Fiscal Costs of Climate Change in the United States

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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 both public expenditures (e.g., on Medicare) and tax revenues. First, the paper presents a novel quantification of fiscal impacts based on an empirical analysis of public healthcare costs associated with extreme temperatures and a literature synthesis. Second, I show theoretically that the social cost of carbon (SCC) must account for climate impacts on both government consumption and household transfers if the marginal cost of public funds exceeds unity. Finally, the numerical results indicate that fiscal impacts are first order for climate policy design: (i) Public expenditure impacts increase the SCC by 23-33%; (ii) climate change is estimated to cost U.S. taxpayers $88 billion per year by 2026 already, and (iii) fiscal considerations increase the projected domestic U.S. welfare benefits of optimized carbon and energy pricing by up to a factor of three.

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1 Introduction

Climate change is increasingly recognized as a potential risk to public finances (CBO 2021a; GAO 2019). Public budgets may be exposed to climate change in numerous ways, including through existing program costs (e.g., Medicare), the need for publicly funded adaptation (e.g., coastal infrastructure), and changes in revenue yields due to climate impacts on production. Despite their intuitive relevance, these fiscal impacts and their general equilibrium effects have to date been ignored by both standard integrated assessment models used to quantify the social cost of carbon (e.g., DICE, Nordhaus 2017) and by leading empirical climate change impact projections (e.g., Hsiang et al. 2017).

This paper presents what is to the best of my knowledge a first attempt to both quantify aggregate fiscal climate change impacts for the United States and to analyze their policy implications. First, I present a novel bottom-up quantification of climate change impacts on existing public program costs by synthesizing prior estimates and by empirically analyzing public healthcare expenditure impacts of changes in extreme temperature realizations. The empirical results indicate that even just one additional day with very hot temperatures can increase total (federal, state, and local) annual public health expenditures in a given county by up to +0.3%. Even when accounting for adaptation to future climate change in line with leading empirical methods (Carleton et al. 2022), forward projections indicate that public healthcare costs could increase by several percentage points in some areas by mid-century from changes in temperature extremes alone. Accounting for other public programs based on prior literature (e.g., crop insurance subsidies as in Diffenbaugh et al. 2021, hurricane-related healthcare costs as in Deryugina 2017, etc.), the results imply an increase in total U.S.government consumption requirements between +1.6-3.8% by 2100 depending on the warming scenario. To put these numbers in context, 3% of total U.S. government consumption would be approximately equivalent to all federal spending on education in the model quantification base year (2016),[1] suggesting that the estimated impacts are substantial in magnitude. Healthcare costs are the largest contributor to these changes.

Second, this paper develops a climate-macroeconomic model with several novel fiscal impact channels in order to analyze their theoretical and quantitative implications for the U.S. economy. Building on the global dynamic general equilibrium climate-economy model with distortionary income taxes of Barrage (2020a), I create a model of the U.S. economy where climate change can affect not only (i) aggregate production and (ii) household utility, but also (iii) government consumption requirements, (iv) government transfers to households,

[1] Calculated based on federal outlays for elementary, secondary, vocational education, higher education, and research and general education aids based on the Office of Management and Budget Historical Tables 3.2, URL (accessed January 2024): [https://www.whitehouse.gov/omb/budget/historical-tables/]

(v) endogenous public adaptation expenditures, (vi) tax revenues via production impacts and (vii) capital depreciation from sea level rise. Though very different in focus, this approach is similar in spirit to a new generation of studies that integrate more detailed empirically based representations of climate change impacts into multi-sector models (e.g., Nath 2023; Conte et al. 2022; Rudik et al. 2022; Casey et al. 2021; Fried 2019; Costinot et al. 2016), whereas the broader integrated assessment climate-macro literature traditionally represents all climate impacts simply as an aggregate productivity or utility loss (e.g., Nordhaus 2017; Golosov et al. 2014; Hassler et al. 2012; Acemoglu et al. 2012; etc.).

Theoretically, I show that the social cost of carbon (SCC) must account for fiscal impacts. Government consumption requirement increases ought to be internalized analogously to private output losses. Perhaps surprisingly, if revenues are raised with distortionary taxes, the SCC should further account for climate impacts on *transfers* to households.[2]

Finally, the numerical results highlight the quantitative importance of fiscal impacts for U.S. policy and welfare. Accounting for public expenditure impacts increases the U.S. social cost of carbon (SCC) by 23-33%. This magnitude of adjustment to the SCC is on par with, for instance, leading new estimates of climate tipping point impacts (Dietz et al. 2021a). Even in the near term, climate change may already cost U.S. taxpayers around $88 billion per year ($2022) in the 2026-35 period according to the benchmark estimates, due to both increased program costs and foregone tax revenues. To put this number in context, in the Fiscal Year 2022, $88 billion would correspond to around 50% of U.S. military personnel expenditures or be on par with the budget of the Department of Homeland Security ($80 billion). Lastly, the domestic welfare benefits of optimizing carbon prices and energy taxes in the United States are estimated to be 20-300% larger once interactions with tax policy are taken into account. Intuitively, this is because the benefits of carbon and energy taxes in terms of both revenues raised and climate damages avoided are valued more highly when public funds are scarce. The range of estimated impacts is large because the magnitude of these effects depends critically on the assumed counterfactual revenue-raising scenario, that is, what kinds of income tax increases can be avoided through carbon and energy taxes.

Of course it must be acknowledged that these results are subject to critical caveats and limitations. Climate change impact quantification is always subject to significant uncertainties. Here, the fiscal cost estimates are moreover based on a first generation of studies of select programs. The model also abstracts from some of the other issues and frontiers that have recently been shown to be important for climate impacts, such as migration and uncertainty. With these caveats in mind, the results nonetheless demonstrate that fiscal costs

[2] Formally, this is because changes in transfers alter the set of equilibria that can be decentralized as a competitive equilibrium.

are plausibly quantitatively important for U.S. policy. At the very least, the results thus also indicate that fiscal costs - which have been arguably underappreciated to date - warrant further consideration by policy makers and researchers alike, especially in light of the fact that the long-term U.S. fiscal outlook is already dire (Treasury 2022).

This paper relates to several strands of the literature. First, it builds on the rich tradition of climate-economic integrated assessment models (IAMs, e.g., Nordhaus 2017; Golosov et al. 2014). This literature has advanced on numerous fronts in recent years such as uncertainty (e.g., van den Bremer and van der Ploeg 2021; Cai and Lontzek 2019), migration and spatial detail (e.g., Cruz and Rossi-Hansberg 2023; Conte et al. 2022), and technological change (e.g., Casey 2024; Acemoglu et al. 2012), to name a few. Most of this literature abstracts from public finances and income taxation, however, and even those that model fiscal policy have generally not considered climate change impacts on public spending to the best of my knowledge (e.g., Barrage 2020a; Douenne et al. 2022).[3]

Second, a large literature has studied interactions of pre-existing taxes and environmental policy (reviewed by, e.g., Bovenberg and Goulder 2002). This literature has, however, again generally abstracted from pollution impacts on government expenditures.[4] One important finding of this literature in recent years has been that the environmental policy implications of distortionary taxes depend very much on whether they are levied in order to raise revenues (in a world where lump-sum levies are infeasible) or in order to redistribute among heterogeneous agents (in a world where targeted transfers are infeasible) (e.g., Douenne et al. 2022; Jacobs and van der Ploeg 2019). This paper focuses on the former case. Numerous studies in this literature have also used sophisticated computable general equilibrium models of the U.S. economy and tax system in order to study climate and fiscal policy interactions (e.g., Goulder and Hafstead 2018; Fried et al. 2018; Goulder et al. 2016; see also models reviewed in Barron et al. 2018; Bovenberg and Goulder 1996; 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 macroeconomic effects including on public budgets.

Third, as noted above, this paper relates to a new literature that integrates detailed and empirically based representations of climate change's impacts into multi-sector models to quantify its general equilibrium effects. This literature ranges from global trade models (e.g., Nath 2023; Costinot et al. 2016) to U.S. models of migration and production (e.g.,

[3] Barrage (2020b) introduces climate change impacts on government consumption and endogenous publicly financed adaptation against general production and utility damages in a stylized global extension of Barrage (2020a). However, the quantification of expenditure impacts is based on an early version of this paper, neither transfer payments nor sea level rise impacts are considered, there are no theoretical results nor empirical estimates, and no results specific to U.S. policy.

[4] Williams (2002) introduces pollution impacts on *private* healthcare spending in a theoretical analysis of environmental policy and distortionary taxes.

Rudik et al. 2022) and models of capital production (Casey et al. 2021). Fried (2019) builds and empirically quantifies a detailed heterogeneous agent model of adaptation to storm events and climate change in the United States, but does not distinguish public and private investments. Phan and Schwartzman (2023) study the interplay between natural disasters, sovereign default, investment, and growth in a model with a quantification for hurricanes in Mexico; Mallucci (2022) presents a similar investigation in the context of the Carribbean. While their modeling and focus are clearly different, these papers ultimately also show how climate change can affect macroeconomic outcomes via adverse impacts on public finances.

