Fiscal Costs of Climate Change in the United States

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In progress. Comments welcome!

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Abstract

This paper explores the fiscal impacts of climate change and their policy implications for the United States. I develop and empirically quantify a climate-macroeconomic model where climate change can affect (i) government consumption requirements (e.g., healthcare), (ii) transfer payments (e.g., income support), (iii) tax revenues, and where (iv) adaptation to sea level rise (e.g., sea walls) must be publicly financed. First, the paper presents a novel bottom-up quantification of fiscal costs based on literature synthesis and an empirical analysis of public healthcare costs associated with extreme temperatures and wildfires. Climate change is projected to increase total government consumption (transfer) requirements by around 1.45% (0.3%) by mid-century in a high emissions scenario, with healthcare accounting for the majority of cost increases. Second, I show theoretically that the social cost of carbon must account for climate impacts on both government consumption and household transfer payments if the marginal cost of public funds exceeds unity. Finally, the numerical results indicate that fiscal considerations are of first order importance for climate policy design. The elasticity of the social cost of carbon with respect to government consumption (transfer) impacts per degree warming is estimated to be around 20 (10). Accounting for fiscal considerations moreover increases the projected domestic U.S. welfare benefits of climate policy by up to a factor of three.

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1 Introduction

Climate change is increasingly recognized as a fiscal risk for many governments (CBO, 2021a; GAO, 2019; IMF, 2008). Public finances may be exposed to climate change in numerous ways, including through existing program costs (e.g., disaster assistance, healthcare), the need for publicly funded adaptation (e.g., coastal protective infrastructure), and revenue yields due to climate change impacts on aggregate production. While neither standard integrated assessment models used to estimate the social cost of carbon (e.g., DICE, Nordhaus, 1992, 2017; FUND, Anthoff and Tol, 2014, etc.) nor recent empirical damage aggregates such as by Hsiang et al. (2017) consider or distinguish fiscal costs as such, they may contribute to the overall costs of climate change. First, some fiscal costs amount to resource losses. For example, while climate health impacts are often quantified based on mortality effects and the value of statistical life (e.g., Anthoff and Tol, 2014; Hsiang et al., 2017), climate change may also increase public healthcare costs. Second, governments typically raise revenues with *distortionary* taxes (e.g., payroll levies which make it more expensive for firms to hire workers). Raising or diverting public funds from such taxes to deal with climate change is socially extra costly. Third, fiscal constraints may result in lower adaptation funding - and thus higher climate change vulnerability - than anticipated by standard models. Consequently, consideration of fiscal impacts may alter both the social cost of carbon and the welfare impacts of climate policy.

This paper explores the policy and welfare implications of climate change's fiscal impacts. First, I present a novel bottom-up quantification of climate change impacts on existing public program costs by synthesizing prior estimates for different programs (e.g., hurricane-related public spending, crop insurance subsidies, etc.), and by empirically analyzing potential climate change impacts on public healthcare expenditures due to extreme heat, cold, and wildfire smoke events. I use these estimates to construct a fiscal climate damage function. The current benchmark results suggest that existing program cost changes will increase total U.S. (federal, state, and local) government consumption requirements by approximately 1.45% and transfers by at least 0.3% by mid-century in a business-as-usual emissions scenario. Healthcare costs are the largest contributor to these changes. Next, for publicly funded adaptation, I focus on sea level rise protection options as quantified by the U.S. Environmental Protection Agency's Coastal Property Model (Neumann et al., 2014a,b). Adding optimized adaptation expenditures increases the total government consumption impacts to over +1.5% by mid-century.

Second, this paper develops a climate-macroeconomic model which extends prior literature by allowing for fiscal impacts. I specifically build on the dynamic general equilibrium climate-economy model with linear distortionary taxes and government spending of Barrage (2020a) and introduce several new channels which allow the climate to affect (i) government consumption requirements, (ii) government transfers to households, and (iii) endogenous public adaptation expenditures. In addition, (iv) revenue impacts arise endogenously due to both production impacts of climate change and capital depreciation impacts of sea level rise. I use the model to analyze the theoretical and quantitative implications of fiscal climate costs for the U.S. economy.

Theoretically, I show that the social cost of carbon must account for fiscal costs. Government consumption requirement increases ought to be internalized analogously to private output losses. Perhaps surprisingly, if revenues are raised with distortionary taxes, the social cost of carbon must further account for the effects of climate change on government *transfers* to households, and the associated changes in the set of equilibria that can be decentralized as a competitive equilibrium. The theoretical setup also indicates that the welfare costs of raising public revenues distort the optimal provision of adaptation to reduce the non-market impacts of climate change (e.g., damages to national parks), but not adaptation to reduce production or capital impacts (e.g., protection of infrastructure). Intuitively, while it is costly to raise revenues to fund these measures, they effectively 'pay for themselves' by increasing aggregate productivity.[1]

Finally, the numerical results are as follows. In the near term, total public expenditures due to climate change are projected to rise from an estimated undiscounted 10-year total of $245 billion in the 2020s to $412 billion in the 2030s and almost $1 trillion in the 2050s ($2012), with the majority coming from existing program cost increases. As these benchmark estimates are subject to fundamental uncertainties, I quantify the social cost of carbon (SCC) under a range of fiscal cost estimates. The results imply an elasticity of the SCC with respect to government consumption requirement (transfer) impacts per degree warming of around 20 (10). That is, a one percent increase in government consumption (transfers) per degree warming translates into a +20% (+10%) increase in the U.S. SCC.[2] The domestic welfare benefits of imposing U.S. carbon pricing are found to be substantial and significantly larger once fiscal considerations are taken into account. The benefits of domestic carbon pricing are projected to increase from around $342-508 billion in a setting without distortionary taxation (in initial period lump-sum consumption equivalent variation, $2012) to between $406-$1,771 billion in a setting with distortionary taxation. That is, the fiscal setting may increase the welfare benefits of carbon pricing by up to a factor of three. Intuitively, this is because the benefits of carbon taxes in terms of both revenues raised and climate damages avoided are valued more highly when public funds are scarce. In sum, these results highlight the importance of fiscal considerations for climate policy design.

[1] This result reflects the well-known property that optimal tax systems should maintain aggregate production efficiency under fairly general conditions (Diamond and Mirrlees, 1971). See also Judd (1999) on public capital inputs to production under distortionary taxation.

[2] The estimated increase in the benchmark optimal carbon price due to fiscal costs is quantitatively on par with prior studies' findings of factors such as climate system tipping points (Lemoine and Traeger, 2014), ambiguity aversion (Lemoine and Traeger, 2016), or model uncertainty (Rudik, 2019).

Of course it must be stressed that these results are subject to critical caveats and limitations. Climate change impact quantifications are generally subject to fundamental uncertainties.[3] Here, the fiscal cost estimates are moreover based on a first generation of studies of select programs, subject to many simplifications. Our model's representation of fiscal policy and the economy are also highly stylized. With these caveats in mind, the results nonetheless show that fiscal costs have the potential to be quantitatively important. That is, the results suggest that *adding* fiscal considerations to standard frameworks can lead to significant increases in the social cost of carbon and in the estimated welfare effects of climate policy. At the very least, the results thus suggest that fiscal costs warrant further empirical investigation and consideration in integrated assessment models.

Our analysis further relates to the literature as follows. First, this study builds on rich literatures on integrated assessment models (IAMs, e.g. DICE, Nordhaus, e.g., 1992, 2008, 2017; PAGE, Hope, 2011; FUND, Anthoff and Tol, 2014; MERGE, Manne and Richels, 2005; etc.) and macroeconomic climate-economy models (e.g., Golosov, Hassler, Krusell, and Tsyvinski, 2014; van der Ploeg and Withagen, 2014; Acemoglu, Aghion, Bursztyn, and Hemous, 2012; etc.), both of which have generally abstracted from fiscal policy and distortionary taxes. A sub-strand of this literature focuses specifically on endogenous adaptation investments in integrated assessment models (e.g., Felgenhauer and Webster, 2013; Agrawala et al., 2010; Bosello, Carraro, and De Cian, 2010; de Bruin, Dellink, and Tol, 2009; Tol, 2007; Hope, 2006.) These frameworks have again generally abstracted from fiscal considerations. Fried (2019) builds and empirically quantifies a detailed macroeconomic model of adaptation to storm events and climate change in the United States, but also does not distinguish public and private investments.

Second, a large literature[4] in environmental economics has demonstrated the importance of pre-existing taxes for the design of pollution mitigation policies, such as carbon taxes or emissions trading schemes (see, e.g., review by Bovenberg and Goulder, 2002). Numerous studies also use sophisticated computable general equilibrium models of the U.S. economy and tax system in order to quantify climate policy interactions with fiscal policy (e.g., Goulder, 1995; Bovenberg and Goulder, 1996; Jorgenson and Wilcoxen, 1996; Babiker, Metcalf, and Reilley, 2003; Carbone, Morgenstern, Williams, Burtraw, 2013; Jorgenson et al., 2013; Goulder, Hafstead, and Williams,

[3] A more formal treatment of uncertainty in the present analysis is in progress.

[4] These include, inter alia: Sandmo (1975); Bovenberg and de Mooij (1994, 1997, 1998); Bovenberg and van der Ploeg (1994); Ligthart and van der Ploeg (1994); Goulder (1995; 1996; 1998); Bovenberg and Goulder (1996); Jorgenson and Wilcoxedn (1996); Parry, Williams, and Goulder (1999); Goulder, Parry, Williams, and Burtraw (1999); Schwarz and Repetto (2000); Cremer, Gahvari, and Ladoux (2001; 2010); Williams (2002); Babiker, Metcalf, and Reilley (2003); Bernard and Vielle (2003); Bento and Jacobsen (2007); West and Williams (2007); Carbone and Smith (2008); Fullerton and Kim (2008); Parry and Williams (2010); d'Autume, Schubert, and Withagen (2011); Kaplow (2013); Carbone, Morgenstern, Williams and Burtraw (2013); Goulder, Hafstead, and Williams (2014); Barrage (2020a), etc.

2014; Goulder and Hafstead, 2017; Fried et al., 2018; Goulder et al., 2019; etc.). While this paper's representation of the economy is vastly simplified compared to these studies, it adds an *integrated assessment* representation of climate change and its economic effects, including on government expenditures and revenues. In contrast, CGE models often assume climate change affects only household utility. This paper also shows how some core insights from this literature, such as on the different treatment of production and non-market externalities, extend to optimal public adaptation expenditures.[5]

Finally, this paper relates to a growing empirical literature that quantifies the economic impacts of climatic risks. I build on the climate adaptive response estimation approach based on Auffhammer (e.g., 2018) and the Climate Impacts Lab (e.g,. Carleton et al., 2020; Nath, 2020, etc.). This approach uses historical plausibly exogenous variation in weather events of interest - such as extreme heat events - to identify economic impacts, but accounts for adaptation to long-run climatic conditions by allowing these effects to vary with the local climate. The literature has used this approach to quantify climate change impacts on outcomes such as energy consumption (Auffhammer, 2018), mortality rates (Carleton et al., 2020), and manufacturing productivity (Nath, 2020). To the best of my knowledge, this paper's findings of public healthcare costs associated with changes in extreme temperature events add to this literature. More broadly, while numerous studies investigate the impacts of temperatures on mortality in the United States (e.g., Barreca et al., 2016; Deschenes and Greenstone, 2011; etc.) less is know about their impacts on (public) healthcare costs. Karlsson and Ziebarth (2018) document significant public healthcare costs of extreme heat days in Germany. Local event case studies have also documented heat-related healthcare costs in the United States (e.g., Limaey et al., 2019). This study also relates to a growing literature on the healthcare costs of wildfires. Numerous studies link specific wildfire events to both poor air quality and increased healthcare utilization (e.g., Ahman et al., 2012; Gan et al., 2017). Most relevant for this paper are some recent national-level estimates. Miller, Molitor, and Zou (2017) empirically document significant increases in Medicare utilization and costs due to wildfire smoke plume exposure measured based on satellite data (see also Liu et al., 2017; Fran et al., 2018). This paper also finds evidence of sigificant increases in *total* public healthcare costs associated with wildfire and smoke events at an annual level. Finally, this paper thus also builds on a recent quantitative studies on the fiscal impacts of severe weather events and climate change (e.g., Deryugina, 2017; Moore et al., 2020, Jerch et al., 2020). In particular, by incorporating prior empirical estimates into a macroeconomic climate-economy model, I highlight their welfare and policy consequences in a general equilibrium framework.

The remainder of this paper proceeds as follows. Section 2 presents the quantification of climate impacts on *existing* public program costs. Section 3 describes the model setup and the

[5] See Belfiori (2015) for an analysis of private adaptation in a similar setting.

theoretical results. Section 4 presents the calibration of the model, including for the two other fiscal climate impact channels of publicly provided adaptation to sea level rise and macroeconomic impacts that affect revenue collection. Section 5 showcases the numerical results, and Section 6 concludes.

2 Existing Program Costs

This section synthesizes quantitative evidence related to climate change impacts on the costs of public programs in the United States. I first synthesize prior estimates and then empirically evaluate potential climate impacts on public health expenditures via changes in the distribution of extreme heat, cold, and wildfire smoke events.

2.1 Prior Estimates

Hurricane-related disaster spending: The Congressional Budget Office (CBO) carefully quantified potential future changes in hurricane damages and their fiscal costs in the United States as follows (CBO, 2016). Central estimates imply an increase in expected annual direct hurricane damages from 0.16 percent of GDP at present to 0.22 percent by 2075. Approximately 45 percent of this increase is estimated to be due to climate change, based on state-level sea level rise scenarios coupled with future hurricane patterns as simulated under a high emissions warming scenario (the Representative Concentration Pathway (RCP) 8.5, Van Vuuren et al., 2011). The remainder is due to projected increases in coastal development. CBO further estimates that, in recent years, federal disaster spending in response to hurricanes has averaged around 62 percent of the direct damage value, or 0.10 percent of GDP. These expenditures include disaster relief through FEMA and the Department of Housing and Urban Development, as well as repair activities by the Army Corps of Engineers, the Department of Transportation, and the Department of Defense, inter alia. Assuming that the federal aid-damage ratio will remain at 62 percent in the future, CBO thus projects a benchmark increase in federal spending from 0.10 to 0.13 percent of GDP by 2075. We consider the climate-related 45% of this change (+0.0135 percent of GDP) as benchmark impact at the associated global mean surface temperature warming.[6]

Hurricane-related health and transfer spending: Deryugina (2017) presents a detailed empirical analysis of hurricane strike impacts on fiscal transfers in the United States. She shows that non-disaster transfers, such as public medical payments and unemployment insurance, increase significantly in response to storms, and that those transfers are generally of much higher value

[6] Mean predicted global temperature changes for RCP 8.5 are $2.0°C$ for 2046-2065, and $3.7°C$ for 2081-2100, above a 1986-2005 baseline (IPCC, 2014). Interpolating linearly yields $2.85°C$ by 2075.

than direct disaster aid. Using her data and code, I construct estimates of the average annual per capita spending impact on a county struck by a hurricane in the ten years following the storm for total medical and income support payments, respectively.[7] Table 1 displays the resulting estimates.

Table 1: Hurricane Impacts on Public Medical and Transfer Spending

Hurricane Saffir-Simpson Category:	Public Medical	Transfers
Cat. 1	3.7%	1.2%
Cat. 2	3.6%	1.8%
Cat. 3+	4.8%	6.76%

Table displays avg. annual county-level per capita percent change in public medical and transfer expenditures across the estimated hurricane impact coefficients for years 0-10 after hurricane strike based on the data and code of Deryugina (2017). Data include federal, state, and local payments.

In order to translate these hurricane impact estimates into projected climate change damages, I use predictions of changes in U.S. hurricane patterns from probability density functions estimated by Bakkensen and Barrage (2019) based on synthetic hurricane tracks under current and future climates from Emanuel et al. (2008), along with historical storm track data from the International Best Track Archive for Climate Stewardship (Knapp et al., 2010). The predicted increases in U.S. storm risk are substantial, implying, for example, an increase in the expected number of Category 3+ storms making landfall from 0.45 per year in the current climate to 2.6 per year by the end of the century under a high emissions warming scenario.[8] I divide these aggregate risk increases across space in the 21 hurricane-vulnerable states considered in Deryugina's analysis by assuming that future cyclone tracks will remain geographically distributed as historical ones, and compute expected medical expenditure increases for each county in the data. The results imply that a ceteris paribus increase in hurricane risk associated with $1°C$ warming increases total annual public medical expenditures in affected sample counties by \$4.9 billion (\$2016), and income support transfers by \$3.0 billion.

