Measuring "State-level" Economic Policy Uncertainty*

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Abstract

We develop 50 indices of State-level Economic Policy Uncertainty (SEPU) based on newspaper coverage frequency using 204 million newspaper articles from January 1990 to December 2019. We assess the validity of our measures. Our SEPU indices vary counter-cyclically with respect to state-specific economic conditions, rise before close gubernatorial elections, and exhibit a large cross-sectional variation. We demonstrate that SEPU indices are associated with the cross-sectional variation in state-level GDP, employment, income as well as industry investment decisions. Our findings highlight the importance of economic policy uncertainty at the state level in addition to the nationwide level.

JEL Classification*: D80, G12, G18, L50*

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"The State governments possess inherent advantages, which will ever give them an influence and ascendancy over the National Government, and will for ever preclude the possibility of federal encroachments." – Alexander Hamilton (1757-1804) Secretary of the Treasury speech to the New York Ratifying Convention, June 17, 1788

1 Introduction

The United States is a union of 50 partially self-governing states. There are large differences in the social, economic, and cultural characteristics among individual states, making the U.S. a very diverse country. From an economic point of view, we observe that various industries are concentrated in a handful of states. Figure 1 displays the relative contribution of a given state to the total domestic industry GDP and its cross-sectional variation. As an example, Michigan represents more than 25% of the total GDP generated by the motor vehicle industry.

Not only do individual states have different economic and social characteristics, but they also have different laws and economic policies. Indeed, the U.S. Constitution grants substantial powers to state governments. Therefore, they have a great deal of political discretion in shaping the state's economic environment through a variety of state policies such as taxation, subsidies, and state government spending among many others. This suggests that economic policy uncertainty is likely to vary considerably across U.S. states because of the various political decisions that are made at the state level. Furthermore, changes to state-level economic policy uncertainty are likely to affect the decisions of businesses and individuals residing in the state.[1]

[Insert Figure 1 Here]

[1] See Besley and Case (1995), Pence (2006), Wald and Long (2007), Francis et al. (2010), Atanassov, Julio and Leng (2015), Bird, Karolyi and Ruchti (2017), Çolak, Durnev and Qian (2017), Jens (2017), and Agarwal et al. (2022), among others.

In light of this potential heterogeneity in economic policy uncertainty across states and given the lack of a measure of state-level economic policy uncertainty (SEPU), our aim in this paper is to fill the gap in the literature by providing such a measure.[2] Specifically, we build 50 SEPU indices, one for each of the 50 states in the U.S, using a total of 204 million state newspaper articles from January 1990 to December 2019. Our results demonstrate that our indices capture a degree of uncertainty above and beyond existing measures of nationwide economic policy uncertainty. Therefore, our results contribute to the literature by demonstrating the importance of accounting for state-level economic policy uncertainty when making financial decisions (e.g., investment decisions by firms).

The news-based approach to construct uncertainty indices has been widely used in the literature.[3] Most notably, Baker, Bloom and Davis (2016) (BBD2016, hereafter) develop a nationwide index of economic policy uncertainty (EPU) and demonstrate that the frequency counts of newspaper articles are a reasonable proxy for economic policy uncertainty. Also, as shown by Rogers and Xu (2019), the EPU index provides real-time uncertainty information, unlike regression-based uncertainty indices which rely on either large financial or economic data that is subject to data revisions.

In brief, our methodology is as follows. We modify the approach in BBD2016 to capture economic policy uncertainty at the state level. We count the frequency of articles in the ten largest newspapers in each state that contain the following quartet of terms: (1) “State-level", (2) “Economic", (3) “Policy", and (4) “Uncertainty". Each category has several words, and we count newspaper articles that contain at least one word for each of the four categories. Different from BBD2016, we remove articles that include a word reflective of nationwide information such as “Federal Reserve" or “White House". We do this because state newspapers cover not only local news but also nationwide news which does not necessarily

[2] We refer to State-Level Economic Policy Uncertainty as SEPU, interchangeably.

[3] E.g., Gentzkow and Shapiro (2010), Hoberg and Phillips (2010), Boudoukh, Feldman and Kogan (2013), Alexopoulos and Cohen (2015), Azzimonti (2018), Husted, Rogers and Sun (2020), and Caldara and Iacoviello (2022), among others.

reflect the uncertainty faced by states.

To address the potential concerns about the reliability of our news-based indices, we test the validity of our indices as follows. First, our SEPU indices contain both an idiosyncratic (i.e. state-specific) component and a systematic (i.e. nationwide) component. This is because the national EPU shock could be transmitted to state-level uncertainty or vice versa. We expect that the idiosyncratic component is canceled out when taking the average of the 50 SEPU indices. To test this prediction, we analyze the time variation of the average SEPU across states and find that it has a positive correlation (i.e., a correlation coefficient of 0.58) with the nationwide level of EPU by BBD2016 with peaks around nationwide major economic policy events.[4] This confirms that the average variation in our SEPU indices is consistent with the nationwide economic policy uncertainty.

Second, we examine the cyclicality of our SEPU indices and confirm that they vary counter-cyclically in line with existing theories on economic uncertainty (e.g., Bloom et al., 2018; Benhabib, Liu and Wang, 2016). This result is robust across the various state-level economic output variables examined in this study: real per capita GDP growth rate, total income growth, consumption growth, and unemployment rate. The counter-cyclicality of our indices is also robust to the nine geographic divisions defined by the U.S. Census Bureau.[5]

Third, we use state-level elections to provide the validity of our SEPU indices since state-level elections provide an exogenous source of political uncertainty.[6] Our tests show that changes in the political affiliation of a state legislature and changes in the difference in the political affiliation between a state Senate and House of Representatives are significantly associated with an increase in our SEPU indices. Also, during the 6 months leading up to a gubernatorial election, our SEPU indices increase sharply when the winner and runner-up

[4]The correlation coefficient of 0.58 appears to be reasonable given that (1) we calculated the SEPU indices using a different set of local newspapers rather than the major national newspapers as in Baker, Bloom and Davis (2016); (2) we removed articles that include nationwide information.

[5]The nine divisions are East North Central, East South Central, Mid-Atlantic, Mountain, New England, Pacific, South Atlantic, West North Central, and West South Central.

[6]E.g., Atanassov, Julio and Leng (2015), Bird, Karolyi and Ruchti (2017), Çolak, Durnev and Qian (2017), Jens (2017), and Agarwal et al. (2022), among others.

candidates are separated by a small difference in the percentages of votes.

Fourth, we correlate our SEPU indices with state-level natural disasters to validate our SEPU indices because natural disasters are exogenous shocks that could directly raise the level of state economic policy uncertainty (e.g., Henriet, Hallegatte and Tabourier, 2012; Ludvigson, Ma and Ng, 2020; Baker, Bloom and Terry, 2022). We find that the level of our state-level economic policy uncertainty indices is positively and significantly correlated with state-level exogenous natural disaster events that caused human losses. Overall, these results provide evidence that supports the validity of our measures in capturing state-level uncertainty (e.g. our indices are positively related to events that are known to increase uncertainty such as state-wide political elections or natural disasters).

Next, we show that our indices exhibit a large cross-sectional variation. This is a necessary condition for our measures to be associated with a cross-sectional variation in the state- and firm-level economic variables. For this reason, we perform the following tests. First, for each state, we examine the time-series properties of our SEPU indices against state-specific major events related to economic policy. We find that our SEPU indices notably align with major state-specific events. For example, the Florida SEPU index peaks with hurricane events while the Texas SEPU index peaks when there is a large oil price drop.[7] This suggests that our SEPU indices carry important information on state-specific economic policy uncertainty that arises from state-specific geopolitical and economic conditions. Second, more formally, we compute the cross-correlation across 50 SEPU indices and find that the average of correlation coefficients is 0.16, which implies a quite large cross-sectional variation in SEPU indices. Third, we examine the correlation between each SEPU index

[7]For example, in the aftermath of Hurricane Michael, the Florida Department of Economic Opportunity (DEO) launched the Small Business Emergency Bridge Loan Program to provide short-term, interest-free loans to affected businesses. They approved a Disaster Preparedness sales tax holiday that exempts from sales taxes qualifying items related to disaster preparedness. In Texas, the government has to either cut expenditures or increase taxes when there is an oil/gas shock which causes uncertainty about the state's budget. This is because taxes from natural resources account for a large portion of the Texas budget (oil production taxes account for 6.1%, and natural gas production taxes account for 2.7% of the total budget, source: Texas Tribune, April 22nd, 2020).

and the national EPU by BBD2016. We find that the average of correlation coefficients is 0.26. Taken together, our examination of a cross-sectional variation uncovers that our SEPU indices exhibit a meaningful cross-sectional variation.

Having empirically established a large cross-sectional variation in SEPU indices, we expect our SEPU indices to be associated with economic activities at both state and firm levels beyond what can be explained by the national EPU. Our intuition hinges on the fact that while the national EPU captures well the overall uncertainty in the U.S., a State-level Economic Policy Uncertainty index can capture state-specific shocks that affect only a particular part of the economy (e.g., a shock in Michigan is likely to affect the Motor vehicle industry). To analyze this prediction, we conduct two different tests.

First, we evaluate whether our SEPU indices shocks are related to future state-level economic fluctuations, which would make them consistent with economic theories predicting the dynamic impact of uncertainty on economic output.[8] We employ a panel VAR setting and study the dynamic response of real output variables to SEPU shocks, controlling for state and time-fixed effects. We show that a unit standard deviation shock to our SEPU indices significantly decrease state GDP, employment, and income with a maximum drop of 0.20% in GDP, 0.17% in employment, and 0.14% in income. Moreover, shocks to SEPU have long-lasting effects on state-level economic output variables.

Second, given the substantial importance of state government policy for firms' decisions, we test whether SEPU indices are associated with firms' economic activities. Since it is challenging to precisely identify the location of firms' economic activities, we rely on industry-level data where we can observe the location of operations. Based on the relative contribution of each state to an industry's GDP, we construct 63 industry-specific economic policy uncertainty indices.[9] We find that our industry-specific EPU indices line up with the realized volatility of industry equity returns. We also show that our industry-specific EPU

[8] E.g., Bernanke (1983), Bloom (2009), and Bloom et al. (2018).

[9] For this exercise, we use the state GDP by industry data from the Bureau of Economic Analysis (BEA) where industries are classified by 63 the North American Industry Classification System (NAICS).

indices are negatively related to the subsequent year's investment decisions at the industry level, consistent with the theoretical and empirical literature showing a negative relationship between investment and uncertainty (e.g., Julio and Yook, 2012; Gulen and Ion, 2015). Moreover, we find that industry-specific EPU indices are significantly associated with one-month-ahead industry equity returns. In general, our tests show that our SEPU indices are useful in understanding both state- and firm-level economic activities beyond what can be explained by the national EPU.

Overall, our results show the importance of considering state-level economic policy uncertainty. However, we do not claim that our measures capture exogenous changes in economic policy uncertainty at the state level. It is well established both theoretically and empirically that uncertainty and economic fundamentals are closely linked to each other.[10] Our measures vary as an endogenous response to economic fundamentals, and it is challenging to filter out endogenous variations in order to obtain only exogenous variations of uncertainty. Therefore, our measures should not be used for causal inference without a plausible empirical strategy.[11] For causal inference, one can use gubernatorial elections instead, as the literature establishes gubernatorial elections as an important exogenous source of political uncertainty at the state level (e.g., Atanassov, Julio and Leng, 2015; Bird, Karolyi and Ruchti, 2017; Çolak, Durnev and Qian, 2017; Jens, 2017; Agarwal et al., 2022).

Our paper contributes to the literature in the following ways. First, the key contribution of our work is to provide researchers with a set of monthly indices of economic policy

[10] See Bloom (2009), Baker, Bloom and Davis (2016), Bloom et al. (2018), Baker, Bloom and Terry (2022), and Ludvigson, Ma and Ng (2021), among others.

[11] One may consider a narrative approach as in Romer and Romer (2010) and Giroud and Rauh (2019) to filter out endogenous variations in our measures using the narrative record such as politicians' speeches and Congressional reports. However, it is not feasible to employ this approach in our setting. This is because our measures vary due to multiple sources of economic policies, and thus it is not possible to identify a variation that is driven by endogenous policies.

uncertainty for each of the 50 states.[12] Second, we show that our indices are significantly associated with the cross-sectional variation across states of GDP, employment, and income. Third, we construct 63 industry-specific EPU indices based on the GDP exposure of industries to each state. Fourth, we show that these indices are instrumental in understanding industry-specific GDP, investment, and equity returns. Overall, our paper shows the importance of accounting for state-level economic policy uncertainty, which differentiates it from the existing literature focusing on the nationwide economic uncertainty.[13]

Our study is related to the literature that establishes the importance of the state-level policy uncertainty (e.g., Atanassov, Julio and Leng, 2015; Bird, Karolyi and Ruchti, 2017; Çolak, Durnev and Qian, 2017; Jens, 2017; Agarwal et al., 2022). Studies in this literature focus on policy uncertainty that exogenously arises from gubernatorial elections. Our study complements these studies by providing continuous proxies of state-level economic policy uncertainty that could accommodate various sources of economic policy uncertainty in addition to local elections.

A subsequent study by Baker, Davis and Levy (2022) also uses state-level local newspapers to construct state-level EPU measures. As in our paper, they find large cross-sectional heterogeneity in economic policy uncertainty, an increase in state-level EPU around guber-

[12]More broadly, our state-level economic policy uncertainty indices can be used to examine the role of geographical factors that include the study of state-level business cycles (e.g., Crone, 2005; Crone and Clayton-Matthews, 2005; Owyang, Piger and Wall, 2005; Hamilton and Owyang, 2012; Caliendo et al., 2018), local labor market condition (e.g., Topel, 1986; Gyourko and Tracy, 1989; Autor, Dorn and Hanson, 2013; Dix-Carneiro and Kovak, 2015; Dao, Furceri and Loungani, 2017; Manning and Petrongolo, 2017; Bloom et al., 2019), implications of geography for stock returns (e.g., Pirinsky and Wang, 2006; Keida and Rajgopal, 2009; García and Norli, 2012; Kim, Pantzalis and Park, 2012; Smajlbegovic, 2019; Parsons, Sabbatucci and Titman, 2020), corporate decisions (e.g., Almazan et al., 2010; Becker, Ivković and Weisbenner, 2011; John, Knyazeva and Knyazeva, 2011) and trading behaviors of local investors (e.g., Coval and Moskowitz, 1999, 2001; Grinblatt and Keloharju, 2001; Huberman, 2001; Massa and Simonov, 2006; Hong, Kubik and Stein, 2008; Seasholes and Zhu, 2010; Bernile, Kumar and Sulaeman, 2015; Gargano and Rossi, 2018; Bhamra, Uppal and Walden, 2019). As we point out, our measures are not exogenous. Therefore, our measures could be useful for the literature where causal inference is not necessary such as studies that examine the determinants of uncertainty (e.g., Baker et al., 2014; Białkowski, Dang and Wei, 2022), the asset pricing literature (e.g., Brogaard and Detzel, 2015; Bali, Brown and Tang, 2017; Bali, Subrahmanyam and Wen, 2021), and studies that need to identify policy-sensitive stocks (e.g., Akey and Lewellen, 2017).

