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Measuring US Regional Economic Uncertainty[1]

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This study constructs a set of regional economic uncertainty (EU) indices for the United States based on internet search volumes. These indices shed light on EU at the regional and local levels along with national EU. Although aggregate state-level EU is highly synchronised, idiosyncratic state EU nonetheless exhibits large variations. Similar to aggregate state-level EU, idiosyncratic state EU is generally countercyclical. There is also a spillover effect among EU in US regions. Lastly, we show that idiosyncratic state EU foreshadows declines in local employment and output.

Keywords: Economic Uncertainty; Uncertainty Shocks; Google Trends; Regional Variations; Business Cycles; Spillover Effect

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1 Introduction

It is well accepted that economic uncertainty (EU) is detrimental for economic activity; the global financial crisis of 2008, the subsequent European debt crisis, and COVID-19 have made this abundantly clear. In 2016, Mark Carney, then Governor of the Bank of England, noted that economic and policy uncertainty could have significant negative effects on the economy. The country reports of IMF (2017) suggest that uncertainty is a key factor leading to weaker economic performance in many countries, such as Mexico and the United States.

Economists have proposed different methods for quantifying the level of uncertainty by various data sources. Some common approaches include the use of option-implied/realised stock market volatility as a proxy for uncertainty (Bloom, 2009) and measuring uncertainty through an econometric forecast based on a broad range of indicators.[5] Specifically, Jurado et al. (2015) define uncertainty as the conditional volatility of the unforecastable component in the future values of a series. They create a macroeconomic uncertainty (MU) index and show that MU is an important source of business cycle fluctuations. Using a text-searching technique, Baker et al. (2016) measure uncertainty as the proportion of uncertainty-related articles to total news articles and show that economic policy uncertainty (EPU) is harmful for the macroeconomy. Castelnuovo and Tran (2017) and Bontempi et al. (2021) use the volume of internet search keywords to measure uncertainty, on the assumption that economic agents require information in response to uncertainty shocks. Many other empirical studies conduct research based on these uncertainty measures (Gulen and Ion, 2016, for capital investments; Brogaard et al., 2015, for asset pricing; Leduc and Liu, 2016, for aggregate economic activity).

Until now, progress in measuring uncertainty has generally focused on country-level analyses, with less attention having been paid to the regional heterogeneity of uncertainty.[6] In addition to country-level uncertainty, we believe that regional uncertainty within a country also has great importance. Intuitively, if the uncertainty across regions is interconnected, then the negative effect of an uncertainty shock on a region can

[5] There have been numerous related indices proposed in the literature during the last decade. Discussing, or even listing, all the relevant contributions is not possible, so we merely choose a few. Interested readers can refer to Bloom's (2014) survey for other important contributions in the field.

[6] Some exceptions include Arslan et al. (2015), Hassan et al. (2017), and Handley and Li's (2018) measures of firm-level uncertainty. Shoag and Veuger (2016), and Shields and Tran (2019) measure state-level uncertainty.

influence other regions, which may in turn induce contagion. For example, Allen and Gale (2000) find that when one region suffers from a banking crisis, banks in other regions that hold claims against the affected region see a devaluation of these assets and erosion in their capital base. Moreover, regions within a country are generally not homogenous economic units. Each region might have varying levels of fiscal, political, and economic disaggregation. Leduc and Liu (2016) show that local labour market rigidity can amplify the effect of an aggregate uncertainty shock on the local economy. Andersson (2008) observes that there is risk sharing among regions within Sweden, and the capital market is the major source for such risk sharing. Based on the Bureau of Economic Analysis, GDP per capita varies considerably across the United States, ranging from $37,376 in Mississippi to $188,782 in the District of Columbia in 2017 (see Figure 1). Based on these findings, the pattern of state EU (SEU) probably has not only a component similar to the uncertainty at the aggregate level, but also has its own idiosyncratic component. Therefore, measuring SEU can bring more insights for regulators, policymakers, and investors.

Building upon the approach in Castelnuovo and Tran (2017) and Shields and Tran (2019), this study constructs a set of new internet search-based SEU indices for the nine census regions in the United States from January 2004 to June 2019. We use principal component analysis (PCA) to extract a common factor from a group of relevant search volume indices of chosen keywords. We find that our index captures a wide range of uncertainties in a timely manner and has a high correlation with existing measures, with some differences because of different measuring approaches. Based on this index, we investigate the effect of SEU on the local economy and show that it has sizeable effects on the real economy, which is consistent with economic theory.[7]

Further, we apply the same strategy to construct SEU, we investigate the properties of SEU and, especially, we isolate the idiosyncratic component of the SEU from national-level EU. We observe that SEU varies across states, although some states are highly correlated with other states within the same region. Additionally, we test whether states' aggregate and idiosyncratic EU indices are countercyclical by regressing

[7] Moreover, when comparing our proposed index with other uncertainty measures in the appendix, the impulse response results suggest that only uncertainty measured by our EU index and the MU index of Jurado et al. (2015) have a significantly negative impact on the economy during the sample period.

them on the cyclical components of business cycle variables and find that most state aggregate EU indices demonstrate strong countercyclicality, but idiosyncratic SEU indices demonstrate weak countercyclicality.

We also study the spillover effect among EU indices using the Diebold and Yilmaz (2009, 2012) approach. Our test covers all nine US census regions and reveals strong spillover effects across these regions. Among all regions, the East North Central and West South Central regions contributed the most to the variance of forecast errors of the rest of the regions. Furthermore, the spillover effect changes across time. We also use the case of the 2013 Detroit bankruptcy to show how EU spills over in a period dominated by a state-specific event.

In our final empirical investigation, we focus on testing the effect of EU on the local economy. As theoretical literature (Bloom et al., 2007; Bloom 2009; Schaal, 2017; Bloom et al., 2018) suggests, we expect that state-level EU will have a negative effect on the local economy. After controlling for state- and time-fixed effects, we show that EU reduces both employment and output measured by Gross State Production (GSP). The results are robust after adding country-level aggregate uncertainty and credit conditions, showing that state-level idiosyncratic uncertainty shocks actually affect the local economy. We perform similar analysis at regional level and observe that the East North Central, Mountain, Pacific, and South Atlantic regions are more sensitive to EU shocks compared with the rest of the economy.

This study contributes to the literature in three ways. First, the present analysis complements the growing literature on uncertainty (Bloom, 2009; Bachmann et al., 2013; Carriero et al., 2015; Jurado et al., 2015; Baker et al., 2016; Leduc and Liu, 2016; Di Tella, 2017; Fajgelbaum et al., 2017; Schaal, 2017; Bloom et al., 2018; Lavertu and Clair, 2018; Mense, 2018) with the additional perspective of idiosyncratic EU at the local level. Similar to these studies, we confirm that EU reduces output and employment. However, instead of focusing only on aggregate uncertainty, we show that state-level idiosyncratic EU, itself, also has a negative effect on the local economy. Second, we find that idiosyncratic EU has its unique variations and can affect other states, even though aggregate EU is generally highly correlated across states. We further use the same approach as Diebold and Yilmaz (2009, 2012) to identify spillover effects of idiosyncratic EU among regions and confirm spillover effect among EU within the United States. Third, building upon the approach in Castelnuovo and Tran (2017), Shields and Tran (2019), and Bontempi et al. (2021), we develop a set of new

EU indices, enabling researchers to investigate EU at higher frequencies. This approach can be easily adapted to high-frequency analysis across geographical areas and the data source is publicly available, thus enabling researchers to replicate and apply it to other countries.[8] As such, the new set of indices is well aligned with Baker et al. (2016), Jurado et al. (2015), Castelnuovo and Tran (2017), and Bontempi et al. (2021).

The studies most closely aligned to our work are Shoag and Veuger (2016), Castelnuovo and Tran (2017), Mumtaz (2018), and Shields and Tran (2019). One clear distinction between ours and that of Castelnuovo and Tran (2017) is that we focus on region/state-level (idiosyncratic) EU, not country-level EU. Shoag and Veuger (2016), and Mumtaz (2018), respectively, use newspaper-based and forecast-based methods to develop state EU and both do not isolate idiosyncratic EU.[9] However, ours are Google search-based EU measures and we emphasise idiosyncratic EU. Lastly, both our work and that of Shields and Tran (2019) develop SEU measures in the United States using Google search data. We use different search terms, and our search terms are refined by considering the search categories.[10] Moreover, we provide more analyses on the properties of idiosyncratic SEU, such as cyclicality and spillover effects. Shields and Tran (2019) only focus on modelling the effect of SEU on the local economy, by developing a global VAR model and incorporating the spillover and feedback effects within and among states.

The remainder of this paper proceeds as follows: Section 2 details the construction and validation of our EU index; Section 3 focuses on local EU, its properties, and its effect on the local economy; and Section 4 concludes the paper.

2 Measuring Economic Uncertainty

2.1 Construction of the EU Index

Common approaches in the literature to constructing an EU index, such as proxying uncertainty as option-implied/realised stock market volatility (Bloom, 2009) or using a text-searching technique for

[8] We will provide our regional EU (REU) indices as the internet appendix in the journal when this paper has been accepted.
[9] The focus of Shoag and Veuger (2016) is on the 2007–2009 Great Recession.
[10] We provide evidence that restricting search volume in "Business News" is helpful for measuring uncertainty, which further strengthens the view that our approach is different to those of Castelnuovo and Tran (2017), and Shields and Tran (2019). Please see details in Section 2.2.C.

newspaper articles to calculate the EPU index (Baker et al., 2016), are not suitable when measuring local-level uncertainty or risk because few states have their own stock market and using local newspapers might introduce selection bias. The econometric forecast approach is also difficult because economic variables at the regional level are often unavailable. Even if the data set contains an adequate number of regional economic variables, their frequency is typically low, such as monthly and quarterly, and they cover only short time periods.

To achieve our goal, we construct EU indices based on internet search volumes, which have the benefit of data availability and can therefore allow analysis across geographical areas at a higher frequency. This assumes that individuals look for information online when they are uncertain and face financial difficulties and implies that search frequency might be related to future risky events, a phenomenon supported by several studies. For example, Lemieux and Peterson (2011) show that individuals intensify their searches for information under greater uncertainty. Similarly, sticky information models predict that "more volatile shocks [i.e., greater uncertainty] lead to the more frequent updating of information, since inattentiveness is more costly in a world that is rapidly changing" (Reis, 2006, p. 803). Thus, it is sensible to use the search volume of relevant keywords to measure the uncertainty level.

Regarding search data, Google is the most popular search engine in the world, accounting for over three quarters of global use in 2017.[11] Hence, we consider internet queries through Google to represent the US internet population's online search queries. In May 2006, Google officially launched Google Trends, which is publicly available and enables ordinary users to query the frequencies of keywords in Google searches in different historical periods and observe trends in these search frequencies. Google Trends does not provide actual search volume but a search volume index (SVI) ranging from 0 to 100 for a given sample period, where 100 represents the date that the given search term achieved its peak relative search volume. Using Google Trends conveys two advantages. First, the index is based on a single source and follows a standardised process and structure. Second, it is easily adaptable to high-frequency analysis across geographical areas. This helps researchers replicate and apply this approach to other countries at regional levels. Many studies apply Google Trends in academic research, including Da et al. (2011, 2015) for financial markets, Chauvet et. al. (2016) for

[11] This statistic is based on NetMarketShare (https://netmarketshare.com, accessed on 25 July, 2019).

modelling mortgage default risk, Baker and Fradkin (2017) and Pan (2019) for modelling job searches, and Castelnuovo and Tran (2017) for measuring aggregate uncertainty in Australia and the United States.

Although Castelnuovo and Tran (2017) also use Google Trends to measure uncertainty, our approaches differ in two main respects.[12] First, we apply the search categories using Google's classifications to indicate the intrinsic meaning of a searched item.[13] For example, if a user searches for "jaguar," they are given the opportunity to indicate whether they mean the animal or the car manufacturer. If the user clicks on the Jaguar store on the search results page for "jaguar," then this specific search query is assigned to the search category "Autos & Vehicles". Alternatively, if the user clicks on animal pictures, then the search query is matched with the search topic "Pets & Animals". We restrict our search volume to the "Business News" category as individuals search for more news under higher uncertainty; this category reports the volume only when individuals click on business news articles. This helps us to rule out unintentional inclusion of unsuitable searches. The search query "depression" is a particularly clear example. Individuals who search for "depression" might be interested in psychological depression, or even a meteorological depression, but not recent news on an economic depression. The SVI of "depression" in the "Business News" and "Psychology" categories are obviously different, as Figure 2 shows. If we restrict the search to "Business News," then we see a major spike between 2007 and 2009, which corresponds to the occurrence of the last financial crisis. However, if we restrict it to "Psychology", then we find cyclical fluctuations only, without any particular spike. Clearly, the former is the pattern for which we expect to measure uncertainty, and not the latter. We also compare it with the case of no restriction on category type (i.e., all categories). The spike still exists but is smaller, which is contrary to our intuition that the recession between 2007 and 2009 was the largest in the last two decades.

