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Reference Details

2205	Cambridge Working Papers in Economics
2022/03	Janeway Institute Working Paper Series
Published	21 January 2022
Revised	11 October 2022
Key Words	Climate change, economic growth, adaptation, United States
JEL-codes	C33, O40, O44, O51, Q51, Q54
Websites	www.econ.cam.ac.uk/cwpe
	www.janeway.econ.cam.ac.uk/working-papers

Climate Change and Economic Activity: Evidence from U.S. States*

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October 11, 2022

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*We are grateful to Tiago Cavalcanti, Francis X. Diebold, Christopher Hajzler, Stephane Hallegatte, Zeina Hasna, John Hassler, Matthew E. Kahn, Per Krusell, Miguel Molico, Peter Phillips, Margit Reischer, Ron Smith, Richard Tol, Carolyn A. Wilkins and seminar participants at the International Monetary Fund (IMF), Bank of Lithuania, Bank of Canada, EPRG, Cambridge Judge Business School, the ERF 24th Annual Conference, the 2018 MIT CEEPR Research Workshop, the 2019 Keynes Fund Research Day, National Institute of Economic and Social Research, Copenhagen Business School, Bank of England, Federal Reserve Bank of San Francisco, London School of Economics, European Central Bank, and RES 2021 Annual Conference for helpful comments and suggestions. We would also like to thank the editor in charge of our paper and two anonymous referees for helpful suggestions. We gratefully acknowledge financial support from the Keynes Fund. The views expressed in this paper are those of the authors and do not necessarily represent those of the IMF or its policy.

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1 Introduction

Kahn et al. (2021a) show that changes in the distribution of weather patterns (i.e., climate change[1]) are not only affecting low-income countries and those in hot climates, but also advanced economies and those in cold climates (albeit to different degrees across climates and income levels).[2] Using estimates from a panel of 174 countries over the past half century, they show that if temperature rises (falls) above (below) its historical norm persistently by 0.01°C annually, income growth will be lower by 0.0543 percentage points per year. They also conduct a range of counterfactual studies and show that in the absence of global mitigation policies, per-capita GDP of the United States would be 10–17 percent lower by 2100.[3] Do these cross-country results hold in a within-country context (e.g., in the United States as an advanced economy with a diverse climate and partial resilience-building success against climate change)? How large are the effects of climate change on state-level economic activity in the U.S.? Are there level or growth effects? Are the effects asymmetrical? What are the channels of impact and which sectors of the U.S. economy are affected the most? What is the role of adaptation? Answers to these questions can inform the development of a long-term mitigation and adaptation strategy for the United States (and by extension climate policies in other advanced economies).

While cross-country studies are informative, they also have drawbacks. Averaging temperature and precipitation data at the country level leads to a loss of information, especially in geographically diverse countries such as the United States. Using within-country data for the U.S. and a novel econometric strategy, which links deviations of temperature and precipitation (weather) from their long-term moving-average historical norms (climate) to various state-specific economic performance indicators at the aggregate and sectoral levels, we investigate the size of the long-term macroeconomic effects of weather patterns transformed by climate change across 48 states over the period 1963–2016. The within-country geographic heterogeneity of the U.S. enables one to compare whether economic activity in 'hot' or 'wet' states responds to a temperature increase in the same way as economic activity does in 'cold' or 'dry' states. The richness of the U.S. data allows for a more disaggregated study of the climate change–growth relationship and enables one to test whether the country

[1] Weather refers to atmospheric conditions over short periods of time (e.g., temperature and precipitation). Climate refers to the long-term average and variability of weather. Climate change is a shift "in the state of the climate that can be identified (e.g., via statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer" (IPCC (2014)).

[2] This finding is in contrast to most papers in the literature—arguing that climate change has a negligible impact on economic activity of advanced countries or even beneficial effects in cold climates; see, for instance, Burke et al. (2015), Dell et al. (2012), and Kalkuhl and Wenz 2020. An exception is a recent paper by Burke and Tanutama (2019).

[3] The upper bound of these losses allow for temperature increases to affect the variability of temperature shocks commensurately. Accounting for transition risks (in addition to physical risks) would lead to larger losses (especially for advanced economies, see, for instance, Klusak et al. 2021 and Agarwala et al. 2021).

at the aggregate level, parts of the country, or particular sectors of the economy have been affected more by climate change. It also allows one to investigate the channels of impact: labour productivity, employment, and output growth in various sectors of the economy.[4]

Additionally, we contribute to the literature along the following dimensions. Firstly, we differentiate between level and growth effects and estimate the long-term macroeconomic impact of persistent increases (decreases) in temperature and precipitation. Secondly, we use the half-panel Jackknife FE (HPJ-FE) estimator proposed in Chudik et al. (2018) to deal with the possible bias and size distortion of the commonly-used FE estimator. Thirdly, we depart from the literature by focusing on changes in the distribution of weather patterns (not only averages of temperature and precipitation but also their variability) and by introducing an implicit model of adaptation. Fourthly, we allow for state-specific and time-varying climate thresholds—a subtle form of nonlinearity[5]—and also test for asymmetric weather effects. Finally, we avoid the econometric pitfalls associated with the use of trended variables, such as temperature, in output growth equations (see Kahn et al. 2021b for details).

Our within-country results provide evidence for the damage that climate change causes in the U.S. using various economic indicators at the state level: growth rates of Gross State Product (GSP), GSP per capita, labour productivity, and employment as well as output in different sectors (e.g., agriculture, manufacturing, services, retail and wholesale trade). We show that if temperature increases by 0.01°C annually above its historical norm across U.S. states persistently, average per-capita real GSP growth will be lower by 0.0273 percentage points per year—a number that is smaller than those obtained in cross-country regressions of Kahn et al. (2021a). We show that while weather shocks have level effects (or temporary growth impacts), climate change—by shifting the long-term average and variability of weather— could impact the U.S. economy's ability to grow in the long-term [6] We also find that the impact of climate change on sectoral output growth is broad based—each of the 10 sectors considered is affected by at least one of the four climate variables. Moreover, in contrast to most cross-country results including Kahn et al. (2021a), the within U.S. estimates tend to be asymmetrical with respect to deviations of climate variables from their historical norms (in the positive and negative directions). Finally, while we acknowledge some

[4] There are likely economic spillovers across states in the form of migration by households and profit shifting by firms to arbitrage differences in cross-state regulatory regimes (tax systems and environmental standards) as well as varying degrees of climate risks, which are important for a model's dynamics. See, for instance, Aquaro et al. (2021) for an example of how heterogeneous spillover effects across regions can be investigated. However, this paper abstracts from such spillovers given its focus on the long-term (equilibrium) macroeconomic effects of climate change.