[13]E.g., Jurado, Ludvigson and Ng (2015), Baker, Bloom and Davis (2016), and Bekaert, Engstrom and Xu (2022), among others.

natorial elections, and declines in state-level economic outputs following shocks to state-level EPU.[14] Their work is different from ours in the following ways. First, they separate national EPU from local EPU for each state. Second, they use a different source of the newspaper archive. Third, they extend the sample period.

The rest of the paper proceeds as follows. Section 2 discusses the related literature. Section 3 explains how we measure SEPU indices. Section 4 performs the validation of our indices. Section 5 examines the cross-sectional variation in our indices. Section 6 tests whether our indices are related to economic activities. Section 7 concludes the paper.

2 Related Literature

A large body of theoretical research on economic uncertainty has documented the important role of economic uncertainty shocks in explaining aggregate economic output (e.g., Bloom, 2009; Bachmann and Bayer, 2013; Sim et al., 2010; Leduc and Liu, 2016; Basu and Bundick, 2017; Bloom et al., 2018). There are multiple mechanisms through which economic uncertainty shocks can lead to large fluctuations in aggregate economic output. First, at the firm level, economic uncertainty shocks lead firms to be more cautious about their investment. Therefore, firms adopt a 'wait-and-see' policy and rapidly reduce hiring and investment (e.g., Bernanke, 1983; Bloom, Bond and Reenen, 2007). Moreover, greater uncertainty raises financing costs which reduce both micro and macro growth in the presence of financial frictions (e.g., Christiano, Motto and Rostagno, 2014; Sim et al., 2010; Arellano, Bai and Kehoe, 2019). Second, at the household level, economic uncertainty shocks cause households to increase precautionary savings and reduce their consumption expenditure (e.g., Leland, 1968; Kimball, 1990; Carroll and Samwick, 1998).

One of the main empirical challenges in evaluating theories on uncertainty is that economic uncertainty is a latent variable and thus not observable. Therefore, empirical studies

[14] The first version of our paper was posted to the Social Science Research Network (SSRN) in November 2020. Baker, Davis and Levy (2022) was posted to SSRN in February 2022.

have mostly relied upon proxies of uncertainty. Bloom (2009) is an early study that uses the stock market volatility (VIX) as a proxy for uncertainty and documents that uncertainty shocks have a large negative impact on economic output. Stock volatility has a lot of merits because the stock market reflects all relevant information about the economic condition, and stock market volatility can be easily computed based on publicly available data at a high frequency. However, stock market volatility may not be closely linked to economic uncertainty. This is because time-varying stock market volatility could reflect time-varying risk preferences of market participants (Constantinides, 1990; Campbell and Cochrane, 1999), sentiment (Baker and Wurgler, 2006), or changes in firms leverage (Black, 1976), without a change in economic uncertainty. To overcome this issue, Jurado, Ludvigson and Ng (2015) introduce new indices of economic uncertainty using a common variation in the unpredictable components of a large set of macro and financial data and show that shocks to their indices are associated with large declines in real activity, which is more significant than the effect of stock volatility.

In an influential paper, Baker, Bloom and Davis (2016) develop an index of news-based economic policy uncertainty based on the frequency of news articles that contain terms related to economic policy uncertainty. They show that their index spikes during major economic policy events. Also, shocks to economic policy uncertainty are associated with declines in the firm's investment, economic output, and employment. They show that an increase in economic policy uncertainty is associated with higher stock volatility, consistent with the theoretical prediction of Pástor and Veronesi (2012) and Pástor and Veronesi (2013). They also find that economic policy uncertainty is more important than economic uncertainty in explaining firm-specific movements in stock volatility.

Our paper is related to Baker, Bloom and Davis (2016) as we also try to quantify economic policy uncertainty using newspaper coverage frequency. We differ from their paper in that our work focuses on the cross-sectional variation in economic policy uncertainty across states over time. Many economic variables are state-specific (e.g., income, unemployment, GDP, etc.), and the literature is currently missing a state-specific measure of uncertainty that can be used to study the effect of uncertainty on such variables. We fill this gap by providing state-specific indices of economic policy uncertainty. We also show that our indices are strongly associated with state-specific time variation in economic variables which the national EPU index cannot explain by construction.

There are a few recent papers that focus on local economic uncertainty (e.g., Shoag and Veuger, 2016; Maggio et al., 2017; Mumtaz, Sundeer-Plassmann and Theophilopoulou, 2018; Mumtaz, 2018). Studies in this literature show the importance of local economic uncertainty in explaining not only local economic activities but also aggregate economic activities. Our work is similar to Shoag and Veuger (2016) which quantify state-level economic policy uncertainty from 2006 through 2009 and find that the cross-sectional variation in a state-level uncertainty is strongly correlated with the cross-sectional variation in the change in the unemployment rate. However, we differ from Shoag and Veuger (2016) in the following important ways. First, Shoag and Veuger (2016) measure the state-level economic policy uncertainty only during the 2007-2008 recession in a cross-sectional setting. In contrast, we provide 50 indices for the longest possible time periods from 1990 to 2019 in a panel setting. Second, Shoag and Veuger (2016) only focus on unemployment changes in a cross-sectional regression setting, whereas we examine both state- and industry-level economic activities in a panel regression setting.

3 Measuring State-level EPU indices

In this section, we describe how we develop novel indices of state-level economic policy uncertainty for all 50 U.S. states based on state newspaper coverage frequency. Our source for news articles is Newslibrary.com, a comprehensive online archive of state newspapers. Newslibrary.com covers around 7,000 newspapers with more than 274 million newspaper articles for 50 U.S. states as well as the District of Columbia, Puerto Rico, Guam, U.S. Virgin

Islands, and American Samoa.

There are several challenges in developing an uncertainty index using state-level newspapers. First, not all available newspapers are relevant to economic policy uncertainty. This is because some newspapers mainly cover topics such as health, sports, travel, and religion. Second, it is possible that some newspapers are politically biased, and overstate or understate the degree of uncertainty depending on their political inclination. To address these issues, we select the set of newspapers in the following ways. We first remove newspapers whose focus is on health, sport, travel, and religion. Then, among the remaining newspapers, we select the ten largest ones in terms of the total number of articles within a five-year period. We repeat this procedure every five-year window, and therefore the composition of newspapers for each state changes every five years. This procedure helps to (1) filter out newspapers unrelated to economic policy uncertainty, (2) mitigate the potential bias caused by including only a few newspapers with a biased political view, and also (3) reduce noise that could arise from the inclusion of small newspapers. This process leaves 204,489,924 articles from 50 states.

Next, using selected newspapers, we search for the number of articles containing words that are related to the following four categories: (1) “State-level", (2) “Economic", (3) “Policy", and (4) “Uncertainty". Each category has a list of words. In order to be counted as an article related to state-level economic policy uncertainty, there should be at least one word for each of the four categories. In doing so, given that state newspapers could cover not only local news but also nationwide news at the same time, we remove articles that include a word reflective of nationwide information such as “Federal Reserve" or “White House". The full list of words used to select articles according to our methodology is reported in Table 1. It is important to note that this step unavoidably removes nationwide articles that also affect the degree of state-level economic policy uncertainty. Therefore, our SEPU indices understate the degree of economic policy uncertainty that arises from the national level faced by each of the U.S. states. However, this does not imply that our indices reflect only idiosyncratic state-specific economic policy uncertainty that is independent of the national EPU. This is because a shock that affects the national EPU may also affect the level of state EPU for a particular state or vice versa. In Subsection 4.1, we present evidence supporting this argument.

[Insert Table 1 Here]

Following BBD2016, we proceed to create an index of economic policy uncertainty for each state as follows. (1) We scale raw counts by the total number of articles for each newspaper. This is to ensure that our measure is not driven by the time variation in overall volumes of newspapers. (2) We then normalize each scaled monthly newspaper-level time series to unit standard deviation. (3) For each month and each state, we average across newspapers. Finally, (4) we normalize each state-level time series to a mean of 100.

4 Validation of State-level EPU indices

A potential concern of a news-based measure of economic policy uncertainty is measurement error. It is possible to erroneously count articles that are not relevant to economic policy uncertainty. It is also possible to remove articles that are relevant to economic policy uncertainty. Given this potential concern, in this section, we perform the validation of our SEPU indices. Because of the unobservable nature of economic policy uncertainty, it is challenging to assess our SEPU indices but we provide several tests to support the validity of our measures.

4.1 Average time variation

We first examine the average time variation in SEPU indices. This is to assess whether the average state economic policy uncertainty is consistent with the nationwide uncertainty.

Since 50 states make up the entire U.S., we can expect that the average time variation in uncertainty would reflect the nationwide uncertainty.

Figure 2 displays the time series of the average of 50 SEPU indices. The blue straight line represents the GDP-weighted average SEPU indices. The orange dashed line represents the equal-weighted average SEPU indices. The figure shows that for both GDP-weighted and equal-weighted averages, our 50 SEPU indices notably peak around important nationwide major events related to economic policy such as Black Monday, Gulf War, September 11 attack, the Lehman Brothers bankruptcy, the Troubled Asset Relief Program (TARP), debt ceiling dispute, and government shutdown as well as NBER recessions. The correlation between the GDP-weighted (equal-weighted) average SEPU indices and the national EPU by BBD2016 is 0.5783 (0.5038). This suggests that our indices exhibit a time variation that is close on average to that of the nationwide economic policy uncertainty. Since our indices understate the degree of economic policy uncertainty that arises from the national level by removing articles about nationwide information, these correlation coefficients are to be interpreted as a lower bound of the correlation between average SEPU indices and the national EPU.

We emphasize that our SEPU indices do not capture only idiosyncratic state-specific economic policy uncertainty that is orthogonal to the national EPU. Rather, our indices measure economic policy uncertainty faced by each of the U.S. states. A shock that increases the SEPU index for a particular state might (or might not) be caused by the same factor affecting the national EPU. Some state-specific shocks are relevant not just for a particular state but also nationwide (e.g., a large shock to oil prices is associated with an increase in both the Texas SEPU index as well as the national EPU index of BBD2016). It follows that our SEPU indices on average are positively correlated with the nationwide economic policy uncertainty measure, and they reflect on average the degree of economic policy uncertainty faced by the U.S. as a whole.

[Insert Figure 2 Here]

4.2 Counter-cyclical feature

One of the key features of economic uncertainty that has been documented by the existing literature is its counter-cyclical time variation. Previous studies provide economic mechanisms through which economic uncertainty exhibits a counter-cyclical time variation. Shocks to economic uncertainty can lead to a contraction in economic output (e.g., Bloom, 2009; Bachmann and Bayer, 2013; Sim et al., 2010; Leduc and Liu, 2016; Basu and Bundick, 2017; Bloom et al., 2018). This is because uncertainty shocks lead firms to be more cautious and reduce investment as well as hiring. An increase in uncertainty also leads households to reduce their consumption. Furthermore, other studies on economic uncertainty demonstrate that economic uncertainty rises due to bad economic outcomes (e.g., Bloom, 2009; Jurado, Ludvigson and Ng, 2015; Bekaert, Engstrom and Xu, 2022). Hence, a reasonably constructed economic uncertainty index should exhibit a counter-cyclical variation.

To assess whether SEPU indices vary counter-cyclically, we use four economic output variables available at the state level: growth rate of real per capita GDP (yearly), total income growth (quarterly), consumption growth (yearly), and unemployment rate (monthly). We compute the correlation between our SEPU indices and these economic output variables by nine U.S. Census Bureau divisions: East North Central, East South Central, Mid-Atlantic, Mountain, New England, Pacific, South Atlantic, West North Central, and West South Central. Table 2 reports the average correlation coefficient for each division. The result shows that our SEPU indices are negatively correlated with GDP, income, and consumption growth rate and also positively correlated with the unemployment rate, exhibiting a statistically significant counter-cyclical variation for all four economic output variables considered in this table. Importantly, this result is robust to all U.S. census divisions. Therefore, our indices are consistent with a key feature of economic uncertainty, in line with existing theoretical and empirical findings.

[Insert Table 2 Here]

4.3 State-level Election

Prior studies regard state-level elections as an important source of local political uncertainty (e.g., Atanassov, Julio and Leng, 2015; Bird, Karolyi and Ruchti, 2017; Çolak, Durnev and Qian, 2017; Jens, 2017; Agarwal et al., 2022). This is because policy decisions could depend on politicians' preferences (Peltzman, 1987; Besley and Case, 1995), and uncertainty arises due to the unpredictability of *who* will make *what* policy actions, and to *which* extent. Therefore, in this subsection, we rely on the state-level election to assess the validity of our SEPU indices.

We aim to understand how our SEPU indices are related to political uncertainty leading up to elections. Do SEPU indices increase (i.e. state-level uncertainty increases) when there is high political uncertainty? Or do they decrease? To capture political uncertainty that arises from local elections, we use the following variables related to political affiliations of local politicians. First, we use the change in the political affiliation of the governor defined as $(\Delta Governor_{s,t})^2$, where $Governor_{s,t}$ is a dummy variable that takes a value of one for a Democratic governor in a given month and a state. Second, we use the change in the political affiliation of a state legislature defined as $(\Delta Legislature_{s,t})^2$, where $Legislature_{s,t}$ is the fraction of Democrats in a state's legislature (both House of Representatives and Senate).[15] Third, we use the change in the difference between the political affiliation of the governor and that of the state legislature, $(\Delta(Governor_{s,t} - Legislature_{s,t}))^2$. This variable varies from 0 (governor and majority of the legislature belong to the same party and the

[15] We use the Book of the States to gather this information.

majority party in the legislature has 100% of the seats) to one (governor and majority of the legislature belong to different parties and the majority party in the legislature has 100% of the seats). Fourth, we build the change in the difference between the political affiliation of the state Senate and the House of Representatives which we define as $(\Delta(\textit{Senate}_{s,t} - \textit{House}_{s,t}))^2$, where $\textit{Senate}_{s,t}$ is the fraction of Democrats in Senate, and $\textit{House}_{s,t}$ is the fraction of Democrats in the House of Representatives.

We also use election-related variables. First, we expect policy uncertainty to be higher when there is a close election, with the winner and runner-up being separated by a small difference in their votes. This is because opposing parties/candidates are likely to have different proposals in terms of economic policies. To capture a close election, we first build a dummy variable *6-month prior election*$_{s,t}$ which takes a value of one for any observation within 6-month periods before a state gubernatorial election. A close election is identified by the interaction of *6-month prior election*$_{s,t}$ with the percentage vote difference between winner and runner up, *Vote difference*$_{s,t}$.

Second, Jens (2017) and Agarwal et al. (2022) point out that term limits create political uncertainty since there is more information about incumbent governors. To evaluate whether our indices reasonably increase when the incumbent is subject to a term limit, we create a dummy variable that takes a value of one if the incumbent is subject to a term limit, *Term limit*$_{s,t}$, and interact with the election dummy variable.

Using the aforementioned variables related to either political affiliations of local politicians or elections, we run the following monthly panel regression with time- and state-fixed effects:

$$Log(1 + SEPU_{s,t}) = \alpha + \beta X_{s,t} + \gamma Economic\_output_{s,t} + \theta_t + \psi_s + \epsilon_{s,t}, \tag{1}$$

where $SEPU_{s,t}$ is the state-level economic policy uncertainty index for state s in month t, $X_{s,t}$ is one of the variables related to either political affiliations of local politicians or elections, described above, $Economic\_output_{s,t}$ is a vector of state-level economic output variables that include state real per capita GDP growth rate, real per capita total income growth rate, and unemployment rate, θ_t is the vector of coefficients for time-fixed effects, and ψ_s is the vector of coefficients for state-fixed effects. We control for economic output variables to mitigate the potential omitted variables bias that might arise from the fact that our SEPU indices vary over time in association with state-level economic conditions.

