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Article

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Measuring Economic Uncertainty in China†

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Abstract

This study develops a new economic uncertainty (EU) index based on Chinese newspapers to address the media coverage bias of existing measures. We investigate how EU affects China's macroeconomy. Our results suggest that EU reduces aggregate output. We find that uncertainty predicts fluctuations in economic activity and actual economic activity also predicts EU, but nonlinearly. Furthermore, we show that uncertainty in the United States leads to uncertainty in China, implying that negative EU on the Chinese economy is coming from the U.S. Finally, we conduct some asset pricing tests, showing that EU can predict stock returns and commands risk premium. Our results are helpful for both researchers and policymakers to stabilize the economy and financial markets in China.

Keywords: economic uncertainty, China, newspapers, Granger causality, nonlinear causality
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Abstract

This study develops a new economic uncertainty (EU) index based on Chinese newspapers to address the media coverage bias of existing measures. We investigate how EU affects China's macroeconomy. Our results suggest that EU reduces aggregate output. We find that uncertainty predicts fluctuations in economic activity and actual economic activity also predicts EU, but nonlinearly. Furthermore, we show that uncertainty in the United States leads to uncertainty in China, implying that negative EU on the Chinese economy is coming from the U.S. Finally, we conduct some asset pricing tests, showing that EU can predict stock returns and commands risk premium. Our results are helpful for both researchers and policymakers to stabilize the economy and financial markets in China.

1 Introduction

Literature on uncertainty has been largely growing since the outbreak of the global financial crisis in 2008 and the subsequent Eurozone debt crisis, as uncertainty is believed to be one of the major causes that slow down economic activity. For example, Bloom (2009) shows that macro uncertainty shocks produce rapid drops and rebounds in aggregate output and employment. Aside from academics, policymakers pay great attention to uncertainty due to its detrimental impact on the economy. For example, the World Bank (2016), in its Global Economic Prospects, notes that the heightened level of policy uncertainty, especially regarding trade, might be amplified by slower potential growth, and increasing vulnerabilities in emerging markets and developing countries.[4] Thus, there is a demand for timely uncertainty indicators for policymakers to take pre-emptive actions instead of simply reacting to downturns after the fact.

The conventional approach of measuring uncertainty is to use option-implied/realized stock market volatility (Bloom, 2009). Meanwhile, several new approaches have been developed in recent years. For example, Jurado et al. (2015) define uncertainty as the conditional volatility of the unforecastable component of the future values of a series. Using a text-searching technique, Baker et al. (2016) measure uncertainty as the proportion of uncertainty-related articles to total news articles. Both studies create uncertainty measures and show that uncertainty is harmful for the macroeconomy.

[4] The original statement is “The heightened level of policy uncertainty, especially regarding trade, that has been exacerbated by recent political developments–most notably in the United States and the United Kingdom–may be amplified over time by mounting protectionist tendencies, slower potential growth, and elevated vulnerabilities in some emerging markets and developing countries.”

However, until now, progress in measuring uncertainty was limited to only a set of the most advanced economies. This study fills this gap to refine the economic uncertainty (EU) measure in China by considering its special characteristics.[5] Following Baker et al.'s (2016) approach, we apply text-searching techniques on newspapers to create a measurement of China's EU relationship. Baker et al. (2016) develop an economic policy uncertainty (EPU) index for China. However, they select only one Hong Kong-based newspaper to deal with media censorship in the Chinese media. Selecting one newspaper is inevitably biased and the uncertainty measure based on the newspaper will likely suffer significantly from any changes in editorial policy or preference. Moreover, the Hong Kong-based newspaper is more likely to report news relevant to the Hong Kong economy, which means it may not reflect the overall level of uncertainty in China very well.

Instead of selecting a few newspapers for the sample, we use all available *financial* and *economic* newspapers in China to measure EU. We select these newspapers because they focus on news related to the economy, and are likely to be timelier in reporting uncertainty or risk events. Another reason is to possibly reduce the impact of the bias in official mass media. As mentioned by Qin et al. (2018), all general-interest newspapers in China are state-owned and suffer from strict censorship. You et al. (2017) compare market-oriented and state-owned media and observe that the former is more critical, accurate, comprehensive, and timely than the latter. Moreover, *financial* and *economic* newspapers are mainly privately owned rather than state owned, which can alleviate the concern of media bias. Furthermore, our sample contains

[5] The term "uncertainty" encompasses both "risk" and "Knightian uncertainty". The former means the probabilities of potential outcomes are known, but which outcome will occur is not, while the latter means neither the probabilities of outcomes nor the eventual outcome are known (Knight 1921). It is difficult to disentangle these two, so in this study we refer to a single concept of uncertainty that incorporates both elements.

newspapers from Taiwan and Hong Kong, which can further reduce the concern about media bias. We show that our constructed indices reflect uncertainty well and co-move with existing EU measures, while overcoming certain drawbacks.[6]

Based on the constructed EU index, we investigate the effect of EU on the economy. We estimate the impulse response of macroeconomic variables to the shock of EU measured by our index using a vector autoregressive model. Consistent with the literature, we observe that output falls in response to an unexpected rise in EU, indicating EU is a driver of business cycle fluctuations. The impact of EU differs across provinces, and we show that some provinces recover more quickly after the shock of EU. The city of Beijing is an exception in that its output responds insignificantly to the shock of EU. This finding is consistent with Chen and Groenewold (2018, 2019) who find that economic shock has less impact on Beijing. These authors explain that Beijing is the economic and administrative center, different in several respects (i.e., geographic extent, industrial structure, and others) and thus, it is not surprising that Beijing is an outlier in this analysis. Further, we focus on the predictive relationship between uncertainty and an economic variable, and also the predictability between China uncertainty and U.S. uncertainty. Using both linear and nonlinear Granger causality tests, we find that there is a predicative relationship from EU to GDP (or business condition indicator), showing that EU has the power to predict macroeconomic variables. Business cycle variables also have predictive power on EU, but nonlinearly. Given the recent trade conflict between the U.S. and China, there is growing interest in studying the uncertainty between them (e.g., Handley and Limão, 2017; Fontaine et al., 2017; Huang et al., 2018; Zhang et al., 2019). For

[6] We will discuss the advantages of our index in comparison with other uncertainty measures in Section 2.

example, Huang et al. (2018) observe a unidirectional spillover of macroeconomic uncertainty from the U.S. to China. We perform similar analysis and observe strong evidence that U.S. EU leads to China EU, which is consistent with the recent trade tension between the U.S. and China. However, China's EU only predicts the fluctuation in U.S. EU in a nonlinear setting, which is consistent with the view that China's EU has impact on the U.S. during some periods, such as during recession (Fontaine et al., 2017). Finally, we show that EU commands risk premium and can predict stock returns by controlling other factors.

This study relates to several strands of literature. First, a set of new EU indices created in this study is well aligned with Baker et al. (2016) and Jurado et al. (2015). This approach can be easily adapted to a monthly analysis (or even higher frequencies) across geographical areas and thus, enables researchers to replicate and apply it to other countries. In contrast with existing measures (Baker et al., 2016; Davis et al., 2019), our index has two distinct features. On the one hand, we use multiple newspapers instead of relying on one particular paper, which probably alleviates the media bias problem in China. On the other hand, we focus on macroeconomic uncertainty instead of policy uncertainty. This might help further research on the interaction between macroeconomic uncertainty and policy uncertainty, which can also help researchers to disentangle the effects of policy uncertainty and macroeconomic uncertainty on the economy.[7] Second, this study is also related to the literature that focuses on the relations between uncertainty and the real economic activity (e.g., Wang et al., 2014; Antonakakis and Floros, 2016; Bordo et al., 2016; Ebrahim and Nguyen, 2016; Wang et al., 2019; Pan et al., 2019). For instance, Chen et al. (2018) find that China's EPU negatively predicts future stock

[7] Policy uncertainty might contribute to a steep economic decline and increase in economic uncertainty (See IMF, 2012, 2013).

market returns, consistent with behavioral asset pricing models in which high uncertainty amplifies behavioral biases and generates speculative mispricing under short-sale constraints. Wang et al. (2014) find that Chinese EPU affects corporate investment for listed companies. Our new EU index allows researchers to estimate the impact of EU on firm decisions, financial markets, or aggregate economic activity in China, as it overcomes the shortcomings of existing China uncertainty measures. It also allows researchers to estimate the impacts of China's EU on international financial markets (e.g., Fontaine et al., 2017; Liow et al., 2018; Zhang et al., 2019; Phan et al., 2020). For example, Phan et al. (2020) show that EPU reduces financial stability, and such effects are subjected to financial system characteristics.

The closest paper to ours is Huang and Luk (2020). Our paper differs from theirs in several important dimensions. First, we focus on measuring pure macroeconomic uncertainty in China, whereas Huang and Luk (2020) measure a mix of macroeconomic uncertainty and policy uncertainty. When constructing their index, Huang and Luk (2020) include an extra set of policy related keywords. However, policy uncertainty may follow economic uncertainty, and not always comove with each other. One pronounced example is that our EU index keeps increasing since 2011 due to continuously slowdown in Chinese economy, whereas their EPU index only has several spikes rather than an obvious upward trend. Economic uncertainty and policy uncertainty could have different asset pricing implications. As shown by Pástor and Veronesi (2013), the economic shocks affect stock prices both directly, by affecting the amount of capital, and indirectly, by leading investors to revise their beliefs about the impact of the prevailing government policy. The pure policy shocks (orthogonal to economic shocks) lead investors to revise their beliefs about the likelihood of the various future government policy choices. Constructing a measure of pure macroeconomic uncertainty allows us to disentangle the effects of macroeconomic uncertainty and policy uncertainty. Second, our index is constructed from 35 Chinese newspapers, including newspapers from regions outside mainland China, whereas Huang and Luk's (2020) index is based on 10 mainland Chinese newspapers. Using a broad selection of newspapers enables us to further mitigate the concern of media biases and develop an EU index for other regions outside mainland China, including Taiwan, Hong Kong, Singapore, Malaysia, and Macau. Third, we examine the effect of uncertainty on economic outputs both at the national level and the province level. We also investigate the lead-lag relationship between U.S. EU and China EU. Finally, we show that EU are priced in stock returns, and also can predict stock return.

The remainder of this paper proceeds as follows. Section 2 provides details on the construction of our EU index and presents several robustness checks. Section 3 discusses estimations on the effect of EU on the economy and the financial market using the constructed index. Instead of focusing on the impact of EU on the domestic economy, we also estimate the predictive relationship between China uncertainty and U.S. uncertainty in this section. Section 4 provides the conclusions.

2 Measuring Economic Uncertainty

In this section, we begin with the construction of the EU index, which is the primary variable of interest and is our key contribution to the literature.[8] We further perform different versions of the EU index to check the robustness of the index. To verify the merits of our index,

[8] Although our main focus is to measure EU in China, we follow the same method to generate EU in other regions outside mainland China, including Taiwan, Hong Kong, Singapore, Malaysia, and Macau. The EU index for these regions are reported in the Appendix.

we compare it with existing uncertainty measures.

2.1 Construction of the Economic Uncertainty Index

Existing studies measure uncertainty using various approaches. One common approach is to use option-implied/realized stock market volatility (e.g., Bloom, 2009) as a proxy of uncertainty, or to measure uncertainty using an econometric forecast based on a broad range of indicators (e.g., Jurado et al., 2015).[9] However, applying these approaches is difficult in the case of China due to challenges in the availability of economic data and the short history of its options markets.

Alternatively, Baker et al. (2016) use a text-searching technique for newspaper articles and calculate the proportion of EPU-related articles to the total number of articles as the EPU index. This approach is feasible for China, and the authors provide a newspaper-based EPU index for China. However, we cannot directly apply China's EPU index because this measure also contains political and policy uncertainty, not purely EU. Measuring EU helps policymakers monitor macroeconomic risk in real time, and differentiate the effect between policy uncertainty and EU.[10] Furthermore, their EPU index relies on a single newspaper from Hong Kong (South China Morning Post) and ignores newspapers from mainland China. There is an inevitable media coverage bias in this approach as the main readers of South China Morning Post are Hong Kong residents. Davis et al. (2019) try to avoid this problem by using two mainland Chinese newspapers, namely the Renmin Daily and the Guangming Daily, both of which are official newspapers of the Central Committee of the Communist Party of China.

[9] Jurado et al. (2015) define uncertainty as the conditional volatility of the unforecastable component of the future values of a series.
[10] The traditional proxy for EU is stock market volatility, but it appears driven by factors associated with time-varying risk-aversion rather than EU (Bekaert et al., 2013).

However, using official media from the Central Committee of the Communist Party of China or the government may also introduce bias because they tend to under-report domestic risk events (see Qin et al., 2018; Chan and Zhong, 2018; Yuan, 2016).[11]

We mimic Baker et al. (2016), but modify their approach in consideration of the above drawbacks. We collect news data from Datago Technology Limited, which covers 300 different Chinese newspapers from January 1998 to the present. They collect newspaper data from several sources, such as each newspaper's website and the China National Knowledge Infrastructure (CNKI) newspaper database, to ensure the accuracy of data. The Datago dataset contains both mainland Chinese newspapers and overseas Chinese newspapers.[12] We select all available newspapers that focus on *economic* and *financial* news in China (the appendix lists all selected newspapers) because these newspapers focus on news related to the economy and as such, are likely more timely in reporting uncertainty or risk events.[13] Furthermore, some of these newspapers are privately owned (not state owned), which may avoid the biases contained in the official mass media (see Qin et al., 2018; Chan and Zhong, 2018; Yuan, 2016).[14] The media bias problem can also be alleviated as we include economic newspapers from outside mainland China, such as from Hong Kong.[15] We identify articles that contain at least one

[11] In fact, in Davis et al.'s (2019) index (available at http://www.policyuncertainty.com/china_monthly.html), China's EPU index from 2000 to 2018 spikes due to overseas risk events, such as the U.S. government shutdown in 2014 and the Iraq Invasion in 2003, and most of the spikes in their economic policy uncertainty index during 1949-1999 are due to domestic events.

[12] Note that we add one additional criterion when using overseas newspapers because it does not only report uncertainty related to China but also its local economy. Here we use "China (中国)", and "mainland China" (中国大陆,内地) as location criteria to ensure that this article is related to China's EU.

[13] Moore (2017) observes that business-focused newspapers have a higher proportion of EU-related articles, given their business focus.

[14] All general-interest newspapers in mainland China are owned and supervised by the Chinese Communist Party Committees. We use economic and financial news instead. Seven out of these 36 (19.44%) newspapers are privately owned.

