MEASURING GLOBAL AND COUNTRY-SPECIFIC UNCERTAINTY*

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Abstract: Motivated by the literature on the capital asset pricing model, we decompose the uncertainty of a typical forecaster into common and idiosyncratic uncertainty. Using individual survey data from the *Consensus Forecast* over the period of 1989-2014, we propose a monthly measure of macroeconomic uncertainty covering 46 countries and construct a measure of global uncertainty as the weighted average of country-specific uncertainties. Our measure captures perceived uncertainty of market participants and derives from two components that are shown to exhibit strikingly different behavior. Common uncertainty shocks produce the large and persistent negative response in real economic activity, whereas the contributions of idiosyncratic uncertainty shocks are negligible.

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1. Introduction

Heightened economic uncertainty, at both national and global levels, greatly contributed to the 2007-09 recession and shaped the speed of the subsequent recovery. Six years after the end of the recession, there is still no sign of a complete global recovery. Advanced economies are uncertain about the effects of monetary policy normalization and emerging market economies are uncertain about the growth challenges ahead. Surrounded with historically high uncertainty, economists face great challenges in understanding the origins of economic uncertainty and analyzing its causal impacts on real economy, e.g. Stock and Watson (2012).

Since there is no objective measure of uncertainty, economists have used numerous different proxies. A ubiquitous proxy is the implied or realized volatility in stock markets, such as VIX, e.g. Bloom (2009). However, the volatility in Wall Street might not reflect uncertainty in Main Street. For instance, changes in the VIX might be due to leverage or financial stress, despite low levels of economic uncertainty; see Bekaert et al. (2013). Jurado, et al. (2015) develop an alternative measure of economic uncertainty: the common variation in uncertainty across hundreds of economic series. Their measure reflects uncertainty around objective statistical forecasts, rather than perceived uncertainty by market participants. Moreover, as they focus on common, not idiosyncratic, uncertainty, there is no role for private information and heterogeneous agent models. A third leading proxy is based on the frequency of references to policy-related uncertainty in the newspapers, e.g. Baker, et al. (2016). As aptly pointed out by Hansen (2015), this news-based uncertainty measure puts a high bar for the attentiveness of reporters and editors, who might miss uncertainty events if they neglect to write a story on the subject. The fourth proxy for uncertainty is cross-sectional disagreement of economic agents, calculated as the dispersion in directional or point forecasts, e.g. Bachmann et al. (2013). When disagreement is taken to indicate uncertainty, the underlying assumption is that this inter-personal dispersion measure is an acceptable proxy for the average dispersion of intra-personal uncertainty. As shown by Lahiri and Sheng (2010), however, disagreement is only a part of uncertainty and misses an important component: the volatility of aggregate shocks.

To address some of the limitations in the existing measures, we develop a comprehensive measure of economic uncertainty by incorporating rich information reflected in the survey of professional forecasters. Similar to Jo and Sekkel (2015), Rossi and Sekhposyan (2015) and Scotti (2016), our measure is based on subjective forecasts of market participants and reflects their perceived uncertainty. In contrast to these three papers, our uncertainty measure includes two components: common uncertainty as emphasized in Jurado et al. (2015) and idiosyncratic uncertainty as documented in the macroeconomics literature. Our decomposition of uncertainty of a typical forecaster into common and idiosyncratic parts is similar to Campbell et al. (2001) that decompose the volatility of a typical stock into market and firm-level volatility. We estimate the common component as the perceived variability of future aggregate shocks and idiosyncratic component as the disagreement among professional forecasters across three different layers. First, we estimate the variable-specific uncertainty for eight nominal and real economic indicators. Second, we measure the country-specific uncertainty as the weighted average of standardized components of variable-specific uncertainty and regional uncertainty as the weighted average of the country-specific uncertainty measures. Finally, we propose an index of global uncertainty, which is a rather new concept in the literature. Constructed from a large set of countries, corresponding to more than 90 percent of the world economy, this global measure is more comprehensive than the previously proposed measures, e.g. Berger and Herz (2014).

Our main findings are summarized as follows. All uncertainty measures are countercyclical and at all layers, combined uncertainty is more countercyclical than its common or idiosyncratic component. A comparison of our country-specific uncertainty measures with alternative leading measures for a subset of countries shows that our measures have fewer peaks, all around the recessions, and have persistent and heightened uncertainty during these recession episodes. Shocks to our measures of uncertainty are associated with large and persistent drops in real activity at both national and global levels. Further investigation shows that common uncertainty shocks produce large and persistent responses in real activity, whereas the contributions of idiosyncratic uncertainty shocks are negligible.[1]

The rest of the paper is organized as follows. Section 2 details the methodology on measuring uncertainty. Section 3 introduces the data used in this paper. Section 4 describes the properties of economic uncertainty measures. Section 5 presents the dynamic relationship between uncertainty and economic activity and Section 6 concludes. The appendix includes detailed information on the dataset and regional measures of uncertainty.

2. Methodology: Estimating Uncertainty

2.1 Uncertainty Decomposition

Let e_{it} be individual i's forecast error at time t. Then consensus forecast error, e_t, is defined as the weighted average of individual forecast errors:

[1] This result is in contrast with Choi and Loungani (2015) who find that idiosyncratic uncertainty shocks, measured by the cross-industry dispersion of stock returns, have persistent and dominant effects on real activity.

$$e_t = \sum_{i=1}^{N} w_{it} \, e_{it}, \tag{1}$$

where w_{it} is the weight of individual forecast error in consensus forecast error. Motivated by the literature on the capital asset pricing model (CAPM), we specify the relationship between individual and consensus forecast errors as follows

$$e_{it} = \beta_i \, e_t + \varepsilon_{it}, \tag{2}$$

where β_i measures individual i's risk arising from exposure to consensus forecast error. The β_i below 1 indicates that an individual forecast error is not highly correlated with consensus forecast error. In equation (2), ε_{it} is orthogonal by construction to e_t. Equations (1) and (2) together impose the following restriction $\sum_{i=1}^{N} w_{it} \, \beta_i = 1$, which is the standard assumption in the CAPM literature that the weighted sums of the different betas equal unity. Equation (2) permits a simple variance decomposition in which the covariance term is zero:

$$Var(e_{it}) = \beta_i^2 Var(e_t) + Var(\varepsilon_{it}). \tag{3}$$

In equation (3), $Var(e_t)$ measures the common volatility and $Var(\varepsilon_{it})$ captures the idiosyncratic volatility. The problem with this decomposition, however, is that it requires knowledge of individual-specific betas that are difficult to estimate and might introduce another layer of uncertainty in parameter estimation. To avoid this problem, we follow the approach in Campbell et al. (2001) that does not require any information about betas on the aggregate level. To fix ideas, let u_{it} denote the difference between e_{it} and e_t :

$$e_{it} = e_t + u_{it}. \tag{4}$$

Plugging equation (4) into equation (2) and re-arranging yields

$$u_{it} = (\beta_i - 1) \, e_t + \varepsilon_{it}. \tag{5}$$

The apparent drawback of equation (4) is that u_{it} and e_t are not orthogonal, and so we cannot ignore their covariance. Taking the variance on both sides of equation (4), we have

$$Var(e_{it}) = Var(e_t) + Var(u_{it}) + 2Cov(e_t, u_{it}) \quad (6)$$

$$= Var(e_t) + Var(u_{it}) + 2(\beta_i - 1)Var(e_t),$$

where the second equality follows from equation (5). Again, taking into account the covariance term introduces the individual forecaster beta into the variance decomposition.

Note, however, that although the variance of an individual forecast error contains the covariance term, the weighted average of variances across forecasters is free of the covariance term:

$$\sum_{i=1}^{N} w_{it}\, Var(e_{it}) = Var(e_t) + \sum_{i=1}^{N} w_{it}\, Var(u_{it}). \quad (7)$$

The covariance term from equation (6) aggregates out due to the standard restriction $\sum_{i=1}^{N} w_{it}\ \beta_i = 1$. The weighted average $\sum_{i=1}^{N} w_{it}\, Var(e_{it})$ can be interpreted as the volatility of a "typical" forecaster, selected randomly from among all forecasters with probability equal to its weight w_{it}, e.g. Giordani and Söderlind (2003). Equation (7) states that the volatility of a typical forecaster can be decomposed into two parts: volatility that is common to all forecasters and volatility that arises from the heterogeneity of individual forecasters.

The observed disagreement among forecasts (or forecast errors) can be expressed as

$$d_t = \sum_{i=1}^{N} w_{it}(e_{it} - e_t)^2 \quad (8)$$

$$= \sum_{i=1}^{N} w_{it}[(\beta_i - 1)e_t + \varepsilon_{it}]^2$$

$$= \sum_{i=1}^{N} w_{it}\, [(\beta_i - 1)^2 {e_t}^2 + {\varepsilon_{it}}^2 + 2(\beta_i - 1)e_t\varepsilon_{it}].$$

The sample variance d_t is a random variable prior to observing the forecasts. Taking expectations, we get an expression for the non-random disagreement, denoted by D_t, as

$$D_t \equiv E(d_t) = \sum_{i=1}^{N} w_{it}\, [(\beta_i - 1)^2 E({e_t}^2) + E({\varepsilon_{it}}^2) + 2(\beta_i - 1)E(e_t\varepsilon_{it})] \quad (9)$$

$$= \sum_{i=1}^{N} w_{it}\, [(\beta_i - 1)^2 Var(e_t) + Var(\varepsilon_{it})],$$

where the last equality holds since $E(e_t \varepsilon_{it}) = 0$ and $E(e_t) = 0$ by assumption. Taking the variance on both sides of equation (5), we have

$$Var(u_{it}) = (\beta_i - 1)^2 Var(e_t) + Var(\varepsilon_{it}). \tag{10}$$

Plugging equation (10) into equation (9) yields

$$D_t = \sum_{i=1}^{N} w_{it} Var(u_{it}). \tag{11}$$

Combining equation (11) with equation (7), we get

$$\sum_{i=1}^{N} w_{it} Var(e_{it}) = Var(e_t) + D_t. \tag{12}$$

Equation (12) decomposes the uncertainty of a typical forecaster into common and idiosyncratic uncertainty. The first component is the empirical variance of the consensus forecast, which is conventionally the common uncertainty in the literature; see Clements (2014). The second component is forecast disagreement and captures idiosyncratic uncertainty.[2] Finally, we need to point out that our uncertainty decomposition is similar to the decomposition as in Lahiri and Sheng (2010) under a panel data framework.

2.2 Estimation

Based on the uncertainty decomposition, we construct time series of uncertainty measures of the two components for each variable and each country. In this subsection, we discuss how we estimate these uncertainty measures.

[2] It is easy to show how our measure of idiosyncratic uncertainty, $\sum_{i=1}^{N} w_{it} Var(u_{it})$, relates to the "true" measure, $\sum_{i=1}^{N} w_{it} Var(\varepsilon_{it})$. To this end, we take the weighted average of equation (10): $\sum_{i=1}^{N} w_{it} Var(u_{it}) = \sum_{i=1}^{N} w_{it} (\beta_i - 1)^2 \, Var(e_t) + \sum_{i=1}^{N} w_{it} Var(\varepsilon_{it})$. The wedge between the two idiosyncratic uncertainty measures is determined by the cross-sectional variance of β_i across all individual forecast errors, $\sum_{i=1}^{N} w_{it} (\beta_i - 1)^2$ and common uncertainty, $Var(e_t)$. Lahiri and Sheng (2008) show that the cross-sectional variance of β_i across all individual forecast errors is sufficiently small. Thus, our measure of idiosyncratic uncertainty can be a reasonable proxy for the "true" measure of idiosyncratic uncertainty.