Table 3 reports the results of the regression model specified in Equation (1). The results show that the change in the political affiliation of a state legislature $(\Delta Legislature_{s,t})^2$ and the change in the difference between the political affiliation of the state Senate and the House of Representatives $(\Delta(Senate_{s,t} - House_{s,t}))^2$ are significantly associated with an increase in the SEPU indices. The coefficients are significant at the 1% level. Moreover, the impact of $(\Delta Legislature_{s,t})^2$ is higher in states where legislators are full time workers. These results show that our SEPU indices strongly reflect an increase in economic political uncertainty that arises from a political impasse that often happens when the state Senate and House have majorities belonging to two opposing parties. Moreover, Column (6) shows that during 6-month before a gubernatorial election, state-level economic policy uncertainty is higher as the difference between the percentages of votes obtained by the first- and second-place candidates is smaller. Finally, Column (7) shows that state-level EPU increases further before elections when the incumbent governor is not eligible for re-election, in line with Jens (2017) and Agarwal et al. (2022). These empirical results imply that our measure properly captures changes in policy uncertainty that arise from state-level elections.

In addition, our results also show that the variables $\Delta(Governor_{s,t})$ and $(\Delta(Governor_{s,t} - Legislature_{s,t}))^2$ are not significant. These results can be interpreted in light of the responsibilities that governors have and the process that states legislators need to follow in order to approve laws to implement new economic policies. Two of the governor's main responsibilities are to influence the legislative process through an executive budget proposal and propose a policy agenda. Although the governor has the power to propose new laws, the primary lawmaker is the state legislature which has the mandate to write and approve bills. This means that uncertainty about the ability of the legislature to pass new laws (captured by the variable $(\Delta(Senate_{s,t} - House_{s,t}))^2$) leads to more uncertainty than having a Governor belonging to a party and the legislature (both Senate and House of Representative) to another. This seems reasonable because when the majority's legislature belongs to the same party, we should expect less uncertainty about policy decisions compared to the case when the partisan composition is split (i.e., Senate majority to one party and House Representative majority to another). In the latter case, the two chambers are likely to delay the approval of bills. In other words, our results show that there is an increase in uncertainty only when there is a high probability of a political impasse due to a split partisan composition. A change in either governor or a split between a governor and legislator composition is not related to an increase in political uncertainty.

[Insert Table 3 Here]

4.4 Natural Disasters

Another important source of uncertainty is natural disasters (e.g., Henriet, Hallegatte and Tabourier, 2012; Ludvigson, Ma and Ng, 2020; Baker, Bloom and Terry, 2022). Local-level natural disasters are exogenous shocks that could directly raise the level of state economic policy uncertainty. Therefore, in this subsection, we rely on state-level natural disasters to validate our SEPU indices. Specifically, we examine the association between state-level natural disasters and state-level economic policy uncertainty. To this end, we exploit the Spatial Hazard Events and Losses Database (SHELDUS), available from the Center for Emergency Management and Homeland Security at Arizona State University. SHELDUS is a rich database of natural hazards that covers 18 types of hazards at the county level. The database provides information on the date of an event, the affected location, and the direct losses caused by the event, such as property and crop losses, injuries, and fatalities, starting from 1960 to the present. We focus on injuries and fatalities to measure the intensity of natural disasters (e.g., Kahn, 2005; Kellenberg and Mobarak, 2008; Bernile, Bhagwat and Rau, 2017). Therefore, we use the following variables for natural disasters: (1) a dummy variable that takes a value of one for a state that experienced natural disasters in the previous 12 months where the duration of the events that caused injuries and fatalities is in the top 1%; (2) a dummy variable that takes a value of one for a state that experienced natural disasters in the previous 12 months where the number of injuries and fatalities per capita caused by the events is in the top 1%; (3) the duration of natural disasters that caused injuries and fatalities in the previous 12 months; (4) the number of injuries and fatalities per capita caused by natural disasters in the previous 12 months.[16]

Using the aforementioned natural disasters-related variables, we run the following monthly panel regression with time- and state-fixed effects:

$$Log(1 + SEPU_{s,t}) = \alpha + \beta X_{s,t} + \gamma Economic\_output_{s,t} + \theta_t + \psi_s + \epsilon_{s,t}, \tag{2}$$

where $SEPU_{s,t}$ is the state-level economic policy uncertainty index for state s in month t, $X_{s,t}$ is one of the natural disasters-related variables described above, $Economic\_output_{s,t}$ is a vector of state-level economic output variables that include state real per capita GDP growth rate, real per capita total income growth rate, and unemployment rate, θ_t is the vector of coefficients for time-fixed effects, and ψ_s is the vector of coefficients for state-fixed effects.

Table 4 reports the results of the regression model specified in Equation (2). Column (1) shows that natural disaster events in the previous 12 months where the duration of the events that caused injuries and fatalities is in the top 1% are significantly associated with a higher level of state-level economic policy uncertainty. Consistent with this finding, Column

[16]We use the top 1% threshold since 96% of our sample has at least one injuries or fatalities caused by a natural disaster.

(3) shows that the duration of natural disasters that caused injuries and fatalities is positively and significantly associated with the level of state-level economic policy uncertainty. However, Columns (2) and (4) show that the number of injuries and fatalities is not significantly associated with the level of state-level economic policy uncertainty. This finding appears to be reasonable because human injuries and fatalities are more likely to lead to significant concerns among local politicians and trigger economic policy uncertainty when natural disasters have caused injuries and fatalities for a longer period of time. Therefore, we find that the level of our state-level economic policy uncertainty indices is reasonably correlated with exogenous local natural disaster events that caused human losses, which further supports the validity of our indices.

[Insert Table 4 Here]

Overall, in this section, we provide compelling evidence that our SEPU indices capture state-level economic policy uncertainty with a time variation that is consistent with changes in macroeconomic conditions, state-level business conditions, state-level political environment due to elections, and state-level natural disasters.

5 Cross-sectional variation in State-level EPU indices

We have so far conducted the validation of our indices and provided evidence that they capture state-level economic policy uncertainty. In what follows, we study the cross-sectional variation in our SEPU indices to gauge how much each SEPU carries independent variation. A large cross-sectional variation in our state-level economic policy uncertainty indices is important since it allows us to examine the cross-sectional association between our indices and various state-level economic variables. For this purpose, we first examine whether our SEPU indices reflect state-specific economic policy-related events. Figure

3 plots the SEPU indices for California, Florida, and Texas, as an example, together with major economic and policy events in each state. The figure shows that our SEPU indices increase during major state-specific events that clearly raise policy concerns at the state level. For example, the California SEPU index shows clear spikes around California-specific events such as the Great Bond Massacre in 1994, the electricity crisis in 2001, and the California budget cut in 2011. As for Florida, the index peaks with hurricane events and Florida-specific events such as the 1989 Miami riot and the West Palm Beach Anthrax attack in 2009. For Texas, it is clear that oil and energy events are closely related to spikes in Texas SEPU. This illustrates that our indices reflect state-specific uncertainty that is not necessarily captured by the nationwide economic uncertainty.

[Insert Figure 3 Here]

Next, we more formally study the cross-sectional variations across state-level EPU indices by examining the cross-correlation of 50 indices. Figure 4 plots a heatmap that visualizes the correlation matrix for 50 SEPU indices where the cross-correlation coefficients are transformed to the color scale. We do not report the states in alphabetical order, rather we cluster states based on their correlations using Hierarchical Clustering and report them based on the proximity of their correlations. The figure shows that overall, the cross-correlations across SEPU indices are small, and there are a handful of states whose uncertainty indices are highly correlated. For example, New Jersey, Virginia, and Washington have uncertainty indices that are highly correlated with each other, and the same is true for Georgia and Alabama. Overall, Figure 4 shows that the cross-correlation coefficients are sparsely distributed, consistent with the idea that each individual state in the U.S. has its own characteristics.

[Insert Figure 4 Here]

We then plot the sample distribution of the cross-correlation coefficients. Panel A of Figure 5 displays the distribution. The cross-correlation coefficients are almost symmetrically distributed around the mean of 0.1615, consistent with the heatmap displayed in Figure 4. The maximum correlation coefficient is 0.4640, and the minimum is -0.1568. This evidence strongly supports that our SEPU indices exhibit a large cross-section variation, which suggests that each index reflects a quite independent variation.

As another way to examine the cross-sectional variation across SEPU indices, we investigate the extent to which our SEPU indices carry state-specific information that cannot be explained by the national EPU by BBD2016. To this end, we examine the sample distribution of the correlation coefficients between each SEPU index and the national EPU. Panel B of Figure 5 displays the distribution. The maximum correlation coefficient is 0.4354, the mean is 0.2632, and the minimum is 0.0082. This result implies that our SEPU indices are overall positively correlated with the national EPU but there is a fairly large variation in the time series between the national EPU and the SEPU index of each individual state. Appendix Figure A.1 displays the distribution of correlation coefficients between SEPU indices and other major uncertainty indices by Jurado, Ludvigson and Ng (2015) and Bekaert, Engstrom and Xu (2022) as well as VIX and realized S&P 500 volatility. The figure shows that the average correlation coefficients range from 0.11 to 0.20 across state-level uncertainty indices. Therefore, our SEPU indices are not fully explained by EPU as well as other major economic uncertainty indices.

[Insert Figure 5 Here]

In summary, we provide evidence that our SEPU indices are not highly correlated with each other and they exhibit a large cross-sectional variation. This is a necessary condition for our indices to be associated with the state-specific time variation in various economic outcome variables, which we investigate in Section 6.

6 State-level EPU and Economic activity

This section aims to understand how our state-level EPU indices are related to state-level economic outcome variables. We start by analyzing the relationship between our state-level EPU indices and state-level business cycles. We then use industry-level data to demonstrate that our state-level EPU indices are associated with the realized volatility of industry equity portfolio returns, industry investment, and also equity returns.

6.1 State-level Business Cycles and State-level EPU

Prior empirical studies on uncertainty have shown a strong correlation between real economic activity and proxies of uncertainty.[17] While most of these studies have studied the nationwide economic outcome variables, we differentiate from them by showing that our SEPU indices can be associated with large variations across states, a feature that is not possible by using a nationwide measure that does not vary across states. Specifically, we consider state-level real per capita GDP, employment, and real per capita income as proxies for state-level business cycles. We estimate a Vector autoregression (VAR) model in a panel setting, and then calculate the impulse response functions (IRF) to understand the dynamic relationship between state-level economic variables and our SEPU shocks.[18] To this end, we run the following VAR equation.[19]

$$\mathbb{Y}_{s,t} = \alpha + \sum_{k=1}^{K} \mathbb{Y}_{s,t-k} + \theta_t + \psi_s + \epsilon_{s,t}, \tag{3}$$

[17] E.g., Bloom (2009), Jurado, Ludvigson and Ng (2015), and Baker, Bloom and Davis (2016), among others.

[18] In this exercise, we do not attempt to forecast future economic outputs using out-of-sample tests. This is because, as in the literature (e.g., Bloom, 2009; Jurado, Ludvigson and Ng, 2015; Baker, Bloom and Davis, 2016; Husted, Rogers and Sun, 2020; Baker, Bloom and Terry, 2022; Caldara and Iacoviello, 2022), the purpose of this VAR exercise is to *estimate* the dynamic relationship between uncertainty shocks and real economic output variables, instead of *forecasting* future economic output variables.

[19] We present two pieces of evidence that support the validity of our VAR setting. First, Appendix Table A.1 performs the two versions of Johansen's cointegration tests. Both tests consistently indicate that there is no cointegrating relation. Second, Appendix Table A.2 shows that residuals from the VAR model in Equation (3) are stationary, which excludes the presence of unit roots.

where $\mathbb{Y}_{s,t}$ is a vector of endogenous variables: *Log(GDP)*, *Log(Employment)*, *Log(Income)*, *SEPU*, *Log(Government spending)*, and *Log(Minimum wage)*. In order to focus on state-specific time variation, we control for time- (θ_t) and state-fixed effects (ψ_s) in our VAR. K is the lag, which is optimally selected to be one by SIC.[20] We use state-level variables at a yearly frequency to estimate our VAR model.[21] Thus, we convert our monthly SEPU indices into yearly frequency by averaging the monthly values within each year. The sample period for this baseline case is from 1997 to 2018, which is determined by the data availability of state-level government spending and minimum wage.

To identify the marginal effect of uncertainty shocks, we orthogonalize shocks in the impulse response analysis using the Cholesky decomposition in a structural VAR setting. In our baseline specification, we order our uncertainty indices after state-level economic output variables, assuming that uncertainty indices have no immediate effect on other output variables, but are allowed to affect them with a lag through the VAR dynamics. This is not to overstate the impact of SEPU indices by ordering them first. Accordingly, we order VAR variables with one lag in the following order.

$$\begin{pmatrix} \textit{Log(GDP)} \\ \textit{Log(Employment)} \\ \textit{Log(Income)} \\ \textit{SEPU} \\ \textit{Log(Government spending)} \\ \textit{Log(Minimum wage)} \end{pmatrix}$$

We also present the result with different orderings of SEPU indices to evaluate the sensitivity of VAR estimates with respect to ordering.

[20]The values of the Akaike information criterion (AIC) and Hannan–Quinn information criterion (HQC) are the smallest when the lag is one, consistent with the optimal lag selection based on SIC. These results are reported in Appendix Table A.3.

[21]We choose to use yearly data because of a longer time series. Indeed, the Bureau of Economic Analysis makes state-level quarterly GDP data only available from 2005 which is a shorter time period compared to our SEPU indices.

Figure 6 displays the dynamic responses of GDP, employment, and income to a unit standard deviation SEPU shock with 95 percent confidence intervals. As it is well known, the ordering of the VAR could lead to very different results. Thus, we show estimates with different orderings of SEPU indices. The result shows that shocks to SEPU are statistically significant, and they sharply reduce GDP, employment, and income level. Importantly, the impact of SEPU indices is not sensitive to orderings of SEPU, and estimates are statistically indistinguishable from each other, confirming that the relation we uncover is likely not spurious. When SEPU is ordered in 4th, most conservatively, the maximum estimated drops are 0.20% for GDP, 0.17% for employment, and 0.14% for income. These magnitudes are moderate in size, corresponding to the bottom 22.1%, 21.6%, and 19.1% of the distribution of GDP, employment, and income growth, respectively in our sample. Bloom (2009) and Jurado, Ludvigson and Ng (2015) report responses of economic output variables to four-standard-deviation shocks to uncertainty. To compare our estimates to theirs, we show the impulse response functions to four-standard-deviation SEPU shocks in Appendix Figure A.2. In this case, the maximum estimated drops are 0.79% for GDP, 0.69% for employment, and 0.54% for income, which correspond to the bottom 15%, 15.9%, and 15.1% of the distribution of GDP, employment, and income growth, respectively.

Furthermore, the shape of responses shows that shocks to SEPU have long-lasting effects on state-level economic output variables. This finding emphasizes that our state-level EPU indices are strongly associated with time variation in state-level business cycles, which would not be possible to do with a nationwide measure of uncertainty that does not vary across states.

