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International Propagation of Shocks: A Dynamic Factor Model Using Survey Forecasts

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International Propagation of Shocks: A Dynamic Factor Model Using Survey Forecasts[1]

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Abstract

This paper studies the pathways for the propagation of shocks across G7 and major Asia-Pacific countries using multi-horizon forecasts of real GDP growth from 1995 to 2017. We show that if the forecasts are efficient in the long run, results obtained using the forecasts are comparable to those obtained from the actual outturns. We measure global business cycle connectedness and study the impact of country-specific shocks as well as common international shocks using a panel factor structural VAR model. Our results suggest strong convergence of business cycles within the group of industrialized countries and the group of developing economies during non-recessionary periods. In particular, we find increased decoupling between the industrialized and developing economies after the 2008 recession. However, the direction of shock spillovers during recessions and other crisis periods are varied, depending on the nature and origin of the episode.

Keywords: GDP growth, business cycle connectedness, transmission of shocks, common international shocks, panel VAR model, Blue Chip Surveys.

JEL Classification: F41, F42, E32, C33

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1. Introduction

Understanding the propagation of economics shocks between countries is essential for policy makers in today's dynamic economic environment. Emerging market economies, with their impressive growth records and increasing influence on trade and international finance, have never been closer to the center stage of the global economy. However, changes in the global business cycle dynamics, especially since the 2008 crisis are confounding the relationships between different emerging market and industrialized economies, with respect to the origin, transmission, and impact of real and financial shocks. While many industrialized countries are still suffering from a slow recovery, major emerging market economies have taken on a robust and vibrant path of continued growth. In fact, whether the world market is witnessing a period of sustained convergence or accelerated decoupling regionally and globally remains unclear both theoretically and empirically.[2]

Debates surrounding the nature and dynamics of global business cycle and international propagation of real and monetary shocks among industrialized countries are not new. There is a long string of theoretical and empirical literature devoted to these issues.[3] However, relatively few studies have documented the propagation of shocks involving emerging market economies, and such studies often concentrate on "normal" instead of "crisis" periods.

[2] Bergholt and Sveen (2014) discuss how open economy DSGE models do not justify the strong cross-country correlations observed in some empirical studies. Kose *et al.* (2012) provide evidence of differing patterns of synchronization within and between regions and country groups.
[3] See, for example, Kim (2001) and Kose *et al.* (2003) and references therein.

As discussed in the literature, e.g., Agenor *et al.* (2000) and Canova (2005),[4] the observed lack of research in emerging market economies reflects several roadblocks. The first difficulty is caused by the limited availability of reliable data. It is well known that quarterly data on national accounts are only available for a few developing economies. Not to mention that when data are available, their reliability is often called into question, even for some of the leading economic powerhouses in the Asia Pacific region. The second difficulty is caused by the nature of unanticipated events affecting the emerging market economies. The impact of natural, political, and economic shocks on emerging market economies is usually more severe than that of a similar event in an industrialized country. Given the limitations imposed by the availability of official data, it is difficult, if not impossible, for researchers to extract statistical regularities in business cycles that are often driven by these unanticipated events. The third difficulty is caused by frequent regime changes and radical reforms, which often follow unanticipated shocks. These changes in emerging market economies are difficult to identify and model.

Recent literature provides mixed evidence on how global and regional shocks interact, highlighting the heterogeneity across economies with varying level of development and openness. For example, Bordo and Helbling (2011), focusing on industrialized countries for the past 125 years, documented strong co-movement in business cycles and the important role of common shocks. Contrasting this finding, Kose *et al.* (2012), using more recent data from 1960 to 2008, found diminished importance of global shocks and less evidence of synchronization of business cycles across countries. However, Kose *et al.* (2012) found evidence of synchronization within the group of industrialized countries and within the group of emerging market economies. In addition,

[4] Canova (2005) used a set of VAR models and quarterly data from 1990 to 2002 to extract regularities regarding the effect of United States shocks on eight Latin American countries. The author specifically documented that the patterns of transmission from the United States to Latin American countries are different from those between developed economies.

a number of researchers have studied the transmission of monetary shocks among developed countries, especially in light of the 2008 crisis. More recently, a number of studies have examined the effects of real shocks on emerging markets.[5] Didier *et al.* (2016) documented the characteristics and drivers of the slowdown in emerging market economies since the crisis, highlighting the importance of internal synchronization among these economies as well as the role of external shocks. Huidrom *et al.* (2017) looked at the importance of spillovers from emerging market economies, and concluded that they are sizeable, but smaller than that from G7 countries. Another recent attempt focusing on developing economies is Park (2017), where the author looked at whether Asia's regional business cycle has become independent of the global trend.

Despite these recent developments, two important issues remain. The first concerns the identification of common and idiosyncratic shocks. Many of the existing studies rely exclusively on annual or quarterly data. They often maintain the assumption a priori that no idiosyncratic shocks transmit contemporaneously in models with common shocks.[6] The use of higher frequency data therefore allows potentially more accurate identification of common shocks. The second issue concerns the instability of the propagation mechanism during crisis periods. Ideally, analysis of a recessionary episode or an economic crisis should be conducted separately from the analysis of non-crisis periods. Unfortunately, as a crisis normally lasts for no more than two to three years, even with monthly data, the number of observations will be small for reliable inference. This is especially a problem when a large number of parameters need to be estimated, such as in a VAR model.

[5] See, among others, Economidou and Kool (2009), Evans and Marshall (2009), Mumtaz and Surico (2009), Chudik and Fratzscher (2011), Kim and Taylor (2011), Abiad *et al.* (2013), Andrle *et al.* (2013), Comin *et al.* (2014), and Duval *et al.* (2014).

[6] Despite the popularity of this identification scheme, it is not the only possible way to identify common shocks. Alternatives include, among others, Eickmeier (2007).

We address these issues by using monthly forecasts instead of the actual values that are available only on a quarterly or annual basis. More specifically, *ex ante* shocks to real GDP growth are obtained from forecast revisions of monthly fixed-target forecasts made 1- to 24-month ahead. We show that when forecasts are efficient in the long run, in the sense that all available information is eventually used in the forecasts, the estimates of our model parameters based on forecasts are comparable to the estimates based on the actual GDP data. Thus, the use of monthly survey data provides a timing advantage for macroeconomic policy makers in identifying, in real time, shocks that could be befalling the economy, often long before the actual values could be observed. We build on Lahiri (2004) and Isiklar and Lahiri (2009), where similar forecasts were used to determine the degree of vulnerability of the Indian economy to shocks coming from its major trading partners.

The real GDP growth forecasts used in this paper are obtained from Consensus Economics Inc.'s monthly surveys of professional forecasters, including the G-7 and Western Europe Consensus Forecasts and the Asia Pacific Consensus Forecasts. Despite the long history of these surveys (which dates back to 1989), hardly anyone has utilized used this data for studying inter-country transmission of shocks.[7]

Our main objective is to quantify the propagation of both international and country-specific shocks across industrialized countries and Asian emerging market economies at monthly granularity. First, forecast efficiency of real GDP forecasts for 16 countries, including the United State, Europe, China, India, and their main trading partners, are examined in a generalized VAR model. The forecast revisions are then analyzed in a factor structural VAR model (FSVAR), where we estimate the impact of these shocks. In addition to analyzing the entire sample period from

[7] Recent examples of how these data are used in studies of forecast performance and efficiency include Loungani (2001), Isiklar *et al.* (2006), Lahiri and Isiklar (2009), and Patton and Timmermann (2011).

1995 to 2017, we separately analyze each crisis and non-crisis period in our sample. We identify and quantify systematic changes in the propagation mechanism surrounding the 1997 and 2008 crises.

We find that the real GDP growth forecasts are efficient, though not perfectly. Depending on their origin, shocks are fully absorbed by forecasters in 3 to 6 months.[8] Home country news tend to be used more efficiently than foreign news. Since both the transmission of real GDP shocks and forecast inefficiency cause serial correlations in forecast revisions, we can infer that the transmission of shocks is no slower than what we observe here. In addition, we find a high level of co-movement within the group of industrialized countries and within the group of emerging market economies. Shocks that are common to the industrialized countries also have significant effect on the emerging market economies. Moreover, we find the pattern of propagation and the role of common international shocks to be different between normal and crisis periods. Country-specific shocks are more important than foreign or international common shocks during crisis periods. During normal periods, common international shocks account for a large portion of variations in real GDP growths across countries.

The rest of this paper is organized as follows. The factor structural VAR model and the monthly real GDP forecasts are described in Section 2. Section 3 briefly discusses the efficiency of the forecasts and its implications. We analyze the transmission and impact of global and country-specific business cycle shocks in Section 4. Section 5 concludes.

[8] These forecasts were also examined in an earlier study by Isiklar *et al.* (2006), who found evidence that news from foreign sources are not utilized instantly. This finding is consistent with what we find in this paper based on a much-expanded sample.

2. Data and Methodology

2.1. Consensus Forecasts and Country Groups

We use monthly consensus forecasts of real GDP growth from the surveys conducted by Consensus Economics Inc., a leading international economic survey organization. The two specific surveys we use are: (1) *Consensus Forecasts - G7 & Western Europe*, which covers major industrialized countries such as United States, United Kingdom, Germany, France, Italy, and Japan since 1989; and (2) *Asia Pacific Consensus Forecasts*, which covers major emerging market economies, such as India, Indonesia, Malaysia, Singapore, Thailand, Philippines, China, Hong Kong, South Korean, and Taiwan since 1990. For each country, Consensus Economics Inc. collects forecasts from surveys about 10 to 30 forecasters. They are generally different for different countries, but are all professional economists representing organizations such as government agencies, large multinational banks, consulting firms, universities, and research institutions. As an example, in Table 1, we list the forecasters included in the January 2009 surveys for United States, United Kingdom, India, and China.

We have two forecasts for each country in each month, one for the current year, the other for the next year. For all the months within a year, the target year of the forecasts remains fixed and the forecast horizon decreases as time progresses: For current-year forecasts, the forecast horizon decreases from 12 months to 1 month from January to December. For next-year forecasts, the forecast horizon decreases from 24 to 13 from January to December. Therefore, for each target year, we get a series of 24 forecasts by combining the next-year forecasts reported in the *previous year* and the current-year forecasts reported in the current year.

As a selective illustration of the data, we plot the forecasts for the US, China, and India in Figure 1a to 1c. The forecasts display interesting variability across both horizons and target years.

In addition, the dynamics of forecasts for different countries are markedly different. For example, it is clear that 24- ahead forecasts of the United States real GDP growth are tightly clustered around 2 to 3.5 percent, whereas for China and India they are highly dispersed. This possibly reflects the growth volatilities of these countries. Since idiosyncrasies of individual forecasters tend to average out in the consensus, large fluctuations in the consensus forecasts can only reflect information that is common to all forecasters.

By tracking the successive revisions in these fixed-target forecasts, we can see the arrival of new information relevant for a future yearly growth. A forecast revision is the difference between two consecutive forecasts of the same target. Take the current-year forecasts of US real GDP growth for 1995 as an example. The forecast revision in December 1995 is calculated as the current-year forecast made in December 1995 minus that made in November 1995, both having the target year 1995. Figures 2a and 2b show the revisions in the forecasts reported in Figure 1, separately for current year and next year. The series of forecast revisions by definition reflect how a forecaster's information set changes *in real time*. Since the information about the target year's GDP growth becomes more definite as horizon shortens, current-year forecast revisions are generally larger than next-year revisions. On the other hand, as forecast horizon shortens towards one, any particular dose of news will have less time to work through the economy to affect the remaining part of the target value, and hence the revisions will become less variable. Note that negative shocks at some horizon can be negated by a positive shock in a subsequent horizon. A case in point is the U.S. growth for the year 2002. The forecast for 2002 during the last quarter of 2001 was rapidly downgraded due to the ongoing Aug 2001-Nov 2001 recession, but was subsequently revised up during the first quarter of 2002 after sensing the brisk quarterly growth of over 5% in that quarter. Likewise, the forecasters begun to sense the negative yearly growth rate for 2009 beginning with the horizon 16 forecast, followed by six more consecutive negative revisions. Cumulatively these revisions took the 2009 forecast to -3.0% in August of 2009 – a value that remained unchanged until the end of the year. The actual 2009 GDP growth turned out to be -3.1%.