The common uncertainty shocks have long been estimated using GARCH-type models, dating back to Engle (1982). Under such a framework, the estimates of common uncertainty depend on innovations to the raw series, denoted by Y_t, and therefore cannot be separated from first-moment shocks. For this reason, we use the stochastic volatility model to estimate common uncertainty in our main analysis.[3] The stochastic volatility model permits construction of a shock to the second moment that is independent of innovations to Y_t. This exogeneity is consistent with the theoretical literature which presumes the existence of an uncertainty shock that independently affects real activity. Estimation of the common uncertainty using a stochastic volatility model has the following specification:

$$e_t = \varphi_0 + \varphi_1 \varepsilon_{t-1} + \varepsilon_t,\ \varepsilon_t | I_{t-1} \sim N(0, \sigma_t^2) \tag{13}$$

$$\ln \sigma_t^2 = \alpha + \beta \ln \sigma_{t-1}^2 + \upsilon_t. \tag{14}$$

We estimate this model using Markov Chain Monte Carlo (MCMC) methods as in Kim et al. (1998). To prevent the impacts of the outliers, we use median forecast errors instead of mean forecast errors in equation (13). Similarly, we measure forecast disagreement as the interquartile range rather than standard deviation in order to mitigate the effect of the outliers. Since these two components of uncertainty measure have different scales, we standardize them using the min-max normalization rule. Applying this rule, both common and idiosyncratic uncertainty components are scaled between 0 and 1, and the sum of these two is bounded between 0 and 2 for all eight variables including GDP, consumption, investment, industrial production, inflation, unemployment rate, short-term and long-term interest rates. We emphasize two features of these variable-specific uncertainty estimates. First, we use surveys

[3] For a robustness check, we also use the GARCH model to estimate common uncertainty. We find that the resulting uncertainty estimates from stochastic volatility model and GARCH model are very similar.

of professional forecasters directly rather than making objective statistical forecasts, as guided by the recent empirical findings that surveys provide more accurate macroeconomic forecasts; see Ang et al. (2007) and Faust and Wright (2013). As a result, our uncertainty estimates are less prone to measurement errors due to potentially misspecified econometric models that yield large forecast errors and inflated uncertainty measures. Second, we use forecast errors, rather than forecasts, to remove the predictable component of the raw series and estimate common uncertainty as the conditional volatility of the purely unforecastable component of the future value of the series.

To estimate country-specific economic uncertainty, we take the weighted average of eight variable-specific uncertainty estimates for each country. This definition emphasizes that economic uncertainty is a measure of common variation in uncertainty across many series, as also pointed out by Jurado, et al. (2015). We present the results using equal weights in the paper. As an alternative, we also estimate the country-specific uncertainty as the first principal component of eight variable-specific uncertainty series and find that the results are very similar.

Unlike the variable-specific and country-specific uncertainty measures, global uncertainty receives little attention in the literature. This is possibly due to insufficient data to estimate global uncertainty. The existing global uncertainty measures are based on too few countries and tend to focus on developed economies. For instance, Hirata et al. (2013) construct a measure of global uncertainty based on 7 advanced economies and Berger and Herz (2014) estimate global uncertainty using 9 advanced economies and two variables: output growth and inflation. To address this limitation, we use a dataset of 46 advanced and emerging market economies, covering more than 90 percent of the world economy today. For these economies, we include eight variables for each country, covering both real and nominal variables. Taking advantage of this rich dataset, we construct a measure of global uncertainty as the PPP-weighted average of the country-specific uncertainties.

3. Data

We use survey data of macroeconomic forecasts to compute uncertainty measures. The forecast data are from the *Consensus Forecasts*, publications of the Consensus Economics Inc., a private macroeconomic survey firm based in London. This survey is a comprehensive dataset with a large coverage of advanced and emerging market economies. For each country the survey asks similar questions to a panel of 10-30 professional forecasters on the first week of each month. For some countries, the definition of variables varies slightly (i.e. manufacturing production instead of industrial production) and for others some questions are omitted because of possible data limitations. Other than these, the surveys have a near uniform design for all countries in the sample, which makes the results comparable across countries. This study covers all 46 countries with monthly forecasts available for the annual growth rates of GDP, consumption, investment, industrial production, and levels of inflation, short-term and long-term interest rates, and the unemployment rate. These eight variables enable us to capture uncertainty both in nominal and real macroeconomic series, where inflation, short-term and long-term interest rates are in nominal and the rest are in real terms. Table A.1 in the appendix provides detailed information on the country, time and variable coverage of the dataset.

Forecasts for all variables except interest rates are fixed event forecasts. At every month, each survey participant provides forecasts for both the current and the next calendar year. These fixed event forecasts get closer to the actual values when the forecasting horizon is shorter. Following Dovern, et al. (2012), we transform the fixed event forecasts of all variables into fixed horizon forecasts with the following adjustment:

$$F_{i,t+12|t} = \frac{k}{12} F_{i,t+k|t} + \frac{12-k}{12} F_{i,t+12+k|t}, \tag{15}$$

where $F_{i,t+k|t}$ and $F_{i,t+12+k|t}$ are the two forecasts based on the information set at time t with horizons of $k \in \{1, \dots, 12\}$ and $k + 12$ months, respectively. The average of two fixed event forecasts weighted by their share in the forecasting horizon approximates the fixed horizon forecast, $F_{i,t+12|t}$, for the next 12 months. For interest rates, survey participants provide both three-month and twelve-month ahead forecasts. To be consistent with the horizon of the forecasts for other variables, we use the twelve-month ahead forecasts for both short-term and long-term interest rates.

Turning to the actual values, monthly series are available for industrial production, inflation, unemployment, short-term and long-term interest rates. For real GDP, consumption and investment, we use quarterly series since they are not available at the monthly frequency. The main sources of actual values are Global Data Source of IMF, Haver Analytics, OECD Analytical databases and country statistical offices. To match the actual values with the fixed-horizon forecasts, we perform the appropriate data transformation.[4] We explore the properties of these forecasts through the Mincer-Zarnowitz regression and find that some forecasts are

[4] Take as an example the survey conducted in January 1991. At the beginning of January, the survey asks forecasts for industrial production and inflation for 1991. For these two monthly variables, we calculate the actual values as the growth rate between December 1990 and December 1991. Similarly, for real GDP, consumption and investment, we calculate the respective actual values as the growth rate between the fourth quarter of 1990 to the fourth quarter of 1991. For the unemployment rate, the actual value reflects the rolling 12-month window average, and in this example equals the average of the unemployment rates from January to December 1991. The forecasts of the two interest rates in this study are easily comparable to the actual values. For both the short- and long-term interest rates, the actual values are the monthly data released for the target date.

biased and inefficient in incorporating new information.[5] Despite these inefficiencies, we use forecast data because of the advantages of surveys over purely model-based forecasts and because these surveys reflect market participants' perceptions of economic development in the future. This perception is key to capturing how economic agents experience uncertainty in the economy.

4. Properties of Economic Uncertainty

We estimate variable-specific uncertainty (VSU) for eight indicators. For most of the economies in the sample, the VSU is countercyclical for all series. Moreover, some VSU estimates are highly correlated. Table 1 shows that for the United States the pairwise correlations are quite high for most of the VSU estimates. Interestingly, pairwise correlations between all VSU estimates except long-term interest rate are higher for the common than the idiosyncratic component. For instance, the correlation between inflation and investment growth is 0.27 for idiosyncratic uncertainty, but 0.78 for common uncertainty. If one estimates uncertainty at the country level using only forecast disagreement, then there would be too many uncertainty spikes due to idiosyncratic shocks in individual series. On the other hand, if one estimates uncertainty using only the common component, then the series would be too smooth. These findings imply that the combined estimate of these two reflects the uncertainty in the entire economy better than any individual component.

[5] Since the forecasters in the survey are not anonymous, the possibility exists that at least part of the bias and inefficiency can be explained by strategic behavior among them. On one hand, forecasters might shade their forecasts toward the consensus to avoid unfavorable publicity when wrong. On the other hand, forecasters might deviate from the consensus in order to stand out from the crowd of competing forecasters. While there is supporting evidence for both types of strategic behavior, their overall effects on forecast accuracy and the resulting uncertainty estimates are not clear. Conducting the detailed analysis of forecasters' objectives and strategies is beyond the scope of this paper and we leave it for future research.

For all countries, common uncertainty is less volatile and on average, higher than idiosyncratic uncertainty. There are very few peaks in common uncertainty and those peaks are usually around recessions. For instance, in the United States, the uncertainty for output, consumption, investment, unemployment rate and short-term interest rates increases during all three recession periods covered in the sample of 1989-2014. Interestingly, some regional recession episodes are associated with higher uncertainty than global recession episodes. For instance, in Indonesia and South Korea, some of the VSU peaks around the 1997 Asian financial crisis are higher than those around the recent global recession. This is consistent with the findings of Hirata, et al. (2013): since the mid-1980s the importance of regional factors has increased and global factors play a lesser role in explaining international business cycles.

Turning to the country-specific uncertainty (CSU), Figure 1 plots the uncertainty estimates for 46 advanced and emerging market economies. The CSU is strongly countercyclical. Almost in all countries, the CSU peaked around 2009, even though the country itself did not experience any recession (i.e. China and Australia). For some emerging market economies, the uncertainty was higher during earlier recessions than the latest global recession. For instance, the largest uncertainty peak for Argentina is around 2001-2002 when there was a deep financial crisis in the country, whereas for Hong Kong it is around 1997-1998 Asian financial crisis.

The uncertainty at the national level influences the variable-specific uncertainty. To explore this impact, Table 2 presents the proportion of variable-specific uncertainty that is explained by the country-specific counterpart. For the entire sample, on average, the explanatory power of the CSU for the variable-specific uncertainty is almost the same during recessions ($R^2 = 0.585$) and expansions ($R^2 = 0.576$). For the advanced economies, however, it is higher during recessions ($R^2 = 0.51$) than expansions ($R^2 = 0.46$). Shorter time coverage of the emerging market economies makes it difficult to compare the explanatory power at different phases of the business cycle. For eight out of fifteen advanced economies, the CSU explains output growth uncertainty the most. Furthermore, the explanatory power varies over business cycles. For instance, in the United Kingdom, the CSU best explains investment growth uncertainty during recessions but least during expansions. In Japan, the variable that the CSU explains the most is inflation uncertainty during recessions but output growth uncertainty during expansions. For emerging market economies, the evidence is rather mixed. For instance, R^2 is highest for industrial production uncertainty in China, Poland, and Czech Republic; for consumption uncertainty in Argentina, Brazil, Colombia, Peru, South Korea, Philippines, Lithuania, and Romania; for investment uncertainty in Bulgaria, Croatia and Russia. Taken together, we see that country-specific uncertainty accounts for a large fraction of the variation in the variable-specific uncertainty. But there is a large amount of idiosyncratic variation in uncertainty across variables, as evident from many R^2 statistics that are much lower than one.

To summarize, our country-specific uncertainty measure complements the uncertainty estimate proposed by Jurado, et al. (2015) in two dimensions. First, they generate forecasts from augmented autoregressive models and measure uncertainty around objective statistical forecasts. In contrast, we use surveys of professional forecasters available for many countries and focus on market participants' perceived uncertainty. Second, they measure macroeconomic uncertainty as the common factor of all uncertainty estimates of hundreds of variables. In contrast, our uncertainty measure captures both common and idiosyncratic uncertainties, which we show to have different effects on economic activity in the next section.

