# Estimating International Transmission of Shocks Using GDP Forecasts: India and Its Trading Partners †

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**Abstract:**

Using a Factor Structural Vector Autoregressive (FSVAR) model and monthly GDP growth forecasts during 1995-2003, we find that Indian economy responds largely to domestic and Asian common shocks, and much less to shocks the from the West. However, when we exclude the Asian crisis period from our sample, the Western factor comes out as strong as the Asian factor contributing 16% each to the Indian real GDP growth, suggesting that the dynamics of transmission mechanism is time-varying. Our methodology on the use of forecast data can help policy makers of especially developing countries with frequent economic crises and data limitations to adjust their policy targets in real time.

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# 1 Introduction

The knowledge of the patterns of inter-country propagation of economic shocks and the degree of vulnerability of a particular country to shocks originating from other countries is crucial for sound macroeconomic management. The relative robustness of the Indian and the Chinese economies to the recent Asian crisis has been remarkable. The availability of this sort of information is particularly important for Central Banks because they design and implement monetary policy mandates for price stability and GDP growth on a day-to-day basis. Because of these reasons, there is a growing interest in the sources of macroeconomic fluctuations and transmission of shocks in an international perspective. However, most of the research in this area has traditionally focused on industrialized countries, and only a few have studied the dynamics of the transmission of shocks involving developing economies.

As Agenor *et al.* (2000) noted there are two primary reasons for this lack of interest. First, the limitations on the quality and frequency of data are constraining factors. Dependable quarterly data on national accounts are available only for a handful of developing countries and even when they are available, the quality of the data is usually lower than that of annual data. Second, since developing countries usually experience many unanticipated crises, it is hard to extract economic regularities in the data that are usually driven by the crisis environment. Moreover, these crises in developing countries are usually followed by radical reforms, causing significant policy changes and possible structural breaks in the data. This makes it even harder to use macroeconomics data to look for regularities. India is a good case in point. India experienced a severe macroeconomic crisis in 1991, which initiated a series of reforms. These reforms have made drastic changes in the Indian economy especially in the 1990s. It is likely that these reforms and the relatively long period of adjustment will cause crucial problems in utilizing the Indian data to study the spatial pattern of macroeconomic shocks among its trading partners. Ghatak (1997, 1998) has firmly established the importance of structural breaks in the case of India.

In this study, we explore the feasibility of a rather unorthodox methodological approach. We use monthly real GDP forecasts of a developing country, India, and its major trading partners during 1995-2002 to study the nature and dynamics of the transmission of shocks. These forecasts are produced by experts from a mix of private consulting firms, public sector agencies, and university research bureaus specialized in a particular country. Using the econometric framework developed by Davies and Lahiri (1995, 1999) and Isiklar, Lahiri and Loungani (2006), we use successive differences in fixed-event (rather than fixed-horizon) forecasts to measure the aggregate economic "news" that befell in a particular month. The advantage of this measure is that the estimated news based on forecasts is independent of actual GDP figures and is observed at monthly frequencies in real time. The actual GDP values are known to be sometimes notoriously unreliable due to successive data revisions. Since we have access to simultaneous forecasts for a large number of countries, we can study the persistence, causality, and spatial transmission of such news in a cross-country context.

It is well known that forecasts from estimated time series models often do not have good track record due to model instability and structural breaks. The forecasts generated by experts tend to respond the current economic news better. However, the idea of using forecast data to extract information regarding actual economic fundamentals is still subject to several concerns, and the use of survey forecasts necessitates an examination of how good these forecasts are. Thus, we first measure the degree of inefficiency in the Indian real GDP growth forecasts. While it is common to test for the rationality of the forecasts for industrialized countries, it is not so for developing countries. Hence our measurement of forecast inefficiency for India can be considered as another contribution of this study.[1]

Our measure of forecast efficiency is partly motivated by the recent interest in the measures of stickiness in information usage. Mankiw and Reis (2001, 2003), hereafter MR, have proposed a "sticky-information" model as an alternative to the classical sticky-

[1] As it will be clear later, for our purpose, we do not need the forecasts to be rational in the sense of Muth (1961); instead, we require a much less stringent condition that the forecasters eventually use all available information. More specifically, the agents may be inefficient (and biased) in absorbing the impact of shocks in their forecasts immediately, but under the condition that they adjust eventually, we show that the forecast

price model. Sticky-information model of MR assumes that economic agents update their expectations only periodically because of costs of collecting and processing information.[2] One implication of such a model is that the average forecast of individuals should follow a smooth path. While this smoothing behavior is well documented[3], not much attention has been given to the extent of it. Mankiw *et al*. (2003) has measured the degree of news utilization in professional forecasts by imposing a structure on the true data generating process. In this study, we also measure the promptness in the utilization of information on Indian real GDP growth forecasts. The difference from Mankiw *et al.* (2003) is that their estimate of stickiness is based on particular assumptions about the data generating process of the actual process and the forecasters' behavior (i.e. sticky-information model). On the other hand, our estimates use only the forecast data without imposing any structure on the true nature of the data generating process or on the behavior of the forecasters.

Using a VAR model of forecast revisions, we measure the degree of forecast inefficiency in Indian real GDP forecasts. Our measure of inefficiency focuses on how quickly agents update their forecasts, and is based on impulse responses and 'intertemporal variance decompositions'. These variance decompositions are similar to the classical variance decompositions but they are not calculated across variables but calculated over time to measure the variance contribution in forecast revisions as time passes.

After establishing the extent of inefficiency in Indian real GDP forecasts, we compute the 'total utilization of news' at successive months after controlling for the stickiness of the forecasters. Under the assumption that the forecasters eventually respond to the news given a sufficient length of time (a concept that we call "long-run efficiency"), we show that the steady-state variance decompositions that are based on cumulative impulse responses give the average variance decompositions of the actual real GDP growth.

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data can be fruitfully used for extracting information about the underlying economic structure.

[2] Sims (2003) has proposed an alternative model of inefficiency that is based on the assumption of limited processing power of agents.

[3] Studies that point out the smoothness are Nordhaus (1987), Clements (1999), and Harvey et al. (2003).

We use two different types of VAR models in this paper. Initially we assume that the transmission of shocks across countries is dominated by foreign country shocks but not by common international shocks. Such a framework implies a classical VAR analysis without any common factors. Secondly, we study whether common international shocks play an important role in the transmission of shocks across countries using a factor structural VAR (FSVAR) framework.

Our conclusions can be summarized as follows: First, we find that Indian real GDP forecasts are efficient with respect to the use of information available domestically but not so with respect to foreign countries and/or common international information. It takes almost 4 months for foreign "news" to be incorporated in the forecasts. Nevertheless, the quality of the Indian forecasts compares very favorably with those of the major industrialized countries. Second, we find that there were two global factors that were important to India during 1995-2003 – one representing US, UK, EU-3 (Germany, Italy, France), and the other representing selected countries in North East and South East Asia. Further, the Indian real GDP growth was mainly driven by the Asian common factor and to a much lesser extent by Western common factor. On average more than 30 percent of the Indian real GDP growth variance was accounted for by the common Asian cycle. The domestic shocks accounted for approximately 40 percent of the variance. However, when we excluded the Asian crisis period (1997.7 - 1998.12) from the sample we found that the share of the domestic shocks increased to 60 percent and both Western and the Asian common shocks account for 16 percent each. Thus, we find that the spatial nature of the transmission mechanism can change within short periods of time

## 2 Consensus Forecasts: Data and Characteristics

Since October 1989, *Consensus Economics Inc.*[4] has been polling more than 600 private market and other economists each month to obtain their forecasts. These surveys cover estimates for the principal macroeconomic variables (including GDP growth, inflation, interest rates and exchange rates) of over 70 countries. The forecasts are compiled into a series of publications, *Consensus Forecasts* (includes industrialized countries and published monthly since 1989), *Latin American Consensus Forecasts* (published bi-monthly since 1993), *Asia Pacific Consensus Forecasts* (published monthly since 1995), and *Eastern Europe Consensus Forecasts* (published bi-monthly since 1998). The numbers of panelists ranges from 10 to 30 for most of the countries, and for major countries the panelists are mostly based in countries they forecast. A sample of forecasters that reports for India is provided in Table 1. As it is seen in the table while some of the forecasters are located in India, others are multinational firms located in leading industrialized countries. Thus, these forecasts reflect widely diverse information sets held by different stakeholders of India.

Even though *Consensus Forecasts* data set is a source of rich economic information, there are only a handful of studies that have used this data. These are Artis (1997), Batchelor (2007), Gallo, Granger and Joen (2002), Harvey *et al.* (2001), Loungani (2001), Juhn and Loungani (2002), Gultekin et al. (2006) and Gultekin and Lahiri (2007). To the best of our knowledge, the *Asia Pacific Consensus Forecasts* including those for India remain largely unused.

In this article we will concentrate on the consensus forecasts of annual average real GDP growth. A consensus forecast is a simple arithmetic average of all of the individual predictions. Although for most of the countries the forecasts are for calendar years, for some countries including India fiscal year is used, (April to March). The rolling forecasts first made 24 months ahead for target years 1995 through 2003 are plotted in Figure 1. The actual real GDP figures are given on the right side of the diagram at horizon 0.[5] These graphs reveal that the monthly forecasts are highly variable that can only be explained by real time news that fell during the preceding months. The graphs also reveal that the consensus forecasts made even one month before the end of the year can sometimes be significantly different form the actual real GDP values (e.g., forecast made in March 1998 for the FY 1998 is almost one percentage point below the actual).[6] Apart from pure unanticipated forecasting error, this discrepancy can also be due to the fact that sometimes the revised GDP figures can be substantially different from the initial

[4] Web: http://www.consensuseconomics.com
[5] These are the latest revisions released in June by Central Statistical Organizations for each year.
[6] This point has been documented by Gallo *et al.* (2002) for GDP forecasts of three developed countries.

announcements. For other years the last forecasts were fairly close. As mentioned before, one advantage of our approach is that it does not depend on the actual GDP values.

The monthly forecast revisions are defined as news as perceived by the forecasters in real-time, and since forecasts are made for the current year and the next year, we can define two monthly news components with respect to these two target years. They are plotted in Figure 2 and Figure 3, and show very similar patterns. It should be emphasized that these series are generated in real time, and are not created at the end of the sample period, see Croushore and Stark (2001). Any student of the Indian economy can easily identify the up and down swings in these graphs. The bullish July 1999 – June 2000 period reflects the optimism surrounding the newly elected BJP government at the Center, its proposed free-market reforms, and the surging stock market. However, the continuing budget deficits, the disappointing Central budget of March 2000, looming inflation fear, etc. were creating variability in the forecasts. During August 2000-January 2002, the Indian economy experienced a series of bad economic news for real GDP growth. This is a period that can be identified as having bad balance of payments situation, soaring oil prices, stalled privatization programs, the earthquake of January 2001, arms bribery scandal, recession in the world economy, the Enron scandal, instability at the Center, the 9/11 attack, and others. However, with the revival of the world economy, and a good monsoon, the Indian economy seemed to have come out of its slump beginning January 2002. The Gujrat riots, attacks on Kashmir, and poor monsoon of 2002 made growth prospects during this period uncertain.