2.2. Measuring Forecast Efficiency: A Generalized VAR Model

For each country i $\in \{1, 2, 3, \ldots,]\}$, let $y_{i,t}$ be the actual value for time period t. In this study, $y_{i,t}$ is the annual real GDP growth rate for country i, year t. Let h denote forecast horizon ($h \in \{1,2,3, \ldots, H\}$), $y^*_{i,t,h}$ is then the h-month ahead forecast of real GDP growth rate for country i, year t. We stack these data as a three-dimensional panel such that the fastest index is over horizon, the slowest index is over individuals, and the target year index is in between. Define forecast revision $^*_{i,t,h}$ as the difference between two consecutive forecasts of the same target, i.e., $^*_{i,t,h} = y^*_{i,t,h} - y^*_{i,t,h+1}$.[9] Since a forecast revision is based on all past and current news or shocks to real GDP growth, it can be written as

$$^*_{i,t,h} = \{3_0 E_{i,t,h} + \{3_1 E_{i,t,h+1} + \{3_2 E_{i,t,h+2} + \{3_3 E_{i,t,h+3} + \cdots, \tag{1}$$

where $E_{i,t,h}$ denotes the news that becomes available between the time when horizon $h+1$ forecast is made and the time when horizon h forecast is made; and $\{3_s$, $s \in \{0,1,2,3, \ldots\}$ represents the usage of news $E_{i,t,s}$. For the purpose of this paper, forecasts are said to be *fully* or *perfectly efficient* if each forecast incorporates all relevant news available at the time the forecast is made. When this is the case, forecast revisions should not contain any news except what becomes available contemporaneously, i.e., $\{3_s = 0 \; \forall \; s \geq 1$.

[9] Note the somewhat unusual notation here: For the forecast revisions, the time dimension is along the forecast horizon as well as the target year. For example, the panel of forecast revisions is of the size $\{] \times (T \times H - 1)\}$, where T is the total number of target years in the sample. $H = 24$ is the maximum forecast horizon. There are] cross-sectional units, i.e., countries, in the panel. For each cross-sectional unit, the time series of forecast revisions is of length $T \times H - 1$, because we lose one revision at h=24 due to first-differencing.

For any open economy, information that is relevant for forecasting a foreign country's real GDP may be of value in forecasting domestic real GDP as well. This mechanism can be represented using a VAR(p) model, where forecast revisions from all the countries are considered together:

$$T^*_{t,h} = c + B_1 T^*_{t,h+1} + B_2 T^*_{t,h+2} + B_3 T^*_{t,h+3} + \cdots + B_p T^*_{t,h+p} + E_{t,h}, \tag{2}$$

where $T^*_{t,h} = ({}^*_{1,t,h}, {}^*_{2,t,h}, {}^*_{3,t,h}, \ldots, {}^*_{J,t,h})'$ is a $(] \times 1)$ vector of forecast revisions of all the countries in the model and B_k, $k = 1,2,3, \ldots p$ is a $(] \times])$ coefficient matrix. Let $E(E_{t,h}, E^l_{t,h}) =$ fl $= \{a_{i,j}\}$, $i, j \in \{1,2,3, \ldots,]\}$. The VMA($\infty$) form of this VAR(p) model explicitly shows how forecast revisions are based on both domestic and international news:

$$T^*_{t,h} = \mu + M_0 E_{t,h} + M_1 E_{t,h+1} + M_2 E_{t,h+2} + M_3 E_{t,h+3} + \cdots, \tag{3}$$

where for normalization, M_0 is assumed to be the identity matrix $/$. Thus, we can interpret (2) as the observable reduced form for the structure (3). Note that even though equations (2) and (3) are written for each t, they can accommodate a general serial correlation pattern in $y_{i,t}$ assuming stationarity.[10]

Rational and efficient forecasters revise their forecasts based on changes in conditional expectations, i.e., $E_{i,t,h} = E(y_{i,t} l'._{t,h}) - E(y_{i,t} l'._{t,h+1})$, where $'._{t,h}$ denotes the information set available to forecasters at horizon h for target year t. The absence of the index i simply means that the information set may contain more than what is specific to country i. Therefore, we can rewrite the model as follows.

$$T^*_{t,h} = \mu + M_0[E(y_t l'._{t,h}) - E(y_t l'._{t,h+1})] \tag{4}$$

[10] Note each forecaster issues two forecasts each month – one for the current year and the second for the next year growth. Any event that affects growth for both the current and the next year will result in a correlation between $y_{i,t}$ and $y_{i,t+1}$, which will be anticipated by a rational forecaster and will result in a corresponding correlation between ${}^*_{i,t,h}$ and ${}^*_{i,t+1,h+12}$, cf. Nordhaus (1987). This correlation is left unrestricted in equation (2).

$$+M_2[E(y_t|\Omega_{t,h+2}) - E(y_t|\Omega_{t,h+3})]$$

$$+M_3[E(y_t|\Omega_{t,h+3}) - E(y_t|\Omega_{t,h+4})]$$

$$+\cdots.$$

Note that when forecasts are efficient, $M_k = 0 \ \forall \ k > 0$ and $\mu = 0$.

If the forecasts are perfectly efficient, forecast revisions should respond to only current news, not past news. Therefore, we can measure the degree of forecast efficiency using impulse response functions: A non-zero response (other than at horizon 0) suggests forecast inefficiency, as it implies that today's news are not fully utilized in today's forecasts in the sense that that it has non-zero effect on future forecasts. The longer it takes the impulse response to decay to zero, the less efficient the forecasts are.

To obtain meaningful interpretations of the model, we need to compute uncorrelated idiosyncratic shocks. The ordering-free generalized VAR model of Koop *et al.* (1996) and Pesaran and Shin (1998) is used for this purpose. We do not use the classical Cholesky decomposition, since it depends on the recursive structure of the model. In the context of this study, no theoretical argument can be made to support a specific ordering of the countries. The $(J \times 1)$ vector of k-period-ahead scaled generalized impulse response function is given by $\Psi_j(k) = \sigma_{jj}^{-1/2} M_k \Sigma e_j$, where e_j is the jth column of an identity matrix. An aggregate measure of the degree of forecast efficiency can be obtained using cumulative intertemporal forecast error decompositions. For country i, the cumulative proportion of the variations in the forecast revisions that can be attributed to news from the last m periods is given by $\theta_{i,m} = [\sum_{h=0}^{m}(e_i' M_h \Sigma M_h' e_i)] / [\sum_{h=0}^{\infty}(e_i' M_h \Sigma M_h' e_i)]$, as shown in Isiklar *et al.* (2006) and Diebold and Yilmaz (2012).

2.3. Factor Structural VAR Analysis

Given the VAR (p) reduced form (2), $E_{t,h}$ is the inefficiency-adjusted "new" information imbedded in the forecast revision $T^*_{t,h}$. To identify and estimate regional and global business cycle shocks, we use the factor structural VAR (FSVAR) model. In addition to equation (2), we impose the following factor structure on the reduced form error $E_{t,h}$:

$$E_{t,h} = A\mathbf{f}_{t,h} + Au_{t,h}, \tag{5}$$

where $\mathbf{f}_{t,h}$ is a (× 1) vector of common shocks, A is a (] ×) matrix of factor loadings, A is a (] ×]) matrix that captures the contemporaneous interaction between countries, and $u_{t,h}$ is a (] × 1) vector of country-specific shocks with $E(u_{t,h}u'_{t,h}) = \mathrm{diag}(a_{\mu 1}, \dots, a_{\mu J}) = D$. We assume no contemporaneous propagation of country-specific shocks within a month, i.e., $A = /$.[11] So the common shocks are the only sources of contemporaneous spillover. Since we use monthly data and consider only real GDP shocks, this assumption is not very restrictive. Combining (3) and (5), we can write

$$\begin{aligned} T^*_{t,h} &= \mu + (A\, f_{t,h} + u_{t,h}) + M_1(A\, f_{t,h+1} + u_{t,h+1}) \\ &\quad + M_2(A\, f_{t,h+2} + u_{t,h+2}) + \cdots, \end{aligned} \tag{6}$$

from which impulse response functions and intertemporal variance decompositions can be computed. As an example, the cumulative proportion of the variance of forecast revisions that can be attributed to the collection of regional and/or global shocks in the past m periods is given by

$$0_i^{\mathbf{f}} = \sum_{h=0}^{m}\sum_{s=1}^{r}(e'_i M_h A\, A' M_h e_s) \Big/ \sum_{h=0}^{oo}\sum_{s=1}^{r}(e'_i M_h fl M_h e_s)\ . \tag{7}$$

[11] For a discussion on alternative identification strategies, see also Stock and Watson (2005).

The FSVAR model formed with equations (3) and (5) has some advantages over alternative methods and models for our purposes. Two other popular alternatives are the global VAR model as in Dees *et al.* (2007) and the factor-augmented VAR model introduced by Bernanke *et al.* (2005). The global VAR model is best suited to study the effects of shocks originated in specific sectors of a specific country, since a VAR model is developed for each country. The factor-augmented VAR models are appropriate for studying the responses of a large set of variables. Another recent approach examining the global business cycle is Aruoba *et al.* (2011). Using a hierarchical multi-country model of the G-7 countries, the authors estimated a latent real activity factor for each country and extracted the common component in a state space framework. Their real activity factor is based on a set of official indicators including real GDP. When a large amount of official data are available both at the aggregate and at the sector level, using these alternatives will add more intuition to our understanding of business cycle synchronization.

When the available official data are not adequate, either due to the limited lengths of some of the series or due to data quality concerns, the FSVAR model using forecasts should be an attractive alternative, since it does not rely on official statistics. This independence from official data also means that, using the FSVAR model with forecast data, policymakers can monitor global economic connectedness in real time. Such timeliness may prove to be particularly beneficial in times of sudden changes in trade policies. The usefulness of our approach is also reflected in its implication on how forecasters may be rationally inattentive, as discussed in Sims (2003). Because most forecasters operate from within their target countries, it is often less costly to monitor and assimilate domestic news than international news. So forecasters may use domestic news more efficiently. In addition, news that has a global scope would be easier to access than news that is only relevant to specific foreign countries. This may cause a rationally inattentive forecaster to use the global news more efficiently. As reported below, we find evidence consistent with these hypotheses. The FSVAR framework corrects for these inefficiencies so that we can study spillovers associated with individual crisis incidents.

2.4. FSVAR Model: Use of actual vs. forecasts

In order to show that the analysis based on fixed-target forecast revisions and forecast errors utilize the same new information, let us write the data generating process for the actual series y_t of a country as a moving average process of order q:

$$y_t = \mu + \mathbf{L}_{k=0}^{q} o_k E_{t,k}, \tag{8}$$

where $E_{t,k}$ is the shock to y_t that hits at time period $t - k$. The optimal forecast at horizon h is the conditional expectation of y_t given the information set $'._{t-h}$ available at time $t - h$:

$$y^{*}_{t,h} \equiv E(y_t|'._{t-h}) = \mu + \mathbf{L}_{k=h}^{q} o_k E_{t,k}, \tag{9}$$

with $Var[E(y_t|'._{t-h})] = a^2 \sum_{k=h}^{q} o_k^2$. Similarly, the variance of the forecast when the forecast horizon is $h - 1$ is $Var[E(y_t|'._{t-h-1})] = a^2 \sum_{k=h-1}^{q} o_k^2$, giving $Var(y^{*}_{t,h-1}) = Var(y^{*}_{t,h}) + o^2_{h-1} a^2$. Thus, the mean squared errors (MSE) of the forecast revisions $^{*}_{t,h} = y^{*}_{t,h} - y^{*}_{t,h+1}$ is $MSR_h \equiv o^2_h a^2$, which is the variance of scaled $E_{t,h}$. We can compute the change in the prediction errors and the corresponding MSEs between two consecutive forecasts as $\Delta MSE_h = MSE(y^{*}_{t,h+1}) - MSE(y^{*}_{t,h})$, which is simply $o^2_h a^2$. This is the new information in the process of y_t between time periods $t - h - 1$ and $t - h$. Note that even though ΔMSE_h is computed using both the actual values and the forecasts (or the forecast errors) while MSR_h is computed using only the forecasts (or forecast revisions), the two measures are numerically identical if the forecasts are unbiased and efficient. In other words, the information contents of the two are the same.