[Insert Figure 6 Here]

It is well-known that a VAR estimation can be sensitive to the specification of the VAR model. Therefore, we use alternative specifications to evaluate the robustness of our results and show that our findings withstand different specifications. This confirms that our results are not driven by the chosen empirical design but they are a consequence of a strong relation between state-level economic variables and our SEPU indices. First, we consider the reverse order of the baseline VAR:

$$\begin{pmatrix} \textit{Log(Minimum wage)} \\ \textit{Log(Government spending)} \\ \textit{SEPU} \\ \textit{Log(Income)} \\ \textit{Log(Employment)} \\ \textit{Log(GDP)} \end{pmatrix}$$

Second, we use a longer sample period from 1991 to 2019 by removing *Log(Minimum wage)* and *Log(Government spending)*. Figure 7 shows the dynamic responses of GDP, employment, and income for these alternative specifications. The figure shows that alternative specifications produce similar patterns as in the baseline specification shown in Figure 6; the magnitudes are slightly different but they are not statistically different from each other. Overall, our results are robust to alternative specifications of the VAR model. We also plot impulse response functions to four standard deviations SEPU shocks for these alternative specifications in Appendix Figure A.3.

[Insert Figure 7 Here]

Next, we compare the dynamic responses of the economic variables to both our SEPU indices and the national EPU by BBD2016. We use the same baseline specification as in Figure 6 with the addition of EPU ordered immediately after the SEPU variable. Since BBD2016 is the nationwide uncertainty index, we exclude time-fixed effects in our panel VAR to estimate the responses to EPU shocks. Figure 8 shows that both SEPU and EPU shocks decrease state-level economic output variables, confirming that our shocks to SEPU are related to economic outcome variables in a similar way as the national EPU. As we argued above, the advantage of our SEPU indices is that they are able to capture cross-sectional variation across states, which is useful for researchers interested in assessing the impact of uncertainty on economic variables that vary across states. The upper panels of Online Appendix Figure A.4 plot the dynamic responses of economic output variables to SEPU indices without controlling for EPU and those with controlling for EPU. The results show that the responses of economic variables to SEPU indices are the same whether EPU is controlled or not. However, the lower panels of the figure show that for EPU, the responses of economic variables to EPU are stronger when SEPU indices are not controlled than the case where SEPU indices are controlled, although the differences are not statistically significant.[22]

However, some caution should be exercised in interpreting this result. Because our indices understate the degree of economic policy uncertainty that arises from the national level by removing articles about nationwide information, the dynamic responses of the economic variable to our SEPU indices could be biased in this case where time-fixed effects are not controlled. This potential bias in our estimates applies to all of our following analyses in this section for the case where we relax time-fixed effects to compare the importance of our SEPU indices relative to the national EPU for economic outcome variables.

[Insert Figure 8 Here]

Appendix Table A.4 performs Granger causality tests. The results show significant Granger-causal relations from our SEPU indices to all of the economic output variables. Among economic output variables, only *Log(GDP)* has a significant Granger-causal relation to our SEPU

[22]When we examine the responses to EPU (SEPU) after controlling for SEPU (EPU) indices, EPU (SEPU) is ordered before SEPU (EPU). Therefore, our comparisons above are not subject to the ordering of endogenous variables.

indices. Thus, it appears that our SEPU indices are important for future real economic output variables, but not in the opposite direction from real economic output variables to our SEPU indices.

In summary, we find that shocks to our state-level EPU are strongly associated with contractions in all state-level economic output variables considered in this section (state-level GDP, employment, and income). We emphasize that our results hold even after controlling for the time- and state-fixed effects. Thus, our finding demonstrates that our indices are strongly associated with state-specific time variation in business cycles.

6.2 Industry-level economic variable and State-level EPU

We now turn to industry-level analysis in order to assess the importance of our SEPU indices for industry-level economic activities. It is known that state governments can greatly affect the state economic environment through the passage of bills, which in turn affect firms' future profitability (e.g., Chhaochharia, Korniotis and Kumar, 2020). Therefore, we expect that firms' economic variables respond not only to the national EPU but also to the state-level EPU. To test this hypothesis, we perform the following analysis. First, we test whether our SEPU indices are associated with the realized volatility of equity returns. Second, we examine whether SEPU indices are associated with firms' investment decisions. Last, we also study whether average equity returns are associated with SEPU indices.

We rely on industry-level data instead of firm-level data because corporate headquarters location is a poor proxy for firms' location of economic activities (e.g., Bernile, Kumar and Sulaeman, 2015; Smajlbegovic, 2019), and it is challenging to precisely identify the location of economic activities for firms. To identify the location of economic activities for each industry, we exploit the state GDP by industry from the Bureau of Economic Analysis (BEA). We construct industry-specific economic policy uncertainty indices in the following steps. First, based on the data of state GDP by industry, we compute the total domestic industry GDP and the percentage of industry GDP that is generated in each state as a fraction of the total domestic industry GDP. Formally, we define

$$w_{s,i,t} = \frac{Ind\_GDP_{s,i,y}}{\sum_{s=1}^{50} Ind\_GDP_{s,i,y}}, \tag{4}$$

where $Ind\_GDP_{s,i,y}$ is real GDP in year y for industry i in state s, $\sum_{s=1}^{50} Ind\_GDP_{s,i,y}$ represents the total domestic GDP for an industry i, and $w_{s,i,t}$ represents the percentage of the total domestic GDP of industry i in state s at time t. The variable $w_{s,i,t}$ represents a proxy for the importance of state s for industry i. Since we observe industry GDP at a yearly frequency, $w_{s,i,t}$ changes on an annual basis. Next, using these weights, we construct an industry-specific economic policy uncertainty index, $Ind\_EPU_{i,t}$. Then, our industry-specific EPU reflects the degree of economic policy uncertainty faced by each industry.

$$Ind\_EPU_{i,t} = \sum_{s=1}^{50} w_{s,i,t} \times SEPU_{s,t} \tag{5}$$

Since BEA classifies industries by 63 the North American Industry Classification System (NAICS) from 1997 to onward, we can also construct 63 industry-specific EPU indices from 1997. To rule out the possibility that our result is spurious, we also construct placebo industry-specific EPU where the re-scaled inverse of the ratio of industry GDP in each state to total domestic industry GDP is used as weights.

$$Ind\_EPU\_Placebo_{i,t} = \sum_{s=1}^{50} w_{s,i,t}^{Placebo} \times SEPU_{s,t}, \qquad w_{s,i,t}^{Placebo} = \frac{1/w_{s,i,t}}{\sum_{s=1}^{50} (1/w_{s,i,t})} \tag{6}$$

We use $Ind\_EPU\_Placebo_{i,t}$ in the tests that we discuss below, and we show that, contrary to our "correct measure" $Ind\_EPU_{i,t}$, it is not statistically significant, therefore confirming that our results are not spurious.

6.2.1 Realized volatility of industry portfolio returns and SEPU

Pástor and Veronesi (2013) theoretically find that policy uncertainty commands a risk premium and that stocks are more volatile in times of high uncertainty. Also, BBD2016 shows that firm-level uncertainty, as proxied by stock volatility, matches their index of economic policy uncertainty. Their findings imply that economic policy uncertainty could be a source of firm-level uncertainty. Following these studies, in this subsection, we analyze whether our industry-specific EPU indices are associated with industry-level uncertainty. To this end, we run the following predictive monthly regression of log industry realized volatility on log industry-specific EPU with industry returns as well as time- and industry-fixed effects.

$$Log(Ind\_RV_{i,t}) = \alpha + \beta\, Log(Ind\_EPU_{i,t-1}) + \gamma\, r_{i,t-1} + \theta_t + \psi_i + \epsilon_{i,t}, \tag{7}$$

where $Ind\_RV_{i,t}$ is realized volatility of an industry i at time t where realized volatility is computed as the square root of the sum of squared daily returns on industry portfolios, and daily industry returns are computed as a market value-weighted average of log returns for each industry. $Log(Ind\_EPU_{i,t})$ is log industry-specific EPU. $r_{i,t}$ is monthly industry returns. As before, we also consider a specification without time-fixed effects and with the national EPU.

Table 5 reports the results of the regression model specified in Equation (7). Column (1) shows that industry-specific EPU is significantly associated with time variation in realized volatility of industry portfolios after controlling for time- and industry-fixed effects. $Log(Ind\_EPU_{i,t})$ is highly statistically significant at the 5% level, with the coefficient of 0.1726 which indicates that a 1% industry-specific EPU increase is associated with around 0.17% increase in industry-level realized volatility. This result is robust to the inclusion of industry returns as an additional control in Column (2), which shows that $Log(Ind\_EPU_{i,t})$ remains significant at the 5% level even after controlling for industry returns.

Columns (3), (4), and (5) relax time-fixed effects to compare the significance of our industry-specific EPU with the national EPU by BBD2016. Column (3) only adds industry-specific EPU. Column (4) only adds the national EPU. Column (5) adds both industry-specific EPU and the national EPU. Column (3) shows that a 1% industry-specific EPU increase is associated with a 0.41% increase in industry-level realized volatility with an R^2 of 0.3225. Column (4) shows that the national EPU is associated with industry-level realized volatility with a smaller magnitude (0.31%) and a smaller R^2 (0.3106) than those for industry-specific EPU. Comparing Column (4) with Column (5) reveals that adding industry-specific EPU to the specification only with the national EPU increases the R^2 to 0.3299 from 0.3106. However, adding the national EPU in the specification only with industry-specific EPU has a negligible effect, only increasing the R^2 to 0.3299 from 0.3225, as indicated by comparing Column (3) with Column (5). Column (5) also shows that the magnitude of industry-specific EPU is larger than that of national EPU. A 1% industry-specific EPU (national EPU) increase is associated with a 0.26 (0.20)% increase in industry-level realized volatility. These pieces of evidence suggest that in explaining industry-level realized volatility, our industry-specific EPU exhibits more explanatory power and a larger magnitude than the national EPU.

Finally, in Columns (6) and (7), we use placebo industry-specific EPU where the rescaled inverse of the ratio of industry GDP in each state to total domestic industry GDP is used as weights. Reassuringly, coefficients on placebo industry-specific EPU are not statistically significant with the negative signs. Overall, our test provides empirical evidence that industry-specific EPU, constructed based on industries' GDP exposure to each state, is tightly linked to the realized volatility of industry portfolios.

[Insert Table 5 Here]

6.2.2 Investment of industry and SEPU

The literature on real options has shown both theoretically and empirically that when investment projects are irreversible (even if just partially), firms become cautious and are more likely to delay investment when there is an increase in uncertainty (e.g., Bernanke, 1983; Bloom, Bond and Reenen, 2007). Consistent with this theory, prior empirical research documents that political uncertainty carries a significant and negative relationship with firms' investment. For example, Julio and Yook (2012) and Jens (2017) find that during national election years or before U.S. gubernatorial elections, firms reduce investments. Gulen and Ion (2015) also show that firms investment decreases following a high level of EPU index by BBD2016.

We use data from Compustat to test whether there is a negative relationship between investment and SEPU indices in this subsection. Specifically, we use Annual Compustat files from 1997 to 2019 where the sample period is determined by the availability of our industry-specific SEPU indices. To reduce the impact of extreme outliers, all variables have been winsorized at the 1% and 99% levels. As in Gutiérrez and Philippon (2016), we exclude utilities (SIC codes 4900 through 4999), real estate (SIC codes 5300 through 5399), financial firms (SIC codes 6000 through 6999), and 'other' SIC codes (SIC codes 9000 to 9999).

To test whether our industry-specific EPU measure can be useful in understanding investment rates, we run the following industry-level yearly predictive regression of industry investment rates on industry-specific EPU with control variables as well as time- and industry-fixed effects.

$$\textit{Investment}_{i,t} = \alpha + \beta \textit{Ind\_EPU}_{i,t-1} + \gamma X_{i,t-1} + \theta_t + \psi_i + \epsilon_{i,t}, \tag{8}$$

where $\textit{Investment}_{i,t}$ is net investment rates defined as capital expenditures ($capx$) scaled by the lagged total property, plant, and equipment ($ppent$) minus depreciation (dp) scaled by the lagged total property, plant, and equipment. $Log(Ind\_EPU_{i,t})$ is log industry-specific EPU. $X_{i,t-1}$ is the set of control variables that include $\textit{Market-to-Book}_{t-1}$, defined as the book value of total assets (at) plus the market value of equity ($csho \times prcc_f$) minus the book value of equity – computed as total assets minus total liabilities (lt) minus total preferred stocks ($pstk$) – scaled by the book value of total assets, $\textit{Total } Q_{t-1}$, which is Tobin's *q* proxy that accounts for intangible capital from Peters and Taylor (2017), and firms' age (i.e., the number of years since the firm first appeared in Compustat).

Table 6 reports the industry-level panel regression estimation result, where our industry-specific EPU indices and the national EPU are normalized to unit standard deviation. In Columns (1), (2), (3), (4), and (5), *Market-to-Book*$_{t-1}$ and age are used for control variables. In Columns (6), (7), (8), and (9), *Total* Q_{t-1} which accounts for intangible capital from Peters and Taylor (2017) and age are used for control variables. Column (1) shows that consistent with the classical q-theory, *Market-to-Book*$_{t-1}$ loads significantly positive onto the investment. Column (2) shows that the industry-specific EPU measure is negatively related to net investment rates. This result is consistent with the firm-level analysis by Gulen and Ion (2015) which show that the level of EPU is also negatively associated with investment rates.

Columns (3), (4), and (5) relax time-fixed effects as before to compare the significance of our industry-specific EPU with the national EPU by BBD2016. Column (3) only adds industry-specific EPU. Column (4) only adds the national EPU. Column (5) adds both industry-specific EPU and the national EPU. Columns (3), (4), and (5) show that both industry-specific EPU indices and the national EPU index load negatively onto the investment, but they are not statistically significant, whether they are added in a regression separately or jointly. Moreover, the values of R^2 are about the same for all three specifications. Therefore, our findings in this test suggest that while both indices are not associated with investment rates in these specifications without time-fixed effects, our industry-specific EPU indices can be useful for explaining industry-specific time and cross-sectional variation in investment rates in Column (2), which include time-fixed effects.

The result in Column (2) is robust to controlling for the total Q which accounts for intangible capital as shown in Column (7). Finally, in Column (9), we use placebo industry-specific EPU and find that the coefficient on the placebo EPU is positive, inconsistent with the real options theory, and statistically insignificant. Therefore, this finding supports that the explanatory power of our industry-specific EPU likely comes from the importance of each state for a given industry.

[Insert Table 6 Here]

6.2.3 Returns of industry portfolio and SEPU

Brogaard and Detzel (2015) find a significant positive relation between future market returns and the EPU index by BBD2016. In light of this finding in the literature, we investigate asset pricing implications of SEPU indices above and beyond EPU. Following the suggestions by prior studies (e.g., Martin and Wagner, 2019; Pukthuanthong, Roll and Subrahmanyam, 2019; Harvey and Liu, 2021; Hasler and Martineau, 2022), we run pooled panel regressions to study the relation between industry returns and SEPU. Specifically, we run the following regression:

$$r^e_{i,t} = \alpha + \beta_1\, Log(Ind\_EPU_{i,t-1}) + \beta_2\, Log(EPU_{t-1}) + \gamma' X_{i,t-1} + \epsilon_{i,t}, \tag{9}$$

where $r^e_{i,t}$ is log excess returns for an industry i at month t. $X_{i,t-1}$ contains a set of control variables that include 12-month rolling betas with respect to market factor, size, value, and momentum factors, interacted with corresponding factors: $\hat{\beta}^{Mkt}_{i,t-2} Mkt_{t-1}$, $\hat{\beta}^{SMB}_{i,t-2} SMB_{t-1}$, $\hat{\beta}^{HML}_{i,t-2} HML_{t-1}$, and $\hat{\beta}^{MOM}_{i,t-2} MOM_{t-1}$.

