Temperatures and Growth: a Panel Analysis of the U.S.

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Abstract

We provide empirical evidence that temperature affects economic growth in the United States. Our analysis documents the importance of focusing on the role of *seasonal* temperatures. While the link between average *annual* temperatures and economic growth is typically hard to establish, our results show that i) rising Summer temperatures depress growth, and ii) rising Fall temperatures increase economic growth. However, Summer temperatures are expected to increase at a faster pace relative to that of Fall temperatures. Thus, in a "horse race," the Summer effect dominates. Our estimation implies that, in net, rising temperatures can decrease the growth rate of US GDP by as much as one third, thus resulting in large welfare losses.

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1 Introduction

The latest report of the Intergovernmental Panel on Climate Change (IPCC (2014)) has warned that global temperatures are expected to increase by as much as 4 degrees Celsius over the next 100 years. In light of these projections, economists and policy makers face an increasing need to quantify the impact of rising temperatures on economic activity. In this paper, we estimate the effect of temperature on the growth rate of US GDP using a panel of US states. Our estimates suggest that if the current trend in rising temperatures does not change, then a drop of economic growth by up to one third could occur.

There is a large empirical literature that analyzes the relationship between temperatures and aggregate economic activity (see the survey by Dell, Jones and Olken (forthcoming)). The typical finding of this literature is that warmer temperatures and increasing droughts have significant effects in *developing economies*. For example, Dell, Jones and Olken (2012) study a large cross-section of 125 countries (including both developing and developed economies, such as the U.S.) between 1950 and 2003, and find a negative effect of higher temperature on growth, but only in emerging economies.[1] Our contribution relative to this literature lies in our ability to quantify the impact of climate related variables directly for the U.S., the largest *developed* economy.

Our empirical analysis is informative for a growing body of literature focused on Integrated Assessment Models (henceforth IAMs). These models constitute the basis of many policy recommendations regarding regulation of greenhouse gas emissions (see, for example, Golosov, Hassler, Krusell and Tsyvinski (2014), Acemoglu, Aghion, Bursztyn and Hemous (2012), Bansal and Ochoa (2011), and Bansal, Ochoa and Kiku (2014)). The fundamental component of these models is a climate "damage function," which spec-

[1]These findings are consistent with other area-based analyses by Hsiang (2010), who focus on 28 Caribbean-basin countries, and Barrios, Bertinelli and Strobl (2010), who focus on countries in Sub-Saharan Africa.

ifies how temperatures (or other weather related variables) affect aggregate economic activity (such as the total factor productivity). In the absence of specific estimates for the U.S., the parameters of this damage function are generally calibrated to match cross-country estimates (for example, see Nordhaus and Sztorc (2013)).[2] US policymakers may be less inclined to adopt policies that curb greenhouse gas emission that are not based on estimates specific to the United States (or other developed countries). In this respect, our analysis helps bridge the gap between the economics literature and policy recommendations.

Our paper provides novel evidence that warmer temperatures have statistically and economically significant effects on U.S. GDP growth. We arrive at this conclusion by collecting a large dataset of daily temperature, precipitation, and snowfall across 135 U.S. weather stations. We aggregate weather data at a county level by weighting each station by the inverse of the distance to each county's centroid. We construct a dataset for state and country-level weather, which is obtained by weighting each county in proportion to its share of total area or population. We combine this dataset with a panel of state GDP, or Gross State Product (henceforth GSP), for the entire cross-section of US states. This allows us to estimate an econometric model which exploits both the cross-sectional and the time-series dimensions.

As a consequence, a number of key results emerge from our panel regressions of GSP growth rates on weather related variables. First, by using annual data aggregated to the country-level, we find no evidence to support the view that temperature affects the growth rate of GSP. This finding is in line with the literature that has typically pointed out the difficulty in identifying the relationship between rising temperatures and aggregate economic activity in developed economies (see Dell et al. (2012) and Dell et al. (forthcoming)).

[2]In a recent survey of IAMs, Pindyck (2013) writes "the choice of values for these parameters [for the climate damage function] is essentially guesswork".

Second, we show that by breaking down annual temperature into its seasonal components, we can establish the existence of an effect of temperature on economic growth.[3] Our results indicate that rising summer temperatures decrease GSP growth, although the opposite is true for Fall temperatures. Specifically, while the estimated coefficients on Summer and Fall have opposite signs, their absolute magnitudes are very similar. This suggests that the annual aggregation of temperature may mask the heterogeneous effects of different seasons, thus explaining the difficulty the literature has had so far in providing any conclusive evidence using annual temperatures.

We investigate the quantitative relevance of these results in terms of climate change. From historical weather data, we document that Summer temperatures are expected to rise by almost twice as much as Fall temperatures, a finding that is broadly consistent with the analysis by Hansen, Sato and Ruedy (2012). This means that even if the effect of Summer and Fall on economic growth is comparable on an annual basis, their compounded effects over *longer time horizons* will differ substantially. Our findings indicate that the projected increase in seasonal temperatures over the next 100 years may result in a drop of GSP growth of up to one-third. This magnitude is economically significant and it reverberates with the argument by Dell et al. (forthcoming) that "growth effects, which compound over time, have potentially first-order consequences for the scale of economic damages over the longer run, greatly exceeding level effects on income, and are thus an important area for further modeling and research."

Last but not least, we compute the welfare costs associated with climate change. This exercise has a long tradition in the macroeconomic literature on quantifying the welfare cost of business cycle fluctuations (see, for example, Lucas (1987)). More recently, Bansal et al. (2014) have extended this framework to investigate the social cost of climate change. Our analysis differs from the existing literature in that we rely on the actual estimates from our empirical analysis. We document that for a reasonably cali-

[3] We define the seasons as Winter, Spring, Summer, and Fall each corresponding to a three months period starting with January.

brated economy, an agent would be willing to accept a reduction of up to 0.3% in the level of her consumption, and of up to 14% in the growth rate of her consumption in order to live in an economy in which temperature does not have an impact on economic growth.

To the best of our knowledge, ours is the first paper to document a negative and statistically significant relationship between rising temperatures and the aggregate economic growth of a developed economy. In a related study, Nordhaus (2010) finds significant effects of extreme weather events such as storms and hurricanes on level of U.S. GDP. Several other studies have focused on specific industries in the U.S., ranging from agriculture (see for example, Schlenker and Roberts (2009), Fisher, Hanemann, Roberts and Schlenker (2012), Deschênes and Greenstone (2012)) to the automobile sector (see inter alia Cachon, Gallino and Olivares (2012)). In a related study, Zivin and Neidell (2014) finds that warmer temperatures reduce labor supply in U.S., thus providing an economic rationale for why climate change might affect economic activity in a developed economy. Finally, our paper is related to Deryugina and Hsiang (2014), who also exploit within-country variation in the U.S. and find that daily temperatures above certain thresholds (15C and 30C) reduce the productivity level. While their study focuses on the *non-linear* effects of *daily* temperatures on the *productivity level*, our paper focuses on the effects of *average seasonal* temperatures on *GDP growth*.