## 3 Measuring the Degree of Forecast Inefficiency

In this study we propose a measure of forecast inefficiency which is not dependent on any assumed model.[7] The “sticky-information” model of MR assumes that economic agents update their expectations only periodically because of costs of collecting and processing information, and this causes stickiness in aggregate expectations. They assume that in any given period each individual faces a constant

[7] In recent years, a number of authors have given alternative behavioral and institutional explanations for the observed lack of rationality in survey forecasts. See, for instance, Ehrbeck and Waldman (1996), Laster et al. (1999), Mankiw and Reis (2001), and Sims (2003).

probability $\lambda$ of updating their information set and therefore only a fraction of the population updates their forecasts on the current state of the economy and computes optimal prices based on that information. The rest of the population continues to set prices on old plans and outdated information. Based on sticky-information model of MR, several studies have estimated the extent of stickiness. Khan and Zhu (2006) use VAR estimates to mimic the price expectations and find that stickiness for US and Canada is less than the stickiness for the UK. Carroll (2003) uses Michigan Survey of Consumers and measures the stickiness in information for households. They treat the forecasts from Survey of Professional Forecasters (SPF) as those of experts and then measure how quickly the households utilize the information in the expert forecasts. They find that about at any point of time, 32 percent of households have inflation expectations that are more than a year out of date.

The model of expectations proposed by MR can be applied to professional forecasters' expectations of other macroeconomic variables too. While sticky information explanation is not originally developed for professional forecasters who have strong incentives to update their information frequently, there may be other reasons for the professional forecasters to update their forecasts with a lag. For example, Sims (2003) points out that the agents may have information processing constraints, which may cause stickiness in information utilization. Also it has been pointed out by several studies that forecasters may avoid changing their predictions and smooth their forecasts in order to maintain credibility. For example, this is consistent with rational bias and reputation effects as put forward Ehrbeck and Waldman (1996) and Laster *et al.* (1999).

As we know, the only study that measures the degree of smoothness for the profession forecasters is Mankiw et al. (2003), where they measure it in an indirect way. They use a VAR over the whole sample to model how rational agents form their expectations and then compare these rational expectations with those of professional forecasters reported in Livingston survey assuming that their sticky-information model is correct. They find that the professional economists surveyed by the Livingston survey update their inflation expectations about every 10 months on average. Note that their estimate of stickiness depends on two assumptions. First the data generating process (i.e.

VAR model) should be valid over the whole sample to generate rational expectations in real time. Second, the behavioral assumption about the forecasters, i.e. the assumption that forecasters have sticky-information, should be valid. In this study we follow a different approach. If the forecasts are smooth for any reason (sticky-information, rational inattention, reputation, rational bias, etc.), then this smoothness can be captured by focusing on the forecast revisions in repeated forecasts for the same target. In the next section we will estimate a VAR model on forecast revisions to capture the degree of inefficiency in a multivariate context without assuming the form inefficiency.

### 3.1 *VAR model*

In order to measure the stickiness in the forecasts we focus on the process of the forecast revisions. [8] Generally speaking, today's forecast revision may be interpreted as accumulation of past news components so that

$$r_{i,t,h} = \beta_0 \varepsilon_{i,t,h} + \beta_1 \varepsilon_{i,t,h+1} + \beta_2 \varepsilon_{i,t,h+2} + \beta_3 \varepsilon_{i,t,h+3} + \dots \qquad (1)$$

where $r_{i,t,h}$ represents the forecast revision in country $i$ real GDP forecasts for year $t$ when the forecast horizon is $h$, $\beta_s$ represents the usage of the new information that has been available $s$ periods ago ($\varepsilon_{i,t,h+s}$). If, for example, the forecasters are fully efficient, then $\beta_j = 0$ for all j>0 should be satisfied. That is, all the information that becomes available should be immediately and no information components should be leftover to be utilized in later revisions.

It is well known that the propagation of shocks from other countries is an important source of GDP shocks to a country. Since forecast revisions indicate the impact of new information on GDP growth, using other countries' forecast revisions in a VAR model provides a way for incorporating the cross-country information for testing and

[8] Before measuring the degree of inefficiency in the forecasts we first tested for the forecast efficiency following Nordhaus (1987). Using a GMM framework similar to Davies and Lahiri (1995) we found that the Indian real GDP growth forecasts are inefficient. Note that the validity of rational expectations has important bearing on tests for Ricardian equivalence, permanent income/consumption hypothesis, etc. See Ghatak and Ghatak (1996) for a serious attempt to grapple with this issue using Indian data.

measuring inefficiency. If we use the forecast revisions of other countries in addition to the own country forecast revisions in a VAR model for J countries, we get

$$r_{t,h} = c + B_1 r_{t,h+1} + B_2 r_{t,h+2} + \cdots + B_p r_{t,h+p} + \varepsilon_{t,h} \qquad (2)$$

where $r_{t,h}$ denote a (J × 1) vector containing the forecast revisions of the relevant countries when the forecast horizon is *h* and target year is *t* and $E(\varepsilon_{t,h}\varepsilon'_{t,h}) = \Omega$ $= \{\sigma_{ij}, i, j = 1, 2, ..., n\}$. $B_k$ denote the (J × J) matrix of coefficients of $r_{t,h+k}$. *VAR (p)* may be rewritten in *VMA (* $\infty$ *)* form, which is multivariate version of equation (1) as

$$r_{t,h} = \mu + M_0\varepsilon_{t,h} + M_1\varepsilon_{t,h+1} + M_2\varepsilon_{t,h+2} + \cdots. \qquad (3)$$

where we usually assume that $M_0 = I$ for normalization.

Notice that if the forecasters are efficient then they will be updating their forecasts exactly in the amount that the new information changes their rational expectations:

$$r_{t,h} = E(y_t \mid \Phi_{t,h}) - E(y_t \mid \Phi_{t,h+1})$$

where $\Phi_{t,h}$ denote the information set when the forecast horizon is *h.* In this setup $E(y_t \mid \Phi_{t,h}) - E(y_t \mid \Phi_{t,h+1})$ denote the new information on $y_t$ and it can be thought as the $\varepsilon_{t,h}$ in equation (3) where due to perfect efficiency we will have $M_k = 0$ for $k > 0$ $r_{t,h} = \varepsilon_{t,h}$.

Note that since $\varepsilon_{t,h+i}$ is assumed to be the information that arrives between forecast horizons *h+i* and *h+i+1*, i.e. $\varepsilon_{t,h+i} = E\left(y_t \mid \Phi_{t,h+i}\right) - E\left(y_t \mid \Phi_{t,h+i+1}\right)$ for $i \geq 0$, the process in equation (3) is the same as:

$$
\begin{aligned}
r_{t,h} = \mu + M_0 & \left( E(y_t \mid \Phi_{t,h}) - E(y_t \mid \Phi_{t,h+1}) \right) \\
& + M_1 \left( E(y_t \mid \Phi_{t,h+1}) - E(y_t \mid \Phi_{t,h+2}) \right) \\
& + M_3 \left( E(y_t \mid \Phi_{t,h+2}) - E(y_t \mid \Phi_{t,h+3}) \right) \\
& + \ldots
\end{aligned} \tag{4}
$$

The estimated VAR system presents us with an important tool to understand the dynamics of the forecasting process in more detail than simple correlations. In its usual interpretation, impulse responses trace the effect of a one standard deviation shock to one of the innovations on the future values of other variables in the system. Our variables are forecast revisions of the sample countries; hence impulse responses show the responses of forecast revisions to innovations over time. But under perfect efficiency, forecast revisions should respond fully to the shocks immediately. If the forecast revisions do not respond to the shocks immediately, i.e. if there are nonzero impulse response values when impulse response horizon is greater than zero, then forecasts are not efficiently using the information immediately, and some of the information is being utilized in the later forecast revisions. In other words, impulse responses of the forecast revisions show the dynamics of how shocks are absorbed in the forecast revisions over time. The longer it takes for the responses to go to zero, the greater is the degree of forecast inefficiency.

Since the shocks of the countries are correlated, we should decompose the correlated shocks into uncorrelated idiosyncratic shocks to find some economically useful representation of the model. The classical way of doing this is by using Cholesky decomposition. The Cholesky decomposition imposes a recursive structure on the contemporaneous interactions among the variables and the resulting impulse response functions become dependent on the ordering of the variables in the VAR. But such a recursive structure is arbitrary and can be very restrictive. To guard against this criticism, we use ordering-free generalized VAR model that was introduced by Koop, Pesaran and Potter (1996) for nonlinear systems. Pesaran and Shin (1998) proposed the method for an ordering free solution in the VAR analysis and they show that $n \times 1$ vector of $k$ period ahead generalized impulse response of the effect of a one-standard deviation shock in the $j^{\text{th}}$ country forecast revision equation is given by:

$$\psi_j(k) = \sigma_{jj}^{-1/2} M_k \Omega e_j \tag{5}$$

where $e_j$ is the $j^{\text{th}}$ column of an identity matrix.

The impulse responses provide one way of judging the speed with which individual country information gets absorbed into forecasts, but it is not an aggregate measure. To look at an aggregate measure of inefficiency we need to focus on the variance decompositions aggregated over all countries. The classical variance decompositions give us estimates of the relative importance of domestic *vis-à-vis* foreign shocks in explaining forecast revision variance in the long run. But another important issue is the *speed* of forecasters' response to news over time.

In order to do this, we need to see how much of the variation in forecast revisions is accounted for by current innovations and how much of it is accounted for by past innovations. Thus, we decompose the variation in forecast revisions over time into its new and old components using cumulative 'intertemporal variance decompositions'. For country *i*, the cumulative percentage of the variation of the revisions due to information that become available in the last *m- periods* can be calculated from

$$\theta_{i,m} = \frac{\sum_{h=0}^{m} e_i' M_h \Omega M_h e_i}{\sum_{h=0}^{\infty} e_i' M_h \Omega M_h e_i} \tag{6}$$

where $e_i$ is the i$^{\text{th}}$ column of an identity matrix, see Isiklar et al. (2006).

While the intertemporal variance decompositions in equation (6) give an aggregate measure for the degree of inefficiency, one may also examine the inefficiency specifically towards foreign or common shocks. We will answer this question using a factor structural VAR model. We discuss this model in the next section.

### 3.2 *Factor Structural VAR model*

In the previous section, we assume that domestic and foreign idiosyncratic country shocks are the most relevant information source for the real GDP figures. In this section we include common international factors in our model using a factor structural VAR (FSVAR) model. FSVAR models have increasingly become popular in studying the international propagation of shocks. Recently Clark and Shin (2000), and Stock and Watson (2005) used these models to shed some light on the sources of economic fluctuations. The FSVAR model can be thought of a structural VAR model. In a FSVAR model, it is assumed that the contemporaneous interaction among variables stem from the common shocks. In other words, idiosyncratic country shocks are assumed to have no effect on other countries contemporaneously. Then, the reduced form errors follow the structure:

$$\varepsilon_{t,h} = \Lambda f_{t,h} + Au_{t,h} \tag{7}$$

where $f_{t,h}$ is $k \times 1$ vector that denote the common international factors with $E(f_{t,h} f_{t,h}') = I$, $\Lambda$ is the $J \times k$ matrix of factor loadings, $A$ is a $J \times J$ matrix of the contemporaneous spillovers across countries, and $u_{t,h}$ is a $J \times 1$ vector of the idiosyncratic country shocks with $E(u_{t,h} u_{t,h}') = diag(\sigma_{u1}^2, ..., \sigma_{uJ}^2)$ =*D*. In the special case with $A = I$, contemporaneous interactions across countries through the errors are not permitted. This special case is the model that is also estimated by Stock and Watson (2005) and will be the main workhorse in this study as well. While assuming that the contemporaneous interaction terms across countries are due to the common shocks and none are due to spillovers (i.e., transmission of idiosyncratic country shocks) is quite restrictive, we do not have much choice because of identification problems.[9] So assuming that $A = I$, our aim becomes to estimate $\Lambda$ and *D*. Once they are estimated we can rewrite the vector moving average model in the form:

[9] Later, we will experiment with some alternative specifications for the *A* matrix by letting some off-diagonal elements to be non-zeros. Note that spillovers in this model take place via the lagged terms of the VAR model. With monthly data, this assumption is less restrictive than with quarterly data, cf. Stock and Watson (2005).

$$r_{t,h} = \mu + (\Lambda f_{t,h} + u_{t,h}) + M_1(\Lambda f_{t,h+1} + u_{t,h+1}) + M_2(\Lambda f_{t,h+2} + u_{t,h+2}) + \cdots. \tag{8}$$

this can be used to compute impulse responses and variance decompositions. So with *J=7*, reduced-form errors will be decomposed into *k+ 7* shocks where *k* is the number of international common factors.

