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The effects of climate risks on economic activity in a panel of US states: The role of uncertainty

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ABSTRACT

We analyse the impact of climate risks (temperature growth and its volatility) on the coincident indicator of the 50 US states in a panel data set-up, over the monthly period of March, 1984 to December, 2019. Using impulse response functions (IRFs) from a linear local projections (LPs) model, we show that climate risks negatively impact economic activity to a similar degree, irrespective of whether such risks are due to changes in temperature growth or its volatility. More importantly, using a nonlinear LPs model, the IRFs reveal that the adverse effect of climate risks is contingent on the regimes of economic and policy-related uncertainty of the states, with the impact being significantly much stronger under relatively higher values of uncertainty, rather than lower values of the same. In addition to this, temperature growth volatility is found to contract economic activity nearly five times more compared to when temperature growth increases by a similar magnitude in the higher uncertainty-based regime of the nonlinear model. Understandably, our results have important policy implications.

1. Introduction

Climate change is one of the most defining challenges of our time, with the potential to impact the health and well-being of every person on the planet by posing a large aggregate risk to the economy (Giglio et al., 2021). In this regard, Descêhnes and Greenstone (2007) and Dell et al. (2009, 2012, 2014) provided empirical evidence that climate risks, as proxied via increased temperatures, tend to negatively impact economic growth. More recently, Donadelli et al., 2017, 2021a,b,c; Kotz et al., 2021) highlight the importance of temperature volatility, in reducing growth. The novelty of these latter group of studies, besides providing empirical evidence, is that Donadelli et al., 2017, 2021a,b,c extended the general equilibrium models of rare disaster risks (originally developed by Barro (2006, 2009)) to incorporate the physical component of climate risks[1] so as to make explicit the theoretical channels through which the economy is impacted. In general, the theoretical framework of these research efforts shows that climate risks tend to undermine economic growth via adversely impacting not only labour productivity and capital quality, but also through the patent obsolescence channel (which dampens research and development (R&D) expenditure growth). In other words, climate risks can impact growth from both the demand- and supply-side of the economy.

Against the backdrop of empirical evidence of the impact of climate risks on output growth, provided primarily at the aggregate individual or a panel of countries, we aim to extend this line of research in two novel ways: First, we analyse, for the first time, the effects of both growth in temperature and its volatility on the economic activity of a panel of 50 states of the United States (US), over the monthly period of 1984 to 2019.[2] Second, and again for

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[1] There are also of course transition risks associated with climate change, e.g. risks stemming from government intervention via carbon taxation and incentives to develop green technologies.

[2] The only other somewhat related paper is that of Donadelli et al. (2020), wherein the authors, *inter alia*, reported negative impacts of tornado activity on the four census regions (Northeast, Midwest, South and West) of the US, but based on annual data. Understandably, a high-frequency analysis like that of ours is more valuable to policymakers in designing responses to mitigating climate risks in a timely-manner than those derived from annual data-centric findings.

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the first time, we test the hypothesis that, the effect of climate risks is contingent on the level of economic- and policy-related uncertainty involving the US states, with the expectation that, the effects of temperature growth and its volatility is likely to be relatively more adverse under a regime of higher-uncertainty compared to a state of lower values of the same.

The theoretical motivation in this regard is derived from the following lines of reasoning: First, higher uncertainty is known to adversely affect the aggregate demand of the economy through the traditional channel associated with the real option theory (Bernanke, 1983), and more recently, Bloom (2009), suggests that decision-making is affected by uncertainty because it raises the option value of waiting. In other words, given that the costs associated with wrong investment decisions are very high, uncertainty makes firms and, in the case of durable goods, also consumers more cautious. As a result, economic agents postpone investment, hiring, and consumption decisions to periods of lower uncertainty. Second, uncertainty is also expected to have a negative effect on the supply-side of the economy through productivity due to the misallocation of factors across firms (Bloom et al., 2018). According to Bloom et al. (2018), unproductive firms contract and productive firms expand during normal times, which in turn helps to maintain high levels of aggregate productivity. But when uncertainty is high, firms reduce expansion and contraction, thus shutting off much of this productivity-enhancing reallocation, which ultimately manifests itself as a fall in measured aggregate total factor productivity. Naturally, given these two channels, the negative effect of climate risks on economic activity via adverse effects on demand and supply conditions is likely to be exacerbated under comparatively higher levels of economic uncertainty.