[5] Non-linearity arises because growth is only affected when temperature (or precipitation) goes above or below a time-varying and state-specific historical threshold (i.e., the norm). It is due to this feature that future growth is affected not only by warming (or cooling if that was the case) but also by its variability.

[6] Our estimates would result in level effects (and no long-term growth impacts) if temperature increases were to stabilize in the future. Burke et al. (2015) find that a shift to a permanently higher (but constant) temperature level would have permanent and compound growth effects. Kalkuhl and Wenz (2020) find that the same shock leads to a permanent reduction in the level of GDP (but not in long-term growth).

resilience-building efforts in different states, the evidence seems to suggest that adaptation has not entirely offset the negative effects of climate change at the country level.

Our paper is related to a growing literature that investigates the macroeconomic effects of subnational temperature and precipitation such as Hsiang et al. (2017), Colacito et al. (2019), Holtermann (2020), Burke and Tanutama (2019), Damania et al. (2020), Kalkuhl and Wenz 2020, Kotz et al. (2021), and Kotz et al. (2022). Previous subnational studies often relied on fixed effects panel regressions to assess the [non-linear] impact of weather shocks on economic growth – hence short-term effects – whereas our method captures the long-term growth effects of persistent temperature/precipitation deviations from their moving-average historical norms. Our approach also avoids the econometric pitfalls associated with the use of trended variables, such as temperature or its square, in output growth equations. Some other studies combined panel insights with cross-sectional analyses – using subnational data – or long-differencing to assess the long-term macroeconomic effects of climate change and to explore the role of adaptation (see Burke and Tanutama (2019) and Kalkuhl and Wenz 2020 for a couple of examples). There are two main challenges with these methods: 1) confounding variables that are correlated with both climate and adaptation; and 2) specification choices that matter greatly in uncovering level and/or growth impacts. We account for adaptation in two ways: (1) by varying the speed with which historical norms are formed; and (2) by testing how the elasticity of per capita GSP to climate variables evolves over time. We show that long-term growth impact only arises if temperature and/or precipitation shocks persist for a long period of time, and find that adaptation can halve these adverse impacts. In other words, if historical norms are formed faster (i.e., adaptation is quicker), the impact of climate change on growth would be smaller. This result is obtained without the need for long-differencing as is typically done. We concur with Damania et al. (2020) in arguing that the spatial aggregation of weather data at the country level can explain why precipitation is found to have no robust and statistically significant impact on aggregate GDP growth in cross-country studies. This result is obtained even without taking into account the precipitation variability (i.e., the distribution of daily rainfall) as in Kotz et al. (2021), and Kotz et al. (2022). We also study the asymmetric growth effects of weather shocks without the need to rely on degree days or binned approaches. The advantage of our approach is in its use of time-varying thresholds and three adaptation speeds rather than relying on constant thresholds or percentiles of weather distribution that are required to measure degree days and bin the observations.

The remainder of this paper is organized as follows. Section 2 presents the empirical results and Section 3 concludes. Appendix A lists the data sources and their compilation.

2 Long-Run Impact of Climate Change on U.S. Economic Growth

We first examine whether temperature across the 48 U.S. states has been increasing between 1963 and 2016. To this end, allowing for the significant heterogeneity that exists across states with respect to changes in temperature over time, we estimate state-specific regressions

$$T_{it} = a_{\mathcal{T}i} + b_{\mathcal{T}i}t + v_{\mathcal{T}i,t}, \text{ for } i = 1, 2, ..., N = 48, \tag{1}$$

where T_{it} denotes the weighted average temperature of state i at year t. The per annum average increase in land temperature for state i is given by $b_{\mathcal{T}i}$, with the corresponding country measure defined by $b_{\mathcal{T}} = N^{-1}\Sigma_{i=1}^{N} b_{\mathcal{T}i}$. Our results suggest that, on average, temperature in the 48 U.S. states has risen by 0.026 degrees Celsius (°C) per year over 1963–2016 (i.e., $\hat{b}_{\mathcal{T}} = 0.0260$ (0.0007); with the standard error in brackets), with this trend estimate being statistically significant at the 1% level. All states experienced statistically significant increases in temperature over time (see Table 1). But, the 48 U.S. states as a whole underwent more warming than the world on average. The U.S. average per annum temperature increase of 0.026 was appreciably higher than the world average rise of 0.018 per annum, which is close to that for Oklahoma, the state which saw the lowest average increase in temperature.

Table 1: Individual U.S. State Estimates of the Average Yearly Rise in Temperature Over the Period 1963–2016

State	$\hat{b}_{\tau,i}$	State	$\hat{b}_{\tau,i}$	State	$\hat{b}_{\tau,i}$
Oklahoma	$0.0171^{\ddagger}$	Indiana	$0.0236^{\ddagger}$	Maine	$0.0288^{\ddagger}$
Missouri	$0.0179^{\ddagger}$	Idaho	$0.0245^{\ddagger}$	Utah	$0.0291^{\ddagger}$
Arkansas	$0.0181^{\ddagger}$	Texas	$0.0245^{\ddagger}$	Montana	$0.0292^{\ddagger}$
Kansas	$0.0186^{\ddagger}$	Kentucky	$0.0250^{\ddagger}$	Maryland	$0.0299^{\ddagger}$
Washington	$0.0186^{\ddagger}$	South Carolina	$0.0250^{\ddagger}$	New Hampshire	$0.0299^{\ddagger}$
Iowa	$0.0198^{\ddagger}$	North Carolina	$0.0257^{\ddagger}$	New Mexico	$0.0300^{\ddagger}$
Oregon	$0.0198^{\ddagger}$	North Dakota	$0.0263^{\ddagger}$	Wisconsin	$0.0307^{\ddagger}$
Mississippi	$0.0205^{\ddagger}$	Ohio	$0.0263^{\ddagger}$	New York	$0.0308^{\ddagger}$
Louisiana	$0.0210^{\ddagger}$	Virginia	$0.0266^{\ddagger}$	Massachusetts	$0.0311^{\ddagger}$
Alabama	$0.0212^{\ddagger}$	West Virginia	$0.0268^{\ddagger}$	Connecticut	$0.0316^{\ddagger}$
Nebraska	$0.0222^{\ddagger}$	California	$0.0270^{\ddagger}$	Arizona	$0.0318^{\ddagger}$
Illinois	$0.0223^{\ddagger}$	Colorado	$0.0271^{\ddagger}$	Vermont	$0.0318^{\ddagger}$
Florida	$0.0228^{\ddagger}$	Nevada	$0.0273^{\ddagger}$	Minnesota	$0.0320^{\ddagger}$
Georgia	$0.0228^{\ddagger}$	Wyoming	$0.0279^{\ddagger}$	Rhode Island	$0.0320^{\ddagger}$
South Dakota	$0.0234^{\ddagger}$	Pennsylvania	$0.0280^{\ddagger}$	New Jersey	$0.0343^{\ddagger}$
Tennessee	$0.0234^{\ddagger}$	Michigan	$0.0285^{\ddagger}$	Delaware	$0.0355^{\ddagger}$

Notes: $\widehat{b}_{\mathcal{T}i}$ are the individual state-level estimates based on $T_{it} = a_{\mathcal{T}i} + b_{\mathcal{T}i}t + v_{\mathcal{T},it}$, where T_{it} denotes the average temperature (°C) in state i in year t. ‡ indicates statistical significance at the 1% level.