The second difference lies in the selection of keywords. Da et al. (2015) identify relevant terms associated with risk. Similar to Kogan et al. (2009), they use historical regressions to identify the most relevant terms related to stock returns. They report 30 keywords with SVIs that are significantly negatively associated with stock returns. The reason that they adopt this approach is that negative terms in the English language are

[12] Our study differs from that of Castelnuovo and Tran (2017) in more than two ways, especially as we discuss regional and state EU.

[13] Please see www.google.com/trends for a full list of categories as well as a detailed description of Google Trends.

the most useful for identifying risk (Tetlock, 2007). Smales (2014) shows that there is a negative relationship between Chicago Board of Exchange (CBOE) market volatility index (VIX) and news sentiment (i.e., more uncertainty, more fears). Bloom (2014) presents a similar discussion, noting that when market sentiment is pessimistic, trading activity slows down, thereby reducing the flow of new information and raising uncertainty. Hence, we believe that using the keywords identified by Da et al. (2015) is appropriate for measuring levels of uncertainty. Since we focus on EU and restrict our search category to "Business News,"[14] we eliminate eight terms that appear to be irrelevant to the economy, resulting in 22 final search terms, as Table 1 shows.[15]

After obtaining all SVIs from these 22 keywords, the last step is aggregating the SVIs of the 22 search items. Some of the abovementioned studies use only one search term and, therefore, do not face the aggregation problem (Baker and Fradkin, 2017), but others include several terms (Castelnuovo and Tran, 2017; Pan, 2019). Castelnuovo and Tran (2017) scale all terms' SVIs down to the search term with the maximum SVI and aggregate the transformed search frequencies of all search terms. This procedure implicitly leads to weighting search terms in a manner whereby the most frequent search terms count the most for their index, but this might not be appropriate because we do not really know if a term better reflects uncertainty or risk simply because its search volume is higher.

Therefore, we follow Baker and Wurgler (2006) and Pan (2019) to perform a PCA to extract a common factor from a group of relevant SVIs, and then capture the highest level of the common trend.[16] We apply the same process for the EU of the individual states and the United States in aggregate. We adjust the resulting common component to reduce the seasonal effect because some search volumes, such as for "unemployment," may be characterised by an element of seasonality.

Figure 3 reports the aggregate EU index, where the shaded area represents a recession period. The index constructed from search volumes appears to adequately capture major events. Spikes occur around known episodes of economic risk/uncertainty, such as the Lehman Brothers collapse in 2008 and the European

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[14] There is a search category titled "Economy News", which is a sub-category of "Business News". We do not use it because it focuses on searches about macroeconomy and ignores some important information related to the economy, such as company news and fiscal policy.

[15] The eight terms that we eliminate are "Car Donation", "Frugal", "Charity", "Donation", "Social Security Card", "Benefits", "Poverty", and "Social Security Office".

[16] This approach follows standard PCA and uses Eviews to extract the common components for each sector representing the EU index. The process is available at http://www.eviews.com/help/content/groups-Principal_Components.html (accessed on 20 July, 2019).

debt crisis in 2011. The indicator also rises around the US government shutdown in 2015. The highest value was recorded during the fall of 2008, and it remained highly elevated through the spring of 2009.

2.2 Validity of the EU Index

A. Changing the set of search terms

It may be argued that excluding eight keywords from Da et al.'s (2015) list of 30 may lead to bias in our EU index. To address this concern, we create an alternative EU index with all 30 SVIs from Da et al. (2015) using the procedure discussed in Section 2.1. Panel A of Figure 4 compares the benchmark EU index with this alternative. It is evident that the benchmark index is highly correlated with the corresponding alternative EU index. The benchmark EU index has a correlation coefficient of over 99.5% with the alternative EU index, showing that the exclusion of these eight search terms does not significantly affect our EU construction.

Moreover, Castelnuovo and Tran (2017) identify 79 keywords by reading the Federal Reserve Beige Book. The Beige Book reports information about the current economic situation based on the views gathered from economists, market experts, and business professionals. We develop an additional EU index based on these 79 words and compare it with our benchmark EU index in Panel A.[17] The general pattern between the benchmark index and alternative index is highly correlated, at around 85%. This indicates that our choice of 22 keywords is appropriate.

B. De-trending using the Hamilton approach

Another concern is there might be long-run trends driven by style changes, the popularity of Google's search engine, or other factors (Püttmann, 2018; Pan, 2019), which may lead to biases in the construction of the EU indices. This issue is particularly important given that the market share of Google among search engines was below 50% during 2004–2006,[18] but Google now dominates the market. We primarily employ the de-trending method proposed by Hamilton (2018), hereafter called the Hamilton filter, which uses a cycle

[17] We also have the results based on the keywords of Castelnuovo and Tran (2017). More results at the regional level are available upon request.
[18] See https://www.zdnet.com/article/comscore-on-top-search-engines-for-december-2004-google-35-yah00-32/.

length of two years for monthly observations (i.e., $h = 24$ months).[19] The Hamilton filter overcomes the problems of the Hodrick–Prescott (HP) filter, which produces a series with spurious dynamic relationships with no basis in the underlying data-generating process.[20] Panel B of Figure 4 compares the benchmark index with the EU index based on the filtered SVIs. Evidently, both series exhibit a similar pattern, and their correlation coefficient is nearly 97%, showing that the general pattern of EU index is not significantly affected by the long-term trend.

C. With and without refinement

This study refines the earlier approaches by considering business-related search information only. This raises an interesting question to which our refinement provides insightful information. To provide some evidence, we produce an EU index based on restricting our search volume to the "Business News" category, and without such restriction (i.e., using all search volumes for each term).[21] Panel C of Figure 4 shows the two indices with and without refinement. We find that the index without refinement does not show a clear spike during the European debt crisis, which is a well-known global uncertainty event. Moreover, the index without refinement shows that the level of uncertainty is much less severe during global financial crisis, which seems less accurate given that the 2007–09 global financial crisis was the most severe since the Great Depression of the 1930s (Reinhart and Rogoff, 2009). In sum, our refinement can contribute to a more precise measure of the EU index.

2.3 Comparison with Other Uncertainty Measures

We compare our EU index with existing risk/uncertainty measures to verify our indices.[22] Primarily, we focus on comparing our aggregate EU index for the United States because other measures are only country-

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[19] The Hamilton filter involves conducting an ordinary least squares (OLS) regression of the variable at date $t + h$ on the four most recent values on date t to avoid these drawbacks and to obtain a cyclical component series. The OLS regression is as follows: $x_t = \beta_0 + \beta_1 x_{t-h} + \beta_2 x_{t-h-1} + \beta_3 x_{t-h-2} + \beta_4 x_{t-h-3} + v_t$, where the cyclical components are the residuals, v_t. We set h = 24 for monthly observation.
[20] There is another reason to avoid using the HP filter in our case: it relies on the full sample period, which may introduce look-ahead bias in our index.
[21] We also perform two additional analyses based on with/without such refinement in Appendix B. First, we report the effect of EU without such refinement on the U.S. macroeconomy. Second, we perform similar analysis using 79 keywords provided by Castelnuovo and Tran (2017). The results support the view that our refinement could help us to provide a more accurate and timely measure of EU.
[22] We also test whether our EU index has negative relationship with the macroeconomy, as predicted by the literature. To save space, we report these results in Appendix B.

level measures. We compare our EU index with Baker et al.'s (2016) EPU index, the VIX, Jurado et al.'s (2015) MU index[23], Castelnuovo and Tran's (2017) Google-based uncertainty index, Bachmann et al.'s (2013) survey-based uncertainty measure, and Davis' (2016) global EPU index as a proxy for global uncertainty.[24]

Figure 5 plots our EU index alongside various other measures, while the correlation matrix is reported in Table 2. Note that we compute the correlation coefficient for both the full sample period and the period after July 2009 to address the concern that such high correlation is caused solely by the 2007–2009 recession. Several observations stand out. First, our constructed index is generally highly correlated with the other uncertainty measures. All these uncertainty measures spike during the global financial crisis and the European debt crisis. For example, while our index correlates very highly with Jurado et al.'s (2015) MU index, at over 80% correlation, it is also highly correlated with Castelnuovo and Tran's (2017) Google-based index (78.8%) and VIX (80.2%).

However, our measure has a weakly positive correlation with Baker et al.'s (2016) US EPU index (22.9%) and Davis et al.'s (2016) global EPU index (-10%). This result seems intuitive because the implementation of policy involves time lags. The most significant divergence occurs from 2015 till the present. At a closer look, we see several spikes in the EPU index, which correspond to the 2016 US presidential election and trade tensions. These events are related more to policy uncertainty than to EU, and therefore, we do not observe a related spike in our index. Our EU index also has a weaker correlation coefficient with Bachmann et al.'s (2013) survey-based uncertainty measure. A reason for such difference is that their index is based on a survey. As noted by the authors, the survey is sent only to large manufacturing firms in the Third Federal Reserve District and, therefore, inevitably suffers from the problem of a limited number of respondents. Moreover, Stephens-Davidowitz (2014, 2017) and Da et al. (2015) advocated for the use of internet search data over survey data because the incentive for truth-telling by survey respondents is low, which can lead to biased survey results. These conclusions are also valid for the post-financial crisis period. Overall, our measure effectively captures uncertainty, although it differs from existing measures in that it is based on search volume.

[23] This is a measure of dispersion in forecast errors constructed using a statistical model.
[24] Davis (2016) calculates the monthly global EPU index based on a GDP-weighted average of national EPU indices for 20 countries.

3 Application to SEU and Idiosyncratic SEU

In Section 2, we discussed how our EU captures uncertainty and we verified its robustness in various ways. However, regions within a country are generally not homogenous economic units. Each region might have varying levels of fiscal, political, and economic disaggregation. For example, Aizenman and Pasricha (2013) argue that state and local fiscal contractions during the 2007–2009 Great Recession roughly offset the fiscal stimulus of the federal government's American Recovery and Reinvestment Act. This issue is particularly prominent in the United States because a state government can have its own legislation on top of federal law. Aside from this, Leduc and Liu (2016) show that local labour market rigidity can amplify the effect of aggregate uncertainty shock on the local economy. Therefore, EU at the regional level will not necessarily be similar to uncertainty at the aggregate level. In this section, we apply a similar approach to measure state-level EU by restricting the SVI results to a specific state. For example, if we are interested in measuring California's EU, then we restrict the SVI to California. Then, we regress the state's aggregate EU on national EU to extract the residuals as the state idiosyncratic uncertainty. Based on the developed SEU indices, we discuss three main findings of local uncertainty, and compare the differences between state aggregate EU and state idiosyncratic EU.[25]

3.1 EU differs across states

Figure 6 displays the aggregate EU for each state and the idiosyncratic EU.[26] As Figure 6 shows, the EU patterns are different, even though they all spike during the 2007–2009 period. For example, the spikes in most states are clear, but in some states, such as Alaska, Wyoming, and South Dakota, the spikes caused by the financial crisis are less obvious. If we remove the national EU components, and look at state idiosyncratic EU, the differences among states' EUs are clearer. Idiosyncratic EUs for some states still have spikes during the 2007–09 period. This might be due to their labour market rigidity amplifying the effect of the aggregate EU shock on these states' economies.

[25] Google identifies the location of the search based on the computer internet protocol (IP) address.
[26] We also aggregate them by census division simply by averaging the state EU indices that belong to that census division, and report the result in the appendix. We define the regions based on the United States Census Bureau. Appendix A reports the classification details.

Table 3 reports the average pairwise correlation of the EU index and the common variance explained by the first component identified through a PCA. Generally, the aggregate SEU is highly correlated, with an average correlation of over 65% among all states. In addition, Table 3 shows that EU is significantly more synchronised in the East North Central and Middle Atlantic regions, with an average correlation of around 90%, and the correlation coefficients are below 60% in the New England and West North Central regions. However, such high correlation comes mainly from the national EU component. If we take out the country-level EU component, we can observe that the average correlation for most regions is below 50%. Only the East North Central region has a high correlation, of around 55%. Similar findings are obtained when analysing the common variance explained by the first component identified through a PCA (Columns 2 and 4). Our findings support the view that aggregate SEU is highly correlated, which is similar to the findings of Mumtaz (2018), who developed quarterly SEU based on eight economic variables using the approach proposed by Jurado et al. (2015). Our results further indicate that idiosyncratic SEU is quite variable across states.

3.2 State-level EU is countercyclical

Bloom (2014), and Girardi and Reuter (2016) observe that uncertainty is countercyclical, and our aggregate EU index also appears to be countercyclical. In this section we investigate whether this is true for SEU. In particular, the idiosyncratic SEU might be distinct with aggregate SEU. We tested whether SEU is cyclical by following Aguiar et al. (2013) and Haltiwanger et al. (2018) to regress the cyclical components of SEU on the cyclical components of business cycle variables, which can be expressed as follows:

$$SEU_{it} = \alpha + \mu_i + d_t + \beta_1 \mathrm{Cycle}_{it} + \varepsilon_{it} \tag{1}$$

where *i* represents the state and *t* represents time. SEU_{it} represents the SEU index. μ_i is the state fixed effect and d_t is the time fixed effect. Cycle_{it} is the filtered log business cycle measure. β_1 is the coefficient of interest; we expect it to be negatively associated with procyclical measures.