The remainder of the paper is organized as follows: Section 2 discusses the data, while Section 3 presents the linear and nonlinear local projections (LPs) method of Jordà (2005), and Ahmed and Cassou (2016) respectively, in the context of a panel data-setting. These methods are then used to obtain the standard and uncertainty-based-regime-specific impulse response functions (IRFs) for the state-level coincident indicator following climate risk shocks in the empirical results segment contained in Section 4. Finally, Section 5 concludes the paper.

2. Data

As far as the behaviour of the real economy is concerned, we measure it through the seasonally-adjusted coincident indicator (CI) of the 50 US states,[3] sourced from the FRED database of the Federal Reserve Bank of St. Louis, which in turn is originally created by the Federal Reserve Bank of Philadelphia. The corresponding average temperature (in degrees Fahrenheit) data for each state is obtained from National Oceanic and Atmospheric Administration (NOAA).[4] From the raw data, we compute month-on-month growth in temperature (*TGrowth*), and on which a stochastic volatility (SV) model of Kastner and Frühwirth-Schnatter (2014)[5] is fitted to obtain the corresponding volatility of state-level temperature (*TGrowth_SV*), following the suggestion of Alessandri and Mumtaz (2021) in terms of modelling climate volatility.

As far as the state-level measure of economic and policy-related uncertainty (SEPU) is concerned, we rely on the work of Elkamhi et al. (2020),[6] who basically follow the newspapers-based approach of Baker et al. (2016). Elkamhi et al. (2020), using news articles from Newslibrary.com,[7] search for the number of articles containing words that are related to the following categories: "State-level", "Economic", "Policy", and "Uncertainty". The authors count an article as related to state-level EPU (*SEPU*) when it contains at least one word for each of the four categories. Because state newspapers could cover not only local but also nationwide news at the same time, Elkamhi et al. (2020) discard articles that contain a word reflective of nationwide information (such as 'congress', 'white house', 'federal reserve').[8] It must be noted that, is the availability of the SEPU data, which defines our period of analysis, i.e., March, 1984 to December, 2019.

In the models estimated, we also control for the effect of monetary policy (*IR*), and hence use the effective Federal funds rate (FFR, derived from the FRED database) from start till December, 1989, and then from January, 1990 till the end of the sample, we rely on the shadow short rate to account for the zero lower bound (ZLB) situations during- and post-the global financial crisis. The SSR is based on models of the term-structure, as developed by Wu and Xia (2016).[9] We work with the first differences of the merged FFR and SSR series to capture the changes in monetary policy decisions over the sample period.

3. Methodology

The linear model for computing the IRFs following the LPs method of Jordà (2005) can be specified as follows:

$$Y_{i,t+s} = \alpha_{i,s} + \beta_s X_t + \sum_{j=0}^{j=1} \gamma_{i,j,s} Z_{i,t-j} + \sum_{j=0}^{j=1} \delta_{j,s} IR_{t-j} + \epsilon_{i,t+s}, \quad \text{for } s = 0, 1, 2, \dots, H \tag{1}$$

where $Y_{i,t+s}$ represents the coincident indicator of US state i at time t, s is the forecast horizon,[10] $\alpha_{i,s}$ measures the fixed effect in a panel specification. β_s captures the responses of the coincident indicator at time $t + s$ following an increase in growth in temperature or its SV (denoted by X_t) at time t. We standardize both the temperature growth and its volatility for each state by dividing with their respective cross-sectional standard deviations,

[3] The Coincident Economic Activity Index includes four indicators: nonfarm payroll employment, the unemployment rate, average hours worked in manufacturing and wages and salaries. The trend for each state's index is set to match the trend for gross state product.