Finally, this paper relates in several ways to a growing empirical literature that quantifies the economic impacts of climatic risks. I build on the climate adaptive response estimation approach from Auffhammer (2022) and the Climate Impacts Lab (Carleton et al. 2022) to quantify climate change impacts on public health expenditures via changes in daily temperature realizations. This approach uses historical plausibly exogenous variation in temperatures within a location over time to identify impacts, but accounts for adaptation to future climatic change 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 2022), mortality (Carleton et al. 2023), and manufacturing productivity (Nath 2023). To the best of my knowledge, this paper's estimates of public healthcare costs associated with changes in extreme temperature events add to this literature. While numerous studies investigate the impacts of temperatures on mortality in the United States (e.g., Heutel et al. 2021; Barreca et al. 2016; Deschenes and Greenstone 2011; etc.), less is known about their impacts on public healthcare costs, though several prior empirical studies have demonstrated significant impacts on specific healthcare utilization services (e.g., hospital and emergency department visits in California (White 2017), mental health-related outcomes (Mullins and White 2019), other countries (e.g. Karlsson and Ziebarth 2018)). Mullins and White (2020) further show that access to community health centers significantly reduced the heat-mortality relationship in the U.S. This paper adds to these prior studies by highlighting another aspect of the climate-healthcare link through fiscal costs. Finally, this paper thus also builds on a recent empirical studies on the fiscal impacts of severe weather events in the United States. While estimates of aggregate or national-level impacts are incorporated into the fiscal damage function and described in Section 2.2, several recent studies also demonstrate significant impacts on municipal outcomes. Jerch et al. (2023) show that hurricane strikes decrease local tax revenues, increase borrowing costs, and decrease public works expenditures significantly for several years after exposure. Liao and Kousky (2022) show that wildfires in California increase the probability of a municipal budget deficit by 25 percentage points. Both Painter (2020) and Goldsmith-Pinkham et al. (2023) show that municipal bond markets are capitalizing sea level rise risk, raising long-term borrowing costs for vulnerable municipalities. Miao et al. (2018) study state-level fiscal impacts of natural disasters and find that, while state expenditures increase, they also receive more federal transfers. Given the critical role of intra-governmental transfers in determining local fiscal outcomes, this paper's quantification and modelling focus on aggregate U.S. impacts. 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 change impacts on existing public program costs. Section 3 describes the model setup and the theoretical results. Section 4 presents the quantification of the model, including for the other fiscal 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 investigates climate change impacts on the costs of existing public programs. Given that public health programs such as Medicare and Medicaid account for more than a quarter of U.S. government expenditures,[5] and given the substantial body of evidence linking extreme temperatures to U.S. mortality, morbidity, and emergency department visits (e.g., Barreca et al. 2016; White 2017; Mullins and White 2019; Heutel et al. 2021; Carleton et al. 2022), I first empirically analyze the potential public healthcare cost impacts of changes in daily temperature distributions. I then synthesize prior literature estimates of other channels to construct "fiscal damage functions" relating global temperature change to U.S. government consumption and transfer payment obligations.

2.1 Public Healthcare Costs of Temperature Extremes

This section first presents the data and empirical model used to study the historical impacts of temperature extremes on U.S. public health expenditures. Second, it describes the data and methods used to project future impacts under a changing climate. Third, this section

[5] Calculated using National Health Expenditure data (CMS, 2022) for the base year 2016 by summing reported expenditures on Medicare, Medicaid, CHIP, Dep. of Defense, Dep. of Veterans Affairs, Indian Health Services, federal, state, and local maternity/child health and vocational rehabilitation programs, SAMHSA, plus other federal, state, and local program expenditures and public health activity, yielding \$1.509 trillion (\$2016). Dividing by total U.S. government expenditures net of interest payments for 2016 from the National Income and Product Accounts (\$5.523 trillion) yields 0.27.

showcases the resulting benchmark projections, their distribution across areas with different racial compositions and income levels, uncertainty surrounding the estimates, and the derivation of an aggregate damage function.

Retrospective Empirical Analysis First, I obtain information on total public medical benefit transfers at the county-year level from the Bureau of Economic Analysis' (BEA) Regional Economic Accounts ("REA", following Deryugina 2017). This 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. 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 and aggregated at the county level. Following prior literature, I divide temperatures into cold, moderate, and high heat bins (e.g., Barreca et al. 2016), where moderate temperature days are the omitted variable. The benchmark specification defines "hot" days as having a daily average temperature above 32° Celsius (90° Farenheit), and "freezing" days as having a daily average temperature below freezing (0° Celsius). Alternatively, I also consider daily maximum (minimum) temperatures above 35° (below 0°) Celsius. 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 second-order polynomial controls for precipitation (Carleton et al. 2022). As the healthcare cost impacts of hurricane strikes are quantified separately in Section 2.2, here I also control for the number of hurricane days in the county-year (based on the National Oceanic and Atmospheric Administration's (NOAA) Storm Events Database[6]). All specifications also include demographic and economic controls (described below), where data on population age and race profiles are from the National Center for Health Statistics. The estimating equation is:

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

Here, $\ln Y_{j,t}$ denotes the logarithm of public medical expenditures in county j in year t.[7]

6 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, URL (accessed February 2021): [https://www.weather.gov/gis/ZoneCounty]

7 Using *per capita* public medical expenditures instead does not affect the coefficients of interest due to

County fixed-effects δ_j absorb cross-sectional differences in public health spending across counties. Year fixed-effects δ_t capture national shocks to public medical spending in a given year. State-specific trends $(\theta_s \cdot t)$ further allow public health spending to follow different trends in different states. The $TD_{m,j,t}$ terms represent temperature realizations with $m \in \{\text{"hot"}, \text{"freezing"}\}$. Following recent advances in the literature (Auffhammer 2022; Carleton et al. 2022), I seek to account for adaptation to climatic risks by allowing the effects of temperature realizations $TD_{m,j,t}$ to depend on a county's long-run climate $\overline{T}_{m,j}$, measured by a 20-year average temperature in the preferred specification.[8] Alternatively, I also consider the average number of "hot" or "freezing" days in the county over the past 20 years. Finally, the vector $\mathbf{X_{j,t}}$ represents other controls. In addition to the aforementioned precipitation and hurricane controls, $\mathbf{X_{j,t}}$ includes the log 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. For robustness, I also consider interactions between precipitation and temperature variables. The analysis focuses on the years 1996-2016. Standard errors $\epsilon_{j,t}$ are heteroskedasticity-robust and clustered at the county level, and observations are weighted by county populations.

Results: Table 1 showcases the results. The key findings are that (i) even just a single extreme heat day can significantly increase public health spending in a given county-year, but that (ii) this effect is significantly smaller in areas with warmer climates. In contrast, for freezing days the results are small and imprecise in line with related studies as discussed further below. Column (1) shows the benchmark specification defining extreme heat (freezing) days based on daily average temperatures. Column (2) adds interaction terms between temperatures and precipitation, which are imprecisely estimated and do not affect the main coefficients of interest meaningfully. Column (3) showcases the specification using the average number of heat and freezing days as respective measures of local climate ($\overline{T}_{m,j}$). Finally, Column (4) uses daily maximum and minimum temperatures to define heat and freezing weather events. Perhaps not surprisingly, the marginal impact of a day with very hot *maximum* temperatures is considerably smaller than of a day with a very hot average temperature; however the marginal public health impact of a very hot day remains positive

the controls for population in the regression.

[8] In contrast to prior literature studying direct health outcomes, such as mortality (e.g., Carleton et al., 2022), I do *not* include an interaction term between temperatures and income levels in (1). That is, while higher income levels have been found to reduce the *mortality* impacts of extreme temperatures, suggestive of adaptation via higher income, here the outcome variable of interest - public health expenditures - would not necessarily be expected to decline with higher income levels. This is because public healthcare may be part of the adaptation to temperature extremes (Mullins and White 2020) and may be less utilized but provided at a higher level in higher income areas. Given these conceptual complications - and the endogeneity of income levels in the model - our specification in (1) thus differs in this dimension from studies such as Carleton et al. (2022).

and precisely estimated in this case as well.

Table 1: Public Health Expenditure Impacts of Temperature Extremes

Dep. Var.:	ln(Public Medical Expenditures)			
	(1)	(2)	(3)	(4)
Extreme Heat Days$_{j,t}$	0.00306***	0.00325***	0.00093***	0.00027**
	(0.00096)	(0.00096)	(0.00012)	(0.00012)
Extreme Heat Days$_{j,t}$ $\times$ $\overline{T}_{m,j}$	-0.00011**	-0.00014***	-0.00001	-0.00000
	(0.00005)	(0.00005)	(0.00000)	(0.00000)
Freezing Days$_{j,t}$	0.00009	0.00016	-0.00041***	0.00020
	(0.00019)	(0.00019)	(0.00012)	(0.00015)
Freezing Days$_{j,t}$ $\times$ $\overline{T}_{m,j}$	-0.00001	-0.00001	0.00001***	-0.00000
	(0.00001)	(0.00002)	(0.00000)	(0.00000)
Obs.	61,080	61,080	61,080	61,080
Adj. R-Sq.	0.999	0.999	0.999	0.999
#Counties (Clusters)	3,054	3,054	3,054	3,054
"Heat" Measure	Avg.>32C	Avg.>32C	Avg.>32C	Max.>35C
"Freezing" Measure	Avg.<0C	Avg.<0C	Avg.<0C	Min.<0C
$\overline{T}_{m,j}$ is average of:	Temp.	Temp.	#Heat/Freeze Days	#Heat/Freeze Days
Demo./Inc./Precip./Hurricane Controls:	Yes	Yes	Yes	Yes
Precip. $\times$ Hot, Cold	No	Yes	No	No
County F.E.s:	Yes	Yes	Yes	Yes
Year F.E.s:	Yes	Yes	Yes	Yes
State-Trends:	Yes	Yes	Yes	Yes

Table shows results of linear regression of log of county-year public medical expenditures (1996-2016, from BEA) on the number of "heat" days (defined as avg. daily temperature>32C in Cols 1-3 and max. daily temperature>35C in Col. 4), "freezing" days (defined as avg. daily temperature<0C in Cols 1-3 and min. daily temperature<0C in Col. 4) both in levels and interacted with climate measures $\overline{T}_{m,j}$ (avg. temperature in Cols. 1-2 and avg. number hot/cold days in Cols. 3-4) (based on data from Schlenker (2020)) along with county fixed effects, linear state-level trends, year fixed effects and controls for log of county populations, log of the population 65 years and older, prior to current year population growth, percent non-hispanic whites (from the National Center for Health Statistics), log and growth of real per capita income (from BEA), precipitation (2nd order polynominal) plus interaction of precipitation and "heat"/"freezing" days in Col. 2 (based on data from Schlenker (2020)), and the number of hurricane days in the county-year (NOAA Storm Events Database). Regressions are weighted by county populations. Standard errors are heteroskedasticity-robust and clustered at the county level. P-values are labeled: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

In order to facilitate the interpretation of the coefficients on the temperature variables, Figure 1 illustrates the estimated marginal public health expenditure impacts of an additional hot day across the continental United States under current climatic conditions (based on the results of Column (1) in Table 5). The results suggest that the impacts of one additional hot day on annual public health expenditures range from zero to +0.3%, depending on a county's baseline climate. In southern states which are well-adapted to hot weather, the predicted impact is small. In contrast, in northern regions which are less adapted to extreme heat, the estimated public medical spending impacts are substantial.