Therefore, with perfectly unbiased and efficient forecasts, the common international shock $f_{t,h}$ relevant to year t that occurred in time period $\mathrm{t} - h$ can then be identified using a simple static factor analysis, where $^{*}_{t,h} = \}.\mathbf{f}_{t,h} + u_{t,h}$. However, as we report in the next section, the forecasts are not perfectly efficient. As a result, we have to model $T^{*}_{t,h}$ as in equations (2) to filter out the inefficiencies. Intuitively, since the forecasts are not fully efficient, it takes more than one period for a forecaster to fully utilize the information contained in any particular shock $E_{i,t,h}$. As a result, we need multiple forecast revisions to estimate each $E_{i,t,h}$. Given the limited number of horizons for which we have data on forecast revisions, the natural assumption to make is that the factor loadings are the same at all horizons. Under this assumption, we can pool the forecast revisions from multiple horizons over the available target years and estimate the panel FSVAR model specified by equations (2) and (5).

To be more precise, let long-run efficiency mean that there exists a p such that $M_i = 0 \; \forall i > \mathrm{p}$, i.e., all relevant information is used within p periods. Given a sufficiently long forecast horizon $h \geq \mathrm{p}$, the news $E_{t,h}$ will be fully utilized at horizon $h - \mathrm{p} \geq 0$. The total degree of utilization of news $E_{t,h}$ in the last forecast that includes the entire series of revision $\sum_{T=0}^{p} T^{*}_{t,h-T}$ is given by $\Gamma \equiv \sum_{i=0}^{p} M_i$, which is the cumulative impulse response function in the FSVAR model. This cumulative impulse response function Γ can also be interpreted as an aggregate measure of *inefficiency-adjusted* utilization of news. Therefore, under the assumption of long-run efficiency, with fixed-target forecasts available for a sufficiently long horizon, the cumulative impulse responses will be the same as that of actual real GDP growth shocks "averaged" over horizons.[12] If official data on $y_{i,t}$ were to be used, $\}._i$ can be estimated directly. When data on $y_{i,t}$ are unavailable, the alternative

[12] Note also that the effect of a shock tend to be hump-shaped over the horizons, see Isiklar and Lahiri (2007) and Lahiri (2012). The cumulative impulse responses should be robust to these horizon-specific heterogeneities.

is to estimate equation (5), where, we pool all the horizon data to obtain enough number of observations.

The steady-state variance decompositions constructed based on the above impulse responses represent the proportion of shocks accounted for by common international factors and country-specific shocks. The total utilization of international news $f_{t,h}$ is $\sum_{i=0}^{p} M_i A$. So the amount of variation accounted for by the jth common factor in country i's real GDP growth variations is

$$_{ij} = (e_j' A e_j)^2 \; \sum_{s=1}^{k} (e_i' A e_s)^2 + \sum_{s=1}^{J} (e_i' M e_j)^2 \;{}^{-1}, \tag{10}$$

where $A = \sum_{i=0}^{p} M_i A$, and $M = \sum_{i=0}^{p} M_i D$ denote the inefficiency-adjusted total utilization of news in common factors and country-specific shocks respectively, cf. Lahiri and Isiklar (2009). Note that $(e_j' A e_j)^2$ is the contribution of the jth common factor shocks, and $(e_i' M e_j)^2$ is the contribution of the sth country-specific shocks to the variation in total news utilization in the ith country's real GDP growth forecasts. Assuming long-run efficiency in $p \leq j$ periods, the share of total news utilization based on forecast revisions should be the same as the average variance decompositions that are based on actual real GDP growths.

Note that the shocks we observe from forecast revisions are purely expectational. They are not based on forecast errors. When forecasters correctly anticipate a change in the economy, they will revise their forecasts before the change actually takes place. As a result, we will observe a shock from forecast revisions that can predate the time of the incident. On the other hand, some anticipations may not materialize – they may be negated by active counter-cyclical policies or neutralized by subsequent revisions. In addition, forecasters may be inattentive, and inefficient in the short run. In the extreme case where a particular change in the economy goes completely unnoticed by forecasters, its effect would not be captured by forecast data. Thus, unlike in standard panel VAR models that use outturn data, we cannot always study the dynamic effects of an unanticipated structural shock originating from a specific episode. This can be a problem in identifying spillovers from a specific shock. On the other hand, the timing of shocks in the standard panel VAR models may be sensitive on the data vintages, model mis-specifications, and recurring structural breaks. One useful feature of the Blue Chip professional forecasts is that the forecast inefficiencies are small, and significant downgrading for forecasts were typically concurrent with recessions. In addition, as we showed, short-run inefficiencies do not affect any of our steady-state estimates. In particular, the usefulness of the model in monitoring business cycle spillovers and directional connectedness is not affected.

2.5. Empirical Strategies

To avoid the curse of dimensionality, we limit the number of countries in the model. Our selection is primarily based on a country's importance in international trade, as bilateral trade connections are closely related to business cycle co-movements (Baxter and Kouparitsas (2005)). We also consider a country's geographic location, data availability, and level of development and impact in the region. Sixteen countries are included in our analysis. Following *Consensus Economics Inc.*, countries in Europe, Northeast Asia, and Southeast Asia are aggregated into three groups before entering the model. China, India, Japan, and the United States enter the model directly. The real GDP growth rate of a country group is the weighted average of that of its member countries. A country's weight is its contribution to the group's total GDP. Namely, the real GDP growth $y_{g,t}$ of a group of countries $g = 1,2, \dots, G$ is given by

$$y_{g,t} = \frac{\sum_{i=1}^{G} Y_{i,t} y_{i,t}}{\sum_{i=1}^{G} Y_{i,t}}, \tag{11}$$

where $Y_{i,t}$ is country i's GDP valued at chained purchasing power parities (PPPs, millions of 2005 US dollars). The weights are recalculated for each year from 1995 to 2017 based on data from the Penn World Table[13]. The country groups and the weights of individual group members are reported in Table 2.

Another issue is that, unlike all the other countries, forecasts for India are made for each fiscal year instead of calendar year. A fiscal year in India starts from April and ends in March. Table 3 contrasts the target year and horizon between calendar-year forecasts and fiscal-year forecasts. For most months of a year, the horizons of calendar-year and fiscal-year forecasts are only 3 months apart. For example, the current-calendar-year forecast made in April 2008 has a horizon of 9 months; the current-fiscal-year forecast reported in April 2008 has a horizon of 12 months – 3 months longer. However, for the forecasts made in January to March, the horizons are 9 months apart between calendar-year forecasts and fiscal-year forecasts. For example, the current-calendar-year forecast made in February 2008 has a horizon of 11 months, while the current-fiscal-year forecast has a horizon of 3 months. We discard forecasts with horizons that are too far apart, i.e., forecasts in bold in Table 3. This results in losing 3 out of 24 observations per target year.

Using monthly data on forecast revisions, we estimate a seven-country[14] generalized VAR model. The lag length of one month is selected based on Akaike and Schwarz's Bayesian information criteria.[15] The same data are used to estimate the FSVAR model in a manner similar

[13] Data obtained through Federal Reserve Economic Data (FRED) by the Federal Reserve Bank of St. Louis. Data for 2015 to 2017 are not available and are assumed the same as 2014. Since the weights are rather stable over time (as reported Table 2), this is not too unreasonable an assumption.
[14] For simplicity of exposition, country groups will also be referred to as countries when it does not result in confusion.
[15] We checked the robustness of our results by using lag order two and three. The results are very similar over the full sample. As reported below, we also estimate our models over different subsamples. Some of our subsamples are not long enough to allow the use of higher lag orders.

to Clark and Shin (2000). We estimate two factors for the FSVAR model.[16] The effect of the second factor on the United States is constrained to be zero for identification. After the VAR part of the model is estimated in the usual way, parameters of the factor model part are estimated by maximum likelihood. Confidence intervals for the impulse responses and variance decompositions are computed using residual-based nonparametric bootstrap method with 1000 replications.

3. Efficiency of Real GDP Forecasts

As discussed above, we can use the generalized impulse responses from the VAR model in equation (2) to measure forecast efficiency, i.e., how quickly forecasters assimilate relevant news from specific origins. Both the transmission of shocks (spillovers) and the inefficiency of the forecasts cause a delay in observing the effect of news from one country on another country's growth forecast. As a result, the impulse responses we observe here show the combined effect of spillovers and inefficiency. While we cannot separate the two effects, we know that either effect is no larger than the total as they do not offset each other. That is, the impulse responses show the upper limit to the speed of spillover and degree of inefficiency. With this point in mind, we use only the term inefficiency in subsequent discussions for simplicity.

Figure 3 shows the impulse responses of the United States, Europe, China, and India. Dashed lines show the point estimates +/- 2 standard errors. The forecasts are at least moderately efficient – it takes no more than about six months for all relevant news to be fully utilized.[17] Figure 3 also shows that domestic news is used more quickly than foreign news, except perhaps Europe, where the difference is small.

[16] The hypothesis of one common factor is strongly rejected by LR test. But the hypothesis of two or three common factors are not rejected. We also conducted all our empirical exercises using FSVAR model with three factors. Results are qualitatively similar.
[17] As a comparison, using a VAR model, Mankiw *et al.* (2003) find that it takes about 10 months for the professional forecasters responding to the Livingston survey to fully update their information set when making inflation forecasts.

As an aggregate measure, the cumulative intertemporal variance decompositions show us how quickly forecasters assimilate all relevant news. These statistics are reported in Table 4. The forecasts for China, India, and the United States are more efficient than the rest – contemporaneously, 75% to 80% of the news is utilized.[18] By the end of the first quarter, except the forecasts for Europe, all other forecasts absorb more than 85% of the news. For all seven countries and country-groups, more than 95% of all relevant news is used by the end of the sixth month, and more than 99% of news is used by the end of the eighth month.

Using estimates from the FSVAR model specified in equations (3) and (5), Figure 4 shows the impulse responses of the forecasts for United States (top left), Europe (top right), China (bottom left), and Indian (bottom right) to the common international news. These common shocks are absorbed almost as quickly as domestic news, generally within 6 months. We can also see that the common international news generally has smaller impact than domestic news, but larger than news originating from individual foreign countries.

The percentage of common international news utilized over the horizons is reported in Table 5. It takes the forecasters no more than five months to use 95% the international news. By the end of month seven, 99% of common international news is utilized. Contemporaneously, forecasts of the United States and Northeast Asia use about 25% to 30% of common international news – about 10% more than the rest. But at the end of the first quarter, there is practically no difference across countries.

Overall, we see that while the forecasts are not perfectly efficient, the degree of inefficiency is low. A period of six months is sufficient for most of the relevant information to be used. Given that the longest forecast horizon in the data is 24 months, we consider the forecasts efficient in the long

[18] Admittedly, the relative inefficiency of Europe, Southeast Asia, and Northeast Asia could be an artifact of the aggregation of the constituent countries.

run. Since what we use are forecast revisions, our conclusions are immune to potential biases or revisions in official statistics. Also, using forecast revisions means there is no need for real time data, as the revisions themselves do not subject to further revisions. In addition, the results here highlight the importance of using monthly data: The instantaneous differences between countries largely disappear before the end of the first quarter. So these differences would not be observable if we were to use quarterly data instead.