Crop-Insurance Subsidies: The U.S. government offers subsidized crop insurance through the Federal Crop Insurance Program. The majority of premium costs - almost two-thirds - are paid

[7] I specifically create outcome variables that are either (i) the log of the sum of Medicare and non-Medicare public medical expenditures per capita, or (ii) the log of the sum of unemployment benefits, income maintenance transfers (e.g., Supplemental Nutrition Assistance Program), and retirement and disability insurance benefits, and re-run the "Wind Speed Regressions" "Event study" specification for these outcomes, which yields impact estimates for the 10 years following the storm. Table 1 presents the average annual impact by hurricane category.

[8] Specifically for 2080-2100 under the IPCC's A1B SRES emissions scenario.

for by the government on average according to the Office of Management and Budget (OMB, 2016). In a joint analysis with the U.S. Department of Agriculture (USDA), OMB (2016) projects program costs to increase 40% by 2080 under RCP 8.5, and 23% by 2080 under RCP 4.5 Given the relevant median projections for future global temperature change in each of those scenarios, we infer that impacts are approximately linear at around a +14% increase in costs per degree warming.[9]

Table 2: Crop Insurance Cost Increase by 2080

	RCP 8.5	RCP 4.5	Source
Increase	+40%	+23%	OMB (2016)
Global Temp. Change (by 2075)	2.85°C	1.6°C	IPCC (2014)
Per 1°C impact:	+14.04%	+14.38%	
Regression Coefficient per 1°C :		+14.05%	

Wildfire Suppression Costs: The OMB (2016) also presents results from a USDA Forest Service (2015) analysis to projected climate change impacts on the wildfire suppression costs incurred by both the Forest Service (FS) and the Department of Interior (DOI). Their central estimates imply annual cost increases of +45% for DOI and 117% for FS by mid-century (2041-2059), and further cost increases of +72% for DOI and +192% for FS by late-century (2081-2099) under the RCP8.5 scenario. Table 2 summarizes these results and the implied cost increases per degree of warming, which again appear close to linear.

Table 3: Wildfire Suppression Cost Increases

	RCP 8.5		Source
	2041-59	2081-99	
Global Temp. Change	2.0°C	3.7°C	IPCC (2014)
Forest Service	+117%	+192%	OMB (2016), USDA FS (2015)
Per 1°C impact:	+58.5	+51.9	
Regression coefficient per 1°C		+52.1%	
DOI	+45%	+72%	OMB (2016), USDA FS (2015)
Per 1°C impact:	+22.5%	+19.5%	
Regression Coefficient per 1°C :		+19.6%	

[9] One relevant question for the appropriate integration of these costs into an IAM is whether this program's benefits are already reflected in agricultural output loss projections included in climate-economy models. To the extent that agricultural impact estimates are based on studies that use private return measures such as land prices (e.g., Nordhaus, Mendelsohn, and Shaw, 1994), they should already reflect net-of-subsidy costs, so that subsidies can be added to the model without modification to the private damage function. Of course we note that this approach ignores potential moral hazard effects of crop insurance on incentives for climate adaptation as documented by Annan and Schlenker (2015).

Urban Drainage Infrastructure: Climate change is projected to alter the costs of maintaining current levels of service in urban infrastructure drainage systems. The U.S. Environmental Protection Agency (EPA, 2017) has produced estimates of these costs across 100 major cities in the United States. Assuming that cities will want to remain prepared for 50-year storm events, the estimated cost increases are presented in Table 3.

Table 4: Urban Drainage Infrastructure Costs

	RCP 8.5		RCP 4.5		Source
	2050	2090	2050	2090	
Global Temp. Change	$2.0°C$	$3.7°C$	$1.4°C$	$1.8°C$	IPCC (2014)
Annual Cost ($2015 bil)	4.3	5.6	3.7	4.1	EPA (2017)
Per $1°C$ impact:	2.2	1.5	2.6	2.3	
Regression coefficient per $1°C$				+$1.83 bil./yr	

Endangered Species Act (ESA): As climate change is predicted to significantly increase the number of species at risk of extinction, it may also increase the number of species listed under the ESA. Protected species incur significant government expenditures at both state and federal levels, for activities ranging from enforcement to research, and at agencies ranging from the U.S. Fish and Wildlife Service to the Army Corps of Engineers. Moore et al. (2020) combine a careful empirical analysis of the determinants of species listings and expenditures with projections of species extinction risk under warming to estimate the associated fiscal costs. Their benchmark results imply that the present value of ESA-related expenditures will increase 12.5% due to $2°C$ of warming, and 47.5% due to $5°C$ warming, implying an average per degree increase of +7.9%. We apply this increase to base year total government ESA expenditures (FWS, 2017) to infer annual spending impacts.

Air Quality-Related Healthcare: Garcia-Menendez et al. (2015) use coupled earth systems and a global atmospheric chemistry model to study climate change impacts on concentrations of fine particulate matter (PM2.5) and ground-level ozone across the United States. A changing climate is projected to alter these pollutants' concentrations through mechanisms such as water vapor and temperature effects on atmospheric chemistry and ventilation. OMB (2016) uses results from the authors on several morbidity outcomes (e.g., respiratory hospital admissions) to quantify associated changes in federal health care costs. Their central estimates are modest, corresponding to an extra *$1.2 billion per year* in today's terms in a 'no policy' baseline (leading to $6°C$ global mean surface temperature change by end of century) compared to a mitigation scenario (limiting warming to $1.5°C$). Importantly and as noted by OMB, as these estimates do not capture climate impacts through changes in wildfire frequencies. We consequently attempt a separate quantification of these impacts below.

2.2 Public Healthcare, Extreme Temperatures, and Wildfires

The results from prior studies considered above suggest that healthcare costs may be one of the biggest contributors to climate change's fiscal impacts. This section thus empirically considers two other potentially important impact channels: Changes in extreme temperature distributions and wildfire events.

Data: First, I obtain information on total public medical benefit transfers from the Bureau of Economic Analysis' (BEA) Regional Economic Accounts ("REA", following Deryugina, 2017). The medical benefits measure includes payments made through federal, state, and local governments through intermediaries to beneficiaries for care provided under programs including Medicare, Medicaid, Children's Health Insurance Program, military medical insurance benefits, and local general assistance medical programs. The REA data also provide information on populations and incomes at the county-year level. The main specification focuses on the years 1996-2018. Next, historical weather data are from Schlenker (2020), who provides processed daily temperature and precipitation data for the contiguous United States at the 2.5x2.5 mile grid level. Following prior literature, I divide temperatures into cold, moderate, and extreme heat bins (e.g., Barreca et al., 2016). The benchmark specification defines "hot" days as having a daily maximum temperature above 35 Celsius (95 Farenheit), and "freezing" days as having a daily minimum temperature below freezing (0 Celsius). Alternatively, I also consider a "hot" ("freezing") day as having an *average* temperature above 32 Celsius (below 0 Celsius). Grid-level data are aggregated into county-level variables via spatial averages (across grid cells), and daily data are aggregated into annual measures by calculating the *total number of hot and freezing days* in each county-year. In line with the literature, I also add quadratic controls for precipitation (e.g., Carleton et al., 2020). Next, information on wildfires and smoke events are from the National Oceanic and Atmospheric Administration's (NOAA) Storm Events Database. The main variable of interest is the number of days in each year during which a county experienced a wildfire or dense smoke.[10] The distribution of this variable is highly skewed; I thus focus on the natural logarithm of fire and smoke days.[11] Data from the National Interagency Fire Center on the number of acres burned by state-year is used to identify the top quartile of states in terms of

[10] The Storm Events Database maps events into counties or "zones". I translate zone events into underlying counties based on the National Weather Service's zone-county correlation file. [https://www.weather.gov/gis/ZoneCounty]

[11] I specifically consider $\ln(\text{FireSmokeDays}+0.00001)$. Using an inverse hyperbolic sine transformation instead also yields a positive and significant coefficient on wildfire and smoke days .

wildfire risk, measured by average acres burned per year relative to state land area. State land areas are obtained from the U.S. Census Bureau. Finally, population age and race profiles by county-year are obtained from the National Center for Health Statistics.

Analysis: The benchmark is a standard panel specification at the county-year level:

$$\begin{aligned} \ln Y_{j,t} \quad &= \quad +\Sigma[\beta_m + \gamma_m DMEAN_{m,j}] \times D_{m,j,t} \\ &\quad\quad +\delta_j + \delta_t + (\theta_s \cdot t) + \mathbf{X_{j,t}}'\boldsymbol{\beta} + \epsilon_{j,t} \end{aligned} \tag{1}$$

Here, $\ln Y_{j,t}$ denotes the natural logarithm of public medical expenditures Y in county j in year t. The δ_j are county fixed-effects, which absorb cross-sectional differences in public medical expenditures across counties. Year fixed-effects δ_t capture aggregate (national) shocks to public medical spending in a given year. State-specific trends $(\theta_s \cdot t)$ further allow public medical spending to follow different trends in different states. The $D_{m,j,t}$ terms represent climatic events $m \in \{$"hot", "freezing", "fire/smoke"$\}$. In line with recent literature in empirical climate impact evaluation (e.g., Auffhammer, 2018; Carleton et al., 2020; Nath, 2021), I seek to account for adaptation to environmental risks by allow the effects of each event $D_{m,j,t}$ to depend on the county's average frequency of the event (e.g., average number of hot days per year), captured by $DMEAN_{m,j}$. Alternatively, I also consider average temperature as measure of $DMEAN_{m,j}$, in line with prior studies (e.g., Carleton et al., 2020). For wildfires, I alternatively also limit the analysis to the most wildfire-vulnerable states as a more appropriate control group, following Deryugina's (2017) approach on hurricanes. Finally, the vector $\mathbf{X_{j,t}}$ represents other control variables. In the benchmark specification, this includes second-order polynomial controls in precipitation, the natural logarithm of counties' populations, of the population 65 years and older, and of real per capita income, controls for prior year to current population and per capita income growth, and the fraction of non-hispanic whites in the county population. I also control for the number of hurricane days in each county-year as they may be correlated with hot days and to avoid double-counting their effects. For robustness, I also consider interactions between precipitation and temperatures. Standard errors $\epsilon_{j,t}$ are heteroskedasticity-robust and clustered at the county level. Finally, observations are weighted by county populations.

Results: Table 5 showcases the main results. The main take-away is that both extreme heat days and wildfire/smoke events appear to significantly increase public medical spending in a given county-year. The coefficient on freezing days is also positive, but imprecisely estimated in all but one specification. Column (1) shows the benchmark specification defining hot days based on daily maximum and minimum temperatures. Column (2) adds interaction terms between temperatures and precipitation. In this specification, the impact of freezing days also appears positive and precisely estimated. Column (3) showcases the specification using temperature averages to define hot and cold days. Not surprisingly, the marginal impact of a day with very hot *average* temperatures is considerably higher than of a day with a very hot maximum temperature. This specification also reveals a precisely estimated adaptation effect, that is, the marginal impact of hot days is significantly smaller in areas with higher average temperatures. Column (4) returns to the benchmark but adds interaction terms for average wildfire events, which leaves the results unchanged. Finally, Column (5) shows results restricted to the top quartile of wildfire states, our preferred specification to estimate fire and smoke impacts. All specifications show a small but highly significant increase in medical spending associated with wildfire and dense smoke events.

Table 5: Public Health Expenditure Impacts

Dep. Var.:	ln(Public Medical Expenditures)				
	(1)	(2)	(3)	(4)	(5)
Hot Days$_{j,t}$	0.0003**	0.0002*	0.0047**	0.0002**	0.0003
	(0.0001)	(0.0001)	(0.0020)	(0.0001)	(0.0002)
Hot Days$_{j,t}$ $\times$ $\overline{\text{HotDays}}_j$	-0.0000	-0.0000	-0.0002**	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Freezing Days$_{j,t}$	0.0002	0.0003**	0.0001	0.0002	0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0003)
Freezing Days$_{j,t}$ $\times$ $\overline{\text{FreezingDays}}_j$	-0.0000	-0.0000	-0.0000**	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ln(FireSmokeDays)$_{j,t}$	0.0007***	0.0007***	0.0006***	0.0007***	0.0008***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
ln(FireSmokeDays)$_{j,t}$				-0.0000	
$\times$ $\overline{\text{ln(FireSmokeDays)}}_j$				(0.0000)	
Obs.	61,080	61,080	61,080	61,080	13,380
Adj. R-Sq.	0.999	0.999	0.999	0.999	0.999
#Counties (Clusters)	3,054	3,054	3,054	3,054	659
"Hot" Measure	Max>35	Max>35	Avg.>32	Max>35	Max>35
"Freezing" Measure	Min<0	Min<0	Avg.<0	Min<0	Min<0
Climate Interaction Measure	$\overline{\text{Hot}}$, $\overline{\text{Cold}}$	$\overline{\text{Hot}}$, $\overline{\text{Cold}}$	$\overline{\text{Temp.}}$	$\overline{\text{Hot}}$, $\overline{\text{Cold}}$	$\overline{\text{Hot}}$, $\overline{\text{Cold}}$
Demo./Inc./Precip./Hurricane Controls:	Yes	Yes	Yes	Yes	Yes
Precip. $\times$ Hot, Cold	No	Yes	No	No	No
Top Wildfire States Only	No	No	No	No	Yes
County F.E.s:	Yes	Yes	Yes	Yes	Yes
Year F.E.s:	Yes	Yes	Yes	Yes	Yes
State-Trends:	Yes	Yes	Yes	Yes	Yes

Table shows results of linear regression of log of county-year public medical expenditures on indicated controls. Standard errors are heteroskedasticity-robust and clustered at county level. Regressions weighted by county populations. Col. (4) restricted to top quartile of wildfire states.

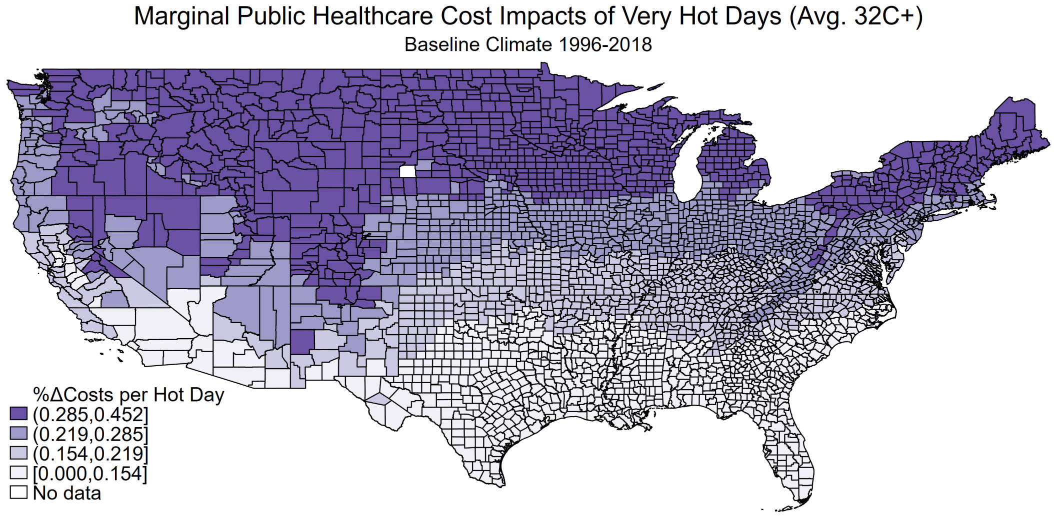

Figure 1: Hot Day Public Medical Spending Impact (Average Temp.)