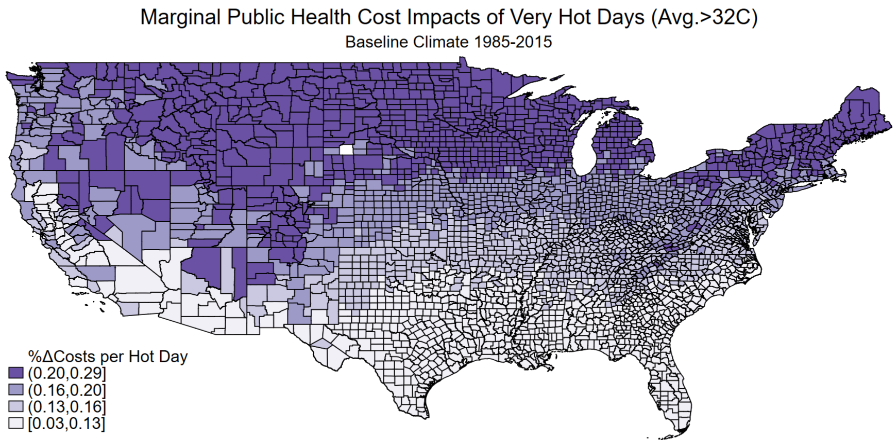

Figure 1: Hot Day Marginal Public Medical Spending Impact

While the results consistently suggest a signficant positive impact of extreme heat days on annual public health expenditures, the results for freezing days are small, imprecise, and vary with the specification. This pattern is in line with findings from related prior studies such as Karlsson and Ziebarth (2018), who find for hospital admissions in Germany that the estimated effects of freezing temperatures differ qualitatively depending on the specification and weather controls. They note that this may be due to the behavioral adjustments to different levels or aspects of colder weather, such as reduced propensity to seek care in emergency departments as documented also by White (2017) for California.[9] The remainder of this Section thus focuses on climate change impact projections for the precisely and consistently estimated impacts of changes in the number of extreme heat days.

Climate Change Impact Projections In order to map the estimated effects into climate change impact projections, one needs forecasts of how the distribution of extreme temperatures will change under a warming climate. Rasmussen et al. (2016) estimate probability density functions for daily temperature realizations over the 21st century resulting from different global warming scenarios for each county in the United States. They build on Coupled Model Intercomparison Project (CMIP) projections but propose methods to construct probabilistic estimates with coverage of tail probabilities which a simple average across CMIP

[9] While White (2017) also finds subsequent increases in emergency department visits after the initial decline, the estimates here considering annual total public health spending impacts of freezing days are small and generally imprecise.

models would not provide. While the quantitative model of this paper endogenizes global temperatures, the remainder of this section uses Rasmussen et al.'s estimates to project impacts for different global temperature levels with the ultimate aim of constructing a "damage function." To illustrate these calculations, Figure 2 showcases the average projected change in the number of days with average temperatures above 32°C for each county computed from Rasmussen et al. (2016) projections (using the surrogate/model mixed ensemble (SMME) method) for around $2.5°C$ global mean surface temperature warming over pre-industrial levels by mid-century (2050-55 formally based on RCP 8.5, van Vuuren et al. 2011). The projections indicate large potential increases in hot days, with up to 44 *additional* extreme heat days per year in some locations. By the end of the century, the corresponding figure would be up to 121 additional hot days per year, although it should be noted that the model projections in this paper do not reach the potentially outdated (Hausfather 2020) very high temperature change levels forseen in the RCP 8.5 scenario by 2100.

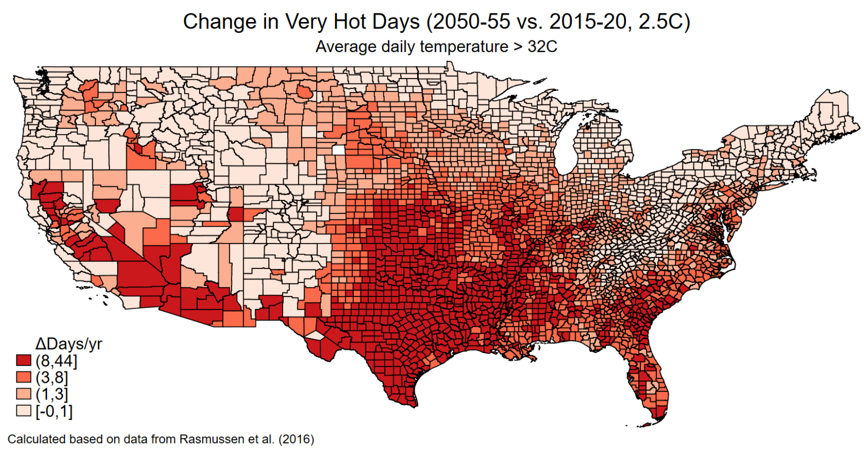

Figure 2: Changes in Hot Days by 2050-55 (Avg.)

The empirical results suggest that a warming climate may affect public health costs in two ways. On the one hand, health spending may increase due to a higher number of extreme heat days, ceteris paribus. On the other hand, as the climate warms, the marginal effect of each hot day may decline as a result of adaptation, as suggested by the negative interaction term between hot days and average temperatures in Table 5. In order to account for the latter effect, I thus first evaluate marginal impacts at future climates, specifically based on the 30-year prior average temperature. The projected *total* change in public healthcare costs is then given by the combination of the two forces.

Figure 3 illustrates projected changes in the public healthcare costs from extreme heat by mid-century compared to the model base period (again assuming $2.5°C$ global warming as an example). The projected changes are large, reaching as high as 3 percentage points per year in many counties. For comparison, the estimated total annual public healthcare cost impact of extreme heat in 2015-20 is estimated to range from +0-5% per year, indicating that the relative increase due to global warming is large. While Figure 3 already shows that the projected impacts are heterogeneous across space, Figure 4 delves further into how projected impacts vary with county demographics (in the model base year). Panel A shows that the increases in public healthcare costs associated with extreme heat days are projected to disproportionately affect counties with larger non-white populations. Indeed, the (unweighted) average impact is approximately double (+1 percentage point) in the bottom quartile of percent non-hispanic white counties compared to the top quartile (+0.5 percentage points), a significant difference (with a two-sided t-test p-value < 0.000). The strong correlation between health cost impacts and race is moreover robust to controlling for per capita income levels (see Online Appendix Figure 1). Panel B shows that projected impacts are also generally larger in low income communities.

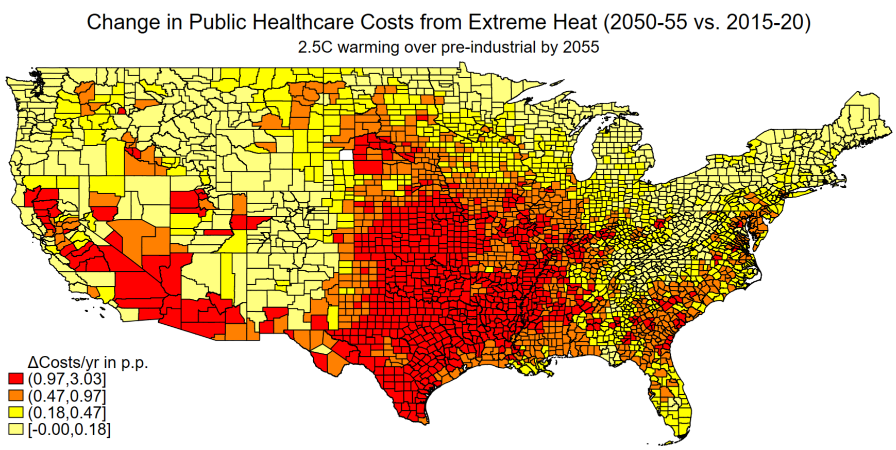

Figure 3: Change in Public Healthcare Cost Impact of Extreme Heat by Mid-Century

In order to gauge uncertainty associated with these projections, I follow the state of the art in the literature (Carleton et al. 2022) in considering both statistical and climate projection uncertainty, specifically through a Monte Carlo analysis based on the standard errors of the estimates in Table 5 and the probabilistic projections from Rasmussen et al. (2016, SMME method). For each future county-year, I take 1,000 draws from the distributions of the marginal cost impact coefficient estimates and from the distributions of the number of extreme heat days and average 30-year temperature, where the climatic variable draws are internally consistent (that is, computed from the same model draw).[10] For parsimony, I report uncertainty in terms of aggregate national impacts, which are computed using base year

[10] I use the very high emissions scenario RCP 8.5 for this purpose because it provides projected impacts for the widest range of global temperature outcomes to use in the "damage function" estimation. I do not, however, assume RCP 8.5 as an outcome in the main analysis.

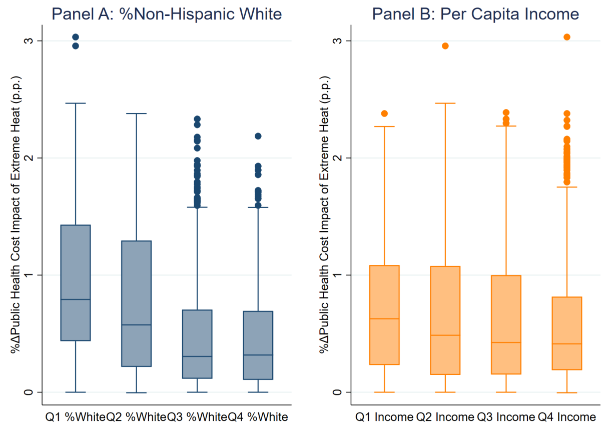

Figure 4: Distributional Impacts of Public Health Cost Changes from Extreme Heat

county shares of national public health expenditures. Figure 5 plots the results. Uncertainty is substantial especially over longer time horizons, in line with both the broader literature (e.g., Carleton et al. 2022; Burke et al. 2015; etc.) and intuition. The projected mid-century aggregate U.S. public health cost impacts at 2.5°C warming have a mean of +1.1%, a median of +0.9%, a 25th-75th percentile range of +0.1% to +2.0%, and a 10th-90th percentile range of -0.7% to +3.2%, where the possibility of negative damages (i.e., cost savings) at this confidence range is again standard in the literature (e.g., Carleton et al. 2022; Burke et al. 2015; etc.).

Damage Function - Extreme Heat One central goal of this paper is to derive a *fiscal* climate damage function. Standard damage functions specify total costs as a function of aggregate warming indicators such as mean global atmospheric surface temperature change (e.g., Nordhaus 2017) and serve the purpose of endogenizing feedback effects between economic activity, policy, and the climate. In order to derive the part of the overall fiscal damage function relating to public healthcare expenditures and extreme heat, I associate the mean impact estimate for each year with the corresponding global surface temperature change over pre-industrial temperatures (based on the MAGICC model, Meinhausen et al. 2011). Figure 6 showcases the results, which suggest that a quadratic damage function appears to provide a remarkably good fit to the estimates. The quantitative model thus uses the estimated damage function $\%\Delta\text{PublicHealthCosts}_t = (0.195)T_t^2$. Estimation details and a discussion of the treatment of the intercept are provided in Appendix 7.1.