Once the FSVAR model is estimated intertemporal variance decompositions can be constructed in a similar way as (6). Also we can construct intertemporal variance decompositions for the utilization of domestic shocks, common shocks or foreign shocks as well. For example, equation (9) gives the cumulative percentage of the variation in the forecast revisions due to total common shock information that become available in the last m-periods:

$$\theta_{i,common\ factors} = \frac{\sum_{h=0}^{m}\sum_{j=1}^{k} e_i' M_h \Lambda\Lambda' M_h' e_j}{\sum_{h=0}^{\infty}\sum_{j=1}^{k} e_i' M_h \Lambda\Lambda' M_h' e_j} \tag{9}$$

The other intertemporal variance decompositions can be constructed in a similar fashion.

Note that in our context FSVAR model is useful for two reasons. First, in recent yeas many studies have emphasized the importance of common factors in the international business cycle propagation, and it would be interesting to explore the impact of common shocks on individual country GDP growth rates and their forecasts. This will be discussed in the next section in detail. Second, a common factor model provides a natural way how forecasters form their expectations based on the rational inattention model of Sims (2003). Following his approach, let us suppose that the forecasters have information processing limitations. In this case, initially they would allocate their resources to the most relevant information sources and ignore the less relevant ones. Clearly, in such a case domestic news is the first to be utilized since usually it is cheap and relevant. After absorbing the domestic news, it is likely that forecasters will next pay attention to the common international shocks. This is because common international news is more accessible and is easier to observe than the news coming from individual countries separately. For example, a forecaster in India may not pay enough attention to announcements of employment figures for all of its trading countries. But it may be easy to observe global news and common international shocks such as wars, oil price shocks, Asian crises or technological innovations. Hence it is reasonable to assume that the forecasters react to the domestic shocks along with the common international shocks but ignore the idiosyncratic foreign country shocks contemporaneously. Notice that one possible problem with this approach is that we may overestimate the impact of common international shocks because we assume that contemporaneous interaction among the forecast revisions occur due to the common international shocks. See footnote 9.

# 4 International Transmission of Shocks

## 4.1 *The Literature*

Interest in international transmission of shocks has been growing in the last few years, see for example, McAdam (2003), Helbling and Bayoumi (2003), Cardarelli and Kose (2004), Monfort *et al*. (2003), Stock and Watson (2005), Ahmed (2003), and Smets and Wouters (2005). These studies usually utilize quarterly or annual GDP data as a measure of economy's overall activity and used a sampling period starting from post WWII period to the present. For example, Smets and Wouters (2005) use real GDP data along with six other macroeconomic data - consumption, investment, prices, real wages, employment and the nominal interest rate - over a sample period from 1947 to 2002 and over a shorter period from 1983 to 2002. Stock and Watson (2005) use real GDP data from G7 countries and estimate an FSVAR model over 1960-1983 and 1984-2001. Since the low degrees of freedom in the unrestricted VAR model would create a considerable sampling uncertainty, Stock and Watson (2005) employed a restricted VAR model in the sense that they used only a single lag for the foreign GDP growth but they use four lags for the own country GDP growth. Monfort et al. (2003) use quarterly GDP figures in addition to monthly industrial production data for the G7 countries from 1970 to 2002. Industrial production, though available monthly, is less suitable compared to GDP because it covers only a small part of the economy, see footnote 13.

The GDP, which is the best indicator for the overall economic activity, is available only quarterly with substantial lag and revisions. This implies that the studies on international transmission of shocks, where the GDP interactions are usually measured among several countries in a multivariate model like VAR, do not have enough degrees of freedom. The situation is much worse for the developing countries, where the availability of data constrains the study even more. Because of this limitation only a limited number papers study the transmission of shocks in developing countries, see Agenor et al. (2000), Kim et al. (2003), and Selover (1999). In addition to the limited data, developing countries also suffer from the frequent crisis and structural breaks, which make the study of transmission of shocks even more difficult. Use of dummy variables is a common but not an ultimate solution to control for the impact of frequent crises; the meaning of the dummy variables is not clear in most of the cases and their use decreases the degrees of freedom even more. For example, Selover (1999) studies the transmission of business cycles in the ASEAN region using annual data between 1961 and 1997. Selover (1999) computes bivariate VAR models due to the restrictions on the degrees of freedom, and fails to find a significant transmission of business cycles among the ASEAN countries. Among several other explanations, he notes that the low significance level can be due to i) small sample size; or ii) large domestic shocks such as wars, coups, natural disasters, insurrections, gross economic policy errors, bad harvests, and commodity price volatility which can add noise to the estimates. In order to correct for these large domestic shocks, he uses a set of level dummies and commodity prices as additional explanatory variables. However, the addition of these explanatory variables decreases the degrees of freedom and increases the uncertainty surrounding the estimates.[10] Moreover, in short samples, the usage of dummy variables can be treacherous and it is possible that the results are highly dependent on the specification and selection of these dummies. If there is uncertainty surrounding the timing and shape of the structural breaks, a better method may be focusing in sub samples.

[10] For example, in his VAR(2) model of Thailand, the number of right-hand side variables is 14 due to the presence of lagged terms, dummy variables and commodity prices. Since Selover (1999) has 35 usable observations (1963-1997), the degree of freedom becomes only 21.

### 4.2 *India During 1990s*

India's situation is a perfect example to show the extent of the problem of such a structural break. In 1991, severe macroeconomic and the balance of payments crisis initiated a set of reforms including devaluation of rupee and liberalization of international trade and foreign investment in India. While in the pre-1991 period, India was largely insulated from the world, in the post 1991 period she started to connect with the world more than ever following the radical reforms in every aspect of the economic life.[11] These reforms resulted in significant changes in the macroeconomic variables in the early 1990s, especially between 1991 and 1996.[12] These changes suggest that in 1991 India started to experience a structural change and was in a transition period until 1995-1996. This structural break and the long transition period clearly complicate the analysis of international transmission of shocks for India causing lack of usable GDP data to study the sources of GDP variations in the long haul.[13]

Because of these restrictions in Indian data, we do not use the actual GDP figures but use the monthly forecasts of it and investigate whether the cross-country forecast data can be used to study the transmission of shocks between India and its major trading partners. Use of forecast data offers several advantages. First of all, the sample size is no longer a problem since the forecasters report two forecasts (for current and next year) every

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[11] For example, the rupee was devalued by 22.8 percent relative to a basket of currencies in 1991 and was made convertible in 1993. The import-weighted average tariff for the whole economy was brought down to 33 percent in 1994-1995 from 87 percent in 1990-1991 and remained relatively stable since then. In 1991, many restrictions on the inflow of foreign direct investment (FDI) were removed although FDI is still prohibited in certain sectors of the economy such as retail trade. See Srinivasan (2001) for a detailed analysis of the reforms that took place in India during the post 1991 period, and Ghatak and Halicioglu (2007) for the role of FDI in the transmission mechanism.

[12] For example, both the exports and imports started to grow as large as 20 percent in the early 1990s until 1995-1996. Since 1996, the growth rates of exports and imports have been mostly less than 10 percent. Similarly, the share of exports plus imports as a percent of GDP increased from 14.4 percent in 1991-1992 to 21.6 percent in 1995-1996 and remained stable since then. Liberalization of FDI policy and reforms boosted the FDI inflows in India in early 1990s until 1996. In 1991 FDI inflows to India were only US$155 million. During 1991-1995 period inflows approximately doubled in every year reaching US$2.1 billion in 1995. Based on the World Investment Reports of UNCTAD, since 1995 FDI inflows has grown relatively slow reaching US$3.4 billion in 2001 and stayed the same in 2002.

[13] An alternative approach would be to use some monthly data such as industrial production. However, the differences in the growth rates of industry, service and agriculture sector and the increasing share of the service sector in the economy causes a problem in using industrial production data. For example, as it is analyzed in detail by Gordon and Gupta (2003), over 1991-2000, the service sector grew by 7.5 percent, while the industry sector grew by 5.8 and agriculture sector by only 3.1 percent resulting in an average GDP growth of 5.8 percent.

month. Secondly, the number of lags required in VAR model on forecast revisions is expected to be much smaller than the number of lags required when we use actual GDP figures. This is because forecasters adjust their forecasts by the amount of the change in their expectations immediately after they observe a shock and they do not wait for the shock's impact to be realized. Under rationality, the lag length is actually zero. Thirdly, due our data frequency we can study the transmission mechanism over a very short period with relatively large sample size. For example, in section 6 we will work on the post 1995 period without using the Asian crisis period to isolate the impact of Asian crisis on the transmission of shocks.

Clearly, there is a disadvantage of using forecast data too. Especially if the forecasters are biased and inefficient, the results arrived by using forecast data may be highly misleading. But note that the most important factor in the reliability in the results is not that the forecasters are biased or inefficient in the short-run but rather their ability of correcting their mistakes in the long-run. Under the assumption that the forecasters can correct their previous misjudgments on the economic activity, we provide a simple method to adjust for the inefficiencies in the forecasts and use the forecast data to study the sources of GDP variations for a country.[14] In the following two sub-sections we consider the cases when the forecasts are efficient and when they are inefficient.

## 4.3 *Estimating the Structure of Transmission of Shocks Using Forecast Data*

### *1.1.1. Under Perfect Efficiency*

As noted earlier under perfect efficiency we have,

$$r_{t,h} = E(y_t \mid \Phi_{t,h}) - E(y_t \mid \Phi_{t,h+1})$$

[14] Our cross-country forecast data can be used to understand how expectations are changing and get affected by changes in expectations of other countries. Such information may be important, for example, to understand the reasons behind Asian financial crisis. One argument as to why the Asian crisis occurred is that the agents had overly optimistic GDP growth expectations before the crisis, which caused them to save less but consume and invest more than optimum, and financed by large capital inflows. But when an external shock led to a sudden change in the expectations, a rapid reversal of capital flows triggered a currency crash. Corsetti *et al.* (1999) offers a number of explanations for the Asian crisis. So in order to understand the importance of expectations role in the crisis, it would be interesting to study how expectations reacted to shocks and how they propagated among the countries.