In order to facilitate the interpretation of the coefficients on the temperature variables, Figures 1 an 2 illustrates the estimated marginal public health expenditures impacts of an additional hot day across the continental United States. Figure 1 uses the average temperature results of Column (3). Taken at face value, the results suggest that the impacts of an additional very hot day on annual public medical expenditures range from zero to 0.45%, depending on a county's baseline climate. In southern states which are well-adapted to hot weather, the predicted impact is zero or small. In contrast, in northern regions which are less adapted to extreme heat, the public medical spending impacts are predicted to be substantial. Figure 2 presents the same figure but based on the maximum temperature definition of hot days from Column (1). To be conservative, I include the estimated adaptation effect despite its imprecision. Broadly speaking, the results tell a similar story, namely that extremely hot days are associated with higher public medical expenditures in areas which are not already accustomed to heat events. Finally, an analogous figure showing freezing day impacts are shown in the Appendix. While these effects of freezing days are less precisely estimated, I consider their potential magnitude so as to account for potential cost savings resulting from reductions in freezing days due to global warming.

Before proceeding, I compare the estimated coefficients on wildfire and smoke days to related prior studies. Taken at face value, the results suggest that a 1% increase in the number of wildfire or smoke days in a vulnerable county increases public medical expenditures by approximately 0.0007%. On the one hand, though not precisely comparable,[12] we can consider this order of magnitude vis-à-vis Fann et al.'s (2018) estimate that U.S. wildfires caused an additional 11,300 hospital admissions in 2008. Given that national hospital admissions resulting from emergency

[12] Fann et al. (2018)'s estimates represent a total effect on hospital admissions at a national level, whereas our estimates represent marginal effects on total expenditures.

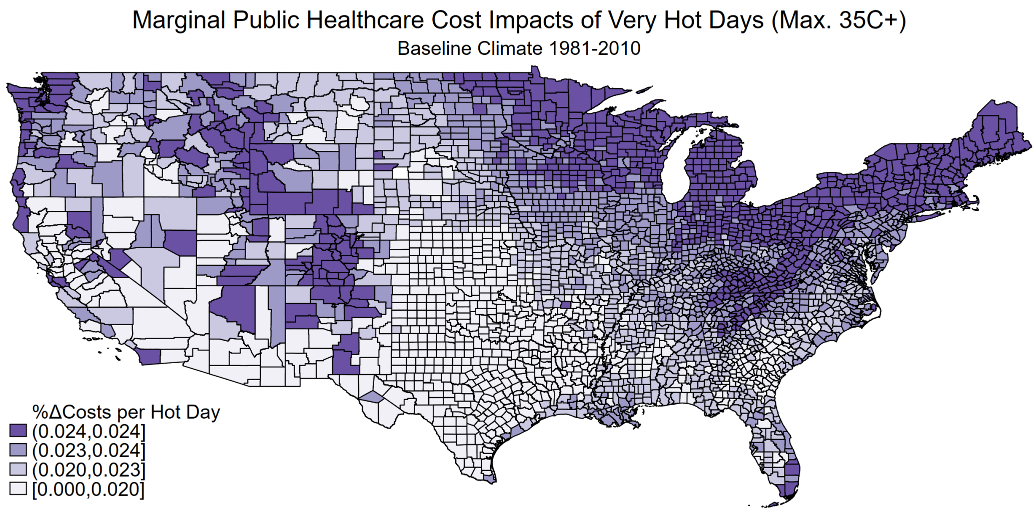

Figure 2: Hot Day Public Medical Spending Impact (Max. Temp.)

department visits were 15 million in 2008, the implied percentage increase is 0.00075% and thus of very similar magnitude. On the other hand, Miller et al. (2017) estimate that an additional wildfire smoke day increases same-day Medicare inpatient spending by 0.6% and outpatient spending by 2.8% among fee-for-service beneficiaries. Using aggregate Medicare spending data from the Centers for Medicare & Medicaid Services, I calculate the implied elasticity of overall Medicare spending with respect to wildfire smoke days as 0.1255.[13] The difference in magnitude may be due to several factors. For example, this paper's estimates focus on annual level aggregates, whereas Miller et al. (2017) study high frequency outcomes at the daily level. In the realm of temperature healthcare cost impacts, Karlsson and Ziebarth (2018) find that aggregation to the annual level reduces estimated effects by 90 percent. Miller et al. (2017) use a spatially detailed remotely sensed measure of smoke exposure, whereas this study's smoke measures are both coarser and likely noisier measures at the county level. Finally, Miller et al. (2017) focus on specific Medicare expenditures, whereas our REA medical benefits variable aggregates various federal and local programs.

Climate Change Impacts - Extreme Temperatures: In order to map the estimated effects into climate change impact projections, one needs forecasts of how the distribution of extreme temperatures may change under a warming climate. Rasmussen et al. (2016) construct down-scaled estimates and probability density functions for temperature changes resulting from different global warming scenarios for each county in the United States. For example, Figure 3 showcases the median projected change in the number of days with maximum temperatures

[13] Over the relevant time horizon (2007-2013), the average Medicare expenditure shares of inpatient and outpatient services were 34.5% and 11.9%, respectively, implying an overall cost increase of 0.54%. Given Miller et al.'s (2017) estimate that the national average Medicare recipient is subject to 23.5 smoke days per year, a 1% increase in smoke days increases Medicare spending by (.2325*0.54%) = 0.1255%.

above 35C for each county based on downscaled Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012) output under a high emissions scenario (RCP 8.5, van Vuuren et al., 2011) by mid-century (2040-59). The projections indicate large potential increases in hot days, with up to 89 *additional* hot days per year in some locations. By the end of the century (2080-99), the corresponding figure is up to 146 *additional* hot days per year. Analogous results for projected changes in the number of freezing days per year range from -29 days to +3 days per year with minimum temperatures below zero by mid-century under RCP 8.5.

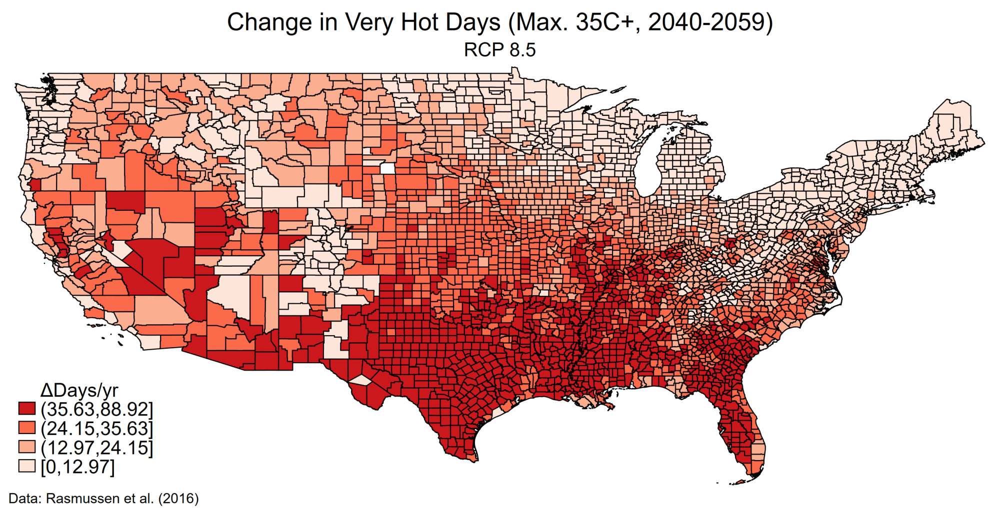

Figure 3: Changes in Hot Days by 2040-59 (Max. Temp)

The empirical results suggest that increases in the number of hot days may affect public healthcare costs in two ways. On the one hand, health spending may increase due to a higher number of hot days, ceteris paribus. On the other hand, however, as the climate warms, the marginal effect of each hot day is likely to decline as a result of adaptation. In order to account for the latter effect, I thus first compute revised marginal impact maps evaluated under future climates. Appendix Figures A3 and A4 present two examples of such maps for mid- and late-century under a high emissions scenario, respectively. Compared to Figure 1, these maps show a significant reduction in the projected public healthcare cost associated with extreme heat events in the future. At the same time, however, the projected increase in the number of heat events is large in many areas, as shown in Figure 3. The projected *total* increase in public healthcare costs is thus given by the combination of the two forces.

Figures 4 and 5 illustrate projected total impacts in mid- and late-century, respectively, under a high emissions scenario. Several points stand out. First, the projected impacts of changes in public healthcare costs due to extreme heat events are quantitatively significant, reaching as high as a 0.5% increase in annual total public medical expenditures in many counties. Second, the geographic distribution of these impacts is heterogeneous and likely to change over time. Some areas, such as Texas, already appear well-adapted to extreme heat, and are thus not projected to suffer large impacts despite a large predicted increase in hot days. Initially, the most affected areas are southern-central and mid-Atlantic states which are not yet as well adapted to extreme heat (see Figures 1 and 2) but which are also projected to see largest increases in extremely hot days (see Figure 3). As these areas adapt to increased heat events, however, their vulnerability is predicted to decline, resulting in lower total warming impacts by late century, as shown in Figure 5. Conversely, northern areas are predicted to experience only modest impacts in the medium run as the projected increase in hot days is initially modest, but later in the century these areas are predicted to see substantial healthcare cost increases as warming increases.

Analogous results for the potential impacts of reductions in freezing days are displayed in Appendix Figure A4, again with the caveat that freezing impacts were mostly imprecisely estimated. Taking the point estimates at face value, the results suggest that some counties may experience cost savings of up to around 0.5% per year, especially in areas such as Virginia or northern Texas which are not well adapted to cold weather and thus suffer disproportionately from freezing days when they do occur. Much of the country, however, appears already well adapted to cold weather and is thus projected to benefit very little from reductions in freezing days.

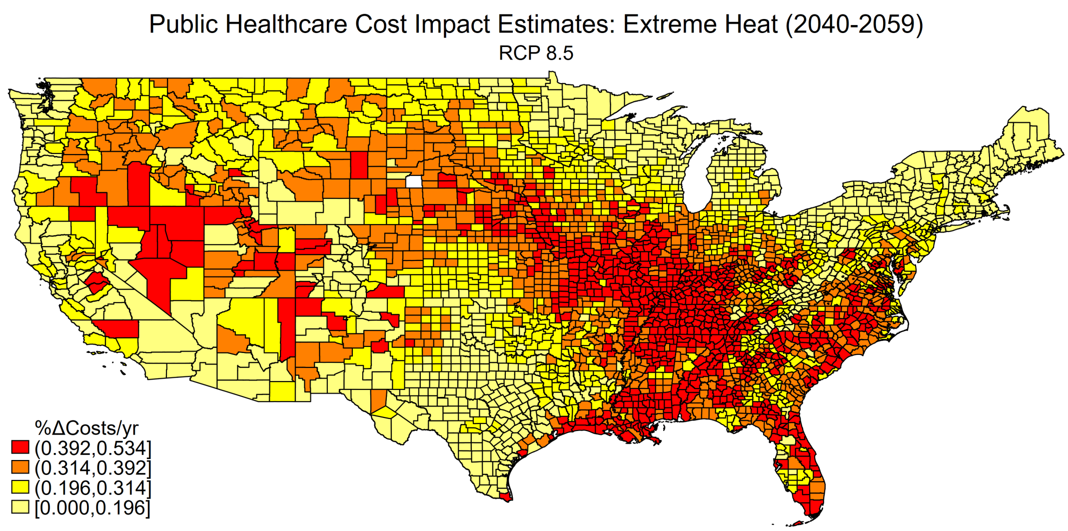

Figure 4: Total Public Healthcare Cost Impact of Extreme Heat by Mid-Century

Damage Function - Extreme Heat: The last step is to convert these estimates into a fiscal climate damage function. Such damage functions generally specify total costs as a function of aggregate warming indicators such as mean global atmospheric surface temperature change (e.g., Nordhaus, 1992, 2017) and serve the purpose of endogenizing feedback effects between economic activity, policy, and the climate. In order to link the above estimates to global temperature

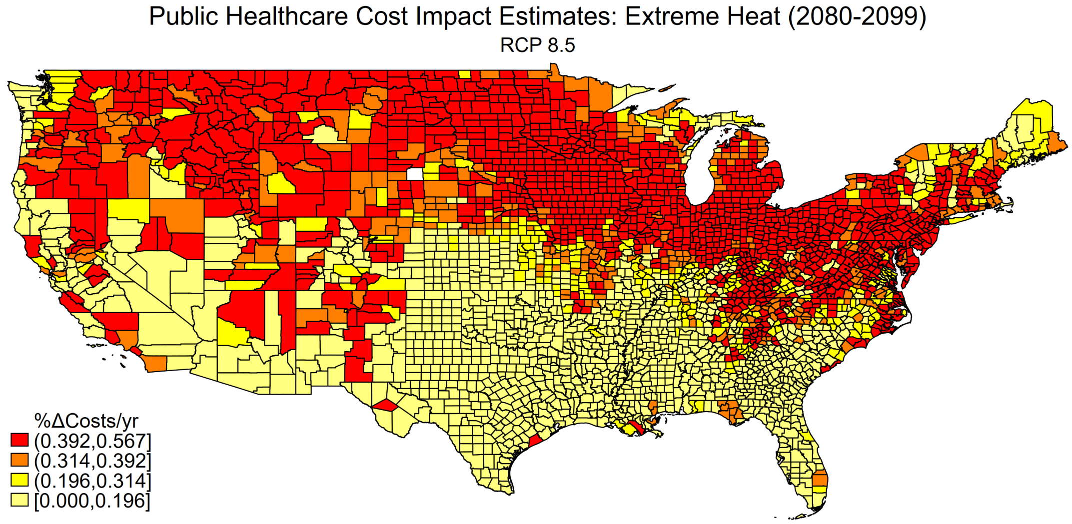

Figure 5: Total Public Healthcare Cost Impact of Extreme Heat by Late-Century

change, I estimated a reduced-form linear downscaling model for each county, linking its projected changes in hot and cold days to mean global surface temperature change in a given scenario (see Appendix for details). Over the range of temperatures considered, the linear mapping appears to provide a good fit. The correlation between the linearly predicted change in counties' number of hot days per year and the Rasmussen et al. (2016) projections is 0.983. Let $\widehat{\lambda}_j$ denote the estimated down-scaling coefficient for county j, that is, the predicted increase in the number of very hot days per year in county j per degree of increase in global temperatures. Combining the down-scaled relationship with the estimated coefficients in (1), one can derive the predicted change in total public medical expenditures as a second order polynomial in global temperature change T_t (see Appendix for details):

$$\%\Delta\text{PublicMedicalCosts}_{j,t} = [\widehat{\beta}_{hot}\widehat{\lambda}_j + \widehat{\gamma}_{hot}DMEAN_{hot,j}\widehat{\lambda}_j] \cdot T_t + [\widehat{\gamma}_{hot}\widehat{\lambda}_i^2] \cdot T_t^2 \tag{2}$$

Finally, I aggregate county-level estimates from (2) into national aggregates based on each county's share of total public medical expenditures in the model base year 2016.

Climate Change Impacts - Wildfires: Wildfire risk is projected to increase rather severely in many parts of the United States (Vose et al., 2012). Table 6 summarizes key projections for the most wildfire-vulnerable states. Some states are projected to experience average annual burn area increases of over 200 percent per degree Celsius of global warming. As a conservative benchmark, I restrict projected healthcare cost increases associated with these changes to these top wildfire states. This approach likely understates true costs both because it ignores impacts in other vulnerable states such as Colorado, and because wildfire smoke plumes can travel long distances (Miller et all., 2017). Figure 6 showcases the projected total public healthcare cost increase due to increases in wildfire activity by mid-century in a high emissions scenario (RCP 8.5). Interestingly, the magnitudes are similar as for extreme heat, with impacts as high as a 0.5% increase in total public medical spending through the wildfire channel alone.