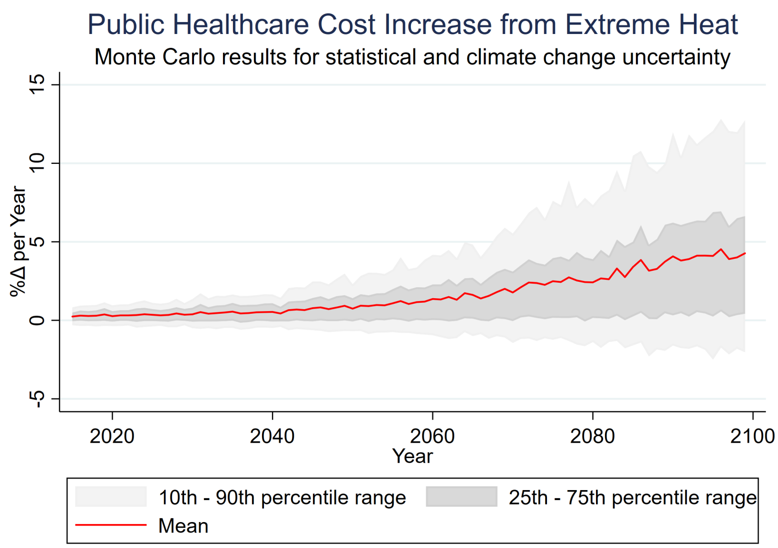

Figure 5: Projected public healthcare cost increase (% per year) due to extreme heat in RCP 8.5 scenario accounting for statistical and climate uncertainty

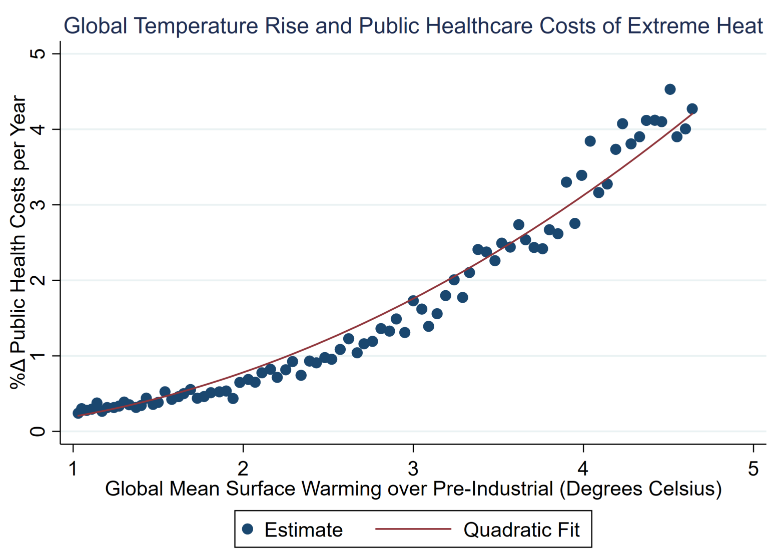

Figure 6: Mean projected U.S. public healthcare cost impact from extreme heat days plotted against mean global surface temperature change over pre-industrial levels in the corresponding scenario year (RCP 8.5)

2.2 Overall Public Program Cost Impacts

Table 2 summarizes estimates of the broader potential public program cost impacts of climate change based on a synthesis and supplementary calculations of prior literature. The headline results are twofold. First, total annual U.S. government consumption expenditure requirements - including federal, state, and local costs - are projected to increase by around 1.6% to 3.8% depending on the emissions scenario.[11] To put these numbers in perspective, 3% of total U.S. government consumption would be approximately equivalent to all federal spending on education in the model base year (2016, see footnote 1), suggesting that the estimated impacts are substantial in magnitude. Second, increases in healthcare costs account for the vast majority (>75%) of the projected impacts. The remainder of this section briefly discusses each of the reviewed programs. Further details on the underlying estimates and calculations are provided in Appendix 7.2.

Table 2: Summary of Public Program Cost Impact Estimates

	%Δ annual costs by 2100			
	Program Costs	Gov. Cons.		Calculations based
	RCP 4.5	RCP 4.5	RCP 8.5	on estimates in:
Healthcare - Extreme heat	+1.22%	+0.82%	+2.44%	Section 2.1
Healthcare - Hurricanes	+0.34%	+0.23%	+0.45%	Deryugina (2017), Bakkensen Barrage (2021)
Healthcare - Air quality	+0.04%	+0.02%	+0.03%	Garcia-Menendez et al. (2015)
Crop-insurance subsidies	+70%	+0.11%	+0.19%	Diffenbaugh et al. (2021), OMB (2016)
Forest Service fire suppr.	+130%	+0.06%	+0.10%	OMB (2016), Forest Service (2016)
Dep. of Interior fire suppr.	+50%	+0.06%	+0.10%	OMB (2016), Forest Service (2016)
Hurricane direct response	+12.5%	+0.05%	+0.09%	CBO (2016)
Urban drainage		+0.13%	+0.22%	EPA (2017)
Road maintenance		+0.09%	+0.15%	EPA (2017)
Endangered Species Act	+20%	+0.007%	+0.01%	Moore et al. (2022)
Total		**+1.58%**	**+3.78%**	

Table shows projected percent change in annual public program costs and total U.S. government consumption requirements, resp., due to end-of-century warming in a moderate (RCP 4.5) and high (RCP 8.5) emissions scenario. Future government consumption shares account for projected increases in health-related expenditures (CBO, 2021b). "Hurricane direct response" includes aid through several programs such as Federal Emergency Management Agency grants and the Army Corps of Engineers (CBO, 2016).

First I consider public healthcare costs beyond those from temperature extremes. 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

[11] RCP 4.5 corresponds to around $2.5°C$ global warming over pre-industrial temperatures by 2100, and RCP 8.5 corresponds to $4.3°C$ warming in the MAGICC model (Meinhausen et al. 2011).

transfers are generally of much higher value 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. The estimated impacts are substantial, ranging from +3.7% to +4.8% for public medical and +1.2% to +6.76% for income support, depending on the hurricane's strength. 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 (2021) based on synthetic hurricane tracks under current and future climates from Emanuel et al. (2008). 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 the expected present value medical expenditure increases for each county in the data (discounting the cost increases over 10 years following each storm at 3% per year). The results imply that hurricane risk changes may increase aggregate U.S. annual public health expenditures by around +0.34% even in a moderate emissions scenario. For income transfers, the corresponding estimate is +0.15%. Further details are provided in Appendix 7.2.

Another potentially important climate change-public health cost impact channel is through air quality. For impacts based on changes in atmospheric chemistry and ventilation, I use estimates from Garcia-Menendez et al. (2015) and OMB (2016), which suggest modest effects (+$1.2 billion per year) on federal healthcare costs in a 'no policy' baseline compared to a mitigation scenario. This aggregate figure is modest in part because of regionally heterogeneous impacts, with some areas projected to see improvements and others deterioration in air quality. Moreover, these estimates do not account for changes in wildfire risks, likely leading to a susbtantial underestimate. That is, while wildfires have been shown to contribute significantly to U.S. particulate matter concentrations (Childs et al. 2022), mortality, morbidity, and healthcare utilization (e.g., Heft-Neal et al. 2022; Miller et al. 2017), and while U.S. wildfire risk is projected to increase substantially due to climate change (e.g., Liu et al. 2010), the impacts of these changes on public health expenditures are not included here, likely biasing our estimates downward, ceteris paribus.[12]

One important nuance in projecting future health expenditures is that, due to factors

[12] Previous versions of this paper included estimates of wildfire healthcare expenditure impacts. These estimates were ultimately discarded, however, due to both their sensitivity to which wildfire activity indicator to use (e.g., NOAA smoke and wildfire day counts vs. MTBS.gov burn areas vs. PM 2.5 smoke days vs. cumulative annual wildfire-induced PM 2.5 exposure with the latter two based on data from Childs et al. 2022) and the lack of precise mappings from some of these indicators to climate change wildfire incidence predictions.

such as aging of the U.S. population and excess cost growth in the health sector, the U.S. Congressional Budget Office projects a doubling in the GDP share of Medicare expenditures between 2021 and 2051 (CBO 2021b). While I generally assume that the GDP shares of the public programs considered in Table 2 would stay constant in the absence of climate change, for health I 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 these CBO projections to adjust the projected overall fiscal impacts of climate change-induced increases in future public health expenditures.

Next I consider a set of non-health public programs for which climate change impact estimates are available. First, the U.S. government offers subsidized crop insurance to farmers through the Federal Crop Insurance Program. The majority of premium costs - almost two-thirds - are paid for by the government on average (OMB 2016). Diffenbaugh et al. (2021) estimate that damages from observed warming from 1991-2017 already accounted for 19% of U.S. crop insurance payments over this time period. Table 2's estimates use both Diffenbaugh et al. and projections from the U.S. Department of Agriculture (USDA as reported in OMB 2016), which suggest substantial potential increases in future program costs. Of course, these estimates assume that the subsidization rate will remain at historical levels going forward, as discussed further below. Second, the costs of wildfire suppression are expected to increase with warming. Table 2 considers estimates of such cost increases from a U.S. Forest Service (2016) analysis to projected climate change impacts on the wildfire suppression costs incurred by both the Forest Service and the Department of Interior, respectively. It should be noted that these estimates do not include state and local costs and thus likely underestimate total impacts. Third, a number of government agencies provide disaster relief after hurricane strikes, including the Federal Emergency Managment Agency, 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. Table 2 uses Congressional Budget Office estimates of future increases in these expenditures due to global warming (CBO 2016). Fourth, climate change is projected to alter the costs of maintaining current levels of service in both urban infrastructure drainage systems and roadways. Table 2 uses Environmental Protection Agency (EPA, 2017) estimates of these costs, where the drainage estimates are limited to 100 major U.S. cities. For roads, it should be noted that reductions in freeze-thaw cycles are projected to decrease maintenance costs but that these savings may be outweighed by cost increase from changes in precipitation and temperatures. Finally, as climate change is projected to increase the number of species protected under the Endangered Species Act, it may then also increase the associated costs for activities ranging from enforcement to research at agencies ranging from the U.S. Fish and

Wildlife Service to the Army Corps of Engineers. Moore et al. (2022) carefully construct such estimates, which are used in Table 2. Further details on how all of these literature estimates are used to construct Table 2's estimates are provided in Appendix 7.2.

