Economics Letters 215 (2022) 110500

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Persistence of state-level uncertainty of the United States: The role of climate risks[☆]

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ARTICLE INFO

Article history:
Received 31 January 2022
Received in revised form 21 March 2022
Accepted 5 April 2022
Available online 11 April 2022

JEL classification:
C23
D80
Q54

Keywords:
Uncertainty
Climate risks
US states
Nonlinear local projections
Impulse response functions

ABSTRACT

Recent theoretical developments tend to suggest that rare disaster risks enhance the persistence of uncertainty. Given this, we analyse the impact of climate risks (temperature growth or its volatility), as proxies for such unusual events, on the persistence of economic and policy-related uncertainty of the 50 US states in a panel data set-up, over the monthly period of 1984:03 to 2019:12. Using impulse response functions (IRFs) from a regime-based local projections (LPs) model, we show that the impact of an uncertainty shock on uncertainty itself is not only bigger in magnitude when the economy is in the upper-regime of temperature growth or its volatility, but is also, in line with theory, is more persistent. Our results have important policy implications.

1. Introduction

Persistence of uncertainty is a well-established empirical fact (see for example, Plakandaras et al. (2019), Gil-Alana and Payne (2020), Abakah et al. (2021) and Solarin and Gil-Alana (2021)). Given this, in a recent theoretical contribution, Sundaresan (2015), motivated by the literature on inattention, developed a model to show that rare disaster risks enhance persistence in the process of uncertainty. In this model, agents choose whether and how to prepare for different possible states of the world by collecting information, but they also optimally ignore sufficiently unlikely events. Hence, the occurrence of such events does not resolve, but increases, uncertainty. With uncertain agents having dispersed beliefs, uncertainty begets uncertainty, and results in endogenous persistence.[1] In empirical terms, this implies that a shock to uncertainty will take longer to die-off, when the economy is simultaneously witnessing rare disaster events.

Since uncertainty dictates how economic agents make consumption, investment, pricing, and portfolio allocation decisions, and generally adversely affects the real economy and financial markets (Bloom, 2009; Jurado et al., 2015; Gupta et al., 2018), understanding the source and nature of persistence in uncertainty is crucial in both macroeconomics and finance. Given the recent trend in the usage of climate risks to serve as proxies for rare disaster events (Donadelli et al., 2017, 2021a,b,c; Kotz et al., 2021), we aim to empirically verify the prediction of the theoretical model of Sundaresan (forthcoming), i.e., whether climate risks, capturing unusual events, enhance the degree of persistence in uncertainty.

To achieve this, we implement a regime-based local projections model, along the lines of Gorodnichenko and Auerbach (2013) and Jordà et al. (2020), whereby, we analyse the impact of an economic and policy-related uncertainty shock on itself, under high- and low-states of climate risks. Note that, following the current literature, climate risks are captured by the growth or volatility of the temperature. For our application, we rely on data involving the 50 states of the United States (US) over the monthly period of 1984:03 to 2019:12.

At this stage, it is important to highlight two important issues: First, the choice of the US is driven by the availability of

☆ We would like to thank an anonymous referee for many helpful comments. However, any remaining errors are solely ours.

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[1] In this regard, it must be pointed out that Baker et al. (2020) in fact prescribes the usage of rare disaster risks to measure uncertainty, i.e., there is one-to-one correspondence between the two.

https://doi.org/10.1016/j.econlet.2022.110500

state-level data on uncertainty and climate risks-related variables. Second, we perform a disaggregated, rather than an aggregate analysis involving the overall US, because of the existing evidence of widespread heterogeneity in the impact of uncertainty across the economic variables of the US states (Mumtaz, 2018; Mumtaz et al., 2018).

To the best of our knowledge, this is the first paper to analyse the role of the regimes of temperature growth and its volatility on the persistence of uncertainty based on regional data of the US. The remainder of the paper is organized as follows: Section 2 discusses the data, while Section 3 presents methodology involving a nonlinear LPs model in a panel-setting. The empirical model is then used to obtain climate risks-based-regime-specific impulse response functions (IRFs) for the metric of state-level uncertainty following a shock to itself, in the empirical results segment contained in Section 4. Finally, Section 5 concludes the paper.

2. Data

We rely on the work of Elkamhi et al. (2020) for the state-level measure of economic and policy-related uncertainty (SEPU), which follows the newspaper-based methodology of Baker et al. (2016).[2] Utilizing news articles from Newslibrary.com,[3] Elkamhi et al. (2020) search the number of articles including terms that are related to the following categories: "State-level", "Economic", "Policy", and "Uncertainty". When at least one term from each of the four categories appears in a news article, the authors consider it to be connected to state-level EPU (SEPU). Due to the fact that state newspapers might cover both local and national news at the same time, Elkamhi et al. (2020) remove articles that include information that is representative of a national scope (such as 'congress', 'white house', 'federal reserve').[4] Based on the availability of the SEPU data, our analysis covers the period of 1984:03 to 2019:12.