[15] There are 34 mainland China newspapers, and two Hong Kong newspapers in our sample.

keyword in each of the two criteria, namely, Economic (E) and Uncertainty (U), and apply these requirements in an automated search of every article published since 1998, subject to data availability. We follow Baker et al. (2016) and use human readings. When an auditor identifies this article as EU-related, he or she also records the terms contained in the passages about EU. Using these records, we identified several terms that appear often in newspaper discussions of EU, which is shown in Table 1 (with their English translation).[16] The search keywords we select are very similar to Baker et al. (2016) and Luk et al. (2020). In particular, these search terms are similar to Luk et al. (2020), which we believe verify our choice because they focus on Hong Kong, one region in the Greater China Region, and Hong Kong and mainland China share similar language usage with China's newspapers.

We divide the total number of all uncertainty-related articles for a given time period by the total number of articles released by these newspapers in the same period. The series is then standardized to have a unit standard deviation over the period from January 1999 to December 2011.[17] We take the average of the standardized series across the newspapers and then re-normalize the resulting index to a mean of 100 during the period. To express the whole procedure more precisely, $Y_{i,t}$ denotes the scaled EU frequency counts for newspaper i = 1, 2, . . . 35 in month t, and t_1 and t_2 are the time intervals used in the standardization and normalization calculations. First, we compute the times-series standard deviation, σ_i, in the interval t_1 for each newspaper i. Then, we standardize $Y_{i,t}$ by dividing its standard deviation

[16] We add "risk" as one of the search terms since it is closely related to "uncertainty", even though these two words are different in English. This situation is closer to Spanish as Ghirelli et al. (2019) also use "risk" as a keyword in Spanish when constructing Spain's EPU index. In fact, Hassan et al. (2019) study the dictionary and newspaper, and decide to use the synonyms of "risk" and "uncertainty" in generating their political risk/uncertainty indices. "Unstable" and "Unpredictable" are also in their list.
[17] We select 1999 as the beginning of our sample because newspaper data before 1998 is sparse.

σ_i, which results in a new series $X_{i,t}$ for each newspaper with unit standard deviation in the interval t_1. Third, we compute the mean of $X_{i,t}$ across all selected newspapers in each month to obtain the time-series Z_t. Lastly, to obtain the normalized aggregate EU index, we calculate the mean of Z_t in the interval t_2, and then use $EU = Z_t * (100/the\ mean\ of\ Z_t)$ to get the final index.

Figure 1 reports the aggregate EU benchmark index. The index appears to capture major events reasonably well. Looking at Figure 1 and Table 2 together, where the latter summarizes key economic events during the sample period, spikes occur around known episodes of financial stress, such as the Lehman Brothers' collapse in 2008, the stock market crash in 2015, and the rising aggregate financial risk since 2016. The indicator also spikes when there is economic risk, such as the export pressure in 2009 and the growth slowdown concerns in 2014. It takes its highest value at the end of 2018 due to concerns about a potential U.S.–China trade war. The U.S. released a tranche of tariffs on Chinese products based on Section 301 in April 2018. It is noteworthy that the level of EU has been rising since the middle of 2011, consistent with Ahir et al.'s (2018) observation that global uncertainty increased significantly since 2011.

2.2 Validity of Economic Uncertainty Index

We construct three other versions of the EU index to check the robustness of our benchmark index. In addition, we compare our EU index with the existing uncertainty measures.

2.2.1 Using all newspapers

One can argue that selection bias exists when only economic and financial newspapers are used for the index. Therefore, we use all newspapers in the database to generate an alternative index to address this concern. The top panel of Figure 2 compares the benchmark index with the 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 92% with the alternative EU index, showing that using only economic and financial newspapers to construct the EU index captures a majority of the variation in EU.

2.2.2 Media bias

One important issue associated with Chinese newspapers is that they are subject to government influence. Although we have selected economic newspapers to reduce this concern to a certain extent, one may still argue that mainland Chinese newspapers still suffer from a certain level of media censorship. Qin et al. (2018) compute media bias for 118 Chinese newspapers and conclude that market competition significantly reduces the problem of media bias. Therefore, to further reduce this concern, we construct an alternative index using nine Chinese newspapers with the least media bias based on Qin et al.'s (2018) results.[18] The middle panel of Figure 2 compares this alternative index with our benchmark. It is clear that the general pattern of both indices is similar, with correlation at nearly 90%. It is noteworthy that the index generated by the least biased newspapers has more pronounced spikes. This indicates that some mainland Chinese newspapers possibly under-report negative news related to the economy, which is consistent with our expectation about media control. However, reporting less negative news does not significantly change the pattern of the EU index, as we still observe spikes in our benchmark index during the sample period.

[18] Table B in the Appendix lists the newspapers used in constructing the alternative EU index.

2.2.3 Changing the set of keywords

One may argue that the keywords used in our criteria are insufficient to capture EU trends because the media probably use eye-catching keywords such as "economic earthquake" when there is a high level of EU activity. To address this concern, we add several words in our second criteria. These keywords (with Chinese translation in brackets) include "earthquake (地震)", "tsunami (海啸)", "crisis (危机)", "caution (小心/谨慎)", "suddenly happened (突发)", and "attention (注意)". The alternative index based on a set of extended keywords is generated and compared at the bottom of Figure 2, which shows that it is highly correlated (nearly 99%) with the benchmark index, indicating that our benchmark index is robust in its choice of keywords.

2.3 Comparison with Alternative Uncertainty Measures

As mentioned above, there are several EU measures for China in the existing literature. To reveal the differences, we compare our aggregate EU index with Baker et al.'s (2016) EPU index for China, the China's EPU indices created by Davis et al. (2019) and Huang and Luk (2020), the National Bureau of Statistics of China's business condition index (BCI) as a proxy for Chinese macroeconomic environments, the stock market volatility computed by the SSE Composite Index,[19] and Davis' (2016) global EPU index as a proxy for global EU.[20] Since there is growing interest in using internet search volume to proxy for uncertainty (e.g. Dzielinski, 2012; Donadelli, 2015; Castelnuovo and Tran, 2017; Donadelli and Gerotto, 2019), we follow the literature to use the average search volume of "GDP", "economy", and

[19] Bekaert et al. (2013), Bloom (2009), and Caggiano et al. (2014) use stock market volatility as a proxy for uncertainty. We follow Bloom (2009) and Caggiano et al. (2014) to calculate the volatility as the within-month standard deviation of daily percentage changes.

[20] Davis (2016) calculates the monthly global EPU index based on a GDP-weighted average of national EPU indices for 20 countries.

"unemployment" as alternative proxy for uncertainty.[21]

Figure 3 plots our EU index alongside these other measures. Several observations stand out, as follows. First, we compare the BCI and EU indices, which have a pronounced negative correlation (especially during and after the 2007 to 2009 global financial crisis), which is consistent with existing findings (e.g., Bloom, 2009; Baker et al., 2016) that uncertainty reduces output and slows down economic activity. Second, we compare our index with stock market volatility. We can see that both measures spike in 2008 and 2015, which indicates that our measures can capture key financial market risk events. However, stock return volatility is only indirectly connected to economic activity, and much of the short-run variations in stock prices are driven by other factors (Shiller, 1981; Cochrane, 2011). Thus, this measure can only have some, but not many, patterns similar to our EU index. Third, our constructed index highly correlates with the China EPU index created by Baker et al. (2016), Davis et al. (2019), and Huang and Luk (2020)—approximately 70%—but with some differences.[22] This result seems to be intuitive because policy implementation involves lags. One noticeable divergence occur in 2004 and 2005. If we combine the information of risky events in Table 2 and this divergence together, we can see that there is an economic slowdown and rising concerns about the price of housing, but such concerns are not large enough to push governments to change their policies.[23] Thus, we observe spikes in the EU index, but not in the EPU. Another noticeable divergence

[21] Thanks to the referee who provided this suggestion. Note that we use Baidu index instead of using Google because Baidu is the largest search engine in China. Moreover, Baidu provides actual search frequencies of each term, not the normalized index like Google. Many studies have used the search volume from this engine to conduct analysis in China (e.g., Zhang et al., 2013; Fang et al., 2014). We simply take the average of these three selected terms to construct this search-based measure.

[22] Note that we only plot Davis et al.'s (2019) beginning from 2000 because their EPU is normalized differently for three different regimes, where the latest regime begins in 2000.

[23] This occurred when Premier Wen Jiabao lowered the 2005 economic growth target, but the fiscal and monetary policies were unchanged (see http://www.chinadaily.com.cn/english/doc/2005-03/06/content_422130.htm).

occurs since 2011. Our EU index kept increasing, whereas EPU did not. This period corresponds to increasing concerns about economic slowdown, which again shows that EU does not always comove with EPU. Indeed, the correlation between our index and Huang and Luk's (2020) one is substantially lower from 2011 to 2018 (only around 9%). We next compare our index with a global EPU measure and find that it is highly correlated with our EU index by around 75%. This implies that under this highly connected global economy, uncertainty in one country is influenced by or comoves with uncertainty in other countries. Moreover, we observe that our news-based EU index highly comoves with internet search-based EU index. Lastly, we notice that Huang et al. (2018) construct macroeconomic uncertainty using Jurado et al.'s (2015) approach. By visually comparing our index with theirs, we observe that both indices have similar patterns and have spikes in 2008-09, 2010-11, and 2015. Overall, we conclude that our measure efficiently captures uncertainty in China. It differs from existing measures because it is more associated with media reporting and the reception of news by individuals.

3 Economic Uncertainty and China's Macroeconomy

This section analyzes the impact of EU on China's macroeconomy using our index. The basic rationale for performing this analysis is that based on previous studies, uncertainty is detrimental to economic development, leading to reductions in output (Bloom 2009; Baker et al., 2016; Leduc and Liu, 2016), among others. Thus, the constructed EU index is expected to have similar effects on the local Chinese economy.

3.1 Evidence from Impulse Response

To do this, we estimate the impulse responses of the macroeconomic variables to shocks with respect to our EU index based on a VAR model. We consider five variables in the following order: log real GDP, log CPI, benchmark interest rate, the log of Shanghai (Securities) Composite Index, and EU index.[24] Given that the measures of EU constructed here are likely to be closer to real activity than to the stock market, we follow Jurado et al. (2015) to put uncertainty last in this VAR analysis. As for the data transformation, we follow Kozeniauskas et al. (2018) to linearly detrend EU index as it is trend-stationary, and take the first-order difference of the remaining four variables because they are nonstationary.[25] All five variables become stationary after the data transformation. Since all macroeconomic variables are quarterly observations, we take a simple average to translate the monthly EU to a quarterly EU index. We employ Cholesky decomposition to identify shocks. The optimal maximum lag in the VAR model is three based on the Hannan-Quinn (HQ) information criterion.

Figure 4 reports the impulse responses of macroeconomic variables to a one-standard-deviation positive innovation to the EU index with a 95% confidence band. The GDP immediately and negatively responds to the shock of EU. Such negative response peaked at the second quarter, where the output decreased by around 0.25%. We also observe that stock market declines in response to EU shock, which is consistent with the literature that uncertainty decreases stock returns (e.g., Pástor and Veronesi, 2012; Bali et al., 2017). Benchmark interest rate, however, initially declines for three quarters but increases in the fourth quarter, suggesting that stimulus policies are implemented in reaction to increased EU. Lastly, CPI does not

[24] The data for the Shanghai (Securities) Composite Index is the three-month-averaged daily closing index obtained from the Wind Info database, the data information system created by the Shanghai-based company Wind Co. Ltd., often referred to as the Chinese version of Bloomberg. The benchmark one-year deposit rate, employment number, and the quarterly real GDP are obtained from Chang et al. (2016) and are available at https://www.frbatlanta.org/cqer/research/china-macroeconomy.aspx?panel=3.

[25] Please see Table 3 and we will discuss the detail in Section 3.2.

significantly respond to EU, which is similar to the findings in Huang et al. (2018) who find that CPI also does not respond to policy uncertainty.

Table B in the Appendix presents results of variance decomposition, which report the percentage of the forecast error in each variable that can be attributed to innovations in EU: from 1 to 20 quarters ahead (short-run to long-run). The results indicate that about 13% of GDP variations can be attributed to EU at a one-year horizon. The EU can explain the greater forecast error variance (about 20%) of benchmark rate at two-quarter horizon. It also shows that shown EU is important for the stock market, especially in the long run, because about 8% to 20% of variation in stock market index is accounted for by EU shocks. However, the changes of CPI that are affected by EU changes are smaller, with about 11% or less attributable to EU shock. Lastly, in column 5, in the first month, about 87% of the variability in EU change is explained by its own innovations. After one year, approximately 78% of the variability is explained by its own innovations, and at five years, still over 70% of the variability is explained by innovations.

For robustness check, we conduct a number of tests using alternative specifications. These include using 1) a bivariate VAR with real GDP and EU only, 2) one lag, 3) two lags[26], 4) adding the China EPU index (after the EU index), 5) adding the stock market volatility (before the EU index), 6) putting EU in the first order, 7) adding the U.S. MU index (after the EU index), 8) all macroeconomic variables are Hodrick–Prescott (HP) detrended ($\lambda = 1{,}600$),[27] 9) generalized impulse responses, and 10) local projections method[28]. As summarized in Figure

[26] The specification of 2) one lag and 3) two lags are the alternative to optimal three lags selected by HQ information criterion in the VAR.
[27] Following Bloom (2009), who argues that all macroeconomic variables should be detrended, we use $\lambda = 1{,}600$ because our variables are quarterly observations.
[28] The local projections method is proposed by Jordà (2005), which is less vulnerable to misspecification of

5, the main results (i.e., a negative output response to the positive shock of EU) remain robust, even though these modifications lead to somewhat different impulse responses. It is noteworthy that most specifications suggest that EU has greatest negative effect on GDP in the second quarter. The finding that the EU measured by our EU index reduces output, indirectly verifies the robustness of our EU index.

3.2 Granger Causality Test

Although a growing body of literature concludes that uncertainty is countercyclical and that it rises during periods of recession (Baker and Bloom, 2013; Bloom, 2014), the predictive relationship between uncertainty and economic activity is unclear. To test whether our EU index can be used to predict national economic activity, we employ the Granger causality test proposed by Toda and Yamamoto (1995).[29] The specification of the traditional Granger causality test is as follows:

$$y_t = C_1 + \sum_{l=1}^{L} \varphi_l y_{t-l} + \sum_{k=1}^{K} \beta_k x_{t-k} + \mu_t, \tag{1}$$

$$x_t = C_2 + \sum_{l=1}^{L} \delta_l x_{t-l} + \sum_{k=1}^{K} \vartheta_k y_{t-k} + \varepsilon_t, \tag{2}$$

Here, y_t is the BCI or real GDP proxy for national economic activity at time *t,* and x_t is the EU index at time *t*. If the joint hypothesis of $\beta_k = 0$ for any *k* is rejected, causality from EU, x_t, to national economic activity, y_t, exists.