The rest of the paper is organized as follows. Section 2 provides a description of the main datasets that we employ in our analysis. Section 3 presents the main results of our empirical investigation. Section 4 quantifies the relevance of our empirical results for climate change and it computes the welfare costs associated with climate change. Section 5 contains a number of robustness checks of the empirical analysis. Section 6 concludes the paper.

2 Data

In this section we describe our data sources and the procedure that we used to aggregate weather related data at state and country level.

Weather stations data. We collect daily station-level weather data from the website of the NOAA Northeast Regional Climate Center, http://drought.rcc-acis.org/. This dataset reports daily data on average temperature, precipitation, and snowfall across 135 U.S. weather stations. Temperature is the variable of main interest, but we include precipitation and snowfall for robustness checks. The longest common sample across all weather stations starts on 1869 and ends in 2012. However, we only use data between 1957 and 2012, the period for which we also have economic data. We then de-seasonalize this data, by regressing daily weather observations on 12 dummies representing each month of the year, and subtracting the estimated seasonal component for the corresponding month from each observation.

ArcGIS and Census data. We collect geographical information that we use to aggregate station level data to state and country level weather data. This task is implemented by using ArcGIS, a geographic information system (GIS) for working with maps and geographic information. We obtained the coordinates for the centroid of each of the 3,144 counties and county equivalents, as well as each weather station using ArcGIS. The country, state, and county borders used in ArcGIS are from 2013 Topographically Integrated Geographic Encoding and Referencing (TIGER) shape files available from the U.S. Census Bureau. We obtained the area and population of each county from the U.S. Census Bureau (https://www.census.gov/econ/cbp/download/).

State aggregate data. We aggregated the station-level weather information to compute measures of state-level temperature, precipitation, and snowfall. We proceeded in two steps. First, for each county we weighted the daily temperature, precipitation, and snowfall of each weather station in a 500 km radius of the county's centroid by the inverse of the straight-line distance between the station and the county. In this way, the closest weather stations were assigned a larger weight in determining each county's weather. Second, for each state we weighted the daily temperature, precipitation, and snowfall of each county in the state in proportion to either the corresponding county's area or population. The first procedure assigns larger weight to larger counties, while the second one over weights densely populated areas. The results are robust to both weighting schemes. The same methodology can be used to construct country aggregate data.

As an example, Figure 1 shows how the weather variables for Jefferson County (KY) were constructed. Jefferson County is the dot roughly in the middle of Figure 1. Note that, even though there are only 3 weather stations in Kentucky, there are 15 weather stations in a 500 km radius of Jefferson. Each weather station receives a weight which is inversely proportional to its distance from Jefferson. This means that Akron (OH) plays a relatively small role in the determination of Jefferson's weather measure relative to Lexington (KY), which is in close proximity to Jefferson. Once daily temperature, precipitation, and snowfall are calculated for all Kentucky's counties, data are aggregated at state level by weighting in proportion to each county's population and area.

GDP by state data. We use data of nominal gross domestic product (GDP) by state (also known as gross state product, or GSP) between 1957 and 2012. By definition, the GDP of a state is the value added in production by the labor and capital of all industries located in that state. Data for 1957-1962 comes from the U.S. Census Bureau Bicentennial Edition Bureau (1975), and data for 1963-2012 comes from the U.S. Department of Commerce's Bureau of Economic Analysis (BEA). We obtain the combined dataset from usgovernmentspending.com.

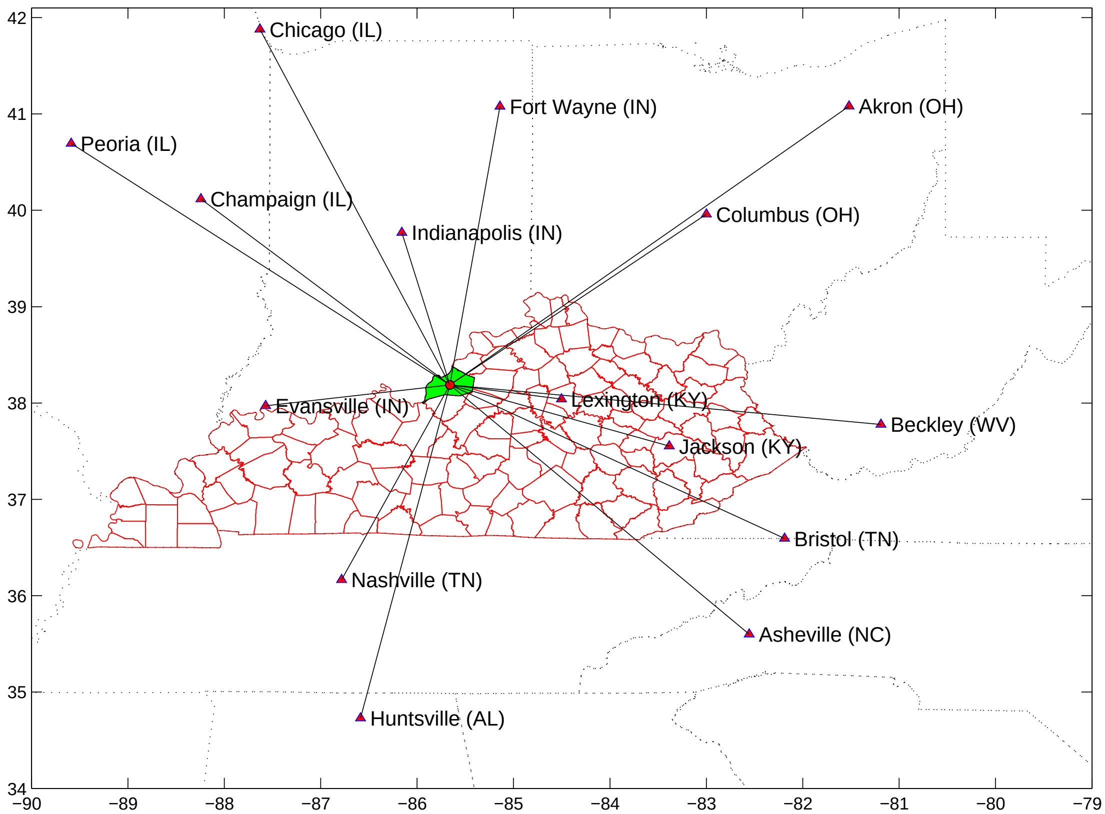

Figure 1: An illustration of the interpolation technique. The county represented by the dot is Jefferson County. Each triangle denotes a weather station located in a 500 km radius of Jefferson County. The length of each line represents the distance between Jefferson County and the associated weather station.

3 Empirical Analysis

In this section we report the results of our empirical analysis. We proceed in two steps. First, we report the results of time-series regressions at the whole country level. Then, we document the improvements that can be obtained in the context of our panel regressions.