4. International Propagation of Shocks

4.1. Time Varying Correlation Analysis

We start with a quick examination of the correlations between forecast revisions. These correlations are natural measures of pair-wise business cycle co-movements. Table 6 reports the correlations calculated over the entire sample. We first observe that the forecast revisions of the industrialized countries, i.e., the United States, Europe, and Japan, are strongly correlated. At the same time, these countries heavily influence Northeast Asia. In addition, the Asian countries, including Japan and China, are highly correlated with each other. But the correlation between the United States and China, the United States and India, as well as Europe and India are notably weaker.

To uncover possible changes in these relationships over time, we calculate the correlations using a rolling window of 36 forecast revisions.[19] The rolling correlations between each of the other countries and the United States (first two plots) and India (next two plots) are shown in Figure 5. The correlations vary dramatically over time. The forecast revisions of the United States correlate more closely (as high as 0.75) with the rest of the countries during the 2001 to 2004

[19] These 36 forecast revisions cover a period of 21 calendar months (36/2+6/2). In each month, two forecasts are available (i.e., current-year forecast and next-year forecast), and six forecasts in a year are discarded due to the mismatch between calendar-year and Indian fiscal-year forecasts.

period and the 2007 to 2009 period. On the other hand, Indian forecast revisions before 2007 have much lower correlations (rarely higher than 0.5) with almost all the other countries, except during the period around the 1997 Asian crisis. But after 2007, correlations between India and other countries increased quickly before starting to slowly decline. Along the time dimension, the United States experienced convergence during the crisis periods around 2001 and 2008 but decoupling during the expansion periods in between. Such swings are much less evident for India, which seems to have been decoupled with the rest of the countries during most of the 2000s.

4.2. FSVAR Model: Full Sample Analysis

There are two common factors in the FSVAR model. Recall that the loadings of the first factor are unrestricted, and the United States is constrained not to load on the second factor. It should also be noted that a significant proportion (around 70%) of variations in forecast revisions of the United States, Japan, and India cannot be explained by the common factors.[20] This observation suggests that country-specific shocks also play an important role for these countries. The substantive positive correlations in forecast revisions reported in Table 6 were no longer statistically significant at the 5% level in the FSVAR residuals $u_{t,h}$, implying that the two common factors successfully extracted the positive cross-country correlations in forecast revisions.

The steady state variance decompositions from the FSVAR model are reported in Table 7. These estimates are calculated using 25-month ahead forecast error variance shares. The biggest two contributions to a country are reported in bold. The first common factor makes major contributions to all the countries except China, for which the two most important sources of variations come from the United States and itself. The second common factor most prominently

[20] Note that our sample starts from1995. The role of common factors can be more formidable had we included periods with severe oil shocks from the pre-globalization period.

influences Southeast Asia, which holds by definition. Shocks originated from the United States have significant impact on Europe (42%) and China (12%). Southeast Asia is strongly affected by both the common factors, which account for 73% of the total variances. Shocks originated from Europe and Southeast Asia seem to have very little effect on the rest of the countries (less than 1%).

4.3. Subsample Analysis: FSVAR Model

Results from the full sample analysis suggest strong co-movement within the industrialized countries, as well as strong co-movement within the group of developing economies. However, these observations could simply be a result of pooling observations from both non-crisis periods and crisis periods. While certain simple methods, e.g., adding recession dummy variables to the model, can be used to mitigate model instability, they are unlikely to fully capture the conceivably complex effect of structural changes. Our sample period includes the 1997 crisis in Asia and the severe and far-reaching 2008 crisis. To obtain more reliable results on international propagation of shocks, we decided to analyze these crisis periods and the remaining non-crisis periods separately.

The results of sub-sample analysis for four subsamples are presented in Table 8. The first subsample, February 1995 - December 1998, covers the time immediately before and during the 1997 Asia financial crisis. The second subsample, January 1999 - November 2006, covers the period after the crisis until one year before the 2008 crisis. During this period, several countries experienced short episodes of recessions/slowdowns.[21] The third subsample, December 2006 to July 2010, covers the 2008 crisis. Finally, the last subsample covers the post-crisis period up to

[21] According to OECD chronology, several European countries and some countries in Asia experienced slowdowns around the time of the 2001 recession in the US, among which the latest trough happened in Feb 2005. As a robustness check, we removed the months beyond this point from this subsample and re-estimated the model. Our conclusions about this subsample stay the same.

March 2017.[22] We report the steady state variance decompositions from the FSVAR model, which are calculated in the same way as the ones reported for the full sample. Same as in the previous table, we report the biggest two contributions in bold.

During the first subsample period that covers the Asian financial crisis, the second common factor accounts for 86% of the variance of Southeast Asia. It also greatly influences Northeast Asia (44%), China (32%), India (23%), and Japan (13%). For all these countries, the second common factor is one of the two largest sources of variations. However, during this period, the United States and Europe are largely unaffected by the second common factor, which accounts for less than 2% of their variances. Meanwhile, the first common factor, which mostly represents shocks common to the industrialized countries, has little impact on any other country except Europe (20%).

The second subsample period shows a distinctly different picture. During this relatively stable period of growth, the idiosyncratic country-specific shocks play a much more prominent role. For all but Europe and Southeast Asia, domestic shocks are one of the two most important sources of variation. Also during this period, the effect of the first common factor greatly exceeds that of the second factor in all the countries except Southeast Asia. Unlike in the previous subsample period, the first common factor now is one of the two most important sources of variations for all the countries. For Southeast Asia, the two common factors together account for 72% of the variation.

The third subsample period is around the 2008 crisis, during which the shocks from the United States accounted for much of the variations in all the countries, including the United States itself (50%). During this period, the first common factor is also important. It accounts for about 20% to 30% of the variance of all the countries except China and India. The second common factor

[22] As discussed before, stacking the current-year forecasts and the next-year forecasts, we have more than 12 observations for each target year. After excluding the observations lost due to fiscal year adjustment and differencing, we have 442 observations in the full sample, and 79, 151, 76, and 136 observations in each of the four subsamples respectively.

generally accounts for 10% or less of the variations. It is clear from these observations that during the 2008 recession period, the world economy was largely driven by the shocks originated from the United States and the shocks common to industrialized countries.

The fourth subsample period features the recovery after the 2008 crisis, during which the shocks originated from the United States and the shocks common to industrialized countries continue to have a large effect on the rest of the world. But unlike the situation during the crisis period, domestic shocks are at least as important as foreign and common shocks.

To further explore the changing nature of the patterns of international transmission of shocks, we recursively estimate the FSVAR model using a 10-year rolling window. The factor loadings from these estimations are reported in Figure 6. The top two plots show the factor loadings for the first common factor and the bottom two plots show the factor loadings for the second common factor. This figure suggests at least two break points in the factor loadings of the first factor and at least one breakpoint in the factor loadings of the second factor. While we cannot precisely identify the time of the breaks due the relatively large size of the rolling window, we note that the breaks roughly coincide with the peak (December 2007) and trough (June 2009) of the 2007-09 U.S. recession.

4.4. Measuring business cycle connectedness

In a series of articles, Diebold and Yilmaz (2009, 2012, 2015a, 2015b) proposed a few measures of global business cycle connectedness in volatility spillovers between asset groups, markets and portfolios across countries. Based on a generalized VAR framework, these measures are in effect sums of the variance decompositions. One measure very similar to our approach is the "total connectedness," which is essentially the sum of variance shares of foreign and common shocks, cf. Lahiri (2004) and Isiklar et al. (2006). In addition, each country's column sum (again, excluding domestic shocks) measures its directional connectedness from foreign countries. A high value means that a country is highly exposed to foreign shocks. Using the variance decompositions in Table 7 and 8, we can easily calculate these measures, which are not affected by the ordering of countries, given the setup of our FSVAR model.

The total connectedness over the entire sample period is 52.3%, meaning that about half of the variations in real GDP growth rates of the economies in our sample can be attributed to foreign shocks. During the 1997 crisis period, the total connectedness remained at 53.3%. Before the 2008 crisis, the measure increased slightly to 58.5%. But during the crisis periods, it temporarily increased to 76.7%, consistent with the world-wide impact of the crisis. During the recovery period after 2010, the total connectedness fell again to 49.6%. In terms of directional connectedness from other countries, the level for the United States is consistently low. These results are similar to those reported in Diebold and Yilmaz (2012), where they found significant cross-market volatility spillovers only during the global financial crisis of 2007 over their sample period 1999-2010. In our case, we find Europe and Asian economies to have relatively high levels of connectedness. In particular, the level of connectedness of Asian economies has steadily increased over the years.

While the measure of "connectedness" summarizes the variance decompositions in volatility, there are additional nuances to be noted from our subsample analysis highlighting time-varying spillovers. During the two non-crisis periods in our sample (viz., 1999-2006 and 2010-2017), the two common factors dominated the international transmission. But during times of crisis (viz., Asian crisis and 2007-2009 recession), depending on the source of the crisis, the patterns of transmission differed. The 1997 crisis featured the effect of the second (Asian) common factor, but the 2007-2009 crisis is characterized by the first common factor and the shocks from the United States. During non-crisis periods, domestic shocks assumed comparatively more dominant role.

Interestingly, the "directional connectedness" from the standpoint of an individual country can be interpreted as a measure of how much a country is "vulnerable" to non-domestic shocks, see Lahiri (2006) and Isiklar et al. (2006). Monitoring the latter matrix can be useful from the standpoint of a domestic macroeconomic policy maker, trying to combat foreign shocks in real time.

5. Conclusions

In this paper, we studied international propagation of shocks within and between groups of industrialized countries and emerging market economies using survey forecasts. Our data are monthly, multi-horizon, and fixed-target real GDP growth forecasts for 16 countries during the period of 1995-2017. We show that under the mild assumption of long-run forecast efficiency, results obtained using forecast data are comparable to what could be obtained using official real GDP statistics. This novel approach does not rely on official statistics at all so that we completely circumvent problems related to data publication lags, data revisions, availability of real-time data vintages, as well as data quality and accessibility issues, which are particularly common in emerging market economies.

We first show that the forecasts used in our study are efficient in the long run, even though they are not fully efficient. Our results suggest that it usually takes no more than three months for domestic news and no more than six months for foreign and international news to be fully incorporated into the forecasts. Since these lags reflect the combined effect of spillover of shocks and forecast inefficiency, they suggest that shocks transmit rather quickly across countries - most of the effect of a shock is realized within a quarter to two.

Next, our cross-correlation analysis suggests a notable level of co-movement within the group of industrialized countries and within the group of emerging market economies. But the level of correlation varies greatly over time. The results from the panel FSVAR model are consistent with the correlation analysis. Steady state variance decompositions show that, over the entire sample, the shocks common to the industrialized countries have significant effect on the world economy. But the shocks common to the emerging market economies have had very little effect on the industrialized countries. The steady state variance decompositions can be used in real time to measure how much a particular country is “vulnerable” to foreign shocks.

To account for possible structural changes over the business cycle, we estimate the FSVAR model separately for four subsamples, each representing an economic crisis or a non-crisis period. Results from these episodic analyses confirm that during periods of crisis like recessions, the importance of shocks vary depending on the nature and origin, while during normal times common international factors become the dominant force to help convergence between countries.

The main contribution of the paper is to show that multi-country survey data of expectations together with the analytical framework developed in this paper can be utilized to monitor time-varying interplay between economic shocks originating from different countries in real time before the actual official data are released. This makes the approach potentially very handy for macroeconomic policy makers and multinational banks.