The data for each state's average temperature (in degrees Fahrenheit) is collected from the National Oceanic and Atmospheric Administration (NOAA).[5] Using the temperature data, we first calculate the month-on-month growth in temperature (*TGrowth*), and then fit the stochastic volatility (SV) model of Kastner and Frühwirth-Schnatter (2014)[6] to obtain the corresponding volatility of state-level temperature (*TGrowth_SV*), as proposed by Alessandri and Mumtaz (2021) in terms of modelling climate volatility.

Considering the potential feedback from the real economy on to uncertainty (Ludvigson et al., 2021), we account for the influence of economic cycles in the estimated model by using the leading indicator of the 50 US states,[7] 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. Furthermore, using the effective Federal funds rate (FFR, derived from the FRED database) from the beginning of our sample period until December 1989 and then the shadow short rate (SSR) until the end of our sample period from January 1990 until the end of our sample period, we are able to capture the impact of monetary policy (IR) on uncertainty (as suggested by Hkiri et al. (2021)). The SSR is based on term-structure models proposed by Wu and Xia (2016).[8] To track the evolution of monetary policy, we use the first-differences of the combined SSR and FFR series. In addition, in line with Gupta and Sheng (2021), who emphasize the relevance of oil shocks in driving US state-level uncertainty, we also incorporate four structural oil shocks, namely, supply, global economic activity, oil-specific consumption demand, and oil inventory demand, based on the work of Baumeister and Hamilton (2019).[9] Finally, to capture the potential spillover of uncertainties across the real economy and oil market (Hailemariam et al., 2019), we also include a measure of oil price uncertainty, as constructed by Nguyen et al. (2021).[10]

3. Methodology

Following Gorodnichenko and Auerbach (2013) and Jordà et al. (2020), we use a regime-dependent model to examine the shock of *SEPU* on itself under high and low regimes of climate risks, i.e., *TGrowth* or *TGrowth_SV*. The econometric framework can be formally outlined as follows:

$$\begin{aligned} SEPU_{i,\ t+s} = {} & \left(1 - F\left(z_{i,t-1}\right)\right)\Bigg[\alpha_{i,s}^{High} + \beta_{i,s}^{High} SEPUshocks_{i,t} \\ & + + \sum_{j=0}^{j=1} \gamma_{i,j,s}^{High} X_{i,t-j} + \sum_{j=0}^{j=1} \delta_{j,s}^{High} Z_{t-j}\Bigg] + F\left(z_{i,t-1}\right) \\ & \times \Bigg[\alpha_{i,s}^{Low} + \beta_{i,s}^{Low} SEPUshocks_{i,t} + + \sum_{j=0}^{j=1} \gamma_{i,j,s}^{Low} X_{i,t-j} \\ & + \sum_{j=0}^{j=1} \delta_{j,s}^{Low} Z_{t-j}\Bigg] + \epsilon_{i,t+s}, \quad \text{for } s = 0, 1, 2, \ldots, H \quad (1) \end{aligned}$$

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

[3] Newslibrary.com covers around 7,000 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.

[4] 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.

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

[6] Letting denote temperature growth by: $y = (y_1, y_2, \ldots, y_T)'$, 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 $v, s \in 1, \ldots, T$. The unobserved process $h = (h_0, h_1, \ldots, h_T)$ 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., $h_0|\mu, \psi, \sigma \sim \mathfrak{N}(\mu, \sigma^2/(1-\psi^2))$. The non-centred parameterization of the model is given by: $y_t \sim \mathfrak{N}(0, \omega e^{\sigma\tilde{h}_t})$, with $\tilde{h}_t = \psi\tilde{h}_{t-1} + v_t$, $v_t \sim \mathfrak{N}(0,1)$, where $\omega = e^{\mu}$. The initial value of $\tilde{h}_0|\psi$ is drawn from the stationary distribution of the latent process, i.e., $\tilde{h}_0|\psi \sim \mathfrak{N}(0, 1/(1-\psi^2))$, and $\tilde{h}_t = (h_t - \mu)/\sigma$. Detailed estimation results for the stochastic-volatility model can be obtained from the authors upon request.