Panel A of Table 7 reports the results with both our industry-specific EPUs and the national EPU by BBD2016. Panel B reports the results only with our industry-specific EPUs. Panel C reports the results only with EPU. Column (1) of Panel A of Table 7 shows that our industry-specific EPUs are positively related to one-month-ahead industry portfolio returns, which is significant at the 1% level. The positive relationship is in line with Brogaard and Detzel (2015). Moreover, the significance of industry-specific EPUs holds after controlling for EPU as shown in Column (2). Column (2) also shows that EPU is not statistically significant (t-stat = 0.01). Our industry-specific EPUs remain significant even after further controlling for risk exposures to other factors from Columns (3) to (5). This implies that our industry EPU indices perform well in capturing industry portfolio returns above and beyond the national EPU as well as widely accepted equity factors. In terms of magnitude, the estimates in Column (5) with full controls imply that a one-standard-deviation increase in industry EPUs is associated with an increase in excess returns by 0.39% points (=0.26 $\times$ 0.0150) or 4.68% points per annum. A one-standard-deviation increase in EPU is associated with an increase in excess returns by 0.20% points (=0.31 $\times$ 0.0063) or 2.34% points per annum. Therefore, our industry EPU indices exhibit much stronger economic and statistical significance than the national EPU.

To isolate the marginal contribution of our industry EPUs over the national EPU, we run the same regressions without the national EPU in Panel B and without our industry EPUs in Panel C. Panel B shows that the values of R^2 are the same as those in Panel A, implying that including the national EPU does not increase the explanatory power for industry returns beyond our industry-specific EPUs. Moreover, comparing Panel A and Panel B, the coefficient estimate on industry EPUs is 0.0199 (*t*-stat = 8.54) in Panel B without EPU versus 0.0150 (*t*-stat = 4.42) in Panel A with EPU. Therefore, the estimate on industry EPUs is not much affected by the inclusion of the national EPU. In contrast, Panel C shows that without our industry EPUs, the national EPU exhibits much stronger economic and statistical significance than the results with industry EPUs: The coefficient estimate on EPU is 0.0146 (*t*-stat = 8.46) in Panel C without our industry EPUs versus 0.0063 (*t*-stat = 2.34) in Panel A with our industry EPUs. Thus, the coefficient estimate on EPU decreases by a factor of more than two after controlling for our industry EPUs. This implies that our industry EPUs mostly subsume the significance of EPU.

In sum, our tests in this subsection show that our industry-specific EPUs are instrumental in understanding not only the volatility of returns but also returns that are less predictable than volatility. In addition, our industry EPU indices exhibit stronger economic and statistical significance than the national EPU, further underscoring the importance of state-specific

EPU.

[Insert Table 7 Here]

Overall, our industry-specific EPU indices seem to properly capture the degree of economic policy uncertainty that industries face given their GDP exposures to each state. These results lend support to the explanatory power of industry-specific EPU indices for industry-level output variables. Hence, we argue that our industry-specific indices would be useful for future research on economic policy uncertainty at the industry level.

However, considerable caution should be exercised in interpreting the links between state-level economic policy uncertainty and economic activities. We acknowledge that our findings do not establish a causal link between our uncertainty indices and state-level economic output. As pointed out in Baker, Bloom and Davis (2016), it is difficult to establish a causal inference because economic policy uncertainty likely reflects economic fundamentals. In the same way, shocks to our uncertainty indices endogenously respond to economic fundamentals.

7 Conclusion

In this paper, we develop new indices of State-level Economic Policy Uncertainty (SEPU) for each of the 50 states in the U.S based on coverage frequency using state-specific newspaper articles. We also develop 63 industry-specific EPU indices based on the GDP exposure of industries to each state. We conduct a variety of tests to confirm the validity and robustness of our indices. As suggested by theory, our SEPU indices vary counter-cyclically. They increase with changes in the political party of a state legislature, before close gubernatorial elections, and after local natural disasters that caused human losses.

State-level economic policy uncertainty indices exhibit a large cross-sectional variation across states. This implies that our indices reflect state-specific information about economic policy uncertainty which is not explained by the national EPU. Therefore, we use our SEPU indices to evaluate the relationship between our indices and economic activities. We find that our SEPU indices are instrumental in understanding state-specific business cycles as well as industry equity returns volatility, investment decisions, and equity returns.

While existing uncertainty indices mainly focus on the nationwide level of uncertainty, our paper shows that state-level uncertainty is associated with a wide variety of state-level economic activities that cannot be analyzed by nationwide economic uncertainty measures, which do not vary across states. Most importantly, our study provides researchers with a set of monthly indices of economic policy uncertainty for the 50 states and 63 industry-specific EPU indices that can be used for future research.

As emphasized before, since our measures are not exogenous, our measures could be particularly useful for the literature where causal inference is not necessary such as studies that examine the determinants of uncertainty (e.g., Baker et al., 2014; Białkowski, Dang and Wei, 2022), the asset pricing literature (e.g., Brogaard and Detzel, 2015; Bali, Brown and Tang, 2017; Bali, Subrahmanyam and Wen, 2021), and studies that need to identify policy-sensitive stocks (e.g., Akey and Lewellen, 2017). Our indices could also be used in practice as an input in investment decision models (e.g. investment decisions in real estate and infrastructure should depend on local state-level uncertainty). Last, our indices could be useful to study the role of economic policy uncertainty at the firm level. For example, researchers with the identification of firms' location of operations can pin down which states matter for each firm and use our indices to study the implications of state-level uncertainty on firm-level investment, employment, etc. We leave these interesting topics for future research.

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Table 1. **Word choices to measure SEPU**

This table reports the keywords used to measure State-level Economic Policy Uncertainty (SEPU). Panel A contains the words that news articles must have to be included in our sample. Articles need to contain at least one word for each of the four categories listed in Panel A (State-level, Economic, Policy, and Uncertainty). If a news article contains the words listed in Panel A but also any of the words listed in Panel B, it is removed from our sample.

Panel A: Words used to include articles

Category	Words
State-level	“state leaders", “state law", “state government", “governor”, “state regulators”, “state agency”, “state grant”, “state assistance", “gubernatorial", or “state capital”
Economic	“economic" or “economy"
Policy	“policy", “tax", “government spending", “regulation", “budget", “deficit", “government", “law", “bill", “legislation", “regulatory", “tax", “auditor", “lawmaker", or “secretary"
Uncertainty	“uncertainty", “uncertain", or “uncertainties"

Panel B: Words used to remove articles

Category	Words
Nationwide	“federal reserve", “interest rate", “congress", “senate", “White House", “fed", “Washington", “DC", “Katrina", “congress", “president", “editorial", “municipal", “federal", “country", “district", “White House", “ECB", “Tariffs", “treasurer”, “Black Monday", “Gulf War I", “Clinton Election", “Russian Crisis/LTCM", “Bush Election", “9/11", “Gulf War II", “GFC", “Lehman", “TARP", “Euro crisis", “Brexit”, “Debt ceiling dispute", “fiscal cliff", “government shutdown", “trade war", “TPP", “Lyndon B. Johnson", “Richard Nixon", “Gerald Ford", “Jimmy Carter", “Ronald Reagan", “George H. W. Bush", “Bill Clinton", “George W. Bush", “Barack Obama", “Donald Trump", “Watergate scandal", “Los Angeles earthquake", “Bill Clinton impeachment", “Florida ballots recount", “Dot-Com bubble", “Bush tax cut", “Katrina", “Iraq war", or “subprime mortgage collapse" as well as names of all central banks.

Table 2. **Correlation of SEPU with State-level economic variables**

This table reports the average correlation between State-level Economic Policy Uncertainty and four economic variables. The economic variables are (1) yearly real per capita GDP growth (GDP) from 1985 to 2019, (2) monthly unemployment rate from 1984:3 to 2019:12, (3) quarterly real per capita total income growth (Income) from 1984:Q2 to 2019:Q4, and (4) yearly consumption growth for each state from 1998 to 2019. Results are grouped using the U.S. Census Bureau divisions, which are defined as follows. East North Central: Illinois, Indiana, Michigan, Ohio, and Wisconsin. East South Central: Alabama, Kentucky, Mississippi, and Tennessee. Mid-Atlantic: New Jersey, New York, and Pennsylvania. Mountain: Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming. New England: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont. Pacific: Alaska, California, Hawaii, Oregon, and Washington. South Atlantic: Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, and West Virginia. West North Central: Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota. West South Central: Arkansas, Louisiana, Oklahoma, and Texas. *p*-values for the null hypothesis of no correlation are in parentheses.

	(1)	(2)	(3)	(4)
	GDP	Unemployment	Income	Consumption
East North Central	-0.2386	0.5040	-0.1165	-0.3562
	(0.0036)	(0.0000)	(0.0043)	(0.0002)
East South Central	-0.1241	0.5009	-0.0348	-0.3414
	(0.2411)	(0.0000)	(0.5062)	(0.0021)
Mid-Atlantic	-0.2515	0.5889	-0.1201	-0.4459
	(0.0125)	(0.0000)	(0.0171)	(0.0002)
Mountain	-0.2757	0.4278	-0.1661	-0.3701
	(0.0003)	(0.0000)	(0.0000)	(0.0000)
New England	-0.1648	0.0600	-0.0480	0.0099
	(0.0534)	(0.0162)	(0.2552)	(0.9157)
Pacific	-0.2996	0.4697	-0.1022	-0.4000
	(0.0007)	(0.0000)	(0.0214)	(0.0000)
South Atlantic	-0.1809	0.4221	-0.0637	-0.2344
	(0.0130)	(0.0000)	(0.0799)	(0.0032)
West North Central	-0.1215	0.2878	-0.0479	-0.3139
	(0.1321)	(0.0000)	(0.2299)	(0.0001)
West South Central	-0.2323	0.2792	-0.1617	-0.4072
	(0.0155)	(0.0000)	(0.0006)	(0.0001)

Table 3. **Change in Political Party/Election and SEPU**

This table reports the monthly panel regression of the log of one plus SEPU on variables related to State-level elections. *Governor*$_{s,t}$ is a dummy variable that takes value of one if the governor is Democratic at time t in state s. $(\Delta Governor_{s,t})^2$ is a dummy variable equal to one if there is a change in governor in state s from month $t-1$ to month t. *Legislature*$_{s,t}$ is the fraction of Democrats in a state's legislature (both House of Representatives and Senate). $(\Delta Legislature_{s,t})^2$ captures changes in the political composition of the legislature in state s at time t. $(\Delta(Governor_{s,t} - Legislature_{s,t}))^2$ captures the change in the political affiliation of the governor and the state legislature and it varies from 0 (governor and the majority of the legislature belong to the same party and majority party in the legislature has 100% of the seats) to one (governor and majority of the legislature belong to different parties and the majority party in the legislature has 100% of the seats). *Senate*$_{s,t}$ is the fraction of Democrats in Senate, *House*$_{s,t}$ is the fraction of Democrats in House of Representatives, and $(\Delta(Senate_{s,t} - House_{s,t}))^2$ is the change between time t and $t-1$ in the difference between political affiliations of state Senate and House of Representatives. *Vote difference*$_{s,t}$ is the difference between the winner and runner-up in a state gubernatorial election. *6-month prior election*$_{s,t}$ is a dummy variable equal to one if the observation falls within 6 months before a state gubernatorial election. *Term limit*$_{s,t}$ is a dummy variable equal to one if the incumbent is subject to a term limit, *GDP growth rate*$_{s,t}$ is a yearly real per capita state GDP growth rate. *Income growth*$_{s,t}$ is a quarterly real per capita total income growth rate. *Unemployment rate*$_{s,t}$ is a state unemployment rate. The *t*-statistics based on standard errors clustered by year-month and state are in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$(\Delta Governor_{s,t})^2$	0.0752						
	(0.96)						
$(\Delta Legislature_{s,t})^2$		1.8836***	1.8441***				
		(21.96)	(8.45)				
$(\Delta Legislature_{s,t})^2 \times$ *Full time*			5.4687**				
			(2.11)				
$(\Delta(Governor_{s,t} - Legislature_{s,t}))^2$				0.4332			
				(1.26)			
$(\Delta(Senate_{s,t} - House_{s,t}))^2$					1.6740***		
					(14.25)		
Vote difference$_{s,t}\times$ 6-month prior election$_{s,t}$						-0.3163**	
						(-2.22)	
Term limit$_{s,t}\times$ *6-month prior election*$_{s,t}$							0.0692*
							(1.70)
6-month prior election$_{s,t}$						0.0553	-0.0135
						(1.43)	(-0.41)
GDP growth rate$_{s,t}$	-1.3068**	-1.3093**	-1.3098**	-1.3087**	-1.3098**	-1.3996***	-1.3900***
	(-2.66)	(-2.66)	(-2.66)	(-2.66)	(-2.66)	(-2.88)	(-2.88)
Income growth$_{s,t}$	-0.3932	-0.4008	-0.4021	-0.3952	-0.4054	-0.1263	-0.1406
	(-0.44)	(-0.45)	(-0.45)	(-0.45)	(-0.46)	(-0.14)	(-0.16)
Unemployment rate$_{s,t}$	4.5428***	4.5480***	4.5462***	4.5354***	4.5481***	4.1382**	4.2207***
	(2.87)	(2.87)	(2.87)	(2.86)	(2.87)	(2.64)	(2.71)
Obs.	14,671	14,671	14,671	14,671	14,671	14,936	14,936
Adjusted R^2	0.1815	0.1815	0.1814	0.1815	0.1815	0.1823	0.1821
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Time & State	Time & State	Time & State	Time & State	Time & State	Time & State	Time & State

Table 4. **Natural Disasters and SEPU**

This table reports the monthly panel regression of the log of one plus SEPU on variables related to State-level natural disasters. *Top 1 injuries & fatalities duration* is a dummy variable that takes a value of one for a state that experienced natural disasters in the previous 12 months where the duration of the events that caused injuries and fatalities is in the top 1%. *Top 1 injuries & fatalities* is a dummy variable that takes a value of one for a state that experienced natural disasters in the previous 12 months where the number of injuries and fatalities per capita caused by the events is in the top 1%. *Injuries & fatalities duration* is the duration of natural disasters that caused injuries and fatalities in the previous 12 months. *Injuries & fatalities* is the number of injuries and fatalities per capita caused by natural disasters in the previous 12 months. *GDP growth rate*$_{s,t}$ is a yearly real per capita state GDP growth rate. *Income growth*$_{s,t}$ is a quarterly real per capita total income growth rate. *Unemployment rate*$_{s,t}$ is a state unemployment rate. The *t*-statistics based on standard errors clustered by year-month and state are in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Top 1 injuries & fatalities duration	0.1297***			
	(3.42)			
Top 1 injuries & fatalities		-0.0205		
		(-0.16)		
Injuries & fatalities duration			0.0065**	
			(2.51)	
Injuries and fatalities				4.7954
				(0.47)
GDP growth rate$_{s,t}$	-1.2296**	-1.2139**	-1.2219**	-1.2145**
	(-2.57)	(-2.54)	(-2.55)	(-2.55)
Income growth$_{s,t}$	-0.4672	-0.4534	-0.4665	-0.4565
	(-0.50)	(-0.48)	(-0.50)	(-0.48)
Unemployment rate$_{s,t}$	3.4102**	3.3903**	3.3501**	3.3864**
	(2.58)	(2.57)	(2.54)	(2.57)
Obs.	14,534	14,534	14,534	14,534
Adjusted R^2	0.1913	0.1910	0.1913	0.1910
Time FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Clustering	Time & State	Time & State	Time & State	Time & State