Following Toda and Yamamoto's (1995) procedure, the first step is to determine the maximum order of integration, *dmax*, for the two time series using unit root. If one series is *I(0)* and the other is *I(1)*, *dmax* = 1. Second, we estimate a k^{th} optimal lag-order VAR model in

VAR model.

[29] Note that Granger causality is defined in the sense of predictive relationship, even though it is called Granger "causality" test.

levels, irrespective of integration order. The optimal lag is selected using the Akaike information criterion. Third, extra *dmax* lags are added to the preferred VAR model as exogenous variables. Finally, we conduct a Wald test to check for lags in the endogenous variables and find that its statistic has an asymptotically chi-squared distribution when VAR (k + *dmax*) is estimated.

Before performing the Granger causality test, we employ the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests to examine the stationarity of variables. Table 3 shows that the level form of BCI and GDP cannot reject the unit root null, but its first different form rejects the null. This indicates that these two variables are non-stationary in their level form (with the setting of intercept only), but stationary in their first-differenced form. However, EU index is trend-stationary because we observe unit root tests reject the null (with the setting of intercept and trend).

Table 4 reports the Granger causality test results where *p*-values are reported in parentheses. To avoid over-parameterization, the lag structure, *(L, K)*, is determined using a search procedure for over a maximum of eight lags and selecting the model that minimizes the HQ criterion (Enders, 1995). There is strong evidence of predictability from the EU to BCI (*p*-value: 0.018, indicating 5% level significance) and from the EU to real GDP (*p*-value: 0.002, indicating 1% level significance), showing that EU has predictive power with regard to fluctuations in national economic activity. However, neither national economic activity indicator predicts EU.

A vast number of empirical studies provide evidence that economic relationships can be nonlinear (e.g., Hiemstra and Jones, 1994; Chiou-Wei et al., 2008; Caggiano et al., 2014). In particular, Caggiano et al. (2014) shows the effects of uncertainty shocks on U.S. unemployment to be larger in periods of recession than what a linear model would suggest.

Thus, we also employ a nonlinear causality test developed by Diks and Panchenko (DP; 2006). Using the DP method is a superior choice, as it avoids the over-rejection problem of Hiemstra and Jones (1994). Given two strictly stationary time series $\{X_t\}$ and $\{Y_t\}$, where *t* is an integer, $\{X_t\}$ is a Granger cause of $\{Y_t\}$ if for some $k \geq 1$,

$$(Y_{t+1}, \dots Y_{t+k})|(F_{X,t}, F_{Y,t}) \neq (Y_{t+1}, \dots Y_{t+k})|(F_{Y,t}), \tag{3}$$

where $F_{Y,t}$ and $F_{X,t}$ are the information sets of Y_t and X_t, respectively. This test is for finding evidence against the null of the hypothesis, which is,

$$H_0: \{X_t\} \text{ does not cause } \{Y_t\}. \tag{4}$$

The conditional independence is examined using lags l_X and l_Y:

$$(Y_{t+1})|(X_t^{l_X}; Y_t^{l_Y}) = (Y_{t+1})|(Y_t^{l_Y}), \tag{5}$$

where $Y_t^{l_Y} = (Y_{t+1-l_Y}, \dots Y_t)$ and $X_t^{l_X} = (X_{t+1-l_X}, \dots X_t)$. Given that the null is actually a proposition for the distribution of $(l_X + l_Y + 1)$-dimensional vector, we set $R_t = (X_t^{l_X}, Y_t^{l_Y}, Z_t)$, where $Z_t = Y_{t+1}$. The joint probability density function $f_{X,Y,Z}(x,y,z)$, along with its marginal, have to satisfy the following:

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \cdot \frac{f_{Y,Z}(y,z)}{f_Y(y)}. \tag{6}$$

Based on equation (4), the null hypothesis in equation (2) is restated as:

$$q = E[f_{X,Y,Z}(X,Y,Z)f_Y(y) - f_{X,Y}(X,Y)f_{Y,Z}(Y,Z) = 0]. \tag{7}$$

Assume $\hat{f}_R(R_i)$ is the local density estimator of a d_R-variate vector R at R_i, that is,

$$\hat{f}_R(R_i) = (2\theta_n)^{-d_R}(n-1)^{-1} \sum_{j,j \neq i} I_{ij}^R, \tag{8}$$

where $I_{ij}^R = I(\|R_i - R_j\| < \theta_n)$, $I(\cdot)$ is the indicator function, and θ_n is the bandwidth depending on the sample size. Then the $T_n(\theta_n)$ statistic is expressed as:

$$T_n(\theta_n) = \frac{n-1}{n(n-2)} \sum_i [\hat{f}_{X,Y,Z}(X_i, Y_i, Z_i)\hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i)\hat{f}_{Y,Z}(Y_i, Z_i)]. \tag{9}$$

Under the conditions of $l_X = l_Y = 1$ and $\theta_n = Cn^{-\beta}$ with $\left(C > 0, \beta \in \left(\frac{1}{4}, \frac{1}{3}\right)\right)$, DP shows that $T_n(\theta_n)$ converges to the standard normal:

$$\sqrt{n}\frac{(T_n(\theta_n) - q)}{S_n} \xrightarrow{d} N(0,1), \tag{10}$$

where S_n is the estimated asymptotic variance of $T_n(\cdot)$. In application, we follow DP (2006) by setting the bandwidth value based on $\theta_n = max\left(Cn^{\frac{-2}{7}}, 1.5\right)$.

Table 5 summarizes the nonlinear Granger causality test results.[30] The null hypothesis of no nonlinear predictability running from EU to BCI is clearly rejected (*p*-value: 0.009), which supports our previous findings. The test result also suggests that there is a nonlinear predictability running from EU to real GDP (*p*-value: 0.027). One different observation with the result using linear Granger test is that BCI or real GDP nonlinearly predicts the EU (*p*-values: 0.022 and 0.062 respectively, indicating the 5% level significance from BCI to EU and 10% level significance from real GDP to EU). This indicates that for some cases, GDP would also affect fluctuations in uncertainty. Our results are consistent with that of Caggiano et al. (2014) and suggest the asymmetric effect of EU on the economy. In summary, based on two Granger causality test results, we conclude that there is a predicative relationship between uncertainty and economic conditions. Our results are generally consistent with Baker and Bloom (2013), who find that uncertainty predicts economic variables, but we complement their studies that economic variables might also predict uncertainty, perhaps in periods of recession.

To further provide evidence on the nonlinear relationship between EU and economic activity, we follow Caggiano et al. (2014) to run a regression of GDP growth rate (or BCI) on its own lags, uncertainty, and interaction terms between these two variables as regressors. The assumption of a linear relationship is rejected if the coefficients of interaction terms are jointly different from zero (Luukkonen et al., 1988). Table 6 summarizes the regression results. It is clear that coefficients of both interactions are significantly different from zero, which further

[30] Note that the nonlinear Granger causality test is based on two variables (EU and GDP (or BCI)) only because this approach only allows for two variables.

supports our findings that there exists a nonlinear relationship between EU and economic activity.

3.3 Provincial Output and EU

So far, we have focused on the impact of EU on the aggregate economy but ignored regional differences. The Chinese economy does not consist of homogenous economic units but instead, of diverse regions with large socio-economic disparities. To investigate which region is more sensitive to the shock of aggregate EU, we apply the same strategy, using the VAR to estimate the impulse response function for each province. Here we change the country-level output to province-level output (GDP), and run the five-VAR model.[31] In addition to the province-level GDP, we also include national GDP to avoid an emission of the cross-regional links.[32]

Figure 6 displays the impulse response of GDP to a one-standard-deviation positive shock of aggregate EU for each province. Several observations emerge. First, regional analysis indicates that the effect of EU on output is similar. This suggests that the local economy recovers to the normal state within four quarters after the shock of EU, with the largest effect being in the second or third quarter. Second, the response of local output to the EU shock varies across provinces. Aggregate EU shock leads to a reduction in GDP in most provinces, such as Fujian, Gansu, Guangdong, Guangxi, Tibet, Xinjiang, and Zhejiang. The GDP of many provinces significantly and negatively responds to the shock of EU in the second or third

[31] The data for the benchmark one-year deposit rate, and the quarterly real GDP are from China Stock Market & Accounting Research (CSMAR). We use the same Shanghai (Securities) Composite Index for aggregate stock market as we did in section 3.1. The sample period begins from the fourth quarter of 2004 to the second quarter of 2018.

[32] Thanks to the referee who provided this useful suggestion.

quarter after the shock. Beijing city behaves differently from the rest of the economy because the 95% confidence bands obviously cover zero. This suggests the EU shock has an insignificant effect on its GDP. This finding is consistent with Chen and Groenewold (2018, 2019), who find that economic shock has a lesser impact on Beijing. These authors provide an explanation that Beijing is an economic and administration center, different in several respects (geographic extent, industrial structure, and others), such that it is not surprising that Beijing is an outlier in this analysis.

We notice that some researchers might criticize the quality of GDP data because of its over-smoothness and government manipulation (e.g., Rawski, 2001; Koch-Weser, 2013). However, we believe that our investigation could still reveal the general pattern of the relationship between the developed EU index and provincial economies. In fact, Holz (2014) investigates China's GDP and believes it is generally accurate. They examine the data and conclude that the National Bureau of Statistics makes no significant use of its influence to falsify data. Nakamura et al. (2016) support this view by using the systematic discrepancies between cross-sectional and time-series Engel curves to construct alternative estimates of Chinese growth and inflation. They conclude that China's Official statistical data provide a smooth version of reality.

3.4 U.S. EU and China EU

The above results indicate that EU has a significant impact on the economy. Based on observations by Klößner and Sekkel (2014), Balli et al. (2017), and Huang et al. (2018), uncertainty that affects domestic economy may come from overseas. Thus, it is worthwhile to investigate the mechanisms by which EU affects the economy. This is an interesting issue given that trade tensions between the U.S. and China have intensified since 2016. This section briefly analyzes the lead-lag relationship between uncertainty in the U.S. and in China to provide some evidence on this issue. Following the methods introduced in Section 3.2, we perform linear and nonlinear Granger causality tests. We employ the macroeconomic uncertainty index by Jurado et al. (2015) as a proxy for the level of EU in the U.S. because this index measures EU, which is the main focus of our study, instead of policy or political uncertainty (like the index of Baker et al., 2016).

Table 7 summarizes the causality test results where panel A reports the linear test and panel B reports the nonlinear test results. The linear Granger test results suggest that there is a one-way Granger-causal relationship from the U.S. to China, which is consistent with recent events wherein uncertainty in U.S. export trade policies have affected China. However, the nonlinear test results suggest that there is a bidirectional Granger-causal relationship, meaning that China EU also affects U.S. EU in some cases. This implies that China's retaliation (i.e., by taxing certain U.S. products) had an impact on the U.S., but in a more complicated manner. This is also consistent with the literature that finds the shock of China's uncertainty to be only significant for the U.S. economy during periods of recession. In summary, there exists a lead-lag relationship between uncertainty in the U.S. and China, but the relationship may be nonlinear. This finding implies that some negative effect of EU on the Chinese economy may be coming from the U.S.

3.5 Cross-sectional asset pricing tests

Motived by the theoretical study of Pástor and Veronesi (2012), and empirical work from (Brogaard and Detzel, 2015; Bali et al., 2017; Chen et al., 2018; Phan et al., 2018; Hillier and

Loncan, 2019; Donadelli et al., 2020), it is worth to investigate how EU affects asset pricing.[33] First, we follow Brogaard and Detzel (2015) and Chen et al. (2018) to test whether our EU affects stock returns instantaneously by the equation:

$$\mathrm{r}_t = \alpha + \varphi_i + \beta_1 \Delta EU_t + \varepsilon_t, \tag{11}$$

and to test whether our EU predict stock returns using the equation:

$$\mathrm{r}_t = \alpha + \varphi_i + \beta_1 \Delta EU_{t-1} + \varepsilon_t, \tag{12}$$

where r_t denotes the log excess return on the aggregate Chinese stock market collected from Shanghai Stock Exchange and EU is our economic uncertainty in China.

Panel A of Table 8 shows the estimation result. Column (1) indicates that an increase in ΔEU associated with a significant drop in excess return, even after control for China's ΔEPU index developed by Huang and Luk (2020) shown in Column (2). Column (3) indicates that the ΔEU also forecasts the next-month stock market return. In particular, one percent increase in ΔEU is associated with around five percent decrease in expected monthly return, which is robust after control for China's ΔEPU index of Huang and Luk (2020) shown in Column (4). These results are similar to Brogaard and Detzel (2015) and Chen et al. (2017) that stock prices drop when an increase in EU.

Then, we focus on whether EU can explain cross-sectional stock returns in China. To test it, we apply the standard Fama–MacBeth two step regression to excess individual stock returns by adding EU and market return in the equation. Aside from controlling market return, we follow Liu et al. (2019) to control for size, value, and sentiment factors, including SMB (small minus big), VMG (value minus growth), and PMO (pessimistic minus optimistic). The authors adjust these factors by incorporating Chinese stock market features, which could serve as better

[33] Thanks to the referee who provided this helpful suggestion.

controls in our study. We test whether EU are priced in individual stock by controlling them, and the second stage results are summarized in the Panel B of Table 8. Note that the more negative β_{EU} reflects greater exposure to EU. We observe that coefficient (γ_{EU}) of β_{EU} is negative, which is similar to Brogaard and Detzel (2015), and Bali et al. (2017). This result suggests that investor command a risk premium for uncertainty because investors expect lower returns for stock that has more positive β_{EU} (lower EU exposure). These results are robust after control for market return, SMB, VMG, and PMO factors.

3.6 Economic Uncertainty and COVID-19 pandemic

In this section, we provide some brief discussion on the EU in the time of Coronavirus disease 2019 (COVID-19), though our data ends in December 2018. COVID-19 outbreak has spread to the world and has led to more than 1.7 million deaths and 78 million cumulative confirm cases between 2019 and 2020.[34] It also causes substantial economic and policy uncertainty, and increases market volatility (e.g., Altig et al., 2020; Baker et al., 2020; Narayan, 2020a, 2020b; Iyke, 2020a, 2020b; Sharma, 2020). Altig et al. (2020) show that COVID-19 creates great uncertainties and more than half of economic contractions observed are due to these COVID-induced uncertainties. Similarly, Iyke (2020a) shows that economic policy uncertainty of China, India, Japan, Korea, and Singapore increases significantly during COVID-19 pandemic. Baker et al. (2020) develop new measures for gauging the COVID-19 risk, demonstrating that the pandemic has a strong impact on the stock market.