[7] The leading index for each state predicts the six-month growth rate of the state's coincident index, with the latter including four indicators: nonfarm payroll employment, the unemployment rate, average hours worked in manufacturing and wages and salaries. In addition to the coincident index, the leading indicator also includes other variables that lead the economy: state-level housing permits, state initial unemployment insurance claims, delivery times from the Institute for Supply Management (ISM) manufacturing survey, and the interest rate spread between the 10-year Treasury bond and the 3-month Treasury bill.

[8] 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.

[9] The four shocks, as obtained from a structural vector autoregressive (SVAR) model by Baumeister and Hamilton (2019), are based on a less restrictive framework (than traditionally used in the literature following Kilian (2009)), by incorporating uncertainty about the identifying assumptions of the SVAR.

[10] Nguyen et al. (2021) has proposed a novel construction of the oil price uncertainty index that is unconditional on a model. These authors develop a measure of oil price uncertainty as the one-period-ahead forecast error variance of a forecasting regression with SV in the residual terms. The novelty of this construction approach lies in its flexibility in including a large number of additional information that is important in explaining fluctuations in oil prices namely, exchange rate, oil production, global economic condition and comovement in the fuel market.

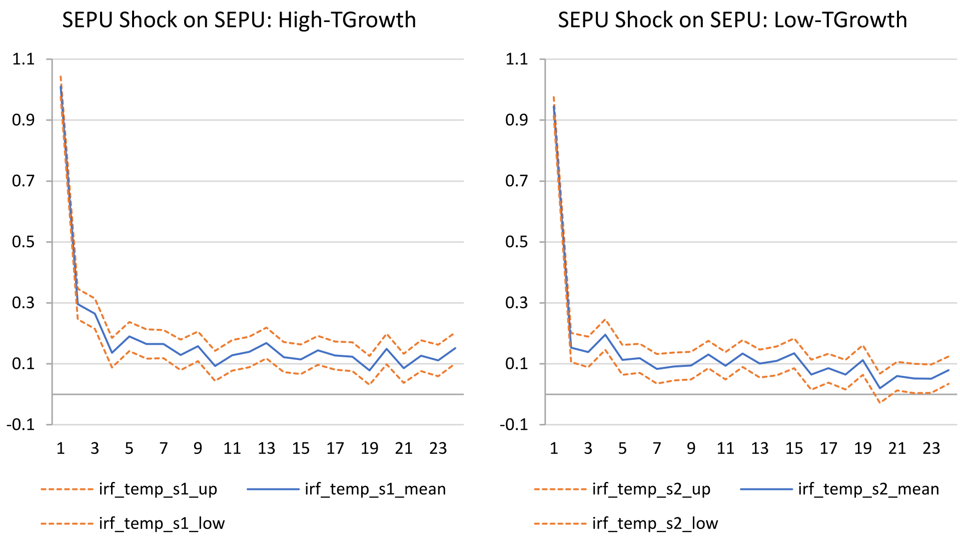

Fig. 1. The Own-Effect of Uncertainty Shock (*SEPU*) under Alternative Regimes of Temperature Growth (*TGrowth*) with Leading Index as a Business Cycles Indicator.
Note: Vertical axis measures the size of the effect, and the horizontal axis the forecast horizon.

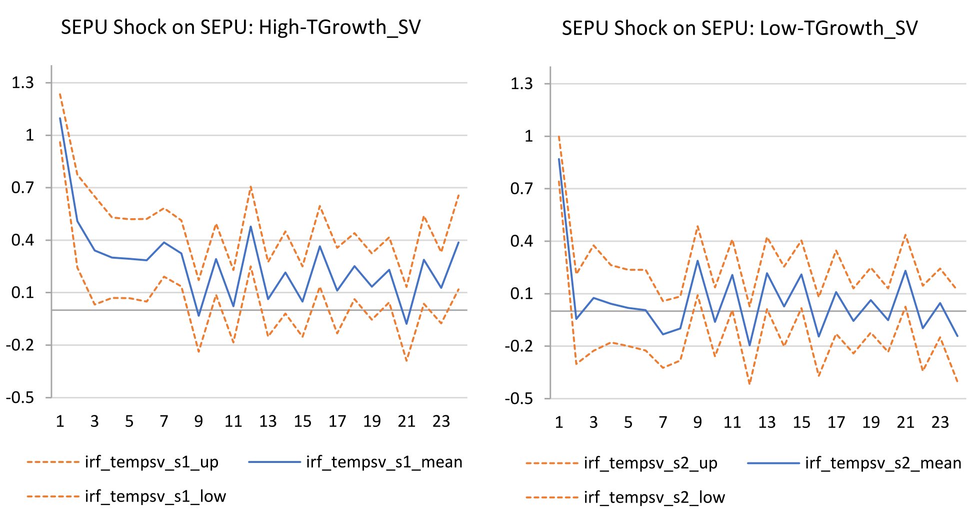

Fig. 2. The Own-Effect of Uncertainty Shock (*SEPU*) under Alternative Regimes of Stochastic Volatility of Temperature Growth (*TGrowth_SV*) with Leading Index as a Business Cycles Indicator.
Note: Vertical axis measures the size of the effect, and the horizontal axis the forecast horizon.