We examine the long-run impact of climate change on aggregate state-level economic activity as well as states' sectoral outputs. Guided by the theoretical growth model with weather and climate variables in Kahn et al. (2021a), we estimate the following panel ARDL model using the half-panel Jackknife FE (HPJ-FE) estimator of Chudik et al. (2018):

$$\Delta y_{i,t} = a_i + \sum_{l=1}^{p} \varphi_\ell \Delta y_{i,t-l} + \sum_{l=0}^{p} \boldsymbol{\beta}_l' \Delta \tilde{\mathbf{x}}_{i,t-l} + \epsilon_{i,t}, \tag{2}$$

where y_{it} is the log of real GSP of state i in year t or real GSP per capita, $\tilde{\mathbf{x}}_{it}(m) = [\tilde{T}_{it}(m)^+, \tilde{T}_{it}(m)^-, \tilde{P}_{it}(m)^+, \tilde{P}_{it}(m)^-]'$, $\tilde{T}_{it}(m) = \left[T_{it} - T^*_{i,t-1}(m)\right]$ and $\tilde{P}_{it}(m) = \left[P_{it} - P^*_{i,t-1}(m)\right]$ are measures of temperature and precipitation relative to their historical norms, T_{it} and P_{it} are the annual average temperature and precipitation of state i in year t, respectively, and $T^*_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} T_{i,t-\ell}$ and $P^*_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} P_{i,t-\ell}$ are the time-varying historical norms of temperature and precipitation of state i over the preceding m years in each t. Climate norms are typically computed as 30-year moving averages (Arguez et al. 2012 and Vose et al. 2014), but to check the robustness of our results, we also consider historical norms with $m = 20$ and 40.[7] With $\tilde{T}_{it}(m)$ and $\tilde{P}_{it}(m)$ separated into positive and negative values, $z^+ = zI(z \geq 0)$ and $z^- = -zI(z < 0)$, we account for potential asymmetrical effects of climate change on long-term economic growth around the time-varying threshold. The (average) long-run effects, θ_i, are calculated from the OLS estimates of the short-run coefficients in equation (2): $\boldsymbol{\theta} = \phi^{-1}\sum_{\ell=0}^{p} \boldsymbol{\beta}_\ell$, where $\phi = 1 - \sum_{\ell=1}^{p} \varphi_\ell$.

Since temperature is trended across the sample of 48 U.S. states, its inclusion in the regression will introduce a linear trend in per capita output growth which is not supported by the data, and can lead to biased estimates. This is the reason for specifying ARDL growth regressions in deviations form (i.e., temperature and precipitation relative to their long-term moving average historical norms), rather than in levels and/or squares of climate variables.[8] Other important econometric considerations behind the use of ARDL regressions are set out in Pesaran and Smith (1995), Pesaran (1997), and Pesaran and Shin (1999) who show that the traditional ARDL approach can be used for long-run analysis; it is valid regardless of whether the underlying variables are $I(0)$ or $I(1)$; and it is robust to omitted variables and bi-directional feedback effects between economic growth and its determinants. These features of the panel ARDL approach are clearly appealing in our empirical application. For validity of this technique, however, the dynamic specification of the model needs to be augmented with a sufficient number of lags so that regressors become weakly exogenous.[9] Since we are interested in studying the growth effects of climate change (a long-term phenomenon), the lag order should be long enough, and as such we set $p = 4$ for all the variables/states.

[7] $m = 30$ corresponds to the official World Meteorological Organization definition of climate (i.e., norm).

[8] For a detailed discussion see Kahn et al. (2021b), where it is shown that including T_{it} and T_{it}^2 in growth regressions will introduce trends in Δy_{it}.

[9] See Chudik et al. (2013), Chudik et al. (2016), and Chudik et al. (2017) for details.

Using the same lag order across all the variables and states avoids data mining that could accompany the use of state and variable specific lag order selection procedures such as Akaike or Schwarz criteria. Note also that our primary focus here is on the long-run estimates rather than the specific dynamics that might be relevant for a particular U.S. state.

Table 2 reports the long-run estimates of weather shocks on growth rates of real GSP and real GSP per capita for 48 U.S. states over the period 1963–2016. We construct the climate variables with 20, 30, and 40-year moving-average historical norms, but consider the estimates based on the 30-year moving average as our central estimates. We observe that the estimated long-run coefficients $\widehat{\theta}_{\Delta \tilde{T}_{it}(m)^-}$, $\widehat{\theta}_{\Delta \tilde{P}_{it}(m)^+}$, and $\widehat{\theta}_{\Delta \tilde{P}_{it}(m)^-}$ are negative and statistically significant in all cases except for one. Climate change affects the U.S. ecosystem not only through increases in average temperatures, but also through changes in the extremes— more intense droughts; heavier snow and rainfall; as well as extreme cold. However, $\widehat{\theta}_{\Delta \tilde{T}_{it}(m)^+}$ is not statistically significant in three out of six specifications. While this finding might be explained by the improving resilience of the U.S. economy to increasing temperature brought about by climate change,[10] the evidence for excessive temperature not affecting the U.S. economy is not conclusive as we will explain below.

While in their cross-country analysis, Kahn et al. (2021a) did not find any statistically significant impact from deviations of precipitation from its historical norms on real output growth, in our within-country study of the United States, we find that deviations of precipitation above and below its historical norm affect various measures of state-level economic activity and these estimates are statistically significant.[11] This is because averaging precipitation at the country level leads to a loss of information, especially in geographically diverse countries with varied precipitation patterns. While the national average precipitation may be close to its historical norm, there is significant heterogeneity across states with some experiencing plenty of rain and snow and others, like California, suffering from drought for many years. By conducting a within-country study, we account for the variation of precipitation across the states, which is important and does indeed affect economic activity (Table 2).