In this case a factor structure or any other economically meaningful structure can be imposed on the forecast revision series. Suppose we believe that FSVAR structure given in (7) is valid. Then, we have

$$r_{t,h} = \Lambda f_{t,h} + u_{t,h} \tag{10}$$

The estimates of $\Lambda$ can be obtained using static factor analysis methods. In this case, maximum likelihood estimates would be based on the variance covariance matrix constructed using the forecast revisions. But notice that since we assume perfect efficiency and no contemporaneous response to foreign country shocks (spillovers) at the same time, this would imply that idiosyncratic country shocks do not propagate across countries at all. Then the estimate of $\Lambda$ from equation (10) would give the average value of the impact of common factors on the real GDP growth rate.

### *1.1.2. Under Long-run Efficiency*

If the forecasts are inefficient to some degree and they do not include all the available information $\Phi_{t,h}$, then we should correct the inefficiency in the revisions to understand the transmission of shock structure across countries using forecast data. Suppose that the forecast revisions follow the process given in (3) but forecasters eventually utilize all the information within $p$ periods, so that there exists $p$ such that $M_i = 0 \;\; i > p$. This implies that when there is sufficient number of forecast horizons, i.e. when $h \geq p$, there should be enough time for the forecasters to utilize all the information before they are finished with forecasting for a target. That is, the impact of news $\varepsilon_{t,h}$ will be reflected in the forecasts by the time they report their forecast $f_{t,h-p}$. But, in this case, the total amount of utilized news will be nothing but $M_0 + M_1 + M_2 + \ldots$, which is the accumulated impulse response function. Then accumulated impulse responses give the total utilization of the information not only included in the first forecast just after $\varepsilon_{t,h}$ is observed, i.e. $f_{t,h}$, but also news utilized in the later forecasts too, i.e. $f_{t,h-1}, f_{t,h-2}, ..., f_{t,h-p}$. More formally when forecast horizon is *h-p* the total utilization of news $\varepsilon_{t,h}$ is given by[15]

$$\Gamma_\varepsilon \equiv \text{total utilization of news } \varepsilon_{t,h} = \sum_{r=0}^{p} M_r ,$$

where (i,j)th element of $\Gamma_\varepsilon$ gives the total utilization of jth element of $\varepsilon_{t,h}$ on variable *i*. Another way of looking at this aggregated measure is "inefficiency adjusted utilization of news". While $M_r$ denote the inefficient response of the forecasters, $\Sigma_{r=0}^{p} M_r$ gives the inefficiency adjusted response. This suggests that if we assume that forecasters eventually use all the available information, cumulative impulse responses from the FSVAR model will equal the impact of the shocks on the actual real GDP growth averaged over horizons. Moreover, steady-state variance decompositions that are based on these cumulative impulse responses will give the share of shocks accounted for by common factors and idiosyncratic country shocks.

We can also calculate the total utilization of common factors and individual country specific news using equation (8). For example from equation (8), it is clear that the total utilization of news in the common factors $f_{t,h}$ is represented by $\Sigma_{r=0}^{p} M_r \Lambda$. Hence under the assumption of long-run efficiency, the variation accounted for by the jth common factor in ith country's real GDP variations is

$$\omega_{ij} = \frac{\left(e_i' \tilde{\Lambda} e_j\right)^2}{\sum_{s=1}^{k}\left(e_i' \tilde{\Lambda} e_s\right)^2 + \sum_{s=1}^{J}\left(e_i' \tilde{M} e_s\right)^2} \qquad (11)$$

where $\tilde{\Lambda}$ and $\tilde{M}$ denote the inefficiency adjusted total utilization of news in common factors and individual country shocks respectively, that is,

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[15] Note that when there is not enough time, i.e., when $h \le p$, the full amount of the information will not be utilized in the forecasts; instead the total utilization of the news will be the sum of the moving average coefficients over the forecast horizon, i.e. $\Sigma_{r=0}^{h} M_r$.

$$\tilde{\Lambda} = \sum_{r=0}^{p} M_r \Lambda \text{, and}$$

$$\tilde{M} = \sum_{r=0}^{p} M_r D \text{,}$$

where, as defined earlier, D is the diagonal matrix that carries the idiosyncratic country variances, $D = E\left(u_{t,h}u_{t,h}'\right) = diag\left(\sigma_{u1}{}^2,...,\sigma_{uJ}{}^2\right)$. Notice that in equation (11), $\left(e_i\tilde{\Lambda}e_j\right)^2$ is the contribution of j[th] common factor shocks, and $\left(e_i\tilde{M}e_s\right)^2$ is the contribution of s[th] country shock to the variation in total news utilization in the i[th] country's real GDP growth forecasts. If our assumption that forecasters are long-run efficient in *p* periods is valid then the share in total news utilization should be related to the average variance decompositions that are based on actual real GDP growths.

# 5 Empirical Results on the Degree of Forecast Efficiency

## 5.1 *Descriptive Statistics and Generalized VAR Results*

We measure the degree of inefficiency in the forecasts using a VAR model of four countries and three country blocks. Since our analysis also examines the impact of foreign country shocks on India, we should be careful about the calendar year and fiscal year differences. If the forecasts are for the calendar year, then survey respondents make their first forecasts when there are 24 months to the end of calendar year; that is, on January of the previous year they start forecasting, and their last forecast is reported at the beginning of December of the year they are forecasting. But this is different for India, where survey respondents make their first forecasts when there are 24 months to the end of fiscal year; that is, on April of the previous year they start forecasting, and their last forecast is reported at the beginning of March of the year they are forecasting. The first official announcement of the fiscal year GDP comes in early July, with an immediate revision in late July and a few revisions thereafter (see Sivasubramonium (2000)).

Table 2 presents the relation between the calendar year and fiscal year forecasts. In each month forecasters report two forecasts: one for the current year and the other for the next year. For example, on January 2000, a current calendar year forecast predicts the average GDP growth rate for year 2000. However, for India, the forecast that is reported on January 2000 is still aiming the current fiscal year, which is year 1999. This difference between the calendar and the fiscal year targets is true for February and March forecasts too. Since we will use these forecasts to analyze the causal relation between India and other countries the forecasts should be comparable in terms of timing. That is, the forecasts should target the same year and also the forecast horizons should not be very different from each other. Notice that for the calendar year forecasts reported in January, February or March that target the next year, there is no contemporaneous match in the fiscal year forecasts. Similarly, for the fiscal year forecasts in January, February and March that target the current fiscal year, there is no contemporaneous match in the calendar year forecasts. So we had no choice but drop these observations from our data set in our VAR analysis. So we drop both the next year calendar forecasts when the forecast horizon is more than 21 and the current year fiscal year forecasts when the forecast horizon is less than 4. This means that forecast horizon for the calendar year forecasts range between 1 and 21 and for the fiscal year forecasts, forecast horizon range between 4 and 24. Thus, for each country and for a target year we have 21 forecasts. Our data set ranges from January 1995 (the first forecast for India in Consensus Economics, Inc. data base) to November 2002. In a VAR(1) model, the total number of observations per country is 148.

Since our main purpose is to analyze the causality of shocks between India and its major trading partners, we choose countries and regions that have significant relationships with India. These are: USA, UK, the European block, Japan, Southeast Asia block, and Northeast Asia block. As reported by Dua and Banerji (2001), the export-based shares of these countries add up to more than 60% of the total. Three largest trade partners of India from Europe, viz., Germany, France and Italy, make up the European block. UK is treated as separate from the European block because of its historical relationship with India, and because it is well known that the British business cycles are quite distinct from the European cycles that is led by Germany. The Southeast and Northeast Asian blocks are defined below (Table 3).[16]

The Consensus Economics Inc. reports the aggregate measures of real GDP growth rates for the two regions in Asia, North East Asia and South East Asia. It uses the 1995 GDP shares for this aggregation. Since the weights are subject to change based on the actual data that is used, (i.e. which revision of the actual is used), we calculated the implied GDP shares by regressing the reported regional GDP growth forecasts on the individual countries GDP forecasts. Our calculations show that the North East Asia region weights for China, Hong Kong, South Korea and Taiwan are 45%, 9%, 29.5% and 16.5% respectively. Similarly, for South East Asia region, weights for Indonesia, Malaysia, Singapore, Thailand and Philippines are 32.5%, 14%, 13.7%, 26.5% and 13.7% respectively. Note that the shares may not add up to 100% due to rounding. The countries and weights are summarized in Table 3.

We estimated a 7-country VAR model with monthly data on forecast revisions over January 1995 – November 2002. We use Akaike and Schwarz information criteria to decide on the number of lags. The results for these information criteria along with some fitness statistics for the Indian equation are given in Table 4. As it is clear from the table the optimum lag length is 1 for our model. Note that the number of usable observations decreases quite rapidly with each additional lag. This is because our data is in the form of a panel data with 9 target years (from 1995 to 2003) and with each additional lag we lose 9 observations.[17]

We estimated generalized impulse responses and presented them in Figure 5. These impulse responses illustrate how quickly new information gets utilized in Indian

[16] We also estimate the VAR model using six individual countries that have the largest trade with India. These are USA, UK, Japan, Germany (representative for European block) Singapore (representative for South East Asian block), and Hong Kong (representative for the North East Asian block). The results with individual seven countries as defined above were very similar to the main conclusions of this paper.

[17] Consider a VAR(3) model. After taking the first difference to calculate the forecast revisions, we are left with 20 observations per country per year. Due to the use of third lag, we have 17 observations per country per year. So from 1996 to 2001 we have 17 observations, for 1995 we have 8 observations (the first available forecast is January 1995), for 2002 we have 16 observations (since the latest available forecast is November 2002) and for 2003 we have 4 observations. So in total we have 17*6+8+16+4=130 observations for each country. Similarly the VAR(1) model will have 148 observations.

real GDP forecasts. The top chart in Figure 5 shows the utilization of domestic news. As shown in this chart, domestic shocks are being absorbed rather quickly in the forecasts. The rest of the charts in Figure 5 show the utilization of foreign country shocks. Notice that the scale of these graphs is different from the first one. Here we see that especially North East Asian and South East Asian shocks are absorbed at a much slower rate than the domestic shocks. Moreover, one can suggest from these graphs that Asian countries seem to have a greater impact on India than the Western countries. But we will discuss more about this issue later.

The impulse responses in Figure 5 provide inefficiency measures in utilizing cross-country information but they do not provide an aggregate measure for news utilization. As an aggregate measure, we construct the intertemporal variance decompositions for India in Figure 6. From this graph it can be seen that 90 percent of revision variance are accounted for by the past two months' shocks. This implies that Indian forecasters are using information quite efficiently on average and, though found inefficient by the Nordhaus test, the Indian forecasts seem to reflect new information quite promptly. Let us note that the aggregate news utilization curve as depicted in Figure 6 is robust to alternative identification schemes (i.e. ordering of the variables, contemporaneous restrictions, etc.) because all the countries have been aggregated in these calculations.

### 5.2 *FS*V*AR results*

The estimation of FSVAR is similar to the estimation of any structural VAR with one important difference. Instead of restrictions on the contemporaneous interaction among variables, or long-run restrictions, we assume that contemporaneous interactions among variables are due to common factors. This implies that the estimation is performed in two steps similar to Clark and Shin (2000). In the first step, VAR is estimated in the usual way. In the second step, we maximize the likelihood function to find the unknowns $\Lambda$ and $\sigma_{ui}$s. The confidence intervals for the impulse responses and variance decompositions are constructed by 500 bootstrap runs.