With national uncertainty at hand, we estimate global uncertainty as the weighted average of country-specific uncertainties in Figure 2. Global uncertainty is strongly countercyclical and rises during the global recessions of 1991 and 2009, identified by Kose and Terrones (2015). The country-specific uncertainty is potentially influenced by global uncertainty because of large trade and financial interconnectedness among economies. Table 3 shows the proportion of the variation in the country-specific uncertainty that is explained by global uncertainty. In some of the Asian economies, global uncertainty explains only a small fraction of the country-specific uncertainty. For instance, R^2 is 0.435 in Hong Kong and 0.079 in Thailand. On the other hand, in some of the Eastern European economies, global uncertainty explains a very large fraction of the country-specific uncertainty, e.g. $R^2 = 0.925$ in Lithuania, 0.904 in Latvia and 0.886 in Bulgaria. In addition, global uncertainty amplifies the country-specific uncertainty for almost half of the sample, where the coefficient is significantly larger than 1. This amplification is less evident for its common component than idiosyncratic component. Finally, global uncertainty has the largest explanatory power relative to its two components. Parallel to other layers of uncertainty, the sum of both components better reflects worldwide uncertainty than any individual component.[6]

Table 4 presents the correlations among uncertainty, its two components, and other uncertainty measures for the United States. Our uncertainty measure has the highest correlation (0.79) with the uncertainty measure proposed by Jurado et al. (2015) and the lowest correlation

[6] Parallel to the global uncertainty measure, Figure A1 presents the uncertainty of functional and regional country groups, categorized as in the *Consensus Forecasts* dataset.

(0.18) with economic policy uncertainty proposed by Baker, et al. (2016). Not surprisingly, the measure of Jurado et al. (2015) has a higher correlation with common uncertainty (0.75) than idiosyncratic uncertainty (0.59). The lower correlation with idiosyncratic uncertainty reflects that disagreement captures other information, such as heterogeneous models and differential interpretation of public information, which are ignored by common uncertainty.

Figure 3 compares our country-specific uncertainty with other uncertainty measures from the literature, where all measures are standardized to have zero mean and unit variance for easy comparison. For almost all twelve countries included in this comparison, the increases in our uncertainty measures are more persistent during recessions compared to alternative uncertainty measures. For the United States, all uncertainty measures are countercyclical. Only our measure and the policy uncertainty measure exceed the 1.65 standard deviation line for all three recession periods. However, the policy uncertainty exceeds this line many times after the end of the latest recession. In contrast, the uncertainty measure of Jurado et al. (2015) exceeds the line only once during the latest recession, and the VXO exceeds the line six times, covering the three recessions and three non-recession periods. For the United Kingdom, the policy uncertainty exceeds the 1.65 standard deviation line five times, whereas our measure exceeds the line in two recessions out of three. For Canada, France and Germany, our measure usually performs better than the policy uncertainty in capturing the recessionary episodes. For the other countries, the comparison is between our measure and the news-based uncertainty index of Baker et al. (2016). Based on the uncertainty-related keyword search on main national newspapers, the news-based indexes often experience large spikes during non-recessionary episodes. On the other hand, our uncertainty measures for these countries reach their peaks during most of the recessionary episodes and remain low during expansions.

5. Uncertainty and Economic Activity

In this section, we analyze economic uncertainty and macroeconomic dynamics. One of the most pronounced reasons for the slow recovery has been the elevated macroeconomic uncertainty during and after the global recession. To explain this slow recovery, some studies emphasize the demand side impacts of uncertainty via consumption and investment. With high uncertainty, households save more and postpone their consumption, especially for durable goods. Similarly, companies delay their investment decisions and choose to "wait and see" until high uncertainty is resolved (Bloom, 2009). Other studies investigated the supply side impacts of uncertainty through credit provision and productivity growth. When economic uncertainty is high, banks are reluctant to provide loans, and credit conditions for companies tighten, especially for new start-up companies which are good sources of innovation and high productivity growth, e.g. Gilchrist, et al. (2014).

The dynamics between uncertainty and economic activity has been analyzed using vector autoregression (VAR) models. To easily benchmark with the results in the literature, we employ the VAR analysis as well. We use an eight-variable VAR model and present the results for the United States only. Our VAR model has the following specification:

$$\begin{bmatrix} \log(S\&P500\ index) \\ Uncertainty\ measure \\ Federal\ funds\ rate \\ \log(wages) \\ \log(consumer\ price\ index) \\ Hours \\ \log(employment) \\ \log(industrial\ production) \end{bmatrix}$$

Figure 4 plots the responses of industrial production and employment to a one standard deviation uncertainty shock. There is clear evidence of overshooting when the VXO or economic policy uncertainty is used as the proxy. In the middle of the third year after the hit of the VXO shock, both industrial production and employment increase over their initial levels. The overshooting is even faster when economic policy uncertainty is used as a proxy. This result is in line with Bloom (2009) but not with Jurado et al. (2015) and Scotti (2016), both of which replicate the analysis in Bloom (2009) and find no evidence of overshooting when variables are not HP-filtered. Both employment and industrial production decline sharply in response to a one standard deviation shock to the uncertainty measure of Jurado et al. (2015) and these declines remain persistent for five years following the initial shock.

We also analyze the impact of the two components of country-specific uncertainty through the VAR model. The idiosyncratic component, forecast disagreement shock, has less significant impacts on industrial production and employment. In contrast, common uncertainty shocks have a large and long-lived impact on both industrial production and employment, with the peak impact occurring after two to three years. Therefore, the "wait-and-see" mechanism is observed in the common component of the uncertainty rather than its idiosyncratic component. This result stands at odds with the conclusion of Choi and Loungani (2015) that aggregate uncertainty (parallel to our common component of uncertainty) has an immediate impact on unemployment, which dissipates within a year, whereas sectoral uncertainty (parallel to our idiosyncratic component of uncertainty) has a long-lived impact on unemployment. Turning to our country-specific uncertainty measure that includes both common and idiosyncratic components, the responses of both industrial production and employment are not significant during the first nine months following the shock. The significantly negative impact on industrial production starts around 10 months after the shock and remains persistent, keeping industrial production below its initial level until the middle of the third year. This finding underscores the larger persistence of our country-specific uncertainty measure as compared to other uncertainty proxies.

Using global uncertainty measure and monthly variables, we conduct a similar exercise in the global dimension. Our VAR model includes seven variables in the following order: stock prices, global uncertainty, short term interest rate, oil prices, food prices, unemployment rate and industrial production. Besides global uncertainty, we also use its common and idiosyncratic components, replacing the uncertainty measure iteratively in the model. Figure 5 shows the impulse response functions. For industrial production (panel A), there is an immediate decline following the global uncertainty shock, but the decrease dissipates within a few months. The response to the idiosyncratic uncertainty shock has a similarly short-lived impact, but an overshooting occurs after six months following the initial shock. The response to the common uncertainty shock, on the other hand, has a long-lived impact on industrial production, with the peak impact occurring after two years. The differences in the impact of the common and idiosyncratic uncertainty shocks show how these two parts capture different features of global uncertainty.

As illustrated in panel B of Figure 5, the global uncertainty shocks lead to a sizable and protracted increase in unemployment, a phenomena that was observed during and after some recessions, notably the recent global recession and its aftermath. The significant increase in unemployment following the uncertainty shock dissipates almost after 30 months. The idiosyncratic uncertainty shocks are associated with high initial response in unemployment rate, which then overshoots after 30 months. The common uncertainty shocks lead to more persistent and high unemployment rates and the impacts peak around 30 months. These findings support the theory that employers “wait-and-see” before they decide to lay off after the initial shock and then hire later on during the recovery. Once again, this result shows that the “wait-and-see” type of behavior is more related to the common rather than idiosyncratic component of global uncertainty.

Due to the imperfect correlation between common and idiosyncratic uncertainty, we perform an additional analysis by jointly studying their roles in explaining business cycle fluctuations. To this end, we include both uncertainty measures in the VAR model specification as follows

$$\begin{bmatrix} \log(stock\ price) \\ common\ uncertainty \\ idiosyncratic\ uncertainty \\ monetary\ policy\ rate \\ \log(consumer\ price\ index) \\ \log(industrial\ production) \end{bmatrix}$$

As shown in Figure 6, the two components of uncertainty have different effects on industrial production. Common uncertainty shocks have large and persistent impacts whereas idiosyncratic uncertainty shocks have short-lived and negligible effects on industrial production. This pattern holds for most of G7 countries, including France, Italy, Japan, United Kingdom and United States. For Canada and Germany, however, both types of uncertainty shocks seem to have very limited and short-lived effects.

6. Conclusion

This paper makes two contributions to the growing literature on economic uncertainty. First, we decompose the uncertainty of a typical forecaster into common and idiosyncratic uncertainty and accordingly propose a new monthly index of uncertainty that has both components, namely, perceived variability of future aggregate shocks and the disagreement among forecasters. By including these two components, the uncertainty measure captures economic uncertainty along different dimensions. Second, we use actual forecasts of market analysts instead of using hindsight to specify econometric forecasts. This choice is especially important since relevant information not used in model estimation and forecasting will lead to spurious estimates of uncertainty. As such, our uncertainty measure incorporates a rich information set and captures perceived uncertainty for market participants.

Compared to alternative leading measures, our country-specific uncertainty measures have fewer peaks, but when they do occur, they are larger and more persistent, a feature particularly relevant for theories where uncertainty is a driving force of recessions. Using the VAR analysis, we find that shocks to country-specific uncertainty are associated with a sizable and protracted decline in real activity. This result also holds for the world economy: global uncertainty shocks have long-lived effects on industrial production and unemployment. A deeper investigation shows that the two components of economic uncertainty exhibit strikingly different behavior. Common uncertainty shocks account for a large fraction of fluctuations in economic activity at business cycle frequencies, whereas idiosyncratic uncertainty shocks play a small role. Future research is warranted to quantify the economic effects of different types of uncertainty and analyze the transmission of uncertainty shocks across countries.

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Table 1. Correlation between Variable-specific Uncertainty Measures:United States

A. Correlation between Variable-specific Uncertainty Measures

	Output	**Inflation**	**Consumption**	**Investment**	**Industrial production**	**Unemployment rate**	**Short-term interest rate**	**Long-term interest rate**
Output	1.00							
Inflation	0.57	1.00						
Consumption	0.79	0.51	1.00					
Investment	0.77	0.64	0.61	1.00				
Industrial production	0.82	0.70	0.61	0.79	1.00			
Unemployment rate	0.77	0.53	0.72	0.70	0.67	1.00		
Short-term interest rate	0.43	0.22	0.55	0.42	0.37	0.28	1.00	
Long-term interest rate	0.41	0.27	0.27	0.42	0.33	0.47	0.24	1.00

B. Correlation between Variable-specific Idiosyncratic Uncertainty Measures

	Output	**Inflation**	**Consumption**	**Investment**	**Industrial production**	**Unemployment rate**	**Short-term interest rate**	**Long-term interest rate**
Output	1.00							
Inflation	0.38	1.00						
Consumption	0.60	0.36	1.00					
Investment	0.54	0.27	0.53	1.00				
Industrial production	0.56	0.46	0.53	0.51	1.00			
Unemployment rate	0.49	0.30	0.53	0.46	0.39	1.00		
Short-term interest rate	0.19	0.02	0.17	0.15	0.02	0.02	1.00	
Long-term interest rate	0.35	0.36	0.33	0.28	0.29	0.17	0.31	1.00

C. Correlation between Variable-specific Common Uncertainty Measures

	Output	**Inflation**	**Consumption**	**Investment**	**Industrial production**	**Unemployment rate**	**Short-term interest rate**	**Long-term interest rate**
Output	1.00							
Inflation	0.53	1.00						
Consumption	0.83	0.50	1.00					
Investment	0.75	0.78	0.60	1.00				
Industrial production	0.87	0.68	0.62	0.83	1.00			
Unemployment rate	0.71	0.54	0.68	0.68	0.69	1.00		
Short-term interest rate	0.54	0.30	0.61	0.53	0.44	0.42	1.00	
Long-term interest rate	0.20	0.20	0.16	0.22	0.19	0.49	0.17	1.00

Note : Output, consumption, investment, and industrial production stand for the growth rates of these indicators. The sample is between 1989M11-2014M7 for all estimates.