Considering the richness of our U.S. database, which includes data on state-level employment from 1976, we can also examine the long-run impact of climate change on labour productivity and employment growth directly, in addition to the analysis above. We, therefore, re-estimate the model for an extended set of outcome variables, with y_{it} being the natural logarithm of: (i) real GSP, (ii) real GSP per capita, (iii) real GSP per employed (measuring labour productivity), or (iv) employment, but over the period 1976 to 2016. These results are reported in Table 3. Across all specifications, the estimated long-run coefficients $\widehat{\theta}_{\Delta \tilde{T}_{it}(m)^-}$ and $\widehat{\theta}_{\Delta \tilde{P}_{it}(m)^-}$ are negative and statistically significant at the 1% level

[10] For example, currently about 90 percent of American households have air conditioning.

[11] The importance of focusing on deviations of climate variables from their historical norms is also highlighted by recent research which demonstrate that different regions of the United States have acclimated themselves to their own temperature niche; see, for instance, Heutel et al. (2016).

Table 2: Long-Run Effects of Climate Change on the Growth Rate of Major Economic Indicators for the United States, 1963–2016

Historical Norm:	**20 Year MA**		**30 Year MA**		**40 Year MA**	
	Real GSP	Real GSP per Capita	Real GSP	Real GSP per Capita	Real GSP	Real GSP per Capita
$\widehat{\theta}_{\Delta \tilde{T}_{it}(m)^+}$	-0.0245***	-0.0143**	-0.0152**	-0.0073	-0.0074	-0.0014
	(0.0081)	(0.0064)	(0.0077)	(0.0061)	(0.0073)	(0.0058)
$\widehat{\theta}_{\Delta \tilde{T}_{it}(m)^-}$	-0.0672***	-0.0444***	-0.0697***	-0.0454***	-0.0485***	-0.0275**
	(0.0162)	(0.0124)	(0.0166)	(0.0124)	(0.0169)	(0.0127)
$\widehat{\theta}_{\Delta \tilde{P}_{it}(m)^+}$	-0.1091***	-0.0906***	-0.1370***	-0.1134***	-0.1339***	-0.1099***
	(0.0411)	(0.0328)	(0.0411)	(0.0327)	(0.0412)	(0.0328)
$\widehat{\theta}_{\Delta \tilde{P}_{it}(m)^-}$	-0.1172**	-0.0651	-0.1477***	-0.0928**	-0.1552***	-0.0990**
	(0.0509)	(0.0411)	(0.0529)	(0.0424)	(0.0558)	(0.0449)
$\widehat{\phi}$	0.7263***	0.8896***	0.7210***	0.8875***	0.7109***	0.8734***
	(0.0491)	(0.0530)	(0.0494)	(0.0532)	(0.0495)	(0.0533)
No. of states (N)	48	48	48	48	48	48
T	48	48	48	48	48	48
$N \times T$	2304	2304	2304	2304	2304	2304

Notes: The HPJ-FE estimates are based on the following specification $\Delta y_{i,t} = a_i + \sum_{l=1}^{p} \varphi_\ell \Delta y_{i,t-l} + \sum_{l=0}^{p} \boldsymbol{\beta}_l' \Delta \tilde{\mathbf{x}}_{i,t-l} + \epsilon_{i,t}$, where y_{it} is the log of real GSP of state i in year t or real GSP per capita, $\tilde{\mathbf{x}}_{it}(m) = [\tilde{T}_{it}(m)^+, \tilde{T}_{it}(m)^-, \tilde{P}_{it}(m)^+, \tilde{P}_{it}(m)^-]'$, $z^+ = zI(z \geq 0)$, $z^- = -zI(z < 0)$, $\tilde{T}_{it}(m) = \left[T_{it} - T^*_{i,t-1}(m)\right]$ and $\tilde{P}_{it}(m) = \left[P_{it} - P^*_{i,t-1}(m)\right]$ are measures of temperature and precipitation relative to their historical norms, T_{it} and P_{it} are the annual average temperature (in Celsius) and precipitation (in metres) of state i in year t, respectively, and $T^*_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} T_{i,t-\ell}$ and $P^*_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} P_{i,t-\ell}$ are the time-varying historical norms of temperature and precipitation of state i over the preceding m years in each t. The long-run effects, θ_i, are calculated from the OLS estimates of the short-run coefficients in equation (2): $\boldsymbol{\theta} = \phi^{-1}\sum_{\ell=0}^{p} \boldsymbol{\beta}_\ell$, where $\phi = 1 - \sum_{\ell=1}^{p} \varphi_\ell$. The lag order, p, is set to 4. Standard errors in parentheses are estimated by the estimator proposed in Proposition 4 of Chudik et al. (2018). Asterisks indicate statistical significance at 1% (***), 5% (**), and 10% (*) levels.

for almost all outcome variables. Therefore, when temperature and precipitation fall below their historical norms, state-level economic activity suffers, employment declines, and labour productivity growth falls (for $\widehat{\theta}_{\Delta\tilde{T}_{it}(m)^-}$).

While in Table 2, the climate variable $\tilde{T}_{it}(m)^+$, did not have a statistically significant impact on state-level output growth in three out of six specifications (over the period 1963–2016), the results change substantially when we consider the 1976–2016 sub-sample in Table 3. Consistent with cross-country estimates, $\widehat{\theta}_{\Delta\tilde{T}_{it}(m)^+}$ is negative and statistically significant for various specifications and dependent variables: real GSP, real GSP per capita, real GSP per employed, and employment. Focusing on our preferred specification (with $m = 30$ and pre-capita real GSP), we estimate that if temperature increases (decreases) by 0.01°C annually above its historical norm across U.S. states for an extended period of time, average per-capita real GSP growth will be lower by 0.0273 (-0.1505) percentage points per year. The estimate for $\widehat{\theta}_{\Delta\tilde{T}_{it}(m)^+}$ is half the size of the elasticity obtained in cross-country regressions of Kahn et al. (2021a), partly reflecting a higher degree of adaptation in the U.S. to climate change. As we discussed in Section 2, on average, temperature in the 48 U.S. states rose by 0.026 degrees Celsius (°C) per year over the period 1963–2016. Applying $\widehat{\theta}_{\Delta\tilde{T}_{it}(m)^+} = 0.0273$ to this past warming rate would imply 7 basis points lower growth rate for 53 years (compounding to a per-capita real GSP level loss of about 4 percent). For comparison, 4 percent income loss is about the same size as the loss in US real GDP per capita in 2020 (resulting from the COVID-19 pandemic), as well as the income loss during the 2008-9 recession. Our results are supported by Deryugina and Hsiang (2014) and Behrer and Park (2017), who exploit county-level variations in climate variables over time in the U.S. and find that hotter temperatures damage economic activity, and also by Colacito et al. (2019) who find that an increase in summer temperatures has adverse effects on GSP growth in the United States, through lower labor productivity. Moreover, they estimate that an increase in the average fall temperature positively affects GSP growth, although to a lesser extent. Contrary to the cross-country findings of Kahn et al. (2021a), we show that the estimated long-term growth effects of climate change are asymmetrical and larger in magnitude for periods in which temperatures fall below historical norms. While persistent decreases in temperatures below historical norms are less likely (given the projected global warming), the swings in (variability of) temperatures could be large, and hence, the negative impact on state-level output growth could be sizable and long lasting.