Before proceeding, important caveats to the above estimates must be noted. First, a range of potentially relevant programs are excluded from Table 2. While this exclusion is deliberate in some cases, such as the National Flood Insurance Program,[13] for most a reliable impact quantification did not seem possible within the scope of this study, including for potentially important channels such as national defense or maintenance of public buildings vulnerable to climatic threats. While the omission of some of these costs and the conservative assumptions made throughout suggest that Table 2's estimates likely understate total impacts, some potential budgetary cost reductions are also omitted, such as decreased participation in Social Security and similar programs through premature mortality (CBO 2021a). The analysis also ignores potential fiscal impacts of air pollution emissions correlated with carbon, though here some studies have found that healthcare cost savings constitute only a very small share of the co-benefits of U.S. climate policy (Woollacott et al. 2018; EPA 2015). Second, the above estimates inevitably make numerous simplifying assumptions, such as that government service provision will be held constant at baseline levels. On the one hand, this assumption seems less problematic for the near-term projections, and the welfare impacts of small changes in public goods provision should moreover be similar to those of the change in public revenue requirements modeled here as the marginal costs of public funds and the marginal benefits of public programs should (in theory) be equated. On the other hand, however, climate change impact projections also extend over long time horizons and future public programs may of course look very different from their base today. Related caveats apply to any climate change impact projections, such that future technological and societal changes may alter climate vulnerability in unforseen ways. As noted above, I also assume populations remain distributed across space as in the base year. On the one hand, this may bias estimates downward as several studies have found that projected future U.S. population and growth patterns will significantly increase aggregate climate change vulnerability (Jones et al. 2015; Wing et al. 2022). On the other hand, optimized migration could reduce climate change damages substantially (Desmet et al. 2021). In spite of these caveats, I proceed using the estimates of Table 2 as a benchmark based on the best available evidence to gauge the plausible order of magnitude of climate change's fiscal costs via existing program costs. The

[13] The National Flood Insurance Program has previously been noted as a significant fiscal liability after accumulating tens of billions of dollars of debt in part due to its failure to charge actuarially fair rates for many policies. Due to recent changes in its pricing approach ("Risk Rating 2.0"), however, insurance premiums are based more closely on individual properties' flood risks, thus presumably limiting fiscal shortfalls from rising flood risks going forward.

quantifications of the associated damage functions other fiscal impact channels in the model are described in Section 3 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 et al. (2014) and Nordhaus (2017) by incorporating a classic dynamic optimal Ramsey taxation framework (as in Chari and Kehoe, 1999) to incorporate distortionary taxation and government revenue requirements. Here, taxes are imposed for the purpose of raising revenues as lump-sum levies are assumed to be infeasible. I here extend the COMET in five ways. First, I introduce climate change impacts on the costs of providing government services and on requisite transfers to households. Second, I introduce endogenous public adaptation expenditures. Third, I introduce a sea level rise module. That is, while standard models commonly summarize 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. Fourth, while the COMET is a global model, here I present a model specific to the United States (US-COMET). Finally, I incorporate several updates such as to the carbon cycle in line with the latest DICE vintage (Barrage and Nordhaus 2024) which responds to concerns that certain recent climate science findings were not reflected in prior DICE vintages (Dietz et al. 2021b; Folini et al. 2024).

In 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 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, (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

[14] Pigouvian carbon tax revenues are assumed to be insufficient to meet government revenue needs, and the government is assumed to be able to commit to future taxes (see Barrage (2020a) for a discussion).

level rise affects the government's optimal expenditures on coastal protection.

Households A representative household has well-behaved preferences over consumption C_t, labor supply L_t, and the climate, summarized by global mean atmospheric surface temperature change over pre-industrial levels T_t. Lifetime utility U_0 is given by:

$$U_0 \equiv \sum_{t=0}^{\infty} \beta^t U(C_t, L_t, T_t) \tag{2}$$

Utility losses from climate change may reflect non-production impacts such as damages to national parks and biodiversity existence value losses. I assume additive separability:

$$U(C_t, L_t, T_t) = v(C_t, L_t) + h(T_t) \tag{3}$$

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_t as well as coastal protection level Λ_t^{slr}. Households take both the climate and coastal protection levels as given. The final consumption good is normalized to be the untaxed good. The household's flow budget constraint each period is thus given by:[15]

$$C_t + \rho_t B_{t+1} + K_{t+1} \leq w_t(1-\tau_{lt})L_t + \left\{1 + (r_t - \delta(SLR_,, \Lambda_t^{slr}))(1-\tau_{kt})\right\} K_t + B_t + \Pi_t + G_t^T(T_t) \tag{4}$$

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

$$\frac{U_{ct}}{U_{ct+1}} = \beta \left\{1 + (r_{t+1} - \delta(SLR_t, \Lambda_t^{slr}))(1-\tau_{kt+1})\right\} \tag{5}$$

$$\frac{-U_{lt}}{U_{ct}} = w_t(1-\tau_{lt}) \tag{6}$$

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

[15] As in Barrage (2020a), I 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.

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, exogenous total factor productivity parameter A_{1t}, and is assumed to satisfy the standard Inada conditions. In addition, output Y_t is affected by the climate T_t via a standard damage function $D(T_t)$:

$$Y_t = (1 - D(T_t)) \cdot A_{1t}\widetilde{F_1}(L_{1t}, K_{1t}, E_t) \tag{7}$$

Production damages are assumed to be unaffected by public expenditures.[16] On the one hand, several prior studies have found that different U.S. policies can both reduce (e.g., Mullins and White 2020; Fried 2019) and increase climate change vulnerability (through moral hazard effects as in Fried 2019; Annan and Schlenker 2015). On the other hand, however, given that the damage estimates used to quantify $D(T_t)$ are based on data of the U.S. as it is - that is, with current policies in place - they should already be "net" of public program impacts on vulnerability. If future expenditures continue to fund programs such as crop insurance and hurricane aid at current rates, as this paper generally assumes, then damages should indeed not be assumed to be reduced by these programs.

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} denote the price of energy inputs, these conditions imply:

$$F_{1lt} = w_t;\ F_{1Et} = p_{Et};\ F_{1kt} = r_t$$

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

$$E_t = A_{2t}F_{2t}(K_{2t}, L_{2t}) \tag{8}$$

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:

$$\Pi_t = (p_{Et} - \tau_{It})E_t - [(1-\mu_t)E_t]\tau_{Et} - w_t L_{2t} - r_t K_{2t} - \Theta_t(\mu_t E_t) \tag{9}$$

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* $E_t^M \equiv (1-\mu_t)E_t$. Both capital and labor are assumed to

[16] Prior versions of this paper also considered public adaptation to reduce climate impacts on production and utility, and derived theoretical results regarding the optimal provision of such spending. As the quality of the quantifications of these general adaptation technologies is not as good as for sea level rise impacts, however, the model now restricts its focus on the latter.

be perfectly mobile across sectors, with associated market clearing conditions:

$$K_t = K_{1t} + K_{2t};\; L_t = L_{1t} + L_{2t} \tag{10}$$

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

$$[p_{Et} - \tau_{It} - \tau_{Et}]F_{2lt} = w_t;\; [p_{Et} - \tau_{It} - \tau_{Et}]F_{2kt} = r_t, \tag{11}$$

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

$$\tau_{Et} = \Theta_t'(\mu_t E_t) \tag{12}$$

Government The government 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. At its discretion, the government can also invest λ_t^{slr} in adaptive capital stock AK_t to produce protection against sea level rise via:

$$\Lambda_t^{slr} = f^{slr}(AK_t) \tag{13}$$

$$AK_t = AK_{t-1}(1 - \delta^{slr}) + \lambda_t^{slr} \tag{14}$$

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 Fried (2019) (see Section 4). Finally, to raise revenues, the government can impose linear taxes on labor and capital income, levy excise taxes on energy inputs and on carbon emissions, and it can issue new, one-period bonds B_{t+1}^G. The public flow budget constraint is thus given by:

$$G_t^C(T_t) + G_t^T(T_t) + \lambda_t^{slr} + B_t^G = \tau_{lt}w_tL_t + \tau_{It}E_t + \tau_{Et}E_t^M + \tau_{kt}(r_t - \delta(SLR_t, \Lambda_t^{slr}))K_t + \rho_t B_{t+1}^G \tag{15}$$

The market clearing condition for government bonds is given by $B_{t+1}^G = B_{t+1}$. This specification captures only the domestic market for U.S. government debt.[17] The *marginal cost of public funds* (MCF_t) - which measures the welfare cost of raising an additional dollar of government revenues - is defined in the standard way by the ratio of public to private marginal utility of consumption:

[17] On the one one hand, ignoring the current stock of foreign-held U.S. debt underestimates the government's future revenue-raising obligations. On the other hand, abstracting from the foreign supply of loanable funds may lead to an overestimate of the costs of U.S. borrowing costs.

$$MCF_t \equiv \frac{\lambda_{1t}}{U_{ct}} \tag{16}$$

where λ_{1t} is the Lagrange multiplier on the resource constraint in the planner's problem (see Appendix). If the government could impose lump-sum taxes, then the marginal cost of public funds would be equal to one. In contrast, if revenues must be raised through distortionary instruments, the costs of raising \$1 equal \$1 plus the marginal deadweight loss of taxation.