Baseline: Time series regressions for aggregate country-level data. Table 1 re-

Table 1: Time Series Regressions on Aggregate US Data

Whole Year	Winter	Spring	Summer	Fall
−0.396	−0.071	−0.027	−0.414	0.042
(0.382)	(0.179)	(0.334)	(0.385)	(0.287)

Notes - The first column reports the estimated coefficient on average annual temperature of a regression of US GDP growth rate on its lag and average annual temperature. Columns 2-5 report the estimated coefficients on each of the four seasonal temperature averages. The numbers in parenthesis are standard errors. The sample is 1957-2012.

ports the results of time series regressions of aggregate U.S. GDP growth on average aggregate country-level temperature. The first lag of GDP growth rate is included as a control variable. The first column of the table documents the well established difficulty of identifying the effect of temperature on economic activity. The next four columns break down the annual average temperature into the four seasonal average temperatures.

Main analysis: Panel regressions for disaggregate state-level data. We explore the impact of average temperature on GDP growth rates by running the following panel regression:

$$\Delta y_{i,t} = \gamma w_{i,t} + \beta \Delta y_{i,t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t} \tag{1}$$

where $w_{i,t}$ denotes the average temperature in state i in year t, $\Delta y_{i,t}$ denotes the growth rate of GSP in state i in year t, and α_i and α_t denote state and year fixed effects, respectively. We consider two specifications: one in which we use the entire cross-section of U.S. states, and one in which we focus on specific regions (North, South, Midwest, and West).[4] Each state is weighted in the regressions by the proportion of its GSP relative to the whole country (in the first specification) or the respective region (in the second specification).

In addition, we also break down the contribution of each seasonal temperature by re-

[4]The four regions are defined according to the US Census Bureau. Appendix C reports the specifics of this classification.

gressing on the average temperatures in Winter, Spring, Summer, and Fall:

$$\Delta y_{i,t} = \sum_{s=1}^{4} \gamma^s w_{i,t}^s + \beta \Delta y_{i,t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}. \tag{2}$$

We define Winter as January, February and March; Spring as April, May and June; Summer as July, August and September; Fall as October, November and December.

We report the results of our analysis in Table 2. The column labeled "Whole Year" refers to the specification reported in equation (1). The numbers seem to indicate that the effect of average temperature at the annual level is never statistically significant. This would seem to confirm our findings in Table 1.

However, when we break down annual temperatures into the four seasonal temperatures (columns labeled "Winter," "Spring," etc., which correspond to the specification in equation (2)), the results change substantially. At the country level, there are relationships between Summer and Fall temperatures and economic growth rates. These effects are both statistically and economically significant: a one degree Fahrenheit increase in Summer temperature *decreases* GDP growth rates by 0.154%, while a one degree Fahrenheit increase in Fall temperature *increases* GDP growth rates by 0.102%.

It is important to note that Summer and Fall affect growth rates in opposite directions. Altough the effect of Summer temperature is negative, the effect of Fall temperature is positive. This could partially explain the difficulty in obtaining statistically significant estimates when using the overall annual temperatures. Even though the magnitudes of Summer and Fall temperatures are comparable, we argue in the next section that the negative coefficient for the Summer is relatively more important, once combined with a steeper trend in Summer temperatures.

Furthermore, when we decompose the effect of seasonal temperatures in the four subregions (North, South, Midwest, and West), we find that the South is responsible for most

Table 2: Panel Analysis

	Whole Year	**Winter**	**Spring**	**Summer**	**Fall**
Whole country	0.006	0.001	0.003	-0.154^{**}	0.102^{*}
	(0.111)	(0.049)	(0.065)	(0.072)	(0.055)
North	0.343	0.329^{*}	0.065	0.240	-0.255
	(0.339)	(0.173)	(0.296)	(0.257)	(0.233)
South	0.283	-0.087	0.152	-0.326^{**}	0.571^{***}
	(0.303)	(0.167)	(0.159)	(0.163)	(0.194)
Midwest	-0.212	0.010	-0.158	0.043	-0.116
	(0.235)	(0.089)	(0.144)	(0.162)	(0.128)
West	-0.144	-0.000	-0.155	0.028	-0.006
	(0.203)	(0.096)	(0.143)	(0.154)	(0.167)

Notes - In each regression, the dependent variable is the GSP growth rate of each state. The first row reports the results for the panel analysis conducted using the entire cross-section of US states. Each of the following rows refers to a different US region, according to the Federal classification. The first column refers to the analysis conducted using annual temperature averages ("Whole Year"). Each of the following columns refers to the analysis conducted by regressing jointly on the four seasonal averages. Winter is defined as the average of January, February, and March temperatures. Spring is defined as the average of April, May, and June temperatures. Summer is defined as the average of July, August, and September temperatures. Fall is defined as the average of October, November, and December temperatures. The numbers in parenthesis are standard errors. Standard errors are clustered by year. Each regression contains year and state fixed effects as well as the lagged GSP growth rate of the corresponding state. The sample period is 1957-2012.

of the overall Summer and Fall effects that we estimate at the whole country level (see the last four rows of Table 2). Also notice that the estimated coefficients for the South are three to six times larger than their whole country counterparts, indicating that this region's GDP growth is substantially more exposed to changes in temperatures. It is worth pointing out that not all regions are negatively exposed to rising temperatures in all seasons. For example, the North displays a strongly positive coefficient for Winter temperature.

We further explore how these estimated coefficients have been evolving through time. Specifically, we run the regression specified in equation (2) by increasing the start date of the sample by one year at a time. We repeat this exercise until the sample starting in 1990 (past this date, the sample size becomes too small to draw any statistically meaningful conclusion from our estimation).