2.1 Adaptation and the U.S. Economy

While there is growing evidence of the benefits of climate-change adaptation at the sectoral and micro level, the macroeconometric-climate literature does not provide conclusive estimates of the economic benefits of adaptation. An exception is Kahn et al. (2021a) who find

Table 3: Long-Run Effects of Climate Change on the Growth Rate of Major Economic Indicators for the United States, 1976–2016

Historical Norm:	**20 Year MA**				**30 Year MA**				**40 Year MA**			
	Real GSP	Real GSP per Capita	Real GSP per Employed	Employment	Real GSP	Real GSP per Capita	Real GSP per Employed	Employment	Real GSP	Real GSP per Capita	Real GSP per Employed	Employment
$\widehat{\theta}_{\Delta\tilde{T}_{it}(m)^+}$	-0.0391***	-0.0279***	-0.0188***	-0.0136**	-0.0379***	-0.0273***	-0.0190***	-0.0135**	-0.0371***	-0.0271***	-0.0188***	-0.0125**
	(0.0108)	(0.0084)	(0.0067)	(0.0065)	(0.0107)	(0.0083)	(0.0067)	(0.0062)	(0.0105)	(0.0082)	(0.0065)	(0.0062)
$\widehat{\theta}_{\Delta\tilde{T}_{it}(m)^-}$	-0.1554***	-0.1199***	-0.0604***	-0.0723***	-0.1951***	-0.1505***	-0.0779***	-0.0954***	-0.2089***	-0.1616***	-0.0847***	-0.1027***
	(0.0315)	(0.0233)	(0.0166)	(0.0183)	(0.0358)	(0.0259)	(0.0191)	(0.0205)	(0.0388)	(0.0283)	(0.0207)	(0.0221)
$\widehat{\theta}_{\Delta\tilde{P}_{it}(m)^+}$	-0.1112*	-0.0930*	-0.0381	-0.0434	-0.1598**	-0.1345***	-0.0443	-0.0853**	-0.1326**	-0.1120**	-0.0299	-0.0792**
	(0.0630)	(0.0500)	(0.0390)	(0.0409)	(0.0634)	(0.0498)	(0.0395)	(0.0395)	(0.0613)	(0.0484)	(0.0385)	(0.0387)
$\widehat{\theta}_{\Delta\tilde{P}_{it}(m)^-}$	-0.2840***	-0.1981***	-0.0510	-0.2082***	-0.3407***	-0.2412***	-0.0553	-0.2515***	-0.3515***	-0.2503***	-0.0530	-0.2763***
	(0.0781)	(0.0600)	(0.0443)	(0.0553)	(0.0837)	(0.0628)	(0.0467)	(0.0594)	(0.0878)	(0.0665)	(0.0490)	(0.0636)
$\widehat{\phi}$	0.5092***	0.6327***	0.7219***	0.4371***	0.5016***	0.6301***	0.7035***	0.4382***	0.4975***	0.6215***	0.6942***	0.4290***
	(0.0503)	(0.0529)	(0.0756)	(0.0445)	(0.0504)	(0.0530)	(0.0756)	(0.0444)	(0.0502)	(0.0530)	(0.0749)	(0.0445)
No. of states (N)	48	48	48	48	48	48	48	48	48	48	48	48
T	36	36	36	36	36	36	36	36	36	36	36	36
$N \times T$	1728	1728	1728	1728	1728	1728	1728	1728	1728	1728	1728	1728