[4] See: https://www.ncdc.noaa.gov/cag/statewide/time-series.

[5] Letting denote temperature growth by: $y = (y_1, y_2, \dots, y_T)'$, the SV model is specified as: $y_t = e^{h_t/2}\varepsilon_t$, with $h_t = \mu + \psi(h_{t-1} - \mu) + \sigma v_t$, where the i.i.d. standard normal innovations ε_t and v_s are by assumption independent for $v, s \in \{1, \dots, T\}$. The unobserved process $h = (h_0, h_1, \dots, h_T)$ that shows up in the state equation is interpreted as a latent time-varying volatility process with initial state distributed according to the stationary distribution, i.e., $h_0|\mu, \psi, \sigma \sim \mathcal{N}(\mu, \sigma^2/(1-\psi^2))$. The non-centred parameterization of the model is given by: $y_t \sim \mathcal{N}(0, \omega e^{\sigma \tilde{h}_t})$, with $\tilde{h}_t = \psi \tilde{h}_{t-1} + v_t$, $v_t \sim \mathcal{N}(0, 1)$, where $\omega = e^{\mu}$. The initial value of $\tilde{h}_0|\psi$ is drawn from the stationary distribution of the latent process, i.e., $\tilde{h}_0|\psi \sim \mathcal{N}(0, 1/(1-\psi^2))$, and $\tilde{h}_t = (h_t - \mu)/\sigma$. Detailed estimation results for the stochastic-volatility model can be obtained from the authors upon request.

[6] We would like to thank the authors of this paper for kindly providing us with the state-level uncertainty data.

[7] Newslibrary.com covers around 7000 newspapers with more than 274 million newspaper articles for 50 US states as well as the District of Columbia (DC), Puerto Rico, Guam, U.S. Virgin Islands, and American Samoa.

[8] The reader is referred to Table 1 of Elkamhi et al. (2020) for the complete list of words used to select articles according to their methodology.

[9] The SSR data can be downloaded from the website of Professor Jing Cynthia Wu at: https://sites.google.com/view/jingcynthiawu/shadow-rates?authuser=0, whereby the framework essentially removes the effect that the option to invest in physical currency (at an interest rate of zero) has on yield curves. This results in a hypothetical "shadow yield curve" that would exist if the physical currency were not available. The process allows one to answer the question: "What policy rate would generate the observed yield curve if the policy rate could be taken as negative?" The shadow policy rate generated in this manner, therefore, provides a measure of the monetary policy stance after the actual policy rate reaches zero.

[10] The maximum length of forecast horizons H is set to 24 months in this study, corresponding to a 2-year forecast horizon.

