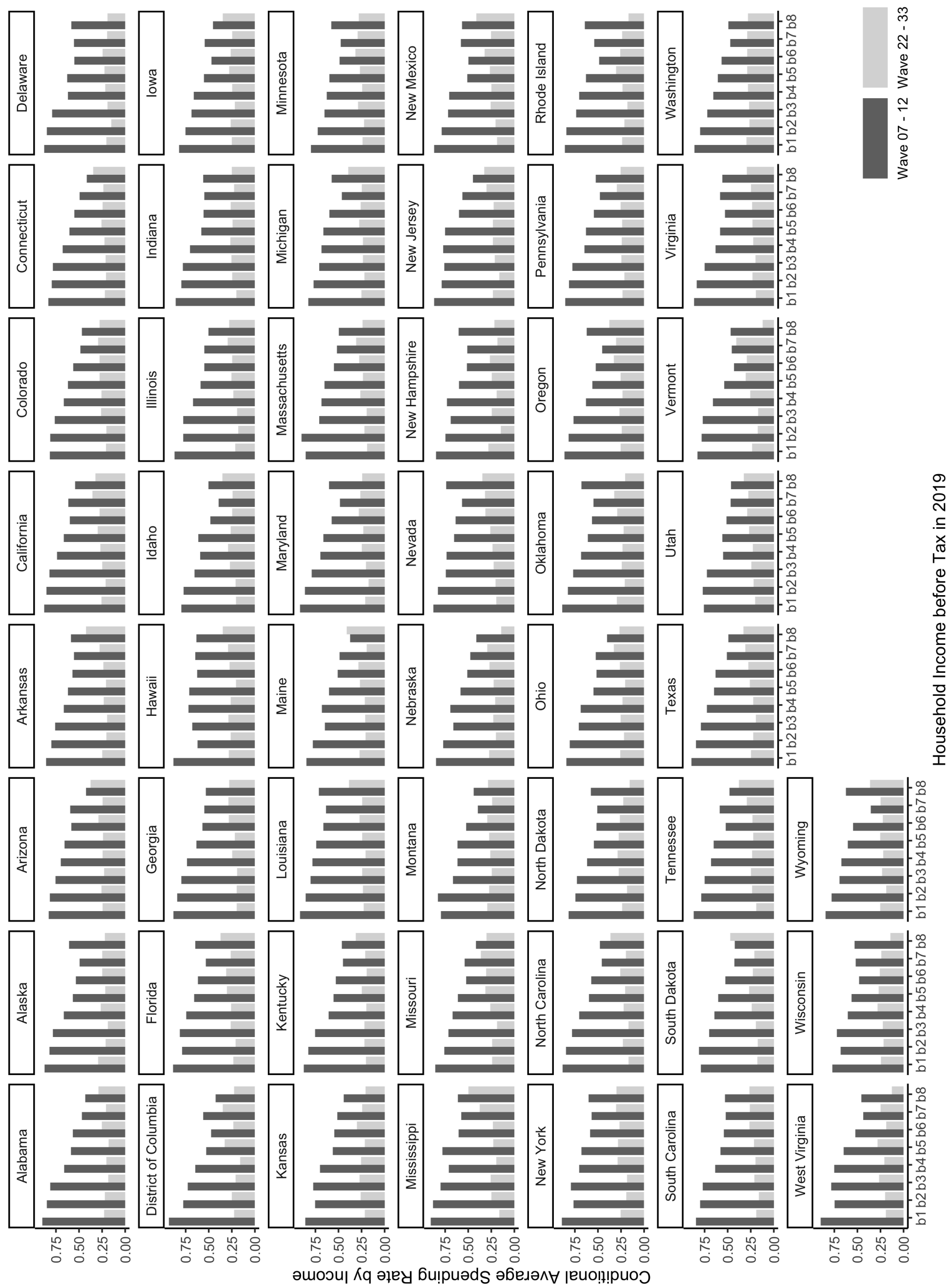
Credit rating	Moody's	Standard & Poor's	Fitch	Numerical code
Highest grade	Aaa	AAA	AAA	1
	Aa1	AA+	AA+	2
High grade	Aa2	AA	AA	3
	Aa3	AA-	AA-	4
	A1	A+	A+	5
Upper medium grade	A2	A	A	6
	A3	A-	A-	7
	Baa1	BBB+	BBB+	8
	Baa2	BBB	BBB	9
	Baa3	BBB-	BBB-	10
Non-investment grade	Ba1	BB+	BB+	11
	Ba2	BB	BB	12
	Ba3	BB-	BB-	13
	B1	B+	B+	14
Low grade	B2	B	B	15
	B3	B-	B-	16
	Caa1	CCC+	CCC+	17
	Caa2	CCC	CCC	18
	Caa3	CCC-	CCC-	19
	Ca	CC	CC	20
	C	C	C	21
Default	N/A	D	DDD/DD/D	22