Table 6: Review of Wildfire Burning Change Estimates

State	Avg. %ΔWildfire Activity per $1°C$ global warming	Sources:
AZ	241	McKenzie et al. (2004), Littell et al. (2009), Liu et al. (2009)
NM	237	McKenzie et al. (2004), Littell et al. (2009), Liu et al. (2009)
UT	240	McKenzie et al. (2004), Littell et al. (2009), Liu et al. (2009)
NV	98	McKenzie et al. (2004), Littell et al. (2009), Liu et al. (2009)
CA	82	Lenihan et al. (2003), McKenzie et al. (2004), Littell et al. (2009)
ID	84.7	Littell et al. (2010), Liu et al. (2010)
OR	72.1	Rogers et al. (2011), Littell et al. (2010), Liu et al. (2010)
WA	72.1	Rogers et al. (2011), Littell et al. (2010), Liu et al. (2010)
TX	14.0	Liu et al. (2010) (SW region estimate)
OK	14.0	Liu et al. (2010) (SW region estimate)
FL	28.2	Liu et al. (2010) (SE region estimate)
AK	43.3	Liu et al. (2010) (US overall estimate)

Table presents average of projections of percentage changes in acres burned per year or, for Liu et al. (2010), annual wildfire potential as measured by the Keetch-Byram Drought Index, normalized across future climate scenarios to a change per $1°C$ global warming. We infer linearity in temperature based on Liu et al. (2010).

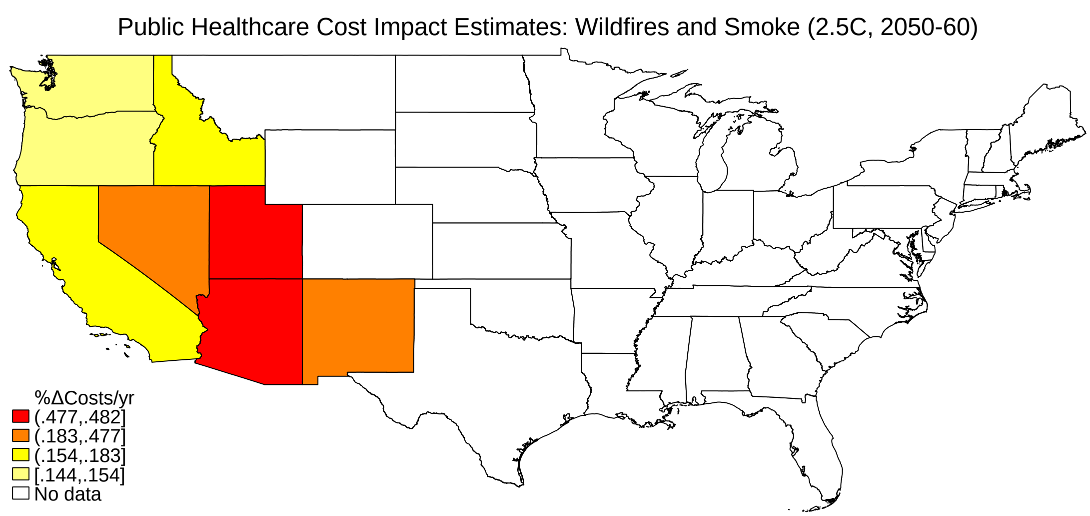

Figure 6: Total Public Healthcare Cost Impact of Wildfires and Smoke by Mid-Century

2.3 Overall Existing Program Cost Impacts

We combine the quantitative estimates described in this section utilizing data on base year (2016) program expenditures and overall (federal plus local) U.S. government consumption from the National Income and Product Accounts of the BEA. Extrapolating into the future requires assumptions about the future government spending share of each program. As a benchmark, the model assumes constant expenditure shares except for healthcare. Due to factors such as aging of the U.S. population and excess cost growth in the health sector, the U.S. Congressional Budget Office projects, for example, a doubling in the GDP share of Medicare expenditures between 2021 and 2051 (CBO, 2021b). I thus calculate the annualized average growth rate in the GDP share of total federal health expenditures (i.e., Medicare net of offsets, Medicare, CHIP, etc.) based on CBO projections (CBO, 2021b) to adjust the projected overall fiscal impacts of climate change-induced increases in future public health expenditures. Table 9 summarizes the resulting estimates, which imply an increase in total U.S. government consumption requirements of +1.45% due to 2.5C warming which is predicted to occur by mid-century (around 2050) in a high emissions scenario (e.g., RCP 8.5 in the MAGICC6 model, Meinhausen et al., 2011). Health expenditures account for the majority (around 75%) of these costs. Incorporating the point estimates of projected health cost savings due to decreases in freezing days (despite their lack of statistical precision) would reduce this estimate only slightly to 1.38%. Government transfer payments are projected to increase by around 0.3%.

Table 7: Existing Program Costs Summary

	%Δ for 2.5C in 2050	
Government Consumption	Program	Aggregate
Hurricane direct response*	+13%	+0.10%
Crop-insurance subsidies	+35%	+0.10%
Fed. Wildfire suppression	+130%	+0.11%
Urban drainage infrastructure		+0.08%
Endangered Species Act	+20%	+0.01%
Fed. healthcare - Air quality		+0.03%
Healthcare - Hurricanes	+1.62%	+0.78%
Healthcare - Extreme heat	+0.41%	+0.19%
[Healthcare - Freezing	-0.16%	-0.073%]
Healthcare - Wildfires		+0.05%
Total Consumption		**+1.45%**
Government Transfers		
Income support - Hurricanes		**+0.3%**

*Includes FEMA aid, HUD, Army Corps of Engineers, DOD, DOT

These estimates likely *understate* climate change impacts. For example, I only consider a subset of public programs and climate impact channels for which some quantification was possible. In addition, even for those programs, some estimates may be lower bounds. For example, for fire suppression, only federal expenditures are included; for urban infrastructure, only 100 cities are included; for wildfire healthcare costs, only impacts on the top quartile of wildfire states are included, etc. On the other hand, however, the above estimates also do not account for some potential budgetary cost reductions, such as decreased participation in Social Security and similar programs through premature mortality (CBO, 2021a). I nonetheless use the estimates of Table 7 as a benchmark based on available evidence to gauge the plausible order of magnitude of climate change's fiscal costs via existing program expenditures. The quantification of other fiscal impact channels is described in Section 4 below.

3 Model

This section presents the model. I build on the COMET (Climate Optimization Model of the Economy and Taxation) model of Barrage (2020a), which, in turn, builds on the climate-economy models of Golosov, Hassler, Krusell, and Tsyvinski (2014) and Nordhaus (2008; 2011) by incorporating a classic dynamic optimal Ramsey taxation framework (see, e.g., Chari and Kehoe, 1999) to incorporate distortionary taxation and government revenue requirements. I now extend this framework in four main ways. First, I introduce climate change impacts on the costs of providing government services (e.g., healthcare) and on requisite government transfers to households (e.g., income support), motivated by the findings of Section 2. Second, I introduce endogenous public adaptation expenditures. While the quantitative model focuses on sea level rise adaptation, the theoretical setup also considers public spending to mitigate general climate impacts on production and on household utility. Third, I introduce a sea level rise module, both in terms of the climate dynamics of sea level rise and in making explicit the resulting capital losses. That is, while standard models commonly summarize all climate change impacts as loss in aggregate output, I separate out capital losses from sea level rise so as to more accurately account for impacts on different tax bases. Finally, while the benchmark COMET is a global model, here I present a model specific to the United States (US-COMET). For a stylized alternative quantification of the model to the global level, see Barrage (2020b).

To briefly preview the model: an infinitely-lived, representative household has preferences over consumption, leisure, and the environment. There are two production sectors. An aggregate final consumption-investment good is produced from capital, labor, and energy inputs. Domestic carbon emissions stem from a carbon-based energy input, which is produced from capital and labor. Rest-of-the-world (ROW) carbon emissions are exogenously given in the benchmark version of the model, although the quantitative analysis also considers a non-zero global emissions response elasticity to U.S. abatement efforts. The government must raise a given amount of revenues for government consumption, transfers, and funding for climate change adaptation through distortionary taxes on labor, capital, intermediate energy inputs, and carbon emissions.[14] Climate change affects the economy through six channels: (i) temperature change alters aggregate productivity, (ii) temperature change enters household utility directly, (iii) sea level rise depreciates the capital stock, (iv) temperature change affects the cost of providing government services, (v) temperature change affects government transfers to households, (vi) sea level rise affects the government's optimal expenditures on coastal protection efforts, and (vii) temperature change affects the government's optimal adaptation expenditures.

Households

A representative household has well-behaved preferences over consumption C_t, labor supply L_t, and the climate, summarized by mean atmospheric surface temperature change T_t. The household's (dis)utility over climate change further depends on society's adaptive capacity to reduce utility damages, Λ_t^u. Lifetime utility U_0 is given by:

$$U_0 \equiv \sum_{t=0}^{\infty} \beta^t U(C_t, L_t, T_t, \Lambda_t^u) \tag{3}$$

Pure utility losses from climate change may reflect domestic non-production impacts, such as damages to national parks and biodiversity existence value losses, or also U.S. household disutility over climate impacts in other countries. We assume additive separability between preferences over consumption, leisure, and the climate, and that adaptive capacity reduces the disutility from climate change via:

$$U(C_t, L_t, T_t, \Lambda_t^u) = v(C_t, L_t) + h[(1 - \Lambda_t^u)T_t] \tag{4}$$

Intuitively, if adaptive capacity was at 100% ($\Lambda_t^u = 1$), climate impacts on utility would be fully neutralized. Each period, the household allocates his income between consumption, the purchase of one-period government bonds B_{t+1} (at price ρ_t), and investment in the capital stock K_{t+1}. The household's income derives from net-of-tax (τ_{lt}) labor income $w_t(1 - \tau_{lt})L_t$, net-of-tax (τ_{kt}) and depreciation ($\delta(SLR_t, \Lambda_t^{slr})$) capital income $\left\{1 + (r_t - \delta(SLR_t, \Lambda_t^{slr}))(1 - \tau_{kt})\right\} K_t$, government bond repayments B_t, profits from the energy production sector Π_t, and government transfers $G_t^T(T_t)$, which are restricted to be non-negative and may be affected by climate change. The capital depreciation rate depends on sea level rise (SLR) SLR_t as well as coastal protection level Λ_t^{slr}. Households take both the climate and adaptive capacities as given. The final consumption

[14] In particular, lump-sum taxes are assumed to be infeasible, in the Ramsey tradition. It is moreover assumed that the revenues raised from Pigouvian carbon taxes are insufficient to meet government revenue needs, and that the government can commit to a tax series ex-ante (see Barrage (2020a) for further discussion).

good is normalized to be the untaxed good. The household's flow budget constraint each period is thus given by:[15]

$$C_t+\rho_t B_{t+1}+K_{t+1} \leq w_t(1-\tau_{lt})L_t+\left\{1+(r_t-\delta(SLR_{,},\Lambda_t^{slr}))(1-\tau_{kt})\right\}K_t+B_t+\Pi_t+G_t^T(T_t) \quad (5)$$

As usual, the household's first order conditions imply that savings and labor supply are governed by the following decision rules:

$$\frac{U_{ct}}{U_{ct+1}} = \beta\left\{1+(r_{t+1}-\delta(SLR_t,\Lambda_t^{slr}))(1-\tau_{kt+1})\right\} \quad (6)$$

$$\frac{-U_{lt}}{U_{ct}} = w_t(1-\tau_{lt}) \quad (7)$$

where U_{it} denotes the partial derivative of utility with respect to argument i at time t.

Production

The final consumption-investment good is produced with a constant returns to scale technology using capital K_{1t}, labor L_{1t}, and energy E_t inputs, and is assumed to satisfy the standard Inada conditions. In addition, output is affected by both the state of the climate T_t and adaptive capacity in final goods production, Λ_t^y :

$$\begin{aligned} Y_t &= (1-D(T_t)(1-\Lambda_t^y))\cdot A_{1t}\widetilde{F_1}(L_{1t},K_{1t},E_t) && (8)\\ &= F_1(A_{1t},T_t,\Lambda_t^y,L_{1t},K_{1t},E_t) && (9)\end{aligned}$$

where A_{1t} denotes an exogenous total factor productivity parameter. Once again, if adaptive capacity were at 100% ($\Lambda_t^y=1$), climate impacts would be neutralized. The modeling of climate production impacts as multiplicative factor was pioneered by Nordhaus (e.g., 1991) and reflects effects aggregated across sectors. Note that the interpretation of $D(T_t)$ here may differ from standard setups in that it represents damages gross of any (public) adaptation.

Profit maximization and perfect competition imply that marginal products of factor inputs, denoted by F_{1it} for input i at time t, are equated to their prices in equilibrium. Letting p_{Et}

15 As in Barrage (2020a), we assume that (i) capital holdings cannot be negative, (ii) consumer debt is bounded by some finite constant M via $B_{t+1}\geq -M$, (iii) purchases of government debt are bounded above and below by finite constants, and (iv) initial asset holdings B_0 are given.

denote the price of energy inputs, these conditions imply:

$$
\begin{aligned}
F_{1lt} &= w_t \\
F_{1Et} &= p_{Et} \\
F_{1kt} &= r_t
\end{aligned}
\tag{10}
$$

Energy inputs E_t are produced from capital K_{2t} and labor L_{2t} with constant returns to scale:

$$E_t = A_{2t}F_{2t}(K_{2t}, L_{2t}) \tag{11}$$

Energy is generally carbon-based, but producers can provide fraction μ_t of energy from clean or zero-emissions technologies at an additional cost $\Theta_t(\mu_t E_t)$. Given perfect competition, energy sector profits are thus given by:

$$\Pi_t = (p_{Et} - \tau_{It})E_t - [(1 - \mu_t)E_t]\tau_{Et} - w_t L_{2t} - r_t K_{2t} - \Theta_t(\mu_t E_t) \tag{12}$$

where p_{Et} represents the price of energy, τ_{It} is an excise intermediate goods tax, and τ_{Et} is an excise tax on carbon *emissions* $E_t^M \equiv (1 - \mu_t)E_t$.[16]

Both capital and labor are assumed to be perfectly mobile across sectors, with associated market clearing conditions:

$$
\begin{aligned}
K_t &= K_{1t} + K_{2t} \\
L_t &= L_{1t} + L_{2t}
\end{aligned}
\tag{13}
$$

Profit maximization thus implies that prices and marginal factors will be equated,

$$
\begin{aligned}
[p_{Et} - \tau_{It} - \tau_{Et}]F_{2lt} &= w_t \\
[p_{Et} - \tau_{It} - \tau_{Et}]F_{2kt} &= r_t
\end{aligned}
\tag{14}
$$

and that energy producers abate μ_t until its marginal cost equals the carbon price τ_{Et} :

$$\tau_{Et} = \Theta_t'(\mu_t E_t) \tag{15}$$

[16] Since producers face two decision margins on energy levels and emissions, we allow for two policy instruments to form a 'complete' tax system in the sense of Chari and Kehoe (1999).

Government

The government faces the following tasks. First, it must raise revenues to finance a sequence of public consumption requirements $\{G_t^C(T_t) > 0\}_{t=0}^{\infty}$ and household transfers $\{G_t^T(T_t) \geq 0\}_{t=0}^{\infty}$, and pay off inherited debt B_0^G. One of the main novelties here is that the cost of providing these services may depend on the climate. Second, at its discretion, the government can devote resources to produce adaptive capacity. Protection against sea level rise depends on an adaptive capital stock AK_t (e.g., sea walls):

$$\Lambda_t^{slr} = f^{slr}(AK_t) \tag{16}$$

which takes AK_0 as given and follows law of motion:

$$AK_t = AK_{t-1}(1 - \delta^{slr}) + \lambda_t^{slr} \tag{17}$$

In the quantitative version of the model, adaptive capacity further depends on the stock of adaptive capital relative to the value of capital at risk, in line with, e.g., Fried (2019). Next, adaptive capacity against other production and utility damages depends on flow expenditures λ_t^y and λ_t^u, respectively:

$$\Lambda_t^i = f^i(\lambda_t^i) \text{ for } i \in \{u, y\} \tag{18}$$

Finally, the government has the following revenue raising instruments at its disposal. It can impose linear taxes on labor and capital income, levy excise taxes τ_{It} on energy inputs and τ_{Et} on carbon emissions, and it can issue new, one-period bonds B_{t+1}^G. The public flow budget constraint is thus given by:

$$G_t^C(T_t)+G_t^T(T_t)+\lambda_t^y+\lambda_t^u+\lambda_t^{slr}+B_t^G = \tau_{lt}w_tL_t+\tau_{It}E_t+\tau_{Et}E_t^M+\tau_{kt}(r_t-\delta(SLR_t,\Lambda_t^{slr}))K_t+\rho_tB_{t+1}^G \tag{19}$$

The market clearing condition for government bonds is given by:

$$B_{t+1}^G = B_{t+1} \tag{20}$$

We note that the benchmark closed model specification (20) captures only the domestic market U.S. government debt. In the quantification of the model, we distinguish domestically owned and foreign-owned U.S. debt to ensure an accurate representation of asset levels currently held by the U.S. public.[17]

One important concept going forward is the *marginal cost of public funds* (MCF_t), which measures the welfare cost of raising an additional dollar of government revenues. If the government could impose lump-sum taxes, then the marginal cost of public funds would be equal to one, as households would give up \$1 in a pure transfer to the government. In contrast, if revenues must be raised through distortionary instruments, the costs of raising \$1 equal \$1 plus the excess burden (or marginal deadweight loss) of taxation. Following the literature, we formally define the MCF_t as the ratio of public to private marginal utility of consumption:

$$MCF_t \equiv \frac{\lambda_{1t}}{U_{ct}} \tag{21}$$

where λ_{1t} is the Lagrange multiplier on the resource constraint in the planner's problem (see Appendix). The wedge between the marginal utility of public and private incomes thus serves as a measure of the distortionary costs of the tax system.