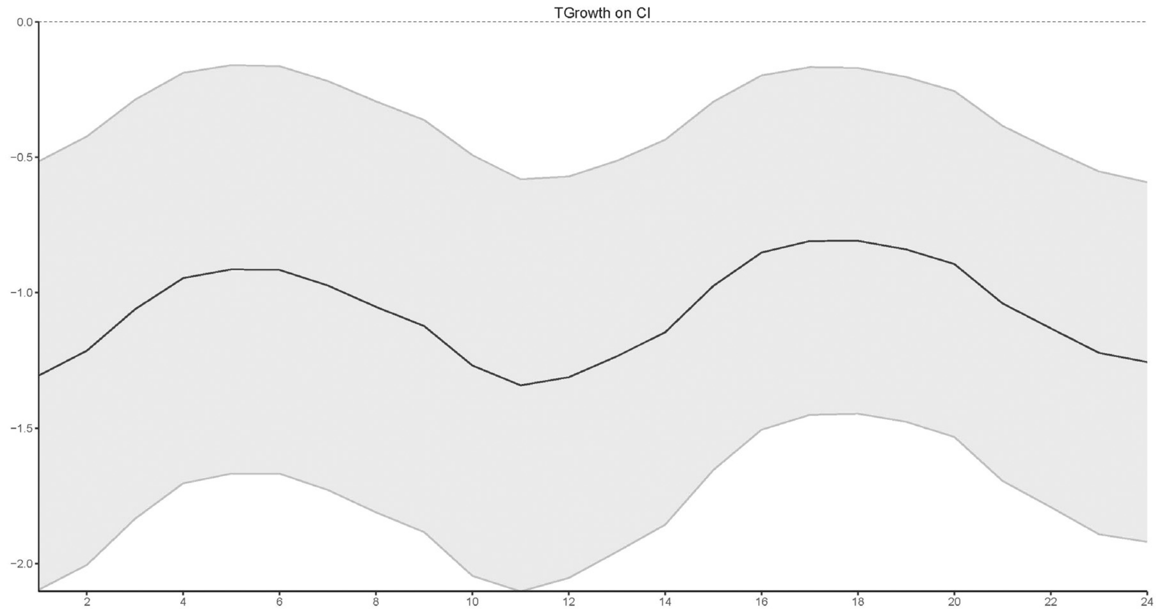

Fig. 1. The US state-level effect of temperature growth (*TGrowth*) on the coincident indicator (*CI*).

to ensure that the effects of these two variables on CI is perfectly comparable in terms of the magnitude.[11] The IRFs are calculated from a sequence of β_s that are estimated by the ordinary least squares (OLS) regression method at each forecast horizon (s).[12] We also control for the contemporaneous and lagged effects of the changes in the US monetary policy rate, and the state-level *TGrowth*, its corresponding SV (*TGrowth_SV*), and *SEPU* (captured by a vector of control variables in Z_i).

We also study whether the effects of temperature growth or its SV on the state-level coincident indicator are regime-dependent, contingent on the (low- and high-) states of *SEPU* in the panel data. Following the approach of Ahmed and Cassou (2016), we expand the linear model defined in Eq. (1) into a nonlinear threshold model using a dummy variable. The model for computing the nonlinear IRFs can be specified as follows:

$$Y_{i,t+s} = (1 - D_t)\left[\alpha_{i,s}^{High} + \beta_{i,s}^{High} X_{i,t} + \sum_{j=0}^{j=1} \gamma_{i,j,s}^{High} Z_{i,t-j} + \sum_{j=0}^{j=1} \delta_{j,s}^{High} IR_{t-j}\right] + D_t\left[\alpha_{i,s}^{Low} + \beta_{i,s}^{Low} X_{i,t} + \sum_{j=0}^{j=1} \gamma_{i,j,s}^{Low} Z_{i,t-j} + \sum_{j=0}^{j=1} \delta_{j,s}^{Low} IR_{t-j}\right] + \epsilon_{i,t+s},\ \text{for} s = 0, 1, 2, \ldots, H \tag{2}$$

where D_{t-1} is a threshold dummy variable which equals 1 if *SEPU* in US state i is in the low-regime, and 0 otherwise. Superscripts *High* and *Low* denote the high- and low-*SEPU* regimes, respectively, denoted by corresponding values above- and below-median respectively.[13]

4. Empirical findings

Fig. 1 presents the estimated linear IRFs of the state-level coincident indicator for a shock to temperature growth over the 1- to 24-month-ahead-forecast horizons in the model specified in Eq. (1). The figure plots the IRFs calculated by LPs to a 1-unit increase of the temperature growth on the future path of the state-level coincident indicator, along with the 95% confidence bands calculated based on panel-corrected standard errors.

In line with theory, our result shows that the state-level coincident indicator responds negatively in a statistically significant manner to an increase in temperature growth, over the entire two-year forecast horizon considered.

A significant negative effect on state-level economic activity is also registered for a 1-unit shock to the SV of temperature growth, again over the entire forecasting horizon, as observed from Fig. 2. Interestingly, this effect is comparatively similar to that in the case of temperature growth.

Hence, in line with existing international evidence, we find that climate risks, as captured by growth in temperature and its volatility, also tend to negatively impact economic activity at the regional-, i.e., state-level of the US.