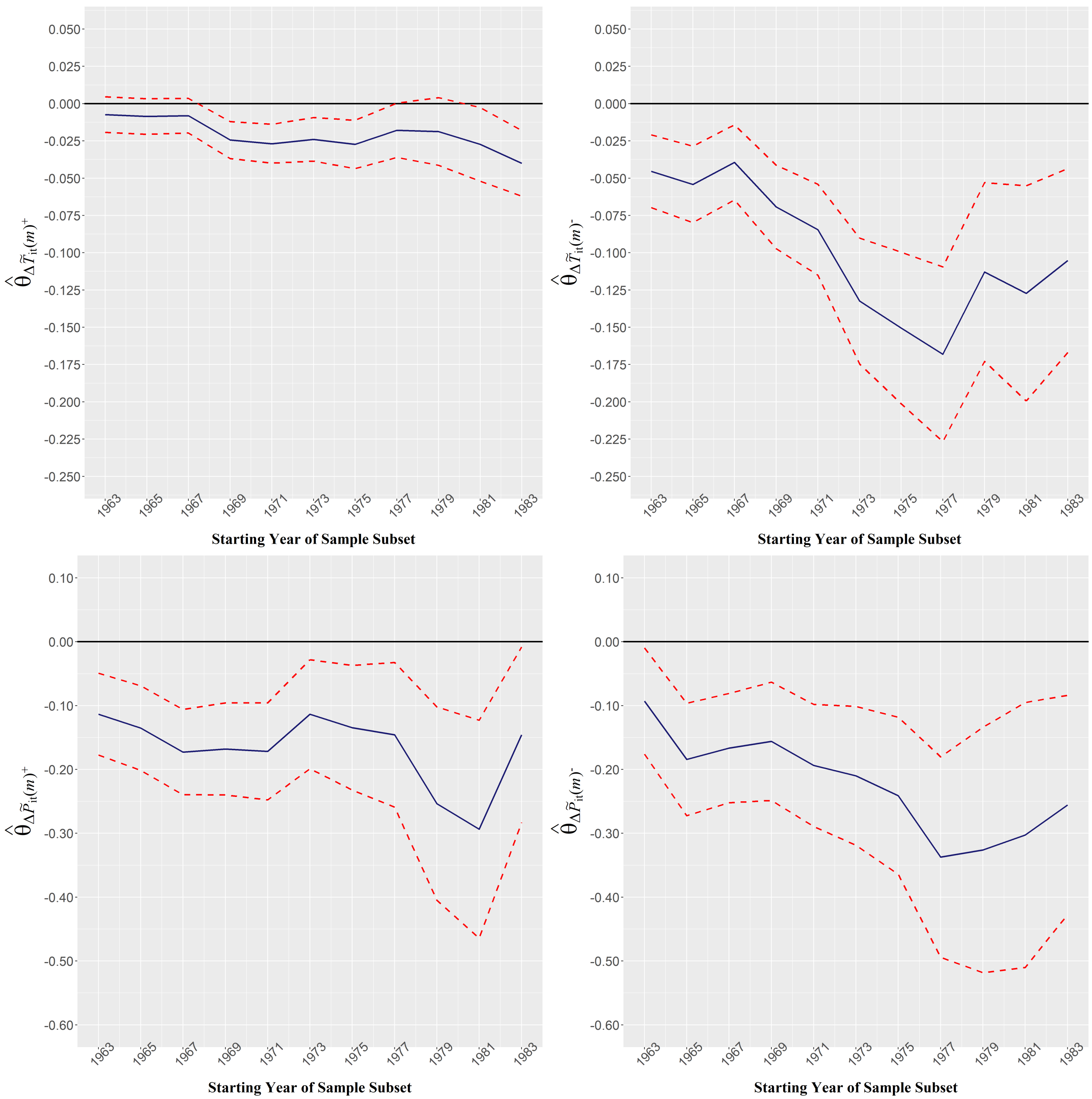
Notes: The HPJ-FE estimates are based on the following specification $\Delta y_{i,t} = a_i + \sum_{l=1}^{p} \varphi_\ell \Delta y_{i,t-l} + \sum_{l=0}^{p} \boldsymbol{\beta}_l' \Delta\tilde{\mathbf{x}}_{i,t-l} + \epsilon_{i,t}$, where y_{it} is the log of (i) real GSP, (ii) real GSP per capita, (iii) real GSP per employed, and (iv) employment of state i in year t, $\tilde{\mathbf{x}}_{it}(m) = [\tilde{T}_{it}(m)^+, \tilde{T}_{it}(m)^-, \tilde{P}_{it}(m)^+, \tilde{P}_{it}(m)^-]'$, $z^+ = zI(z \geq 0)$, $z^- = -zI(z < 0)$, $\tilde{T}_{it}(m) = \left[T_{it} - T^*_{i,t-1}(m)\right]$ and $\tilde{P}_{it}(m) = \left[P_{it} - P^*_{i,t-1}(m)\right]$ are measures of temperature and precipitation relative to their historical norms, T_{it} and P_{it} are the annual average temperature (in Celsius) and precipitation (in metres) of state i in year t, respectively, and $T^*_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} T_{i,t-\ell}$ and $P^*_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} P_{i,t-\ell}$ are the time-varying historical norms of temperature and precipitation of state i over the preceding m years in each t. The long-run effects, θ_i, are calculated from the OLS estimates of the short-run coefficients in equation (2): $\boldsymbol{\theta} = \phi^{-1}\sum_{\ell=0}^{p} \boldsymbol{\beta}_\ell$, where $\phi = 1 - \sum_{\ell=1}^{p} \varphi_\ell$. The lag order, p, is set to 4. Standard errors in parentheses are estimated by the estimator proposed in Proposition 4 of Chudik et al. (2018). Asterisks indicate statistical significance at 1% (***), 5% (**), and 10% (*) levels.

that adaptation has the potential to halve the long-term growth effects of global warming. They model adaptation by assuming different speeds of the formation of historical norms. Their results hold in our within-country study of the U.S. states. Another way to assess adaptation is to test how the elasticity of growth to climate variables evolves over time. Specifically, if the U.S. economy were adapting to climate change, ceteris paribus, should we not expect the impact of deviations of temperature and precipitation from their historical norms to be shrinking over time? To investigate this hypothesis, we re-estimate the model over different time windows using real GSP per capita growth as the dependent variable. We start with the full sample, 1963–2016, and then drop a year at a time (with the last estimation being carried out for the sub-sample 1983–2016). The results are plotted in Figure 1, showing that the estimated coefficients are becoming larger (in absolute value) over time.

Do these results cast doubt on the efficacy of adaptation efforts in the United States over the last five decades? Probably not. Ceteris paribus, while it is expected that adaptation weakens the relationship between climate change and economic growth over time, we cannot conclude that the U.S. economy has not been adapting to climate change based on Figure 1. First, adaptation efforts might be concentrated in certain sectors. Second, it may be the case that adaptation is not keeping pace with climate change; i.e., global temperatures have increased at an unprecedented pace over the past 40 years. Third, the effects of adaptation might have been offset by structural changes to the U.S. economy (that is a shift of value added to sectors that are more exposed to climate change). Fourth, if firms underestimate the likelihood or severity of future weather events, they may not adapt sufficiently; i.e., adaptation technologies are readily available but the take-up is limited by firms. In a survey of private sector organizations across multiple industries within the Organization for Economic Cooperation and Development (OECD) countries, Agrawala et al. (2011) find that only few firms have taken sufficient steps to assess and manage the risks from climate change. Fifth, according to Deryugina and Hsiang (2014) firms tend to under-invest in adaptation owing to its high cost.[12] We argue that there has been some adaptation in the U.S. given that the estimates in Tables 2 and 3 are generally smaller than those obtained in the cross-country study of Kahn et al. (2021a) and they are increasing with m (if expressed in per annum terms)—i.e., the faster is the change in historical norms, the less is the size of income losses across U.S. states. However, the evidence suggests that adaptation efforts should be complemented with mitigation policies to minimize the adverse effects of climate change.

[12] For a discussion of costs associated with diverting funds away from productive capital, see Mohaddes and Williams (2020). Other reasons for underinvestment include knowledge spillovers and networks externalities.

Figure 1: Long-Run Effects of Climate Change on per capita Real GSP Growth in the United States, 1963–2016



Notes: Figures show the long-run effects (and their 95% standard error bands) of climate change on state-level economic growth in the United States over different windows, using the ARDL specification (2). We start the estimation with the full sample (1963–2016) and then drop one year at a time, ending with the final estimates based on the 1983–2016 sub-sample.