Climate System

Global temperature change depends on the history of *global* greenhouse gas emissions, that is, the sum of rest-of-world (ROW) emissions $E_t^{M,ROW}$ and domestic emissions $\{E_s^M\}_{s=0}^t \equiv \{(1-\mu_s)E_s\}_{s=0}^t$. . Atmospheric temperature change T_t at time t then formally depends on the history of carbon emissions, initial conditions $\mathbf{S}_0$ (e.g., carbon stocks, ocean temperatures, etc.), and exogenous shifters $\{\boldsymbol{\eta}_s\}_{s=0}^t$ (e.g., land-based emissions) via:

$$T_t = F\left(\mathbf{S}_0, E_0^M + E_0^{M,ROW}, E_1^M + E_1^{M,ROW}, ..., E_t^M + E_t^{M,ROW}, \boldsymbol{\eta}_0, ...\boldsymbol{\eta}_t\right) \tag{22}$$

where:

$$\frac{\partial T_{t+j}}{\partial E_t^M} \geq 0 \ \forall j, t \geq 0$$

Sea level rise at time t, in turn, is modeled as a function of the history of global temperature change, along with initial condition SLR_0, following the semi-empirical specification due to Rahmsdorf (2007):

$$SLR_t = G(SLR_0, T_1, T_2, ...T_t) \tag{23}$$

[17] Of course abstracting from foreign demand for U.S. government debt raises additional potential issues. On the one one hand, ignoring the current stock of foreign-held debt may under-estimate the government's future revenue-raising obligations in the intertemporal budget constraint. On the other hand, abstracting from the foreign supply of loanable funds may lead to an over-estimate of the costs of borrowing for the U.S. government.

Competitive Equilibrium and Optimal Policy

Competitive equilibrium in this economy is defined in the conventional way. The social planner's problem is to maximize the representative agent's lifetime utility (3) subject to the constraints of (i) feasibility, (ii) the optimizing behavior of households and firms, and (iii) laws of nature (22)-(23). We follow the primal approach of solving for optimal *allocations* after having shown that and how one can construct prices and policies such that the optimal allocation will be decentralized by optimizing households and firms.[18] Solving for optimal allocations, rather than for optimal tax rates, also avoids normalization issues such as documented by Williams (2001).

Before proceeding to the model quantification, this section theoretically characterizes some of the implications of fiscal costs. First, one may ask how fiscal impacts affect the social cost of carbon, or the optimal carbon price. For notational convenience, first define the discount factor $M_{t,j}$ as:

$$M_{t,j} \equiv \begin{cases} 1 & \text{if } j = 0 \\ \beta^j \prod_{m=1}^{j} \frac{1}{(1+r_{t+m}-\delta_{t+m})} & \text{o.w.} \end{cases} \tag{24}$$

Result 1 *The optimal carbon price in period $t > 0$, that is, the carbon price that can decentralize*

[18] See, e.g., Chari and Kehoe (1999) for a general introduction, and Barrage (2020a) for the relevant proof of the validity of the setup in the benchmark COMET.

the optimal allocation along with other taxes set appropriately, is implicitly defined by:

$$\tau^*_{Et} = \sum_{j=0}^{\infty} M_{t,j} \cdot \underbrace{\left[\frac{-\partial Y_{t+j}}{\partial T_{t+j}}\right]}_{\text{Output Impacts}} \cdot \frac{\partial T_{t+j}}{\partial E^M_t} \tag{25}$$

$$+\sum_{j=0}^{\infty} \beta^j \left(\frac{1}{MCF_t}\right) \underbrace{\left[\frac{-U_{Tt+j}}{U_{ct}}\right]}_{\text{Utility Impacts}} \frac{\partial T_{t+j}}{\partial E^M_t} \tag{26}$$

$$+\sum_{j=0}^{\infty} \underbrace{\left[\sum_{m=0}^{\infty} M_{t,j+m} \cdot \frac{\partial \delta K_{t+m}}{\partial SLR_{t+m}} \frac{\partial SLR_{t+m}}{\partial T_{t+j}}\right]}_{\text{Sea Level Rise Impacts}} \frac{\partial T_{t+j}}{\partial E^M_t} \tag{27}$$

$$+\sum_{j=0}^{\infty} M_j \cdot \left[\underbrace{\frac{\partial G^C_{t+j}}{\partial T_{t+j}}}_{\text{Gov't Cons. Impacts}}\right] \frac{\partial T_{t+j}}{\partial E^M_t} \tag{28}$$

$$+\sum_{j=0}^{\infty} \beta^j \left(\frac{MCF_t - 1}{MCF_t}\right) \underbrace{\left[\frac{\partial G^T_{t+j}}{\partial T_{t+j}}\right]}_{\text{Gov't Transfer Impacts}} \underbrace{\left(\frac{U_{ct+j}}{[U_{cct}C_t + U_{ct} + U_{lct}L_t - U_{cct}G^T_t(T_t)]}\right)}_{\text{Offer Curve Impacts}} \frac{\partial T_{t+j}}{\partial E^M_t} \tag{29}$$

Intuitively, this expression represents the present discounted vaule sum of marginal damages from another ton of U.S. carbon emissions at time t, adjusted for the fiscal setting. The impacts of emissions on future temperature change are captured by $\frac{\partial T_{t+j}}{\partial E^M_t}$. Each period's temperature change, in turn, contributes to sea level rise, as captured by the additional summation term $\frac{\partial SLR_{t+m}}{\partial T_{t+j}}$ in (27). The economic impacts of these climatic changes are then valued as follows. First, the present discounted value of output impacts in (25) are valued fully, in line with prior literature. Second, and in contrast, utility impacts in (26) are "discounted" by the marginal cost of public funds. That is, in a setting with distortionary taxes where $MCF > 1$, the optimal carbon tax internalizes less than the full Pigouvian cost of marginal utility damages. This result is well known from the literature focusing on the *revenue* impacts of pollution levies alongside distortionary taxes (see Bovenberg and Goulder, 2002). Third, capital losses due to sea level rise are again valued fully in (27), as they fall on the production side of the economy. Fourth, the optimal carbon price should fully internalize government consumption cost increases due to climate change in (28). To the best of our knowledge, this type of impact has not been considered in prior literature. Finally, and perhaps most surprisingly, we find that *the social cost of carbon must account for government transfer impacts of climate change if the marginal cost of public funds exceeds unity* (29). In a standard setting where it is implicitly assumed that governments can raise revenues through lump-sum transfers, $MCF = 1$ and externality effects on transfers would not be included in the calculation of social cost. Here, however, a first-order welfare effect arises due to climate-induced changes in government transfer payments, and the resulting changes in households' offer curves, which may tighten the set of equilibria that can be decentralized as a competitive equilibrium. Importantly, these results showcase that consideration of climate change's fiscal costs may alter the structure of the optimal carbon price, calling for the inclusion of effects - such as on transfer payments - which are generally not considered.

The next theoretical question one may ask is: How does accounting for the welfare costs of raising public funds affect optimal public adaptation expenditures?

Result 2 *Public funding of both (i) flow adaptation inputs to reduce climate impacts on final goods production and (ii) investment in adaptation capital to reduce sea level rise impacts on capital depreciation should remain undistorted regardless of the welfare costs of raising revenues. That is, these adaptation expenditures should be fully provided at the optimum.*

Proof: See Appendix. While the actual dollar amount of optimal spending will differ across fiscal scenarios, Result 2 implies that there is no "wedge" (or distortion) in the optimality condition for adaptation spending to reduce production and capital damages from climate change: the government should invest until the additional benefit of avoided output losses equals the marginal adaptation cost.[19] Intuitively, while it is costly for the government to raise revenues, at the optimal level these expenditures 'pay for themselves' by increasing productivity and thereby expanding the bases of labor and capital income taxes. More broadly, this result follows from the well-known property that optimal tax systems maintain aggregate production efficiency under fairly general conditions (Diamond and Mirrlees, 1971).[20]

Next, and in contrast, consider the adaptation spending to reduce utility impacts of climate change (e.g., beach nourishment to maintain public parks). While these expenditures increase utility, they do not yield a productivity benefit that could counteract the macroeconomic costs of raising the revenues required to fund them. Consequently, we find that the optimal provision of these adaptation expenditures is distorted in a setting with costly taxation.

Result 3 *Public adaptation funding to reduce direct utility losses from climate change should be distorted proportionally to the marginal cost of raising public funds. That is, provision of*

[19] More formally, the optimal policy equates the marginal rate of transformation between consumption C_t and adaptive capacity Λ_t^y through adaptation expenditures λ_t^y and avoided output losses from climate change in the final goods sector.

[20] By noting that flow adaptation expenditures constitute a public input to production, this result is partly also in the vein of Judd (1999), who shows that public flow productive inputs should always be fully provided, regardless of the distortionary costs of raising revenues.

the climate adaptation good should be effectively taxed alongside the consumption of other final goods if the government raises revenues with distortionary taxes.

Proof: See Appendix. Result 3 implies that residual (net-of-adaptation) climate damages may be higher in a setting with distortionary taxes as even optimized public adaptation expenditures may be lower compared to a standard setting without fiscal constraints.

4 Model Calibration

4.1 Production

First, as is common in the literature, I assume a Cobb-Douglas aggregate production technology for the final good in (8):

$$\widetilde{F_1}(K_{1t}, L_{1t}, E_t) = K_{1t}^{\alpha} L_{1t}^{1-\alpha-v} E_t^{v}$$

Expenditure shares are set at standard values $\alpha = 0.3$ and $v = 0.03$ (e.g., GHKT, 2014). Base year total factor productivity (TFP) A_{10} in (8) is inferred by matching initial U.S. output ($17.4 trillion in $2012, Source: FRED) given initial capital, labor, and energy inputs. Base year energy input E_0 is set at 1.375 gitatons of carbon (GtC, Source: EPA, 2017). Normalizing available work time per annum to unity, L_0 is set at initial labor time share 0.2324 based on OECD data for the United States in 2015 (OECD, 2020), times the initial population of 320 million. This aggregate labor is distributed between the final good and energy sectors based on profit maximization and initial energy production.[21] The initial aggregate private capital stock K_0 is inferred assuming a real interest rate of 5% and a depreciation rate of 10%, and this capital stock is distributed across sectors to be consistent with profit maximization and initial energy production.[22] Future productivity growth is taken as exogenous and quantified based on the 2010 RICE Model parameters for the United States (Nordhaus, 2011). The base year savings rate is set to match 20.258% of GDP as per World Bank data for the United States in 2015.

Both fossil fuel-based and clean energy are produced with Cobb-Douglas technology:

$$E_t = A_{2t}(K_{2t}^{1-\alpha_E} L_{2t}^{\alpha_E}) \tag{30}$$

The labor share is set to $\alpha_E = 0.403$ based on Barrage (2020a). The quantification of abatement cost function $\Theta_t(\mu_t E_t)$ structurally follows the same approach as the global COMET but for the United States, that is, it converts the RICE model's U.S. abatement cost estimates (Nordhaus,

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[21] The labor share in final goods production is $(1-\alpha-v)/(\alpha_E \cdot v + 1 - \alpha - v) = 98.23\%$ at benchmark values.

[22] The capital share in final goods production is $(\alpha)/((1-\alpha_E)v + \alpha) = 94.37\%$ at benchmark values.

2011) into a per-ton cost measure through a logistic approximation (see Appendix and Barrage, 2020a).

4.1.1 Climate Damages

Production Climate change impacts on production are modeled in a standard quadratic form:

$$(1 - D_t(T_t)) = \frac{1}{1 + \alpha_{y,1} T_t + \alpha_{y,2} T_t^2} \tag{31}$$

I consider two quantifications. The first is based on U.S. damage estimates from the RICE model (Nordhaus, 2011) with two important adjustments. One, given that sea level rise impacts are modeled explicitly in the model, I remove them from the RICE damages to avoid double counting. Two, the DICE/RICE model family aggregates all impacts - both production and non-market - into an output-*equivalent* damage function $D(T_t)$. In a setting with distortionary taxes, the distinction between these two damages becomes welfare-relevant. I therefore disaggregate the sectoral impact estimates underlying the U.S. RICE damage function into production and utility damages following the delineation of Barrage (2020a), which, for the United States, implies around 70% of damages from $2.5°C$ warming in the production sector, and 30% affecting utility directly. The parameter θ_1 in (31) is set to match the resulting production loss estimate of 0.616 percent output loss due to $2.5°C$ warming, yielding $\alpha_{y,1} = 0$ and $\alpha_{y,2} = 0.00099171$.

As an alternative I also consider more recent empirical estimates of U.S. damages by Hsiang et al. (2017), which imply aggregate output-equivalent damages of 1.62 percent of output due to $2.5°C$ warming. Importantly, this figure includes both some non-market impacts (mortality and crime) and coastal impacts, both of which should be separated out for an appropriate calibration of $D(T_t)$ in our setting. Lacking such a separation, I presently interpret their estimates as pure production impacts and set direct utility impacts in the Hsiang et al. damage runs to zero. This specification may over-estimate the revenue impacts of climate change. The relevant parameters in (31) are $\alpha_{y,1} = 0.00283$ and $\alpha_{y,2} = 0.00146$.

Sea Level Rise Both gross sea level rise damages and the costs and benefits of adaptation are quantified based on the EPA's Coastal Property Model runs for the Climate Change Impacts and Risk Analysis project (EPA, 2017). The Coastal Property Model (Neumann et al., 2014a,b) considers detailed locally differentiated property values and vulnerabilities, sea level rise effects (based on Kopp et al., 2014; and NOAA, 2017), and tropical cyclone surge impacts of climate change (building on Emanuel et al., 2008). It estimates costs resulting both from increased storm surge damages and property abandonement. Importantly, the model also considers and optimizes adaptation responses, as described below.