The business cycle variables include quarterly GSP from the U.S. Bureau of Economic Analysis (BEA) and monthly state-level employment data from the U.S. Bureau of Labor Statistics.[27] Table 4 reports the panel regression results for both aggregate SEU and idiosyncratic SEU. Clearly, there are strong negative associations between the aggregate SEU and GSP at the 1% level. Similarly, the cyclical SEU also have negative correlation with cyclical employment. These confirm that aggregate SEU is countercyclical, that is, aggregate SEU increases significantly when employment/GSP is lower. Regarding idiosyncratic SEU, our results suggest that idiosyncratic SEU is also countercyclical. By comparing the magnitudes of these two uncertainties, we clearly observe that aggregate SEU demonstrates stronger countercyclicality, which is due to the country-level EU component in the aggregate SEU. The countercyclicality we found here is intuitive, because recessions in the economy and turmoil in the labour market generally increase the level of EU.

To provide more insights on this issue, we perform similar panel regression analyses for nine main regions in the United States, where each region contains different state-level observations. Table 5 reports the cyclicality of SEU for each region. Two noticeable observations are drawn from this table. On the one hand, aggregate EU in certain regions, especially the Middle Atlantic region, demonstrates weaker countercyclicality as we observe business cycle variables lose their statistical significance. On the other hand, idiosyncratic SEU demonstrates much weaker countercyclicality compared to aggregate SEU. We observe idiosyncratic SEU generally negatively associated with GSP or employment in most regions, whereas aggregate SEUs are strongly associated with both two business measures at the 1% level for most regions.

In short, our result confirms existing findings that uncertainty is countercyclical. Further, we provide new evidence that certain regions demonstrate countercyclicality. Moreover, idiosyncratic SEU is also countercyclical, but its countercyclicality is less obvious than that of aggregate SEU.

3.3 EU has spillover effects across regions

Previous studies find that uncertainty has spillover effects across countries (e.g., Klößner and Sekkel, 2014; Balli et al., 2017; Antonakakis et al., 2018; Huang et al., 2018). However, limited studies provide

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[27] The Hamilton filter is based on a two-year sample length (i.e., $h = 2$ for annual observations, $h = 8$ for quarterly observations, and $h = 24$ for monthly observations). Thus, we set h = 8 when extracting the cyclical component of GSP, as it is a quarterly observation.

evidence on the uncertainty spillovers across regions within a country. Although we show that EU is correlated among states, this does not imply that it has spillover effects on other regions, especially for the idiosyncratic regional EU (REU). Diebold and Yilmaz's (2009) approach is to calculate uncertainty spillover indices which are based on standard variance decompositions in VARs. That approach allows us to investigate the dynamics of spillovers changing over time, and it also allows us to calculate pairwise directional spillovers and aggregate them further into a consistent single measure. However, the Diebold and Yilmaz (2009) approach is based on Cholesky decomposition, which depends on the ordering of variables. Diebold and Yilmaz (2012) extend their work by using the generalised VAR framework of Pesaran and Shin (1998), which is invariant of variable ordering. We follow the Diebold and Yilmaz (2012) framework because it produces variance decompositions which are invariant to the ordering. This approach is also widely used in investigating spillover effects across countries or regions (Yin and Han, 2014; Balli et al., 2017; Yang, 2018; Tsai and Chiang, 2019).

Consider a VAR(p) model, $y_t = \sum_{i=1}^{p} \varphi_i y_{t-i} + \epsilon_t$, where y_i is a $\mathrm{N} \times 1$ vector of endogenous variables, and $\epsilon_t \sim (0, \sum)$ is a vector of disturbances that are independently distributed over time. The *H*-step-ahead generalised forecast error variance decompositions are summarised by:

$$\vartheta_{ij} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i)}$$

where $\sum$ is the variance matrix of errors, e_i is a selection vector with a value of 1 for the i-th element and 0 otherwise, and σ_{jj} is the standard deviation of the error term for j-th equation. The net pairwise spillover index summarises all spillover information into one single number, which is based on the following:

$$NPS_{ij}(H) = \left(\frac{\tilde{\vartheta}_{ji}(H)}{\sum_{i,k=1}^{N} \tilde{\vartheta}_{ik}(H)} - \frac{\tilde{\vartheta}_{ij}(H)}{\sum_{j,k=1}^{N} \tilde{\vartheta}_{jk}(H)}\right) \times 100$$

$$= \left(\frac{\tilde{\vartheta}_{ji}(H) - \tilde{\vartheta}_{ij}(H)}{N}\right) \times 100$$

where this index shows the net pairwise spillover from region *i* to region *j*.

Following Klößner and Sekkel (2014) and Antonakakis et al. (2014), we employ a 60-month rolling window to calculate spillovers evolving over time. We apply the above approach on idiosyncratic EU rather than aggregate EU. This helps us to (partially) reduce the concern that possible spillover effects come from country-level economic shocks.[28] It also helps to partially reduce the concern that shocks are correlated across regions. Table 6 reports the correlation matrix for both aggregate and idiosyncratic EU across regions. The correlation of idiosyncratic REU is substantially lower than that of aggregate REU, which justifies the use of idiosyncratic REU as being more suitable. The spillover effects of nine census regions are summarised in Table 7,[29] which shows the average variance of the forecast error that each region receives from (rows) and transmits to (columns) another region. The spillover index for the full sample is 77.4%, indicating that around 77% of the total variance of the forecast errors for the nine regions is explained by spillovers or shocks across regions. Roughly one-fourth of this variance is explained by idiosyncratic region-specific shocks. Among all regions, the East North Central region (120.2) contributed the most to the variance of forecast errors of the rest of the other regions, as shown in the “Contribution to others” row. One possible explanation for this is that the manufacturing sector, including the automobile industry, accounts for the larger proportion in this region, as this sector is particularly sensitive to economic recessions (see IHS Markit, 2020 commentary). The West South Central region contributed the second most (118.9) to the variance of forecast errors of the rest of the other regions. This may be associated with oil price volatility, as the economies of oil-producing states are typically more volatile than those of other states (Raimi et al., 2019).

Figure 7 displays the dynamics of the spillover index from January 2009 to June 2020. As expected, there is time variation in the spillover index. From 2011 to the first half of 2016, the spillover index was relatively high. It then fell significantly in September 2016 and remained at the lower level to the end of sample period. Thus, we can see that EU shocks seem to have been rather idiosyncratic in recent years, resulting in a fall in the spillover index.

The above spillover analysis is for the whole sample period. It would be insightful to show how REU is spilled over in a subperiod dominated by a state-specific event. To this end, we use the 2013 Detroit bankruptcy as an example. Detroit's bankruptcy in 2013 (estimated at $18–20 billion) is the largest municipal bankruptcy filing in U.S. history by debt. In March 2013, Michigan appointed Kevyn Orr as Detroit City's

[28] We choose to test for nine regions rather than 51 states, because it is computationally challenging for VAR to deal many variables. For robustness, we also apply the same strategy for post 2007-09 crisis period, which further reduce this concern. The results are qualitatively the same. We also test it using 48-month, 72-month rolling window, and the results are qualitatively the same.
[29] Note that these findings are simply a comment on statistical causal relationship, not structural interpretation.

emergency manager, the role of such an appointee being to aim to get creditors to willingly "take a haircut". This negotiation failed in the end, and Detroit filed for Chapter 9 bankruptcy on July 18, 2013. The Michigan and federal governments have implemented several plans to help Detroit and avoid further bankruptcy proceedings. Detroit finally exited the bankruptcy in December 2014. This event largely increased the EU of the East North Central region in which Detroit is located. Many news articles discussed that local residents and businesses were uncertain about the legal process and the future of the city (New York Times, 2013; Reuters, 2013; Wharton Business Daily, 2014). Such shock is generally considered as exogenous shock, at least in the short run (Baker et al., 2020). We apply Diebold and Yilmaz (2012) to calculate the spillover index within this period. Note that we only calculate the simple spillover measure, not a rolling measure, because the sample size is small. We expect the East North Central region to contribute the most to the variance of the forecast error. Table 8 reports the spillover table for this subperiod. The spillover index for the full sample is 72.5%, indicating that around 72.5% of the total variance of the forecast errors for the nine regions is explained by spillovers or shocks across regions. Among all regions, the East North Central region (100.3), as expected, contributes the most to the variance of forecast errors of the rest of the other regions. The Middle Atlantic region (48.6) contributes the least to the variable of forecast errors. In sum, we observe spillover effect of EU based on these two findings.

3.4 Local Economy and Economic Uncertainty

Here we aim to examine whether state-specific EUs have an effect on the economy. If state-specific uncertainty is important, then the SEU should have a significant effect on the economy, such as reducing output and employment. Following Jayaratne and Strahan (1996), we use the following regression to test it:

$$\text{Growth}_{i,t} = \mu_i + d_t + \beta_1 SEU_{i,t-1} + \beta_2 Y_{i,t-1} + \gamma X_t + \varepsilon_{i,t} \tag{4}$$

where $\text{Growth}_{i,t}$ is the growth rate of quarterly GSP or monthly employment for state *i* at time *t*; $SEU_{i,t-1}$ refers to the idiosyncratic SEU; and β_1 is the coefficient of interest, which captures the average effect of SEU on employment or output growth. We also control for the level of GSP or employment at time *t*-1 (i.e., a one-period lag of the economic outcome variables), which is denoted as $Y_{i,t-1}$. Additionally, we consider other control variables, X_t, in Section 3.5. One potential challenge we face here pertains to omitted variables. Many unobservable characteristics can bias our estimation. If these unobservable variables remain stable over time, then we can use state fixed effects to control them. To handle time-varying omitted variables (e.g the increasingly widespread use of computer-based technologies or the time-series output pattern), we include time fixed effects. To mitigate the concern of reverse causality, we test whether the SEU at time *t-1* would affect economic activity at time *t* (i.e., next period). Finally, the standard errors are clustered by state and month (or quarter) to control for potential cross-sectional and serial correlations in the error term.

Table 9 reports the estimation results for the effect of SEU on GSP growth and employment growth. In Column 1, the coefficient of EU is -0.192 (t-statistic = -3.097), which is statistically significant at the 1% level. We find a similar outcome when testing the relationship between EU and employment growth, showing that employment decreases significantly when EU is higher. The results are robust after controlling for a one-period lag of the level dependent variable (see Columns 3 and 4). Again, one might argue that this negative relationship between local EU and the economy might come from aggregate country-level EU fluctuations. To reduce this concern we add our country-level EU into the regressions, and the results in Columns 5 and 6 indicate that local EU still has a negative relationship with GSP and employment growth, which confirm the finding of Shoag and Veuger (2016), who show that state-specific policy uncertainty has significant impact on state economic outcomes.

Instead of looking at all states together, we also test the effect of SEU on the economy for nine regions, for which the panel regression results are summarised in Table 10. For the sake of brevity, we report only the coefficient of local EU. Clearly, four regions, including the East North Central, Mountain, Pacific, and South Atlantic regions, are significantly affected by the shock of local EU. The remaining regions are not sensitive to the EU shock.

3.5 Robustness checks

To check whether uncertainty really matters to regional economic activity, we control for other concurrent amplification channels. We replicate Equation (4) by regressing output or employment on state-level uncertainty while including controls for local credit conditions, and other types of uncertainties.[30]

Controlling for local credit conditions

Several studies point out that credit constraints help to explain real economic fluctuations, especially during the financial crisis between 2007 and 2009 (Chodorow-Reich, 2013; Greenstone et al., 2014; Guerrieri and Lorenzoni, 2017). For example, Greenstone et al. (2014) emphasise that local credit crunches led to a decline in employment and wages during the 2007–2009 financial crisis. To rule out the possibility that the credit market drives the effect of uncertainty on output or employment, we include an aggregate credit-to-GDP ratio collected from the Bank for International Settlements, and local household credit measures from the Federal Reserve Bank of New York, into the baseline regression separately. We use the credit-to-GDP ratio as a proxy for aggregate credit conditions and household debt per capita for each state as a proxy for local credit conditions.[31]

Table 11 reports the estimation results when controlling for credit conditions. The first two columns indicate that the negative effect of EU on employment and GSP remains significant, even if we control for aggregate credit conditions.[32] The last two columns show the results when controlling local credit conditions. Again, our main results remain robust. Thus, credit constraints do not explain the negative relationship between EU and economic outcomes. One worthwhile note is that our results suggest that local credit constraints matter more for regional economic outcomes than do aggregate credit constraints.

Controlling for other types of uncertainty

[30] Note that we report results for all states only. The results for individual region are available upon request.
[31] The credit data are based on the New York Fed's project, Consumer Credit Panel, which is constructed from a nationally representative random sample of Equifax credit report data.
[32] Note that since the credit-to-GDP ratio is available on a quarterly basis only, we modify the monthly employment data by taking its simple average. Similarly, the local credit measure is available at an annual frequency, so we take the same approach to translate GSP and employment to the annual frequency.