$$F\left(z_{i,t}\right) = \exp(-\gamma z_{i,t})/1 + \exp(-\gamma z_{i,t}),\ \gamma > 0, \tag{2}$$

where $SEPU_{i,t+s}$ represents *SEPU* at t, with s being the forecast horizon.[11] $SEPUshocks_{i,t}$ are the shocks to *SEPU*.[12] A smooth transition function $F\left(z_{i,t}\right)$ is included in the model to distinguish between the high- and low-regimes of the climate risks variables. $z_{i,t}$ is a switching variable capturing state-level climate risks (as measured by *TGrowth* or *TGrowth_SV*) and is normalized to have a zero mean and unit variance. $F\left(z_{i,t}\right)$ is the smooth transition function that has a bound between 0 and 1, with values close to 1 representing the low-climate risk regime, and 0 otherwise. We also control for the contemporaneous and lagged effects of the state-level leading indicator (i.e., X_i), and the same for the national-level variables namely, the first-difference of *IR*, the four structural oil shocks and oil market uncertainty (captured by Z).

Based on our models in Eqs. (1) and (2), we will obtain our conjectured results, if the response of *SEPU* to *SEPU* shocks will persist and also be stronger, under the *High*- compared to the *Low*-regime associated with *TGrowth* or *TGrowth_SV*. We are basically expecting $\beta_{i,s}^{High} > \beta_{i,s}^{Low}$ under both the cases of *TGrowth* or *TGrowth_SV*, considered as transition variable.

4. Empirical results

In Fig. 1, we present the impact of one unit increase in the *SEPU* shock on *SEPU*, under high- and low-regimes of temperature growth (*TGrowth*). As can be seen, the initial impact is relatively stronger, and in general continues to be so over the entire forecast horizon considered, when the states of the US are witnessing higher climate risks. Moreover, while the effect shows a similar pattern, it is clearly more persistent under the high-regime of the climate risk variable, with the same becoming insignificant under the low-regime around the 20th-period after the shock. But, the state-based effect of *SEPU* shock on itself is more prominent in terms of size and persistence, when we use the *TGrowth_SV* (volatility of temperature growth) as the

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

[12] We calculate *SEPU* shocks by running a fixed-effects panel data regression of *SEPU* on its 12 lags.

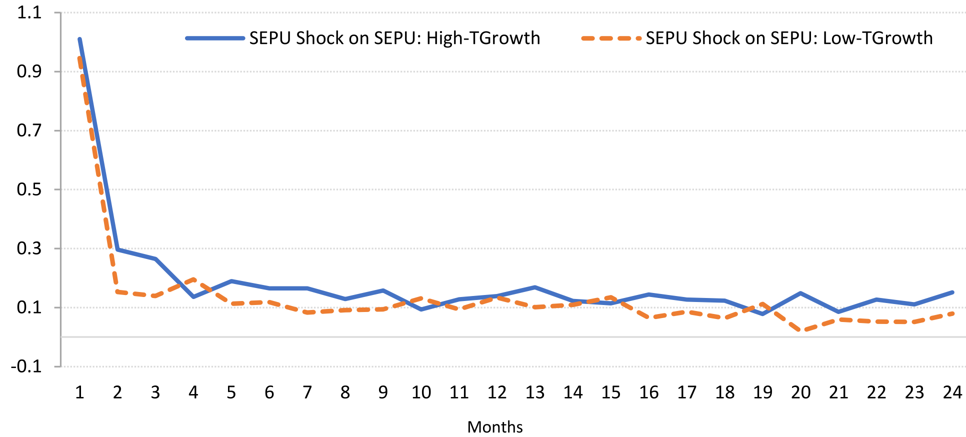

Fig. A.1. The Own-Effect of Uncertainty Shock (*SEPU*) under Alternative Regimes of Temperature Growth (*TGrowth*) Plotted Together with Leading Index as a Business Cycles Indicator.
Note: Vertical axis measures the size of the effect, and the horizontal axis the forecast horizon.