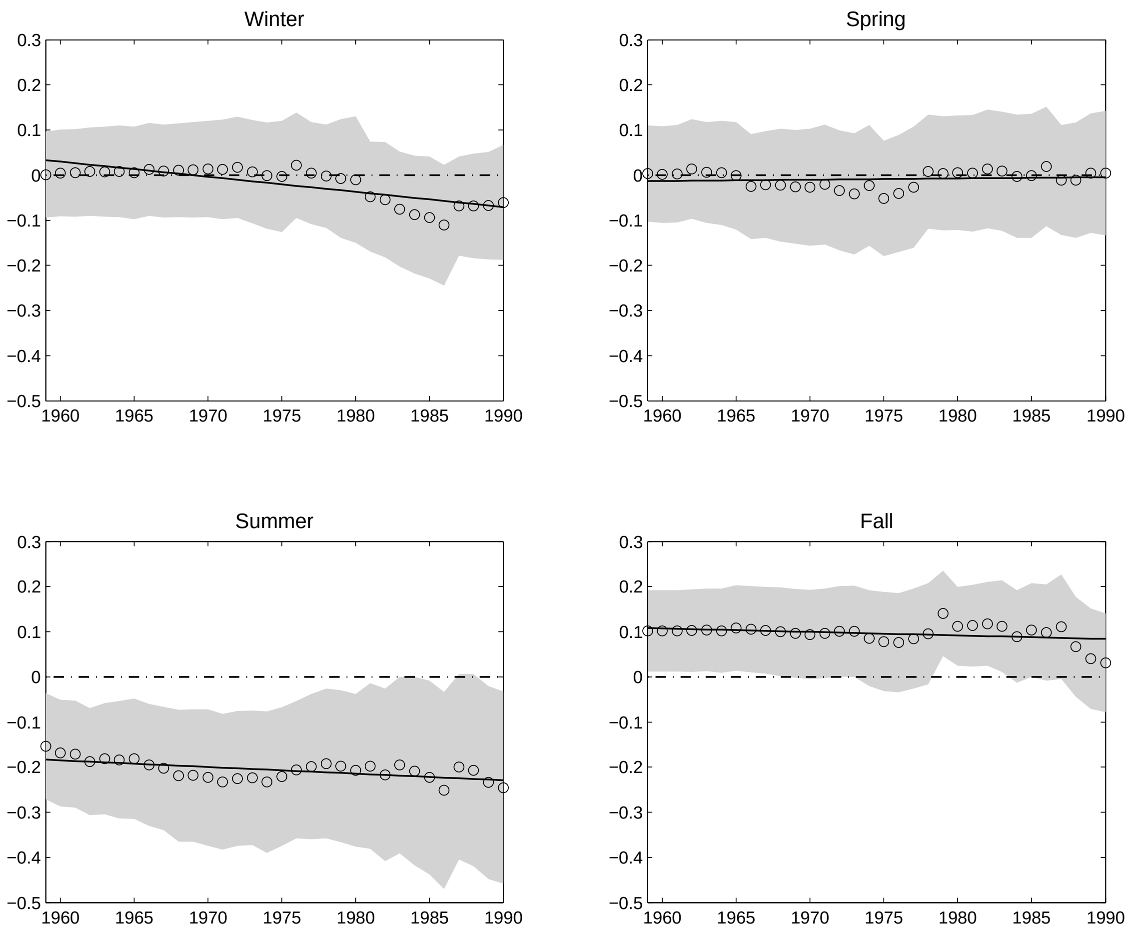

Figure 2: Each panel reports the estimated coefficients of average temperature for the corresponding season. Each dot corresponds to the coefficients estimated over the sample that starts on the year reported on the horizontal axis and ends in 2012. The panel regressions are for the entire cross-section of the U.S.. Each state is weighted by its relative GSP. Regressions include state and year fixed effects. The grey areas represent 90% confidence intervals. Standard errors are clustered at the year level. The solid lines are linear fits of the dots in each panel.

The results are reported in Figure 2. Several things emerge from this figure. First of all, the findings that we reported for the longest available sample are robust to all the sub-samples that we considered. Equivalently, Summer and Fall temperatures appear to be the only ones playing a role for economic growth. Additionally, it seems that the estimated coefficients for the Fall are quite stable through time, while the estimated coefficients for the Summer become increasingly negative. This result is potentially suggestive of an increased negative effect of rising Summer temperatures on U.S. economic growth over time.

4 Interpreting the results

Estimation of trends in temperature. In order to quantify the relevance of the coefficients estimated in Table 2, we need to get a better understanding of the projected path of temperature. To this end, we estimate the temperature process via the following regression:

$$w_{i,t} = \mu_w^i + \rho_w^i w_{i,t-1} + \beta_i \cdot t + \sigma_w^i \varepsilon_{w,t}^i \tag{3}$$

where i indexes the four seasons. For consistency with the estimations reported in the earlier sections, we focus on the $1960 - 2012$ sample period. We report the results of this estimation in Table 3.

Several results emerge from looking at Table 3. First, there is a clear positive trend in the average temperature that affects all the seasons across all U.S. regions. Second, the Summer trend is roughly twice as large as the Fall trend. (It appears that the strongest trend takes place for the Winter, followed by Spring and Summer, and ultimately by the Fall.) Third, the estimated autoregressive coefficients are typically not statistically significant. The only relevant exception has to do with some of the Fall coefficients (in the North, South and Midwest), and these autoregressive coefficients are negative. This is consistent with why the trend in Fall temperatures is only weakly increasing.

The numbers in Table 3 offer a direct quantification of the estimated coefficients of our panel regressions. If we focus on Summer and Fall (the seasons whose coefficients were statistically significant in Table 2), the first row of Table 3 suggests that in 100 years

Table 3: Dynamics of Average Temperature (1960-2012)

		Whole Year	**Winter**	**Spring**	**Summer**	**Fall**
Country	Trend	0.041^{***}	0.071^{***}	0.034^{***}	0.036^{***}	0.021^{**}
		(0.006)	(0.015)	(0.010)	(0.008)	(0.009)
	AR(1)	0.077	−0.048	0.143	0.061	−0.212
		(0.149)	(0.146)	(0.143)	(0.141)	(0.139)
North	Trend	0.048^{***}	0.080^{***}	0.041^{***}	0.035^{***}	0.036^{***}
		(0.008)	(0.023)	(0.011)	(0.009)	(0.012)
	AR(1)	0.047	0.147	−0.000	−0.184	-0.328^{**}
		(0.143)	(0.149)	(0.138)	(0.132)	(0.133)
South	Trend	0.040^{***}	0.075^{***}	0.033^{***}	0.031^{***}	0.019^{**}
		(0.008)	(0.022)	(0.012)	(0.009)	(0.009)
	AR(1)	0.160	0.200	0.070	−0.047	-0.359^{***}
		(0.151)	(0.146)	(0.145)	(0.140)	(0.132)
Midwest	Trend	0.042^{***}	0.088^{***}	0.028^{*}	0.031^{***}	0.017
		(0.011)	(0.027)	(0.016)	(0.011)	(0.013)
	AR(1)	0.185	0.072	0.158	0.017	-0.247^{*}
		(0.149)	(0.148)	(0.144)	(0.141)	(0.137)
West	Trend	0.040^{***}	0.064^{***}	0.035^{***}	0.040^{***}	0.020
		(0.007)	(0.012)	(0.013)	(0.008)	(0.013)
	AR(1)	0.001	-0.271^{**}	0.126	−0.024	0.003
		(0.143)	(0.136)	(0.141)	(0.143)	(0.142)

Notes - Notes - The table reports the estimates of the autoregressive coefficient and of the time trend for temperature. The column labeled “Whole Year” refers to the annual temperature estimation, while the columns labeled “Winter”, “Spring”, “Summer”, and “Fall” refer to the corresponding season. The row labeled “Whole country” reports the estimates obtained using US aggregate temperature data, while the following rows refer to the corresponding regions. All the regressions also include an intercept, that is not reported in the interest of space. The sample is 1960 to 2012.

seasonal temperatures are on average going to be 3.6 and 2.1 degrees Fareinhait higher, respectively. This implies that rising Summer temperatures could decrease the growth rate of U.S. GDP by $0.154\% \times 3.6 = 0.554\%$. This effect would be partially mitigated by rising Fall temperatures (by a factor of $0.102\% \times 2.1 = 0.214\%$). Equivalently, assuming no change in the way in which seasonal temperatures affect economic growth, the positive trends in Summer and Fall temperature are on average going to reduce U.S. growth by 0.33% in the next 100 years. Given an average growth rate of about 2%, rising temperatures could reduce growth by as much as one-third.