One might argue that the negative effect of local EU is due to aggregate MU or other uncertainties. To address this concern, we add Baker et al.'s (2016) EPU, Jurado et al.'s (2015) FU and MU indices, as well as the CBOE Volatility Index (VIX) into the regression. These measures are common proxies for different types of uncertainty. Table 12 summarises the estimation results. Our finding that state-level EU has a negative effect on real economic activity does not change (see Columns 1 and 2 of Table 11). Further, this highlights the importance of state-specific uncertainty.

4 Conclusion

In this study, we construct a new set of SEU indices for the United States, using Google Trends for the period from January 2004 to June 2019. We show that the index is not an artefact of arbitrary choices made in its construction and is highly correlated with existing measures, and our index complements the existing measures from the additional perspective of idiosyncratic EU at the local level. Moreover, we find that a rise in regional uncertainty indeed depresses real economic activities such as output and employment, consistent with economic theory and other literature.

Further, we apply this approach to measure regional uncertainty and confirm that aggregate SEU indices are generally highly correlated across regions, while idiosyncratic SEU is noticeably different. We find that East North Central's EU is more synchronised. Both aggregate and idiosyncratic EU is countercyclical, showing that they both increase in the time of recessions. We also observe spillover effects across regions. Finally, we show that state-level EU reduces output and employment even if we control for credit conditions and other types of uncertainty; this result emphasises the importance of idiosyncratic REU.

We believe that this data set and approach can be valuable to researchers for many applications. First, the data set can be used to examine the relationship between economic and social variables and EU across regions in the United States. For example, one might investigate how local EU affects household economic decisions, or what determines local EU. Second, this approach can be applied across countries to tackle important research questions hitherto unexplored due to data limitations.

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Table 1. Search terms used in constructing uncertainty index

	Search Term
1	GOLD PRICES
2	RECESSION
3	GOLD PRICE
4	DEPRESSION
5	GREAT DEPRESSION
6	GOLD
7	ECONOMY
8	PRICE OF GOLD
9	THE DEPRESSION
10	CRISIS
11	GDP
12	BANKRUPTCY
13	UNEMPLOYMENT
14	INFLATION RATE
15	BANKRUPT
16	THE GREAT DEPRESSION
17	CAPITALIZATION
18	EXPENSE
19	SAVINGS
20	THE CRISIS
21	DEFAULT
22	UNEMPLOYED

Table 2: Correlation matrix among uncertainty measures

Panel A: Full sample							
	EU	MU	VIX	Global EPU	US EPU	GTU	Survey-based EU
EU	1.000						
MU	0.826***	1.000					
VIX	0.803***	0.756***	1.000				
Global EPU	-0.053	-0.113	0.200***	1.000			
US EPU	0.259***	0.098	0.428***	0.798***	1.000		
GTU	0.788***	0.612***	0.530***	-0.050	0.253***	1.000	
Survey-based EU	0.411***	0.447***	0.393***	0.165	0.212**	0.207**	1.000
Panel B: After financial crisis							
	EU	MU	VIX	Global EPU	US EPU	GTU	Survey-based EU
EU	1.000						
MU	0.673***	1.000					
VIX	0.741***	0.513***	1.000				
Global EPU	-0.173*	-0.236**	0.039*	1.000			
US EPU	0.211**	-0.076	0.296***	0.676***	1.000		
GTU	0.789***	0.599***	0.521***	-0.018	0.351***	1.000	
Survey-based EU	0.522***	-0.045	0.250	0.188	0.404**	0.315*	1.000

Notes: This table shows the correlation matrix among all risk/uncertainty indices during sample period. **, *** denotes that the correlations are significantly different from zero at the 5, and 1 per cent level, respectively. MU denotes macroeconomic uncertainty index by Jurado et al. (2015). VIX is the Chicago Board of Exchange (CBOE) market volatility index, The global EPU index is constructed by Davis (2016), US EPU index by is from Baker et al. (2016), with all data available at www.policyuncertainty.com. GTU denotes another Google Trend-based uncertainty index by Castelnuovo and Tran (2017). Survey-based EU is the EU index constructed by Bachmann et al.'s (2013).

Table 3. Co-movements of regional economic uncertainty

	Aggregate EU		Idiosyncratic EU	
	Correlation	Variance Explained by First Factor—PCA	Correlation	Variance Explained by First Factor—PCA
All States	0.670	0.691	0.323	0.352
New England	0.490	0.581	0.213	0.405
Middle Atlantic	0.880	0.920	0.312	0.545
East North Central	0.906	0.925	0.563	0.651
West North Central	0.552	0.636	0.274	0.386
South Atlantic	0.733	0.772	0.261	0.372
East South Central	0.695	0.775	0.407	0.559
West South Central	0.680	0.762	0.386	0.541
Mountain	0.630	0.685	0.314	0.411
Pacific	0.618	0.722	0.248	0.413

Notes: The classification is based on United States Census Bureau. See the Appendix A. Region's correlation and explained variance is calculated as the simple average of SEU correlation and explained variance within a region.

Table 4. State economic uncertainty over business cycle

	Aggregate state EU		Idiosyncratic state EU	
	(1)	(2)	(3)	(4)
GSP	-5.248***		-0.867***	
	(0.712)		(0.255)	
EMP		-6.155***		-3.797***
		(0.634)		(0.729)
Constant	-6.37E-15	-1.98E-13	-9.27E-16	-1.22E-13
	(0.015)	(0.010)	(0.008)	(0.012)
Time FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Adj. R^2	0.789	0.724	0.354	0.255
Observations	2,295	8,109	2,295	8,109

Notes**:** The dependent variable in all regressions is the economic uncertainty (EU) index. All variables are detrended based on Hamilton approach (see Hamilton, 2018). Independent variables include regional gross state production (GSP), and employment (EMP). Sample period of columns (1) and (3) is from the first quarter of 2006 to fourth quarter of 2018, while sample period of columns (2) and (4) is monthly observations from April 2006 to June 2019. The standard errors are clustered by state and time and corrected for heteroscedasticity. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5. The cyclicality of economic uncertainty for each region

Panel A: Aggregate State EU

	GSP	Obs.	Adj. R^2	EMP	Obs.	Adj. R^2
East North Central	-0.640	225	0.955	-6.765***	765	0.920
	(1.383)			(1.876)		
East South Central	-16.766***	180	0.860	-4.076***	612	0.732
	(2.959)			(1.309)		
Middle Atlantic	-1.455	135	0.954	-0.744	459	0.928
	(1.932)			(3.464)		
Mountain	-9.080***	360	0.806	-9.796***	1,224	0.685
	(1.797)			(1.834)		
New England	5.025**	270	0.658	-1.162	918	0.547
	(2.215)			(2.322)		
Pacific	-10.980***	225	0.772	-7.891***	765	0.677
	(2.439)			(2.269)		
South Atlantic	-7.421***	405	0.817	-7.777***	1,377	0.768
	(1.487)			(1.534)		
West North Central	-2.186***	315	0.684	-5.939***	1,071	0.604
	(0.839)			(2.066)		
West South Central	-1.284	180	0.705	-5.345***	612	0.663
	(1.573)			(1.841)		

Panel B: Idiosyncratic State EU

	GSP	Obs.	Adj. R^2	EMP	Obs.	Adj. R^2
East North Central	-0.445	225	0.656	-5.083**	765	0.610
	(0.936)			(2.531)		
East South Central	-5.364***	180	0.552	0.717	612	0.269
	(1.627)			(1.753)		
Middle Atlantic	0.598	135	0.492	11.499**	459	0.675
	(1.330)			(4.794)		
Mountain	-1.225**	360	0.422	-2.100	1,224	0.281
	(0.570)			(2.063)		
New England	0.235	270	0.322	-6.664**	918	0.250
	(1.206)			(2.698)		
Pacific	-0.562	225	0.200	-1.137	765	0.151
	(0.733)			(2.464)		
South Atlantic	-0.898	405	0.176	-6.978***	1,377	0.241
	(1.045)			(1.778)		
West North Central	-0.494***	315	0.297	-7.183***	1,071	0.189
	(0.145)			(2.617)		
West South Central	-0.319*	180	0.373	-6.831**	612	0.136
	(0.159)			(2.714)		

Notes**:** The dependent variable in all regressions is the economic uncertainty (EU) index. All variables are detrended based on Hamilton approach (see Hamilton, 2018). Independent variables include regional gross state production (GSP), and employment (EMP). To conserve space, we suppressed the constant, Time FE, State FE in this table. The standard errors are clustered by state and time and corrected for heteroscedasticity. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6. Correlation among REUs

Panel A: Aggregate REU

Aggregate REU	East North Central	East South Central	Middle Atlantic	Mountain	New England	Pacific	South Atlantic	West North Central	West South Central
East North Central	1.000								
East South Central	0.937	1.000							
Middle Atlantic	0.968	0.931	1.000						
Mountain	0.934	0.933	0.927	1.000					
New England	0.913	0.917	0.877	0.885	1.000				
Pacific	0.949	0.928	0.951	0.918	0.908	1.000			
South Atlantic	0.970	0.917	0.965	0.934	0.901	0.957	1.000		
West North Central	0.952	0.927	0.929	0.922	0.908	0.941	0.916	1.000	
West South Central	0.957	0.954	0.941	0.914	0.926	0.948	0.938	0.937	1.000

Panel B: Idiosyncratic REU

	East North Central	East South Central	Middle Atlantic	Mountain	New England	Pacific	South Atlantic	West North Central	West South Central
East North Central	1.000								
East South Central	0.481	1.000							
Middle Atlantic	0.678	0.471	1.000						
Mountain	0.508	0.532	0.487	1.000					
New England	0.277	0.581	0.195	0.243	1.000				
Pacific	0.504	0.419	0.562	0.409	0.250	1.000			
South Atlantic	0.676	0.364	0.665	0.521	0.222	0.586	1.000		
West North Central	0.604	0.484	0.483	0.489	0.349	0.537	0.388	1.000	
West South Central	0.574	0.602	0.492	0.393	0.381	0.507	0.452	0.515	1.000

Table 7. Spillover table for full sample

	East North Central	East South Central	Middle Atlantic	Mountain	New England	Pacific	South Atlantic	West North Central	West South Central	From Others
East North Central	24.1	12.3	6.9	5.1	9.4	5.5	8.5	11.3	17	75.9
East South Central	15.8	20.7	5.8	4.7	10.6	8.6	7.1	10.5	16	79.3
Middle Atlantic	15.3	14.3	18.6	5.5	8.6	6.5	6.9	10.3	13.9	81.4
Mountain	14.3	14.1	6.7	20.4	7.3	5.4	9.5	9.8	12.5	79.6
New England	15.2	11.7	3.8	3.4	23.9	7.7	9	10.7	14.6	76.1
Pacific	11.2	10.8	2.7	1.9	13.5	24.5	8.2	10.8	16.3	75.5
South Atlantic	16.7	9.9	4.8	6.1	11.3	6.4	24.7	6.4	13.7	75.3
West North Central	15.6	11.4	6.6	5.2	8.4	9.3	7.2	21.5	14.8	78.5
West South Central	16.1	13.3	4	3.4	11	9.6	7.7	10	24.9	75.1
Contribution to others	120.2	97.9	41.4	35.4	80	58.9	64.2	79.9	118.9	696.8
Contribution including own	144.3	118.6	60	55.8	103.9	83.4	88.9	101.3	143.8	77.4%

Note: this table shows the Spillover table for the period of January 2004 to June 2019. The columns show the fraction of the forecast error variance that the headline region contributes to all regions. The rows indicate the fraction of the forecast error variance that the headline region come from other regions.

Table 8. Spillover table for sample period of Detroit bankruptcy

	East North Central	East South Central	Middle Atlantic	Mountain	New England	Pacific	South Atlantic	West North Central	West South Central	From Others
East North Central	20.6	7.1	5.0	9.9	3.2	14.2	16.9	11.4	11.7	79.4
East South Central	11.7	34.1	0.9	13.4	9.8	8.2	2.4	5.0	14.4	65.9
Middle Atlantic	8.5	0.9	35.1	14.0	11.7	8.2	6.8	8.2	6.7	64.9
Mountain	12.1	9.9	10.1	25.2	4.8	9.2	7.2	11.0	10.6	74.8
New England	6.1	11.2	13.0	7.5	39.0	10.5	0.8	5.0	6.9	61.0
Pacific	14.9	5.2	5.1	7.9	5.9	21.7	13.6	12.8	12.9	78.3
South Atlantic	21.5	1.9	5.0	7.4	0.6	16.4	26.1	11.2	9.8	73.9
West North Central	12.9	3.4	5.5	10.2	3.0	13.9	10.1	23.4	17.6	76.6
West South Central	12.6	9.4	4.2	9.4	3.9	13.3	8.3	16.7	22.2	77.8
Contribution to others	100.3	48.9	48.6	79.7	42.9	93.9	66.1	81.4	90.7	652.6
Contribution including own	120.9	83.1	83.7	104.9	81.9	115.6	92.3	104.8	112.9	72.5%

Note: this table shows the spillover table for the period of March 2013 to December 2014. The columns show the fraction of the forecast error variance that the headline region contributes to all regions. The rows indicate the fraction of the forecast error variance that the headline region come from other regions.