EU increases in the time of COVID-19 because COVID-19 results in lockdowns and social distancing, and stimulus packages. These actions directly lead to a slowdown of

[34] https://covid19.who.int/ (accessed on 25 Dec 2020).

economic activity and cause individuals to feel uncertain about future economic states. In the US, a recent ABC News/Ipsos Poll shows that 86% of the respondents were concerned about being infected, while 72% were worried about a premature restart of their businesses.[35] In China, it is believed that China's EU has a surge in the early stage of COVID-19, but then it may recover to normal state faster than other countries because the COVID-19 pandemic is properly controlled in China and its economy recovers fast.[36]

4 Conclusion

This study constructs a set of EU indices for China from January 2000 to December 2018 by addressing the shortcomings of existing approaches. We validate this index by trying alternative constructions and comparing the resulting versions of the index with existing uncertainty measures. We show that our index reflects EU well, as it is positively correlated with existing uncertainty or risk measures, such as Baker et al.'s (2016) EPU index, with some differences and spikes around major events. Based on this index, we show that uncertainty is harmful for the Chinese economy. It significantly reduces output, and such negative effects last for several quarters. We also test the relationship between uncertainty and economic activities. Using linear and nonlinear Granger causality tests, we conclude that EU predicts fluctuations in economic activities. In the last empirical exercise, we show that U.S. EU leads to China EU, but China EU nonlinearly predicts U.S. EU. In this globalized world, not only can this uncertainty index be used to investigate the impact of China's domestic economy and financial markets, but also international financial markets, such as U.S. markets. Lastly, we show that

[35] https://www.ipsos.com/en-us/news-polls/abc-news-coronavirus-poll
[36] https://www.wsj.com/articles/chinas-economy-continues-broad-recovery-despite-covid-19-surge-elsewhere-11608013339

EU commands risk premium and helps predict stock returns, which are consistent with the literature. Future research will explore the possibility of constructing daily frequency of EU in China. Another research line could be developing uncertainty indices based on the frequency of internet searches. Although we attempt to compare our index with some search frequencies of economic terms, it may not be enough and worth further investigation to different topics, such as Donadelli and Gerotto (2019), and Bontempi et al. (2019).

Appendix

Table A. List of selected financial newspapers used in the construction of the benchmark EU index

Chinese	English Translation	Time Coverage
中华工商时报	China Business Times	Mar 2000 to Dec 2018
西部商报	Western Business Paper	Jul 2001 to Jun 2018
中国经济时报	China Economic Times	Dec 1999 to Dec 2018
上海经济报	Shanghai Economy	Nov 1999 to Sep 2004
民营经济报	Private Economic News	May 2003 to Dec 2018
工商时报	Commercial Times	Feb 2000 to Dec 2018
每日经济新闻	National Business Daily	Dec 2004 to Dec 2018
四川经济日报	Sichuan Economics Daily	Apr 2002 to Jul 2014
辽宁经济日报	Liaoning Economic Daily	Sep 2000 to Dec 2003
证券时报	Securities Times	Jan 2003 to Dec 2018
安徽商报	Anhui Business Daily	Oct 2000 to Apr 2008
经济日报	Economic Daily	Mar 2000 to Dec 2018
21 世纪经济报道	21st Century Business Herald	Dec 2002 to Dec 2018
今晚经济周报	Tonight Economic Weekly	Aug 2012 to Aug 2017
国际金融报	The Financial Times	Jan 2003 to Jul 2018
金融时报(中国)	Financial News	Jan 2003 to Dec 2018
上海证券报	Shanghai Securities News	Dec 2000 to Dec 2018
河南商报	Henan Business Daily	May 2003 to Dec 2008
经济参考报	Economic Information Daily	Dec 2002 to Aug 2012
上海商报	Shanghai Business Daily	Dec 2002 to Apr 2005
经济观察报	The Economic Observer	Jan 2003 to Dec 2018
上海金融报	Shanghai Financial News	Dec 2000 to Dec 2018
中国证券报	China Securities Journal	Dec 1999 to Dec 2018
新农村商报	New Countryside Commerce	Oct 1999 to Dec 2018
北京商报	Beijing Business Today	Jan 2003 to Dec 2018
财经时报	China Business Post	Jul 2001 to Sep 2008
成都商报	Chengdu Economic Daily	Jun 2000 to Jul 2014
国际商报	Commercial News	Jun 2000 to Dec 2018
第一财经日报	China Business News	Nov 2004 to Dec 2018
重庆商报	Chongqing Economic Times	Jun 2000 to Dec 2018
中国经济导报	China Economic Herald	Nov 1999 to Dec 2018
深圳商报	Shenzhen Economic Daily	Jul 2000 to Dec 2018
上海证券报	Shanghai Securities News	Dec 2000 to Dec 2018
香港商报	Hong Kong Commercial Daily	Jan 1999 to Dec 2018
香港经济日报	Hong Kong Economic Times	Jan 1999 to Dec 2018

Note: We select all available newspapers that focus on *economic* and *financial* news in China because these newspapers focus on news related to the economy and as such, are likely to be more timely in reporting uncertainty or risk events. Another reason is that some of these newspapers are privately owned (not state owned), which may avoid the biases contained in the official mass media. The media-bias problem can also be alleviated as we include economic newspapers outside mainland China, such as Hong Kong.

Table B. List of newspapers with least bias

Chinese	English Translation
北京青年报	Youth Express
北京晚报	Beijing Evening News
北京娱乐信报	Beijing Daily Messenger
竞报	The First
辽沈晚报	Liaoshen Evening News
武汉晨报	Wuhan Morning Post
武汉晚报	Wuhan Evening News
燕赵晚报	Yanzhao Evening News
羊城晚报(佛山)	Yang Cheng Evening News

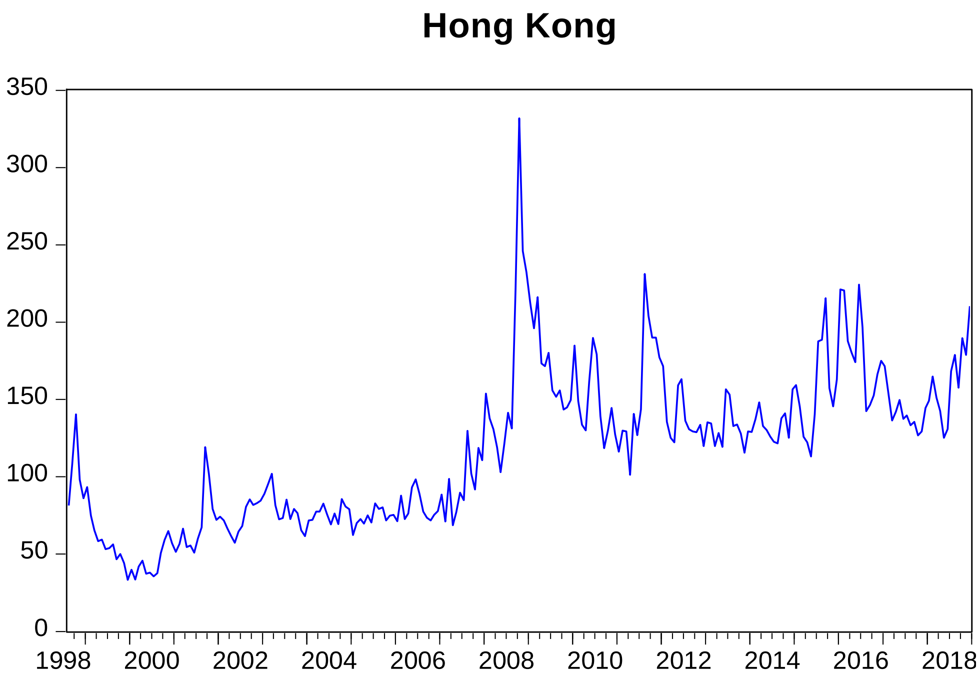
Table C. Correlation matrix of detrended and first differenced uncertainty measures

Panel A: HP filter detrended					
	EU	Stock Return Volatility	Baker et al.'s EPU	David et al.'s EPU	Global EPU
EU	1.000	0.250	0.399	0.304	0.497
Stock Return Volatility	0.250	1.000	0.052	-0.130	0.049
Baker et al.'s EPU	0.399	0.052	1.000	0.348	0.817
David et al.'s EPU	0.304	-0.130	0.348	1.000	0.353
Global EPU	0.497	0.049	0.817	0.353	1.000
Panel B: First differenced					
	EU	Stock Return Volatility	Baker et al.'s EPU	David et al.'s EPU	Global EPU
EU	1.000	0.065	0.221	0.209	0.333
Stock Return Volatility	0.065	1.000	0.052	-0.163	0.060
Baker et al.'s EPU	0.221	0.052	1.000	0.223	0.646
David et al.'s EPU	0.209	-0.163	0.223	1.000	0.265
Global EPU	0.333	0.060	0.646	0.265	1.000

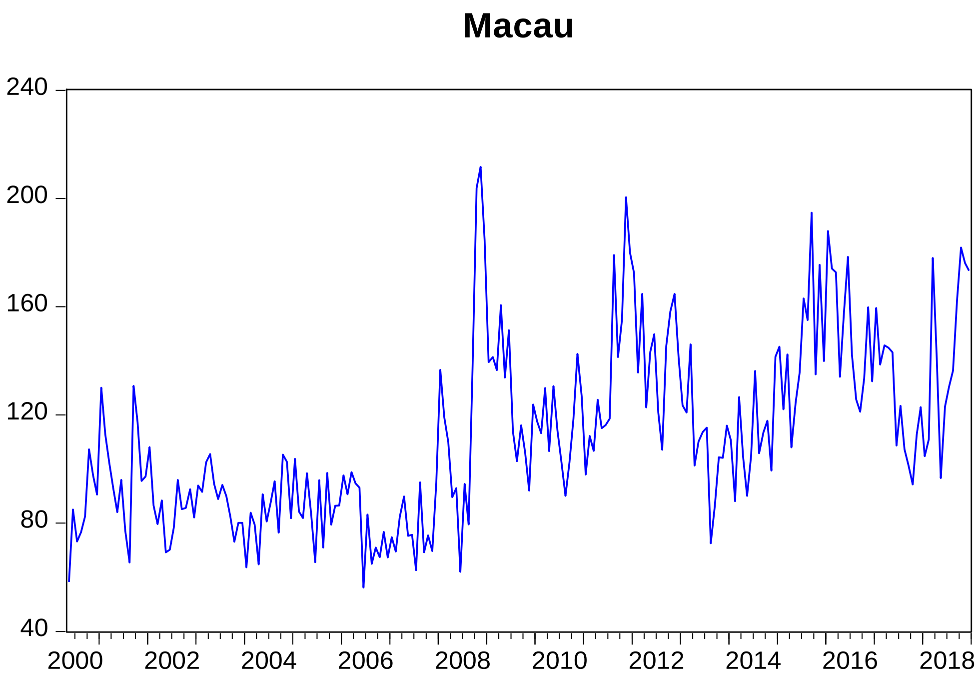
Table D. Granger causality test (five-variable VAR)

	Lag structure	**Chi-square**
From EU to BCI	3, 3	7.663* (0.054)
From EU to GDP	1, 1	10.795*** (0.001)
From BCI to EU	3, 3	3.256 (0.354)
From GDP to EU	1, 1	0.057 (0.811)

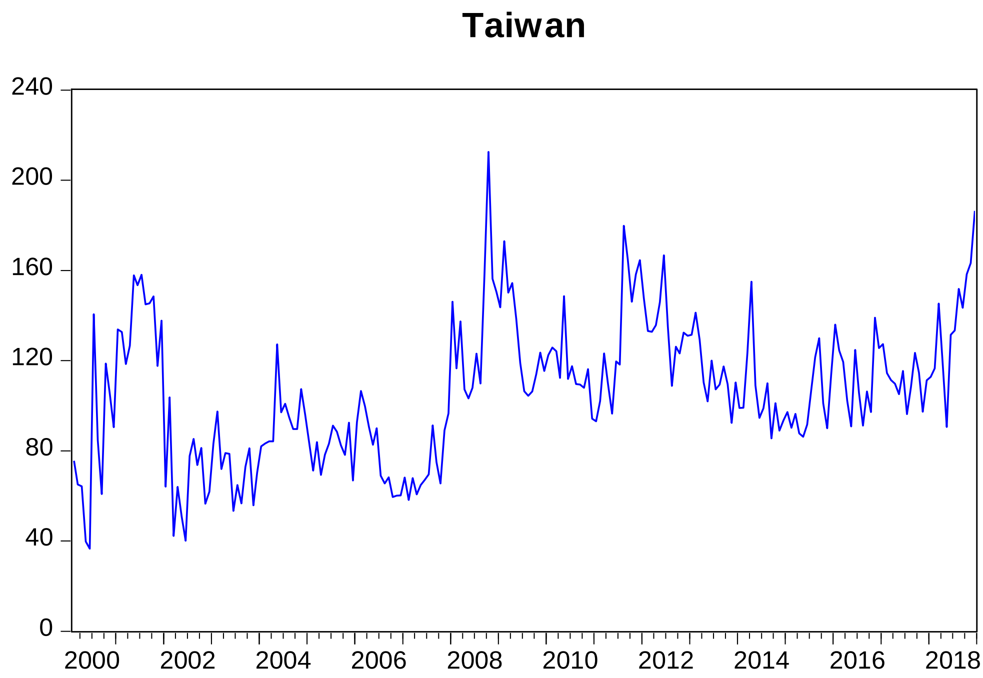
Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. P-values are reported in parentheses. EU refers to the economic uncertainty index. BCI is the business condition index. The null hypothesis is no Granger cause from variable A to B. Note that we separately use GDP and BCI to proxy for aggregate output.