Table 5. **Realized volatility of industry and Industry-specific EPU**

This table reports the monthly panel regression of log realized volatility of industry portfolio returns on industry-specific EPU, computed based on our SEPU indices. Realized volatility is computed as the sum of squared daily returns on industry portfolios. Daily industry returns ($Industry\ returns_{i,t}$) are computed as a size-weighted average of log returns for each industry. The number of industries is 63 based on the North American Industry Classification System (NAICS). $Log(Ind\_EPU_{i,t})$ is the log of an industry-specific EPU, computed as a weighted average of the SEPU for the 50 states with weights being the ratio of industry GDP in each state to total domestic industry GDP. $Log(EPU_t)$ is the log of nationwide economic policy uncertainty measure by Baker, Bloom and Davis (2016). $Log(Ind\_EPU\_Placebo_{i,t})$ is the log of an industry-specific placebo EPU, computed as a weighted-average SEPU with weights being the re-scaled inverse of the ratio of industry GDP in each state to total domestic industry GDP. *t*-statistics based on standard errors clustered by year-month and industry are in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Log(Ind\_EPU_{i,t-1})$	0.1726**	0.1684**	0.4122***		0.2554**		
	(2.51)	(2.46)	(4.63)		(2.51)		
$Log(EPU_{t-1})$				0.3060***	0.1999**		
				(3.77)	(2.05)		
$Industry\ returns_{i,t-1}$		-0.4347***	-1.6796***	-1.6444***	-1.6427***		-0.4370***
		(-4.93)	(-6.10)	(-5.97)	(-6.12)		(-4.93)
$Log(Ind\_EPU\_Placebo_{i,t-1})$						-0.0236	-0.0231
						(-1.36)	(-1.34)
Obs.	13,953	13,953	13,953	15175	13,953	13,953	13,953
Adjusted R^2	0.7130	0.7153	0.3225	0.3106	0.3299	0.7125	0.7148
Time FE	Yes	Yes	No	No	No	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Time & Industry	Time & Industry	Time & Industry	Time & Industry	Time & Industry	Time & Industry	Time & Industry

Table 6. **Industry-Level Investment and Industry-specific EPU**

This table reports the panel regression of firms' investment rates on industry-specific EPU, computed based on our SEPU indices. Investment rates are net investment rates defined as capital expenditures scaled by the lagged total property, plant, and equipment (gross investment rates) minus depreciation scaled by the lagged total property, plant, and equipment. $Ind\_EPU_{i,t-1}$ is an industry-specific SEPU, computed as a weighted average of the SEPU for the 50 states with weights being the ratio of industry GDP in each state to total domestic industry GDP. The number of industries is 63 based on the North American Industry Classification System (NAICS). EPU_{t-1} is the nationwide economic policy uncertainty measure by Baker, Bloom and Davis (2016) normalized by its standard deviation. For ease of interpretation, we normalize $Ind\_EPU_{i,t-1}$ and EPU_{t-1} to unit standard deviation. *Market-to-Book*$_{t-1}$ is defined as the book value of total assets plus the market value of equity minus the book value of equity (computed as total assets minus total liabilities minus total preferred stocks) scaled by the book value of total assets. *Total* Q_{t-1} is Tobin's q proxy that accounts for intangible capital from Peters and Taylor (2017). *Firm Age*$_t$ is the number of years since the firm first appeared in Compustat. $Ind\_EPU\_Placebo_{i,t}$ is an industry-specific placebo EPU, computed as a weighted-average SEPU with weights being the re-scaled inverse of the ratio of industry GDP in each state to total domestic industry GDP. The t-statistics based on standard errors clustered by year and industry are in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Ind\_EPU_{i,t-1}$		-2.6247**	-0.5065		-0.2159		-2.6265**	-0.1535	
		(-2.39)	(-1.39)		(-0.92)		(-2.57)	(-0.73)	
EPU_{t-1}				-0.5207	-0.4186			-0.3458	
				(-1.65)	(-1.67)			(-1.44)	
Market-to-Book$_{t-1}$	0.0239***	0.0239***	0.0238***	0.0238***	0.0238***				
	(4.66)	(4.66)	(4.65)	(4.66)	(4.66)				
Total Q_{t-1}						-0.0196	-0.0196	-0.0195	-0.0195
						(-1.68)	(-1.68)	(-1.67)	(-1.67)
Firm Age$_{t-1}$	-0.0202	-0.0206	-0.0288	-0.0161	-0.0163	-0.0574**	-0.0579**	-0.0431**	-0.0551**
	(-0.68)	(-0.70)	(-1.43)	(-0.74)	(-0.74)	(-2.42)	(-2.44)	(-2.45)	(-2.38)
$Ind\_EPU\_Placebo_{i,t-1}$									1.0285
									(1.29)
Obs.	71,220	71,220	71,220	71,219	71,219	70,270	70,270	70,269	70,270
Adjusted R^2	0.0026	0.0027	0.0023	0.0023	0.0023	0.0014	0.0014	0.0011	0.0014
Time FE	Yes	Yes	No	No	No	Yes	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Time & Industry	Time & Industry	Time & Industry	Time & Industry	Time & Industry	Time & Industry	Time & Industry	Time & Industry	Time & Industry

Table 7. **Industry portfolio equity returns and Industry-specific EPU**

This table reports the pooled panel regression of firms' one-month-ahead excess returns of industry portfolios on industry-specific EPU, computed based on our SEPU indices and EPU. The number of industries is 63 based on the North American Industry Classification System (NAICS). $Log(Ind\_EPU_{i,t})$ is the log of an industry-specific EPU, computed as a weighted average of the SEPU for the 50 states with weights being the ratio of industry GDP in each state to total domestic industry GDP. $Log(EPU_t)$ is the log of nationwide economic policy uncertainty measure by Baker, Bloom and Davis (2016). $\beta_{mkt,i,t}$, $\beta_{smb,i,t}$, $\beta_{hml,i,t}$, and $\beta_{mom,i,t}$ denote 12-month rolling betas with respect to market factor (Mkt_t), size (SMB_t), value (HML_t), and momentum (MOM_t) factors, respectively. The *t*-statistics based on standard errors clustered by industry are in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Panel A: Industry-specific EPUs and BBD EPU (horse race)					
$Log(Ind\_EPU_{i,t-1})$	0.0195***	0.0195***	0.0152***	0.0149***	0.0150***
	(8.01)	(5.55)	(4.34)	(4.43)	(4.42)
$Log(EPU_{t-1})$		0.0000	0.0060**	0.0063**	0.0063**
		(0.01)	(2.17)	(2.34)	(2.34)
$\hat{\beta}^{Mkt}_{i,t-2}Mkt_{t-1}$			0.1696***	0.1817***	0.1827***
			(9.44)	(10.10)	(10.20)
$\hat{\beta}^{SMB}_{i,t-2}SMB_{t-1}$				-0.0028	-0.0035
				(-0.12)	(-0.15)
$\hat{\beta}^{HML}_{i,t-2}HML_{t-1}$				0.0950**	0.0993**
				(2.51)	(2.46)
$\hat{\beta}^{MOM}_{i,t-2}MOM_{t-1}$					0.0129
					(0.54)
Obs.	13,953	13,953	13,246	13,246	13,246
Adjusted R^2	0.004	0.004	0.021	0.023	0.023

	(1)	(2)	(3)	(4)
Panel B: Industry-specific EPUs only				
$Log(Ind\_EPU_{i,t-1})$	0.0195***	0.0199***	0.0198***	0.0199***
	(8.01)	(8.45)	(8.62)	(8.54)
$\hat{\beta}^{Mkt}_{i,t-2}Mkt_{t-1}$		0.1685***	0.1805***	0.1815***
		(9.42)	(10.06)	(10.17)
$\hat{\beta}^{SMB}_{i,t-2}SMB_{t-1}$			-0.0048	-0.0055
			(-0.20)	(-0.23)
$\hat{\beta}^{HML}_{i,t-2}HML_{t-1}$			0.0942**	0.0985**
			(2.49)	(2.44)
$\hat{\beta}^{MOM}_{i,t-2}MOM_{t-1}$				0.0129
				(0.54)
Obs.	13,953	13,246	13,246	13,246
Adjusted R^2	0.004	0.020	0.023	0.023

Table 7. Industry portfolio equity returns and Industry-specific EPU (Cont'd)

	(1)	(2)	(3)	(4)
	Panel C: BBD EPU only			
$Log(EPU_{t-1})$	0.0111***	0.0145***	0.0146***	0.0146***
	(6.78)	(8.44)	(8.53)	(8.46)
$\hat{\beta}_{i,t-2}^{Mkt} Mkt_{t-1}$		0.1498***	0.1610***	0.1613***
		(9.14)	(9.88)	(9.85)
$\hat{\beta}_{i,t-2}^{SMB} SMB_{t-1}$			0.0117	0.0115
			(0.55)	(0.53)
$\hat{\beta}_{i,t-2}^{HML} HML_{t-1}$			0.0936**	0.0950**
			(2.52)	(2.39)
$\hat{\beta}_{i,t-2}^{MOM} MOM_{t-1}$				0.0042
				(0.17)
Obs.	15,175	14,432	14,432	14,432
Adjusted R^2	0.002	0.016	0.018	0.018

Figure 1. **Percentage of Industry GDP in each state**

This figure displays the percentage contribution of each state to the total domestic industry GDP. We compute the percentage contribution of each state as the ratio of industry GDP in the state to the total domestic industry GDP. The North American Industry Classification System (NAICS) is used for the following codes: Motor vehicles (3361), Oil and Gas (211 and 324), Technology (334 and 518), Textile (313), Forestry, fishing, and related activities (113), Securities and financial activities (523).

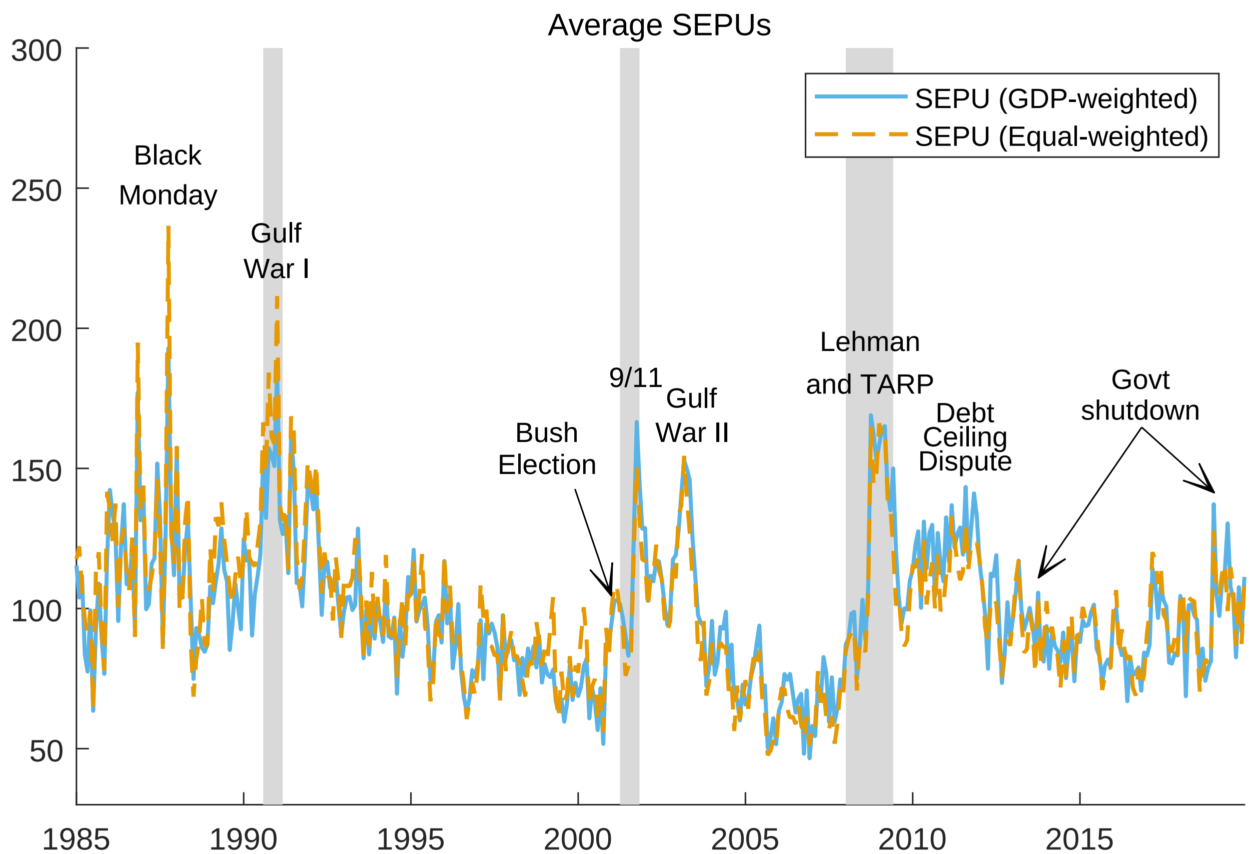

Figure 2. **Average State-level EPU Index**

This figure plots the average State-level Economic Policy Uncertainty (SEPU) across the 50 states of the United States of America. Shaded areas denote NBER recession periods.