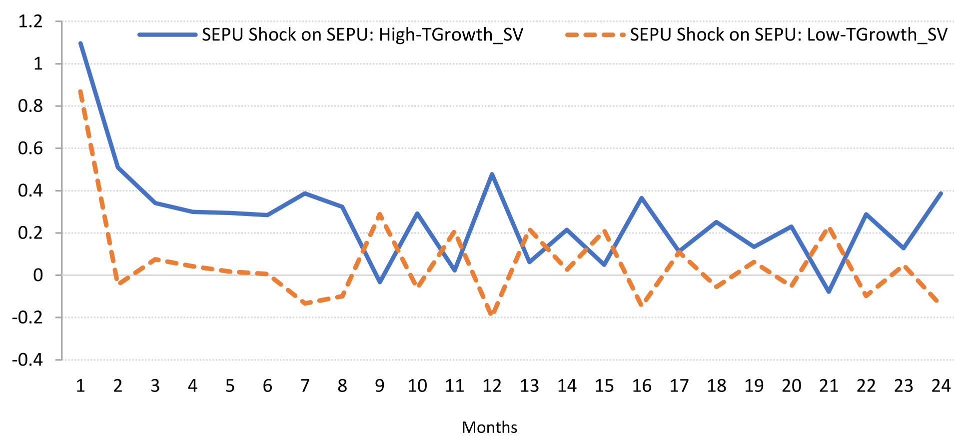

Fig. A.2. The Own-Effect of Uncertainty Shock (*SEPU*) under Alternative Regimes of Stochastic Volatility of Temperature Growth (*TGrowth_SV*) Plotted Together with Leading Index as a Business Cycles Indicator.
Note: Vertical axis measures the size of the effect, and the horizontal axis the forecast horizon.

switch variable in Fig. 2. In fact, under the low-regime associated with temperature volatility, the effect becomes virtually insignificant in the statistical sense after the first-period, i.e., uncertainty persistence is not of concern.[13] To make the findings regarding the strength of the effects and the degree of persistence of *SEPU* across high- and low-regimes of climate risks: *TGrowth* and *TGrowth_SV*, we present the results of Figs. 1 and 2 in Figs. A.1 and A.2, in the Appendix of the paper, without the 95% confidence bands, and the IRFs of the two-regimes together.[14]

Overall, our empirical findings corroborate the predictions of the theoretical model of Sundaresan (forthcoming), in the sense that, heightened rare disaster risks, proxied by climate risks, enhance the degree of persistence in the US state-level newspapers-based-metric of uncertainty. Moreover, similar-sized *SEPU* shocks across regimes of climate risks also tends to have a stronger effect on uncertainty, when temperature growth and its volatility are relatively higher.

5. Conclusion

Recent theoretical developments tend to posit that rare disaster risks enhance the persistence of the process of uncertainty. In light of this, our paper analyses the impact of an economic and policy-related uncertainty shock on itself, under high- and low-states of climate risks (growth in temperature and its volatility), proxying for rare disaster risks. Based on impulse responses derived from a regimes-based model, applied to state-level data of the US over the monthly period of 1984:03 to 2019:12, we find that the degree of persistence of uncertainty is indeed higher under the upper-regime of climate risks compared to its lower-regime, especially when we look at the volatility of temperature growth. Besides this, the magnitude of the effect of an uncertainty shock on uncertainty itself also tends to be higher when climate risks are in their upper state.

Given that uncertainty tends to adversely affect macroeconomic and financial decisions, our results have important implications for policymakers. In particular, policy authorities must be

[13] One possible reason that uncertainty shock in the lower-regime of temperature growth volatility does not affect its persistence is that the effect of temperature growth volatility on *SEPU* is actually insignificant, while temperature growth tends to have a delayed, though short-lived, significant positive impact on *SEPU*. We obtained these findings, which are available upon request from the authors, based on the IRFs of a linear panel data-based LPs model of Jordà (2005) involving *SEPU* as the dependent variable, and the climate risks (*TGrowth* or *TGrowth_SV*), along with the state-level leading index, monetary policy rate, four oil shocks, and oil volatility, as the set of independent predictors.

[14] We conducted a robustness test whereby we replaced the leading indicator with the coincident indicator, also obtained from the FRED database. We found that our results continue to hold under an alternative measure of business cycles, to the extent that they virtually indistinguishable irrespective of whether we use a leading or a coincident indicator of real economic activity. Complete details of these results are available upon request from the authors.

aware that when the economy is witnessing heightened values of disaster risks, and an uncertainty shock hits the economy, expansionary policy responses must be stronger and of longer duration to prevent deep recessions. As part of future research, it would be interesting to extend our state-level analysis to a cross-section of countries, contingent on the availability of continuous data on temperature, given that newspapers-based measure of uncertainty is available for multiple countries.

Appendix

See Figs. A.1 and A.2.

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