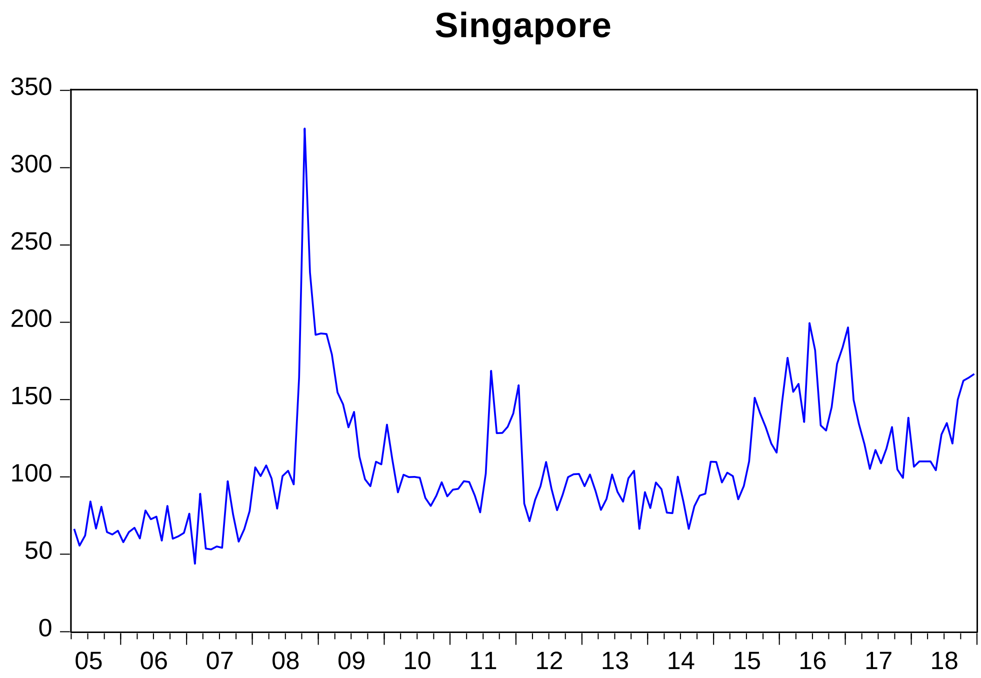
Note: The figure shows the economic uncertainty index for Hong Kong from August 1998 to December 2018. We searched for articles that contain at least one keyword in each of the two criteria listed in Table 1. All other procedures are the same as those for mainland China. The newspapers used are Oriental Daily (東方日報), MingPao (明報), Hong Kong Economic Times (香港經濟日報), Hong Kong Commercial Daily (香港商報), and Sing Tao Daily (星島日報).



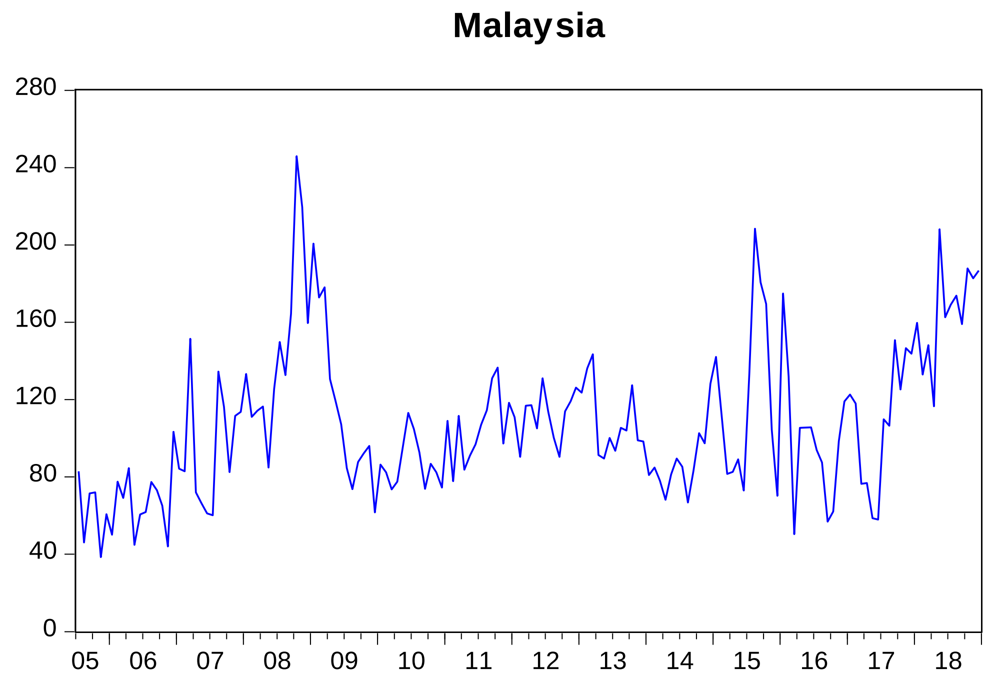
Note: The figure shows the economic uncertainty index for Macau from May 2000 to December 2018. We search for articles that contain at least one keyword in each of the two criteria listed in Table 1. All other procedures are the same as those for mainland China. The newspapers used are Journal San Wa Ou (新華澳報) and Macao Daily News (澳門日報).



Note: The figure shows the economic uncertainty index for Taiwan from February 2000 to December 2018. We search for articles that contain at least one keyword in each of the two criteria listed in Table 1. All other procedures are the same as those for mainland China. The newspapers used are Economic Daily News (經濟日報(台灣)), Lihpao (臺灣立報), Apple Daily (蘋果日報(台灣)), Taiwan Daily (台灣日報), Taiwan Times (臺灣時報), Taiwan Shin Sheng Daily News (台灣新生報), China Times (中國時報), and Liberty Times (自由時報).



Note: The figure shows the economic uncertainty index for Singapore from April 2005 to December 2018. We search for articles that contain at least one keyword in each of the two criteria listed in Table 1. All other procedures are the same as those for mainland China. The newspapers used are Lianhe Wanbao (联合晚报(新加坡)), ZaoBao SG (联合早报(新加坡)), and Nanyang Siang Pau (南洋商報).



Note: The figure shows the economic uncertainty index for Malaysia from July 2005 to December 2018. We search for articles that contain at least one keyword in each of the two criteria listed in Table 1. All other procedures are the same as those for mainland China. The newspapers used are Malaysia Sin Chew Daily (星洲日報(馬來西亞)), Nanyang Siang Pau (南洋商報), and Guang Ming Daily (光明日報(馬來西亞)).

Table B. Percent contribution of EU shock to the variability of each variable

Period	GDP	Benchmark Rate	CPI	Stock	EU
1	0.000	0.000	0.000	0.000	86.893
2	13.480	14.457	3.770	8.707	80.273
3	13.977	21.830	5.400	12.583	79.153
4	12.391	19.821	5.035	14.118	78.610
5	11.517	19.136	5.023	15.101	75.910
6	10.823	18.062	5.207	17.527	74.531
7	10.551	17.344	6.029	19.512	73.562
8	10.354	17.153	7.659	19.733	72.910
9	10.162	16.967	8.738	19.603	72.495
10	10.072	16.831	9.424	19.515	72.286
11	10.277	16.759	9.573	19.582	72.174
12	10.837	16.860	9.542	19.709	72.126
13	11.687	17.140	9.550	19.837	72.102
14	12.635	17.511	9.701	19.886	72.073
15	13.522	17.868	9.952	19.891	72.042
16	14.245	18.161	10.238	19.876	72.012
17	14.770	18.359	10.485	19.870	71.986
18	15.117	18.474	10.658	19.886	71.965
19	15.327	18.527	10.757	19.921	71.950
20	15.446	18.541	10.801	19.963	71.938

References

Adams, F. G., & Chen, Y. (1996). Skepticism about Chinese GDP growth–The Chinese GDP elasticity of energy consumption. *Journal of Economic and Social Measurement*, *22*(4), 231-240.

Ahir, H., Bloom, N., & Furceri, D. (2018). The world uncertainty index. Working paper. SSRN Working Paper.

Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., ... & Mizen, P. (2020). Economic uncertainty before and during the COVID-19 pandemic. *Journal of Public Economics*, 191, 104274.

Antonakakis, N., & Floros, C. (2016). Dynamic interdependencies among the housing market, stock market, policy uncertainty and the macroeconomy in the United Kingdom. *International Review of Financial Analysis, 44,* 111-122.

Baker, S. R., & Bloom, N. (2013). Does uncertainty reduce growth? Using disasters as natural experiments. (No. w19475). National Bureau of Economic Research.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593-1636.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *The Review of Asset Pricing Studies*, 10(4), 742-758.

Bali, T. G., Brown, S. J., & Tang, Y. (2017). Is economic uncertainty priced in the cross-section of stock returns? *Journal of Financial Economics, 126*(3), 471-489.

Balli, F., Uddin, G. S., Mudassar, H., & Yoon, S. M. (2017). Cross-country determinants of economic policy uncertainty spillovers. *Economics Letters*, *156*, 179-183.Bekaert, G., Hoerova, M., & Duca, M. L. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics, 60*(7), 771-788.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics*, *98*(1), 85-106.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica, 77*(3), 623-685.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives, 28*(2), 153-76.

Bontempi, M. E., Frigeri, M., Golinelli, R., & Squadrani, M. (2019). Uncertainty, perception and the internet. SSRN Working Paper.

Bordo, M. D., Duca, J. V., & Koch, C. (2016). Economic policy uncertainty and the credit channel: Aggregate and bank level US evidence over several decades.

Journal of Financial Stability, *26*, 90-106.

Brogaard, J., & Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science*, 61(1), 3-18.

Caggiano, G., Castelnuovo, E., & Groshenny, N. (2014). Uncertainty shocks and unemployment dynamics in US recessions. *Journal of Monetary Economics*, *67*, 78-92.

Castelnuovo, E., & Tran, T. D. (2017). Google it up! a google trends-based uncertainty index for the United States and Australia. *Economics Letters*, 161, 149-153.

Chan, J. T., & Zhong, W. (2018). Reading China: Predicting policy change with machine learning. SSRN Working Paper.

Chang, C., Chen, K., Waggoner, D. F., & Zha, T. (2016). Trends and cycles in China's macroeconomy. *NBER Macroeconomics Annual*, *30*(1), 1-84.

Chen, A., & Groenewold, N. (2018). The regional effects of macroeconomic shocks in China. *China Economic Review*, *48*, 139-154.

Chen, A., & Groenewold, N. (2019). Macroeconomic shocks in China: Do the distributional effects depend on the regional source? *The Annals of Regional Science*, *62*(1), 69-97.

Chen, J., Jiang, F., & Tong, G. (2018). Economic policy uncertainty in China and stock market expected returns. *Accounting & Finance*, *57*(5), 1265-1286.

Chiou-Wei, S. Z., Chen, C. F., & Zhu, Z. (2008). Economic growth and energy consumption revisited—Evidence from linear and nonlinear Granger causality. *Energy Economics*, *30*(6), 3063-3076.

Cochrane, J. H. (2011). Presidential address: Discount rates. *The Journal of Finance*, *66*(4), 1047-1108.

Davis, S. J. (2016). An index of global economic policy uncertainty (No. w22740). National Bureau of Economic Research.

Davis, S. J., Liu, D., & Sheng, S. X. (2019). Economic policy uncertainty in China since 1949: The view from mainland newspaper. Working paper.

Diks, C., & Panchenko, V. (2006). A new statistic and practical guidelines for nonparametric Granger causality testing. *Journal of Economic Dynamics and Control*, *30*(9-10), 1647-1669.

Donadelli, M. (2015). Google search-based metrics, policy-related uncertainty and macroeconomic conditions. *Applied Economics Letters*, 22(10), 801-807.

Donadelli, M., & Gerotto, L. (2019). Non-macro-based Google searches, uncertainty, and real economic activity. *Research in International Business and Finance*, 48, 111-142.

Donadelli, M., Gufler, I., & Pellizzari, P. (2020). The macro and asset pricing implications of rising Italian uncertainty: Evidence from a novel news-based macroeconomic policy uncertainty index. *Economics Letters*, 197, 109606.

Dzielinski, M. (2012). Measuring economic uncertainty and its impact on the stock market. *Finance Research Letters*, 9(3), 167-175.

Ebrahim, M. S., & Nguyen, D. K. (2016). Evolving capital markets in the era of economic uncertainty. *International Review of Financial Analysis*, *46*, 237-238.

Enders, W. (1995). *Applied econometric time series*. New York: Wiley.

Fang, X., Jiang, Y., & Qian, Z. (2014). The effects of individual investors' attention on stock returns: Evidence from the ChiNext market. *Emerging Markets Finance and Trade*, 50(sup3), 158-168.

Fontaine, I., Didier, L., & Razafindravaosolonirina, J. (2017). Foreign policy uncertainty shocks and US macroeconomic activity: Evidence from China. *Economics Letters*, *155*, 121-125.

Garnaut, R., Song, L., & Fang, C. (Eds.). (2018). *China's 40 years of reform and development: 1978-2018*. ANU Press.

Ghirelli, C., Pérez, J. J., & Urtasun, A. (2019). A new economic policy uncertainty index for Spain. *Economics Letters*. Forthcoming.

Han, Y., Liu, Z., & Ma, J. (2019). Growth cycles and business cycles of the Chinese economy through the lens of the unobserved components model. *China Economic Review*, 101317.

Handley, K., & Limão, N. (2017). Policy uncertainty, trade, and welfare: Theory and evidence for China and the United States. *American Economic Review*, *107*(9), 2731-83.

Hassan, T. A., Hollander, S., van Lent, L., & Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, *134*(4), 2135-2202.

Hiemstra, C., & Jones, J. D. (1994). Testing for linear and nonlinear Granger causality in the stock price-volume relation. *The Journal of Finance*, *49*(5), 1639-1664.

Hillier, D., & Loncan, T. (2019). Political uncertainty and stock returns: evidence from the Brazilian political crisis. *Pacific-Basin Finance Journal*, 54, 1-12.

Holz, C. A. (2014). The quality of China's GDP statistics. *China Economic Review, 30*, 309-338.

Huang, Y., & Luk, P. (2020). Measuring economic policy uncertainty in China. *China Economic Review*, *59*, 101367.

Huang, Z., Tong, C., Qiu, H., & Shen, Y. (2018). The spillover of macroeconomic uncertainty between the US and China. *Economics Letters*, *171*, 123-127.

International Monetary Fund. (2012, October). *World economic outlook: Coping with high debt and sluggish growth.* IMF Press.

International Monetary Fund. (2013, April). *World economic outlook: Hopes, realities, risks.* IMF Press.

Iyke, B. N. (2020a). Economic policy uncertainty in times of COVID-19 pandemic. *Asian Economics Letters*, 1(2), 17665.

Iyke, B. N. (2020b). COVID-19: The reaction of US oil and gas producers to the pandemic. *Energy Research Letters*, 1(2), 13912.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1), 161-182.

Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring uncertainty. *American Economic Review*, *105*(3), 1177-1216.

Kilian, L. (1998). Small-sample confidence intervals for impulse response functions. *Review of Economics and Statistics, 80*(2), 218-230.