Table 2. R-square: Variable-specific Uncertainty on Country-specific Uncertainty

	Output	Consumption	Investment	Industrial production	Unemployment rate	Inflation	Short-term interest rate	Long-term interest rate	Average
United States									
Full sample	0.822	0.678	0.763	0.734	0.690	0.506	0.348	0.303	0.606
Recessions	0.833	0.628	0.657	0.662	0.506	0.807	0.065	0.000	0.520
Expansions	0.715	0.554	0.618	0.550	0.513	0.158	0.292	0.364	0.471
United Kingdom									
Full sample	0.777	0.805	0.564	0.659	0.479	0.627	0.512	0.511	0.617
Recessions	0.721	0.803	0.857	0.648	0.124	0.662	0.424	0.157	0.550
Expansions	0.618	0.663	0.240	0.413	0.534	0.438	0.414	0.646	0.496
France									
Full sample	0.696	0.498	0.612	0.640	0.429	0.224	0.342	0.422	0.483
Recessions	0.903	0.150	0.875	0.712	0.811	0.747	0.038	0.686	0.615
Expansions	0.465	0.519	0.401	0.418	0.343	0.004	0.444	0.442	0.380
Germany									
Full sample	0.698	0.528	0.399	0.568	0.251	0.342	0.540	0.317	0.455
Recessions	0.855	0.101	0.667	0.839	0.031	0.544	0.793	0.251	0.510
Expansions	0.645	0.700	0.326	0.477	0.378	0.273	0.459	0.365	0.453
Italy									
Full sample	0.424	0.520	0.701	0.275	0.385	0.650	0.281	0.703	0.492
Recessions	0.431	0.375	0.705	0.272	0.303	0.581	0.247	0.641	0.444
Expansions	0.356	0.372	0.561	0.182	0.367	0.627	0.393	0.709	0.446
Canada									
Full sample	0.753	0.696	0.484	0.675	0.793	0.601	0.583	0.660	0.656
Recessions	0.097	0.395	0.016	0.541	0.596	0.349	0.622	0.802	0.427
Expansions	0.688	0.572	0.436	0.593	0.746	0.533	0.557	0.638	0.595
Japan									
Full sample	0.663	0.323	0.577	0.363	0.183	0.432	0.535	0.220	0.412
Recessions	0.745	0.477	0.553	0.257	0.705	0.834	0.744	0.148	0.558
Expansions	0.618	0.241	0.593	0.372	0.082	0.286	0.524	0.304	0.378
Spain									
Full sample	0.814	0.801	0.907	0.785	N/A	0.751	0.094	0.428	0.654
Recessions	0.478	0.319	0.768	0.743	N/A	0.579	0.682	0.143	0.530
Expansions	0.726	0.624	0.854	0.752	N/A	0.624	0.062	0.472	0.588
Australia									
Full sample	0.539	0.188	0.430	0.379	0.587	0.647	0.641	0.410	0.478
Recessions	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansions	0.539	0.188	0.430	0.379	0.587	0.647	0.641	0.410	0.478
New Zealand									
Full sample	0.826	0.483	0.316	0.588	0.242	0.341	N/A	N/A	0.466
Recessions	0.678	0.493	0.057	0.772	0.001	0.216	N/A	N/A	0.370
Expansions	0.794	0.424	0.386	0.510	0.194	0.271	N/A	N/A	0.430
Netherlands									
Full sample	0.514	0.041	0.414	0.508	N/A	0.180	0.017	0.562	0.319
Recessions	0.705	0.243	0.125	0.772	N/A	0.239	0.400	0.836	0.474
Expansions	0.155	0.088	0.388	0.153	N/A	0.176	0.000	0.224	0.169
Norway									
Full sample	0.669	0.372	0.446	0.025	N/A	0.103	0.634	0.514	0.395
Recessions	0.567	0.805	0.735	0.070	N/A	0.065	0.401	0.544	0.455
Expansions	0.665	0.329	0.419	0.084	N/A	0.105	0.740	0.556	0.414
Sweden									
Full sample	0.788	0.529	0.646	0.676	N/A	0.532	0.224	0.368	0.538
Recessions	0.739	0.155	0.802	0.739	N/A	0.269	0.774	0.785	0.609
Expansions	0.746	0.456	0.596	0.596	N/A	0.499	0.223	0.480	0.514
Switzerland									
Full sample	0.760	0.183	0.723	0.568	N/A	0.362	N/A	0.166	0.460
Recessions	0.893	0.027	0.660	0.890	N/A	0.802	N/A	0.209	0.580
Expansions	0.691	0.123	0.679	0.494	N/A	0.282	N/A	0.191	0.410
Euro Zone									
Full sample	0.857	0.710	0.887	0.860	0.680	0.568	N/A	N/A	0.760
Recessions	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansions	0.857	0.710	0.887	0.860	0.680	0.568	N/A	N/A	0.760

Table 2. Continued

	Output	Consumption	Investment	Industrial production	Unemployment rate	Inflation	Short-term interest rate	Long-term interest rate	Average
Turkey									
Full sample	0.919	0.897	0.817	0.889	N/A	0.687	0.259	N/A	0.745
Recessions	0.936	0.818	0.905	0.904	N/A	0.000	0.307	N/A	0.645
Expansions	0.926	0.876	0.828	0.857	N/A	0.659	0.203	N/A	0.725
Argentina									
Full sample	0.824	0.921	0.812	0.833	N/A	0.858	0.793	N/A	0.840
Recessions	0.976	0.832	0.881	0.737	N/A	0.503	0.536	N/A	0.744
Expansions	0.903	0.927	0.831	0.852	N/A	0.924	0.824	N/A	0.877
Brazil									
Full sample	0.783	0.808	0.732	0.535	N/A	0.056	0.201	N/A	0.519
Recessions	0.696	0.805	0.555	0.466	N/A	0.128	0.458	N/A	0.518
Expansions	0.806	0.816	0.782	0.555	N/A	0.031	0.136	N/A	0.521
Chile									
Full sample	0.786	0.731	0.392	0.650	N/A	0.405	0.204	N/A	0.528
Recessions	0.143	0.278	0.816	0.852	N/A	0.244	0.842	N/A	0.529
Expansions	0.748	0.714	0.207	0.683	N/A	0.211	0.161	N/A	0.454
Colombia									
Full sample	0.693	0.725	0.454	0.624	N/A	0.544	N/A	N/A	0.608
Recessions	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansions	0.693	0.725	0.454	0.624	N/A	0.544	N/A	N/A	0.608
Mexico									
Full sample	0.832	0.719	0.612	0.739	N/A	0.507	0.132	N/A	0.590
Recessions	0.852	0.652	0.012	0.676	N/A	0.372	0.555	N/A	0.520
Expansions	0.728	0.554	0.385	0.609	N/A	0.560	0.287	N/A	0.521
Peru									
Full sample	0.658	0.840	0.770	N/A	N/A	0.459	N/A	N/A	0.682
Recessions	0.689	0.918	0.933	N/A	N/A	0.676	N/A	N/A	0.804
Expansions	0.711	0.850	0.736	N/A	N/A	0.391	N/A	N/A	0.672
Venezuela									
Full sample	0.898	0.566	0.609	N/A	N/A	0.092	0.785	N/A	0.590
Recessions	0.901	0.443	0.917	N/A	N/A	0.107	0.922	N/A	0.658
Expansions	0.883	0.574	0.696	N/A	N/A	0.076	0.742	N/A	0.594
Taiwan									
Full sample	0.766	0.744	0.694	0.755	0.873	0.508	0.138	0.569	0.631
Recessions	0.864	0.752	0.721	0.959	0.667	0.745	0.910	0.708	N/A
Expansions	0.679	0.687	0.637	0.685	0.823	0.396	0.132	0.320	0.545
Hong Kong									
Full sample	0.807	0.707	0.779	0.716	0.907	0.694	0.705	0.139	0.682
Recessions	0.806	0.688	0.858	0.794	0.335	0.826	0.858	0.009	0.647
Expansions	0.807	0.598	0.677	0.682	0.899	0.521	0.465	0.245	0.612
India									
Full sample	0.435	N/A	0.357	0.183	N/A	0.281	0.117	0.042	0.236
Recessions	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansions	0.435	N/A	0.357	0.183	N/A	0.281	0.117	0.042	0.236
Indonesia									
Full sample	0.927	0.900	0.888	0.803	N/A	0.886	0.803	0.229	0.777
Recessions	0.439	0.289	0.272	0.013	N/A	0.261	0.703	0.648	0.375
Expansions	0.882	0.810	0.852	0.781	N/A	0.789	0.760	0.351	0.746
South Korea									
Full sample	0.894	0.925	0.904	0.537	0.884	0.872	0.727	0.210	0.744
Recessions	0.611	0.560	0.607	0.338	0.723	0.641	0.335	0.310	0.516
Expansions	0.875	0.920	0.880	0.569	0.861	0.840	0.654	0.085	0.711
Malaysia									
Full sample	0.835	0.778	0.727	0.620	N/A	0.363	0.383	0.628	0.619
Recessions	0.826	0.706	0.866	0.142	N/A	0.395	0.613	0.919	0.638
Expansions	0.789	0.778	0.727	0.617	N/A	0.229	0.333	0.535	0.573
Philippines									
Full sample	0.762	0.764	0.536	0.713	N/A	0.109	0.001	N/A	0.481
Recessions	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansions	0.762	0.764	0.536	0.713	N/A	0.109	0.001	N/A	0.481
China									
Full sample	0.377	0.491	0.407	0.777	N/A	0.623	N/A	0.671	0.558
Recessions	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansions	0.377	0.491	0.407	0.777	N/A	0.623	N/A	0.671	0.558

Table 2. Continued

	Output	Consumption	Investment	Industrial production	Unemployment rate	Inflation	Short-term interest rate	Long-term interest rate	Average
Singapore									
Full sample	0.713	0.543	0.559	0.438	N/A	0.375	0.208	0.280	0.445
Recessions	0.716	0.200	0.651	0.158	N/A	0.541	0.230	0.554	0.436
Expansions	0.667	0.545	0.526	0.511	N/A	0.350	0.167	0.254	0.431
Thailand									
Full sample	0.884	0.862	0.763	0.407	N/A	0.446	0.004	0.244	0.516
Recessions	0.888	0.903	0.928	0.426	N/A	0.537	0.603	0.071	0.622
Expansions	0.849	0.766	0.482	0.529	N/A	0.146	0.000	0.092	0.409
Russia									
Full sample	0.902	0.894	0.945	0.944	N/A	0.527	N/A	N/A	0.842
Recessions	0.920	0.894	0.931	0.944	N/A	0.022	N/A	N/A	0.742
Expansions	0.902	0.849	0.976	0.968	N/A	0.807	N/A	N/A	0.900
Bulgaria									
Full sample	0.791	0.701	0.941	0.899	N/A	0.742	N/A	N/A	0.815
Recessions	0.790	0.582	0.924	0.812	N/A	0.607	N/A	N/A	0.743
Expansions	0.575	0.732	0.896	0.885	N/A	0.794	N/A	N/A	0.776
Ukraine									
Full sample	0.951	0.938	0.827	0.893	N/A	0.145	N/A	N/A	0.751
Recessions	0.977	0.962	0.929	0.961	N/A	0.057	N/A	N/A	0.777
Expansions	0.936	0.923	0.811	0.844	N/A	0.262	N/A	N/A	0.755
Czech Republic									
Full sample	0.869	0.880	0.874	0.897	N/A	0.656	N/A	0.479	0.776
Recessions	0.934	0.878	0.865	0.902	N/A	0.823	N/A	0.652	0.842
Expansions	0.808	0.876	0.888	0.912	N/A	0.792	N/A	0.297	0.762
Slovakia									
Full sample	0.892	0.641	0.717	0.769	N/A	0.274	N/A	N/A	0.659
Recessions	0.537	0.520	0.028	0.420	N/A	0.106	N/A	N/A	0.322
Expansions	0.871	0.505	0.707	0.818	N/A	0.309	N/A	N/A	0.642
Estonia									
Full sample	0.906	0.869	N/A	0.840	N/A	0.905	N/A	N/A	0.880
Recessions	0.937	0.952	N/A	0.891	N/A	0.909	N/A	N/A	0.922
Expansions	0.876	0.739	N/A	0.754	N/A	0.936	N/A	N/A	0.826
Latvia									
Full sample	0.868	N/A	0.504	0.862	N/A	0.913	N/A	N/A	0.787
Recessions	0.586	N/A	0.526	0.207	N/A	0.504	N/A	N/A	0.456
Expansions	0.790	N/A	0.467	0.842	N/A	0.909	N/A	N/A	0.752
Hungary									
Full sample	0.780	N/A	0.026	0.742	N/A	0.079	0.849	0.693	0.528
Recessions	0.782	N/A	0.095	0.836	N/A	0.075	0.876	0.902	0.594
Expansions	0.610	N/A	0.004	0.666	N/A	0.010	0.652	0.301	0.374
Lithuania									
Full sample	0.890	0.902	0.848	0.798	N/A	0.748	N/A	N/A	0.837
Recessions	0.235	0.725	0.339	0.590	N/A	0.000	N/A	N/A	N/A
Expansions	0.867	0.823	0.766	0.691	N/A	0.881	N/A	N/A	0.806
Croatia									
Full sample	0.687	0.707	0.808	0.455	N/A	0.390	N/A	N/A	0.609
Recessions	0.791	0.672	0.802	0.394	N/A	0.239	N/A	N/A	0.580
Expansions	0.784	0.918	0.980	0.948	N/A	0.955	N/A	N/A	0.917
Slovenia									
Full sample	0.853	0.032	0.842	0.468	N/A	0.689	N/A	N/A	0.577
Recessions	0.897	0.000	0.776	0.582	N/A	0.803	N/A	N/A	0.612
Expansions	0.858	0.076	0.908	0.265	N/A	0.690	N/A	N/A	0.559
Romania									
Full sample	0.906	0.936	0.904	0.738	N/A	0.134	N/A	N/A	0.724
Recessions	0.906	0.999	0.456	0.947	N/A	0.581	N/A	N/A	0.778
Expansions	0.893	0.925	0.928	0.758	N/A	0.173	N/A	N/A	0.735
Poland									
Full sample	0.735	0.132	0.561	0.804	N/A	0.123	N/A	N/A	0.471
Recessions	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Expansions	0.735	0.132	0.561	0.804	N/A	0.123	N/A	N/A	0.471