In order to construct a gross-of-adaptation SLR damage function, I utilize model results from 'no adaptation' runs for both RCP scenarios 4.5 and 8.5[23] Total gross damages appear approximately linear in global mean sea level rise (see Appendix Figure A5). I translate these level damages into depreciation rates by (i) deflating future values into base year property value equivalents, and (ii) dividing by the base year capital stock. Regressing the resulting observations of depreciation rates on global sea level rise values yields a benchmark estimate of 0.0186% capital loss per decade per centimeter SLR (over 2000 base period values). Letting $\overline{\delta}$ denote baseline capital depreciation, I consequently set capital depreciation in (5) to be:

$$\begin{aligned} \delta(SLR_t, \Lambda_t^{slr}) &= \overline{\delta} + \delta^{SLR} \cdot SLR_t \cdot (1 - \Lambda_t^{slr}) \\ &= \overline{\delta} + 0.000186 \cdot SLR_t \cdot (1 - \Lambda_t^{slr}) \end{aligned} \tag{32}$$

4.2 Government

4.2.1 Government Consumption and Transfer Requirements

Government consumption $G_t^C(T_t)$ and transfer $G_t^T(T_t)$ requirements are specified as follows. Let $\{\overline{G_t^C} > 0\}_{t=0}^{\infty}$ and $\{\overline{G_t^T} > 0\}_{t=0}^{\infty}$ denote the exogenous baseline sequences of government consumption and transfer requirements gross of climate change. According to U.S. National Income and Product Accounts data (BEA, 2019), total U.S. government expenditures in the model base year 2015 included \$2.7 trillion in transfer payments and \$2.7 trillion in consumption and subsidies (\$2015). Base year values for $\overline{G_t^T}$ and $\overline{G_t^C}$ are set accordingly. In future years, total baseline (i.e., without climate change) government expenditures grow at the rates of population and productivity growth (following, e.g., Goulder, 1995), and that the consumption share remains at its base year value (49.7 percent)

Climate change impacts on these expenditure requirements are modeled based on the existing program cost estimates described in Section 2, and specified as:

$$\begin{aligned} G_t^C(T_t) &= \overline{G_t^C}(1 + \alpha_{C,1,t}(T_t) + \alpha_{C,2,t}(T_t)^2) \\ G_t^T(T_t) &= \overline{G_t^T}(1 + \alpha_{T,1}(T_t) + \alpha_{T,2}(T_t)^2) \end{aligned} \tag{33}$$

I calibrate the fiscal damage function parameters to match the estimates underlying Table 7, and, for heat-related healthcare expenditure impacts, the damage function (2). The consumption impact coefficients further have time subscripts $\alpha_{C,1,t}$ to reflect projected future increases in healthcare cost shares due to demographic and other factors (CBO, 2021b). I incorporate CBO

[23] We are extremely grateful to Jeremy Martinich for sharing both model results and input assumptions.

projections implying an annualized average public health expenditure share growth rate of 1.623% through 2050 and assume the public healthcare expenditure share remains constant thereafter.[24] Figure 7 showcases examples of the resulting fiscal damage functions (evaluated at year 2020 and year 2050 relative healthcare cost shares, respectively).

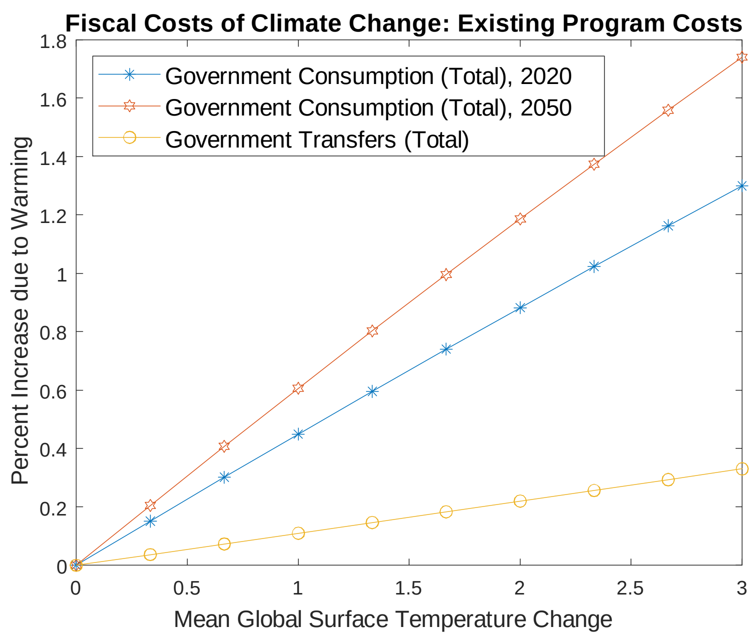

Figure 7: Climate Fiscal Damage Functions

4.2.2 Endogenous Public Sea Level Rise Adaptation

Adaptation technology is quantified based on the EPA's Coastal Property Model (Neumann et al., 2014a,b) runs for the Climate Change Impacts and Risk Analysis project (EPA, 2017). The model optimizes adaptation responses to sea level rise in the forms of beach nourishment, shoreline armoring (e.g., sea walls), and property elevation. I quantify aggregate adaptation effectiveness based on their model results from 'adaptation' runs for RCP scenarios 4.5 and 8.5. These provide information on both annual expenditures on different coastal protection measures, and residual damages incurred. As per (17), I assume that adaptive capital at time t is given by:

$$AK_t \equiv \sum_{s=0}^{t-1}(\lambda_s^{slr}(1-d^{slr})^s) + \lambda_s^{slr} \tag{34}$$

In line with prior literature (e.g., Fried, 2019), adaptive capacity depends on the protective

[24] The resulting parameter values are $\alpha_{T,2} = 0.0011$, $\alpha_{T,2} = 0$, and: $\alpha_{C,1,t} = 0.002 + 0.0026 \cdot (1.01623)^{10 \cdot t}$ until 2045-55 and 0.0062 thereafte, and $\alpha_{C,2,t}$=$-0.00008 \cdot (1.01623)^{10 \cdot t}$ until 2045-55 and -0.0001297 thereafter.

capital stock *relative* to gross damages (i.e., capital at risk) via:

$$\Lambda_t^{SLR} = \left(\gamma_1 \frac{AK_t}{(\delta^{SLR} \cdot SLR_t \cdot K_t)}\right)^{\gamma_2} \tag{35}$$

I quantify adaptation cost parameters γ_1, γ_2, and d^{slr} by minimizing the sum of squared deviations between equations (34), (35), and an intra-temporal optimality condition for adaptation expenditures,[25] and the 'observations' of Λ_t^{SLR}, AK_t, and gross damages obtained from the EPA's Coastal Property Model, all aggregated to the decadal level.[26] That is, we effectively fit parameters to create a reduced-form aggregate representation for the detailed EPA model results. The deviation-minimizing parameters are $\gamma_1 = 10.1752$, $\gamma_2 = 0.0945$, and $d^{slr} = 0.2462$, implying an *annual* protective capital depreciation rate of 2.79%.

4.2.3 Other Public Adaptation

While there are many examples and some quantifications of public adaptation measures beyond coastal protection, mapping out these potential expenditures and their corresponding benefits at a systemic level is difficult and fraught with uncertainties. For utility damages, relevant examples range from expenditures to protect and repair national parks from climate damages to public funding for mental health support after disasters (e.g., FEMA Crisis Counseling Assistance and Training Program). However, properly accounting for the relationship between these public expenditures and climate damages would require these impact channels to also be accounted for in the damage function, which does not currently match this level of detail in its foundations. Similar issues arise with public inputs to reduce production damages, such as research funding on climate-resilient crops. While Barrage (2020b) uses a stylized representation of public adaptation efforts at a global level based on prior literature (Argawal et al., 2010), for the present analysis we currently abstract from highly speculative potential quantifications of these measures and focus on sea level rise adaptation Λ_t^{slr} for which higher quality and U.S.-specific estimates are available as outlined in the prior section.

[25] The intra-temporal optimality condition for minimizing the sum of gross damages and adaptation costs is that $\frac{\partial \Lambda_t^{slr}}{\partial \lambda_t^{slr}} = \frac{1}{\text{GrossDamages}_t}$.

[26] We further add one assumption-based moment, namely that spending only 50% of prescribed adaptation funds in the base 2010-2020 period would achieve 60% of the benchmark adaptation effectiveness. This moment was added as the Coastal Property Model results imply very high levels of optimal adaptation effectiveness, around 95% or higher, across all periods, thus limiting the range of 'observations' available to quantify the full curvature of the adaptation cost function.

4.2.4 Initial Taxes and Debt

Base year effective tax rates: According to OECD estimates, the average effective labor tax wedge in the United States between 2010-2018 has fluctuated between 29.6% and 31.8% with an average value of 30.8778%. The average effective consumption tax has been estimated at 6.1% (Carey and Tchilinguirian, 2000), implying an overall effective labor-consumption wedge of 35.09%.[27] For tax burdens on capital, a detailed review by the Congressional Budget Office (2014) estimates a 29% effective marginal rate on business capital.[28]

Government Debt: The benchmark calibration sets B_0 based on the 2015 federal debt held by the domestic public at 41.1% of base year GDP (FRED, 2020).

4.2.5 Preferences

The specification of preferences is as in the benchmark COMET but with quantitative adjustments for the U.S. setting. Utility is defined over per-capita consumption $c_t \equiv C_t/N_t$, where N_t is the period t population and labor supply is $l_t \equiv L_t/N_t$. The dynastic household maximizes the population-weighted lifetime utility:

$$\sum_{t=0}^{\infty} \beta^t N_t U(c_t, l_t, T_t)$$

The U.S. population grows from 320 million in 2015 to 417.5 million by 2105 and asymptotes towards 448 million, matching projections from RICE (Nordhaus, 2011).

The utility function is specified as follows:

$$U(c_t, l_t, T_t) = \frac{\left[c_t \cdot (1 - \varsigma l_t)^{\gamma}\right]^{1-\sigma}}{1-\sigma} + \frac{\left(1 + \alpha_u T_t^2\right)^{-(1-\sigma)}}{1-\sigma} \tag{36}$$

Preference parameters are set to jointly match base year labor supply $l_{2015} = 0.2324$ and a Frisch elasticity of labor supply of 1.83, which is the average between the benchmark micro and macro estimates identified by Chetty et al. (2011), given initial tax rates[29] and assumed values of $\sigma = 1.5$ and a decadal utility discount factor of $\beta = (.985)^{10}$. In the benchmark model where damages are quantified based on the RICE model, the climate disutility parameter α_u is chosen to match an aggregate global consumption loss-equivalent of disutility from climate change at $2.5°C$ of 0.26% of output (for further discussion see Barrage, 2020a). In the version of the model

[27] Following Carey and Tchilinguirian (2002), the labor-consumption wedge is computed as $\tau_{cl} = \tau_l + (1 - \tau_l)\tau$.

[28] CBO (2014) also estimate a lower rate of 18% if owner-occupied housing is included, but this figure does not account for local property taxes, leading us to prefer the more self-contained estimate for business capital.

[29] Initial tax rates are set to zero in the lump-sum taxation (theoretical first-best) scenarios.

where damages are quantified based on Hsiang et al. (2017), non-market impacts are included in the aggregate damage function so that I set $\alpha_u = 0$.

4.2.6 Carbon Cycle and Climate Model

At present, the COMET adopts the carbon cycle and climate model from the DICE model (Nordhaus, 2010, 2016). An update to incorporate revisions in line with recent climate science evidence as described by Dietz et al. (2020) is in progress. Sea level rise resulting from the history of temperature changes is quantified based on Rahmsdorf (2007).

Given the U.S. focus of the model, rest of the world emissions must be specified. As a baseline I take business-as-usual emissions projections the 2010 RICE Model, (Nordhaus, 2011). I further allow for the possibility that rest-of-the-world emissions respond to U.S. abatement efforts as a reduced form for, e.g., international climate policy agreements and technology spillovers. The baseline model assumes a global abatement response elasticity of 0.3, implying that for every percentage point of U.S. emissions reductions, the rest of the world abates 0.3 percentage points of emissions.

5 Quantitative Results

5.1 Main Results

We present model results across four income tax and two climate policy scenarios. The income tax scenarios are as follows:

1. "First-Best": The government can levy non-distortionary lump-sum taxes. This assumption is standard in IAMs in the literature.

2. "Optimized Distortionary": The government can fully optimize its revenue-raising taxes, but cannot impose lump-sum levies.

3. "Fixed Labor, Variable Capital Income Taxes": Labor taxes are held fixed at business-as-usual levels $\overline{\tau_l} = 35.1\%$ but the government can raise additional revenues by raising capital income taxes. Depending on the scenario, the planner can also tax carbon and energy.

4. "Fixed Capital, Variable Labor Income Taxes": Capital income taxes are held fixed at business-as-usual levels $\overline{\tau_k} = 29\%$ but the government can raise additional revenues by raising labor income taxes. Depending on the scenario, the planner can also tax carbon and energy.

For U.S. carbon and energy taxation, two scenarios are considered:

1. "No": This business-as-usual scenario assumes no carbon or energy taxes throughout the 21st Century (until 2115).

2. "Opt." The government freely optimizes carbon and energy taxes.

Another critical modeling choices include the rest-of-world carbon emissions response elasticity to U.S. abatement. Our benchmark results assume an elasticity of 0.3, but results for a value of zero (exogenous rest-of-world emissions) are also presented. Finally, all results use RICE-based damages unless otherwise noted.

One important point to note is that the social planner in the model considers only domestic impacts of climate change in the United States. That is, the "optimal" carbon price or social cost of carbon estimates from the model are not reflective of rest of the world damages, and are thus too low from a broader efficiency perspective. For a discussion of fiscal costs at the global level, see Barrage (2020b).

Results: To begin, Figure 8 presents the projected government expenditure impacts of climate change in the near-term, which increase from around \$245 billion in the 2015-2025 period to around \$1 trillion in the 2055-2065 period.[30] Increases in existing program costs - especially healthcare - are projected to account for the majority of these costs.

Next, Table 10 presents policy and welfare results for the benchmark model with and without U.S. climate policy. In the first-best setting - the standard in climate-economy models - labor and capital income taxes are both zero, and the MCF is equal to unity. Introducing the optimal U.S. carbon price sequence in this setting yields a domestic welfare gain of \$342 billion dollars (\$2015 in terms of initial period equivalent variation consumption transfer). Second, in a setting with optimized distortionary taxes, the government raises most revenues from the labor-consumption wedge, with an equilibrium marginal cost of public funds of 1.10. In this setting, while the optimal carbon price level is slightly lower, the welfare gains associated with U.S. climate policy are around 30% higher than in the standard setting, estimated at \$435 billion. Third, in a more realistic 'business as usual' fiscal setting where labor income taxes are fixed at current levels, the government raises additional revenues in part from capital income taxes. Without a carbon price,

[30] These figures are from the "Optimized Distortionary" income tax scenario with optimized domestic carbon taxes in the face of business-as-usual global emissions. Expenditures in the near term are not too different in other climate policy scenarios due to delays in the climate system assumed in the DICE model and the stock nature of sea level rise. The former may change with a switch to a climate system representation as recommended by Dietz et al. (2020).

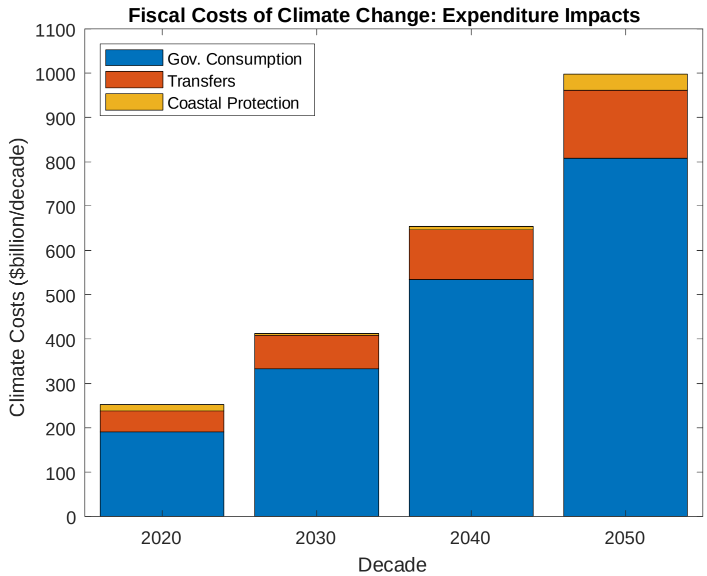

Figure 8: Expenditure Impacts: Levels

the average effective capital income tax is 35.9% at a marginal cost of funds of 1.56. Introducing climate policy could lower capital income tax rates to 34.9% on average, thus also lowering the MCF to 1.53, and, importantly, yielding overall welfare gains of more than $1 trillion. That is, in a fiscally constrained setting, the welfare gains associated with carbon pricing are more than *triple* their value in the first-best setting generally assumed in the literature. The reasons for this difference include both the higher value of revenues raised from carbon taxes and of fiscal cost savings achieved through avoided climate change. Fourth, if capital income taxes remain fixed and the government raises additional revenue mainly through labor income taxes, the marginal cost of funds is again low at 1.10. The optimal carbon price in this setting nonetheless yields a welfare gain of $406 billion, around 20% higher than in a first-best world. Appendix Table A1 presents analogous results for a setting with exogenous rest-of-world emissions. While the *levels* of optimal carbon prices and welfare gains associated with carbon pricing are generally lower in this setting, most relevant for this paper's focus, the relative importance of fiscal interactions is unchanged.