Klößner, S., & Sekkel, R. (2014). International spillovers of policy uncertainty. *Economics Letters*, *124*(3), 508-512.

Knight, F. H. (1921). *Risk, uncertainty, and profit* (pp. 210-235). Boston: Houghton Mifflin Co.

Koch-Weser, I. N. (2013). The reliability of China's economic data: An analysis of national output. US-China Economic and Security Review Commission Staff Research Project, 4.

Kozeniauskas, N., Orlik, A., & Veldkamp, L. (2018). What are uncertainty shocks? *Journal of Monetary Economics*, *100*, 1-15.Leduc, S., & Liu, Z. (2016). Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics*, *82*, 20-35.

Li, C., Zheng, H., & Liu, Y. (2020). The hybrid regulatory regime in turbulent times: The role of the state in China's stock market crisis in 2015-2016. *Regulation & Governance*. Forthcoming.

Liow, K. H., Liao, W. C., & Huang, Y. (2018). Dynamics of international spillovers and interaction: Evidence from financial market stress and economic policy uncertainty. *Economic Modelling*, *68*, 96-116.

Liu, J., Stambaugh, R. F., & Yuan, Y. (2019). Size and value in China. *Journal of Financial Economics*, 134(1), 48-69.

Luk, P., Cheng, M., Ng, P., & Wong, K. (2020). Economic policy uncertainty spillovers in small open economies: The case of Hong Kong. *Pacific Economic Review*, 25, 21-46.

Luukkonen, R., Saikkonen, P., & Teräsvirta, T. (1988). Testing linearity against smooth transition autoregressive models. *Biometrika*, *75*(3), 491-499.

Moore, A. (2017). Measuring economic uncertainty and its effects. *Economic Record*, *93*(303), 550-575.

Nakamura, E., Steinsson, J., & Liu, M. (2016). Are Chinese growth and inflation too smooth? Evidence from Engel curves. *American Economic Journal: Macroeconomics*, *8*(3), 113-44.

Narayan, P. K. (2020a). Has COVID-19 changed exchange rate resistance to shocks?. *Asian Economics Letters*, 1(1), 17389.

Narayan, P. K. (2020b). Did bubble activity intensify during COVID-19. *Asian Economics Letters*, 1(2), 17654.

Pástor, L., & Veronesi, P. (2012). Uncertainty about government policy and stock prices. *The Journal of Finance*, *67*(4), 1219-1264.

Pástor, L., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, 110(3), 520-545.

Pan, W.F., Wang, X., & Yang, S. (2019). Debt Maturity, Leverage, and Political Uncertainty, *North American Journal of Economics and Finance*, 50, 100981

Phan, D. H. B., Sharma, S. S., & Tran, V. T. (2018). Can economic policy uncertainty predict stock returns? Global evidence. *Journal of International Financial Markets, Institutions and Money*, 55, 134-150.

Phan, D. H. B., Iyke, B. N., Sharma, S. S., & Affandi, Y. (2020). Economic policy uncertainty and financial stability–Is there a relation? *Economic Modelling.* Forthcoming.

Qin, B., Strömberg, D., & Wu, Y. (2018). Media bias in China. *American Economic Review*, *108*(9), 2442-76.

Ravn, M. O., & Uhlig, H. (2002). On adjusting the Hodrick-Prescott filter for the frequency of observations. *Review of Economics and Statistics*, *84*(2), 371-376.

Rawski, T. G. (2001). What is happening to China's GDP statistics? *China Economic Review*, *12*(4), 347-354.

Sharma, S. S. (2020). A note on the Asian market volatility during the COVID-19 pandemic. *Asian Economics Letters*, 1(2), 17661.

Shiller, R. (1981). Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review, 71*(3), 421-436.

Stock, J. H., & Watson, M. W. (2012). Disentangling the Channels of the 2007-2009 Recession. *Brookings Panel on Economic Activity* (Spring 2012). 81–135.

Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics*, *66*(1-2), 225-250.

Wang, Y., Chen, C. R., & Huang, Y. S. (2014). Economic policy uncertainty and corporate investment: Evidence from China. *Pacific-Basin Finance Journal*, *26*, 227-243.

Wang, X., Xu, W., & Zhong, Z. (2019). Economic Policy Uncertainty, CDS Spreads, and CDS Liquidity Provision, *Journal of Futures Markets* 39, 461-480

World Bank. (2016). Weak Investment in Uncertain Times, Global Economic Prospects.

You, J., Zhang, B., & Zhang, L. (2017). Who captures the power of the pen? *The Review of Financial Studies*, *31*(1), 43-96.

Yuan, H. (2016). Measuring media bias in China. *China Economic Review*, *38*, 49-59.

Zhang, D., Lei, L., Ji, Q., & Kutan, A. M. (2019). Economic policy uncertainty in the US and China and their impact on the global markets. *Economic Modelling*, *79*, 47-56.

Zhang, W., Shen, D., Zhang, Y., & Xiong, X. (2013). Open source information, investor attention, and asset pricing. *Economic Modelling*, 33, 613-619.

Table 1. Relevant Chinese keywords (with translations to English) for compiling China Economic Uncertainty Index

Criteria	English	Chinese
(1) Economic	Economic/Economy/Financial	经济/金融
(2) Uncertainty	Uncertainty/Uncertain/Risk	不确定/不明确/风险
	Volatile	波动/震荡/动荡
	Unstable/Unclear	不稳/未明/不明朗/不清晰/未清晰
	Unpredictable	难料/难以预料/难以预测 难以预计/难以估计/无法预料/无法预测/无法预计/无法估计/不可预料/不可预测/不可预计/不可估计

Table 2. Summary of key economic events

Date	Event
April 2001 to August 2001	Growth slowdown concerns due to foreign demand decline
September 2001	9/11 attack
October 2008	Lehman Brothers bankruptcy and China stimulus
November 2011	Eurozone and protectionism fears
July 2013	Rising interest rates and liquidity concerns
December 2014	Economic Slowdown Concerns
September 2015	Stock market crash
January 2016	Rising financial risk concerns and financial regulation tighten
April 2018 to December 2018	US and China trade tension concerns

Notes: Interested readers can refer to Chang et al. (2016), Garnaut et al. (2018), Han et al. (2020), and Li et al. (2020).

Table 3. Unit root test results

	ADF		PP	
	Level	First Differenced	Level	First Differenced
EU	-3.613**	-9.351***	-3.628**	-9.648***
BCI	-1.422	-5.203***	-1.796	-9.173***
Log GDP	3.567	-2.925**	6.184	-16.097***

Notes: ADF is the test statistic from the Augmented Dickey-Fuller test. PP is the test statistic from the Perron-Phillips test. We follow Pfaff (2008) to first assume that data have trend and intercept. If the data is stationary, we conclude that this variable is trend-stationary, and decide to use unit root test with trend and intercept. If the variable is nonstationary under the specifications of both trend and intercept, we then check if the trend is significant or not by its t-test. If trend is not significant, we will then test unit root under the intercept only. Finally, we include trend and intercept when testing the economic uncertainty (EU) index, while including only intercept when testing GDP or the business cycle index (BCI). **, *** indicate significance at the 5% and 1% levels, respectively.

Table 4. Granger causality test

	Lag structure	Chi-square
From EU to BCI	5, 5	13.704** (0.018)
From EU to GDP	1, 1	9.874*** (0.002)
From BCI to EU	5, 5	8.789 (0.118)
From GDP to EU	1, 1	2.667 (0.102)

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. P-values are reported in parentheses. EU refers to the economic uncertainty index. BCI is the business condition index. The null hypothesis is no Granger cause from variable A to B.

Table 5. Nonlinear Granger causality test results $(\theta_n = 1.5)$

	Lag structure	T-Statistics
From EU to BCI	3, 3	2.384*** (0.009)
From EU to GDP	1, 1	1.919** (0.027)
From BCI to EU	3, 3	2.022** (0.022)
From GDP to EU	1, 1	1.537* (0.062)

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. P-values are reported in parentheses. Once the p-value is smaller than respective criteria (0.1, 0.05, or 0.01), the null hypothesis is that no nonlinear from A to B is rejected at respective significance levels. EU refers to the economic uncertainty index. BCI is the business condition index.

Table 6. Test for nonlinear relationship

	GDP growth	BCI
EU	0.020	55.523
	(0.273)	(108.777)
Economic growth (-1)	-74.912*	-61.721**
	(44.888)	(26.387)
Economic growth (-2)	87.265**	65.866***
	(43.769)	(25.346)
EU* Economic growth (-1)	16.451*	13.704**
	(9.758)	(5.730)
EU*Economic growth (-2)	-18.927**	-14.393***
	(9.515)	(5.503)
Constant	-0.085	-252.689
	(1.258)	(500.903)

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. EU refers to the logarithm of economic uncertainty index constructed in this study. BCI is the business cycle index.

Table 7. Granger causality test results for U.S. and China EU

	Lag structure	T-Statistics
Panel A: Linear		
From China to U.S.	3, 3	2.318 (0.509)
From U.S. to China	3, 3	13.878*** (0.003)
Panel B: Nonlinear		
From China to U.S.	3, 3	1.662** (0.048)
From U.S. to China	3, 3	1.814** (0.035)

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. P-values are reported in parentheses. Once the p-value is smaller than respective criteria (0.1, 0.05, or 0.01), the null hypothesis is that no nonlinear from A to B is rejected at respective significance levels. China refers to the EU index constructed in this study. U.S. refers to U.S. economic uncertainty proxy by Jurado et al.'s (2015) macroeconomic uncertainty index.

Table 8. Stock return and EU

Panel A: Aggregate stock return

	(1)	(2)	(3)	(4)
ΔEU_t	-0.089***	-0.089***		
	(0.031)	(0.031)		
ΔEPU_t		-0.016*		
		(0.008)		
ΔEU_{t-1}			-0.054*	-0.053*
			(0.030)	(0.030)
ΔEPU_{t-1}				-0.018*
				(0.010)
Constant	0.003	0.003	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
No of Obs	240	240	239	239
Adj R^2	0.035	0.049	0.010	0.020

Panel B: Risk Premium and EU

	(1)	(2)	(3)
γ_{EU}	-0.019***	-0.015***	-0.014***
	(0.0014)	(0.0013)	(0.0012)
γ_{Mkt}	0.006***	0.006***	0.006***
	(0.0013)	(0.001)	(0.001)
γ_{SMB}		0.0002	0.0002
		(0.0006)	(0.0006)
γ_{VMG}		-0.002***	-0.002***
		(0.0005)	(0.0005)
γ_{PMO}			-0.0004
			(0.0002)

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. EU refers to economic uncertainty, proxies by our EU index. EPU refers to economic policy uncertainty proxies by Huang and Luk's (2020) EPU index. The sample period is from January 2000 through December 2018. The dependent variable is the return of Shanghai SE composite index in Panel A and is the return of individual A-share stocks in Panel B. The Newey–West standard errors corrected for heteroskedasticity and autocorrelation are given in parentheses.

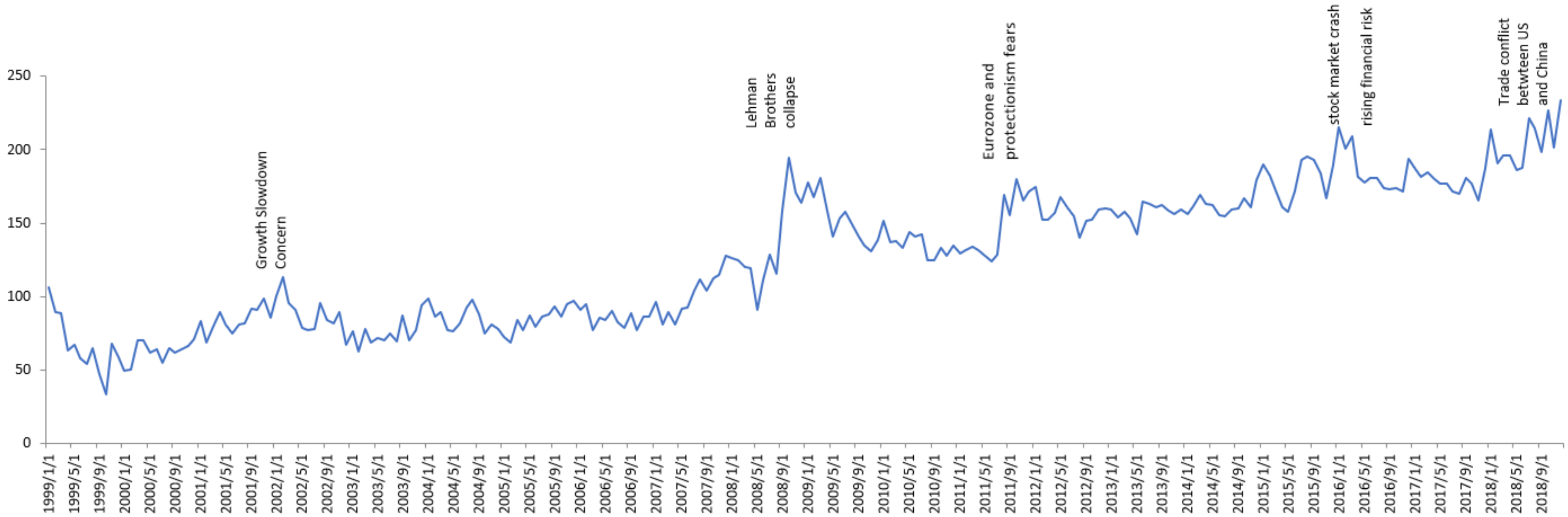


Figure 1. Chinese Economic Uncertainty Index

Sources: Author’s calculations; Datago.