Table 9. Effect of economic uncertainty on local economy

	(1)	(2)	(3)	(4)	(5)	(6)
	GSP	EMP	GSP	EMP	GSP	EMP
Local EU	-0.189***	-0.013***	-0.213***	-0.012***	-0.156***	-0.027***
	(0.030)	(0.002)	(0.030)	(0.002)	(0.049)	(0.003)
Lagged variable			-3.945***	0.006	-4.483***	-0.129**
			(0.457)	(0.054)	(0.491)	(0.061)
Country-level EU					-0.076**	-0.018***
					(0.032)	(0.001)
Constant	0.326***	0.063***	48.224***	-0.018	54.761***	1.896***
	(0.022)	(0.001)	(5.551)	(0.778)	(5.966)	(0.881)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	--	--
Adj. R^2	0.209	0.478	0.230	0.478	0.130	0.325
Observations	2,805	9,435	2,805	9,435	2,805	9,435

Notes: The standard errors are clustered by province and corrected for heteroscedasticity.
*, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
GSP refers to gross state production, and EMP refers to employment.

Table 10. Effect of economic uncertainty for each region

Panel A: Without country-level EU

	GSP			EMP		
	Local EU	Obs.	Adj. R^2	Local EU	Obs.	Adj. R^2
East North Central	-0.415*** (0.062)	275	0.621	-0.014*** (0.005)	925	0.783
East South Central	-0.065 (0.097)	220	0.600	-0.010 (0.011)	740	0.324
Middle Atlantic	0.198 (0.224)	165	0.046	-0.007 (0.005)	555	0.765
Mountain	-0.325*** (0.088)	440	0.292	-0.021*** (0.004)	1,272	0.657
New England	0.002 (0.078)	330	0.341	0.003 (0.003)	1,110	0.451
Pacific	-0.756*** (0.221)	275	0.309	-0.026*** (0.004)	925	0.482
South Atlantic	-0.275*** (0.068)	495	0.199	-0.016*** (0.004)	1,665	0.483
West North Central	-0.152 (0.100)	385	0.248	-0.003 (0.002)	1,295	0.397
West South Central	-0.052 (0.134)	220	0.249	0.010 (0.006)	740	0.377

Panel B: Adding country-level EU

	GSP			EMP		
	Local EU	Obs.	Adj. R^2	Local EU	Obs.	Adj. R^2
East North Central	-0.268*** (0.079)	275	0.356	-0.046*** (0.005)	925	0.496
East South Central	-0.109 (0.102)	220	0.173	0.004 (0.009)	740	0.122
Middle Atlantic	-0.012 (0.162)	165	0.089	0.008 (0.006)	555	0.237
Mountain	-0.175** (0.079)	440	0.124	-0.026*** (0.004)	1,272	0.479
New England	0.016 (0.074)	330	0.071	0.007*** (0.002)	1,110	0.284
Pacific	-0.560*** (0.216)	275	0.162	-0.011** (0.004)	925	0.245
South Atlantic	-0.233*** (0.064)	495	0.101	-0.013*** (0.004)	1,665	0.316
West North Central	-0.187** (0.094)	385	0.091	-0.003 (0.002)	1,295	0.235
West South Central	-0.060 (0.127)	220	0.063	-0.002 (0.006)	740	0.284

Notes: For the sake of brevity, we only report the coefficient of local EU. Similar to Table 9, we control for constant and lagged dependent variable (GSP or EMP). The standard errors are clustered by province and corrected for heteroscedasticity.
*, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
GSP refers to gross state production, and EMP refers to employment.

Table 11. Controlling for credit conditions

	(1)	(2)	(3)	(4)
	GSP	EMP	GSP	EMP
EU	-0.270***	-0.024***	-0.429**	-0.302***
	(0.027)	(0.002)	(0.184)	(0.078)
Credit-to-GDP	-0.008	-1.284***		
	(0.860)	(0.045)		
Local Credit			-14.071***	-3.479***
			(1.963)	(0.902)
Lagged variable	-4.653***	-0.570***	10.859***	-119.516***
	(0.523)	(0.055)	(3.396)	(21.520)
Constant	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Time FE	--	--	Yes	Yes
Adj. R^2	0.122	0.255	0.470	0.688
Observations	2,695	8,869	624	672

Notes: The standard errors are clustered by province and corrected for heteroscedasticity.
*, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
GSP refers to gross state production, and EMP refers to employment

Table 12. Control for other uncertainties

	(1)	(2)
	GSP	EMP
EU	-0.190**	-0.007***
	(0.040)	(0.003)
MU	-2.271***	-0.566***
	(0.485)	(0.026)
FU	2.156***	-0.117***
	(0.280)	(0.023)
VIX	-0.553***	0.011
	(0.176)	(0.013)
EPU	-0.612***	-0.064***
	(0.097)	(0.006)
Other controls and Constant	Yes	Yes
State FE	Yes	Yes
Time FE	--	--
Adj. R^2	0.151	0.339
Observations	2,695	9,065

Notes: The standard errors are clustered by province and corrected for heteroscedasticity.
*, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
GSP refers to gross state production, and EMP refers to employment. MU and FU refer to macroeconomic uncertainty and financial uncertainty index from Jurado et al (2015). EPU refers to the economic policy uncertainty index from Baker et al. (2016). VIX is the CBOE's volatility index. We remove the time fixed effect as these uncertainty measures are cross-sectional invariant variables.

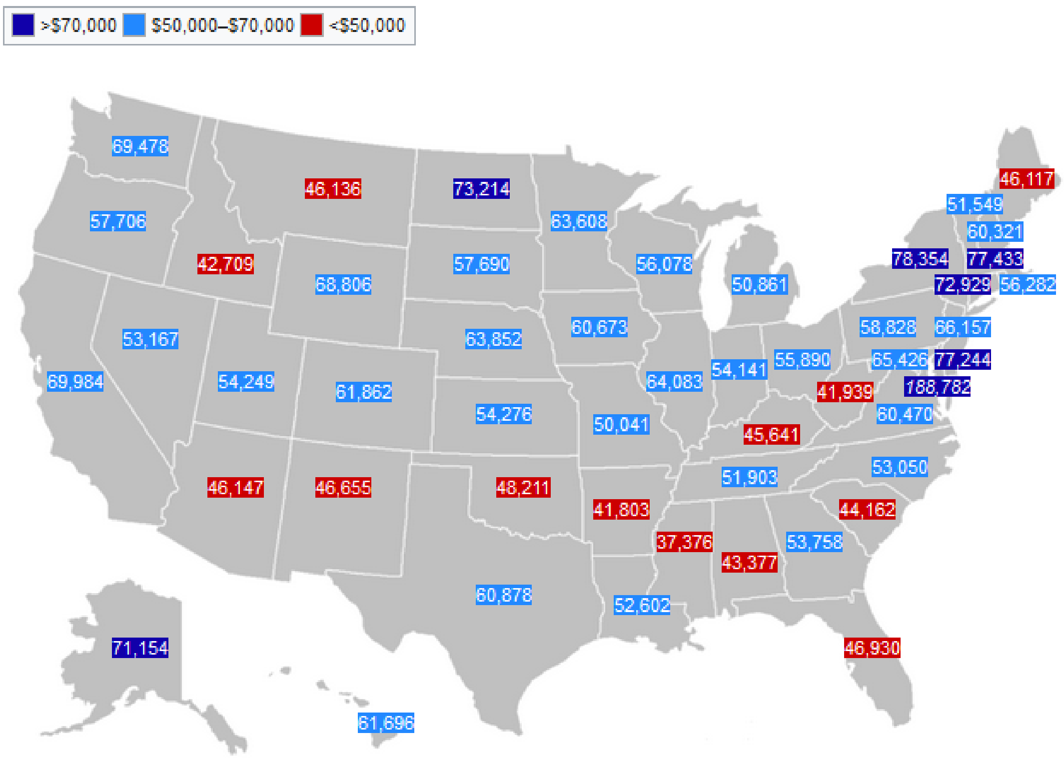

Figure 1. GDP Per Capita by State in the US in 2017

Sources: Wikipedia (https://en.wikipedia.org/wiki/List_of_U.S._states_by_GDP_per_capita)
It is based on Bureau of Economic Analysis (BEA) data.

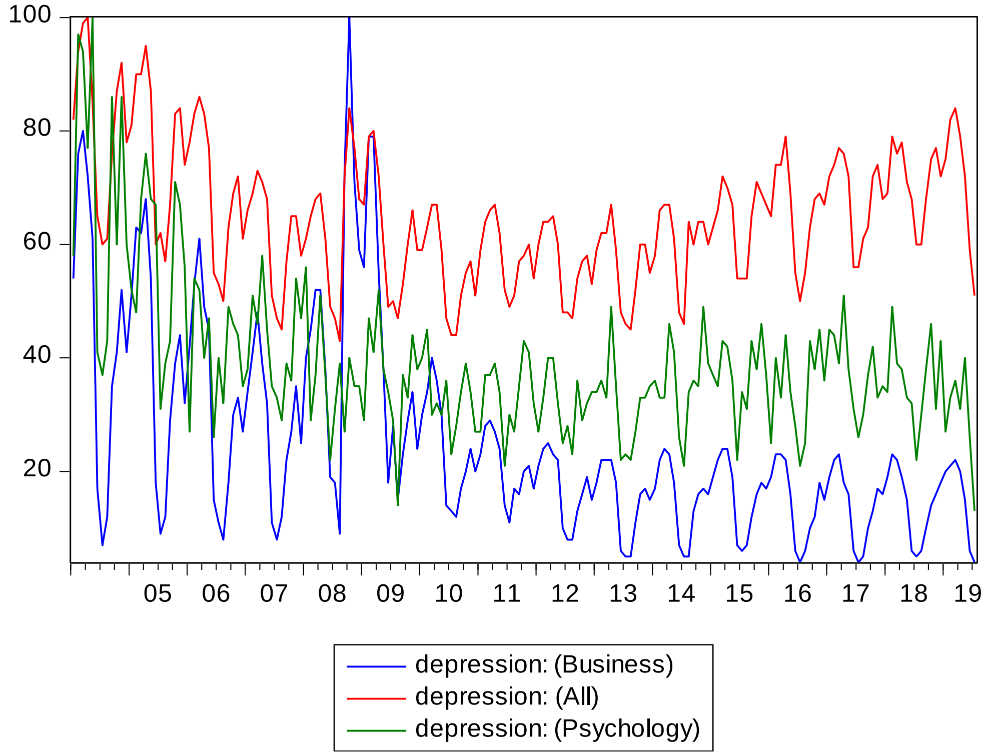

Figure 2. Google search volume index for the "depression" using three different extraction methods, Jan 2004-Jun 2019

Note: X-axis is sample period where year is labelled (e.g. 05 refers to year 2005). Y-axis is the value of Google's search volume index (SVI). Google Trends do not provide actual search volume but SVI that ranging from 0 to 100 for a given sample period, where 100 represents the date that the given search term achieves its peak relative search volume. 0 does not represent the search volume is zero, but it represent that search volume at that time is lowest during the sample period.

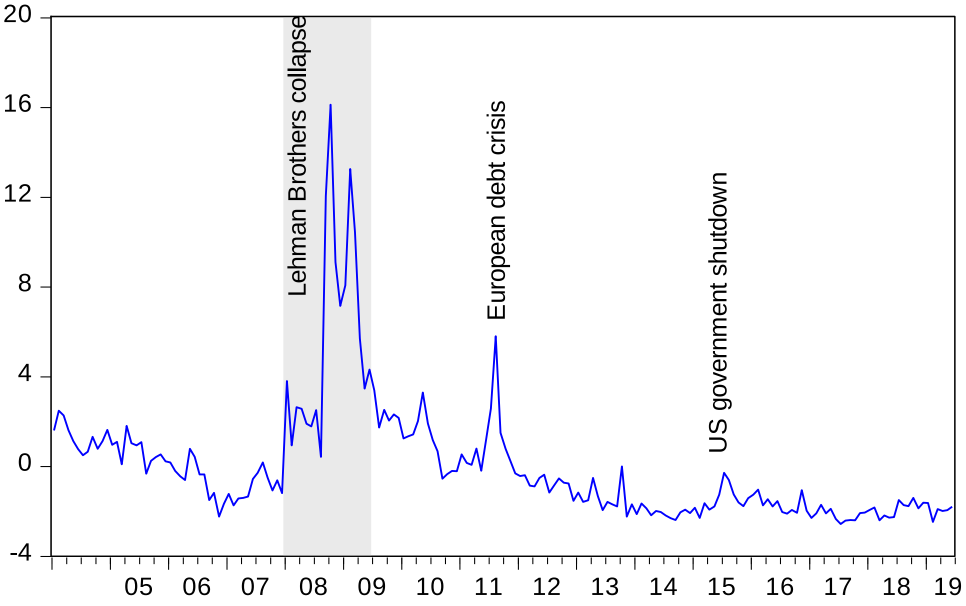

Figure 3. Aggregate Economic Uncertainty Index, NBER recession shaded

Note: X-axis is sample period where year is labelled (e.g. 05 refers to year 2005). Y-axis indicates the value of EU index created in this study. Since we apply PCA to extract common components of different SVIs and do not normalize resulting times series, the EU could be negative. We simply need the pattens and fluctuations of EU. When the value of EU index goes beyond zero, this simply means that at that point of time, EU is very low, comparing to other periods.