Welfare analysis. Is this section, we address the question of how much would an agent be willing to pay in order to reduce the impact of climate change on economic growth. We answer this question by computing the permanent reduction of consumption that would make an agent indifferent between living in an economy, which evolves according to the growth and temperature parameters estimated in Tables 2 and 3, and another economy in which rising temperatures affect growth to a smaller extent.[5]

Formally, we consider the problem of an agent that ranks consumption profiles according to the following recursive preferences:

$$U_t = (1-\delta)\log(C_t) + \delta\theta \log E_t \left[\exp\left\{ \frac{U_{t+1}}{\theta} \right\} \right]$$

where $\theta = 1/(1-\gamma)$, γ denotes risk aversion, and δ is the subjective discount factor. This utility function was introduced by Hansen and Sargent (1995) and it corresponds to Epstein and Zin (1989) preferences for the case in which the intertemporal elasticity of substitution is equal to 1. There is now an extensive literature in economics and finance that employs this utility function (see, inter alia, Anderson (2005), and Bansal and Yaron (2004)). They collapse to the standard case of time additive preferences if $\theta \to -\infty$. Tallarini (2000) used these preferences to revisit Lucas (1987)'s conclusion concerning the welfare costs of business cycle fluctuations.

Let consumption and temperature dynamics be described by the following law of motion:

$$\begin{aligned} \Delta c_t &= \mu_c + \sum_{i=1}^{4} \lambda_i w_{i,t} + \sigma_c \varepsilon_{c,t}, \\ w_{i,t} &= \mu_w^i + \rho_w^i w_{i,t-1} + \beta_i \cdot t + \sigma_w^i \varepsilon_{w,t}^i, \quad \forall i = \{1,2,3,4\} \end{aligned} \tag{4}$$

where $\Delta c_t \equiv \log(c_t/c_{t-1})$ is consumption growth. We assume the shocks $\varepsilon_{c,t}$ and $\left\{\varepsilon_{w,t}^i\right\}_{i=1}^4$ are orthogonal, *i.i.d.*, and distributed as standard normals. If we interpret $w_{i,t}$ as the

[5] A full IAM model, whose climate damage function is calibrated to match our estimates of the effects of rising temperatures on U.S. GDP growth is outside of the scope of this paper, and is left for future research.

average temperature in season i, then λ_i corresponds to the marginal impact of a one degree increase in temperature on economic growth. Similarly, β_i and ρ_w^i reflect the trend and the autocorrelation in the average temperature in season i.

Consider the case in which λ_i, β_i and ρ_w^i can be proportionally reduced by Δ^λ, Δ^β, and Δ^ρ. In this case, consumption growth evolves according to:

$$\begin{aligned}\Delta\widetilde{c}_t &= \mu_c + \sum_{i=1}^{4}\left(1-\Delta^\lambda\right)\lambda_i\widetilde{w}_{i,t} + \sigma_c\varepsilon_{c,t} \qquad (5)\\ \widetilde{w}_{i,t}^{\Delta} &= \mu_w^i + \left(1-\Delta^\rho\right)\rho_w^i\widetilde{w}_{i,t-1} + \left(1-\Delta^\beta\right)\beta_i\cdot t + \widetilde{\sigma}_w^i\varepsilon_{w,t}^i, \quad \forall i=\{1,2,3,4\}.\end{aligned}$$

We can think of a reduction in λ^i's by Δ^λ as reflecting *adaptation* to climate change, while reductions in ρ_w^i's by Δ^ρ and β^i's by Δ^β can be interpreted as *mitigation* of the dynamics of climate related variables.

It is apparent that an agent would prefer to live in an economy in which consumption dynamics evolve according to (5) as opposed to the baseline case in (4). We assess the welfare cost of climate change by computing the permanent reduction in the level of consumption, Δ_0, and the permanent reduction in the growth rate of consumption, Δ_1, that makes the agent indifferent between (a) living in an economy in which consumption growth evolves according to $\Delta\widetilde{c}_t$, and (b) living in an economy in which consumption evolves according to Δc_t.[6] The values of Δ_0 and Δ_1 are computed by equalizing the expected discounted utilities associated to the two consumption profiles:

$$E_t\left[U\left(\{C_j\}_{j=t}^{\infty}\right)\right] = E_t\left[U\left(\left\{\widetilde{C}_j\cdot\exp\left(\Delta_0+\Delta_1\cdot j\right)\right\}_{j=t}^{\infty}\right)\right], \ \forall t. \qquad (6)$$

[6] To see this, define the consumption profile on the right hand side of equation (6) as C_t^Δ. Then:

$$\log C_t^\Delta = \log\widetilde{C}_t + \Delta_0 + \Delta_1\cdot t,$$

From this equation, it can be seen that Δ_0 denotes the permanent change in the level consumption, and Δ_1 denotes the change in the growth rate of consumption (because $\Delta c_t^\Delta = \Delta\widetilde{c}_t + \Delta_1$). We need to take into account a reduction in both the level and the growth rate of consumption, because the assumed dynamics of consumption include a time trend.

Table 4: Welfare Analysis with Trend in Temperature (Whole Country)

Panel A: permanent reduction of the level (Δ_0)

		Δ^{β}					
		0%	20%	40%	60%	80%	100%
Δ^{λ}	0%	0.0	−0.1	−0.1	−0.2	−0.2	−0.3
	20%	−0.1	−0.1	−0.1	−0.2	−0.2	−0.3
	40%	−0.1	−0.1	−0.2	−0.2	−0.2	−0.3
	60%	−0.2	−0.2	−0.2	−0.2	−0.3	−0.3
	80%	−0.2	−0.2	−0.2	−0.3	−0.3	−0.3
	100%	−0.3	−0.3	−0.3	−0.3	−0.3	−0.3

Panel B: permanent growth rate reduction (Δ_1/μ_c)

		Δ^{β}					
		0%	20%	40%	60%	80%	100%
Δ^{λ}	0%	0.0	−2.8	−5.6	−8.4	−11.2	−14.0
	20%	−2.8	−5.0	−7.3	−9.5	−11.8	−14.0
	40%	−5.6	−7.3	−9.0	−10.6	−12.3	−14.0
	60%	−8.4	−9.5	−10.6	−11.8	−12.9	−14.0
	80%	−11.2	−11.8	−12.3	−12.9	−13.4	−14.0
	100%	−14.0	−14.0	−14.0	−14.0	−14.0	−14.0

Notes - Panel A reports the permanent reduction in the level of consumption that makes an agent indifferent between living in an economy with the estimates of β and λ reported in Tables 2 and 3 and an economy in which β and λ have been reduced by the percentage reported in the corresponding row and column. Panel B reports the permanent reduction in the growth rate of consumption that makes an agent indifferent between living in an economy with the estimates of β and λ reported in Tables 2 and 3 and an economy in which β and λ have been reduced by the percentage reported in the corresponding row and column. The analysis is performed assuming $\delta = 0.9879$ and $\gamma = 10$.