Table 7: Benchmark Results						
Scenario		Labor Tax	Capital Tax	MCF	Carbon Tax ($/mtC)	ΔWelfare EV ΔC_{2015} ($2015 bil.)
Income	Carbon & Energy	Avg. 2025-2215			2015-25	
First-Best	No	0	0	1.00	0	
First-Best	Opt.	0	0	1.00	34	342
Opt.	No	40.4	5.4	1.10	0	
Opt.	Opt.	40.4	5.6	1.10	29	435
BAU $\overline{\tau_l}$, vary τ_k	No	$\overline{35.1}$	35.9	1.56	0	
BAU $\overline{\tau_l}$, vary τ_k	Opt.	$\overline{35.1}$	34.9	1.53	25	1,049
BAU $\overline{\tau_k}$, vary τ_l	No	39.7	$\overline{29.0}$	1.10		
BAU $\overline{\tau_k}$, vary τ_l	Opt.	39.7	$\overline{29.0}$	1.10	28	406
Rest-of-world emissions response elasticity 0.3, RICE Production Damages						

Table 8 shows results analogous to the benchmark in Table 7 but with climate change production impacts quantified based on Hsiang et al. (2017). As expected, both the optimal carbon price and the welfare gains associated with climate policy are higher in this setting. Importantly for the purposes of this study, however, the importance of fiscal considerations is robust. Domestic climate policy can lower the marginal cost of public funds non-trivially, and its welfare benefits increase by up to a factor of three once the fiscal setting is taken into account.

Table 8: Robustness - Hsiang et al. (2017) Production Damages						
Scenario		Labor Tax	Capital Tax	MCF	Carbon Tax ($/mtC)	ΔWelfare EV ΔC_{2015} ($2015 bil.)
Income	Carbon & Energy	Avg. 2025-2215			2015-25	
First-Best	No	0	0	1.00	0	
First-Best	Opt.	0	0	1.00	48	508
Opt.	No	40.1	5.4	1.07	0	
Opt.	Opt.	40.1	5.4	1.07	42	697
BAU $\overline{\tau_l}$, vary τ_k	No	$\overline{35.1}$	41.4	1.77	0	
BAU $\overline{\tau_l}$, vary τ_k	Opt.	$\overline{35.1}$	39.9	1.71	37	1,771
Rest-of-world emissions response elasticity 0.3						

Sensitivity: As previously noted, the benchmark model's quantification of fiscal climate impacts is subject to significant uncertainty and likely presents a lower bound. While a formal treatment of this uncertainty is in progress, Figure 8 showcases how the social cost of carbon in the initial decade (2015-2025), specifically measured by the optimal U.S. carbon price, varies as a function of the existing program fiscal cost changes per degree warming. The results indicate that, even at seemingly small values, fiscal costs can have significant implications for the social cost of carbon. Each percentage point increase in government consumption (transfers) per degree warming translates into optimal carbon price increases of around 20% (10%). Even at our benchmark values, the estimated implications of fiscal costs for climate policy are thus quantitatively on par with the importance of factors such as climate tipping points (Lemoine and Traeger, 2014), ambiguity aversion (Lemoine and Trager, 2016), or model uncertainty (Rudik, 2019) documented in prior studies.

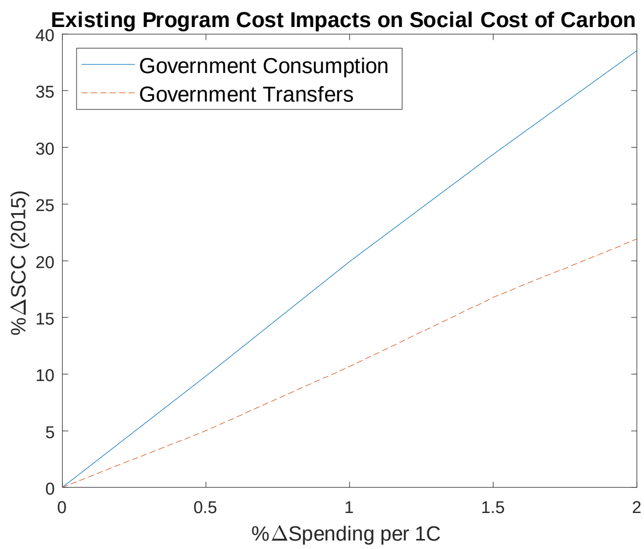

Figure 9: Fiscal Cost Impacts on the SCC

6 Conclusion

Climate change is increasingly being recognized as a potential threat to fiscal sustainability. Both policy and academic studies have documented numerous channels through which a changing climate may alter public budgets (e.g., Egenhofer et al., 2010; CBO, 2021). This paper presents what is to the best of our knowledge a first systematic quantification and integration of these channels into a macroeconomic integrated assessment model. The analysis first demonstrates that fiscal costs have *qualitative* implications for climate policy: the social cost of carbon must account for climate impacts on both government consumption and, perhaps surprisingly, transfer payments to households when the marginal cost of raising public funds exceeds unity. I then present a novel bottom-up quantification of climate impacts on government expenditures in the United States. The quantification synthesizes prior studies and adds an empirical analysis of public healthcare costs of extreme temperatures and wildfires. *Quantitatively*, while the resulting estimates are obviously subject to fundamental uncertainties, I find large potential effects of both public expenditure impacts and fiscal interactions of climate policy more. For example, the domestic benefits of U.S. climate policy may be under-estimated by up to a factor of three by conventional climate-economy models that abstract from distortionary taxes and government expenditure requirements.

The analysis makes important simplifying assumptions. For example, local, state, and federal finances are all aggregated into a central fiscal authority. In reality, the distribution of climate change's fiscal impacts across levels of government may be important. Certain costs - such road elevation to protect against flooding - may fall disproportionately on local governments which also face a higher cost of raising public funds. Indeed, recent empirical work has found significantly higher long-term municipal bond issuance costs in U.S. counties more vulnerable to climate change (Painter, 2020), consistent with less-than-complete risk sharing. Consideration of regional heterogeneity also raises distributional questions which are currently outside the scope of the analysis. More broadly, our framework does not account for income inequality and redistribution as important aspects of the tax system. Indeed, very little work to date has considered climate policy in dynamic heterogeneous agent economies in general, let alone with tax policy. These are all critical areas for future research. Importantly, however, we conjecture that consideration of factors such as higher local fiscal exposure to climate risks would likely serve to increase the potential relevance of climate fiscal costs for policy design.

At the time of this writing, the United States faces significant fiscal challenges. Due to the COVID-19 pandemic and response, the U.S. federal debt held by the public has risen from 79 to 105 percent of GDP between the first and second quarters of 2020 (FRED, 2020). The U.S. Congressional Budget Office moreover projects continued increases in U.S. debts under current policy (CBO, 2020). This paper's results suggest that climate change may exacerbate these trends. Importantly, however, the analysis also finds that appropriately designed domestic climate policy and international climate agreements may allow for lower tax burdens and yield large net economic benefits for the U.S. economy.

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7 Appendix

7.1 Climate Impacts Quantification

Figure A1 showcases the estimated marginal impact of an additional freezing day (with minimum temperatures below 0C) on public health expenditures based on Table 5 Column (1) results evaluated at a baseline climate of 1981-2010. It must be noted that these estimates were not statistically different than zero. Next, Figures A2 and A3 show the projected marginal impacts of an additional hot day evaluated at mid- and late-century climates, that is, inclusive of projected adaptation (based on Table 5 Column (1) results).

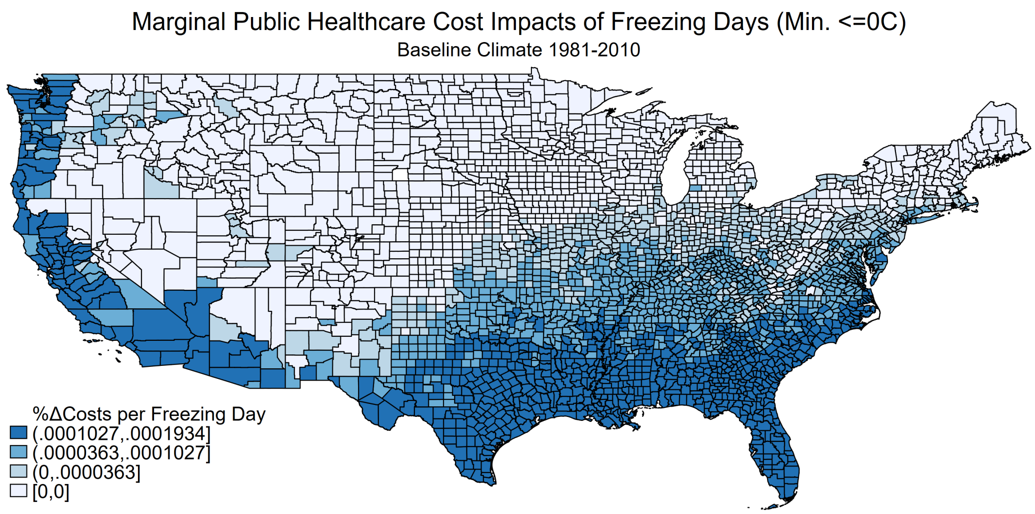

Figure A1

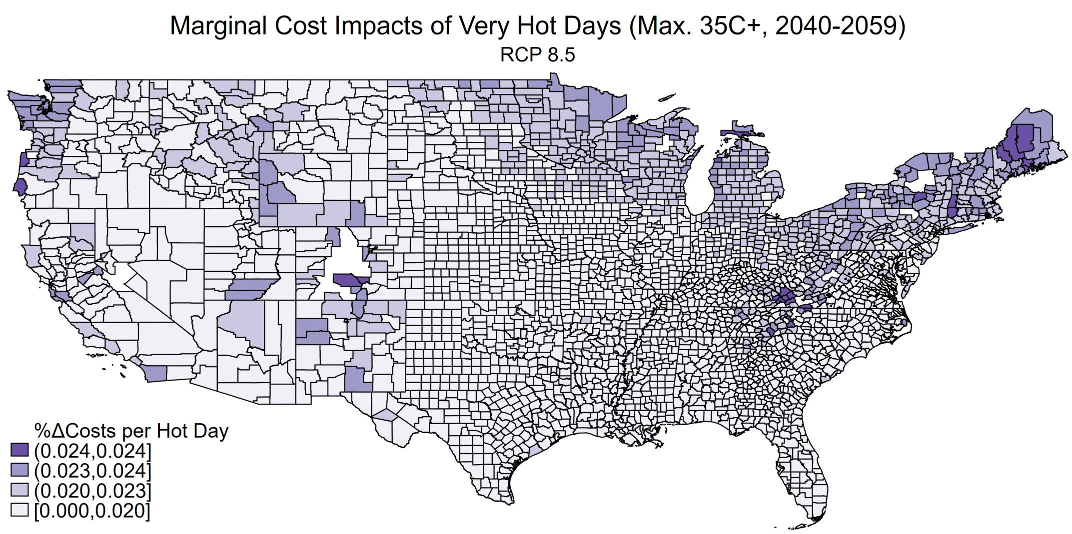

Figure 10: Figure A2

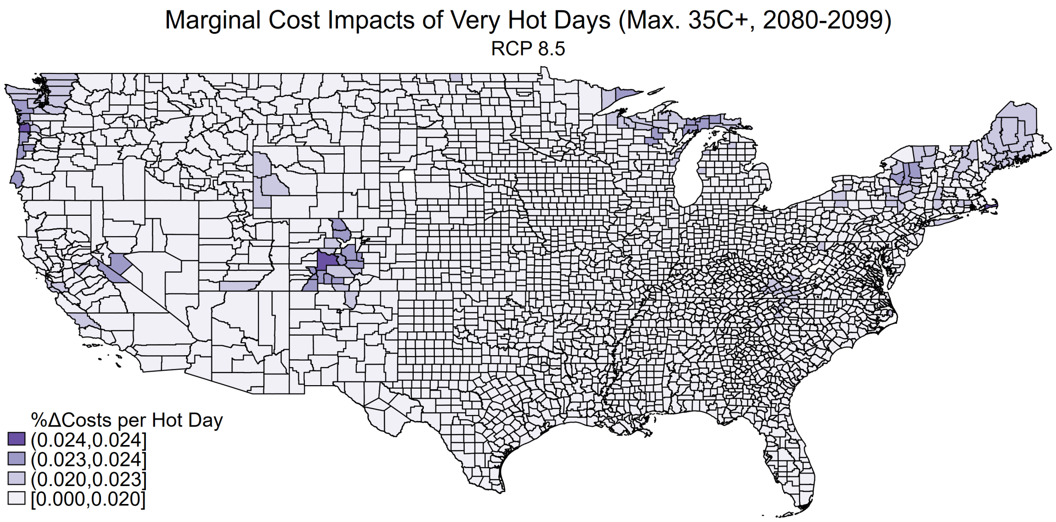

Figure 11: Figure A3

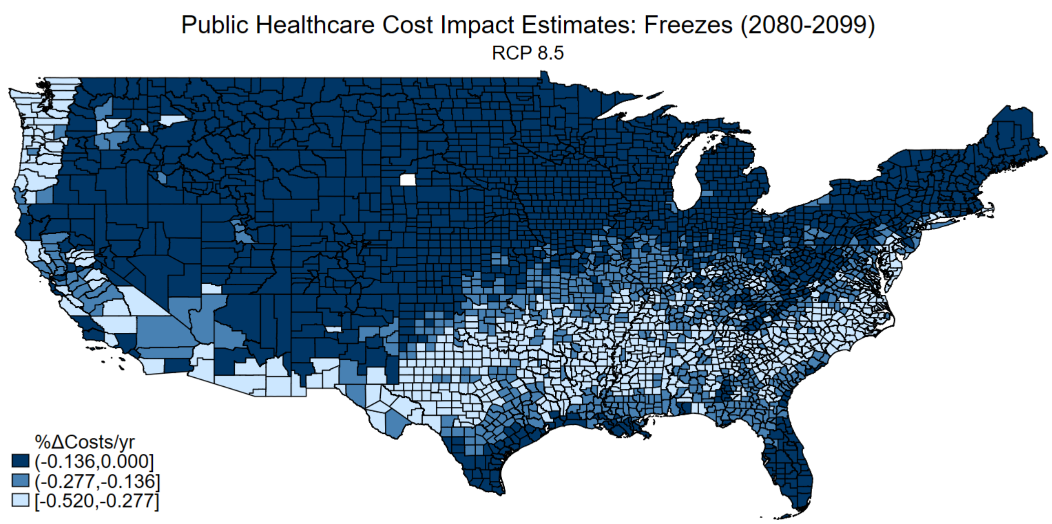

Figure 12: Figure A4

7.1.1 Reduced-Form Downscaling

In order to map the warming scenario-specific estimates of county-level weather outcomes from Rasmussen et al. (2016) into an aggregate fiscal damage function specified as a function of mean global atmospheric surface temperature change, I estimate a reduced-form linear downscaling model for each county j :

$$\Delta D_{m,j,\tau} = \lambda_{j,m} T_\tau \tag{37}$$

Here, $\Delta D_{m,j,\tau}$ denotes the predicted change in our variable of interest with $m \in \{$"hot" days, "freezing" days$\}$, such as the predicted change in the number of hot days per year in county j in period $\tau \in \{2020-2039, 2040-2069, 2080-2099\}$ under the RCP 8.5 warming scenario. The variable T_τ represents the corresponding mean global surface temperature warming in period τ under RCP 8.5, which I obtain from a MAGICC6 climate model run (Meinhausen et al., 2011). Figure A3 compares the linearly predicted changes in the number of hot days per year for each county-period from this regression ($\widehat{\Delta D_{hot,j,\tau}} = \widehat{\beta_{j,hot}} T_\tau$) against the detailed Rasmussen et al. (2016) values (median value based on the CMIP5 ensemble). The linear model (37) appears to fit these projections well, with a correlation coefficient of 0.984. Figure A4 repeats this exercise but for $m =$"freezing" days, where the linear fit again appears good with a correlation coefficient of 0.983.