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), and exogenous shifters $\{\boldsymbol{\eta}_s\}_{s=0}^t$ (e.g., non-CO_2 forcings) via:

$$T_t = F\left(\mathbf{S}_0, E_0^M + E_0^{M,ROW}, E_1^M + E_1^{M,ROW}, ..., E_t^M + E_t^{M,ROW}, \boldsymbol{\eta}_0, ...\boldsymbol{\eta}_t\right) \tag{17}$$

Sea level rise is modeled as a function of the history of global temperature change, along with initial condition SLR_0, following Rahmstorf (2007):

$$SLR_t = G(SLR_0, T_1, T_2, ...T_t) \tag{18}$$

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 (2) subject to the constraints of (i) feasibility, (ii) the optimizing behavior of households and firms, and (iii) laws of nature (17)-(18). Before proceeding to the model quantification, this section theoretically characterizes how fiscal climate impacts affect the social cost of carbon, or the optimal carbon price. For notational convenience, first define the discount factor $M_{t,j}$ as:

$$M_{t,j} \equiv \begin{cases} 1 & \text{if } j = 0 \\ \beta^j \prod_{m=1}^{j} \frac{1}{(1+r_{t+m}-\delta_{t+m})} & \text{o.w.} \end{cases} \tag{19}$$

Proposition 1 *The optimal carbon price internalizes climate change impacts on both government consumption and transfer payment requirements (if revenues are raised with distortionary taxes). Formally, the optimal carbon price in period $t > 0$, that is, the carbon price that can decentralize the optimal allocation along with other taxes set ap-*

propriately, is implicitly defined by:

$$\tau^*_{Et} = \sum_{j=0}^{\infty} M_{t,j} \cdot \underbrace{\left[\frac{-\partial Y_{t+j}}{\partial T_{t+j}}\right]}_{\text{Output Impacts}} \cdot \frac{\partial T_{t+j}}{\partial E_t^M} \tag{20}$$

$$+\sum_{j=0}^{\infty} \beta^j (\frac{1}{MCF_t}) \underbrace{\left[\frac{-U_{Tt+j}}{U_{ct}}\right]}_{\text{Utility Impacts}} \frac{\partial T_{t+j}}{\partial E_t^M} \tag{21}$$

$$+\sum_{j=0}^{\infty} \underbrace{\left[\sum_{m=0}^{\infty} M_{t,j+m} \cdot \frac{\partial \delta K_{t+m}}{\partial SLR_{t+m}} \frac{\partial SLR_{t+m}}{\partial T_{t+j}}\right]}_{\text{Sea Level Rise Impacts}} \frac{\partial T_{t+j}}{\partial E_t^M} \tag{22}$$

$$+\sum_{j=0}^{\infty} M_j \cdot \underbrace{\left[\frac{\partial G^C_{t+j}}{\partial T_{t+j}}\right]}_{\text{Gov't Cons. Impacts}} \frac{\partial T_{t+j}}{\partial E_t^M} \tag{23}$$

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

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 $\frac{\partial T_{t+j}}{\partial E_t^M}$. 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 (22). The economic impacts of these climatic changes are then valued as follows. First, the present discounted value of output impacts in (20) is valued fully, in line with prior literature. Second, utility impacts in (21) are "discounted" by the marginal cost of public funds. This result is well known from the literature on pollution pricing alongside distortionary taxes imposed for revenue-raising purposes (see Bovenberg and Goulder, 2002). Third, capital losses due to sea level rise are again valued fully in (22), as they fall on the production side of the economy. Fourth and more interestingly for the present analysis, the optimal carbon price must internalize government consumption impacts of climate change in (23). To the best of my knowledge, this type of impact has not been considered in prior literature. Finally, and perhaps most surprisingly, I 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. In a standard setting where it is implicitly assumed that governments can raise revenues through lump-sum taxes, $MCF = 1$ and 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. The next section seeks to evaluate the quantitative importance of these factors.

4 Model Quantification

Production Production of the final consumption-investment good is Cobb-Douglas with standard expenditure shares ($\alpha = 0.3$ and $v = 0.03$ as in, e.g., Golosov et al. 2014):

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

Base year total factor productivity is inferred by matching initial U.S. output given initial capital, labor, and energy inputs. Base year energy use is 1.375 gigatons of carbon (GtC; 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 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.[18] 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.[19] Future productivity growth follows the RICE Model (Nordhaus 2010). Base year savings 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:

$$E_t = A_{2t}(K_{2t}^{1-\alpha_E} L_{2t}^{\alpha_E}) \tag{24}$$

The labor share is set to $\alpha_E = 0.403$ (Barrage 2020a). The quantification of abatement cost function $\Theta_t(\mu_t E_t)$ 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 into a per-ton cost measure through a logistic approximation (see Online Appendix and Barrage 2020a).

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

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

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

$$(1 - D_t(T_t)) = \frac{1}{1 + \alpha_y T_t^2} \quad (25)$$

I consider two quantifications. The first is based on U.S. damage estimates from RICE (Nordhaus, 2010) with two adjustments. One, given that sea level rise impacts are modeled explicitly in the COMET, 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 output-equivalent damages $D(T_t)$. 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 (25) is set to match the resulting production loss estimate of 0.616 percent output loss due to $2.5°C$ warming, yielding $\alpha_y = 0.0009917$.

Alternatively 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 due to $2.5°C$ warming. Given the high importance of value of statistical life loss in their estimates, I assume a lower share of 50% of production damages, yielding $\alpha_y = 0.0013$.

Sea Level Rise Sea level rise resulting from the history of temperature changes is quantified based on Rahmstorf (2007) as described in Appendix 7.4. 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, and tropical cyclone surge impacts of climate change. It estimates costs resulting both from increased storm surge damages and property abandonment. 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[20] Total gross damages appear approximately linear in global mean sea level rise (see Online Appendix). I translate these level damages into depreciation rates by (i) deflating future values into base year property value equivalents,[21] 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

[20] I am grateful to Jeremy Martinich for sharing both model results and input assumptions.

[21] The projections assume that property values will increase in future years in line with GDP growth at an elasticity of 0.45 (Neumann et al. 2010). I use the relevant GDP projections used by EPA (2017).

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 (4) to be:

$$\begin{aligned}\delta(SLR_t, \Lambda_t^{slr}) &= \overline{\delta} + \delta^{SLR} \cdot SLR_t \cdot (1 - \Lambda_t^{slr}) \\ &= \overline{\delta} + 0.000186 \cdot SLR_t \cdot (1 - \Lambda_t^{slr})\end{aligned} \tag{26}$$

In order to quantify adaptation costs and effectiveness, I use the 'adaptation' model runs which optimize over beach nourishment, shoreline armoring (e.g., sea walls), and property elevation. The model estimates annual expenditures on these coastal protection measures and residual damages incurred. In line with prior literature, notably Fried (2019), adaptive capacity in the model depends on the protective capital stock *relative* to gross damages (i.e., capital at risk) via:

$$\Lambda_t^{SLR} = \left(\gamma_1 \frac{AK_t}{(\delta^{SLR} \cdot SLR_t \cdot K_t)}\right)^{\gamma_2} \tag{27}$$

I quantify adaptation cost parameters γ_1, γ_2, and d^{slr} by minimizing the sum of squared deviations between equations (14), (27), an intra-temporal optimality condition for adaptation expenditures,[22] and the observed values of Λ_t^{SLR}, AK_t, and gross damages obtained from the EPA's Coastal Property Model, all aggregated to the decadal level.[23] The deviation-minimizing parameters are $\gamma_1 = 10.7965$, $\gamma_2 = 0.0840$, and $d^{slr} = 0.2780$, implying an *annual* protective capital depreciation rate of 3.2%. Though not targeted thereto, this value is very close to the adaptation capital depreciation rate in Fried (2019) of 3% per year.

Government Spending, Initial Taxes, and Debt 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 from the Bureau of Economic Analysis, total U.S. government expenditures in the model base year 2016 included \$2.8 trillion in transfer payments and \$2.7 trillion in consumption and subsidies (\$2016). Base year values for $\overline{G_0^T}$ and $\overline{G_0^C}$ are set accordingly. For future projections, it is helpful to separate government consumption into its health ($\overline{G_t^{C,H}}$) and non-health

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

23 I 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.

($\overline{G_t^{C,N}}$) components. First, all three types of government expenditures are projected to grow at the rates of population and productivity growth.[24] Second, health expenditures are additionally projected to increases (as a share of both GDP and government spending) due to demographic and other factors (CBO, 2021b). I incorporate CBO 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. Third, climate change can increase all three types of expenditures. I quantify those effects in line with the empirically estimated damage function of Sections 2.1 and 2.2 as *fiscal damage functions* for health, non-health consumption, and transfer expenditure obligations, respectively:

$$G_t^{C,H} = \overline{G_t^{C,H}}(1 + (.0020)T_t + (.00195)T_t^2) \tag{28}$$
$$G_t^{C,N}(T_t) = \overline{G_t^{C,N}}(1.0049)T_t \tag{29}$$
$$G_t^{T}(T_t) = \overline{G_t^{T}}(1.0006)T_t \tag{30}$$

For initial taxes, according to OECD estimates, the average effective labor tax wedge in the United States between 2010-2018 has been 30.9%. 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%. For tax burdens on capital, a detailed review by the Congressional Budget Office (2014) estimates a 29% effective marginal rate on business capital income.[25] For 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 as per FRED Data.

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 (quantified based on RICE) and labor supply is $l_t \equiv L_t/N_t$. The dynastic household maximizes the population-weighted lifetime utility:

$$\sum_{t=0}^{\infty} \beta^t N_t U(c_t, l_t, T_t)$$
$$U(c_t, l_t, T_t) = \frac{\left[c_t \cdot (1 - \varsigma l_t)^{\gamma}\right]^{1-\sigma}}{1-\sigma} + \frac{\left(1 + \alpha_u T_t^2\right)^{-(1-\sigma)}}{1-\sigma}$$

Benchmark preference parameters are set to jointly match base year labor supply $l_{2015} = 0.2324$ and a Frisch elasticity of labor supply of 0.78, which is the central micro estimates

[24] This assumption is in line with, e.g., Bovenberg and Goulder (1996) and similar also to, e.g., Goulder et al. (2016) where government expenditures grow at the steady state growth rate of the model.

[25] CBO (2014) estimate a lower rate (18%) if owner-occupied housing is included, but this figure does not account for local property taxes. The more self-contained estimate for business capital is thus preferred.

identified by Chetty et al. (2011), given initial tax rates[26] and assumed values of $\sigma = 1.5$ and a pure rate of social time preference of 1.5% per year, implying $\beta = (.985)^{10}$. Alternative discounting and labor supply parameterizations are considered as well. The climate disutility parameter α_u is chosen to match an aggregate consumption loss-equivalent of disutility from climate change at $2.5°C$ of 0.26% (0.81%) of output for the RICE (Hsiang et al. 2017) damages specification, yielding $\alpha_u = .00006$ (= 0.00019).

Carbon Cycle and Climate Model The COMET-US builds on the updated representation of the climate system and carbon cycle of the FAIR model (Millar et al. 2017) as implemented in DICE-2023 (Barrage and Nordhaus 2024). This framework addresses concerns raised about the previous DICE model carbon cycle based on recent climate science (e.g., Dietz et al. 2021b). Details of its implementation in the COMET are provided in the Online Appendix.

Given the U.S. focus of the model, rest of the world emissions must be specified. As a baseline I consider business-as-usual emissions projections from the RICE Model, including both industrial and land use-based CO_2 emissions. Absent U.S. climate policy, these emissions lead to around $3.5°C$ warming over pre-industrial temperatures by 2100, substantially below the RCP 8.5 scenario but closely in line with the broader IAM literature.[27] I further allow for the possibility that ROW 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. However, key results are also presented for alternative values. Non-CO_2 forcings are also considered but taken as exogenous.