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Table 1: Forecasters for Selected Countries in Jan 2009 Survey

United States	United Kingdom	India	China
Bank of America Corp	Bank of America	Bank of Tokyo-Mitsubishi UFJ	Bank of China (HK)
Barclays Capital	Barclays Capital	CRISIL	Bank of East Asia
Credit Suisse	Beacon Econ Forecasting	Citigroup	Citigroup
DuPont	BNP Paribas	Dresdner Bank	Credit Suisse
Eaton Corporation	Cambridge Econometrics	Experian Business Strat	Deutsche Bank
Econ Intelligence Unit	Capital Economics	Goldman Sachs	Econ Intelligence Unit
Fannie Mae	Citigroup	HSBC	Goldman Sachs Asia
First Trust Advisors	Confed of British Industry	ICICI Bank	HSBC Economics
Ford Motor Corp	Credit Suisse	IHS Global Insight	Hang Seng Bank
General Motors	DTZ Research	JP Morgan Chase	IHS Global Insight
Georgia State University	Economic Perspectives	Moody's Economy.com	ING
IHS Global Insight	HBOS	Morgan Stanley	JP Morgan Chase
Inforum - Univ of Maryland	HSBC	Nomura	Nomura
JP Morgan	IHS Global Insight	Tata Services (DES)	Oxford Economics
Macroeconomic Advisers	ING Fincial Markets	UBS	UBS
Merrill Lynch	ITEM Club		
Moody's Economy.com	JP Morgan		
Morgan Stanley	Liverpool Macro Research		
Northern Trust	Lloyds TSB Fincial Markets		
Oxford Economics	Merrill Lynch		
Swiss Re	Oxford Economics		
The Assn of Home Builders	RBS Fincial Markets		
The Conference Board	Schroders		
Univ of Michigan - RSQE	Societe Generale		
Wachovia Corp			
Wells Capital			

Table 2: Countries in Country Groups and Their Weights

Year	Europe				Northeast Asia			Southeast Asia				
	UK	France	Germany	Italy	HK	Korea	Taiwan	Indonesia	Malaysia	Philippines	Singapore	Thailand
1995	0.219	0.218	0.337	0.226	0.121	0.533	0.346	0.437	0.122	0.154	0.049	0.239
1996	0.226	0.217	0.334	0.224	0.123	0.529	0.348	0.434	0.123	0.154	0.049	0.240
1997	0.231	0.219	0.329	0.222	0.125	0.523	0.351	0.440	0.129	0.153	0.055	0.223
1998	0.230	0.222	0.325	0.223	0.123	0.502	0.376	0.434	0.132	0.160	0.058	0.216
1999	0.231	0.223	0.326	0.221	0.116	0.517	0.367	0.413	0.142	0.162	0.064	0.219
2000	0.237	0.227	0.317	0.219	0.119	0.518	0.364	0.394	0.150	0.161	0.075	0.220
2001	0.238	0.229	0.314	0.219	0.119	0.530	0.351	0.399	0.147	0.157	0.075	0.222
2002	0.241	0.233	0.313	0.212	0.117	0.538	0.345	0.384	0.152	0.154	0.079	0.231
2003	0.246	0.225	0.317	0.212	0.116	0.542	0.341	0.367	0.157	0.150	0.080	0.246
2004	0.251	0.226	0.315	0.208	0.118	0.546	0.337	0.367	0.158	0.143	0.090	0.243
2005	0.251	0.228	0.315	0.207	0.122	0.544	0.334	0.371	0.160	0.134	0.098	0.238
2006	0.250	0.227	0.315	0.207	0.122	0.544	0.333	0.376	0.157	0.132	0.097	0.238
2007	0.244	0.230	0.317	0.209	0.123	0.545	0.332	0.381	0.154	0.131	0.097	0.237
2008	0.238	0.231	0.320	0.212	0.126	0.553	0.322	0.404	0.157	0.128	0.087	0.224
2009	0.235	0.236	0.316	0.214	0.121	0.559	0.320	0.427	0.144	0.128	0.083	0.219
2010	0.227	0.237	0.326	0.210	0.118	0.557	0.325	0.440	0.136	0.124	0.086	0.214
2011	0.222	0.237	0.332	0.208	0.121	0.555	0.324	0.472	0.131	0.118	0.081	0.198
2012	0.227	0.236	0.333	0.205	0.120	0.557	0.323	0.468	0.131	0.119	0.080	0.202
2013	0.231	0.239	0.332	0.199	0.120	0.557	0.324	0.475	0.131	0.125	0.079	0.190
2014	0.235	0.236	0.336	0.194	0.118	0.554	0.328	0.478	0.134	0.128	0.077	0.183
2015	0.235	0.236	0.336	0.194	0.118	0.554	0.328	0.478	0.134	0.128	0.077	0.183
2016	0.235	0.236	0.336	0.194	0.118	0.554	0.328	0.478	0.134	0.128	0.077	0.183
2017	0.235	0.236	0.336	0.194	0.118	0.554	0.328	0.478	0.134	0.128	0.077	0.183

Table 3: Target and Horizon for Calendar Year and Fiscal Year Forecasts for 2008 Surveys

Survey Month (Year = 2008)		Jan	Feb	Mar	Apr	May	…	Dec
Calendar Year Forecasts								
Current Year Forecasts	Target Year	2008	2008	2008	2008	2008	…	2008
	Horizon	12	11	10	9	8	…	1
Next Year Forecasts	Target Year	**2009**	**2009**	**2009**	2009	2009	…	2009
	Horizon	**24**	**23**	**22**	21	20	…	13
Fiscal Year Forecasts								
Current Year Forecasts	Target Year	**2007**	**2007**	**2007**	2008	2008	…	2008
	Horizon	**3**	**2**	**1**	12	11	…	4
Next Year Forecasts	Target Year	2008	2008	2008	2009	2009	…	2009
	Horizon	15	14	13	24	23	…	16

Table 4: Cumulative Intertemporal Variance Decomposition (VAR Model) − Proportion of Total News Utilized

Months	USA	Europe	Japan	India	China	S.E. Asia	N.E. Asia
1	0.764	0.459	0.667	0.801	0.804	0.541	0.505
2	0.914	0.686	0.813	0.919	0.923	0.757	0.736
3	0.964	0.818	0.901	0.962	0.966	0.869	0.862
4	0.984	0.897	0.949	0.981	0.984	0.931	0.929
5	0.993	0.943	0.974	0.991	0.992	0.965	0.964
6	0.996	0.969	0.987	0.995	0.996	0.982	0.982
7	0.998	0.984	0.993	0.998	0.998	0.991	0.991
8	0.999	0.991	0.997	0.999	0.999	0.995	0.995
9	1.000	0.995	0.998	0.999	1.000	0.998	0.998
10	1.000	0.998	0.999	1.000	1.000	0.999	0.999
11	1.000	0.999	1.000	1.000	1.000	0.999	0.999
12	1.000	0.999	1.000	1.000	1.000	1.000	1.000

Table 5: Cumulative Intertemporal Variance Decomposition (FSVAR Model) − Proportion of Common International News Utilized

Months	USA	Europe	Japan	India	China	S.E. Asia	N.E. Asia
1	0.326	0.181	0.187	0.109	0.160	0.160	0.257
2	0.634	0.570	0.561	0.530	0.567	0.610	0.639
3	0.826	0.793	0.799	0.783	0.795	0.829	0.838
4	0.921	0.907	0.911	0.903	0.907	0.926	0.929
5	0.965	0.958	0.961	0.957	0.958	0.968	0.969
6	0.984	0.982	0.983	0.981	0.981	0.986	0.986
7	0.993	0.992	0.992	0.992	0.992	0.994	0.994
8	0.997	0.996	0.997	0.996	0.996	0.997	0.997
9	0.999	0.998	0.999	0.998	0.998	0.999	0.999
10	0.999	0.999	0.999	0.999	0.999	0.999	0.999
11	1.000	1.000	1.000	1.000	1.000	1.000	1.000
12	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 6: Correlations between Forecast Revisions

Correlations	USA	Europe	Japan	India	China	S.E. Asia
Europe	0.404					
Japan	0.304	0.384				
India	0.202	0.204	0.231			
China	0.188	0.290	0.239	0.271		
S.E. Asia	0.200	0.297	0.378	0.342	0.444	
N.E. Asia	0.422	0.528	0.502	0.368	0.404	0.661

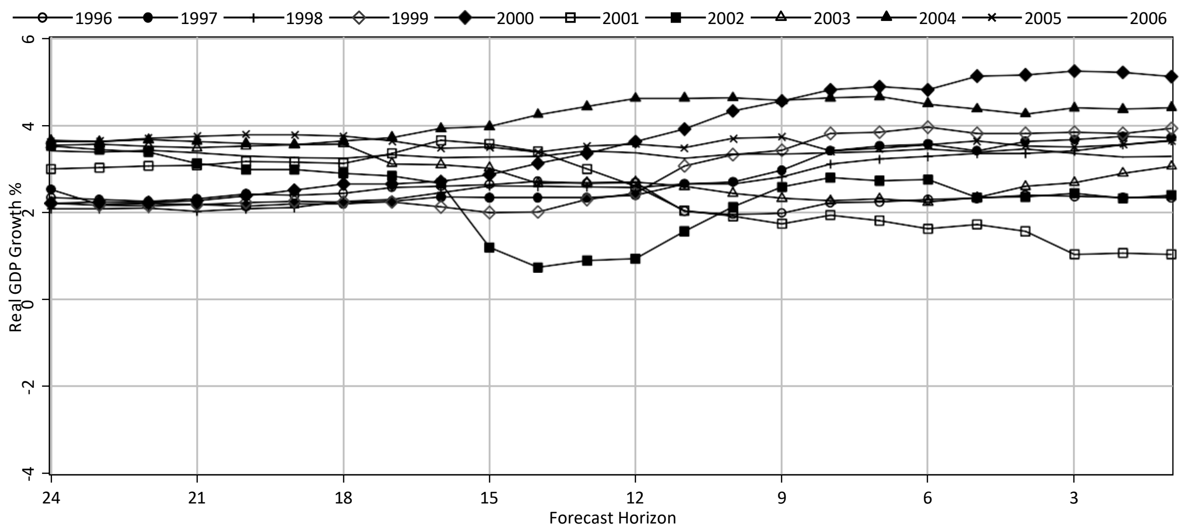
Table 7: Steady State Variance Decomposition (FSVAR Model) − Full Sample

Country	USA	Europe	Japan	India	China	S.E. Asia	N.E. Asia
USA	**0.712**	**0.420**	0.089	0.074	**0.120**	0.108	0.165
Europe	0.003	0.226	0.002	0.002	0.004	0.001	0.002
Japan	0.004	0.002	**0.619**	0.002	0.004	0.010	0.003
India	0.001	0.004	0.015	**0.722**	0.001	0.001	0.001
China	0.015	0.016	0.030	0.052	**0.685**	0.005	0.015
S.E. Asia	0.003	0.001	0.000	0.000	0.001	0.121	0.011
N.E. Asia	0.014	0.013	0.017	0.005	0.003	0.026	**0.254**
Factor 1	**0.246**	**0.315**	**0.199**	**0.093**	0.089	**0.170**	**0.409**
Factor 2	0.002	0.002	0.029	0.049	0.094	**0.559**	0.140