Note: Each cell presents the R-square of the regressions of respective variable-specific uncertainty on country-specific uncertainty measures. Recession episodes are from Claessens, Kose, Ozturk, Terrones (2016, forthcoming). The last column presents the average of the R-square in each economy. Numbers in red are the smallest values and numbers in green are the largest values in the row they stand.

Table 3. R-square: Country-specific Uncertainty on Global Uncertainty

	Uncertainty (total)		Idiosyncratic Uncertainty		Common Uncertainty	
	β	R^2	β	R^2	β	R^2
Estonia	1.597***	0.880	1.369***	0.698	1.190***	0.816
Bulgaria	1.396***	0.886	1.247***	0.586	1.012***	0.812
Lithuania	1.351***	0.925	1.136***	0.686	1.024***	0.873
Latvia	1.346***	0.904	1.122***	0.772	1.032***	0.802
Taiwan	1.320***	0.891	1.228***	0.692	1.007***	0.875
Peru	1.296***	0.694	1.075***	0.373	0.943***	0.644
Russia	1.268***	0.836	1.147***	0.481	0.922***	0.678
Philippines	1.255***	0.857	1.216***	0.490	0.913***	0.780
United States	1.212***	0.782	1.249***	0.686	0.808***	0.670
Canada	1.211***	0.677	1.008***	0.488	0.891***	0.703
United Kingdom	1.210***	0.711	1.230***	0.654	0.844***	0.702
New Zealand	1.161***	0.798	1.071***	0.557	0.820***	0.678
Euro Zone	1.144***	0.679	1.329***	0.623	0.863***	0.618
Czech Republic	1.122***	0.906	0.866***	0.706	0.889***	0.817
Mexico	1.108***	0.789	1.132***	0.642	0.801***	0.819
Romania	1.104***	0.803	0.902***	0.483	0.761***	0.687
Turkey	1.081***	0.849	0.800***	0.386	0.947***	0.887
China	1.071***	0.428	1.334***	0.418	0.678***	0.354
Hong Kong	1.047***	0.435	0.844***	0.306	0.814***	0.476
Colombia	1.043***	0.724	0.954***	0.538	0.773***	0.562
Chile	1.023***	0.724	1.152***	0.596	0.730***	0.685
Sweden	1.000***	0.517	0.832***	0.328	0.819***	0.592
Singapore	0.988***	0.708	0.891***	0.494	0.739***	0.721
Brazil	0.970***	0.731	0.947***	0.535	0.747***	0.800
Australia	0.968***	0.566	1.071***	0.534	0.660***	0.592
Switzerland	0.961***	0.808	0.856***	0.506	0.769***	0.780
Japan	0.954***	0.692	0.867***	0.465	0.747***	0.671
Germany	0.946***	0.625	0.765***	0.457	0.723***	0.636
Ukraine	0.911***	0.544	0.863***	0.269	0.649***	0.428
France	0.903***	0.571	0.740***	0.385	0.717***	0.584
Slovakia	0.890***	0.872	0.856***	0.489	0.698***	0.837
Croatia	0.885***	0.711	0.588***	0.274	0.799***	0.651
Spain	0.860***	0.378	0.830***	0.397	0.660***	0.366
Hungary	0.783***	0.819	0.933***	0.571	0.614***	0.833
Slovenia	0.722***	0.537	0.833***	0.441	0.562***	0.452
Italy	0.702***	0.315	0.584***	0.221	0.609***	0.388
Poland	0.632***	0.788	0.899***	0.616	0.391***	0.775
Malaysia	0.605***	0.180	0.553***	0.156	0.477***	0.191
Netherlands	0.541***	0.451	0.648***	0.234	0.406***	0.504
South Korea	0.500***	0.090	0.495***	0.109	0.400***	0.106
India	0.460***	0.432	0.292***	0.053	0.373***	0.504
Norway	0.452***	0.215	0.356***	0.054	0.382***	0.407
Argentina	0.412***	0.076	0.311***	0.048	0.352***	0.092
Thailand	0.350***	0.079	0.327***	0.049	0.300***	0.110
Indonesia	0.208***	0.017	0.276***	0.029	0.163***	0.021
Venezuela	0.039	0.001	0.183***	0.026	-0.022	0.000

Note: Economies are sorted with respect to their estimated coefficients in uncertainty (total). Each result is based on bivariate regressions of country-specific uncertainty on global uncertainty. *** indicates significance at 1 percent level.

Table 4. Correlations of Uncertainty Measures: United States

	Country-specific uncertainty	Common uncertainty	Idiosyncratic uncertainty	Economic policy uncertainty	News-based policy uncertainty	Jurado et al. (2015)	VXO
Country-specific uncertainty	1.00						
Common uncertainty	0.94	1.00					
Idiosyncratic uncertainty	0.80	0.54	1.00	0.00			
Economic policy uncertainty	0.18	0.05	0.36	1.00			
News-based policy uncertainty	0.19	0.07	0.35	0.90	1.00		
Jurado et al. (2015)	0.79	0.75	0.59	0.28	0.27	1.00	
VXO	0.54	0.48	0.49	0.40	0.49	0.60	1.00

Note: News-based policy uncertainty and economic policy uncertainty measureas are from the policy uncertainty website of Baker, Bloom, and Davis (2016).

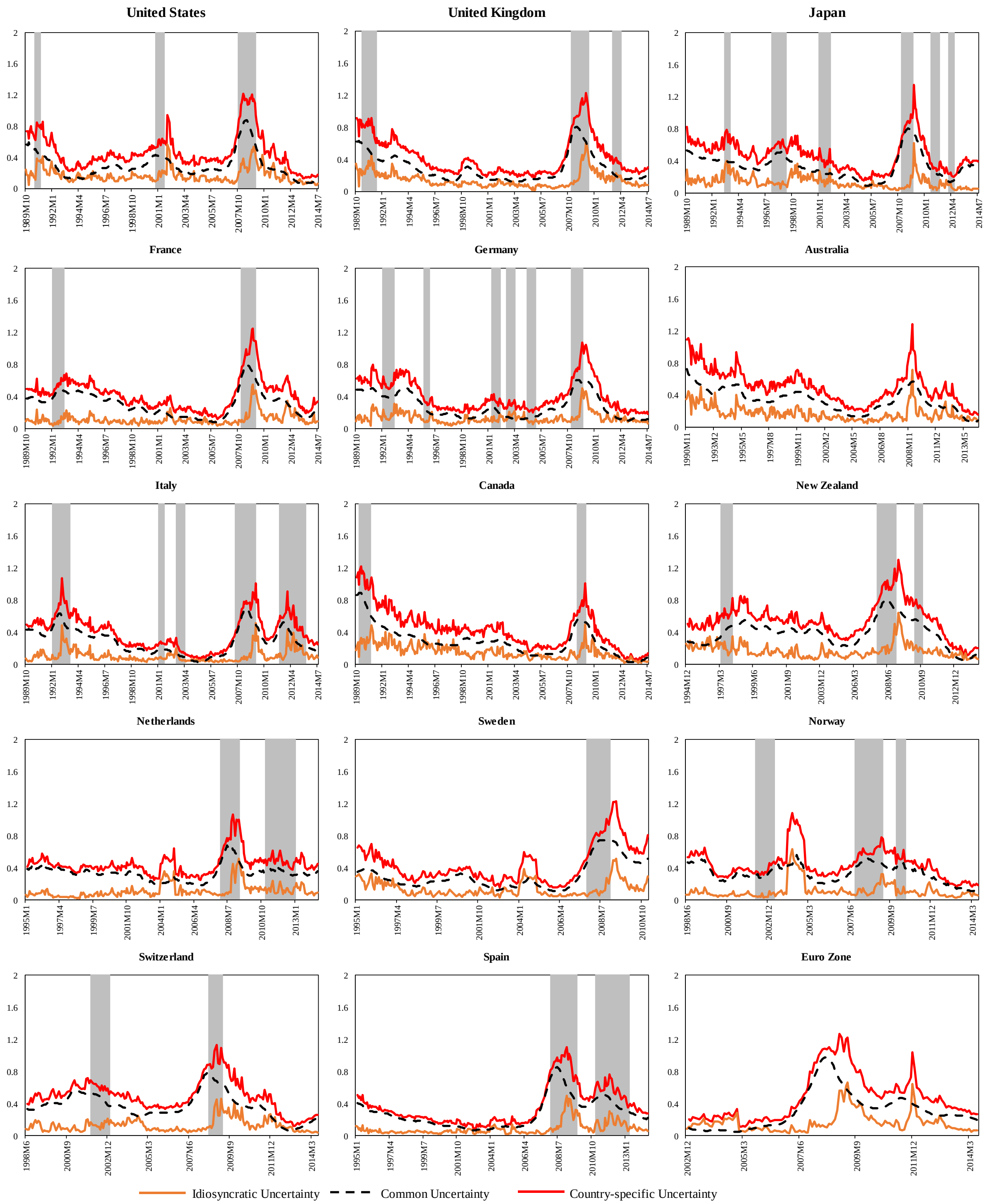

Figure 1. Country-Specific Uncertainty

Note : Country-specific uncertainty is the sum of idiosyncratic and common uncertainty. Gray bars indicate the period of recessions as identified in Claessens, et. al. (2016, forthcoming).