Next, in Fig. 3, we plot the estimated nonlinear IRFs of the state-level coincident indicator following a shock to temperature growth over 24 months. Recall, in this case, we distinguish between the high- or low-regimes of the *SEPU* in individual states, based on the model specified in Eq. (2). We find that responses of the coincident indicator under the two *SEPU* regimes are very similar to those obtained from the linear model, in terms of its behaviour, i.e., we obtain negative and significant impacts, barring the horizon of 15 to 20-months-ahead in the low-*SEPU* state. But, more importantly, in accordance with our hypothesis, we find

[11] In terms of the results we obtain below in Section 4 based on the level of CI, the qualitative story remains the same if we work with the growth rate of CI. Note that, we worked with the untransformed CI, since standard panel data-based unit root tests (namely, Breitung (2000) and Levin et al. (2002)), confirmed stationarity. Complete details of all these results are available upon request from the authors.

[12] See Jordà (2005) for detailed discussions about the LPs method.

[13] Note that, due to concerns of endogeneity (Ludvigson et al., 2021), we actually calculate *SEPU* shock (rather than directly using the *SEPU* variable in the model) by running a fixed effects panel regression of *SEPU* on its lags and also lags of coincident indicators, and then using the residuals of this regression.

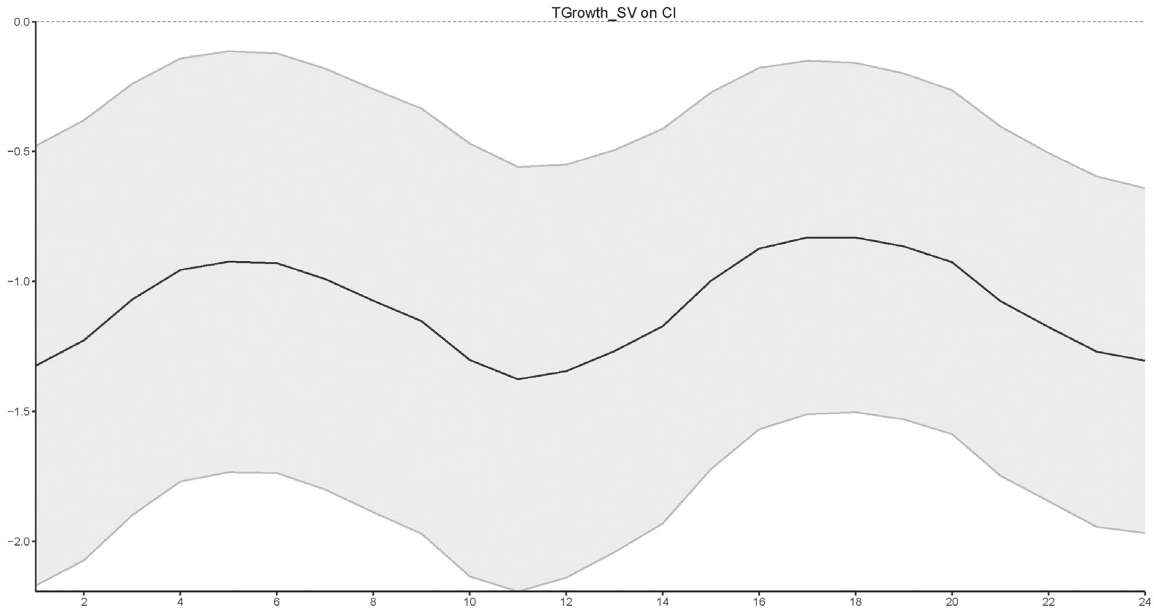

Fig. 2. The US state-level effect of SV of temperature growth (*TGrowth_SV*) on the coincident indicator (CI).