In order to estimate the FSVAR model, first we have to make sure that identification conditions are satisfied and also we have to decide on the number of common factors in the model. The order condition implies that for exact identification of this structural VAR, we need 7x6/2=21 restrictions and we can estimate 7x8/2=28 parameters (i.e. the number of single elements of the variance covariance matrix $\Omega$). This implies that our FSVAR model is overidentified (in terms of the order condition) when $k \leq 3$. In order to uniquely identify the factor loadings we need to normalize the effect of one of the common factors (when k=2) or two of the common factors (when k=3). For example when k=2, we set the impact of the second factor on US to zero. Then the total number of parameters to be estimated becomes *(2*7-1)+7=20*. Similarly, when k=3, we set the impact of the second and third factors on US, and the impact of third factor on Japan to zero.[18] Then the total number of parameters to be estimated becomes *(3*7-3)+7=25*. So the FSVAR structure imposes 28-(7.1)+7=*14* restrictions when *k=1*, *28-20=8* restrictions when *k=2* and 28-*25=3* restrictions when *k=3*.

Using these restrictions, we tested the overidentifying restrictions and presented results in Table 5. The hypothesis of one common factor is strongly rejected while the hypothesis of 2 and 3 common factors are not rejected at the conventional significance levels. So we use an FSVAR model with two common factors.

The estimated impulse response functions to the domestic shocks and two common factors are given in Figure 7. The first chart of Figure 7 shows the utilization of the domestic information and 95% confidence intervals. Similar to the findings with generalized impulse responses, we observe that impulse responses to domestic shocks go to zero almost immediately. The second and the third charts in Figure 7 show the utilization of the international common factors. As opposed to the quick utilization of the domestic information, we observe some stickiness in utilization of information in the common factor. Especially, the information related with second common factor is very slowly absorbed in the forecasts. As we will discuss later, this second common factor can

[18] Note that while the interpretation of common factors change depending on which countries are used for normalization, the intertemporal variance decompositions and so the results of this study are not affected by the normalization scheme.

be considered as the Asian common shock, which implies that Indian forecaster may increase their forecast efficiency by utilizing the Asia-related shocks more promptly.

To construct an aggregate measure of inefficiency we calculated the intertemporal variance decompositions for Indian forecast revisions. Figure 8 presents the intertemporal variance decompositions calculated from the FSVAR (1) model. The figure clearly shows that more than 90 percent of the forecast revision variation is captured within 2 months the information becomes available. Also notice the similarity between Figure 8 with Figure 6. If the model were exactly identified then the aggregate measure of inefficiency calculated in the previous section would be exactly same as the aggregate measure of the model calculated here. This is because $(1/TH)\Sigma\hat{\varepsilon}\hat{\varepsilon}' = \hat{\Omega}$ would be exactly satisfied for exactly identified systems. But since the model is over-identified, our constructed errors do not satisfy $(1/TH)\Sigma\hat{\varepsilon}\hat{\varepsilon}' = \hat{\Omega}$ exactly, and hence this aggregate measure of inefficiency could be different from the previous estimate. This implies that better the restriction imposed by equation (7) fits the model, the closer the two estimates of aggregate measure of inefficiency would be. So the similarity between Figure 8 and Figure 6 implies that the FSVAR model fits the data well and this can be taken as additional support for the FSVAR specification.

We compute the individual intertemporal variance decompositions, i.e. domestic, foreign countries and common factors. In order to be brief, we only present the most interesting results, which are the utilization of information in the common factors. The intertemporal variance decomposition for the combined common factors which is based on equation (9) is given in Figure 9. Similar to the findings in the impulse responses presented in Figure 7, we find that forecasters tend to under utilize news from common international factors initially. It takes up to 4 months to reach 90 percent threshold in terms of explaining the revision variance accounted for by the two international common factors.

To be briefly we find that Indian forecasts are not efficient in the sense that forecast revisions are serially correlated (e.g., Nordhaus (1987)) but the degree of inefficiency is quite low. As we have mentioned earlier several models may explain this observed inefficiency. The evidence of inefficiency may be due to sticky-information, rational inattention, credibility issues or rational bias. Another explanation may come from the inefficiency of the statistical agency processing the available information. Faust *et al.* (2005) found that the actual data revisions that are produced by statistical agencies of UK, Italy and Japan are highly predictable, but they are much less so for US. This implies that some part of the observed forecast inefficiency can be due to the inefficiency of the statistical agencies rather that of the forecasters.[19]

We should again point out that our methodology for testing for forecast efficiency and studying the causality of international shocks are independent of the actual values that are only subsequently observed. That is, we do not need the actual forecast errors in our analysis. Apart from the fact that forecast errors are observed much later than when forecasts are made, any analysis based on forecast errors (i.e., actual minus predicted) has very little value in real time. In addition, the forecast errors depend on data revisions, which are sometimes substantial. Not surprisingly, the Indian GDP figures go through substantial data revisions. For instance, the initial June value of the year-over-year growth rate in real GDP for FY 2000 was revised from 6.0% in June 2001 to 4% in February 2002. Since 1995 such revisions have been nearly 0.5% on the average.

## 6 Empirical Results on Transmission of Shocks as Implied by Forecast Data

### 6.1 *Under Perfect Efficiency - Static Factor Analysis*

Under the assumption that forecast data is efficient the cross-country correlations of forecast revisions show the importance of cross country linkages in monthly shocks. We provide these correlations in forecast revisions across seven selected countries and country groups in Table 6. As seen in this table, the correlations for India with USA, EU-3 and UK are only around 0.12; the corresponding values for South East Asian region (0.39), Japan (0.31), and North East Asian region (0.38) are much higher. By contrast, the correlations between North East Asia region and South East Asia region, and between EU-3 and USA, EU-3 and the UK are in excess of 0.50. Note that these contemporaneous correlations can be due to production, consumption and FDI interdependencies, or

[19] It will be interesting to examine if the real GDP revisions produced by CSO of India have any predictable

common exogenous shocks with out such interdependencies, see Canova and Marriman (1998) and Ghatak and Halicioglu (2007).

To observe how these correlations change over our sample we constructed the correlations of the forecast revisions of the three countries and three country groups with respect to Indian forecast revisions over a rolling window of 36 observations. The results are presented in Figure 4. The first figure presents the correlations for Japan, South East Asia and North East Asia and the second figure presents the correlations for the US, the three countries of the European Union and the UK. On the horizontal axis we give the periods over which the correlations are calculated. Notice that 36 observations represent 21 month period, this is because the forecasters report 2 forecasts each month, and also we drop three observations to match the fiscal year and calendar years. The correlations show that typically forecast revisions of the Asian countries have larger correlations with Indian forecast revisions than those of the US, the EU or the UK. Especially from 1997 to 1998, a period that covers Asian crisis, the correlations with North East Asia and South East Asia increase over 0.60. Another interesting observation from the first figure is that the correlations of the Asian countries seem to be moving together, which may suggest an existence of a common Asian business cycle. Later, when we present our results of the FSVAR model, we will address this issue again and show that there is really somewhat strong common factor that affects the Asian countries.

As discussed earlier, if we assume that the forecasts are efficient then static factor analysis methods provide evidence about how common factors impact individual country's real GDP growth. We use factor analysis to shed light on how the economies naturally group together in terms of the reaction to the common factors. Table 7 presents such factor loadings for the selected countries and country blocks estimated based on Equation (10). Identification problem can be solved in two different ways in the static factor analysis. One way is to impose a normalization pattern on the estimated factor loadings as we discuss earlier. Second approach is applying an orthogonal transformation on the estimated factor loadings. In Table 7, we used Varimax transformation to get meaningful estimates for the factor loadings. We report the results for two and three

component, see Faust et al. (2005) and Mankiw and Shapiro (1986).

common factors. The null hypothesis that the number of factors is sufficient is not rejected for both the models with p-values of 0.61 and 0.57 for the two and three common factor models respectively. When we consider two factors, we see that the first common factor contributes highly to the forecast revisions of South East Asian and North East Asian country groups. It also contributes to the Indian and Japanese forecast revisions but to a lesser extent. The second common factor contributes highly on EU-3 group and also to the USA and the UK. These results imply that when we assume two common factors we observe two distinct business cycles. The first one affects mainly the East Asian countries and India, and the second common factor affects the Western countries, i.e. EU-3, USA and UK.

With three common factors, the first common factor contributes to NE and SE Asian countries as before and the second common factor contributes to EU-3, USA and UK as before. The last common factor now contributes mainly to the Indian forecast revisions implying that the Indian business cycles may have some distinct movements that are not captured by either the East Asian or Western business cycles. Also let us note that Western common factor (factor 2) does not contribute any significant amount to the Indian real GDP forecast revisions. These results imply that India is affected more by the East Asian common factor than the Western common factors, and it is also largely affected by domestic shocks. So far we have assumed that the forecasts are efficient. In the next section we assume that the forecasts are not efficient in the short-run but efficient in the long-run.

### 6.2 *Under Long-run Efficiency – FSVAR Model Results*

The estimated variance decompositions are given in Table 8. The first international common factor seems to be the common factor among US, UK and EU-3 (Western common factor). The second factor, on the other hand, can be interpreted as the common factor across the Asian countries. Especially for South East Asia the importance of this second factor is very large. It accounts for 76 percent of the South East Asian real GDP growth shocks. Since our sample period covers the Asian financial crisis, it is very likely that this second common factor is mainly capturing the common behavior of the GDP growth rates of the region countries during the Asian crisis. The Asian crisis started in Thailand in July 1997 and quickly spread the other South East Asian countries. The north east Asian region is affected less by this common shock partly because China is a member of this group, which was much less affected compared to other Asian countries. India is another country that was not affected much from the Asian crisis but the variance decompositions show that while Asian common factor accounts for 38 percent of the Indian GDP growth variance, share of domestic shocks in Indian GDP growth is around 42 percent.

In the mid 1997 and 1998 we see that current and next year forecasts have very large common movements due to Asian crisis, which may cause increased comovement of the GDP variations over a short period time. In order to test for the impact of the Asian crisis on our estimates, we estimate the model after excluding the survey data from 1997.7- 1998.12 period. The results with two common factors are reported in the first panel of Table 9. As expected the share of the Asian common factor decreases to 16 percent and share of domestic shocks become 61 percent. In addition to the decreasing effect of the second common factor, we also see that the first common factor's importance increases for all of the countries including India.[20] After Asian crisis period is excluded, what we labeled as the 'Western' cycle becomes more like a "world shock" that is affecting all the countries significantly. Moreover, results for South East Asia region suggest that we may not need the second common factor at all. When we exclude the Asian crisis, the share of domestic shocks in South East Asia Region becomes zero and factor 1 and factor 2 together explain 85 percent of the total GDP variation in SE-Asia region, which suggests that the use of only one common factor may be preferable. So we estimate the model assuming a single common factor and the results are reported in the second panel of the table. The p-value from the LR test for the null hypothesis of a single common factor is now 0.02 and not rejecting the null hypothesis at 1 percent significance level. The single common factor now accounts for a significant share of the GDP variation in all of the countries. Since the impact of the common factor is widespread, we can now think of this common factor as a world shock. For India, it

[20] We also estimated models after discarding three obvious outliers during the Asian crisis. These outliers are the current and next year forecasts reported on 1998.6 and next year forecasts reported on 1998.5. The results are similar to the ones reported in the sense that Asian common factor's contribution decreases

accounts for 23 percent of the variation while India's domestic shocks account for 65 percent of the total variation.