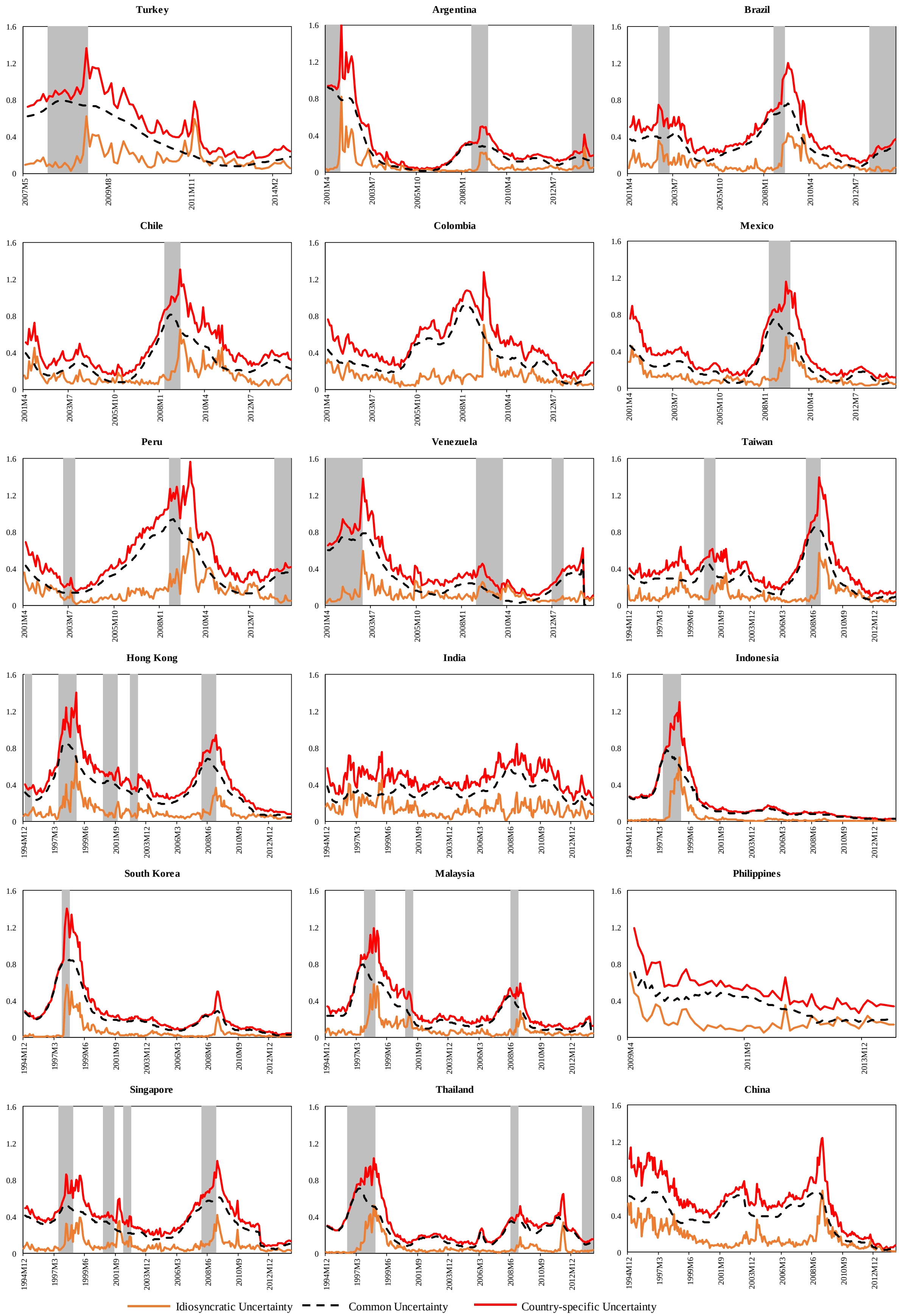

Figure 1. Country-Specific Uncertainty (continued)

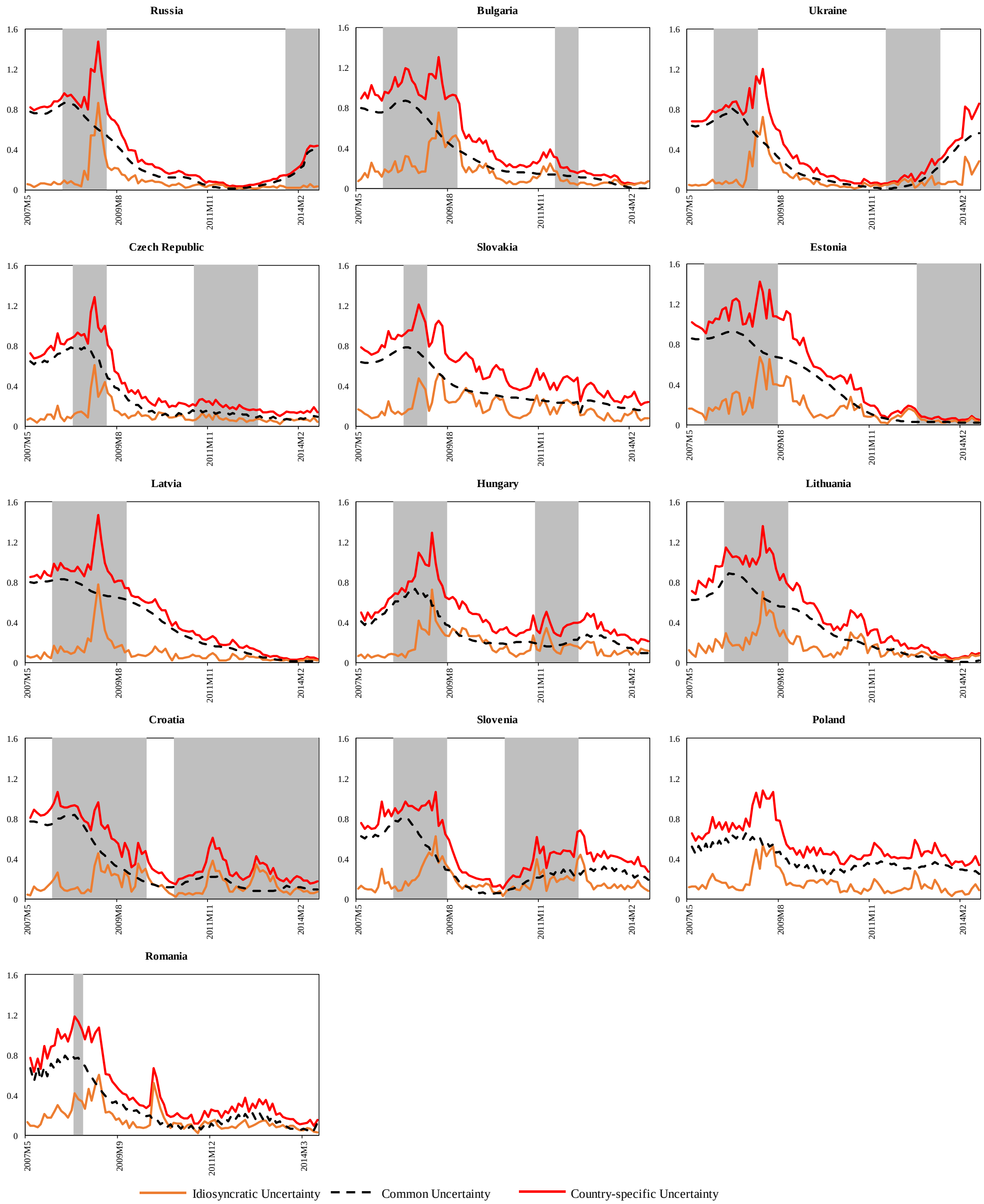

Figure 1. Country-Specific Uncertainty (continued)

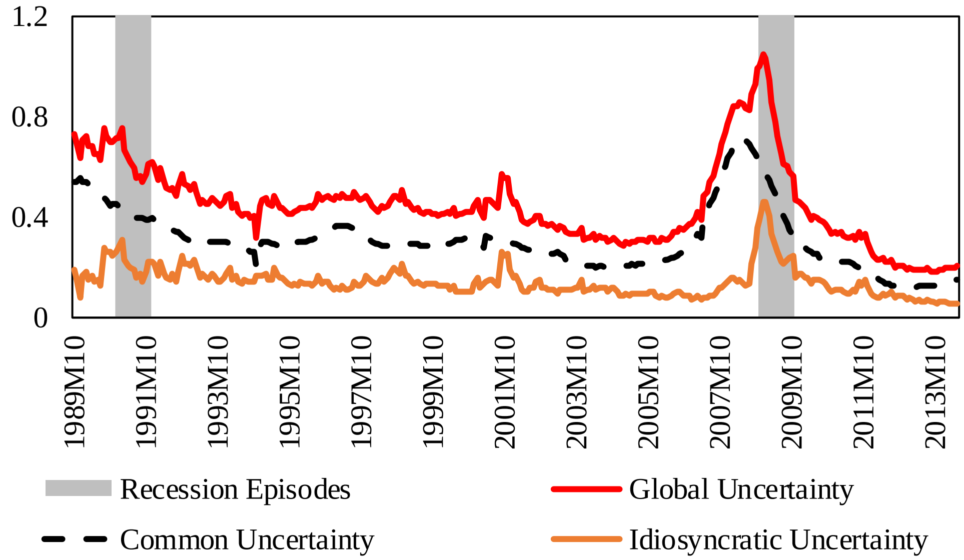

Figure 2. Global Uncertainty

Note: Each line presents the PPP-weighted average of the respective measure for 46 economies. Gray bars present the global recession episodes identified by Kose and Terrones (2015).

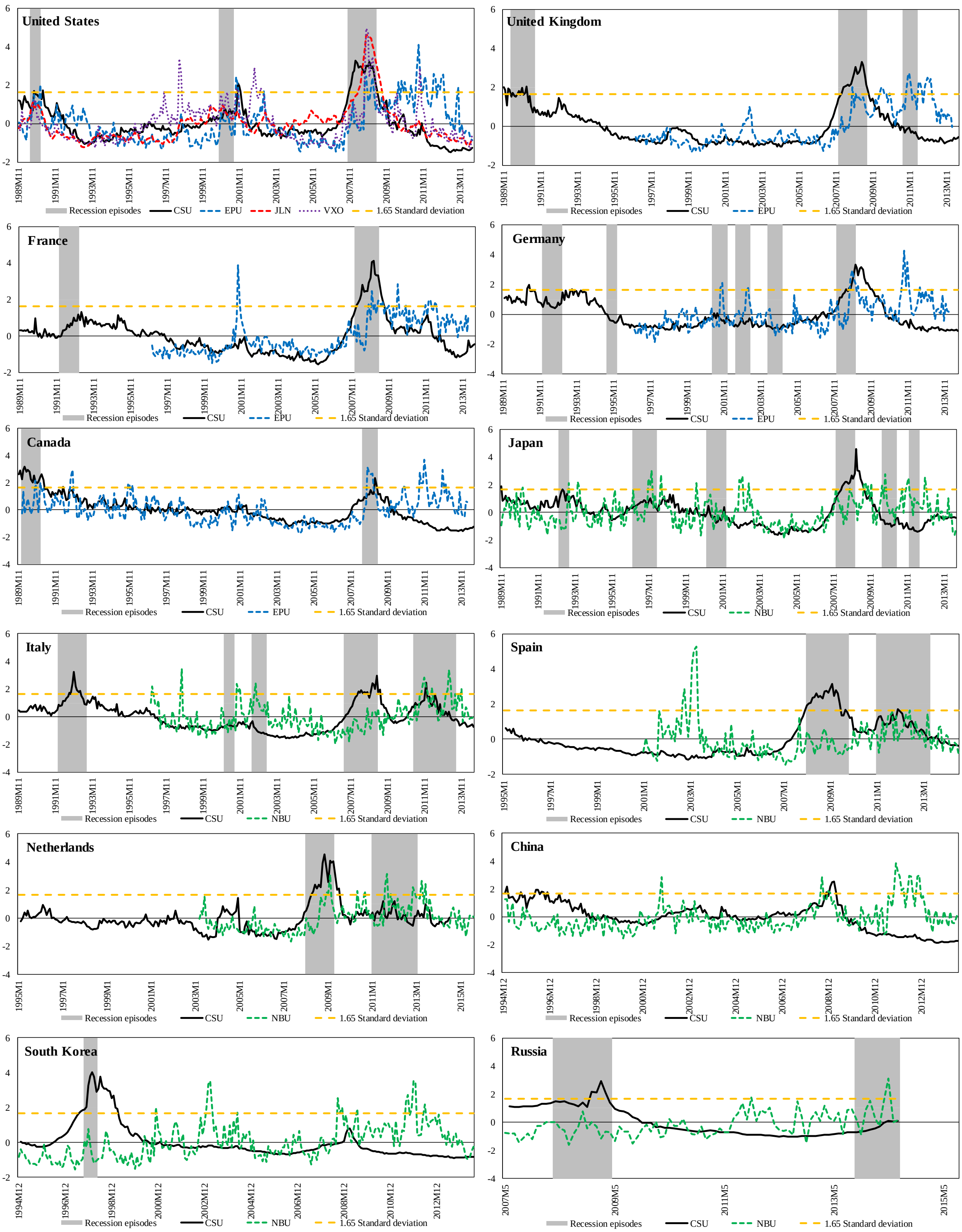

Figure 3. Comparison of Uncertainty Measures

Note: Each uncertainty measure is standardized by subtracting the mean and dividing by the standard deviation. CSU = country-specific uncertainty, JLN=uncertainty measure from Jurado et al (2015), EPU=economic policy uncertainty (Baker et al, 2016), NBU=news-based uncertainty (Baker et al, 2016).