Table 8: Steady State Variance Decomposition (FSVAR Model) − Subsamples

Country	USA	Europe	Japan	India	China	S.E. Asia	N.E. Asia
Subsample 1: Feb 1995 to Dec 1998							
USA	**0.905**	**0.688**	0.007	0.013	0.016	0.015	0.022
Europe	0.000	0.019	0.000	0.000	0.000	0.001	0.000
Japan	0.014	0.009	**0.706**	0.010	0.072	0.004	0.022
India	**0.056**	0.050	0.002	**0.678**	0.013	0.004	0.002
China	0.004	0.012	0.035	0.036	**0.503**	0.003	0.006
S.E. Asia	0.002	0.002	0.003	0.003	0.006	**0.065**	0.009
N.E. Asia	0.003	0.002	0.078	0.012	0.004	0.025	**0.390**
Factor 1	0.009	**0.205**	0.043	0.022	0.070	0.022	0.109
Factor 2	0.006	0.014	**0.126**	**0.225**	**0.317**	**0.861**	**0.439**
Subsample 2: Jan 1999 to Nov 2006							
USA	**0.416**	**0.286**	0.044	0.035	**0.134**	0.079	0.112
Europe	0.001	0.128	0.000	0.000	0.002	0.001	0.001
Japan	0.037	0.028	**0.606**	0.012	0.094	0.024	0.017
India	0.007	0.005	0.038	**0.762**	0.007	0.002	0.006
China	0.020	0.015	0.040	0.025	**0.597**	0.014	0.010
S.E. Asia	0.001	0.001	0.000	0.001	0.002	0.051	0.001
N.E. Asia	0.081	0.075	0.029	0.018	0.023	0.099	**0.343**
Factor 1	**0.431**	**0.459**	**0.197**	**0.116**	0.105	**0.339**	**0.499**
Factor 2	0.007	0.005	0.045	0.032	0.036	**0.391**	0.011
Subsample 3: Dec 2006 to Jul 2010							
USA	**0.506**	**0.363**	**0.303**	**0.227**	**0.271**	**0.319**	**0.290**
Europe	0.074	0.178	0.055	0.048	0.053	0.077	0.070
Japan	0.011	0.024	0.149	0.018	0.017	0.031	0.024
India	0.011	0.011	0.030	**0.239**	0.004	0.019	0.013
China	0.090	0.122	0.143	0.153	**0.496**	0.154	0.154
S.E. Asia	0.025	0.029	0.035	0.026	0.030	0.053	0.032
N.E. Asia	0.000	0.000	0.000	0.003	0.001	0.001	0.007
Factor 1	**0.275**	**0.261**	**0.193**	0.181	0.116	**0.326**	**0.291**
Factor 2	0.006	0.011	0.092	0.105	0.013	0.021	0.119
Subsample 4: Aug 2010 to Mar 2017							
USA	**0.897**	**0.338**	0.036	**0.134**	0.191	**0.577**	0.242
Europe	0.001	**0.337**	0.006	0.001	0.005	0.002	0.005
Japan	0.003	0.001	**0.654**	0.003	0.028	0.003	0.008
India	0.009	0.005	0.003	**0.749**	0.012	0.006	0.003
China	0.021	0.015	0.011	0.027	**0.477**	0.013	0.006
S.E. Asia	0.001	0.002	0.001	0.003	0.010	**0.254**	0.000
N.E. Asia	0.000	0.001	0.003	0.001	0.005	0.000	0.160
Factor 1	**0.068**	0.091	**0.216**	0.057	**0.227**	0.076	**0.323**
Factor 2	0.000	0.209	0.069	0.025	0.045	0.067	**0.253**

Figure 1a: Forecasts of Real GDP Growth: United States 1996 to 2017



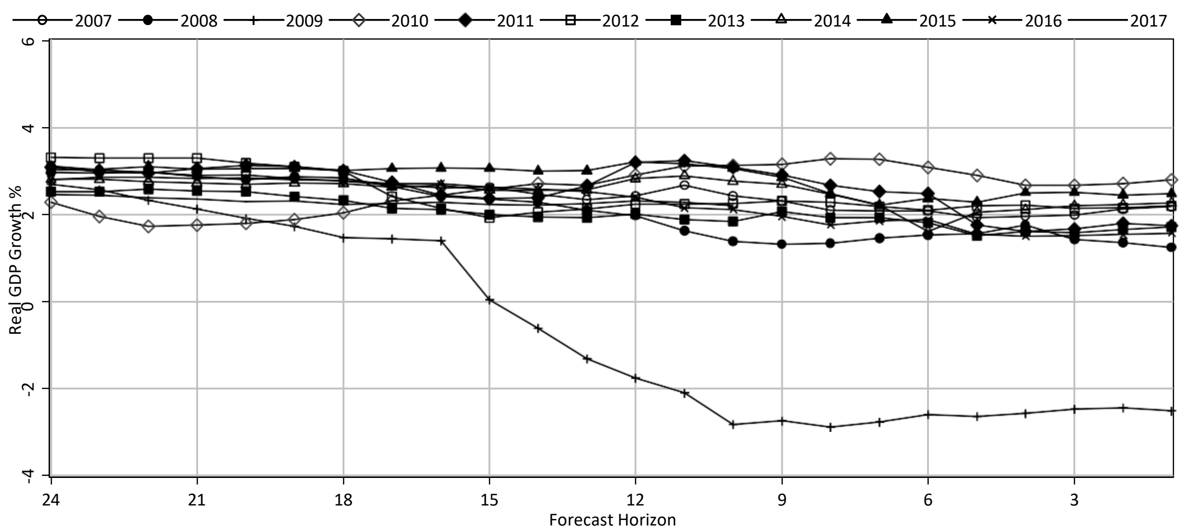
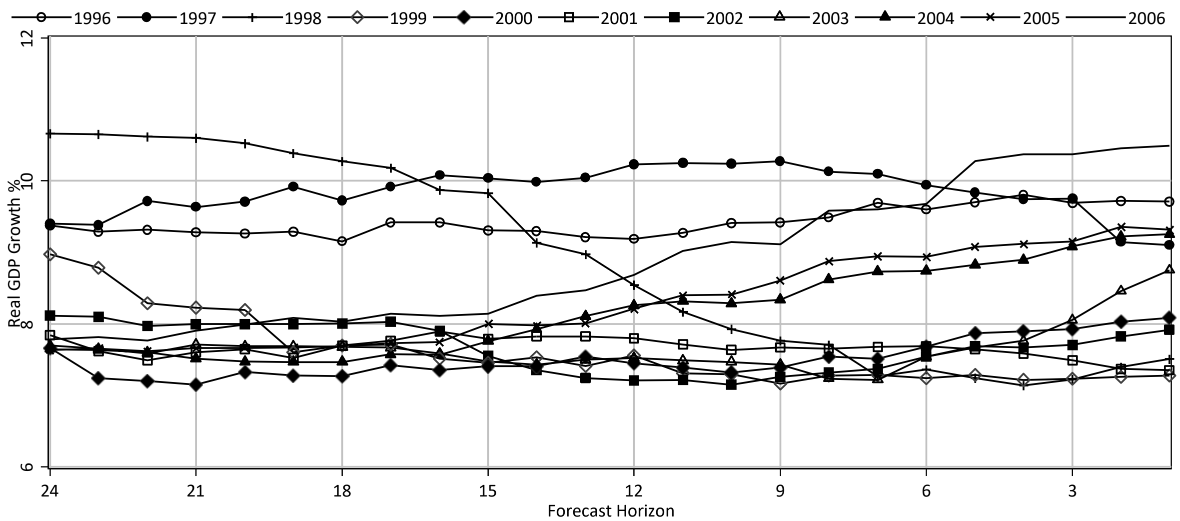


Figure 1b: Forecasts of Real GDP Growth: China 1996 to 2017



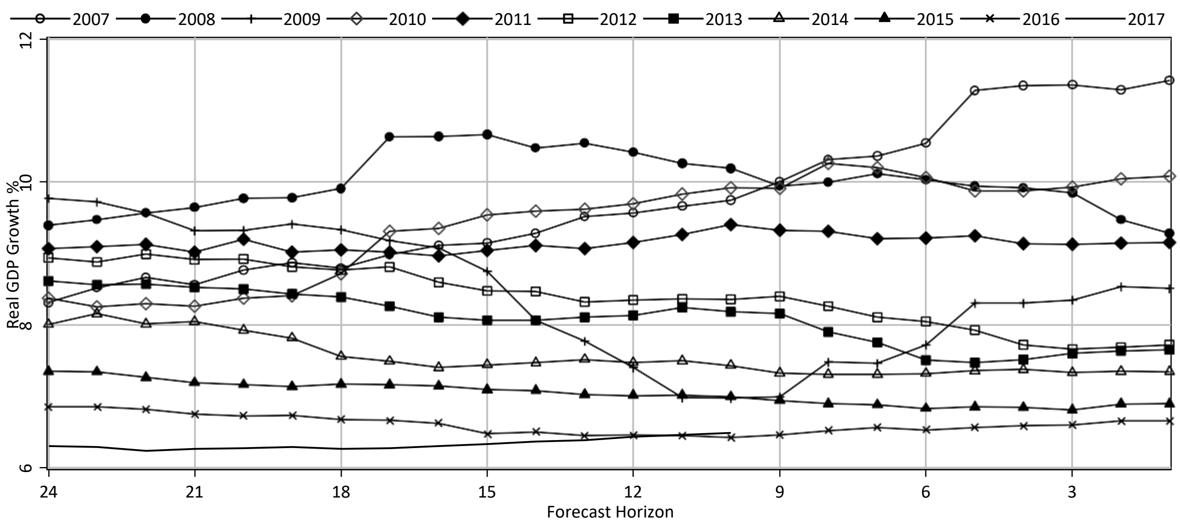
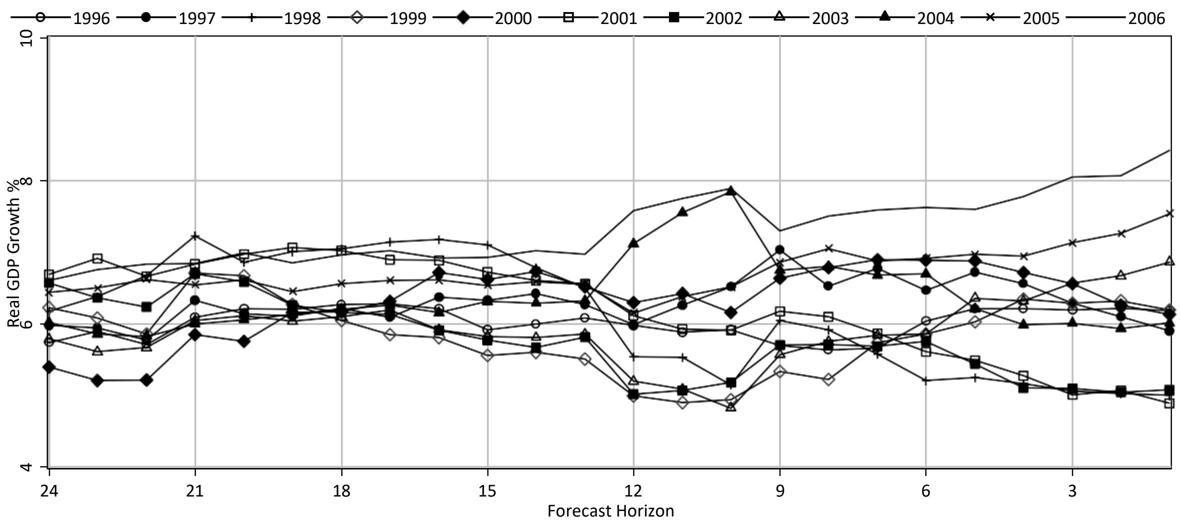