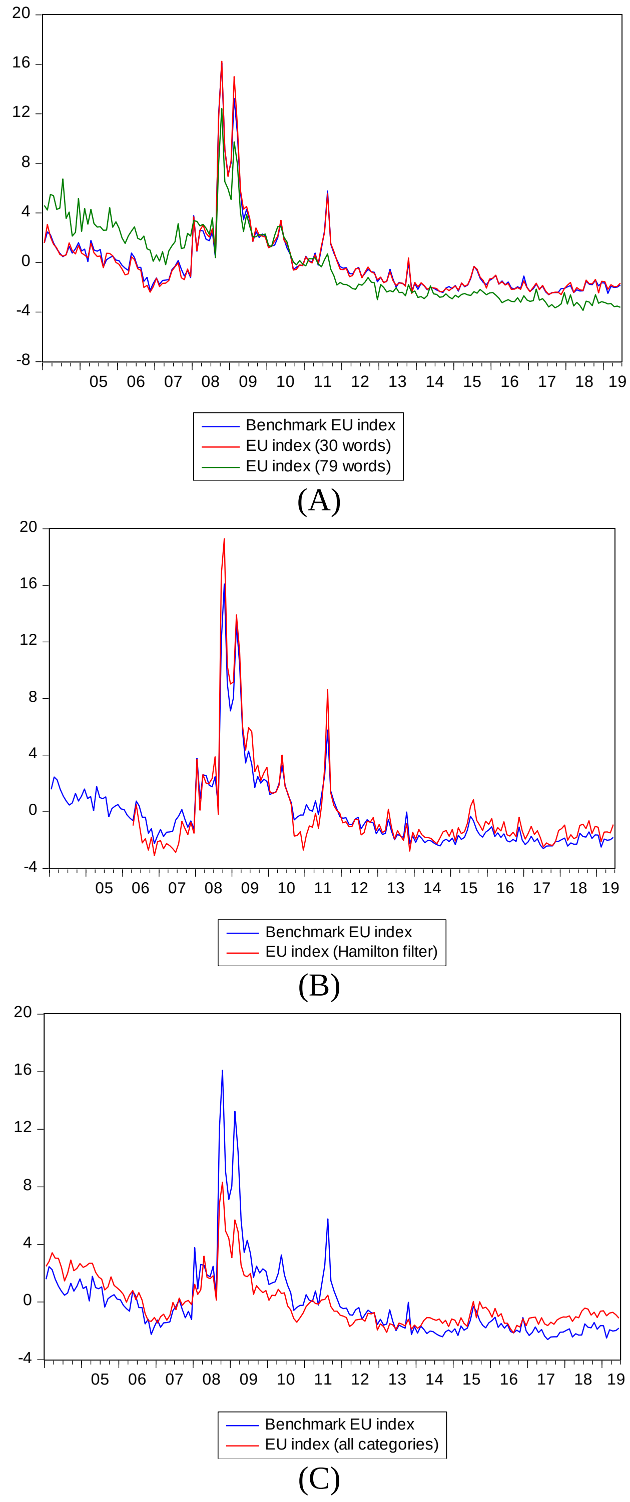

Figure 4. Comparison among benchmark index and alternatives

Note: X-axis is sample period where year is labelled (e.g. 05 refers to year 2005). Y-axis indicates the value of EU index created in this study. Since we apply PCA to extract common components of different SVIs and do not normalize resulting times series, the EU could be negative. We simply need the pattens and fluctuations of EU. When the value of EU index goes beyond zero, this simply means that at that point of time, EU is very low, comparing to other periods.

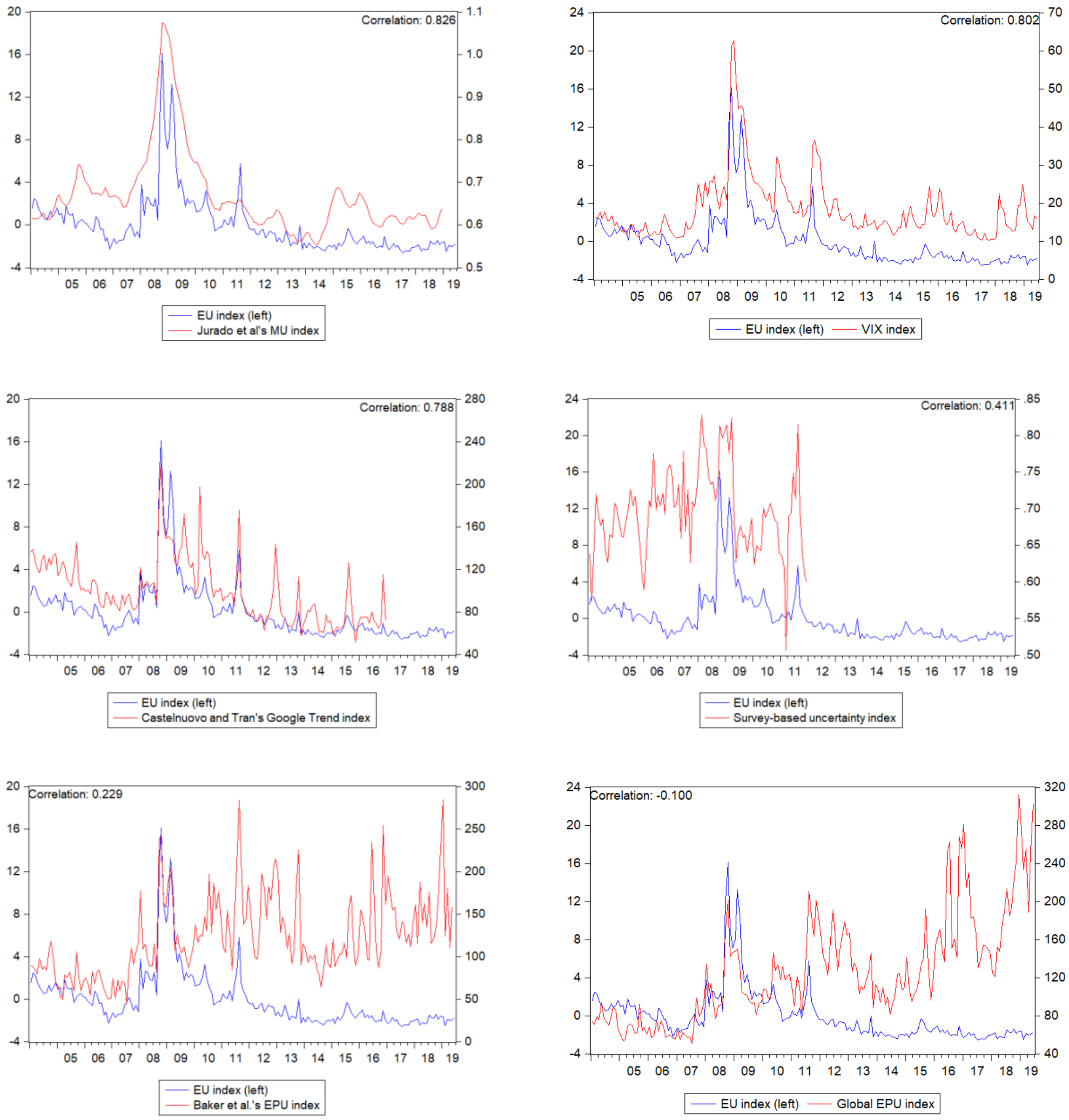

Figure 5. Comparison with other uncertainty measures

Note: X-axis is sample period where year is labelled (e.g. 05 refers to year 2005). Y-axis indicates the value of EU index created in this study. Since we apply PCA to extract common components of different SVIs and do not normalize resulting times series, the EU could be negative. We simply need the pattens and fluctuations of EU. When the value of EU index goes beyond zero, this simply means that at that point of time, EU is very low, comparing to other periods.