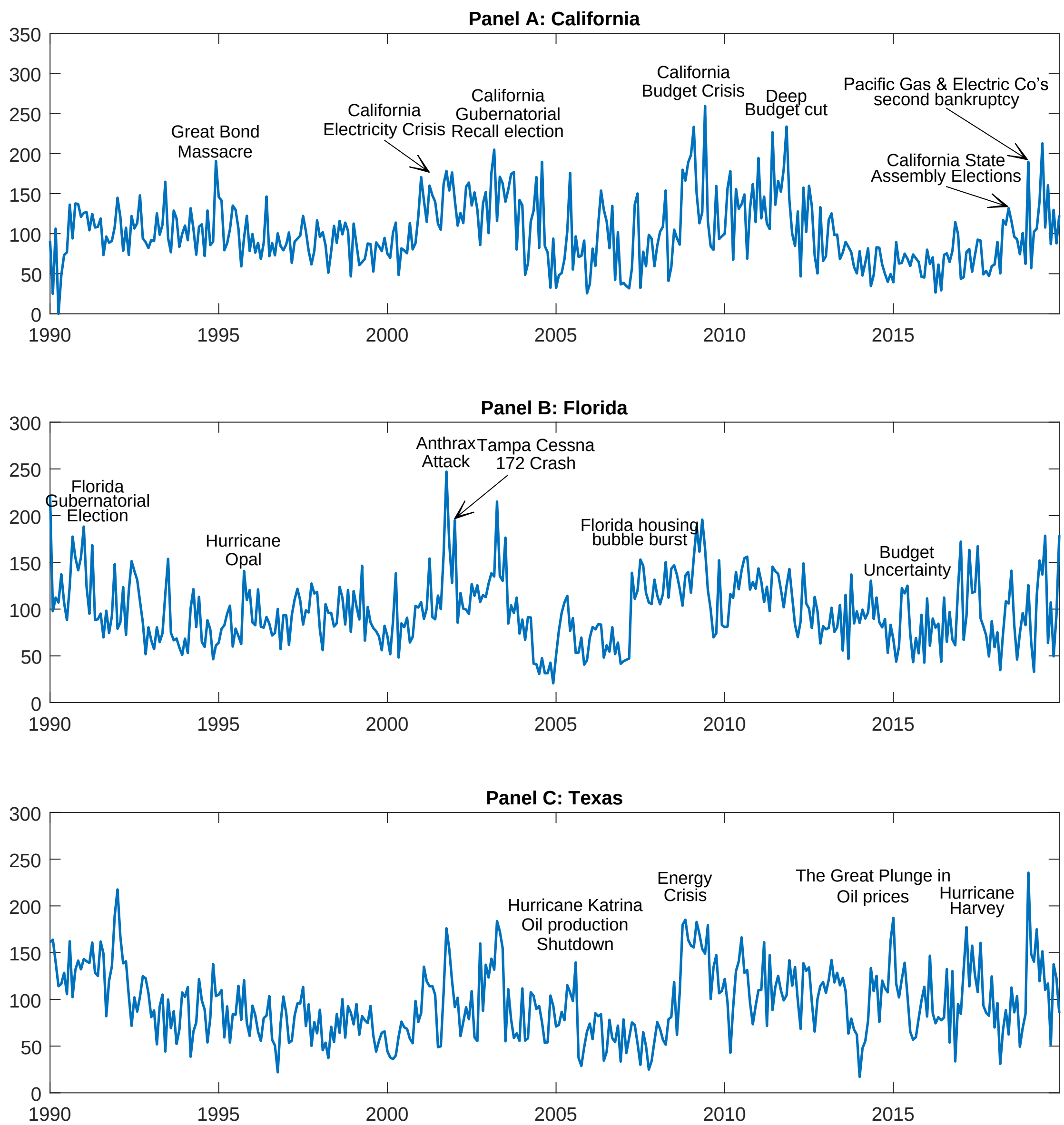

Figure 3. **SEPU index for California, Florida, and Texas**

This figure plots the State-level Economic Policy Uncertainty indices for California, Florida, and Texas.

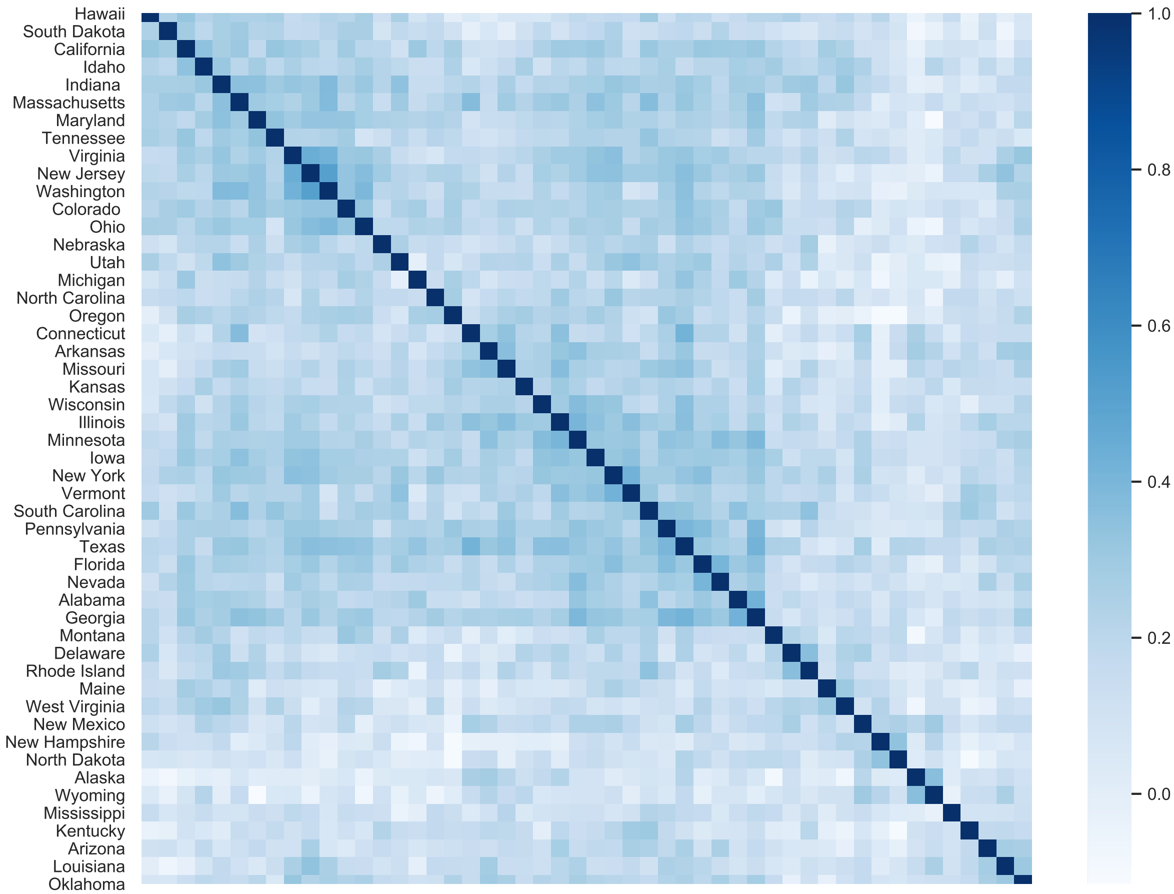

Figure 4. **Cross-correlation of SEPUs**

This figure plots the cross-correlation of State-level Economic Policy Uncertainty indices across the U.S. States. The States are clustered based on their correlations using Hierarchical Clustering.

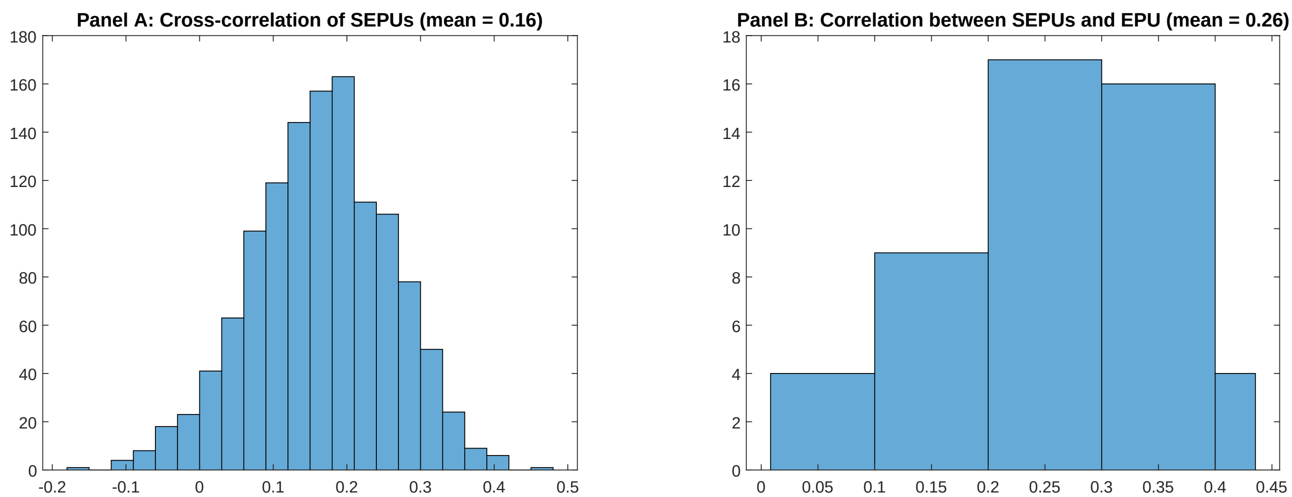

Figure 5. **Distribution of correlation coefficients**

Panel A plots the distribution of the cross-correlation coefficients of State-level Economic Policy Uncertainty across the U.S. States. Panel B plots the distribution of the cross-correlation coefficients between each State-level Economic Policy Uncertainty index and the national Economic Policy Uncertainty index by Baker, Bloom and Davis (2016).

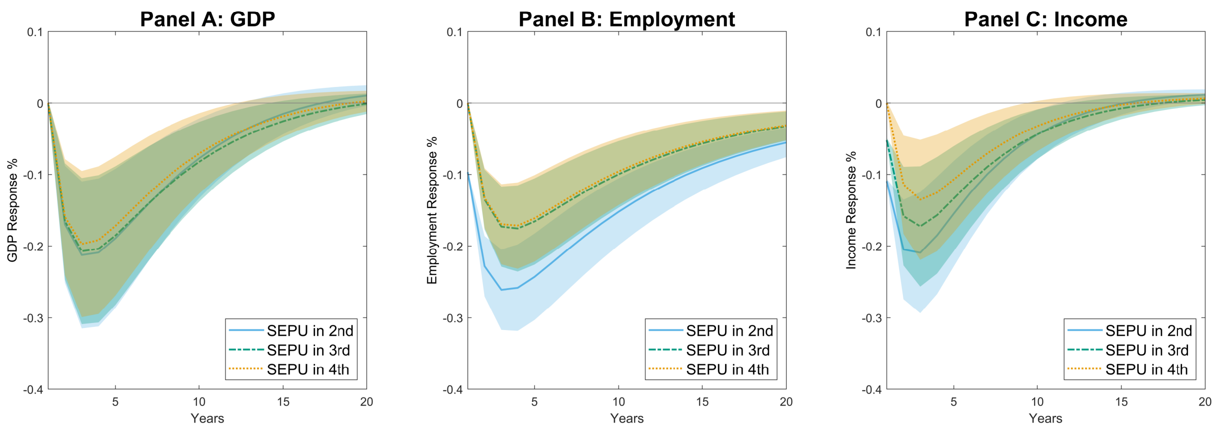

Figure 6. **Responses of State-economic output to SEPU Shock**

This figure plots impulse response functions for GDP (left), employment (middle), and income (right) with respect to a unit standard deviation shock to SEPU with the 95 percent confidence interval. For identification, the Cholesky decomposition with one lag is used. The straight line is the result for the specification where SEPU is ordered 2nd: *Log(GDP)*, *SEPU*, *Log(Employment)*, *Log(Income)*, *Log(Government spending)*, and *Log(Minimum wage)*. The dash-dotted line is the result for the specification where SEPU is ordered 3rd: *Log(GDP)*, *Log(Employment)*, *SEPU*, *Log(Income)*, *Log(Government spending)*, and *Log(Minimum wage)*. The dotted line is the result for the specification where SEPU is ordered 4th: *Log(GDP)*, *Log(Employment)*, *Log(Income)*, *SEPU*, *Log(Government spending)*, and *Log(Minimum wage)*. We control for both time- and state-fixed effects. Yearly data from 1997 to 2018 is used.

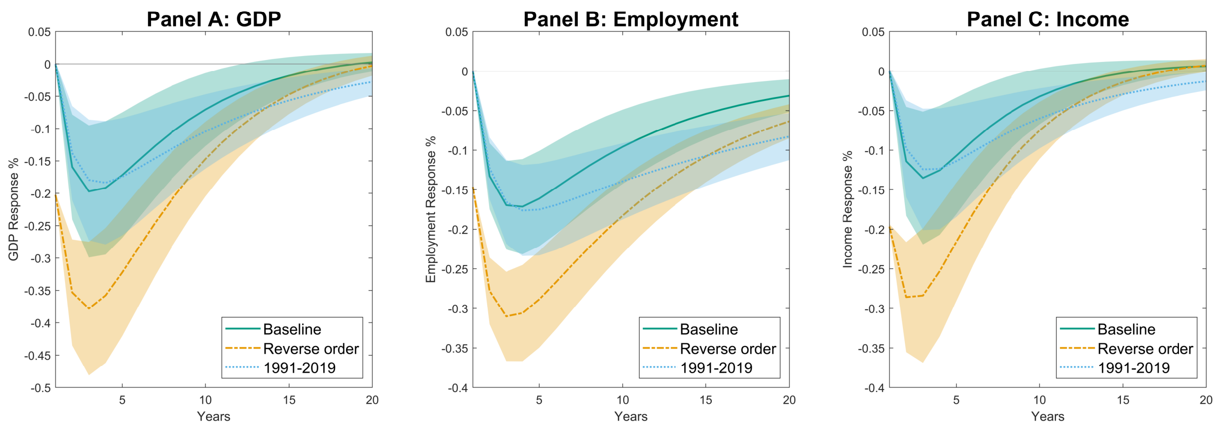

Figure 7. **Responses of State-economic output to SEPU Shock, Alternative Specifications**

This figure plots impulse response functions for GDP (left), employment (middle), and income (right) with respect to a unit standard deviation shock SEPU with the 95 percent confidence interval. For identification, the Cholesky decomposition with one lag is used. The straight line is the result for the baseline specification ordered as follows: *Log(GDP)*, *Log(Employment)*, *Log(Income)*, *SEPU*, *Log(Government spending)*, and *Log(Minimum wage)*. The dashed-dotted line is the reverse order specification where the variables are in reverse order compared to the baseline specification. For both the baseline and the reverse order specifications, data from 1997 to 2018 are used. The dotted line is the specification with a longer sample (1991-2019) obtained by removing *Log(Government spending)* and *Log(Minimum wage)* with the order of endogenous variables the same as the baseline specification. We control for both time- and state-fixed effects.

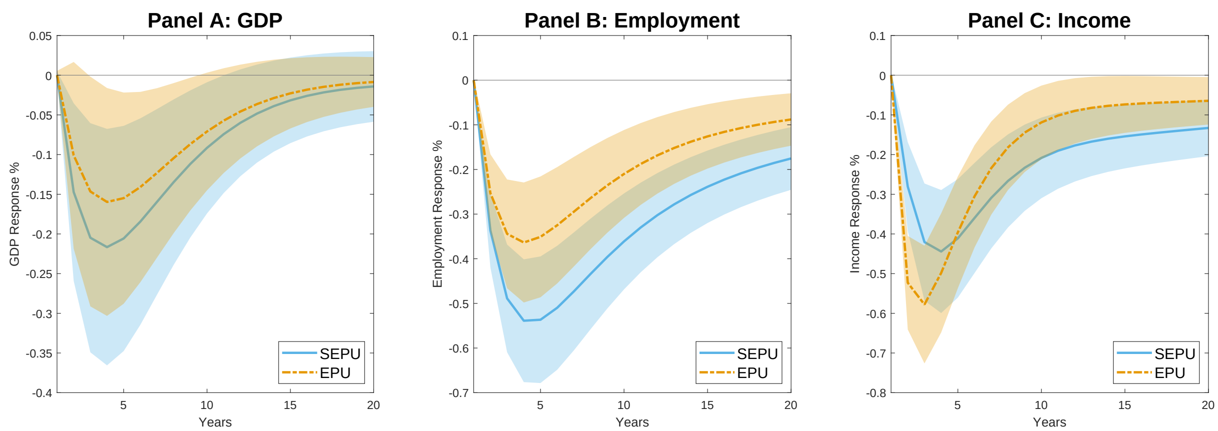

Figure 8. **Responses of State-economic output to SEPU and EPU Shock**

This figure plots impulse response functions for GDP (left), employment (middle), and income (right) with respect to a unit standard deviation shock to SEPU with the 95 percent confidence interval. For identification, the Cholesky decomposition with one lag is used, and variables are ordered as follows: *Log(GDP)*, *Log(Employment)*, *Log(Income)*, *SEPU*, *EPU*, *Log(Government spending)*, *Log(Minimum wage)*. State-fixed effects are included. Yearly data from 1997 to 2018 are used.