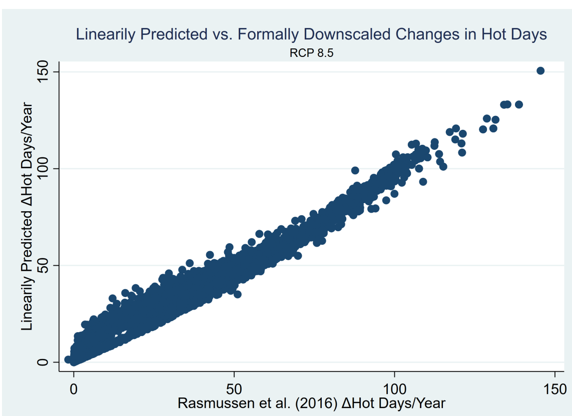

Figure A3

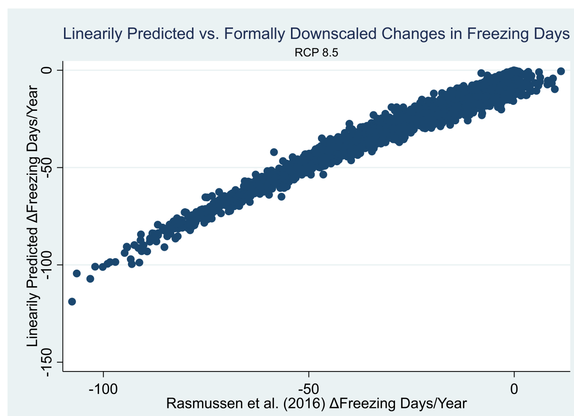

Figure A4

7.1.2 Extreme Heat Damage Function

Conceptually, an aggregate damage function should tell us the change in public medical expenditures due to a change in global temperatures T_t. For each county this change can informally be decomposed as:

$$\frac{\%\Delta\text{MedicalCosts}}{\Delta\text{GlobalTemperature}} = \frac{\%\Delta\text{MedicalCosts}}{\Delta\text{HotDays}} \frac{\Delta\text{HotDays}}{\Delta\text{GlobalTemperature}} \tag{38}$$

where county subscripts are omitted for notational simplicity. From the impact estimating equation (1), we have that:

$$\frac{\%\Delta \text{MedicalCosts}}{\Delta \text{HotDays}} = [\widehat{\beta}_{hot} + \widehat{\gamma}_{hot} DMEAN_{hot,\tau}] \tag{39}$$

where τ denotes the time period. From the reduced-form downscaling (37), we also have that:

$$\frac{\Delta \text{HotDays}}{\Delta \text{GlobalTemperature}} = \widehat{\lambda} \tag{40}$$

Importantly, (40) also implies that we can write the future mean number of hot days as a function of the base year climate, the downscaling coefficient, and global temperature change:

$$DMEAN_{hot,\tau} = DMEAN_{hot,0} + \widehat{\lambda} T_\tau \tag{41}$$

Combining (38)-(41) and arranging to obtain the predicted total change in public medical expenditures as a function of global temperature change T_τ yields the desired expression (2):

$$\%\Delta \text{PublicMedicalCosts}_{j,t} = [\widehat{\beta}_{hot} \widehat{\lambda}_j + \widehat{\gamma}_{hot} DMEAN_{hot,j,0} \widehat{\lambda}_j] \cdot T_t + [\widehat{\gamma}_{hot} \widehat{\lambda}_i^2] \cdot T_t^2$$

7.1.3 Sea Level Rise Costs

Figure A5 showcases estimates of gross of adaptation sea level rise damages from EPA (2017) over time and across two emissions scenarios, plotted against corresponding median global sea level rise values from Kopp et al. (2017).

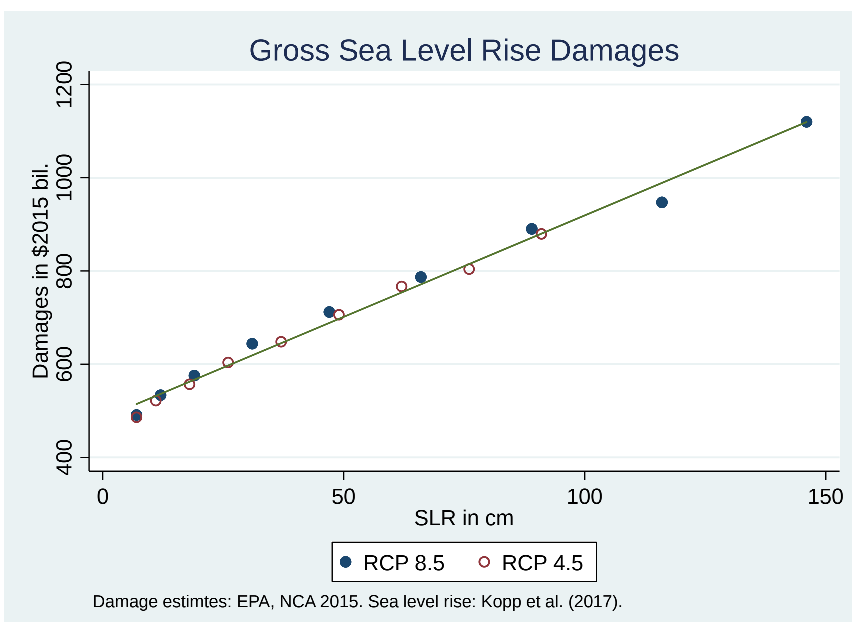

Figure A5: Gross Sea Level Rise Costs from EPA (2017)

7.2 Theory Setup and Results

It is straightforward to show (following an analogous derivation to the one in Barrage, 2020a) that the primal social planner's problem for our framework is as follows:

$$
\begin{aligned}
&\max \sum_{t=0}^{\infty} \beta^t \underbrace{[[v(C_t, L_t) + h[T_t] + \phi\left[U_{ct}C_t + U_{lt}L_t - U_{ct}G_t^T(T_t)\right]]}_{\equiv W_t} \\
&+\sum_{t=0}^{\infty} \beta^t \lambda_{1t} \left[\begin{array}{c} \left\{[1-D(T_t)] \cdot A_{1t}\widetilde{F_{1t}}(L_{1t}, E_t, K_{1t})\right\} + (1-\delta(SLR_t, \Lambda_t^{slr})K_t \\ -C_t - K_{t+1} - G_t^C(T_t) - \lambda_t^y - \lambda_t^u - \lambda_t^{SLR} - \Theta_t(\mu_t E_t) \end{array} \right] \\
&+\sum_{t=0}^{\infty} \beta^t \xi_t [T_t - F\left(\mathbf{S}_0, (1-\mu_0)E_0, (1-\mu_1)E_1, ..., (1-\mu_t)E_t, \boldsymbol{\eta}_0, ...\boldsymbol{\eta}_t\right)] && (42) \\
&+\sum_{t=0}^{\infty} \beta^t \zeta_t [SLR_t - f^{slr}(T_0, T_1, ...T_t)] && (43) \\
&+\sum_{t=0}^{\infty} \beta^t \lambda_{lt}\left[L_t - L_{1t} - L_{2t}\right] \\
&+\sum_{t=0}^{\infty} \beta^t \lambda_{kt}\left[K_t - K_{1t} - K_{2t}\right] \\
&+\sum_{t=0}^{\infty} \beta^t \omega_t\left[F_{2t}(A_{Et}, K_{2t}, L_{2t}) - E_t\right] \\
&+\sum_{t=0}^{\infty} \beta^t \eta_{St}\left[f^{SLR}(AK_t) - \Lambda_t^{SLR}\right] && (44) \\
&+\sum_{t=0}^{\infty} \beta^t \eta_{akt}[AK_t(1-\delta^{slr}) + \lambda_t^{slr} - AK_{t+1}] && (45) \\
&-\phi\left\{U_{c0}\left[K_0\left\{1 + (F_{1k0} - \delta)(1 - \overline{\tau_{k0}})\right\} + B_0\right]\right\}
\end{aligned}
$$

7.2.1 Result 1

To derive our optimality conditions of interest, first combine the planner's first-order conditions for $t > 0$ with respect to SLR_t and T_t to express the social cost of carbon emissions in utility terms, ξ_t :

$$(-U_{Tt}) + \phi U_{ct}\frac{\partial G_t}{\partial T_t} - \lambda_{1t}\frac{\partial Y_t}{\partial T_t} + \lambda_{1t}\frac{\partial G_t^c}{\partial T_t} + \sum_{m=0}^{\infty}[\beta^m \lambda_{1t+m}\frac{\partial \delta}{\partial SLR_{t+m}}K_{t+m}]\frac{\partial SLR_{t+m}}{\partial T_t} = \xi_t \qquad (46)$$

Next, the first order condition with respect to mitigation μ_t for $t > 0$ implies that, at the optimum, marginal abatement costs are equated to the present value of future marginal damages:

$$\Theta_t'(\mu_t E_t) = \sum_{j=0}^{\infty} \frac{\xi_{t+j}}{\lambda_{1t}} \beta^j \frac{\partial T_{t+j}}{\partial E_t^M} \tag{47}$$

Combining (46) and (47) yields an expression for the optimal carbon price τ_{Et}^* in equilbrium as per (15). In order to derive the expression of Result 1 in the paper, one needs to substitute out for the public marginal utility of income λ_{1t} and for the Lagrange multiplier on the implementability constraint, ϕ. With regards to the former, the planner's optimality condition with respect to the aggregate private capital stock $[K_{t+1}]$ for $t > 0$ implies that:

$$\frac{\lambda_{1t}}{\beta \lambda_{1t+1}} = [F_{Kt+1} + (1 - \delta(.))] \tag{48}$$

Substituting the equilibrium condition for capital returns (10) into (48) links to the rate of return term in M_j (24). With regards ot the latter, taking the first order condition with respect to $[C_t]$ for $t > 0$ reveals that:

$$\phi = \frac{\lambda_{1t} - U_{ct}}{[U_{cct} C_t + U_{ct} + U_{lct} L_t - U_{cct} G_t^T(T_t)]} \tag{49}$$

Substituting (49) into (46), multiplying by $\frac{U_{ct}}{U_{ct}}$, invoking the definition of the $MCF_t = \frac{\lambda_{1t}}{U_{ct}}$, and rearranging yields the expression for the optimal carbon price τ_{Et}^* in Result 1.

7.2.2 Result 2

Production adaptation In order to demonstrate that the optimal provision of general production adaptation Λ_t^y is undistorted, we note that combining the first order conditions with respect to $[\Lambda_t^y]$ and $[\lambda_t^y]$ for $t > 0$ yields optimality condition (50):

$$\underbrace{(-\widetilde{F_{1Tt}} D(T_t))}_{\mathrm{MRT}^{F_{1t}}_{C_t,\Lambda_t^y}} = \underbrace{\frac{1}{f_{\lambda_t}^y}}_{\mathrm{MRT}^{f_t^y}_{C_t,\Lambda_t^y}} \tag{50}$$

Here, $\widetilde{F_{1Tt}}$ denotes the marginal output losses due to a change in temperature at time t, and $D(T_t)$ is the damage function from (8). The left-hand side of (50) thus measures the increase in the final consumption good available due to a marginal increase in adaptive capacity in the final goods sector (Λ_t^y). Conversely, the right-hand side represents the marginal rate of transformation between the consumption good C_t and adaptive capacity through adaptation expenditures λ_t^y. While condition (50) will be evaluated at different allocations depending on the tax system, it demonstrates that there is no wedge distorting adaptation provision at the optimum, as indicated in Result 2.

Sea level rise protection With regards to public sea level rise adaptation, combining the planner's first order conditions with respect to adaptive capacity $[\Lambda_t^{slr}]$, capital $[AK_{t+1}]$, and investment $[\lambda_t^{slr}]$ yields an Euler equation governing optimal public investment in coastal protection:

$$\frac{\lambda_{1t}}{\beta\lambda_{1t+1}} = \frac{\partial\Lambda^{SLR}_{t+1}}{\partial AK_{t+1}}\frac{\partial\delta}{\partial\Lambda^{slr}_{t+1}}K_{t+1} + (1-\delta^{slr}) \tag{51}$$

The right-hand side captures the intertemporal marginal rate of transformation between the consumption-investment good today and in the future through investments in sea level rise adaptation capital. The left-hand side denotes the social planner's intertemporal marginal rate of substitution. Comparison of (23) to (48) demonstrates that, at the optimum, the planner equates the marginal rates of transformation between sea level rise and general capital, indicating that there is again no distortion in the provision of this asset even if it is funded through distortionary taxation.

7.2.3 Result 3

Finally, for Result 3, combining the planner's first order conditions with respect to $[\Lambda^u_t]$ and $[\lambda^u_t]$ for $t > 0$ yields the optimality condition for public provision of utiliy adaptation:

$$\begin{aligned} \frac{-U_{Tt}T_t}{\lambda_{1t}} &= \frac{1}{f^u_{\lambda_t}} \\ \frac{(-U_{Tt}T_t)/U_{ct}}{MCF_t} &= \frac{1}{f^u_{\lambda_t}} \end{aligned} \tag{52}$$

Multiplying the left-hand side of (52) by U_{ct}/U_{ct} and invoking the definition of the MCF_t in (21) then yields the following optimality condition governing public utility adaptation expenditures for $t > 0$:

$$\underbrace{\frac{(-U_{Tt}T_t)}{U_{ct}}}_{\mathrm{MRS}_{C_t,\Lambda^u_t}}\underbrace{\frac{1}{MCF_t}}_{\text{wedge}} = \underbrace{\frac{1}{f^u_{\lambda_t}}}_{\mathrm{MRT}^{f^u_t}_{C_t,\Lambda^u_t}} \tag{53}$$

The first term on the left-hand side of (53) is the household's marginal rate of substitution (MRS) between consumption and adaptive capacity to reduce climate change utility impacts. The right-hand side equals the marginal cost of increasing this adaptive capacity, or the marginal rate of transformation (MRT) between consumption and adaptive capacity (through λ^u_t). Importantly, there is a wedge between the MRS and MRT at the optimum, demonstrating that the provision of the public utility adaptation good is distorted as stated in Result 3.

7.3 Further Calibration Details

7.3.1 Clean Energy Costs

The production of clean energy, in addition to (), has costs $\Theta_t(\mu_t E_t)$ which approximate the RICE model's (Nordhaus, 2011) estimates of a U.S. abatement cost curve from per-percentage into a per-ton cost measure through a logistic approximation:

$$\Theta_t(\mu_t E_t) = \frac{\overline{a}P^{backstop}_t}{1 + a_t\exp(b_{0t} - b_{1t}(\mu_t E_t))^{b_2}} \cdot (\mu_t E_t)^{bx} \tag{54}$$

where $P_t^{backstop}$ is the backstop technology price in year t, taken directly from RICE (Nordhaus, 2011). We note that $P_t^{backstop} = 0$ for $t > 2255$. The remaining parameters minimize the sum of squared errors of abatement costs implied by (54) versus RICE (see Barrage, 2020a for details), namely:

$\overline{a}$	0.0662
a_t	$= 49.8896{+}0.8551 \log(t)$
b_{0t}	$= 14.3338{-}6.4698 \log(t)$
b_{1t}	$= 15.1937{-}6.6864 \log(t)$
b_2	$9.4680e - 04$
bx	2.6931

7.4 Further Numerical Results

Table A1 presents analogous resluts to Table 7 but assuming rest-of-the-world emissions are fixed at business-as-usual levels.

Table A1: Main Results with Exogenous ROW Emissions

Scenario: Income	Scenario: Carbon & Energy	Labor Tax (Avg. 2025-2215)	Capital Tax (Avg. 2025-2215)	MCF (Avg. 2025-2215)	Carbon Tax ($/mtC) 2015-25	ΔWelfare EV ΔC_{2015} ($2015 bil.)
First-Best	No	0	0			
First-Best	Opt.	0	0	1.00	11.3	129
Opt.	No	40.4	5.7	1.10	0	
Opt.	Opt.	40.3	4.3	1.10	8.7	170
BAU $\overline{\tau_l}$, vary τ_k	No	$\overline{35.1}$	35.9	1.55	0	
BAU $\overline{\tau_l}$, vary τ_k	Opt.	$\overline{35.1}$	34.8	1.52	7.3	497
BAU $\overline{\tau_k}$, vary τ_l	No	39.9	$\overline{29.0}$	1.10	0	
BAU $\overline{\tau_k}$, vary τ_l	Opt.	39.6	$\overline{29.0}$	1.10	8.7	144

Rest-of-world emissions fixed at BAU levels; RICE Production Damages