As mentioned earlier our estimates are biased in favor of finding a large share for the common factors and underestimating the impact of individual country shocks. This means that the large shares of common factors given in Table 8 and Table 9 in the US and EU-3 GDP variations may be actually driven by idiosyncratic shocks of US and/or Europe. But our current model does not let us identify this since so far we assume that $A=I$ in equation (7). Remember that $A$ matrix shows the contemporaneous utilization of news from transmission of idiosyncratic shocks across countries (i.e., spillovers).

The suspiciously high contribution of the common factor to US and EU-3 real GDP variations prompts for a robustness check. To test this we make slight modifications to the $A$ matrix in equation (7). We let $A$ have nonzero elements in the column that corresponds to the US data, so that we let US shocks to be utilized contemporaneously in other countries' GDP growth forecasts. But if we let US shocks to have an effect on the other countries in the model then the impact of common factors and US will not be individually identified.[21] In order to identify the model, we need to impose additional restrictions on $\Lambda$. Based on our previous findings, we assume that the first common factor does not have contemporaneous impact on Japanese GDP growth and the second common factor does not have contemporaneous impact on EU-3.[22] In this way, degree of freedom becomes 9 for the single factor model and 4 for the two-common factor model. The results of the estimations along with the corresponding LR test results are presented in Table 10.

The first part of Table 10 presents the results with two common factors. As expected, the share of the US shocks on other countries increases. For example, US shocks account for 90 percent of the US GDP growth variations and 58 percent of the EU-3 GDP growth variations. But still we see that the US shocks do not account for more

substantially but it does not decrease as much as when we exclude the Asian crisis period altogether.

[21] More specifically, in the variance decompositions the sum of shares of the variances accounted for by the common factors and the US will be fixed. So the other countries' share in the variance decompositions will be identified but not between the US and the common factors.

[22] Remember that we have already one restriction on the impact of the second common factor on US.

than 5 percent of the real GDP variations in Asian countries. Also note that the results with two common factors are not very reasonable in the sense that idiosyncratic EU-3 shocks account for less than 1 percent of the EU-3 GDP growth variations. Also the first common factor looks irrelevant because, except EU-3, no other country is affected by this common shock significantly. Because of these reasons, we also give the results of the model with a single common factor in the second part of the table. The results in this table imply that the first common factor is a common factor across the Asian countries and the US factor is the first or the second largest contributor of the GDP variations in most of the countries. But even in this model India seems not to be affected from US shocks. In addition, the overidentifying test statistics has a p-value less than 1 percent and the null of a single common factor is strongly rejected.

The finding that India's GDP shocks are driven mainly by the Asian common factor and not by the Western countries is reasonable when India's 'Look East Policy' that has been in effect since early 1990s is considered. It is very possible that with the signing of new trade agreements between India and the other Asian countries, the importance of the Asian factors will increase in the future even more.[23]

So far we have identified the existence of an Asian common factor, but we did not discuss what constitutes this "Asian common factor". Since we only analyze the post 1995 period we can think of these common factors as regional shocks that affected the Asian countries exclusively. The change in the demand for semi-conductors, Japanese stagnation, appreciation and depreciation of USA dollar against Japanese yen and European currencies since 1994 which affected most of the Asian countries since their currencies are pegged against US dollar can be given as examples.

## 7 Concluding Remarks

In this paper we study the sources of Indian real GDP variations using monthly forecast data. Since 1989, the *Consensus Economics Service Inc.* has been providing such data on a number of macroeconomic variables for a large number of countries. Because

[23] India has signed bilateral free trade agreements with Nepal, Sri Lanka and, in August 2004, with Thailand. Such agreements with other Asian countries including China and Singapore are also underway.

these forecasts come on a monthly basis, the usefulness of such information for real time macro-economic management (e.g., inflation and GDP growth targeting) can not be overemphasized. The track record of automated forecasts based on macro models has been disappointing due to structural breaks and specification instability. As a result, there has been a renewed interest in survey forecasts. Even though these forecasts tend to respond to current news well, they are found to be somewhat sluggish in their adjustments. Many behavioral and institutional explanations have justified the apparent irrationality of these forecasts.

In order to use the forecast data to extract important information on the economic fundamentals, we start our analysis by providing forecast evaluation tests for fixed-event forecasts. We propose an econometric framework to analyze monthly fixed-target real GDP forecasts of India where forecasts for its major trading partners are also considered simultaneously. Our framework is useful not only for testing the forecast efficiency but also to estimate the degree of efficiency. Using monthly data over January 1995 – November 2002, we found that the real GDP forecasts are not fully rational. In addition to India, we also considered forecasts for US, UK, European block, Japan, Southeast Asia and Northeast Asia to examine if Indian forecasters incorporate news coming from these country blocks correctly. Indeed, our evidence suggests, whereas the domestic information is incorporated in forecast revisions in a rational manner, foreign news take a little longer to be fully reflected in forecast up-dating. Thus, the observed inefficiency in Indian real GDP forecasts is due to forecasters' sluggishness in reacting to foreign news. It takes nearly 4 months for foreign news to get fully reflected in Indian forecast revisions. Nevertheless, the quality of these forecasts compare very favorably to those of the US and Canada.

After detecting the degree of inefficiency in the forecasts, we provide an 'efficiency adjusted' utilization of cross-country news components and then study the transmission of shocks across countries including common international shocks in our model. By assuming that the forecasters are long-run efficient we construct average variance decompositions for Indian real GDP shocks and found that almost 60% of the real GDP shocks for India come from foreign countries, and the rest is explained by domestic shocks. We see that the Asian common factor is the second largest contributor after the domestic shocks accounting for 38 percent of the Indian real GDP growth variations. However, when we exclude the surveys reported during the Asian crisis (1997.7 to 1998.12), we see that the contribution of domestic shocks increase to 61 percent and Asian common factor contributes only 16 percent of the variations, which is also the same as the contribution of the Western common factor. The relatively large contribution of domestic shocks in consistent with a basic distinguishing characteristic of developing countries where much of the forecast revisions can be attributed to volatile domestic shocks due to political uncertainty, vagaries of monsoon, natural disasters, monetary policies, budget announcements, data revisions, and the like.

One advantage of our approach is that the analysis of transmission of shocks is studied in real time, and does not depend on the actual values of the variable that are observed much later than the forecasts. Apart form the uncertainty due to data revisions, any analysis based on forecast errors has very little value in real time

Much remains to be done in utilizing this multi-country forecast data. In addition to real GDP, one can also use forecast information on inflation, interest rates and exchange rates available in the data set to build multivariate models that can discriminate between demand shocks and supply shocks. The forecasts for real GDP, inflation and exchange rates will move in the same or opposite directions depending on the nature of shocks. The type of shocks in turn determines the type of monetary, fiscal, and exchange rate policies the government should undertake. Since these shocks can potentially be identified on a monthly basis in real time, appropriate stabilization policies can conveniently be fine-tuned for sound macroeconomic management. Given all these potential, as years pass, the value of this forecast data is sure to grow like old wine.

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**Table 1 Economic Forecasters for India**

| | |
|---|---|
| • ANZ Investment Bank | • Hindustan Lever |
| • Bank of Tokyo Mitsubishi | • HSBC Securities |
| • Chase JF | • JP Morgan |
| • CDE-DSE Research | • Morgan Stanley Asia |
| • Confed of Indian Industry | • Natl Cncil Apl Eco Rsrch |
| • Credit Suisse First Bstn | • SG Securities |
| • Deutsche Bank | • SSB Citibank |
| • Dresdner Bank | • Tata Services (DES) |
| • DSP Merrill Lynch | • UBS Warburg |
| • Global Insight | • UTI Securities |
| • Goldman Sachs Asia | • WEFA Group |

**Table 2 Relation between the Calendar year and Fiscal Year (April to March) Forecasts**

| | | | Year = 2000 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | ..……..Dec |
| Calendar Year Forecast | Current Year Forecast | Horizon | 12 | 11 | 10 | 9 | 8 | 7 | 6 | 5 | ,…………,1 |
| | | Target year | 2000 | 2000 | 2000 | 2000 | 2000 | 2000 | 2000 | 2000 | ,……..,2000 |
| | Next Year Forecast | Horizon | 24 | 23 | 22 | 21 | 20 | 19 | 18 | 17 | ,..………,13 |
| | | Target year | 2001 | 2001 | 2001 | 2001 | 2001 | 2001 | 2001 | 2001 | ……..,2001 |
| | | | | | | | | | | | |
| Fiscal Year Forecast | Current Year Forecast | Horizon | 3 | 2 | 1 | 12 | 11 | 10 | 9 | 8 | ,…………,4 |
| | | Target year | 1999 | 1999 | 1999 | 2000 | 2000 | 2000 | 2000 | 2000 | ,……..,2000 |
| | Next Year Forecast | Horizon | 15 | 14 | 13 | 24 | 23 | 22 | 21 | 20 | ,………..,16 |
| | | Target year | 2000 | 2000 | 2000 | 2001 | 2001 | 2001 | 2001 | 2001 | ,……..,2001 |

Note: The gray area shows the data that are not used.

**Table 3 Definition of Country Groups and country weights**

| Country Group | Countries and GDP shares [a] |
|---|---|
| Europe-3 | Germany (46%), France (30%) and Italy (24%) |
| South East Asia | Indonesia (32.5%), Malaysia (14%), Singapore (13.75%), Thailand (26.6%) and Philippines (13.75%) |
| North East Asia | China (45%), Hong Kong (8.9%), South Korea (29.5%) Taiwan (16.5%). |

[a] The Europe-3 weights are calculated using the 1995 GDP shares from International Financial Statistics-February 2002. The remaining weights are computed by regressing the regional total data provided by the Asia Pacific Consensus reports on the individual country GDP forecasts using survey data from 2001-2002. The shares may not add up to 100% due to rounding.

**Table 4 Selection of lag length in VAR**

| Model | Akaike-IC [a] | Schwarz IC [a] | $\bar{R}^2$ (India) | $R^2$ (India) |
|---|---|---|---|---|
| VAR(1) | -5.34 | -4.20 | .10 | .14 |
| VAR(2) | -5.14 | -2.92 | .08 | .18 |
| VAR(3) | -4.71 | -1.30 | .05 | .20 |

[a] Akaike and Schwarz Information Criteria statistics for the whole VAR system and not only for the equation of India.