Note: From "Impact of the Dodd-Frank Act on Credit Ratings," by V. Dimitrov, D. Palia, and L. Tang, 2015, Journal of Financial Economics, 115, p. 519 (https://doi.org/10.1016/j.jfineco.2014.10.012).

Table B.1: Numerical transformation of alphanumeric rating codes

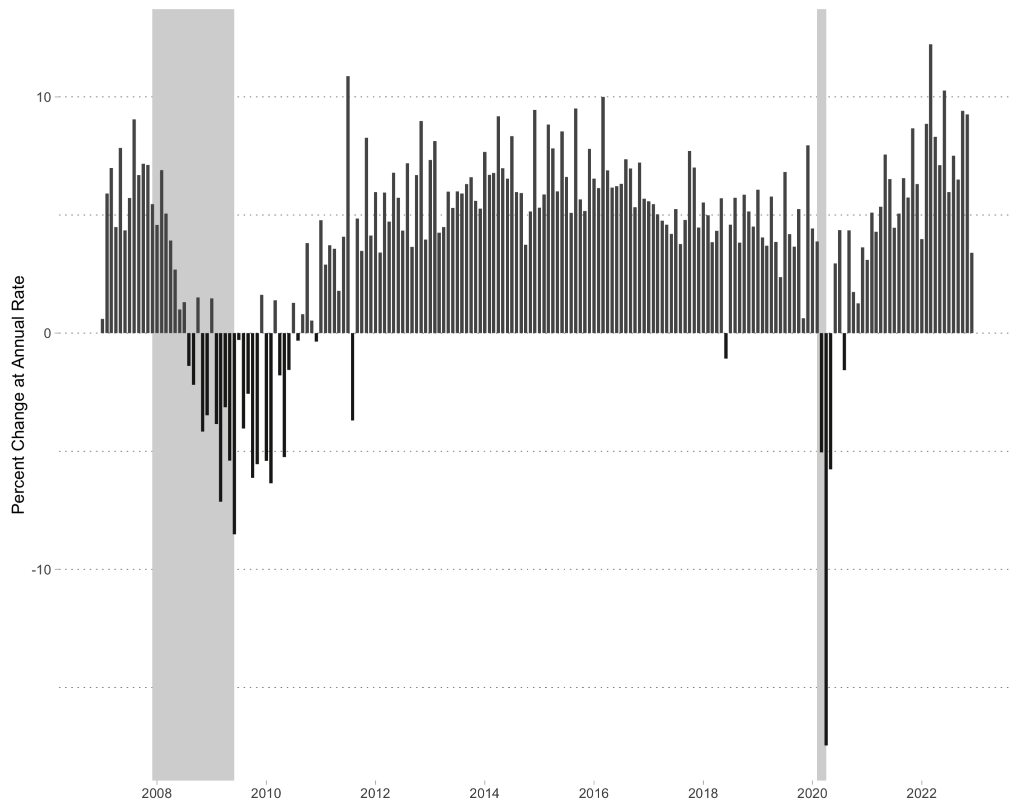
Appendix C

Appendix for Chapter 3



Note: b1 = (less than \$25,000), b2 = (\$25,000 - \$34,999), b3 = (\$35,000 - \$49,999), b4 = (\$50,000 - \$74,999), b5 = (\$75,000 - \$99,999), b6 = (\$100,000 - \$149,999), b7 = (\$150,000 - \$199,999), b8 = (\$200,000 and above). This figure plots the proportion of the respondents reporting "mostly spend" by income among households who received or were expected to receive a payment for each state and the District of Columbia.

Figure C.1: **FOR ONLINE APPENDIX** Conditional Average Spending Rate by 2019 Household Income before Tax



Note: Shaded area represents recession as determined by the National Bureau of Economic Research (NBER).
Source: Board of Governors of the Federal Reserve System (US), Percent Change of Total Consumer Credit [TOTALSLAR], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/TOTALSLAR, May 4, 2023.

Figure C.2: **FOR ONLINE APPENDIX** Annualized Monthly Percent Change in Consumer Credit

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