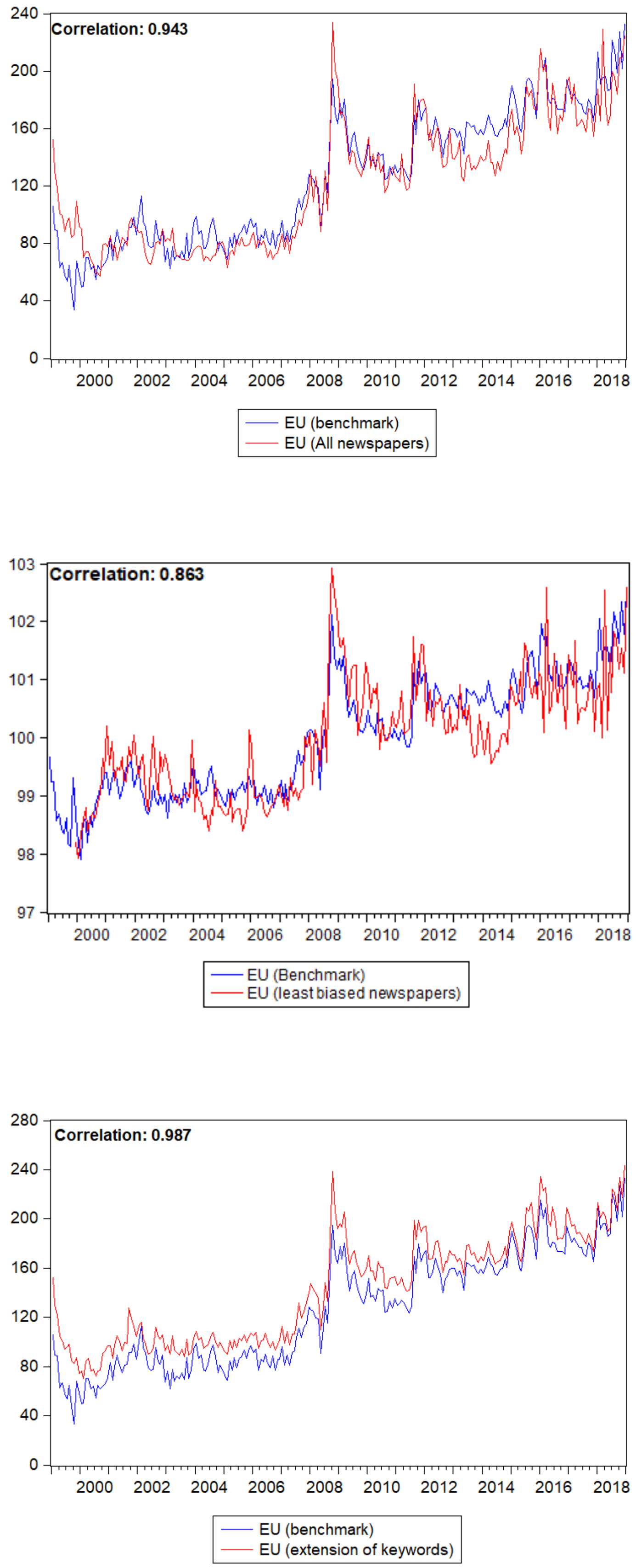


Figure 2. Benchmark Economic Uncertainty Index and its alternatives

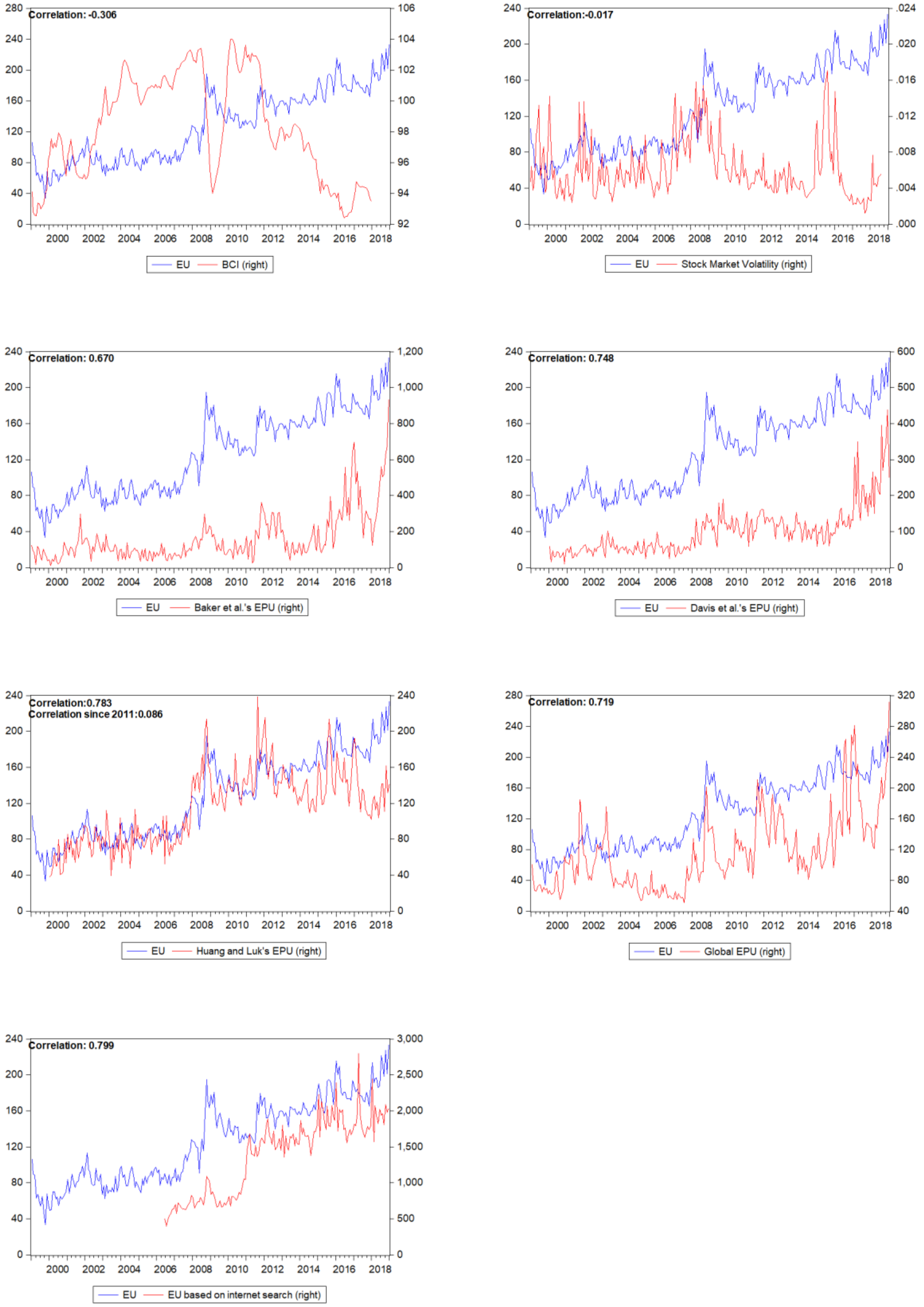


Figure 3. Comparison among uncertainty measures

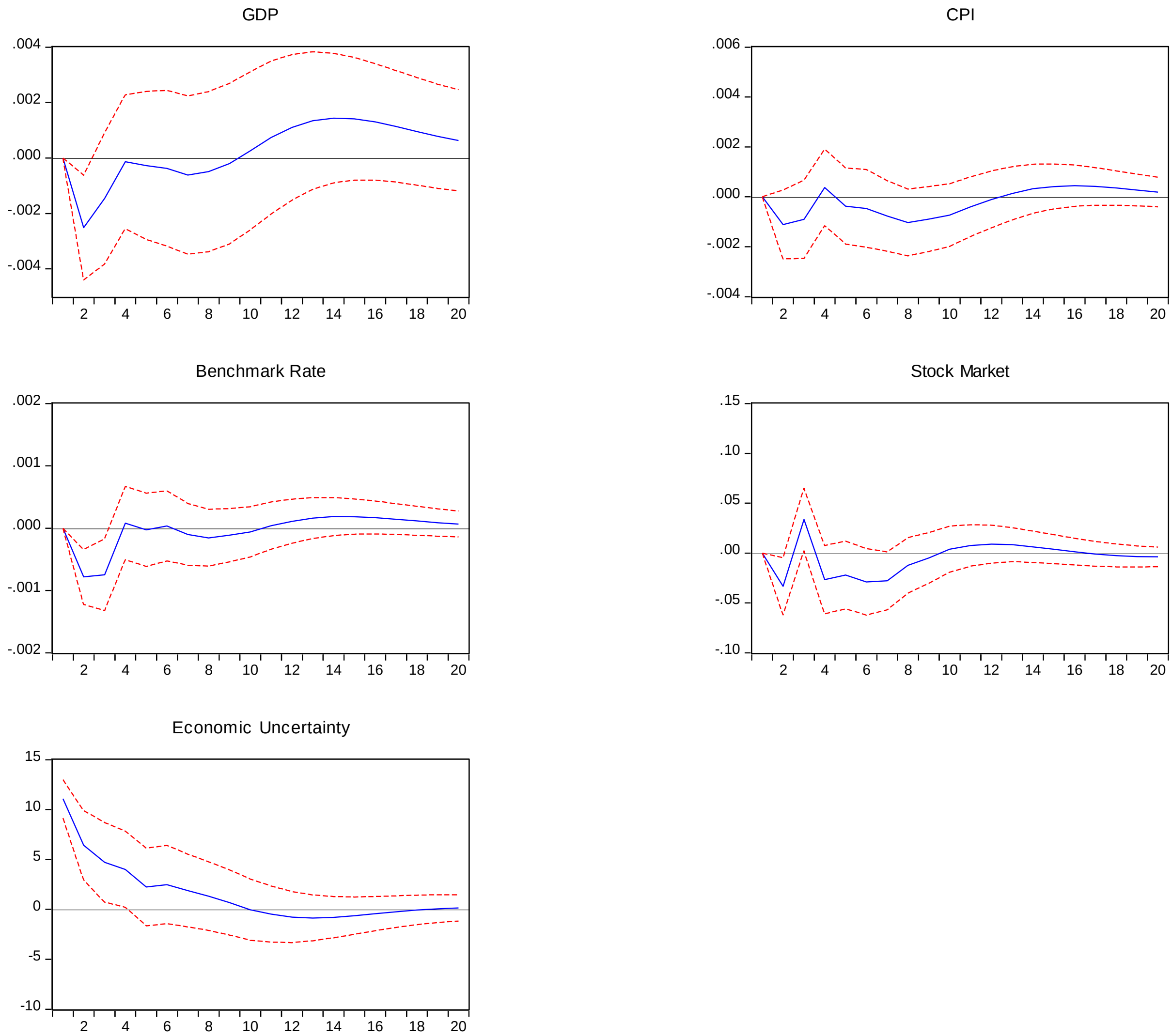


Figure 4. Impulse responses to a one-standard-deviation innovation in the EU index

Note: The red solid lines denote the median impulse response functions. The dashed lines show 95% (bootstrap) confidence intervals following Kilian (1998), which adjusted for the skewness and bias in the small-sample distribution of the impulse response functions. X-axis indicates the quarter after EU shock.

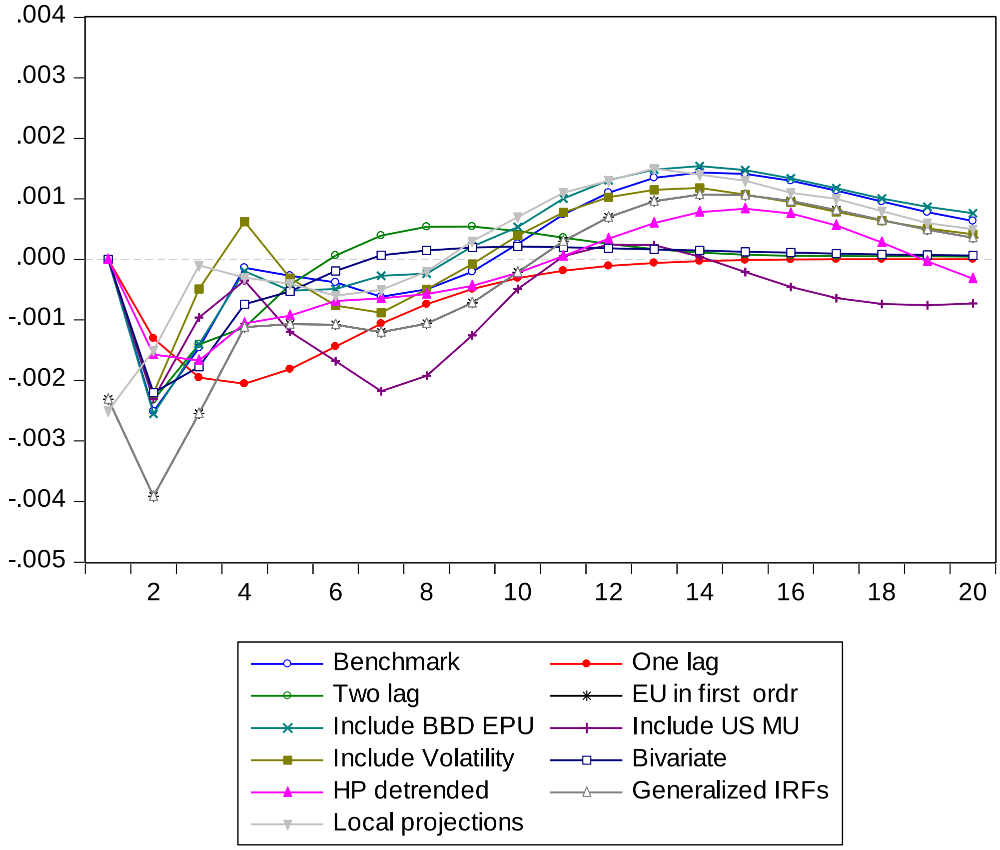


Figure 5. GDP response to an EU shock, with alternative specifications

Notes: MU refers to macroeconomic uncertainty, proxy by Jurado et al.'s (2015) MU index. BBD EPU refers to the economic policy uncertainty index developed by Baker, Bloom, & Davis (2015). HP detrended refers to variables that detrended by Hodrick-Prescott filter.