**Table 5 Tests for Overidentifying Restrictions from FSVAR(1) model (k-factor versus unrestricted error covariance matrix)**

| Number of factors | d.f. | LR Statistic | p-value |
|---|---|---|---|
| 1 | 14 | 81.58 | .00 |
| 2 | 8 | 8.69 | .37 |
| 3 | 3 | 2.38 | .50 |

**Table 6Correlations of Forecast Revisions-**

| | EU-3 | India | Japan | NE-Asia | SE-Asia | UK | USA |
|---|---|---|---|---|---|---|---|
| **EU-3** | 1.00 | | | | | | |
| **India** | 0.12 | 1.00 | | | | | |
| **Japan** | 0.49 | 0.31 | 1.00 | | | | |
| **NE-Asia** | 0.14 | 0.38 | 0.33 | 1.00 | | | |
| **SE-Asia** | 0.16 | 0.39 | 0.40 | 0.75 | 1.00 | | |
| **UK** | 0.75 | 0.14 | 0.43 | 0.24 | 0.30 | 1.00 | |
| **USA** | 0.59 | 0.11 | 0.38 | 0.31 | 0.21 | 0.47 | 1.00 |

**Table 7 Static Factor Analysis**

| | **2 Factors** | | **3 Factors** | | |
|---|---|---|---|---|---|
| | **Factor 1** | **Factor 2** | **Factor 1** | **Factor 2** | **Factor 3** |
| EU-3 | 0.05 | **0.91** | 0.03 | **0.88** | 0.07 |
| India | 0.42 | 0.11 | 0.25 | 0.06 | **0.97** |
| Japan | 0.40 | 0.28 | 0.35 | 0.29 | 0.21 |
| NE-Asia | **0.81** | 0.29 | **0.75** | 0.31 | 0.18 |
| SE-Asia | **0.94** | 0.04 | **0.97** | 0.05 | 0.16 |
| UK | 0.28 | **0.50** | 0.26 | **0.51** | 0.05 |
| USA | 0.18 | **0.64** | 0.16 | **0.66** | 0.03 |

Note: Table presents the factor patterns estimated by Maximum Likelihood estimation and that are transformed using an orthogonal transformation (Varimax). The test statistics for the null hypothesis on the sufficiency of the number of factors have p-values 0.61 and 0.57 for the two and three factor models respectively, not rejecting the null hypothesis. Entries greater than 0.5 are shown in bold.

**Table 8 Steady State Variance Decompositions for all countries from FSVAR(1) model with 2 common factors (full sample results)**

**Two Common Factors**
**(Over Identification test p-value=0.37)**

| Impact on: | Source of the shock: | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Factor 1** | **Factor 2** | **US** | **Japan** | **EU-3** | **UK** | **SE-Asia** | **NE-Asia** | **India** |
| US | **52%** | 0% | **40%** | 2% | 0% | 1% | 1% | 2% | 2% |
| Japan | 13% | **34%** | 1% | **36%** | 2% | 3% | 1% | 9% | 1% |
| EU-3 | **65%** | 3% | 1% | 0% | **14%** | 9% | 1% | 1% | 5% |
| UK | **25%** | 6% | 1% | 1% | 0% | **65%** | 1% | 0% | 2% |
| SE-Asia | 5% | **76%** | 1% | 1% | 2% | 3% | **9%** | 4% | 0% |
| NE-Asia | 14% | **56%** | 0% | 0% | 2% | 3% | 2% | **22%** | 0% |
| India | 8% | **38%** | 0% | 1% | 2% | 5% | 1% | 3% | **42%** |

Note: Steady-state variance decompositions are calculated from 31-period ahead forecast error variance shares (from squares of the aggregated impulse responses) of the FSVAR (1) model with two common factors. The largest two contributions for each country are shown in bold.

**Table 9 Steady State Variance Decompositions for all countries from FSVAR(1) model (Excluding the Asian Crisis 1997.7- 1998.12 survey data)**

**Two Common Factors**
**(Over Identification test p-value=0.45)**

| Impact on | Source of shock: | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Factor 1** | **Factor 2** | **US** | **Japan** | **EU-3** | **UK** | **SE-Asia** | **NE-Asia** | **India** |
| US | **61%** | 0% | **26%** | 2% | 0% | 1% | 0% | 8% | 2% |
| Japan | **34%** | **22%** | 0% | **31%** | 0% | 1% | 0% | 7% | 4% |
| EU-3 | **72%** | 0% | 0% | 0% | **8%** | 6% | 0% | 6% | 7% |
| UK | **36%** | 13% | 2% | 0% | 1% | **43%** | 0% | 2% | 3% |
| SE-Asia | **37%** | **48%** | 0% | 0% | 1% | 1% | 0% | 10% | 2% |
| NE-Asia | **41%** | **24%** | 1% | 1% | 1% | 1% | 0% | **30%** | 2% |
| India | **16%** | **16%** | 0% | 0% | 1% | 2% | 0% | 3% | **61%** |

**One common Factor**
**(Over Identification test p-value=0.02)**

| Impact on: | Source of shock | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Factor 1** | **US** | **Japan** | **EU-3** | **UK** | **SE-Asia** | **NE-Asia** | **India** |
| US | **63%** | **25%** | 2% | 0% | 1% | 0% | 7% | 2% |
| Japan | **48%** | 0% | **34%** | 1% | 1% | 5% | 7% | 4% |
| EU-3 | **68%** | 0% | 0% | **13%** | 7% | 0% | 6% | 7% |
| UK | **42%** | 2% | 0% | 1% | **46%** | 4% | 1% | 4% |
| SE-Asia | **51%** | 0% | 1% | 2% | 1% | **33%** | 10% | 2% |
| NE-Asia | **54%** | 1% | 1% | 1% | 1% | 11% | **29%** | 2% |
| India | **23%** | 0% | 0% | 1% | 2% | 5% | 3% | **65%** |

Note: Steady-state variance decompositions are calculated from 31-period ahead forecast error variance shares (from squares of the aggregated impulse responses) of the FSVAR (1) model with one and two common factors. The surveys that are reported between July-1997 and December-1998 are excluded from the analysis. The largest two contributions for each country are shown in bold.

**Table 10 Steady State Variance Decompositions for all countries from FSVAR-US (1) model when Forecast Horizon for India ≥ 6**

**Two common Factors**
**(Over Identification test p-value=0.28)**

| Impact on: | Source of the shock | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Factor 1** | **Factor 2** | **US** | **Japan** | **EU-3** | **UK** | **SE-Asia** | **NE-Asia** | **India** |
| US | 2% | 0% | **90%** | 2% | 0% | 1% | 1% | 2% | 2% |
| Japan | 1% | **42%** | 4% | **37%** | 0% | 3% | 1% | 9% | 1% |
| EU-3 | **24%** | 0% | **58%** | 0% | 0% | 10% | 1% | 1% | 5% |
| UK | 2% | 13% | 10% | 1% | 0% | **71%** | 1% | 0% | 2% |
| SE-Asia | 3% | **77%** | 0% | 1% | 0% | 3% | **12%** | 4% | 0% |
| NE-Asia | 1% | **68%** | 3% | 0% | 0% | 4% | 2% | **21%** | 0% |
| India | 1% | **45%** | 2% | 1% | 0% | 5% | 2% | 3% | **42%** |

**One common Factor**
**(Over Identification test p-value=0.00)**

| Impact on: | Source of the shock | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Factor 1** | **US** | **Japan** | **EU-3** | **UK** | **SE-Asia** | **NE-Asia** | **India** |
| US | 1% | **90%** | 2% | 1% | 1% | 2% | 1% | 2% |
| Japan | **33%** | 14% | **37%** | 4% | 4% | 3% | 5% | 1% |
| EU-3 | 0% | **43%** | 0% | **35%** | 12% | 3% | 1% | 6% |
| UK | 8% | 11% | 1% | 1% | **77%** | 2% | 0% | 2% |
| SE-Asia | **56%** | 7% | 1% | 5% | 3% | **26%** | 2% | 0% |
| NE-Asia | **61%** | **15%** | 0% | 4% | 4% | 4% | 10% | 0% |
| India | **35%** | 8% | 1% | 3% | 5% | 3% | 2% | **42%** |

Note: Steady-state variance decompositions are calculated from 31-period ahead forecast error variance shares (from squares of the aggregated impulse responses) of the FSVAR-US (1) model with one and two common factors. The largest two contributions for each country are shown in bold.