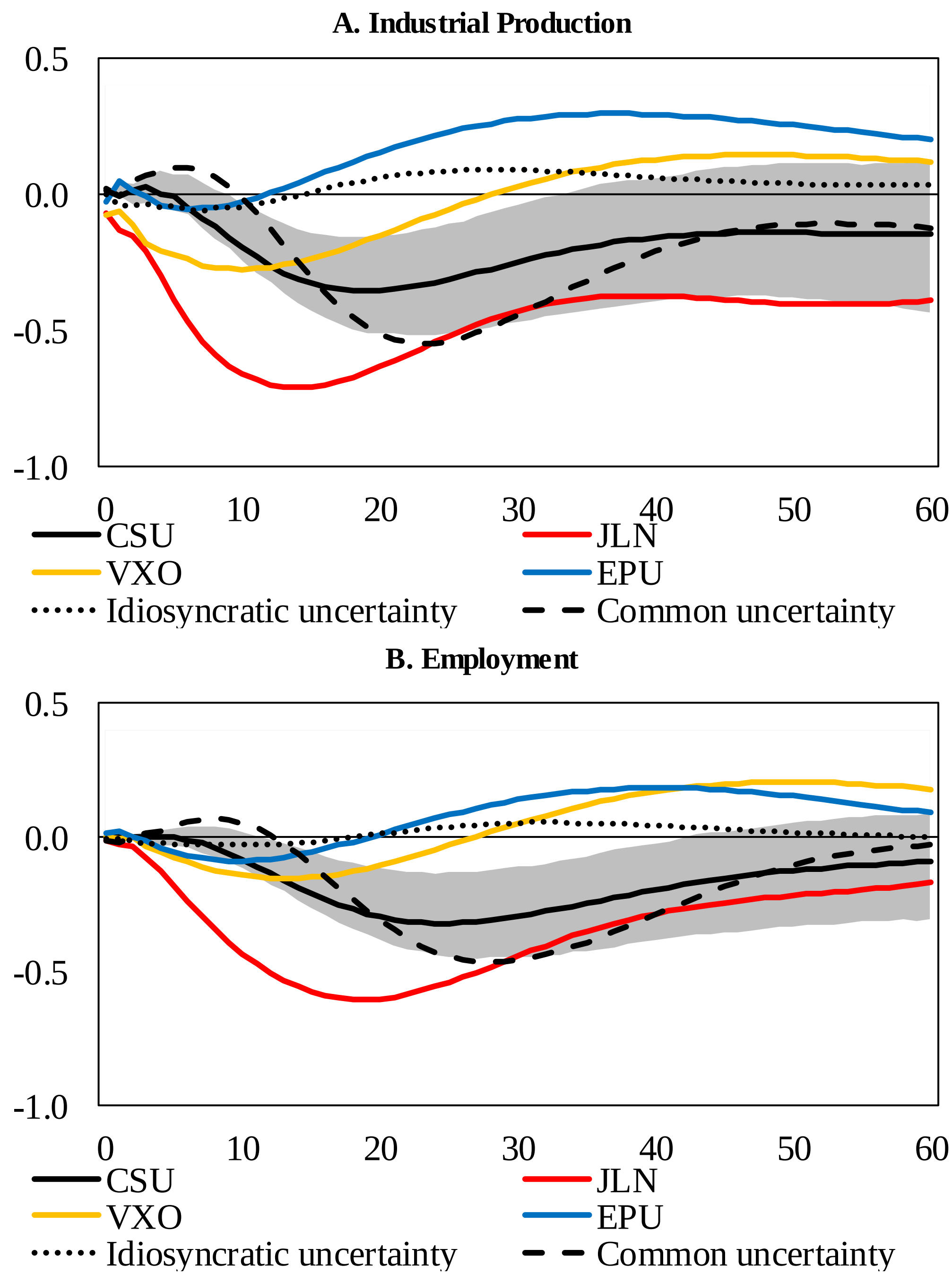

Figure 4. Responses to Uncertainty Shocks

Note : Panel A (Panel B) plots the responses of industrial production (employment) to uncertainty shocks identified recursively in eight-variable VAR system estimated separately for each of the uncertainty measures. CSU=country-specific uncertainty; JLN=uncertainty estimate from Jurado et. al (2015), EPU= economic policy uncertainty estimate from Baker et. al (2016). Dotted (dashed) line is the response to the forecast disagreement shocks, where CSU is replaced with idiosyncratic uncertainty (common uncertainty) component. Shaded regions present 64 percent confidence intervals using Killian (1998) bias-corrected bootstrap.

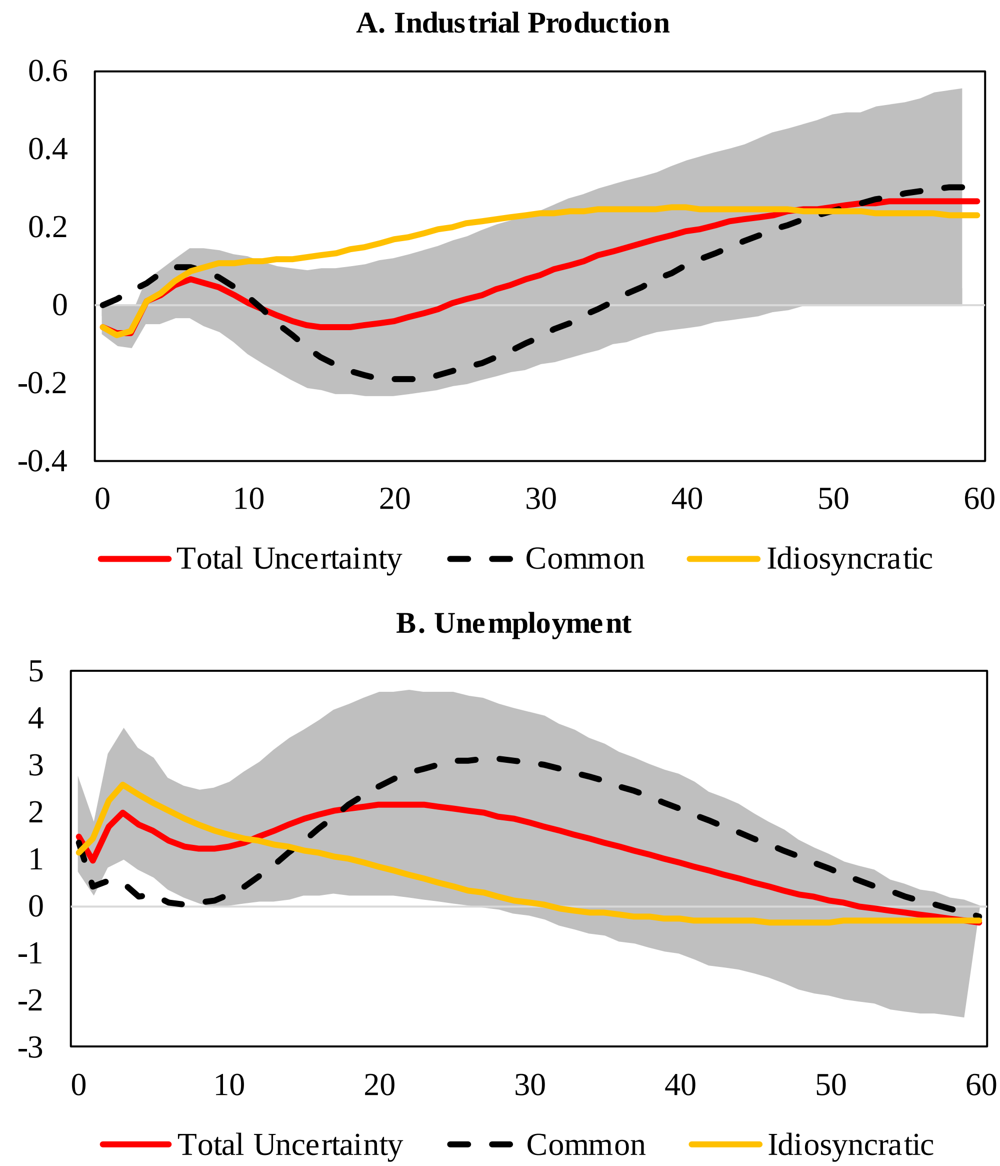

Figure 5. Responses to Global Uncertainty Shocks

Note: Panel A (Panel B) plots the responses of industrial production (unemployment rate) to uncertainty shocks identified recursively in a seven-variable VAR system estimated separately for total uncertainty and its common and idiosyncratic components.