5 Quantitative Results

The model runs seek to address three core questions: (1) How big are the fiscal impacts of climate change in the United States? (2) How quantitatively important are fiscal costs for the Social Cost of Carbon? (3) How does consideration of fiscal general equilibrium effects affect our understanding of the welfare impacts of climate policy? To this end, the model runs cross four income tax and two climate policy scenarios, namely:

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

[27] For example, the average reference scenario warming projection for 2100 in a recent multi-model study was $3.6°C$ (Gillingham et al. 2018). The latest DICE model projects $3.8°C$ warming in the base scenario (Barrage and Nordhaus 2024).

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

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

3. "BAU, Vary Capital Income Taxes": Labor taxes are held fixed at $\overline{\tau_l} = 41.5\%$ and the government can vary capital income taxes.

4. "BAU, Vary Labor Income Taxes": Capital income taxes are held fixed at $\overline{\tau_k} = 37\%$ and the government can vary labor income taxes.

One important point to note is that the model has difficulty solving if income taxes remain at their observed initial levels, in line with other projections highlighting the fiscal challenges posed by current U.S. policy (e.g., Treasury 2022). Scenarios 3 and 4 thus consider modified business-as-usual income taxes. For U.S. carbon and energy taxes, the model either optimizes both ("Opt"), or assumes no carbon or energy taxes until 2115 ("No").

One important point to note is that the social planner in the model considers only domestic climate change impacts. 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 much too low from a broader efficiency perspective. This choice is motivated by the facts that (i) the central goal of this paper is to quantify the relative importance of the newly quantified fiscal costs, and (ii) this paper only quantifies said fiscal costs for the United States. That is, in order to produce an appropriate counterfactual for the global SCC with and without fiscal costs, one would need to empirically estimate fiscal impacts for the rest of the world, which is beyond the scope of the present study.

Fiscal Costs of Climate Change: Magnitudes To begin, Figure 7 presents the projected fiscal impacts of climate change in the near-term (in fiscal BAU scenario 3 with optimized U.S. climate policy). The central finding is that the estimated impacts are large. Already as of 2026, climate change is estimated to cost U.S. taxpayers around \$88 billion (\$2022) per year due to both increased public program costs (66%) and foregone tax revenues (33%). Public health expenditure impacts account for the plurality of estimated impacts (39%). To put this figure in perspective, \$88 billion in the Fiscal Year 2022 budget corresounded to around 50% of U.S. Military Personnel expenditures and is on par with the budge of the Department of Homeland Security (\$80 billion). By mid-century, the fiscal costs of climate change are projected to increase to \$220 billion per year. It should be noted that these estimates are conservative in that they use observed initial labor and capital income

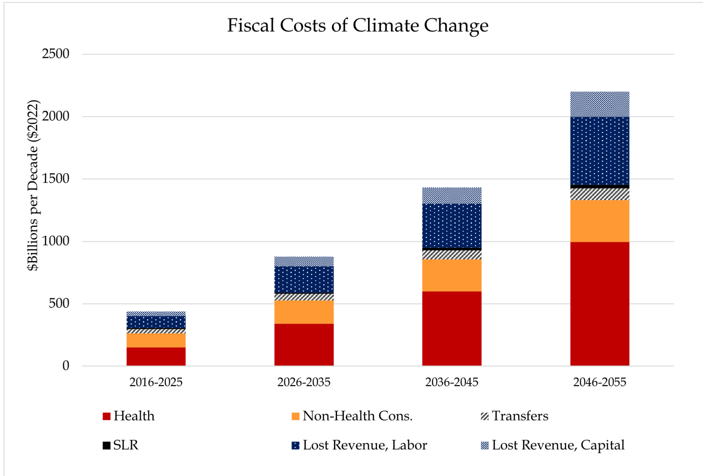

Figure 7: Fiscal impacts of climate change in the benchmark fiscal BAU scenario with optimized U.S. climate policy and an international emissions response elasticity of 0.3

tax rates, rather than the projected required higher future tax rates, to quantify foregone tax revenues. In sum, the results suggest that climate change is already having an economically significant adverse impact on U.S. public finances, and that these impacts may increase significantly going forward.

Public Expenditure Impacts and the Social Cost of Carbon Next I consider how the main empirical novelty of this paper - the estimated impacts of climate change on public expenditure obligations - affect the social cost of carbon, or, equivalently, how quantitatively important the result of Proposition 1 - demonstrating their theoretical relevance to the SCC - is in the U.S. context. To this end, Table 3 presents estimates of the U.S. SCC (formally the optimal carbon price in the "Optimized Distortionary" income tax scenario) in the 2026-35 period across a variety of parameter choices both without (as in prior literature) and with public expenditure impact functions (28) $-$ (30) included in the model. The central finding is that consideration of fiscal costs increases the social cost of carbon substantially by +23-33%. Somewhat remarkably, while the *level* of the SCC varies significantly across scenarios, the *relative impact of fiscal costs* is quite stable across all cases considered. Finally, one can contextualize the SCC increase by noting that the latest estimates of the effects of climate tipping points on the SCC are around 25% (Dietz et al. 2021a), indicating that fiscal costs may be of comparable importance for researchers and policy-makers to consider going forward, at least in terms of expected impacts on the SCC.

Climate Policy, Fiscal Impacts, and Welfare Finally, Table 4 presents policy and welfare results for the benchmark model. The central finding is that the estimated welfare gains

Table 3: Fiscal Impacts and the Social Cost of Carbon

Scenario	U.S. SCC Fiscal Costs: Yes	No	%Δ
Benchmark	60	47	+28%
Hsiang et al. damages	95	77	+23%
Lower ROW elasticity = 0	22	17	+29%
Higher ROW elasticity = 1	156	117	+33%
Lower rate of time preference (1%/yr)	89	70	+27%
Higher Frisch elasticity (1.56)	59	45	+31%

Table shows estimates of the U.S. social cost of carbon ($2022/mtC) in 2025 both with and without fiscal damage functions for public healthcare, non-health consumption, and transfer impacts and the percent change in the SCC due to fiscal costs in each scenario, namely the benchmark, higher climate production and utility damages based on Hsiang et al. (2017), lower/higher rest of the world emissions response elasticities to U.S. climate policy, a lower rate of time prefernece, and a higher Frisch elasticity of labor supply. All runs assume "Optimized Distortionary" income taxes.

from optimized carbon and energy pricing are 20-300% higher when fiscal general equilibrium effects are taken into account. In the first-best setting - the standard in climate-economy models - there are no income taxes and the MCF is equal to unity. Introducing carbon and energy taxes yields a domestic welfare gain of around $700 billion dollars (initial period equivalent variation consumption transfer). In contrast, when distortionary income taxation is considered, the welfare gains rise to between $826 billion and $2.1 trillion, depending on the fiscal scenario. Intuitively, this is because both the revenues raised from carbon and energy taxes and the public expenditure savings of avoided climate change are significantly higher in a world with scarce public funds. Interestingly, the welfare gains of carbon pricing are higher even though the optimal stringency of climate policy is lower in the presence of distortionary taxes. This latter result is matches many prior studies (e.g., Bovenberg and Goulder 1996; Barrage 2020a). The reason for this somewhat counterintuitive result is that fiscal interactions alter both the costs and benefits of carbon pricing policies.

6 Conclusion

Climate change is increasingly being recognized as a potential threat to fiscal sustainability. This paper presents what is to the best of my knowledge a first systematic quantification and integration of fiscal costs of climate change into a macroeconomic integrated assessment model with a focus on the United States. The central finding is that fiscal costs of climate change appear substantial - already on the order of $88 billion per year in 2026 - and have

Table 4: Fiscal Policy, Climate Policy, and Welfare

Scenario Income	Scenario Carbon & Energy	Labor Tax	Capital Tax	MCF	Carbon Tax (\$/mtC)	ΔWelfare EV ΔC_{2020}
		Avg. 2025-2215			2025-35	(\$2022 bil.)
First-Best	No	0.0	0.0	1.0	0	
First-Best	Opt.	0.0	0.0	1.0	66	693
Opt.	No	46.3	6.3	1.10	0	
Opt.	Opt.	46.4	5.0	1.09	60	881
BAU $\overline{\tau_l}$,	No	41.5	39.3	1.59	0	
vary τ_k	Opt.	41.5	36.4	1.65	56	2,118
BAU $\overline{\tau_k}$,	No	45.2	37.0	1.06		
vary τ_l	Opt.	45.2	37.0	1.06	60	826

Each row shows (constrained) optimal fiscal and climate policy outcomes across a given model scenario. For each income tax scenario, outcomes without and with carbon and energy taxation are shown in the first and second rows, respectively. The last column shows the welfare effects of allowing carbon and energy taxes in initial lump-sum equivalent variation (\$2022).

both qualitatively and quantitatively significant implications for climate policy, such as a substantial increase in both the U.S. SCC (+23-33%) and the projected domestic welfare gains from optimized carbon and energy taxation.

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 sea level rise (Painter 2020; Goldsmith-Pinkham et al. 2023). The empirical results of this paper also suggest that healthcare cost increase from warming may fall disproportionately on lower income areas, adding to recent evidence documenting inequities in fiscal impacts of other climatic risks, such as hurricanes (Jerch et al. 2023). Of course, income inequality and redistribution are also important aspects of the tax system. Consideration of fiscal impacts in the context of redistribution and spatial heterogeneity are thus critical areas for future research.

This paper also focuses on the United States. Other countries' fiscal climate change vulnerabilities may be even larger if, for example, they have larger public health systems, or more economically significant in poor countries which already have limited fiscal space to respond to natural disasters (Noy and Nualsri 2011; Phan and Schwartzman 2023). Extending this type of analysis to other countries is thus another important avenue for future work.

The United States faces significant long-term fiscal challenges (Treasury 2022). This paper's results suggest that climate change may exacerbate these challenges. 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 Damage Function

In order to derive a damage function for public healthcare costs from extreme heat, I associate mean cost estimates with global mean surface temperature change projections as shown in Figure 6. One noteworthy nuance is that these estimates pertain to the *total* annual public healthcare costs due to extreme heat, whereas a damage function should describe *additional* costs from global warming. Unfortunately, the Rasmussen et al. (2016) data do not provide downscaled estimates of daily temperature distributions in U.S. counties in a counterfactual world with pre-industrial temperatures. Econometrically, one can attempt to extrapolate by regressing total healthcare cost impacts in each year t $\%\Delta\text{HealthCosts}_t$ on the square of global temperature change T_t in the relevant scenario and attempt to infer damages absent warming based on the regression intercept β_0 :

$$\%\Delta\text{HealthCosts}_t = \beta_0 + \beta_1 T_t^2 + \varepsilon_t$$

The results of this regression, shown in Column (1) of Table A1 below, reveal a *negative* intercept estimate. Consequently, a regression-based extrapolation does not suggest positive public healthcare costs from extreme heat in a counterfactual world where temperatures are at pre-industrial levels. Given that the damage estimates do not actually include extreme heat day information for $T_t = 0$, however, our preferred specification assumes that costs at pre-industrial temperatures would be zero by imposing $\beta_0 = 0$. The results for this specification are shown in Column (2) of Table A1.