2.2 Further Evidence from U.S. Sector Level Data

Adaptation and mitigation can occur in the short-term through a reallocation of resources, and in the long-term through investment in research and development, innovation, or a shift in the economic structure of the country towards an industry mix that is less vulnerable to climate change. Given that adaptation is relatively easier and more effective to implement in some industries than others, we first need to assess which sectors/industries are more likely to be affected by climate change in the U.S. economy. Focusing on different sectors/industries also helps shed light on the channels through which climate change affects the United States economy. We consider ten sectors, and due to lack of worker per sector data at the state level, we only report the results for state-level output growth.[13]

The long-run sectoral effects of climate change estimated on the panel of the 48 U.S. states over the period 1963–2016 are reported in Table 4. The estimates show that the impact is broad based—each of the 10 sectors is affected by at least one of the four climate variables. Specifically, the agricultural sector is negatively impacted by a rise in temperature above its historical norm, $\widehat{\theta}_{\Delta \tilde{T}_{it}(m)^{+}} < 0$. In addition, precipitation above and below the norm also exert negative effects on agricultural output growth. These results are in line with the findings of Burke and Emerick (2016), who consider corn and soy farming in the U.S. over the period 1955–2005, and find that, despite some adaptation efforts by farmers, agricultural output is damaged by extreme heat and excessive precipitation. Note also that the cost of adaptation to climate change is high in the agricultural sector—constructing greenhouses or varying crop mixes involves heftier investments than fitting air conditioning units in offices.

Table 4 also illustrates that deviations of all four climate variables from their historical norms have adverse effects on output growth in the manufacturing sector. While the negative impact of climate change on agricultural production is well studied, the adverse effects on the manufacturing sector in the United States are only being discussed in the new climate economy literature (using micro-data analyses). For example, Cachon et al. (2012) use weekly production data from 64 automobile plants in the U.S. and find that climate variations (extensive periods of rain and snow, high heat, and severe winds), lead to costly production volatility, and have adverse effects on labour productivity, in line with our results. Moreover, our estimates show that output growth in mining, construction, transport, retail trade, wholesale trade, services and government sectors are all negatively affected by unusually cold days in the U.S. as consumer spending falls (households may delay shopping or even cut from spending owing to higher heating costs or home-repair expenses); supply chains are interrupted;[14] and construction projects are delayed. See also Bloesch and Gourio (2015) for further supporting evidence. Heavy rain can also reduce access to mountainous mining

[13] See Appendix A for further details.

[14] For example, steel production along the coast of Lake Michigan was majorly disrupted during the brutal 2013-14 winter, because frozen Great Lakes meant that cargoes could not be moved via boats as usual.

Table 4: Long-Run Effects of Climate Change on the Output Growth of Various Sectors in the United States, 1963–2016

	Agriculture Forestry Fisheries	Mining	Construction	Manufacturing	Transport Communication Public Utilities	Wholesale Trade	Retail Trade	Finance Insurance Real Estate	Services	Government
$\widehat{\theta}_{\Delta\tilde{T}_{it}(m)^+}$	-0.0323*	-0.0030	-0.0587***	-0.0666***	-0.0261**	-0.0628***	-0.0531***	0.0730***	-0.0336***	0.0182*
	(0.0178)	(0.0400)	(0.0204)	(0.0163)	(0.0112)	(0.0209)	(0.0126)	(0.0161)	(0.0110)	(0.0107)
$\widehat{\theta}_{\Delta\tilde{T}_{it}(m)^-}$	-0.0184	-0.1887***	-0.1777***	-0.1136***	-0.0633***	-0.2365***	-0.1674***	0.0050	-0.1201***	-0.0446**
	(0.0315)	(0.0728)	(0.0400)	(0.0270)	(0.0175)	(0.0389)	(0.0237)	(0.0309)	(0.0252)	(0.0199)
$\widehat{\theta}_{\Delta\tilde{P}_{it}(m)^+}$	-0.3054***	-0.6052***	-0.2164**	-0.2382***	0.1340**	-0.0917	-0.0711	-0.0242	-0.1182*	0.0000
	(0.0826)	(0.2161)	(0.1069)	(0.0792)	(0.0547)	(0.1115)	(0.0660)	(0.0803)	(0.0635)	(0.0555)
$\widehat{\theta}_{\Delta\tilde{P}_{it}(m)^-}$	-0.5499***	-0.2973	-0.2000	-0.2689***	-0.1022	-0.2987**	-0.2390***	0.0462	-0.1317*	0.0184
	(0.1188)	(0.2884)	(0.1344)	(0.1019)	(0.0685)	(0.1312)	(0.0846)	(0.1013)	(0.0772)	(0.0787)
$\widehat{\phi}$	1.8892***	0.8133***	0.6412***	0.9599***	0.8536***	0.4830***	0.5787***	0.5944***	0.4135***	0.3902***
	(0.0843)	(0.0459)	(0.0331)	(0.0726)	(0.0581)	(0.0394)	(0.0312)	(0.0546)	(0.0414)	(0.0458)
No. of states (N)	48	47	48	48	48	48	48	48	48	48
T	48	48	48	48	48	48	48	48	48	48
$N \times T$	2304	2256	2304	2304	2304	2304	2304	2304	2304	2304

Notes: The HPJ-FE estimates are based on the following specification $\Delta y_{i,t} = a_i + \sum_{l=1}^{p} \varphi_\ell \Delta y_{i,t-l} + \sum_{l=0}^{p} \boldsymbol{\beta}_l' \tilde{\mathbf{x}}_{i,t-l} + \epsilon_{i,t}$, where y_{it} is the log of sectoral real output in state i in year t, $\tilde{\mathbf{x}}_{it}(m) = [\tilde{T}_{it}(m)^+, \tilde{T}_{it}(m)^-, \tilde{P}_{it}(m)^+, \tilde{P}_{it}(m)^-]'$, $z^+ = zI(z \geq 0)$, $z^- = -zI(z < 0)$, $\tilde{T}_{it}(m) = \left[T_{it} - T_{i,t-1}^*(m)\right]$ and $\tilde{P}_{it}(m) = \left[P_{it} - P_{i,t-1}^*(m)\right]$ are measures of temperature and precipitation relative to their historical norms, T_{it} and P_{it} are the annual average temperature (in Celsius) and precipitation (in metres) of state i in year t, respectively, and $T_{i,t-1}^*(m) = \frac{1}{m}\sum_{\ell=1}^{m} T_{i,t-\ell}$ and $P_{i,t-1}^*(m) = \frac{1}{m}\sum_{\ell=1}^{m} P_{i,t-\ell}$ are the time-varying historical norms of temperature and precipitation of state i over the preceding m years in each t (with $m = 30$ in this case). The long-run effects, θ_i, are calculated from the OLS estimates of the short-run coefficients in equation (2): $\boldsymbol{\theta} = \phi^{-1}\sum_{\ell=0}^{p}\boldsymbol{\beta}_\ell$, where $\phi = 1 - \sum_{\ell=1}^{p}\varphi_\ell$. The lag order, p, is set to 4. Standard errors in parentheses are estimated by the estimator proposed in Proposition 4 of Chudik et al. (2018). Asterisks indicate statistical significance at 1% (***), 5% (**) and 10% (*) levels.

regions, where large deposits are generally found, thereby reducing output growth in the mining sector. Construction and transportation activities are also affected by rain/snow.