Figure 1c: Forecasts of Real GDP Growth: India 1996 to 2017



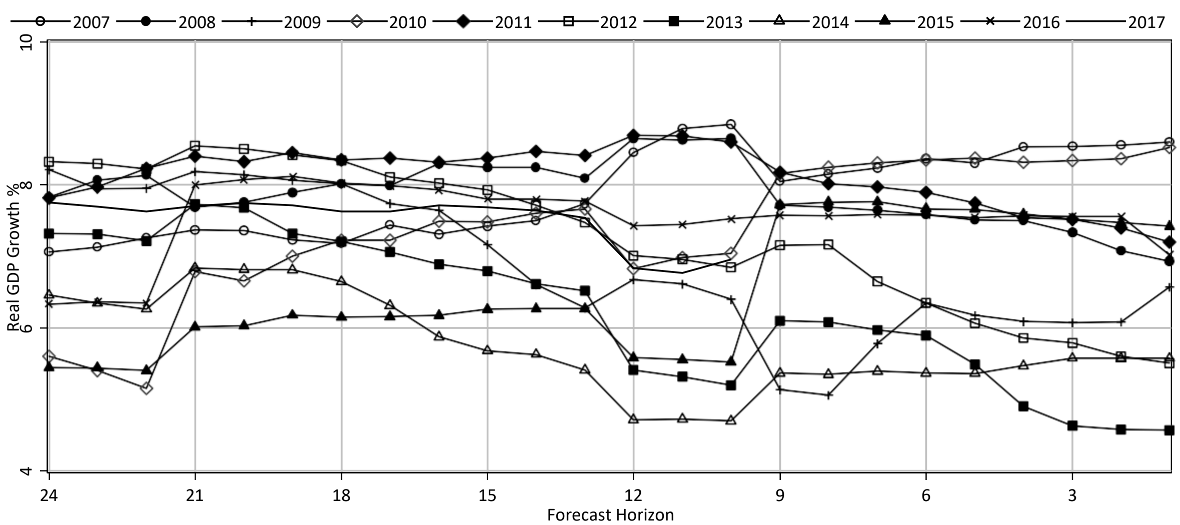


Figure 2a: Current Year Forecast Revisions of United States Real GDP Growth: 1996 to 2017

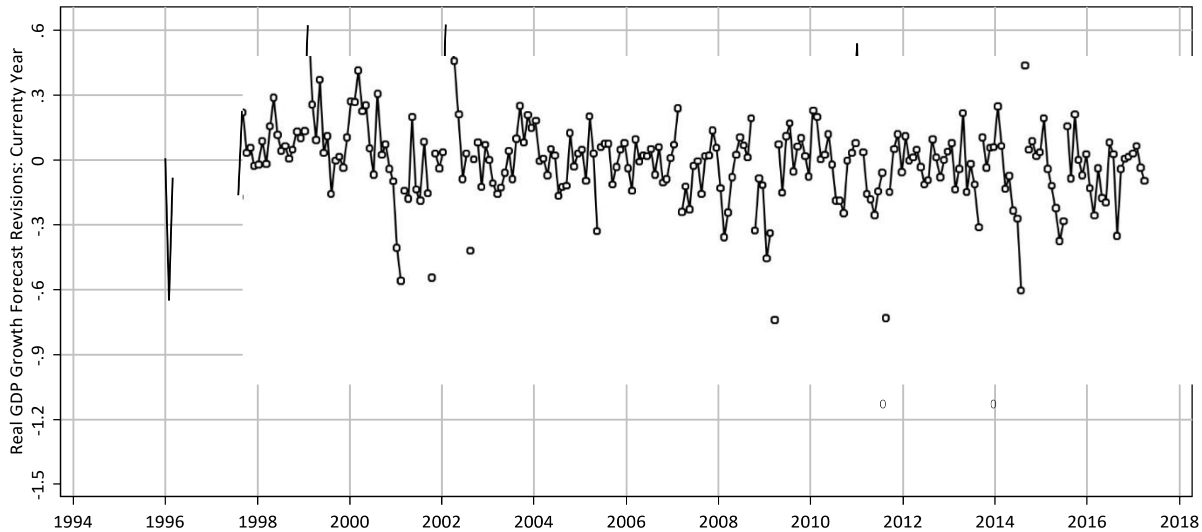


Figure 2b: Next Year Forecast Revisions of United States Real GDP Growth: 1996 to 2017

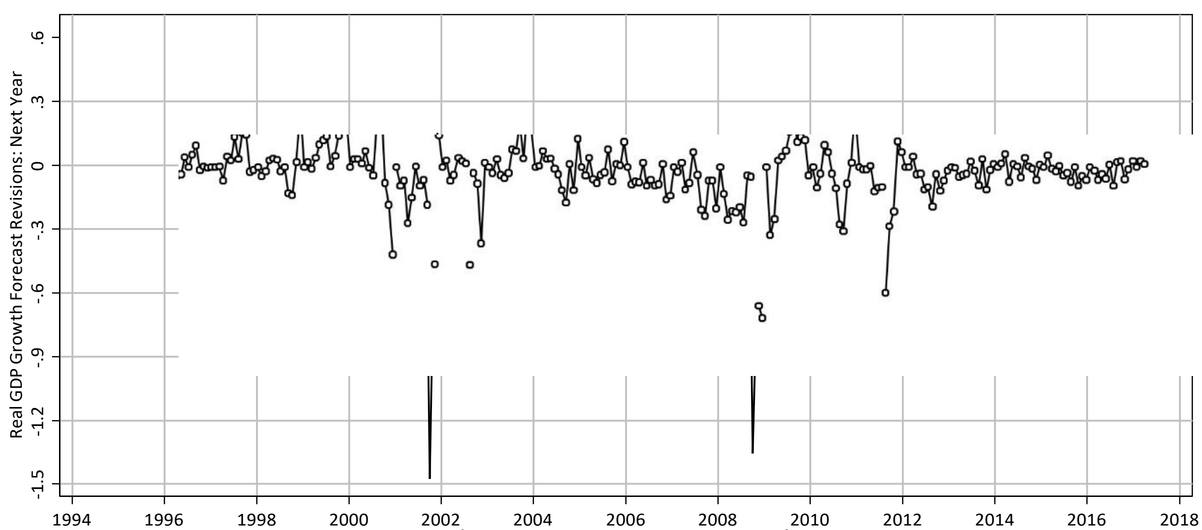


Figure 3: Generalized Impulse Responses: United States, Europe, China, and India

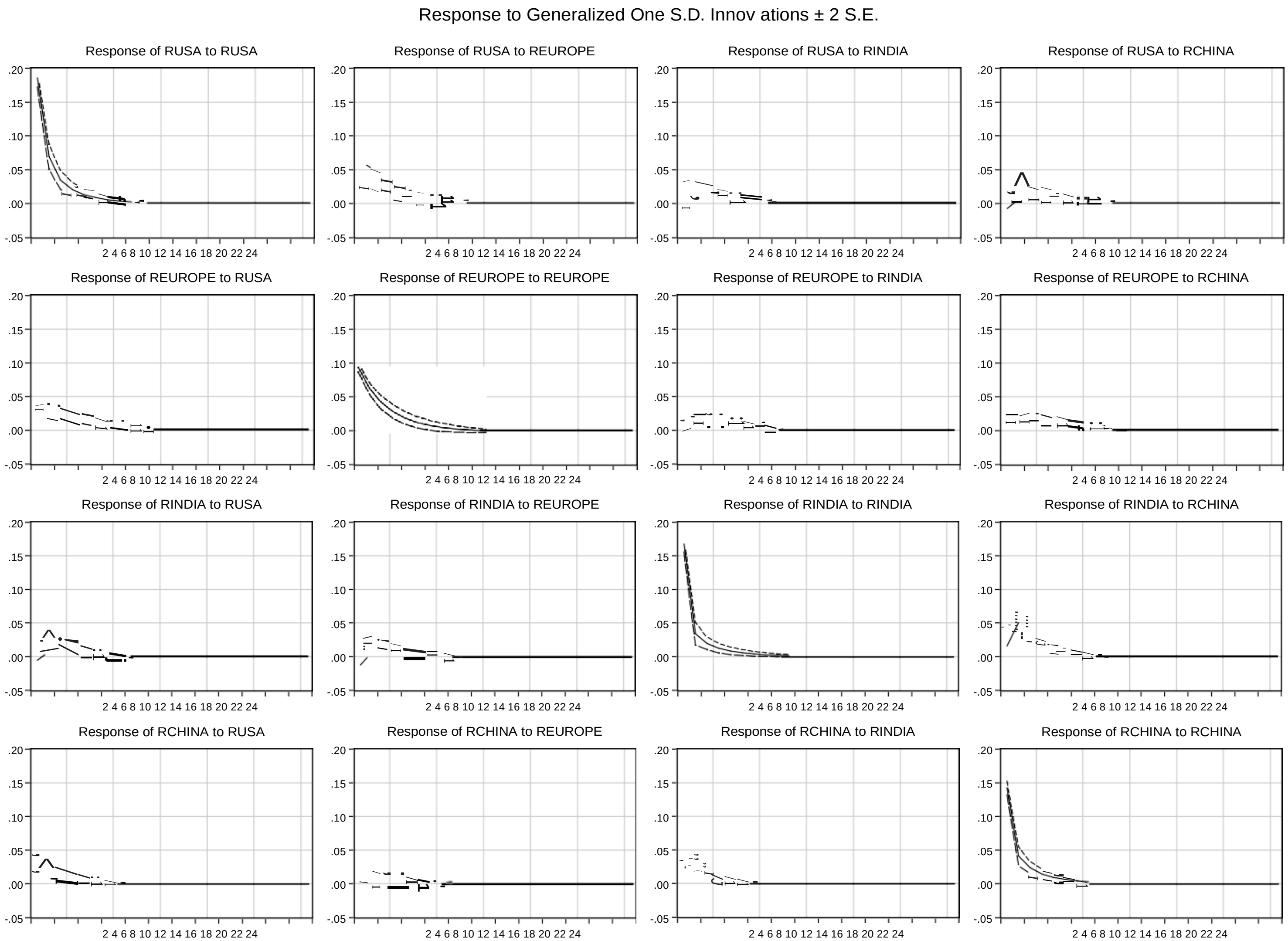


Figure 4: FSVAR Impulse Responses to Domestic and Common International Shocks: United States, Europe, China, and India