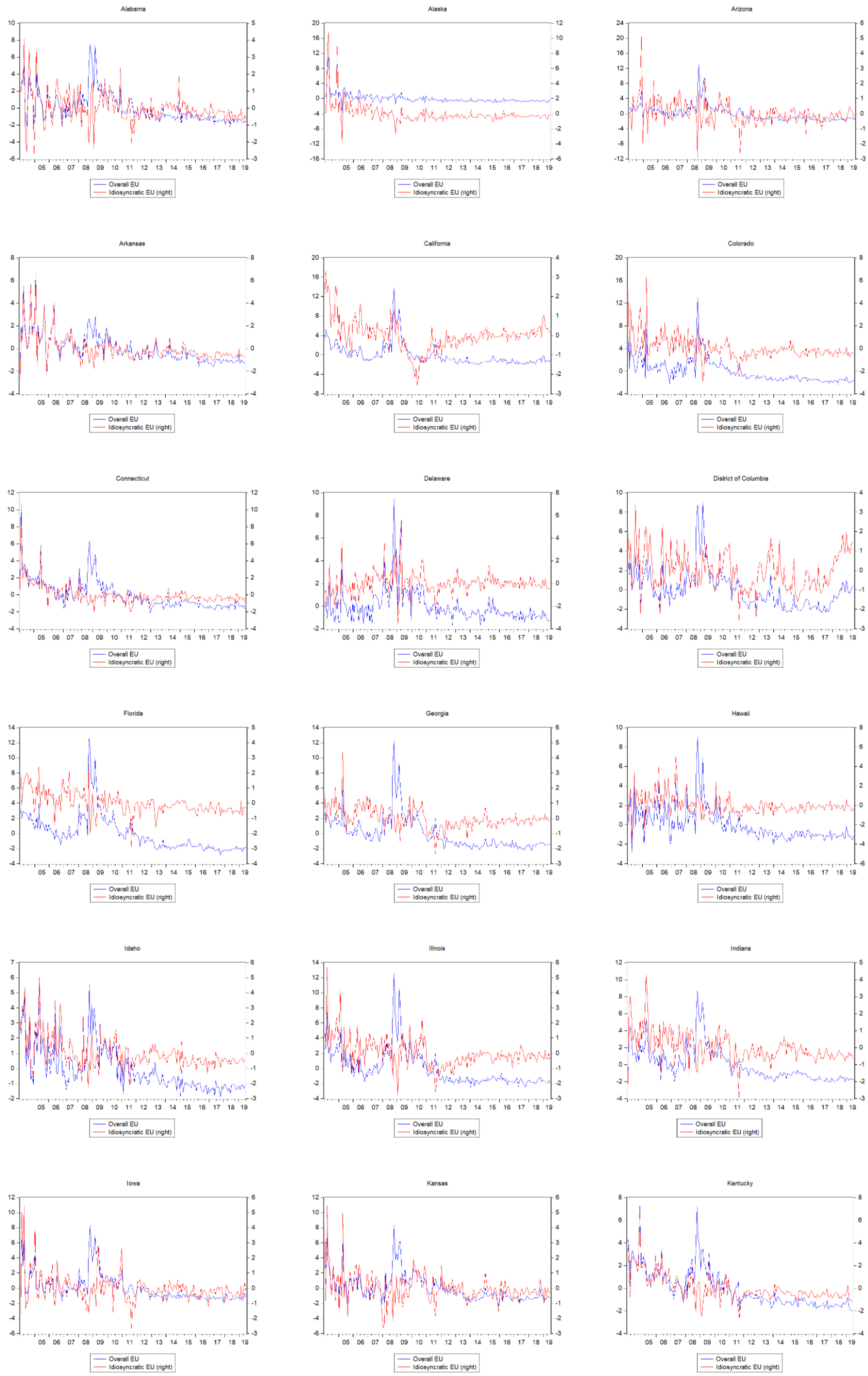

Figure 6: State's economic uncertainty

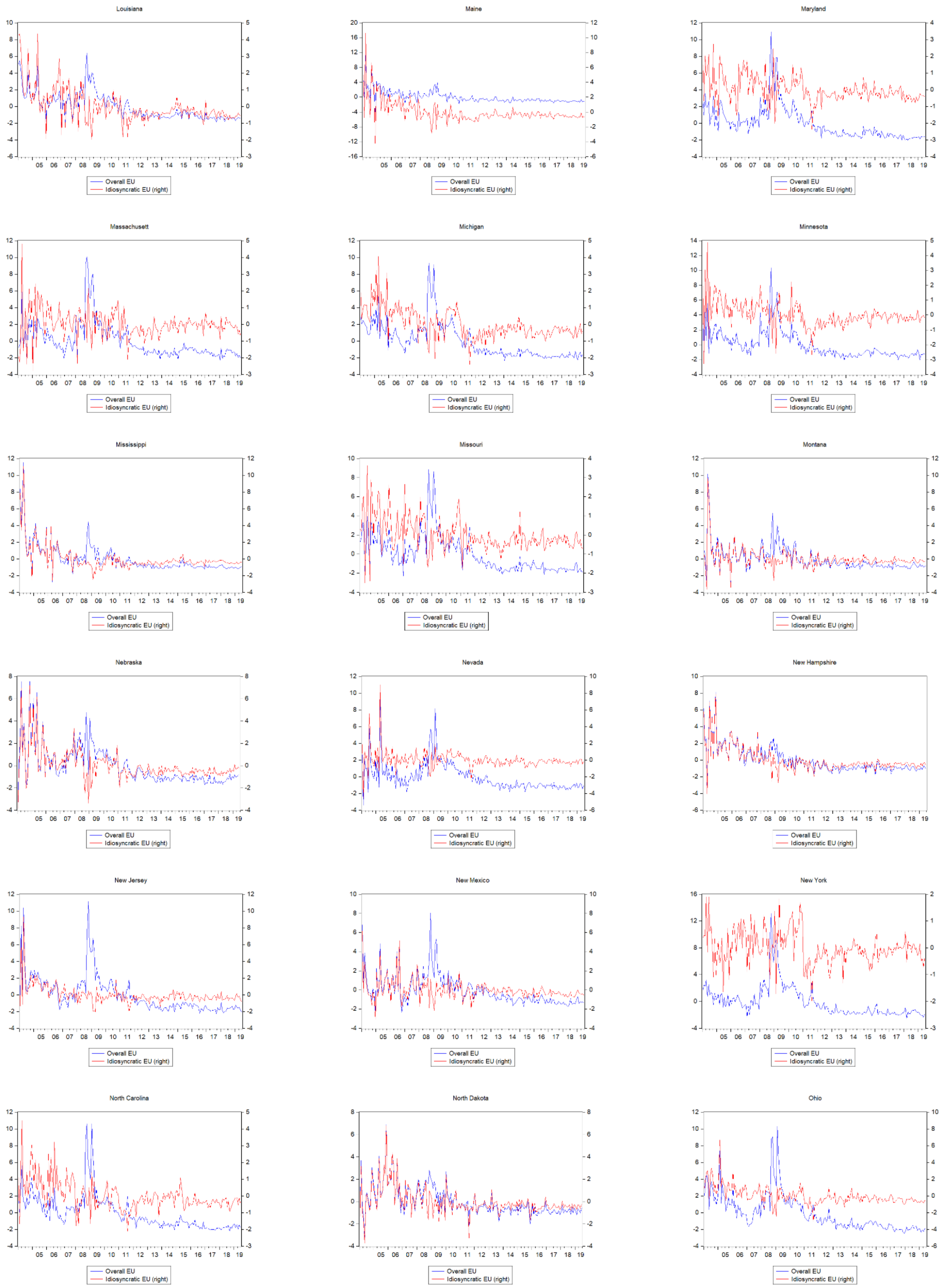

Figure 6: State's economic uncertainty

Figure 6: State's economic uncertainty

Note: X-axis is sample period where year is labelled (e.g. 05 refers to year 2005). Y-axis indicates the value of EU index created in this study. Since we apply PCA to extract common components of different SVIs and do not normalize resulting times series, the EU could be negative. We simply need the pattens and fluctuations of EU. When the value of EU index goes beyond zero, this simply means that at that point of time, EU is very low, comparing to other periods.

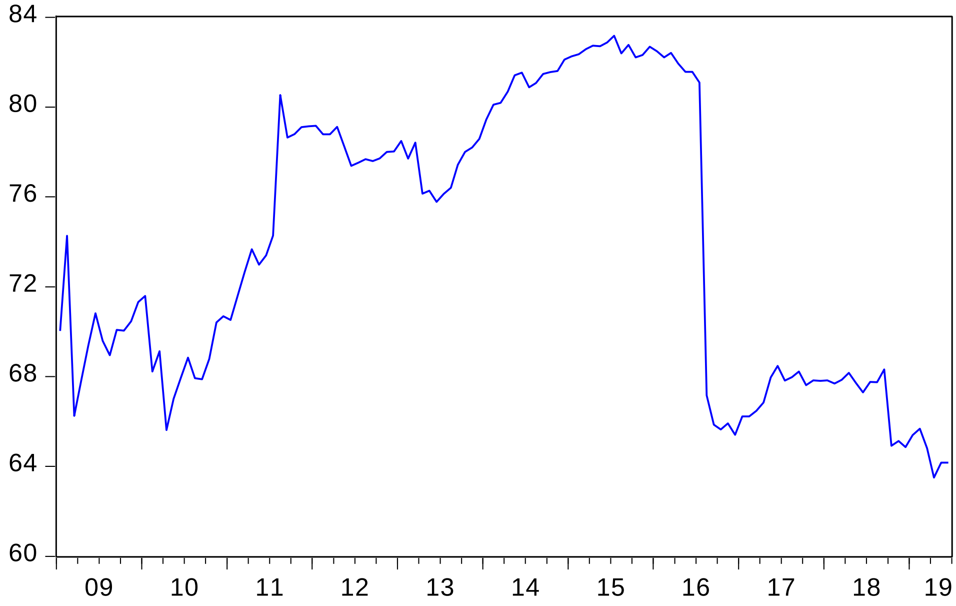

Figure 7. Spillover index

Note: X-axis is sample period where year is labelled (e.g. 05 refers to year 2005). Y-axis indicates the value of spillover index using Diebold and Yilmaz (2012) approach.

Appendix A

The list of region classification:

New England Region: Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut

Middle Atlantic Region: New York, New Jersey, Pennsylvania

East North Central Region: Ohio, Indiana, Illinois, Michigan, Wisconsin

West North Central Region: Minnesota, Iowa, Missouri, North Dakota, South Dakota, Nebraska, Kansas

South Atlantic Region: Delaware, Maryland, District of Columbia, Virginia, West Virginia, North Carolina, South Carolina, Georgia, Florida

East South Central Region: Kentucky, Tennessee, Alabama, Mississippi

West South Central Region: Arkansas, Louisiana, Oklahoma, Texas

Mountain Region: Montana, Idaho, Wyoming, Colorado, New Mexico, Arizona, Utah, Nevada

Pacific Region: Washington, Oregon, California, Alaska, Hawaii

Appendix B. Additional analysis

The US Macroeconomy and Economic Uncertainty

This appendix briefly analyses the impact of EU on the US macroeconomy using our index. The basic rationale for performing this analysis is that uncertainty usually has an important dynamic relationship with real economic activity. In particular, it reduces output, investment, and employment (e.g., Bloom et al., 2007; Bloom 2009; Jurado et al., 2015; Baker et al., 2016; Di Tella, 2017; Fajgelbaum et al., 2017; Schaal, 2017; Bloom et al., 2018). Thus, if our measure is reliable, then it should have a similar effect on the US economy. Below, we use vector autoregressive models (VARs) to estimate the response of economic variables to the innovations in our EU index, and we compare them with the responses to innovations in the other economic uncertainty measures.

Following Bloom (2009), we estimate the impulse response of an eight-variable VAR model with the following ordering: log of the S&P 500 index; uncertainty index; federal funds rate (FFR); log wage; log consumer price index (CPI); hours; log employment; and log industrial production.[33] We use the Cholesky decomposition to identify shocks. The optimal lags in the VAR model are based on the Akaike information criterion.

Figure A1 presents the impulse responses to a one-standard-deviation positive innovation to the uncertainty index, together with a 95% confidence band. The first row reports our EU index's response to shock; the shock leads to an immediate reduction in industrial production with the greatest impact at about the 10-month mark, where the output is reduced by approximately 1%. These effects persist well past the depicted 20-month time horizon. The shock also reduces employment, and such negative effect persists throughout the 20-month horizon. It is also interesting to compare the dynamic correlations of our uncertainty measures with common uncertainty proxies. We first compare with Jurado et al.'s (2015) MU and obtain a similar result (see the second row). The MU shock sharply reduces production and employment, with a magnitude that is slightly larger than our EU.

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[33] We collect the S&P 500 index data from Shiller's website (http://www.econ.yale.edu/~shiller/data.htm) and the data for the other variables from the Federal Reserve Economic Data (FRED) database (https://fred.stlouisfed.org/). One difference in our specifications is that we use the log of total private employment instead of employment in manufacturing sectors only.

We also compare the results using the VIX, Castelnuovo and Tran's (2017) Google-based uncertainty index, and Bachmann et al.'s (2013) survey-based uncertainty measure. We report the results in Rows 3–5 of Figure A1. Both the magnitude and the persistence of the production and employment responses are much smaller in these three cases. Indeed, the responses of employment and production are barely statistically different from zero at all periods, which obviously differs from the results of the original papers. There are three possible explanations for this difference. First, our sample period spans from April 2006 to June 2019, which is much more recent than the sample periods of the previous studies. Second, the negative effect of uncertainty that Bloom (2009) and Bachmann et al. (2013) find might be sensitive to the macro variables that are HP-filtered (see the discussion in Jurado et al., 2015). Third, we report our results at 95% confidence bands rather than at the 68% confidence bands used in previous studies, thus ensuring a stricter approach. In the last row, we report the results using EU index without refinement of restricting search volume within "Business News". Clearly, without such refinement, the uncertainty's effect on the macroeconomy is slightly smaller, indicating that "without refinement" may underestimate the effect of EU.

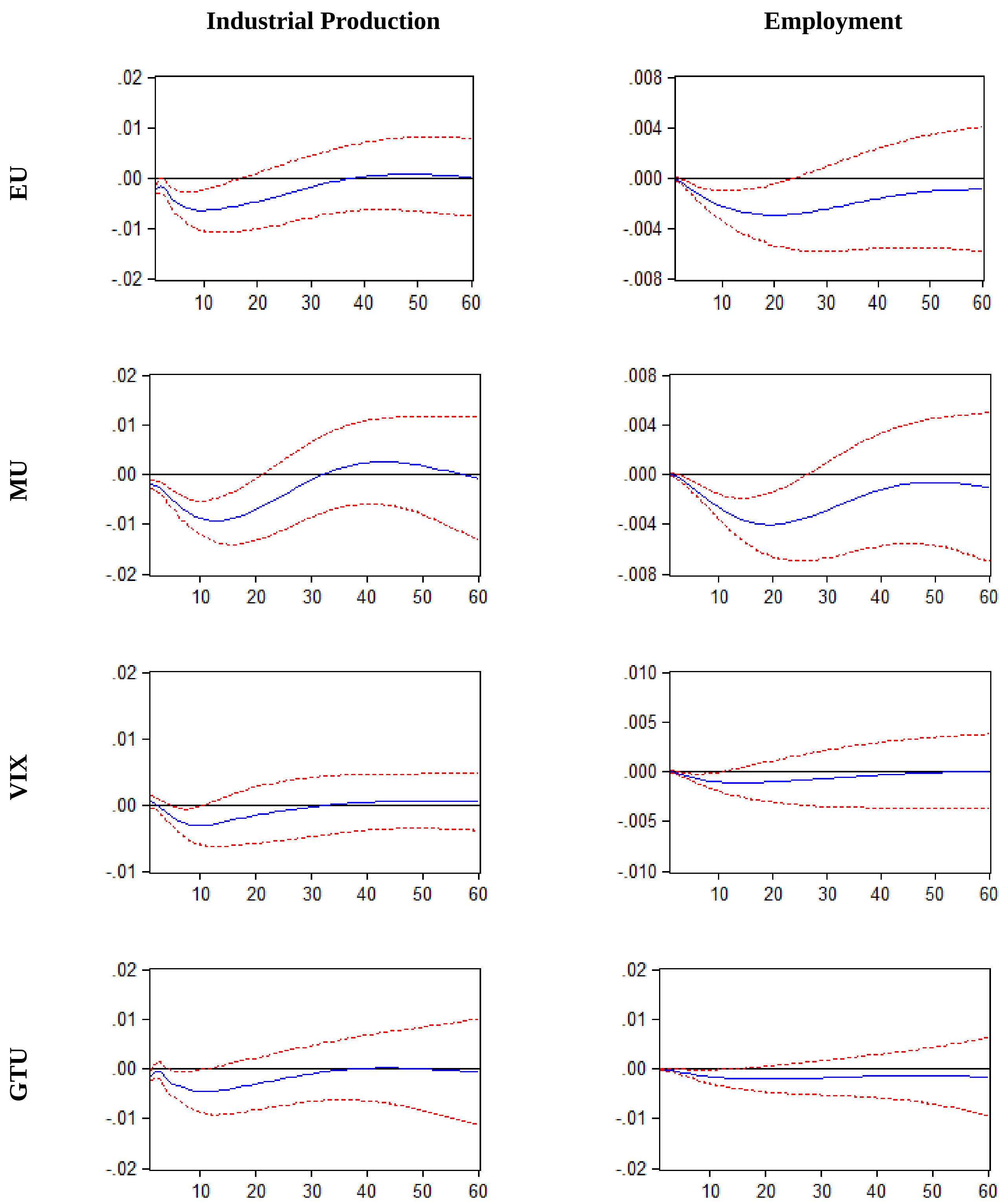
We conduct several checks using alternative specifications. These include a bivariate VAR model with industrial production/employment and EU only, and Baker et al.'s (2016) six-variable VAR model.[34] This also includes the addition of the US EPU index before our EU index, adding VIX, using a local projections method (Jordà, 2005) to estimate the impulse response[35], and using de-trended macroeconomic variables[36]. We also put the EU in the last order of our VAR analysis for robustness given that the measures of EU constructed here are likely to be closer to real activity than to the stock market (see Jurado et al., 2015, and Ludvigson et al., 2015 for discussion). Figure A2 reports the impulse responses of production and employment to the EU shock based on various specifications. Although these modifications lead to somewhat different impulse responses, the main conclusion, that EU reduces employment and output, remains robust. In short, similar to the literature, our results suggest that EU reduces aggregate output and employment. This indirectly

[34] They employ the following order in the VAR-5 model: uncertainty index; log of S&P 500 index; FFR; log employment; and log industrial production.