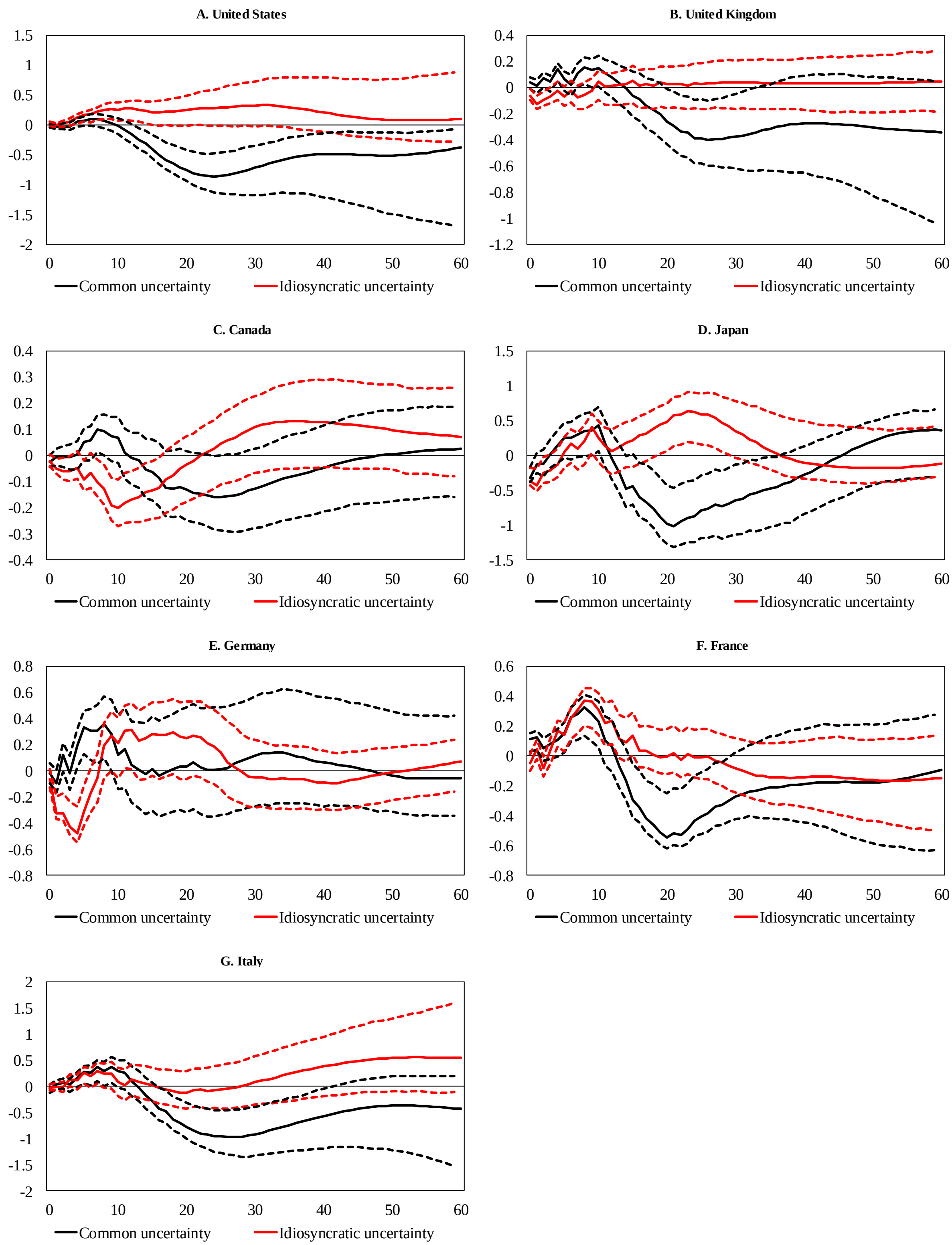

Figure 6. Response of industrial production to common and idiosyncratic uncertainty shocks

Note: Dashed lines present 64 percent confidence intervals using Killian (1998) bias-corrected bootstrap.

Table A.1. Data Coverage of Survey-based Forecast Dataset

	Data Coverage	GDP growth	Consuption growth	Investment growth	Industrial production growth	Inflation rate	Unemployment rate	Short-term interest rate	Long-term interest rate
Advanced Economies									
G7 Countries									
Canada	1989M11-2014M7	✓	✓	✓	✓	✓	✓	✓	✓
France	1989M11-2014M7	✓	✓	✓	✓	✓	✓	✓	✓
Germany	1989M11-2014M7	✓	✓	✓	✓	✓	✓	✓	✓
Italy	1989M11-2014M7	✓	✓	✓	✓	✓	✓	✓	✓
Japan	1989M11-2014M7	✓	✓	✓	✓	✓	✓	✓	✓
United Kingdom	1989M11-2014M7	✓	✓	✓	✓	✓	✓	✓	✓
United States	1989M11-2014M7	✓	✓	✓	✓	✓	✓	✓	✓
Western Europe									
Euro zone	2002M12-2014M7	✓	✓	✓	✓	✓	✓	✗	✗
Netherlands	1995M1-2014M7	✓	✓	✓	✓	✓	✗	✓	✓
Norway	1998M6-2014M7	✓	✓	✓	✓	✓	✗	✓	✓
Spain	1995M1-2014M7	✓	✓	✓	✓	✓	✗	✓	✓
Sweden	1995M1-2014M7	✓	✓	✓	✓	✓	✗	✓	✓
Switzerland	1998M6-2014M7	✓	✓	✓	✓	✓	✗	✓	✓
Asia-Pacific									
Australia	1990M11-2014M7	✓	✓	✓	1991M01	✓	✓	✓	✓
New Zealand	1994M12-2014M7	✓	✓	✓	✓	✓	✓	✓	✓
Emerging Market Economies									
Latin America									
Argentina	2001M4-2014M7	✓	✓	✓	✓	✓	✗	✓	✗
Brazil	2001M4-2014M7	✓	✓	✓	✓	✓	✗	✓	✗
Chile	2001M4-2014M7	✓	✓	✓	✓	✓	✗	✓	✗
Mexico	2001M4-2014M7	✓	✓	✓	✓	✓	✗	✓	✗
Venezuela	2001M4-2014M7	✓	✓	✓	✓	✓	✗	✓	✗
Colombia	2001M4-2014M7	✓	✓	✓	✓	✓	✗	✗	✗
Peru	2001M4-2014M7	✓	✓	✓	✓	✓	✗	✗	✗
Eastern Europe									
Bulgaria	2007M5-2014M7	✓	✓	✓	✓	✓	✗	✗	✗
Croatia	2007M5-2014M7	✓	✓	✓	✓	✓	✗	✗	✗
Czech Republic	2007M5-2014M7	✓	✓	✓	✓	✓	✗	✓	✓
Estonia	2007M5-2014M7	✓	✓	✓	✓	✓	✗	✗	✗
Hungary	2007M5-2014M7	✓	✓	✓	✓	✓	✗	✓	✓
Latvia	2007M5-2014M7	✓	✓	✓	✓	✓	✗	✗	✗
Lithuania	2007M5-2014M7	✓	✓	✓	✓	✓	✗	✗	✗
Poland	2007M5-2014M7	✓	✓	✓	✓	✓	✗	✓	✓
Romania	2007M5-2014M7	✓	✓	✓	✓	✓	✗	✗	✗
Russia	2007M5-2014M7	✓	✓	✓	✓	✓	✗	✗	✓
Slovakia	2007M5-2014M7	✓	✓	✓	✓	✓	✗	✓	✓
Slovenia	2007M5-2014M7	✓	✓	✓	✓	✓	✗	✗	✗
Turkey	2007M5-2014M7	✓	✓	✓	✓	✓	✗	✓	✗
Ukraine	2007M5-2014M7	✓	✓	2008M06	✓	✓	✗	✗	✗
Asia Pacific									
China	1994M12-2014M7	✓	✓	✓	✓	✓	✗	✗	2003M07
Hong Kong	1994M12-2014M7	✓	✓	✓	✓	✓	2003M06	✓	✓
India	1994M12-2014M7	✓	✗	✓	✓	✓	✗	✓	✓
Indonesia	1994M12-2014M7	✓	✓	✓	✓	✓	✗	✓	✓
Malaysia	1994M12-2014M7	✓	✓	✓	✓	✓	✗	✓	✓
Philippines	2009M4-2014M7	✓	✓	✓	✓	✓	✗	✓	✗
Singapore	1994M12-2014M7	✓	✓	✓	✓	✓	✗	✓	✓
South Korea	1994M12-2014M7	✓	✓	✓	✓	✓	✓	✓	✓
Taiwan	1994M12-2014M7	✓	✓	✓	✓	✓	2003M09	✓	2006M03
Thailand	1994M12-2014M7	✓	✓	✓	✓	✓	✗	✓	✓

Source: Consensus Forecasts database of the Consensus Economics, Inc.

Notes: ✓ sign indicates the dataset covers the related variable; ✗ sign indicates that the dataset does not cover the related variable. If a series starts later than the others for a country, the check or cross signs are replaced with the start date of that specific series.

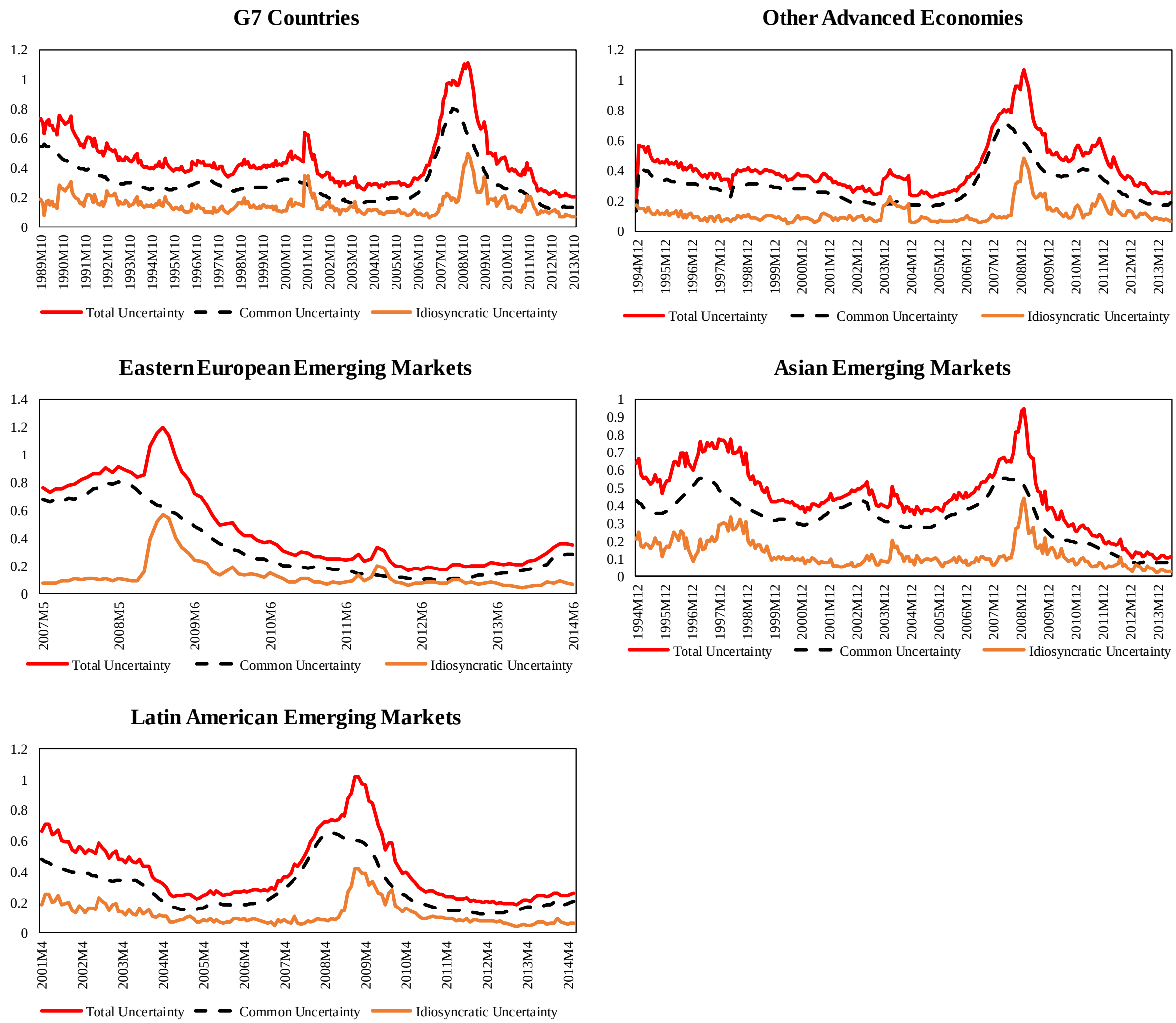

Figure A.1. Functional and Regional Country Groups Uncertainty

***Note*:** Each line presents the PPP-weighted average of the respective measure for the countries in the corresponding group. Other Advanced Economies include Netherlands, Norway, Sweden, Switzerland, Euro Zone, Spain, Australia, and New Zealand. Eastern European Emerging Markets include Turkey, Bulgaria, Russia, Ukraine, Czech Republic, Slovakia, Estonia, Latvia, Hungary, Lithuania, Croatia, Slovenia, Poland, and Romania. Asian Emerging Markets include Taiwan, Hong Kong, India, Indonesia, South Korea, Malaysia, Singapore, Thailand, and China. Latin American Emerging Markets include Argentina, Brazil, Chile, Colombia, Mexico, Peru, and Venezuela.