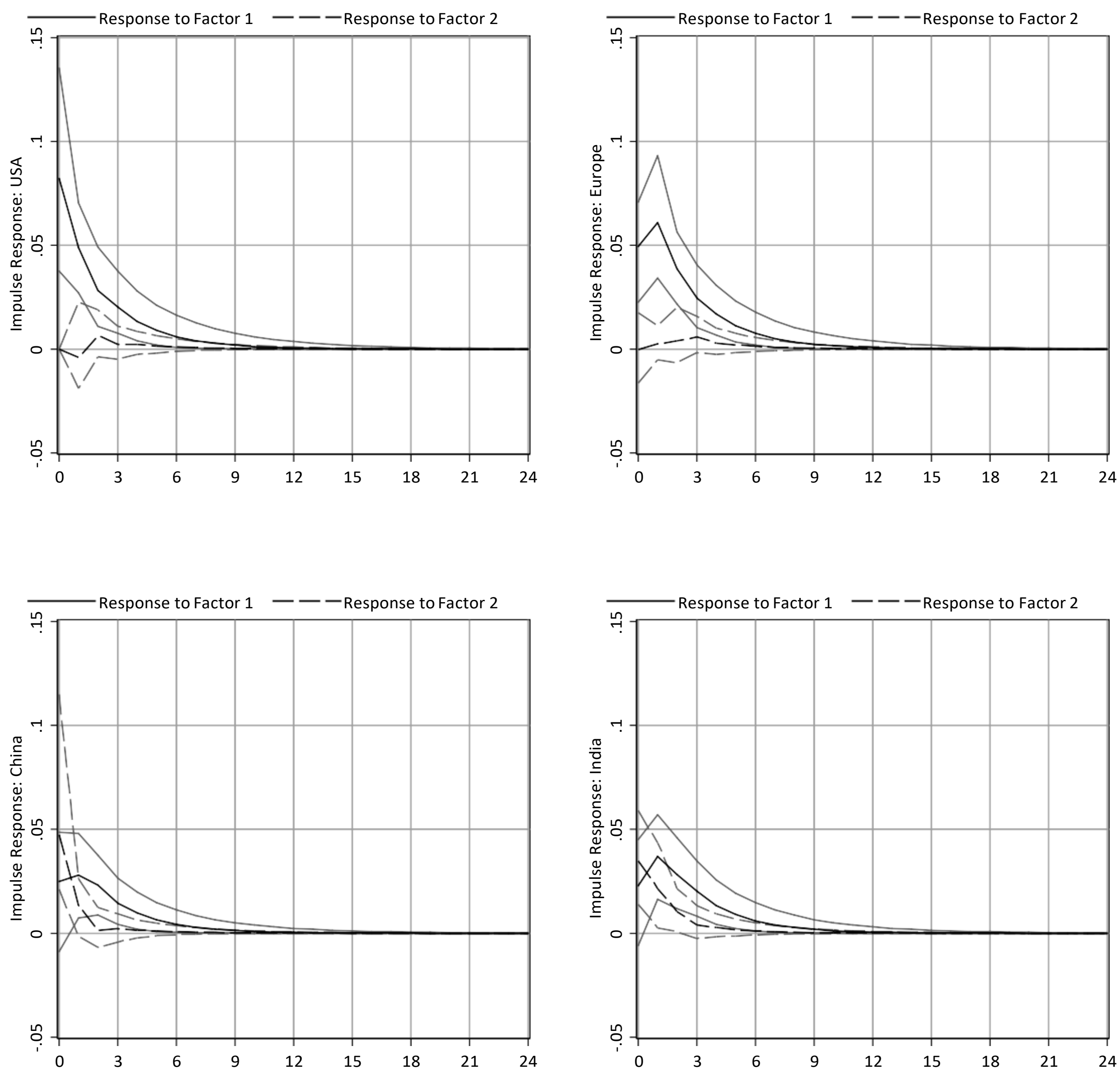
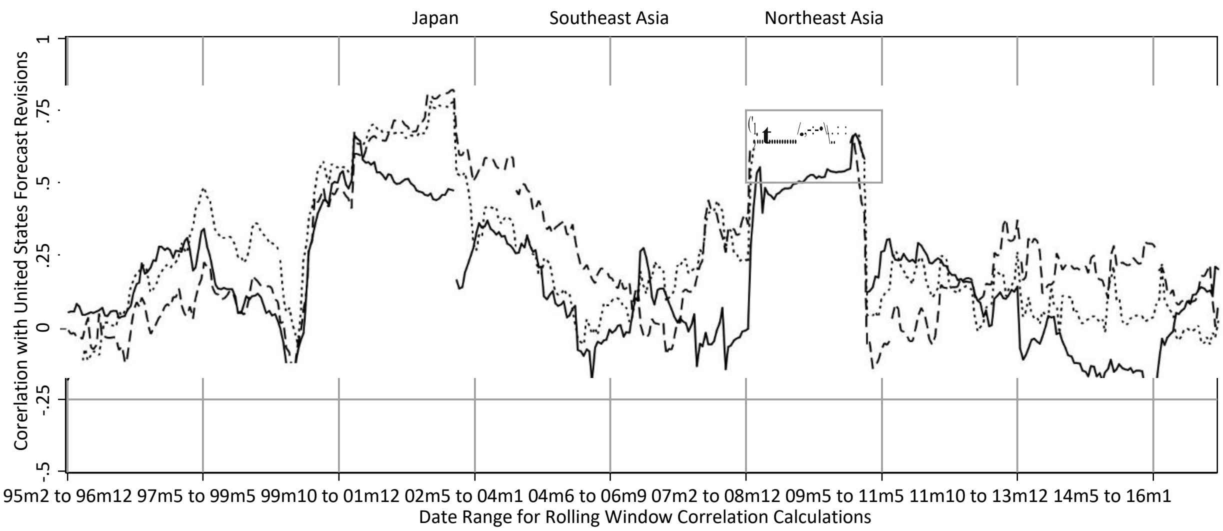
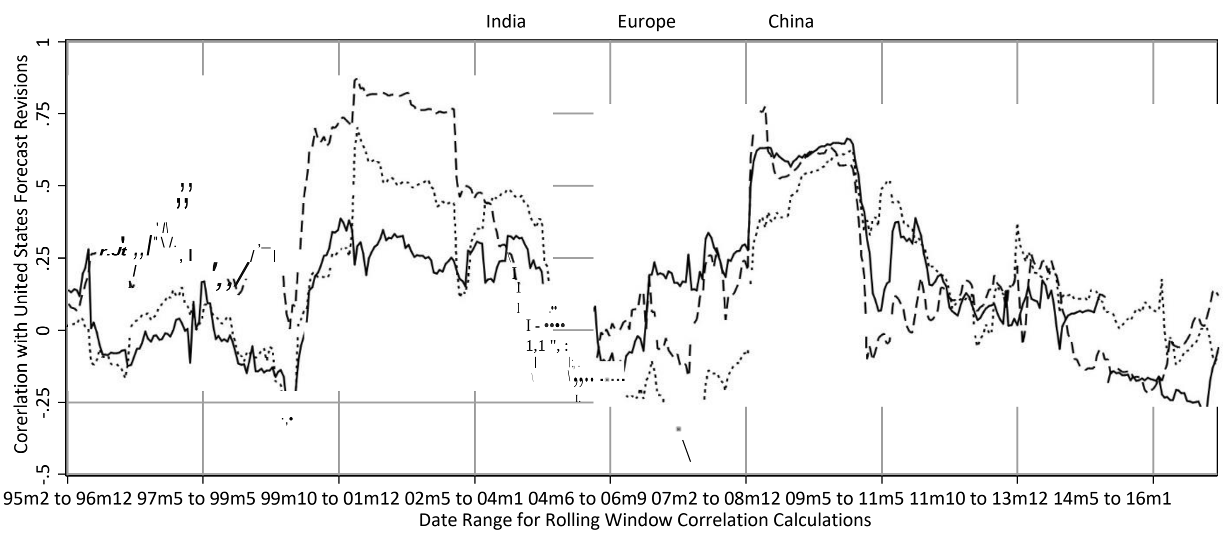


Figure 5: Rolling Correlations of 36 Forecast Revisions (21 Months): United States and India





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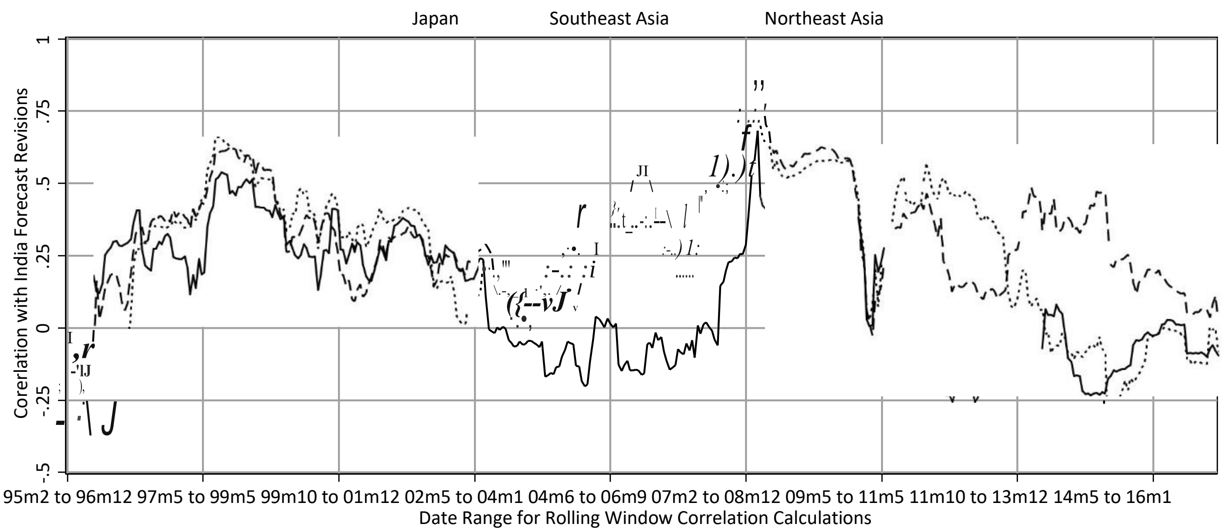


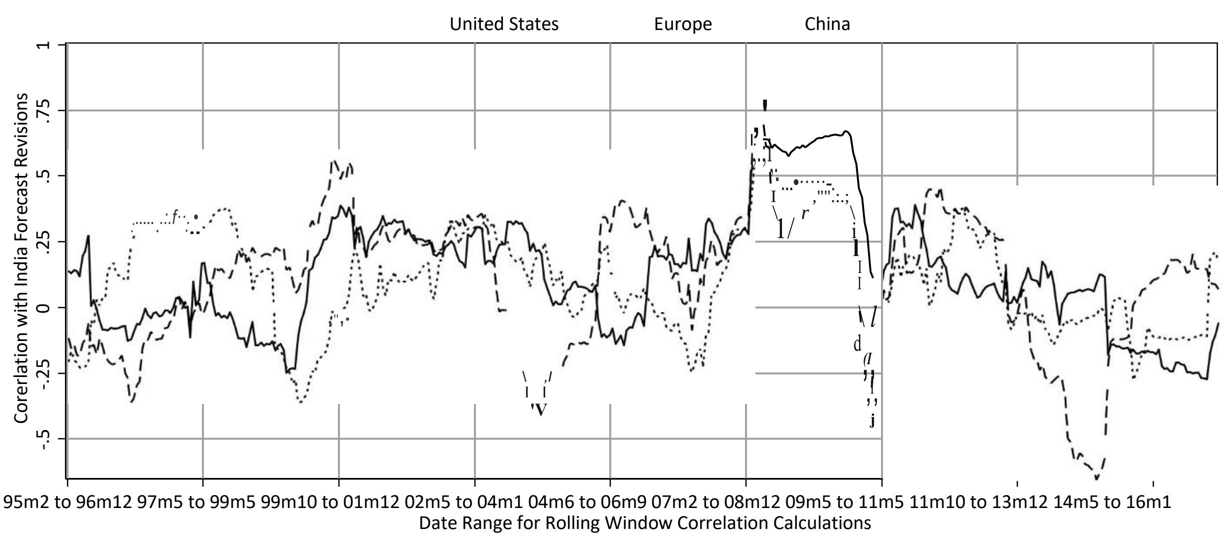
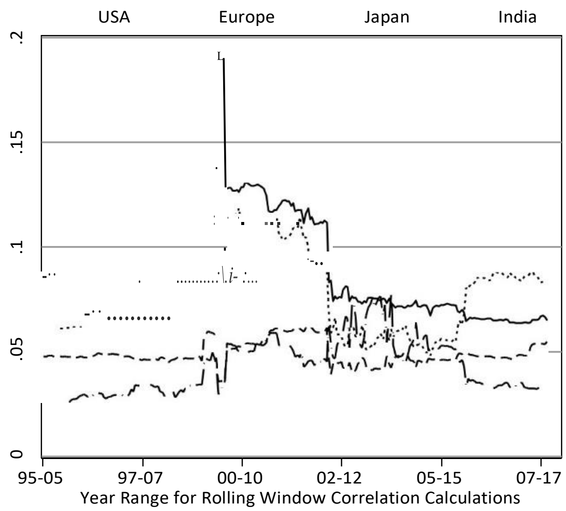
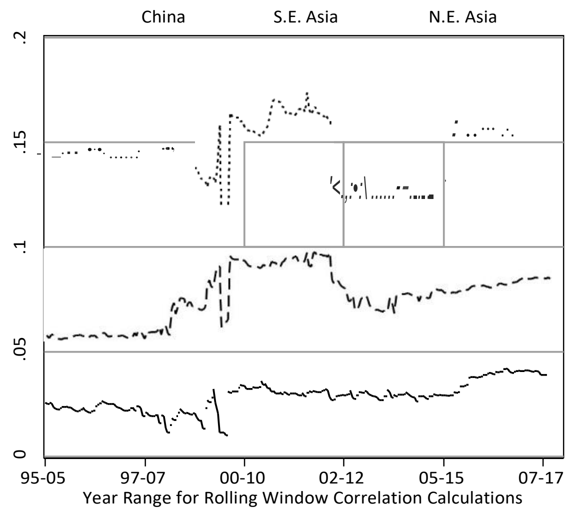


Figure 6: Factor Loadings from Recursive Estimation of FSVAR Model

Factor 1





Factor 2