A Appendix

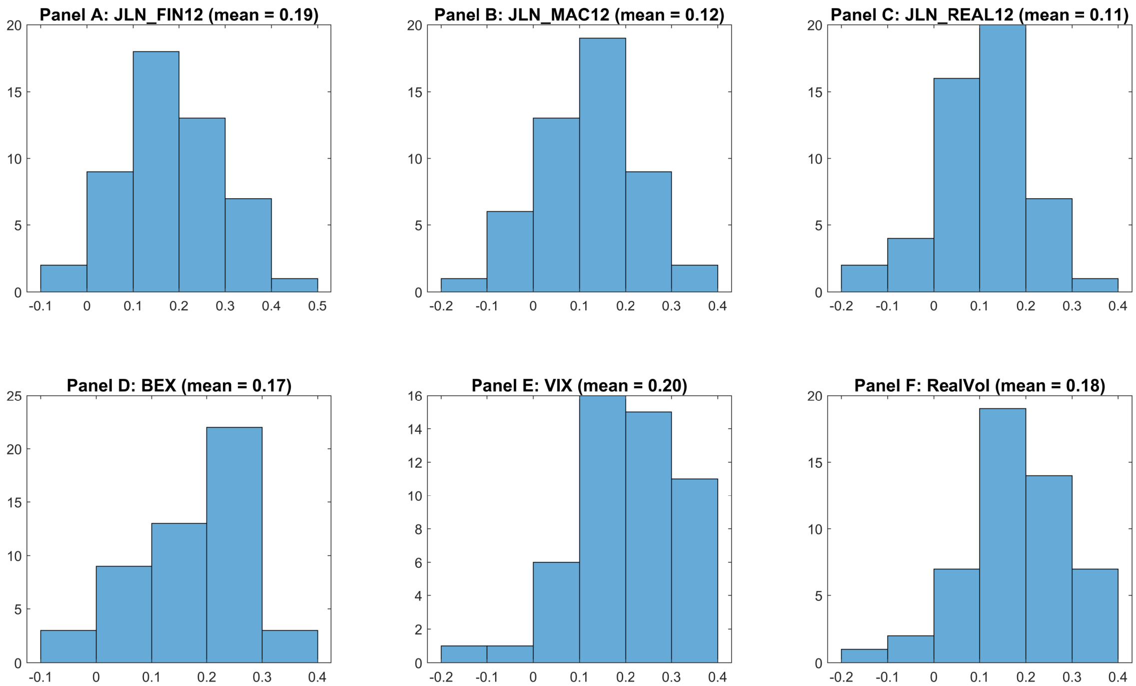

Figure A.1. **Distribution of correlation between SEPU and other uncertainty indices**
This figure displays the distribution of correlation coefficients between SEPU indices and other major uncertainty indices. Panel A, B, and C are the results for financial, macro, and real uncertainty indices, respectively, by Jurado, Ludvigson and Ng (2015) with a 12-month horizon. Panel D is the result for the economic uncertainty index by Bekaert, Engstrom and Xu (2022). Panel E is the result for the CBOE VIX index. Panel F is the result for realized volatility of S&P500 defined as the square root of the sum of squared daily returns over the month.

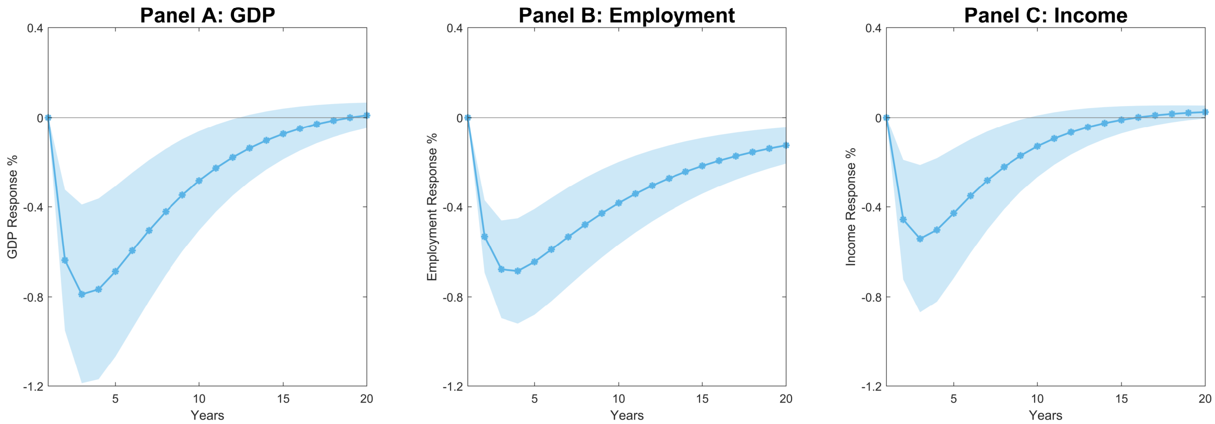

Figure A.2. **Responses of State-economic output to four standard deviations of SEPU Shock**

This figure plots impulse response functions for GDP (left), employment (middle), and income (right) with respect to four standard deviation shocks to SEPU with the 95 percent confidence interval. For identification, the Cholesky decomposition with one lag is used and variables are ordered as follows: *Log(GDP)*, *Log(Employment)*, *Log(Income)*, *SEPU*, *Log(Government spending)*, *Log(Minimum wage)*. We control for both time- and state-fixed effects. Yearly data from 1997 to 2018 is used.

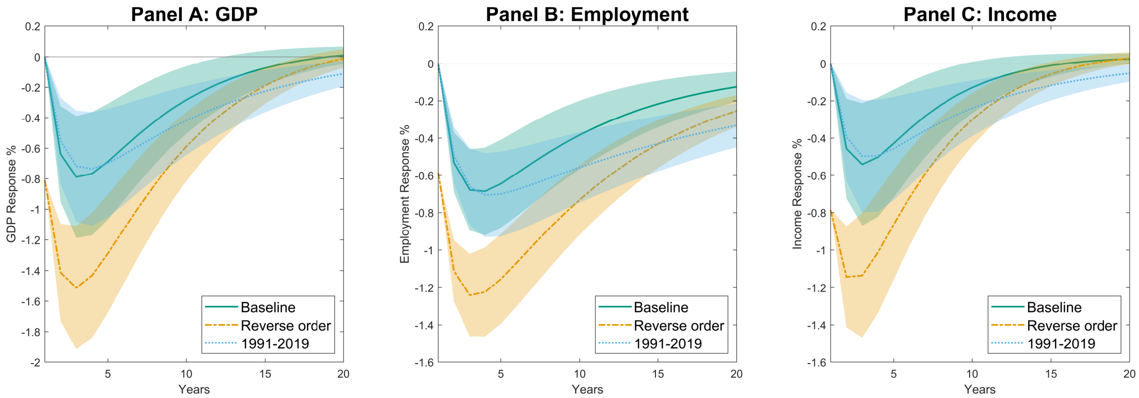

Figure A.3. **Responses of State-economic output to four standard deviations of SEPU Shock, Alternative Specifications**

This figure plots impulse response functions for GDP (left), employment (middle), and income (right) with respect to four standard deviation shocks to SEPU with the 95 percent confidence interval. For identification, the Cholesky decomposition with one lag is used. The straight line is the result for the baseline specification ordered as follows: *Log(GDP)*, *Log(Employment)*, *Log(Income)*, *SEPU*, *Log(Government spending)*, and *Log(Minimum wage)*. The dashed-dotted line is the reverse order specification where the variables are in reverse order compared to the baseline specification. For both the baseline and the reverse order specifications, data from 1997 to 2018 are used. The dotted line is the specification with a longer sample (1991-2019) obtained by removing *Log(Government spending)* and *Log(Minimum wage)* with the order of endogenous variables the same as the baseline specification. We control for both time- and state-fixed effects.

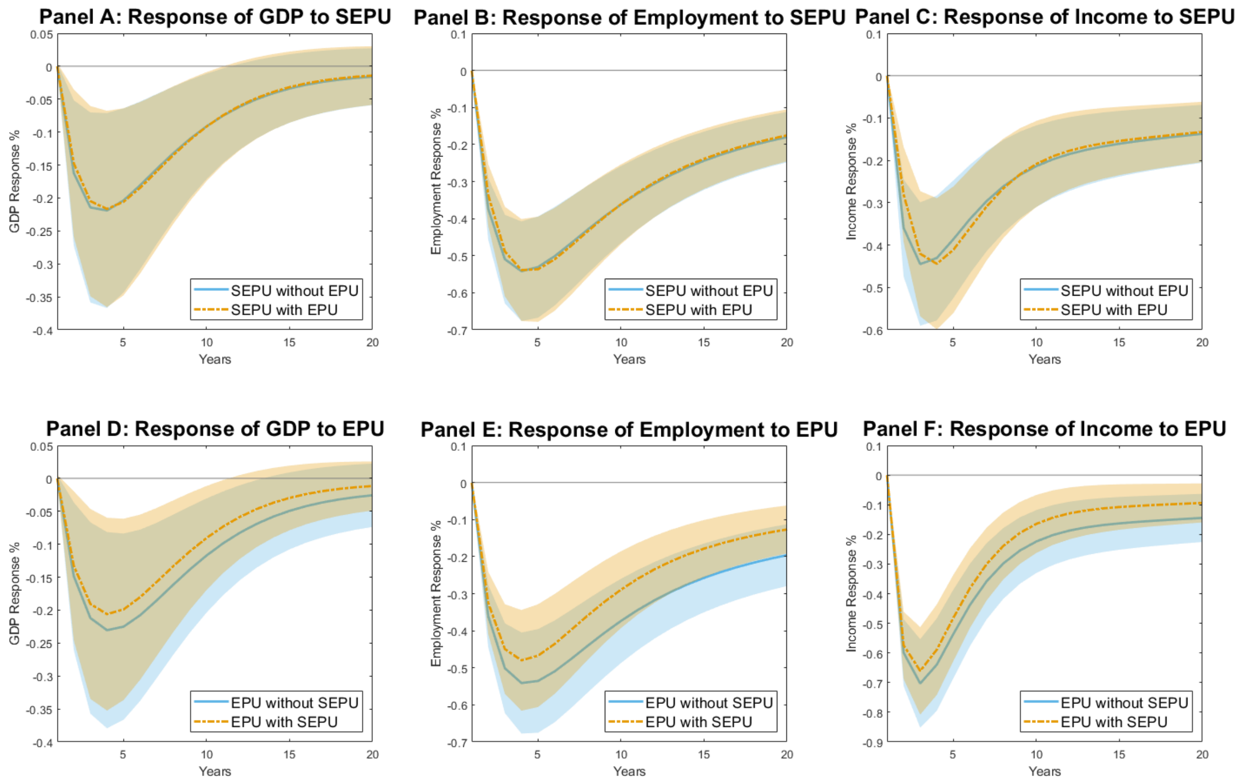

Figure A.4. **Responses of State-economic output to SEPU or EPU Shock**

This figure plots impulse response functions for GDP (left), employment (middle), and income (right) with respect to a unit standard deviation shock to SEPU or EPU with the 95 percent confidence interval. For identification, the Cholesky decomposition with one lag is used. The straight line is the result for the specification where either SEPU or EPU is separately used. In this case, either SEPU or EPU is ordered after *Log(GDP)*, *Log(Employment)*, and *Log(Income)* and before *Log(Government spending)* and *Log(Minimum wage)*. The dash-dotted line is the result for the specification where both SEPU and EPU are jointly used. In doing so, for the upper panels (Panels A, B, and C), SEPU is ordered before EPU. For the lower panels (Panels D, E, and F), EPU is ordered before SEPU. Both SEPU and EPU are ordered after *Log(GDP)*, *Log(Employment)*, and *Log(Income)* and before *Log(Government spending)* and *Log(Minimum wage)*. For all specifications, we control for state-fixed effects, and data from 1997 to 2018 are used.

Table A.1. **Johansen's cointegration tests**

This table reports Johansen's cointegration tests. Critical values are for the 1% significance level based on MacKinnon (1996).

Maximum rank	0	1	2	3	4	5
Panel A: Trace test						
Test statistics	982.72	542.70	368.47	232.98	124.39	42.40
Critical value (1%)	104.96	77.82	54.68	35.47	19.94	6.63
Panel B: Maximal Eigenvalue test						
Test statistics	440.03	174.23	135.49	108.59	81.99	42.40
Critical value (1%)	45.87	39.37	32.72	25.86	18.52	6.63

Table A.2. **Augmented Dickey–Fuller tests**

This table reports Augmented Dickey–Fuller unit root tests on residuals from the VAR model with lag one in Equation (3).

	SEPU	*Log(GDP)*	*Log(Employment)*	*Log(Income)*
Panel A: No constant and No trend				
Test statistics	-32.9212	-27.7810	-15.9219	-24.5029
p-values	0.001	0.001	0.001	0.001
Panel B: Constant and No trend				
Test statistics	-32.9042	-27.7667	-15.9137	-24.4903
p-values	0.001	0.001	0.001	0.001
Panel C: Constant and trend				
Test statistics	-32.8867	-27.7524	-15.9055	-24.4776
p-values	0.001	0.001	0.001	0.001

Table A.3. **Optimal Lag Selections**

This table reports the values of SIC (Schwarz Information Criterion), AIC (Akaike information criterion), and HQC (Hannan–Quinn information criterion) with different lags in Equation (3).

Lag	1	2	3	4
SIC	-1.6881	-0.8909	-0.7573	-0.5501
AIC	-1.8685	-1.2672	-1.3471	-1.3739
HQC	-1.7998	-1.1236	-1.1215	-1.0579

Table A.4. **P-values of Granger Causality tests**

This table reports p-values of Granger Causality tests. The following six endogenous variables are used: *Log(GDP)*, *Log(Employment)*, *Log(Income)*, *SEPU*, *Log(Government spending)*, *Log(Minimum wage)*. The lag of one is optimally selected based on SIC. We control for both time and state-fixed effects. Yearly data from 1997 to 2018 is used. In Panel A, the null hypothesis is that *SEPU* does not Granger Cause an economic output variable. In Panel B, the null hypothesis is that an economic output variable does not Granger Cause *SEPU*.

Panel A: From *SEPU* to *Economic output*				
		To		
		Log(GDP)	*Log(Employment)*	*Log(Income)*
From	*SEPU*	0.003	0.000	0.013
Panel B: From *Economic output* to *SEPU*				
		From		
		Log(GDP)	*Log(Employment)*	*Log(Income)*
To	*SEPU*	0.028	0.804	0.202