We document in the Appendix A that the amounts Δ_0 and Δ_1 are equal to:

$$\begin{aligned}\Delta_0 &= A - A^{\Delta} - \frac{\delta}{1-\delta}(D - D^{\Delta}) \\ \Delta_1 &= D - D^{\Delta}\end{aligned}$$

where

$$
\begin{aligned}
A &= \frac{\delta}{1-\delta}\left[\sum_i \frac{\lambda_i}{1-\delta\rho_w^i}\left(\mu_w^i + \frac{\beta_i}{1-\delta} + \frac{\lambda_i(\sigma_w^i)^2}{2\theta(1-\delta\rho_w^i)}\right)\right] \\
A^{\Delta} &= \frac{\delta}{1-\delta}\left[\sum_i \frac{\left(1-\Delta^{\lambda}\right)\lambda_i}{1-\delta\left(1-\Delta^{\rho}\right)\rho_w^i}\left(\mu_w^i + \frac{\left(1-\Delta^{\beta}\right)\beta_i}{1-\delta} + \frac{\left(1-\Delta^{\lambda}\right)\lambda_i(\sigma_w^i)^2}{2\theta(1-\delta\left(1-\Delta^{\rho}\right)\rho_w^i)}\right)\right] \\
D &= \frac{\delta}{1-\delta}\sum_i \frac{\beta_i\lambda_i}{1-\delta\rho_w^i} \\
D^{\Delta} &= \frac{\delta}{1-\delta}\sum_i \frac{\left(1-\Delta^{\beta}\right)\beta_i\left(1-\Delta^{\lambda}\right)\lambda_i}{1-\delta\rho_w^i}.
\end{aligned}
$$

We calibrate the preference parameters by following the long-run risks literature (see, for example, Bansal and Yaron (2004) and Colacito and Croce (2011)). Specifically, we set the coefficient of risk aversion, γ, to be equal to 10 and the subjective discount factor, δ, to 0.9879. Since the losses associated with climate change are small over short horizons, but large over long horizons, the results of our welfare analysis depend on how patient agents are. We discipline our choice of the subjective discount factor by targeting a risk-free interest rate of 1.5%.

The parameters in the system of equation (4) are set to mimic our estimates for the whole country analysis reported in the first row of Table 2. The parameters λ_1 and λ_2 are assumed to be equal to zero, while $\lambda_3 = -0.0015$ and $\lambda_4 = 0.0010$. This choice implies that Winter and Spring weather (whose associate coefficients are λ_1 and λ_2) do not affect economic growth, while Summer (λ_3) and Fall (λ_4) have opposite effects on growth. We set the time trend coefficients $\beta_3 = 0.03584$ and $\beta_4 = 0.0206$ to reflect that Summer temperature is expected to rise at a faster rate relative to Fall temperature. The autocorrelation coefficients ρ_i are set equal to zero to reflect our finding that the persistence of temperature is not statistically different from zero, once we control for the time trend. The intercepts of the seasonal weather processes, μ_w^i, are set equal to 0, since our estimates deal with mean-zero, de-seasonalized series. The conditional volatilities of

Winter and Spring temperatures (σ_w^1 and σ_w^2) are set equal to zero, while the coefficients for Summer and Fall are calibrated to the point estimates of our estimation ($\sigma_w^3 = 0.78$ and $\sigma_w^4 = 1.16$). We calibrate the average annual growth rate of the economy, μ_c, to 0.02.

Table 4 reports the results of our analysis for various combinations of values for Δ^λ and Δ^β. We abstract from performing the analysis with respect to Δ^ρ, since the corresponding parameters are set equal to zero in our benchmark case. The top panel documents that the permanent reduction of the *level* of consumption associated with any degree of mitigation of and adaptation to climate change is quite modest, typically varying between 0 and 0.3%. The bottom panel, instead, shows that an agent living in this economy would be willing to accept a permanent reduction in the *growth* rate of up to 14% to eliminate the negative impact of climate change on the economy.

Focusing on some of the intermediate cases, our results in Table 4 indicate that an agent would be willing to sacrifice 8.4% of the current growth rate of the economy in order to live in an economy in which the pace of temperature increase is reduced by 60%, while leaving the extent of impact of temperature on the economy unaltered. A reduction of the temperature's trend is likely to be accompanied by a reduced impact of climate related events on economic growth. Our results suggest that an additional 20% reduction of such effect would be equivalent to a permanent reduction of consumption growth of 9.5%. Taken together, these results indicate that there are substantial welfare losses associated with inaction to climate change.

5 Robustness and Additional Results

In this section we document the robustness of our results to different specifications of our main regression analysis. Table 5 reports the results obtained from using different

Table 5: Other weighting schemes

	Whole Year	**Winter**	**Spring**	**Summer**	**Fall**
GSP (varying)	0.010	0.008	-0.008	-0.148^{*}	0.105^{*}
	(0.119)	(0.051)	(0.067)	(0.077)	(0.058)
Area	0.054	0.018	0.012	-0.098	0.079
	(0.123)	(0.062)	(0.074)	(0.066)	(0.063)
Population	0.057	0.028	-0.025	-0.132^{*}	0.131^{**}
	(0.123)	(0.053)	(0.069)	(0.071)	(0.061)

Notes - In each regression, the dependent variable is the GSP growth rate of each state. The first row reports the results for the panel analysis conducted using the entire cross-section of US states. Each of the following rows refers to a different US region, according to the Federal classification. The first column refers to the analysis conducted using annual temperature averages ("Whole Year"). Each of the following columns refers to the analysis conducted by regressing jointly on the four seasonal averages. Winter is defined as the average of January, February, and March temperatures. Spring is defined as the average of April, May, and June temperatures. Summer is defined as the average of July, August, and September temperatures. Fall is defined as the average of October, November, and December temperatures. The numbers in parenthesis are standard errors. Standard errors are clustered by year. Each regression contains year and state fixed effects as well as the lagged GSP growth rate of the corresponding state. The sample period is 1957-2012.

weighting schemes for the cross-section of U.S. states. Specifically, we consider the cases of population, area, and time varying GSP weighting. The latter is used to take into account possible changes in the relative distribution of GSP across U.S. states. The results indicate that the signs of the estimated coefficients are generally aligned with our baseline case. The statistical significance of Summer and Fall temperatures is preserved in all cases, with the exception of area weighting.

In Tables 6 and 7 we include respectively average precipitation and temperature volatility in our main specification. We find that controlling for these two additional set of control variables does not alter our main set of conclusions regarding the role of Summer and Fall temperatures on U.S. economic growth.

6 Concluding Remarks

We have provided evidence of a statistically and economically significant relationship between rising temperatures and economic growth. Our analysis reveals the importance of studying this relationship using seasonal temperatures. Rising temperatures in the Summer depress growth, while rising temperatures in the Fall increase growth, with both effects particularly strong in the South. However, after taking into account the different trends in Summer and Fall temperatures, we conclude that the Summer effect dominates. In net, rising temperatures can depress U.S. GDP growth by up to a third, and are associated with significant welfare losses. Our analysis is informative for the calibration of the "climate damage function" in general equilibrium models, which are used to form prescriptions for optimal climate policies.