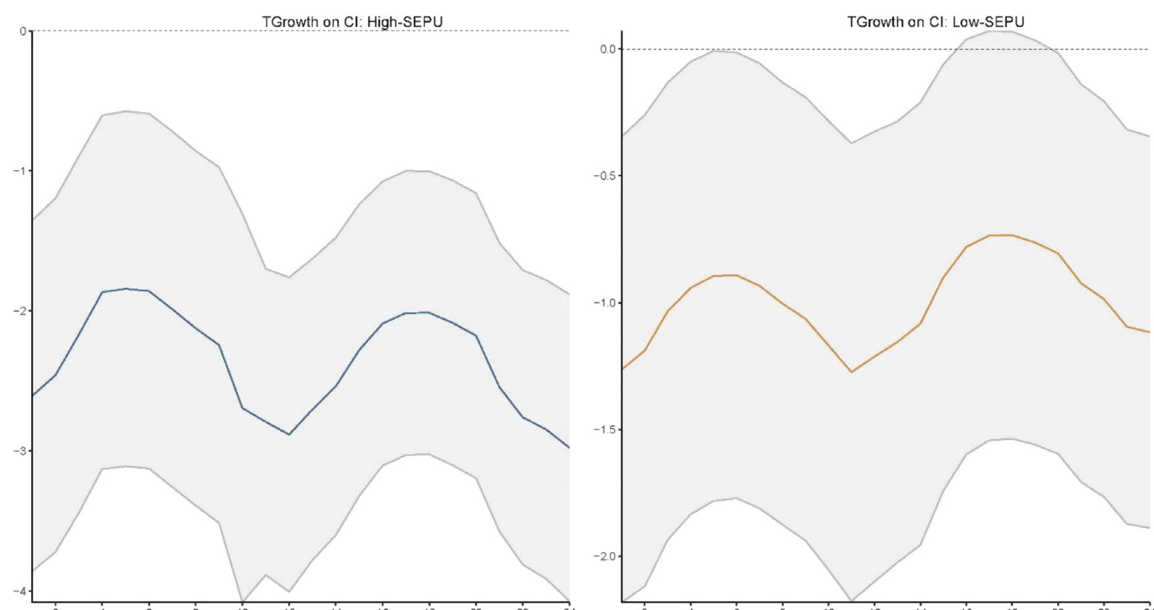

Fig. 3. The US state-level nonlinear effect of temperature growth (*TGrowth*) on the coincident indicator (*CI*) contingent on regimes of the *SEPU*.

that the effect of temperature growth on the coincident indicator is indeed regime-dependent, with a stronger adverse impact on economic activity under the higher SEPU-regime, compared to the same in the lower *SEPU*-state. In fact, the effect when *SEPU* is relatively higher is essentially double than when *SEPU* is lower.

As with the effects of growth in temperature on the coincident indicator in the nonlinear case, from Fig. 4, we observe a stronger significant negative impact on economic activity under the high-regime of the *SEPU* (relative to its lower-value-state, where over horizons 15 to 20-months-ahead, the effect is insignificant), when we consider an increase in climate risks emanating from the volatility of temperature growth. Interestingly, the strength of the negative impact on the coincident indicator in the high-*SEPU* state is basically 10 times stronger than in the low-regimes of the *SEPU*.

An important result that we need to highlight is that, while the effects of the temperature growth increase and its corresponding rise in volatility produce a similar-sized impact on the coincident indicator at the lower-regime of uncertainty, similar to the linear model, the effects are starkly different in magnitude during the upper-regime of *SEPU*. In fact, when uncertainty is high, the second-moment impact of temperature growth is about 5 times more than the corresponding impact of temperature growth on the real economy.

Overall, taking into account the IRFs from the nonlinear model, we provide strong evidence in favour of our hypothesis that, in general, relatively higher values of economic and policy-related uncertainty would tend to enhance the adverse effects of climate risks on economic activity, by exaggerating the demand- and supply-side transmission channels through which temperature growth and its volatility affect the real economy.