Table A1: Damage Function Estimation

	%Δ Annual Public Healthcare Costs due to Extreme Heat	
	(1)	(2)
T_t^2	0.2072***	0.1953***
	(.0036)	(0.0023)
Constant	-0.1546***	
	(.0383)	
Obs.	85	85
R-Sq.	0.9753	0.9885

Table shows results of linear regression of mean of estimated public healthcare cost impact of extreme heat (days with avg. temperatures>32C) on the square of the corresponding mean global surface temperature change (in RCP 8.5 in the MAGICC model, Meinhausen et al. 2011) in Col. (2) along with a constant in Col. (1). *** $p<0.01$, ** $p<0.05$, * $p<0.1$

7.2 Literature Synthesis Details

The estimates presented in Table 2 focus on impacts by 2100 in emissions scenarios RCP 4.5 and RCP 8.5, for which we use global mean surface temperature change predictions from the MAGICC model (Meinhausen et al. 2011) corresponding to around $2.5°C$ and $4.3°C$ over pre-industrial levels, respectively. This section fills in further details on Table 2.

Healthcare - Extreme heat: I evaluate the damage function from Section 2.1 at $2.5°C$ and $4.3°C$, respectively, to infer projected changes in public health expenditures (+1.22% and +3.61%, resp). I then compute the future percent share of public health in total government consumption expenditures based on the 2016 share adjusted for future baseline health cost increases (CBO 2021b), which increase both health expenditures and the overall level of government consumption. As CBO only projects cost increases through 2050, I assume no further relative cost changes beyond this point.

Healthcare & Income Support - Hurricanes: For the estimation using the Deryugina (2017) data I 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 A2 shows the results. I then calculate the present value of the 10-year impacts for each storm category assuming an annual discount rate of 3%.

To quantify baseline hurricane risk, I first calculate the average number of Category 1, 2, and 3+ hurricanes experienced by each county in the Deryugina data (1969-2014). To quantify future risks, I use Monte Carlo simulation results of future annual U.S. landfall-making storm realizations (number and wind speeds) from Bakkensen and Barrage (2021) which, in turn, are based on synthetic tropical tracks under a future climate (2080-2100 under the IPCC's A1B emissions scenario processed through different climate models of which I focus on NOAA's Geophysical Fluid Dynamics Laboratory model) from Emanuel et al. (2008). Compared to historical data in the satellite era (1971-2020, NOAA 2023), the average number of annual hurricane landfalls is projected to increase from 0.74 to 1.9 for Category 1, from 0.34 to 1.02 for Category 2, and from 0.5 to 1.66 for Category 3+ storms. Given that (i) the A1B scenario is associated with $2.8°C$ warming over 1980-1999 temperatures (IPCC AR4 multi-model mean), (ii) cyclone intensity can be assumed to increase linearly with global temperatures (Holland and Bruyere 2014) but only above the base period (GFDL, 2018), I then calculate the percent increase in each type of hurricane activity per $1°C$ warming above the 1980-1999 level. After raising each county's baseline cyclone risk for each storm category proportionately, I then calculate the associated local percent increase in annual public health expenditures, and then aggregate to the national level by calculating the base year total public health transfer share-weighted total amount, which is \$2.7 billion dollars per year. For income support payments, the corresponding figure is \$1.7 billion dollars per year (in the 2016 economy). I then divide by total public health expenditures (see footnote 6) and government transfers (from NIPA) in 2016 to compute the corresponding percent program expenditure increases per $1°C$ warming, and finally multiply by projected warming *over 1980-1999 temperatures* in the RCP 4.5 and 8.5 scenarios to derive the numbers in Table 2, where I assume $0.61°C$ warming from pre-industrial until the end of the 20th century in line with IPCC estimates.

Table A2: Hurricane Strike Impacts

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.

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. 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 suggest 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 scenario limiting warming to $1.5°C$. I interpolate linearly and divide by the same respective denominators as for other healthcare impacts to derive the figures in Table 2.

Crop-Insurance Subsidies: In a joint analysis with USDA, OMB (2016) projects program costs to increase 40% by 2080 under RCP 8.5, and 23% by 2080 under RCP 4.5. I translate dollar terms into percentages using base period crop insurance program expenditures of slightly over $6 billion per year on average. Given the relevant median projections for future global temperature change, these estimates imply an approximately linear increase of around +14% increase in costs per degree warming, as shown in Table A3 below.

Table A3: 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%	

Diffenbaugh et al. (2021) estimate that damages from observed warming from 1991-2017 accounted for 19% of U.S. crop insurance payments over this time period. The observed global temperature anomaly over this time period increased from $0.58°C$ to $1.19°C$ relative to 1881-1910 levels. These estimates thus imply an approximately 25% increase in crop insurance costs due to 0.61° additional warming, implying a linear effect of +41% per $1°C$. The calculations in Table 2 take the average of the Diffenbaugh et al. (2021) and OMB (2016) estimates, yielding +28% per $1°C$.

Federal Wildfire Suppression Costs: The USDA (2015) projections reported in OMB (2016) imply annual cost increases of +45% for the Department of Interior (DOI) and 117% for Forest Service (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 A4 summarizes these results and the implied cost increases per degree of warming, which again appear close to linear. Base year wildfire suppression expenditures for each agency are from the National Interagency Fire Center.[28]

[28] URL (last accessed January 2024): [https://www.nifc.gov/fire-information/statistics/suppression-costs]

Table A4: 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 (2016)
Per 1°C impact:	+58.5	+51.9	
DOI	+45%	+72%	OMB (2016), USDA FS (2016)
Per 1°C impact:	+22.5%	+19.5%	

Hurricane-related disaster spending: The CBO's (2016) central estimates imply an increase in expected annual direct hurricane damages from 0.16% of GDP at present to 0.22% by 2075 under RCP 8.5. Approximately 45% of this increase is due to climate change, based on changes in sea levels and hurricane patterns. The remainder is due to projected increases in coastal development. CBO further estimates that, in recent years, federal hurricane aid has average around 62% of direct damages, or 0.10% of GDP. 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% of GDP by 2075. I consider the climate-related 45% of this change as impact at the associated global temperature change. Importantly, for hurricanes, I again focus on temperature change over a more recent baseline as changes in hurricane patterns were not yet apparent in the 20th Century (GFDL 2018). The 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 AR5). Interpolating linearly yields 2.85°C by 2075. Linearizing also for hurricane changes (Holland and Bruyere 2014) suggests +0.005% of GDP per 1°C over 1986-2005 temperatures. Multiplying by the relevant temperature change in each RCP and by the relevant (future health-spending adjusted) government consumption shares of GDP yields the Table 2 estimates.

Urban Drainage Infrastructure: The EPA (2017) estimates of the costs of maintaining service levels in urban drainage infrastructure - assuming cities will want to remain prepared for 50-year storm events - are shown in Table A5. Given that impacts appear roughly linear - and certainly not convex - I use a benchmark estimate from a linear regression of projected costs on global temperature change, yielding \$1.83 billions per year per 1°C (in today's terms) for the calculations in Table 2.

Table A5: 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	

Road Maintenance: EPA (2017) estimate changes in U.S. road maintenance costs with both reactive and optimized proactive adaptation to changing climate conditions. I take the average between these two limiting cases and across the climate models considered, which implies annual costs of \$6.35 billion in RCP 8.5 and \$2.55 billion in RCP 4.5, and compute the figures in Table 2 based on the corresponding per-degree costs.

Endangered Species Act (ESA): Moore et al. (2022) estimate 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%. I apply this increase to base year total government ESA expenditures (FWS, 2017) to infer annual spending impacts.

7.3 Theory Setup and Proposition 1

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

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

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

$$
(-U_{Tt}) + \phi U_{ct} \frac{\partial G_t}{\partial T_t} - \lambda_{1t} \frac{\partial Y_t}{\partial T_t} + \lambda_{1t} \frac{\partial G_t^c}{\partial T_t} + \sum_{m=0}^{\infty} [\beta^m \lambda_{1t+m} \frac{\partial \delta}{\partial SLR_{t+m}} K_{t+m}] \frac{\partial SLR_{t+m}}{\partial T_t} = \xi_t \quad (31)
$$

Next, the first order condition with respect to mitigation μ_t for $t > 0$ equates marginal abatement costs with the present value of marginal damages:

$$\Theta_t'(\mu_t E_t) = \sum_{j=0}^{\infty} \frac{\xi_{t+j}}{\lambda_{1t}} \beta^j \frac{\partial T_{t+j}}{\partial E_t^M} \tag{32}$$

Combining (31) and (32) yields an expression for the optimal carbon price τ_{Et}^* in equilbrium as per (12). Next, one needs to substitute out for the public marginal utility of income λ_{1t} and for the Lagrange multiplier on the implementability constraint, ϕ. Taking the optimality condition with respect to the aggregate private capital stock $[K_{t+1}]$ for $t > 0$ and substituting in the equilibrium condition for capital returns one can replace the $\lambda_{1t}'s$ with expressions of M_j (19). Taking the first order condition with respect to $[C_t]$ for $t > 0$ reveals that:

$$\phi = \frac{\lambda_{1t} - U_{ct}}{[U_{cct}C_t + U_{ct} + U_{lct}L_t - U_{cct}G_t^T(T_t)]} \tag{33}$$

Substituting (33) into (31), 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 Prop. 1.

7.4 Sea Level Rise

Rahmstorf (2007) estimates that sea level rise can be approximated as proportional to global temperature change over pre-industrial levels at a rate of 3.4 millimeters/year per $°C$. I thus model SLR_t in cm over 1993-2008 levels as:

$$SLR_t = SLR_{t-1} + (\frac{T_t + T_{t-1}}{2}) \cdot 0.34 \cdot 10$$

with $SLR_{2020} = 5.6$ cm, the average across scenarios from NOAA (2017 Tech. Rep. NOS CO-OPS 83) as relevant for the EPA modeling.