Table 6: Controlling for Precipitation

		Whole Year	**Winter**	**Spring**	**Summer**	**Fall**
USA	Temp.	0.004	0.003	0.008	-0.169^{**}	0.093^{*}
		(0.113)	(0.047)	(0.069)	(0.077)	(0.056)
	Prec.	−0.012	−0.050	−0.044	0.006	0.037
		(0.056)	(0.033)	(0.032)	(0.032)	(0.028)
North	Temp.	0.366	0.333^{*}	0.103	0.122	−0.256
		(0.348)	(0.189)	(0.302)	(0.272)	(0.263)
	Prec.	−0.063	−0.118	−0.098	0.061	0.161
		(0.175)	(0.106)	(0.083)	(0.091)	(0.116)
Midwest	Temp.	−0.232	0.009	−0.164	−0.014	−0.112
		(0.239)	(0.091)	(0.142)	(0.168)	(0.122)
	Prec.	−0.076	0.025	−0.047	−0.013	−0.015
		(0.117)	(0.064)	(0.044)	(0.059)	(0.086)
South	Temp.	0.323	−0.091	0.214	-0.402^{**}	0.561^{***}
		(0.325)	(0.164)	(0.188)	(0.162)	(0.195)
	Prec.	0.056	0.019	-0.083^{*}	0.017	0.058
		(0.125)	(0.055)	(0.049)	(0.061)	(0.056)
West	Temp.	−0.142	0.006	−0.124	0.045	−0.006
		(0.204)	(0.095)	(0.144)	(0.159)	(0.170)
	Prec.	0.133^{*}	0.020	0.092	0.080^{*}	0.003
		(0.072)	(0.041)	(0.082)	(0.045)	(0.033)

Notes - In each regression, the dependent variable is the GSP growth rate of each state. The first row reports the results for the panel analysis conducted using the entire cross-section of US states. Each of the following rows refers to a different US region, according to the Federal classification. The first column refers to the analysis conducted using annual temperature averages ("Whole Year"). Each of the following columns refers to the analysis conducted by regressing jointly on the four seasonal averages. Winter is defined as the average of January, February, and March temperatures. Spring is defined as the average of April, May, and June temperatures. Summer is defined as the average of July, August, and September temperatures. Fall is defined as the average of October, November, and December temperatures. The numbers in parenthesis are standard errors. Standard errors are clustered by year. Each regression contains year and state fixed effects as well as the lagged GSP growth rate of the corresponding state. The sample period is 1957-2012.

Table 7: Controlling for Temperature Volatility

		Whole Year	**Winter**	**Spring**	**Summer**	**Fall**
Whole country	Mean	0.004	-0.009	-0.013	-0.138^{*}	0.106^{*}
		(0.111)	(0.050)	(0.062)	(0.071)	(0.055)
	Vol	-0.002	0.002	-0.001	0.002	-0.000
		(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
North	Mean	0.324	0.363^{**}	0.113	0.189	-0.201
		(0.340)	(0.176)	(0.296)	(0.251)	(0.214)
	Vol	-0.004	-0.004	0.001	-0.003	-0.003
		(0.006)	(0.005)	(0.004)	(0.004)	(0.003)
Midwest	Mean	-0.212	0.009	-0.177	0.047	-0.117
		(0.236)	(0.085)	(0.149)	(0.154)	(0.121)
	Vol	-0.001	0.004	0.002	0.003	-0.001
		(0.003)	(0.005)	(0.003)	(0.002)	(0.002)
South	Mean	0.273	-0.121	0.135	-0.280^{*}	0.580^{***}
		(0.299)	(0.173)	(0.154)	(0.154)	(0.208)
	Vol	-0.005	0.002	0.006^{*}	0.003	-0.004
		(0.005)	(0.003)	(0.003)	(0.005)	(0.003)
West	Mean	-0.146	-0.004	-0.148	0.040	-0.031
		(0.204)	(0.099)	(0.144)	(0.155)	(0.181)
	Vol	-0.000	-0.001	-0.000	0.002	-0.001
		(0.003)	(0.002)	(0.002)	(0.003)	(0.002)

Notes - In each regression, the dependent variable is the GSP growth rate of each state. The first row reports the results for the panel analysis conducted using the entire cross-section of US states. Each of the following rows refers to a different US region, according to the Federal classification. The first column refers to the analysis conducted using annual temperature averages ("Whole Year"). Each of the following columns refers to the analysis conducted by regressing jointly on the four seasonal averages. Winter is defined as the average of January, February, and March temperatures. Spring is defined as the average of April, May, and June temperatures. Summer is defined as the average of July, August, and September temperatures. Fall is defined as the average of October, November, and December temperatures. The numbers in parenthesis are standard errors. Standard errors are clustered by year. Each regression contains year and state fixed effects as well as the lagged GSP growth rate of the corresponding state. The sample period is 1957-2012.

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Appendix

A Computation of Welfare Equivalents

The economy is populated by a representative agent with recursive preferences:

$$U_t = (1-\delta)\log(C_t) + \delta\theta \log E_t \left[\exp\left\{ \frac{U_{t+1}}{\theta} \right\} \right]$$

where $\theta = 1/(1-\gamma)$, γ denotes risk aversion, and δ is the subjective discount factor. Consumption growth evolves according to the following law of motion:

$$\Delta c_t = \mu_c + \sum_{i=1}^{4} \lambda_i w_{i,t} + \sigma_c \varepsilon_{c,t}$$

where

$$w_{i,t} = \mu_w^i + \rho_w^i w_{i,t-1} + \beta_i \cdot t + \sigma_w^i \varepsilon_{w,t}^i, \quad \forall i = \{1,2,3,4\}$$

and the shocks $\varepsilon_{c,t}$ and $\left\{\varepsilon_{w,t}^i\right\}_{i=1}^4$ are orthogonal and $i.i.d.$ distributed as standard normals. Denote the logarithm of the utility-consumption ratio as V_t:

$$\begin{aligned} V_t &= U_t - \log(C_t) \\ &= \delta\theta \log E_t \exp\left\{ \frac{V_{t+1} + \Delta c_{t+1}}{\theta} \right\}. \end{aligned}$$

Guess that the solution for V_t is linear in $\{w_{i,t}\}_{i=1}^4$ and t

$$V_t = A + \sum_i B_i w_{i,t} + D \cdot t,$$

and find the coefficients A, $\{B_i\}_{i=1}^4$, and D that verify the proposed solution:

$$\begin{aligned}
V_t &= \delta\theta \log E_t \exp\left\{\frac{1}{\theta}\left[A + D\cdot t + D + \sum_i (B_i+\lambda_i)\left(\mu_w^i + \rho_w^i w_{i,t} + \beta_i \cdot t + \sigma_w^i \varepsilon_{w,t+1}^i\right) + \mu_c + \sigma_c \varepsilon_{c,t+1}\right]\right\} \\
&= \delta\left[A + \sum_i (B_i+\lambda_i)\mu_w^i + \sum_i \beta_i (B_i+\lambda_i) + D + \mu_c\right] + \frac{\delta}{2\theta}\left[\sigma_c^2 + \sum_i (B_i+\lambda_i)^2 (\sigma_w^i)^2\right] \\
&\quad + \delta \sum_i (B_i+\lambda_i)\rho_w^i w_{i,t} + \delta\left[\sum_i \beta_i (B_i+\lambda_i) + D\right]\cdot t
\end{aligned}$$