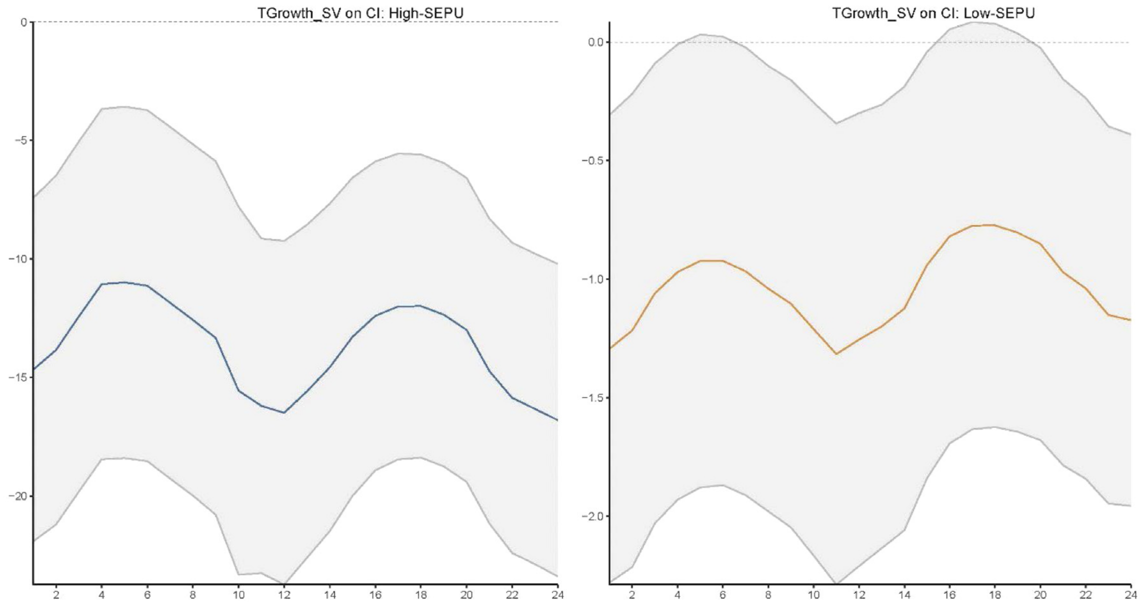

Fig. 4. The US state-level nonlinear effect of SV of temperature growth (*TGrowth_SV*) on the coincident indicator (*CI*) contingent on regimes of the *SEPU*.

5. Conclusion

In this paper, we analyse the effects of climate risks, i.e., growth in temperature and its volatility on the economic activity of the 50 states of the US, over the monthly period of 1984 to 2019, conditional on the high- and low-regimes of corresponding state-level economic and policy-related uncertainty. Our results, based on linear and nonlinear models of local projections, show that, while climate risks negatively impact economic activity, these effects are immensely magnified when uncertainty is relatively high. This is because, uncertainty leads to enhancement of the effects of the demand- and supply-side channels through which climate risks tend to impact economic activity. Furthermore, while effects of temperature growth and its volatility on economic activity under the linear model and in the lower uncertainty-regime are of similar magnitude, the effect is five-folds higher for a temperature growth volatility increase relative to a similar-sized temperature growth rise under the upper-regime of the nonlinear model. Our findings imply that, while policies aiming at reducing climate change will improve economic activity, the size of such positive effects would be contingent on the level of the underlying uncertainty. In other words, policymakers would need to pursue complementary and transparent policies, in the sense that such measures would need to ensure simultaneous reduction of climate risks and economic- and policy-based uncertainty, to produce the desired real effects. In addition, stronger expansionary policy responses are required when uncertainty is relatively high, and economic contraction originates due to a rise in the volatility of temperature growth, compared to the case when growth in temperature increases by a similar magnitude.