[35] The local projections method is a popular tool to estimate impulse responses because it allows easier modeling of non-linearities and is robust for model misspecifications. To avoid misspecifications, this approach collects values for each forecast horizon, h, by regressing the dependent variable vector at $t+h$ on the information set at time t.

[36] We use the Hamilton (2018) filter instead of the HP filter.

verifies the robustness of our EU index.



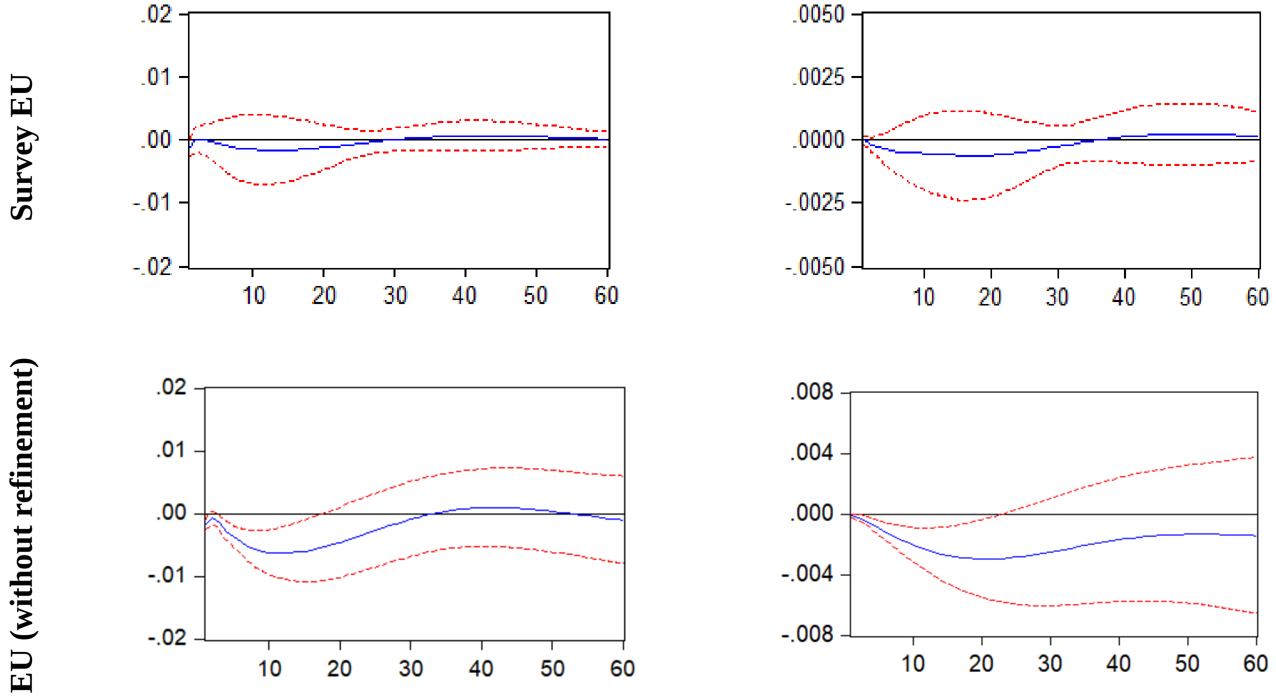


Figure A1. Impulse responses to a one-standard-deviation innovation in EU index

Note: The red solid lines denote the median impulse response functions. The dashed lines denote 5 and 95% error bands using 1,000 Monte Carlo simulations. X-axis indicates month after shock.

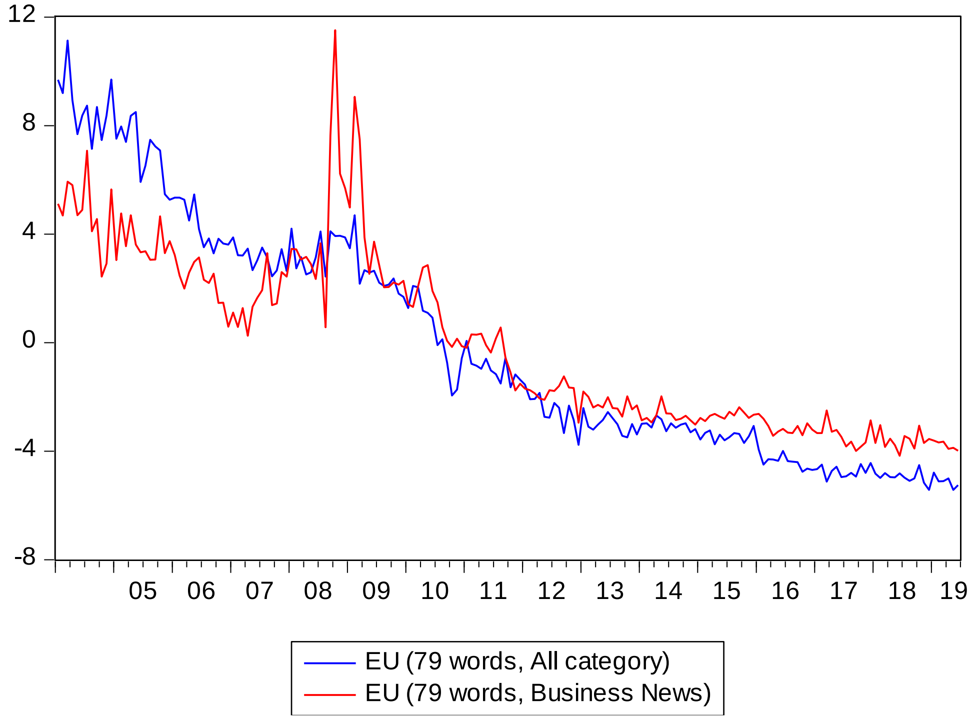
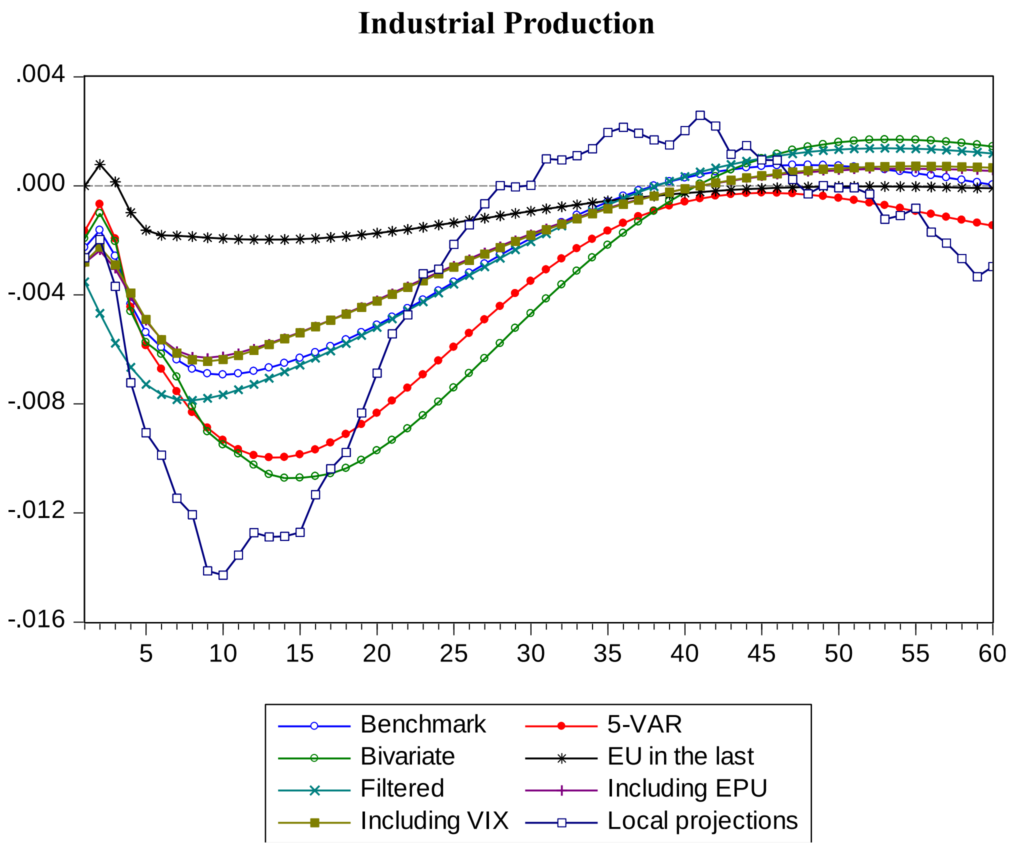


Figure A2. EU index based on 79 keywords (refinement w/o)

Note: X-axis is sample period where year is labelled (e.g. 05 refers to year 2005). Y-axis indicates the value of EU index created in this study. Since we apply PCA to extract common components of different SVIs and do not normalize resulting times series, the EU could be negative. We simply need the pattens and fluctuations of EU. When the value of EU index goes beyond zero, this simply means that at that point of time, EU is very low, comparing to other periods.



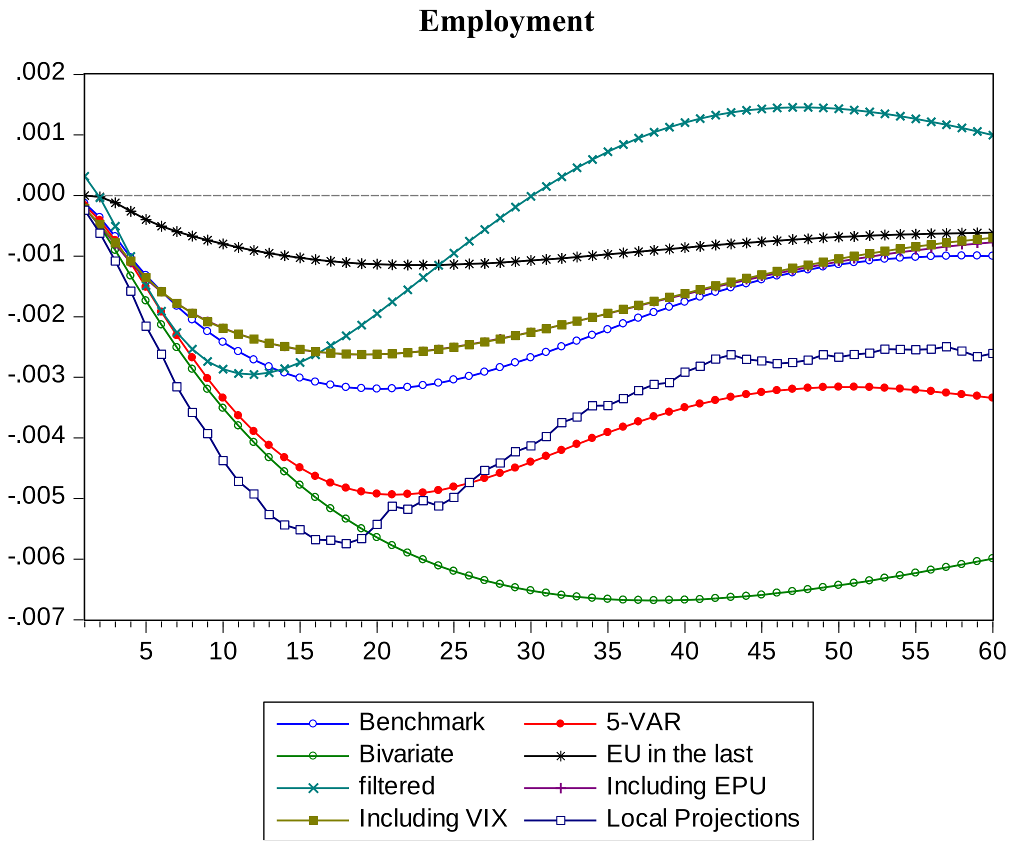


Figure A2: Output and Employment response to an EU shock, with alternative specifications

Note: The benchmark specification is the same as in Figure A1. The other cases department from the benchmark as indicated.

Appendix C

Table B. Unit root test results of EU

Region	ADF	PP
New England	-2.273**	-3.343***
Middle Atlantic	-2.423**	-2.827***
East North Central	-2.227**	-2.707***
West North Central	-2.408**	-2.945***
South Atlantic	-1.997**	-2.999***
East South Central	-2.842***	-3.748***
West South Central	-2.829***	-2.990***
Mountain	-2.006**	-4.118***
Pacific	-3.090***	-3.803***

Notes: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Appendix D. Economic Uncertainty across Census Divisions