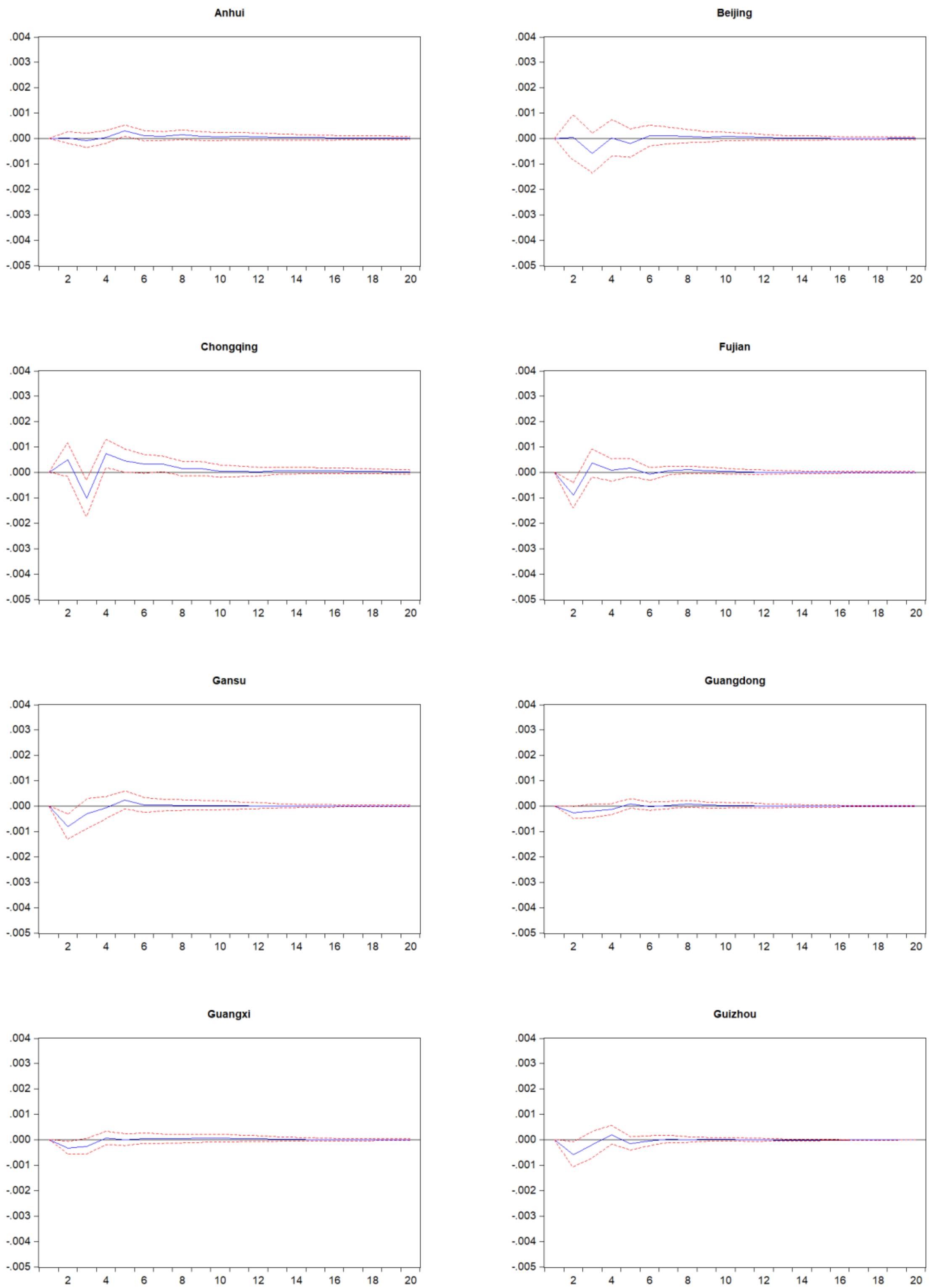


Figure 6. The responses of local GDP to EU shock

Note: The red solid lines denote the median impulse response functions. The dashed lines show 95% (bootstrap) confidence intervals following Kilian (1998), which adjusted for the skewness and bias in the small-sample distribution of the impulse response functions. X-axis indicates the quarter after EU shock.

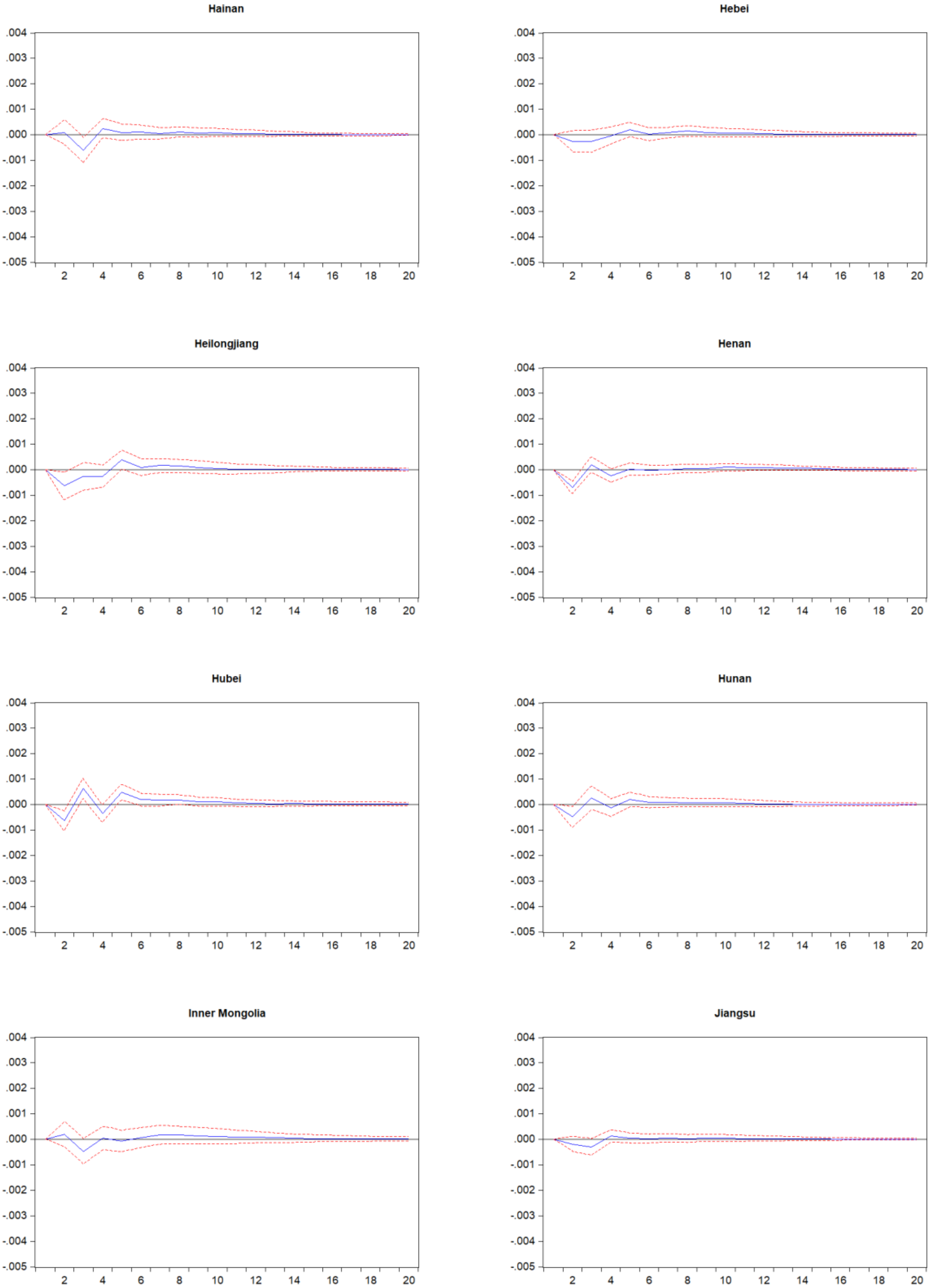


Figure 6 (Continued). The responses of local GDP to EU shock

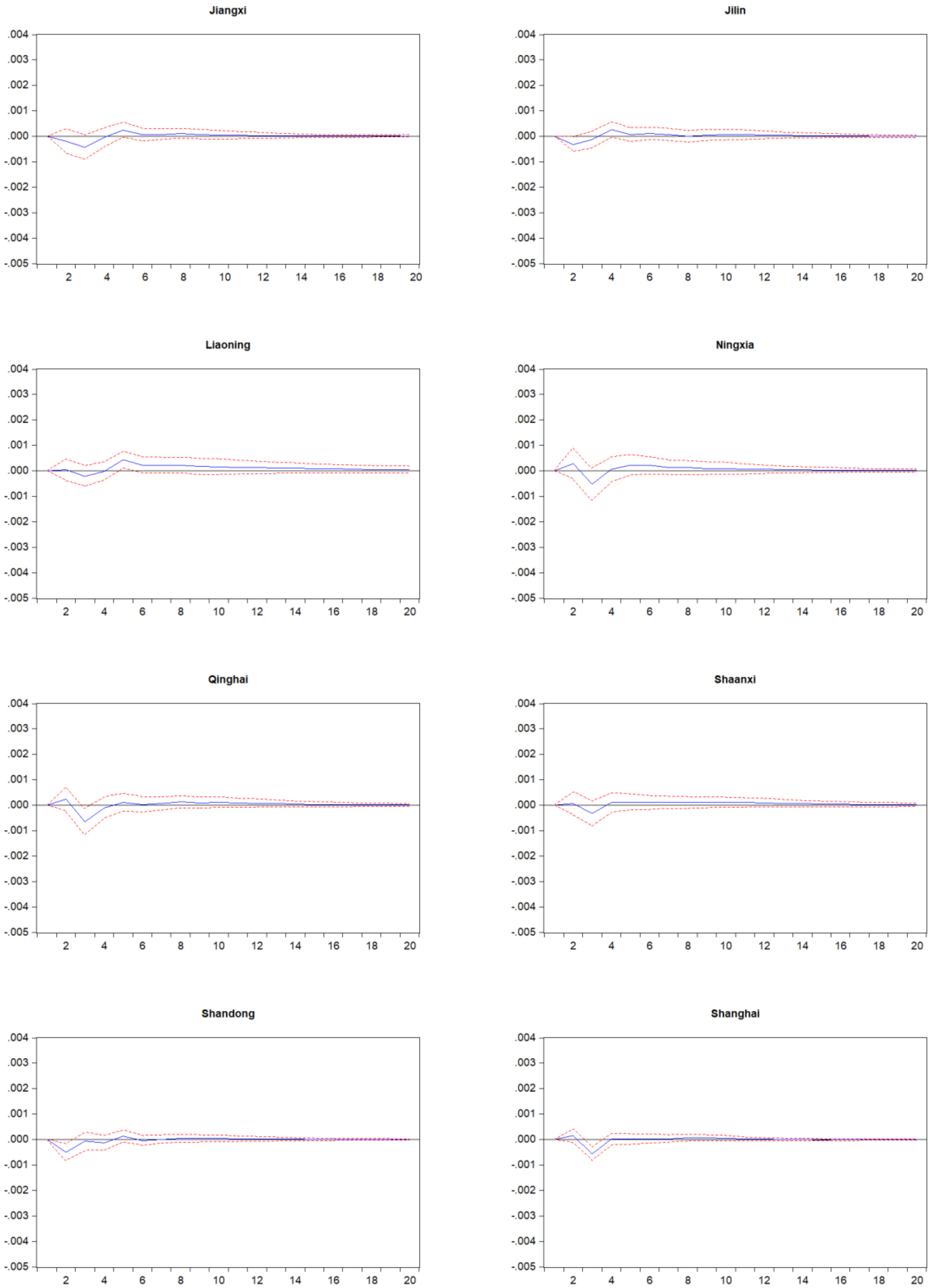


Figure 6 (Continued). The responses of local GDP to EU shock

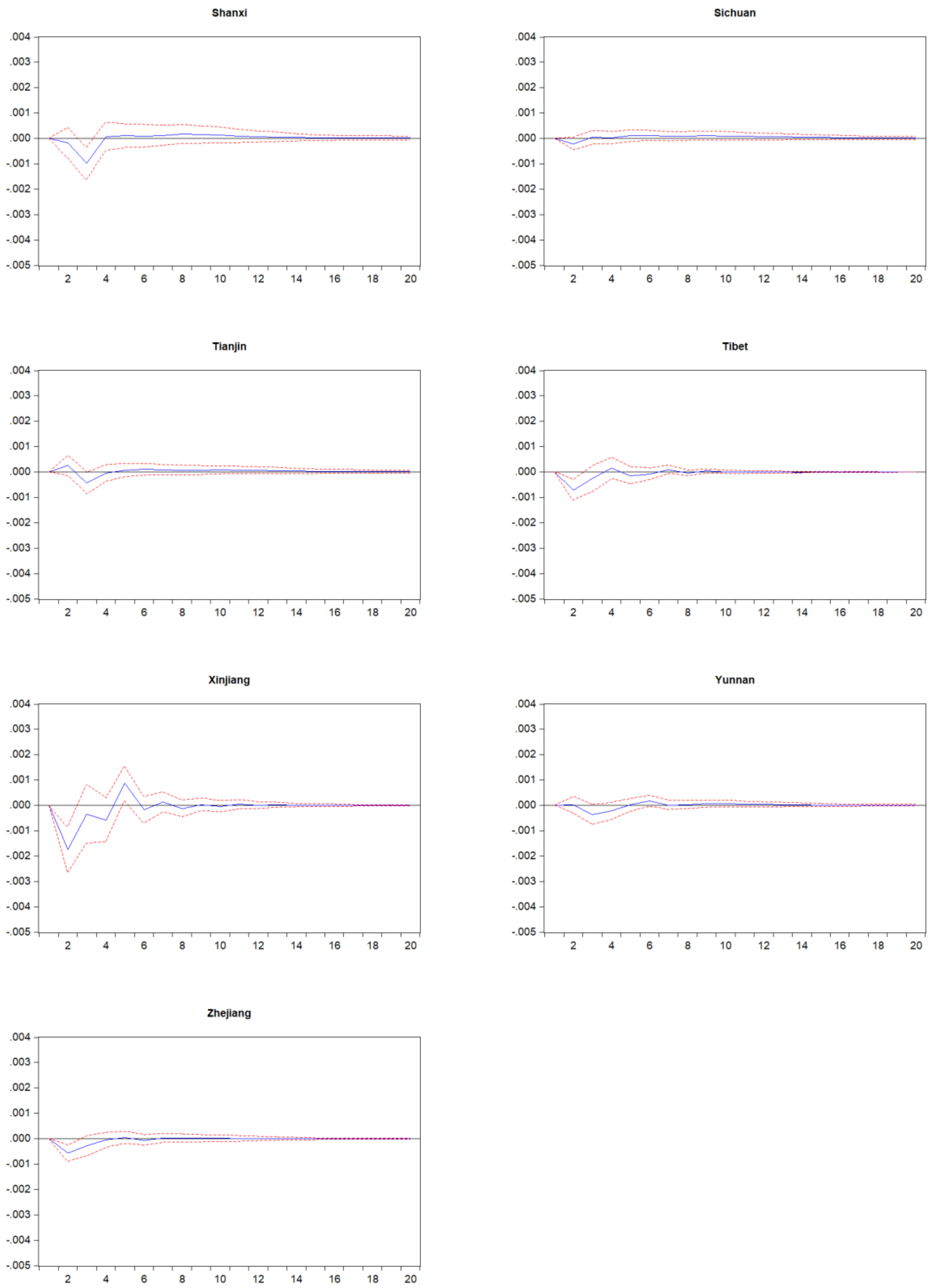


Figure 6 (Continued). The responses of local GDP to EU shock