References

Ahmed, M.I., Cassou, S.P., 2016. Does consumer confidence affect durable goods spending during bad and good economic times equally? J. Macroecon. 50, 86–97.
Alessandri, P., Mumtaz, H., 2021. The Macroeconomic Cost of Climate Volatility. School of Economics and Finance, Queen Mary University of London, Working Paper No. 928.
Baker, S.R., Bloom, N.A., Davis, S.J., 2016. Measuring economic policy uncertainty. Q. J. Econ. 131 (4), 1593–1636.
Barro, R.J., 2006. Rare disasters and asset markets in the twentieth century. Q. J. Econ. 121, 823–866.
Barro, R.J., 2009. Rare disasters, asset prices, and welfare costs. Amer. Econ. Rev. 99 (1), 243–264.
Bernanke, B., 1983. Irreversibility, uncertainty, and cyclical investment. Q. J. Econ. 98, 85–106.
Bloom, N.A., 2009. The impact of uncertainty shocks. Econometrica 77 (3), 623–685.
Bloom, N.A., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., Terry, S.J., 2018. Really uncertain business cycles. Econometrica 86 (3), 1031–1065.
Breitung, J., 2000. The local power of some unit root tests for panel data. In: Baltagi, B. (Ed.), Nonstationary Panels, Panel Cointegration, and Dynamic Panels, Advances in Econometrics, Vol. 15. JAI: Amsterdam, pp. 161–178.
Dell, M., Jones, B.F., Olken, B.A., 2009. Temperature and income: reconciling new cross-sectional and panel estimates. Amer. Econ. Rev. 99, 198–204.
Dell, M., Jones, B.F., Olken, B.A., 2012. Temperature shocks and economic growth: Evidence from the last half century. Am. Econ. J. Macroecon. 4, 66–95.
Dell, M., Jones, B.F., Olken, B.A., 2014. What do we learn from the weather? The new climate-economy literature. J. Econ. Lit. 52, 740–798.
Descênhes, O., Greenstone, M., 2007. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. Amer. Econ. Rev. 97, 354–385.
Donadelli, M., Ghisletti, M., M. Jüppner, M., Paradiso, A., 2020. Tornado activity, house prices, and stock returns. North Am. J. Econ. Finance 52, 101162.
Donadelli, M., Grüning, P., Jüppner, M., Kizys, R., 2021a. Global temperature, R & D expenditure, and growth. Energy Econ. 104, 105608.
Donadelli, M., Jüppner, M., Paradiso, A., Schlag, C., 2021b. Computing macro-effects and welfare costs of temperature volatility: A structural approach. Comput. Econ. 58, 347–394.
Donadelli, M., Jüppner, M., Riedel, M., Schlag, C., 2017. Temperature shocks and welfare costs. J. Econom. Dynam. Control 82, 331–355.
Donadelli, M., Jüppner, M., Vergalli, S., 2021c. Temperature variability and the macroeconomy: A world tour. Environ. Res. Econ. http://dx.doi.org/10.1007/s10640-021-00579-5.
Elkamhi, R., Jo, C., Salerno, M., 2020. Measuring state-level economic policy uncertainty. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3695365.
Giglio, S., Kelly, B., Stroebel, J., 2021. Climate finance. Ann. Rev. Financial Econ. 13, 15–36.
Jordà, Ò., 2005. Estimation and inference of impulse responses by local projections. Amer. Econ. Rev. 95 (1), 161–182.
Kastner, G., Frühwirth-Schnatter, S., 2014. Ancillarity-sufficiency interweaving strategy (ASIS) for boosting MCMC estimation of stochastic volatility models. Comput. Statist. Data Anal. 76, 408–423.
Kotz, M., Wenz, L., Stechemesser, A., Kalkuhl, M., Levermann, A., 2021. Day-to-day temperature variability reduces economic growth. Nature Clim. Change 11, 319–325.
Levin, A., Lin, C.-F., Chu, C-S.J., 2002. Unit root tests in panel data: Asymptotic and finite-sample properties. J. Econometrics 108 (1—24).
Ludvigson, S.C., Ma, S., Ng, S., 2021. Uncertainty and business cycles: Exogenous impulse or endogenous response? Am. Econ. J. Macroecon. 13 (4), 369–410.
Wu, J.C., Xia, F.D., 2016. Measuring the macroeconomic impact of monetary policy at the zero lower bound. J. Money Credit Bank. 48 (2–3), 253–291.