Matching the coefficients, we get

$$\begin{aligned}
A &= \frac{\delta}{1-\delta}\left[\sum_i (B_i+\lambda_i)\mu_w^i + \sum_i \beta_i (B_i+\lambda_i) + D + \mu_c + \frac{\sigma_c^2}{2\theta} + \sum_i \frac{(B_i+\lambda_i)^2(\sigma_w^i)^2}{2\theta}\right] \\
B_i &= \frac{\delta}{1-\delta\rho_w^i}\lambda_i\rho_w^i, \quad \forall i = \{1,2,3,4\} \\
D &= \frac{\delta}{1-\delta}\sum_i \beta_i (B_i+\lambda_i).
\end{aligned}$$

Note that

$$B_i + \lambda_i = \frac{\lambda_i}{1-\delta\rho_w^i}, \qquad \sum_i \frac{\lambda_i}{1-\delta\rho_w^i}\beta_i + D = \frac{1}{1-\delta}\sum_i \frac{\lambda_i\beta_i}{1-\delta\rho_w^i}$$

which allows to rewrite A and D as

$$\begin{aligned}
A &= \frac{\delta}{1-\delta}\left[\sum_i \frac{\lambda_i}{1-\delta\rho_w^i}\left(\mu_w^i + \frac{\beta_i}{1-\delta} + \frac{\lambda_i(\sigma_w^i)^2}{2\theta(1-\delta\rho_w^i)}\right) + \frac{\sigma_c^2}{2\theta} + \mu_c\right] \\
D &= \frac{\delta}{1-\delta}\sum_i \frac{\beta_i\lambda_i}{1-\delta\rho_w^i}.
\end{aligned}$$

Now consider an economy in which consumption growth evolves according to

$$\begin{aligned}
\Delta\widetilde{c}_t &= \mu_c + \sum_{i=1}^4 \widetilde{\lambda}_i w_{i,t} + \sigma_c\varepsilon_{c,t} \\
w_{i,t} &= \mu_w^i + \widetilde{\rho}_w^i w_{i,t-1} + \widetilde{\beta}_i \cdot t + \sigma_w^i \varepsilon_{w,t}^i, \quad \forall i = \{1,2,3,4\},
\end{aligned}$$

where $\widetilde{\lambda}_i = \lambda_i \left(1 - \Delta^\lambda\right)$, and $\widetilde{\rho}_w^i = \rho_w^i \left(1 - \Delta^\rho\right)$.

We shall compute the values of Δ_0 and Δ_1 which make the agent indifferent between living in an economy in which consumption growth evolves according to $\Delta \widetilde{c}_t$ and and economy in which consumption evolves according to Δc_t. Recall equation 6:

$$E_t\left[U\left(\{C_j\}_{j=t}^{\infty}\right)\right] = E_t\left[U\left(\left\{\widetilde{C}_j \cdot \exp\left(\Delta_0 + \Delta_1 \cdot j\right)\right\}_{j=t}^{\infty}\right)\right].$$

Define the consumption profile on the right hand side as

$$\log C_t^{\Delta} = \log \widetilde{C}_t + \Delta_0 + \Delta_1 \cdot t,$$

and note that Δ_0 denotes the permanent change in the level consumption that makes the agent indifferent, and Δ_1 denotes the change in the growth rate that the agent is willing to accept:

$$\Delta c_t^{\Delta} = \Delta \widetilde{c}_t + \Delta_1.$$

Guess that the solution of the log-utility-consumption ratio when the dynamics of consumption are described by $\log C_t^{\Delta}$ is of the form

$$\widetilde{V}_t = \left(\widetilde{A} + \Delta_0 + \frac{\delta}{1-\delta}\Delta_1\right) + \sum_i \widetilde{B}_i w_{i,t} + \left(\widetilde{D} + \Delta_1\right) t,$$

and verify that

$$\begin{aligned}
\widetilde{A} &= \frac{\delta}{1-\delta}\left[\sum_i \frac{\widetilde{\lambda}_i}{1-\delta\widetilde{\rho}_w^i}\left(\widetilde{\mu}_w^i + \frac{\widetilde{\beta}_i}{1-\delta} + \frac{\widetilde{\lambda}_i(\widetilde{\sigma}_w^i)^2}{2\theta(1-\delta\widetilde{\rho}_w^i)}\right) + \frac{\sigma_c^2}{2\theta} + \mu_c\right] \\
B_i &= \frac{\delta}{1-\delta\widetilde{\rho}_w^i}\widetilde{\lambda}_i\widetilde{\rho}_w^i, \quad \forall i = \{1,2,3,4\} \\
D &= \frac{\delta}{1-\delta}\sum_i \frac{\widetilde{\beta}_i\widetilde{\lambda}_i}{1-\delta\widetilde{\rho}_w^i}.
\end{aligned}$$

This implies that

$$\begin{aligned}\Delta_0 &= A - \widetilde{A} - \frac{\delta}{1-\delta}(D - \widetilde{D}) \\ \Delta_1 &= D - \widetilde{D}.\end{aligned}$$

B Properties of autoregressive process

Consider the process

$$w_t = \mu_w + \rho_w w_{t-1} + \beta \cdot t \sigma_w \varepsilon_{w,t},$$

then it follows that

$$E_t\left[w_{t+j}\right] = \beta \sum_{i=1}^{j} \rho_w^{(j-i)} \cdot i + \mu_w \sum_{i=0}^{j-1} \rho_w^i + \rho_w^j \cdot w_t + \beta \left(\sum_{i=0}^{j-1} \rho_w^i\right) \cdot t.$$

Assume $\mu_w = 0$, $t = 0$, and $w_0 = 0$. Then:

$$\begin{aligned}E_0\left[w_j\right] = \beta \sum_{i=1}^{j} \rho_w^{(j-i)} \cdot i \leq \beta \cdot j &\iff \rho_w \leq 0 \\ E_0\left[w_j\right] = \beta \sum_{i=1}^{j} \rho_w^{(j-i)} \cdot i \geq \beta \cdot j &\iff \rho_w \geq 0,\end{aligned}$$

where the equality holds for the case in which $\rho_w = 0$.

C Definitions of US regions

We follow the US Census Bureau and identify 4 regions:

1. North: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Ver-

mont, New Jersey, New York, and Pennsylvania;

2. Midwest: Illinois, Indiana, Michigan, Ohio, Wisconsin, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota;

3. South: Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, Washington D.C., West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, and Texas;

4. West: Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming, Alaska, California, Hawaii, Oregon, and Washington.