Most discussions of climate change focus on the expected increase in average global temperatures over the next century (i.e. global warming). However, the frequency and severity of weather events (such as heat or cold waves, droughts and floods, as well as natural disasters) depend heavily on the variability of temperatures and precipitation as well as their mean. The larger the swings, the more often extremely hot or cold and wet or dry conditions can wreak havoc; see, for instance, Swain et al. 2018. Given current projections of rising average global temperature over the next century, the likelihood that temperatures persistently drift above their historical norm is very high. As we showed above, this could lead to a permanent negative impact on state-level output growth (that is lower production growth in all sectors of the United States economy apart from the mining, government, and finance, insurance and real estate sectors). While persistent deviations of precipitation from its historical norm (either above and below) or below-the-norm temperatures are less likely, the swings (variability) could be unprecedentedly large owing to climate change, and hence, the negative impact on state-level output growth could be sizable and long lasting.

Overall, the industry-level results in Table 4 and the state-level results in Tables 2–3, show that deviations of temperature below its historical norms in the U.S. as well as deviations of precipitation from its historical norm are detrimental to long-run state-level and industry-level output growth. When it comes to deviations of temperature above its historical norms, the estimates are negative and statistically significant at the aggregate state-level (in the more recent sample) and for all economic sectors apart from mining, government, and finance, insurance and real estate sectors. In fact $\widehat{\theta}_{\Delta\tilde{T}_{it}(m)^{+}}$ is positive and statistically significant for government services (at the 10% level) and finance, insurance and real estate sectors, but most likely this reflects government spending on relief measures and higher insurance premiums in response to climate change.

We acknowledge some resilience building activities in advanced economies, but the evidence from our U.S. within-country study seems to suggest that while adaptation might have reduced the negative effects in certain sectors, it has not completely offset them at the macro level (see Table 3 and Figure 1). Behrer and Park (2017) note that even the most well-adapted regions in the United States suffer negative production effects from hotter temperatures and Colacito et al. (2019) show that an increase in average summer temperatures will have negative effects on nominal output in various sectors, such as agriculture, construction, retail, services, and wholesale trade.

3 Concluding Remarks

Using data on 48 U.S. states from 1963 to 2016, and a novel econometric strategy (that differentiates between level and growth effects including in the long term; accounts for bi-directional feedbacks between growth and climate change; considers asymmetric weather effects; allows for nonlinearity and an implicit model of adaptation; and deals with temperature being trended), we provided evidence for the damage that climate change causes in the U.S. using GSP, GSP per capita, labour productivity, and employment as well as output growth in ten economic sectors (such as agriculture, construction, manufacturing, services, retail and wholesale trade). While certain sectors in the U.S. economy might have adapted to higher temperatures, economic activity in the U.S. overall and at the sectoral level continues to be sensitive to deviations of temperature and precipitation from their historical norms.

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A Data Appendix

We obtain state-level economic activity data from the Bureau of Economic Analysis (BEA). Real Gross State Product (GSP) data is available from 1977, but nominal GSP data is available from 1963. We deflate the nominal GSP series using the consumer price index (CPI) for each state, and splice the resulting data over 1963–1977 with the real GSP from 1977 using annual growth rates, to construct a real GSP series for 1963–2016.

BEA provides output by sector at the state level from 1963. However, there are two issues with this database. Firstly, there was a change in industrial classifications in 1997: from 1963 to 1997, the Standard Industrial Classification (SIC) consists of ten divisions, while from 1997 onwards, the North American Industry Classification System (NAICS) gradually replaces the SIC, further branching the ten divisions into fifteen sectors.[15] Secondly, as with the GSP data, only nominal sectoral output data (by SIC divisions) is available before 1977. Real sectoral output is available in both SIC and NAICS classification in 1997. This allows us to construct the real sectoral output series from 1963–2016. Specifically, building a series over the period 1963 to 2016 involves two steps: (i) reconciling SIC and NAICS classifications (see Table A.1), and (ii) splicing the most recent real series (1997–2016) backwards using growth rates from the deflated nominal series (1963–1997).

Table A.1: Division (SIC) and Sector (NAICS) Classifications

Division (SIC)	Sector (NAICS)
Agriculture, Forestry, Fisheries	Agriculture, Forestry, Fishing & Hunting
Mining	Mining
Construction	Construction
Manufacturing	Manufacturing
Transport, Communication, and Public Utilities	Transportation & Warehousing Information Utilities
Wholesale Trade	Wholesale Trade
Retail Trade	Retail Trade
Finance, Insurance, and Real Estate	Finance/Insurance/Real Estate/Rental/Leasing
Services	Professional & Business Services Educational Services/Health Care/Social Assistance Arts/Entertainment/Recreation/Accommodation/Food Services Other Services, Ex Government
Government	Government

We use BEA's producer price index (PPI) data to deflate the nominal industry outputs under SIC for the years 1963–1976. As the PPI data is constructed based on NAICS, we use the SIC-NAICS matching in Table A.1 for the PPI deflator. Where there is more than one NAICS sector matched to a SIC division, we take a simple arithmetic average of the PPI of all matched NAICS sectors. From 1997 onwards, real output by sector is available based on NAICS classification. We, therefore, aggregate the NAICS real output by industry to SIC divisions using our matching scheme, and splice these series backwards using the growth rates of real sectoral output under SIC in 1963–1997. This gives us real output by sector and state for the period 1963 to 2016.[16]

[15] See Kort (2001) for more details.

[16] Note that "Agriculture, Forestry, Fishing & Hunting" and "Mining" data is not available for Rhode

We collect monthly state-level, area-weighted climate data from the NOAA's National Centres for Environmental Information (NCEI). The NCEI reports monthly average temperature and precipitation[17] for each state from aggregates of climate readings across weather stations, adjusting for the distribution of stations and terrain. Temperature is measured in degrees Fahrenheit and precipitation in inches. We convert them into degrees Celsius and metres, respectively. The monthly averages in each year within the sample period are then used to obtain annual averages.

Finally, we obtain U.S. employment data from the Bureau of Labor Statistics (BLS). We take annual, state-level number of employed persons that encompasses "persons 16 years and over in the civilian noninstitutional population" under a wide range of employment conditions.

Island in 2016 and agricultural data in 2016 is also unavailable for Delaware. Moreover, the mining industry of Delaware is excluded from our sample due to multiple irregular missing entries.

[17] Snow is included as melted precipitation in rain gauges under NOAA methodology.