**Figure 1 Multistep Forecasts of Indian Real GDP Growth (FY1996-FY2001)**

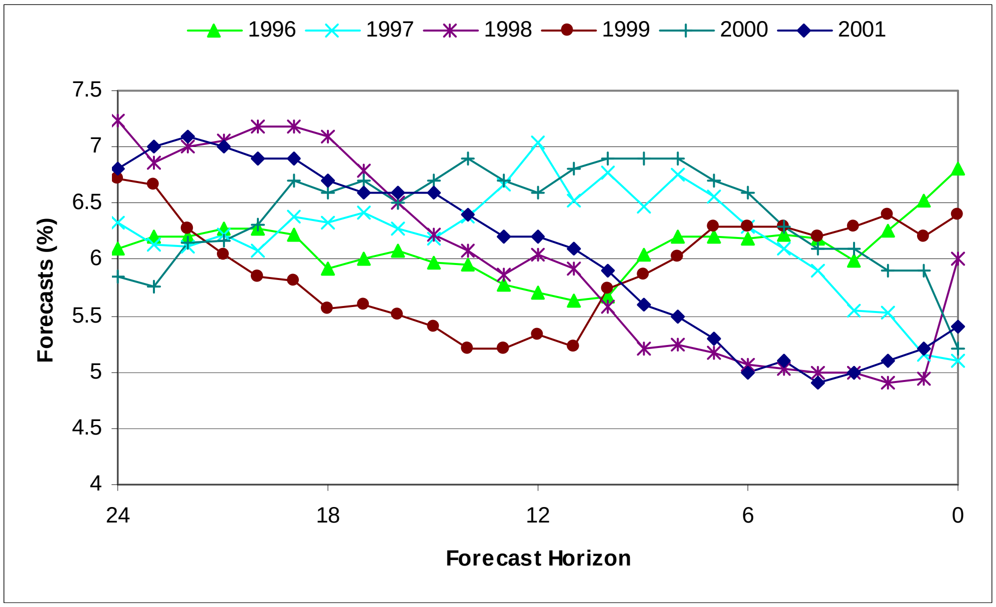



**Figure 2 Indian Real GDP Shocks based on Current Year Forecast Revisions**

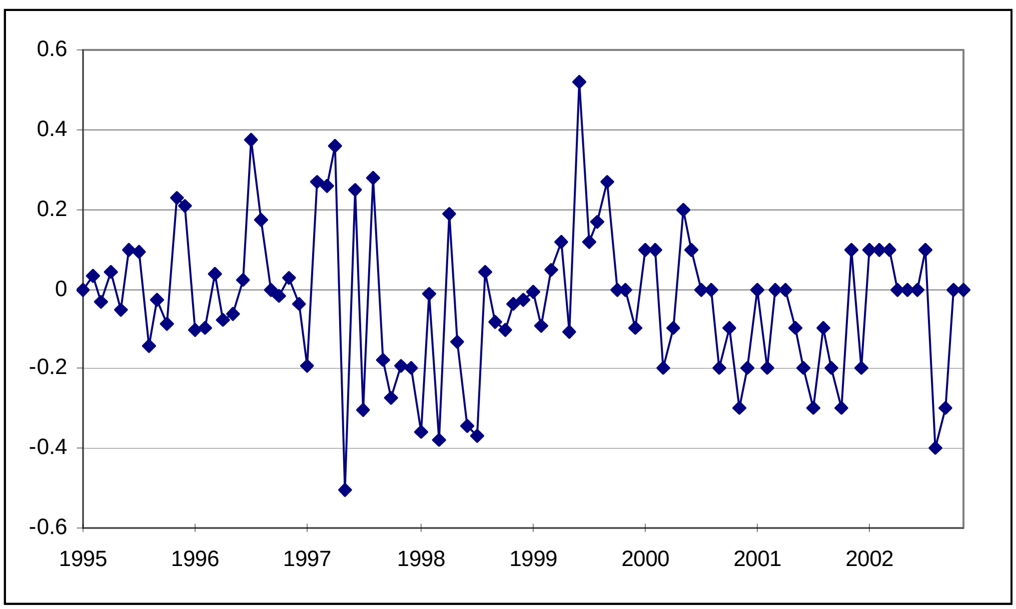


**Figure 3 Indian Real GDP Shocks based on Next Year Forecast Revisions**

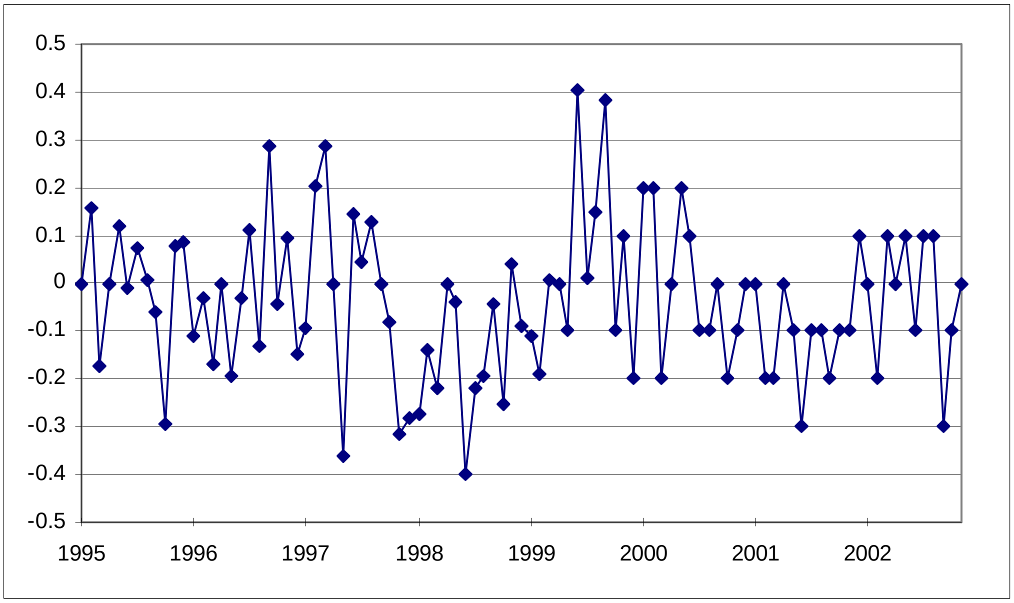
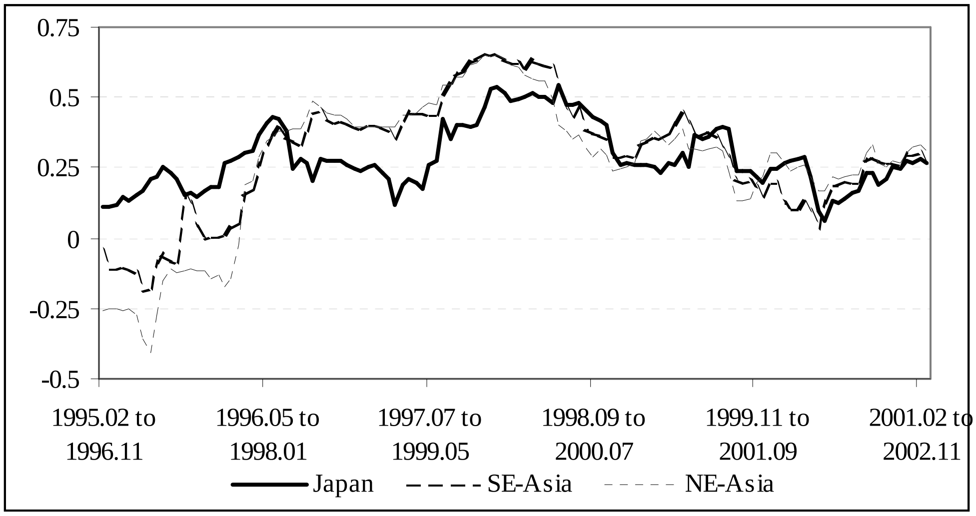


**Figure 4 Rolling Correlations with Indian Forecast Revisions using a window of 36 observations**



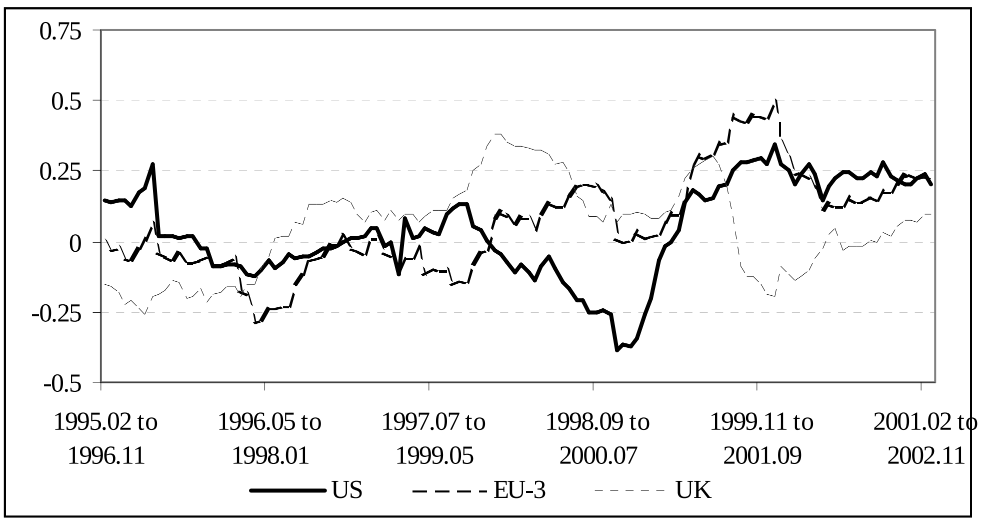



**Figure 5 Generalized Impulse Responses of Indian Forecast Revisions**

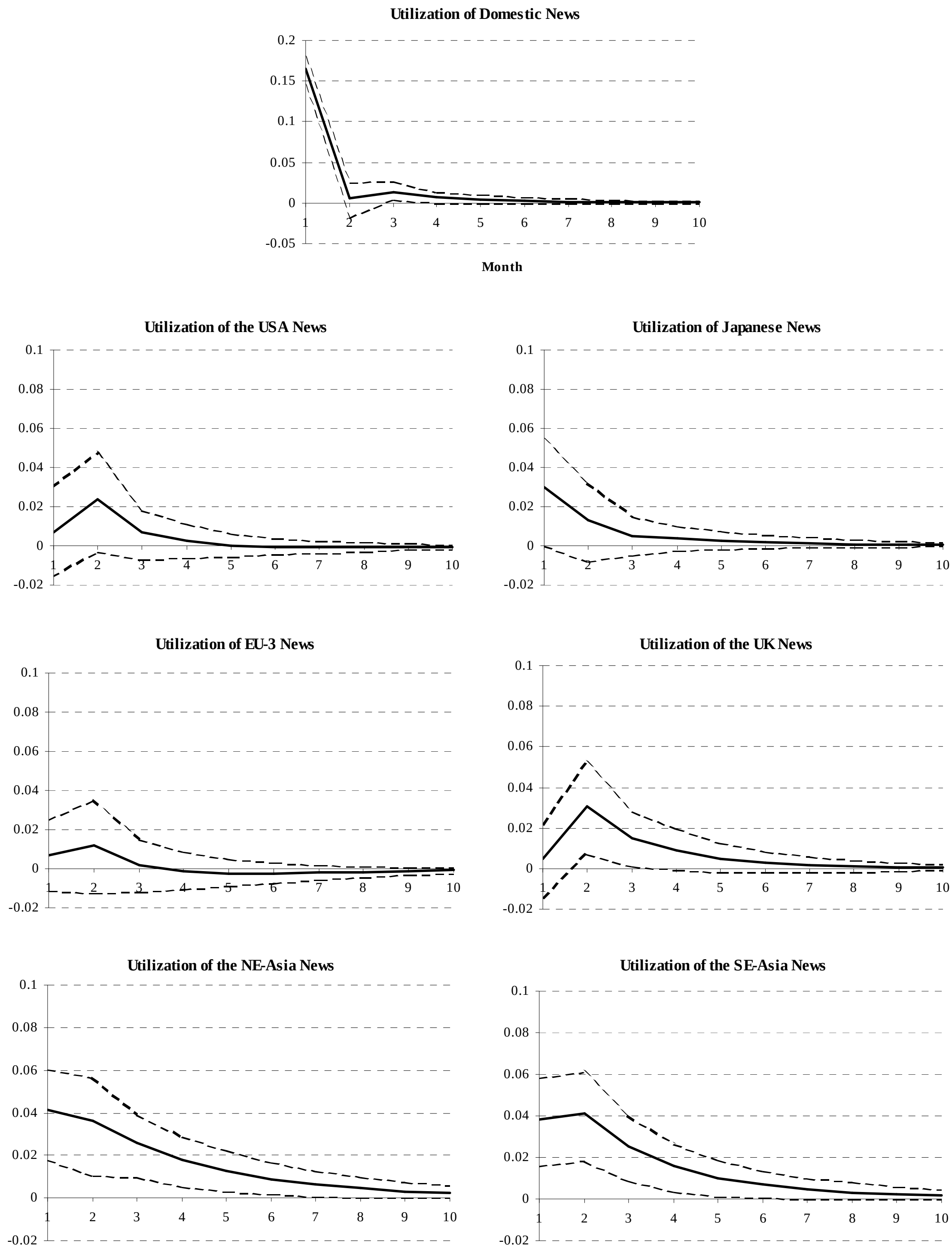


**Figure 6 Intertemporal Variance Decompositions from exactly identified VAR(1) and 95% Confidence Bands - Total (Cumulative, %)**

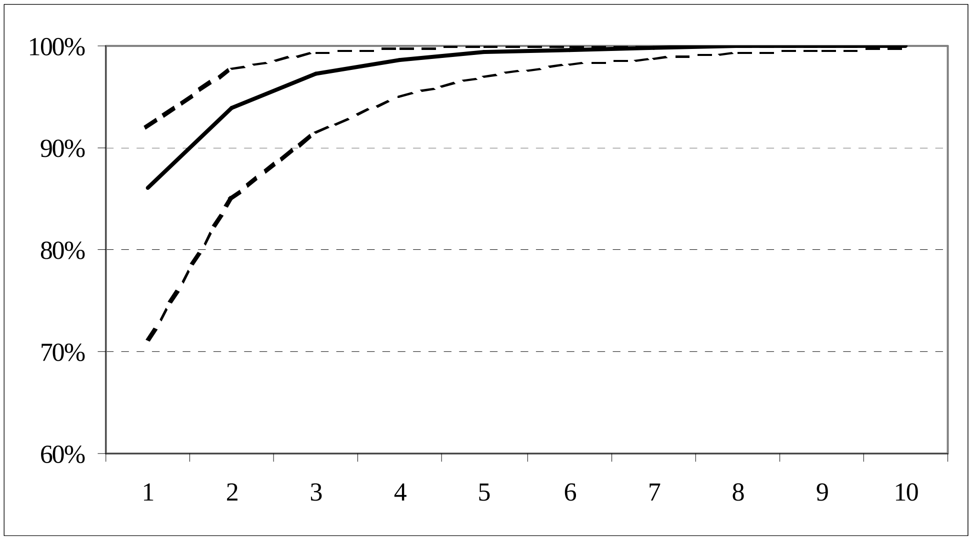
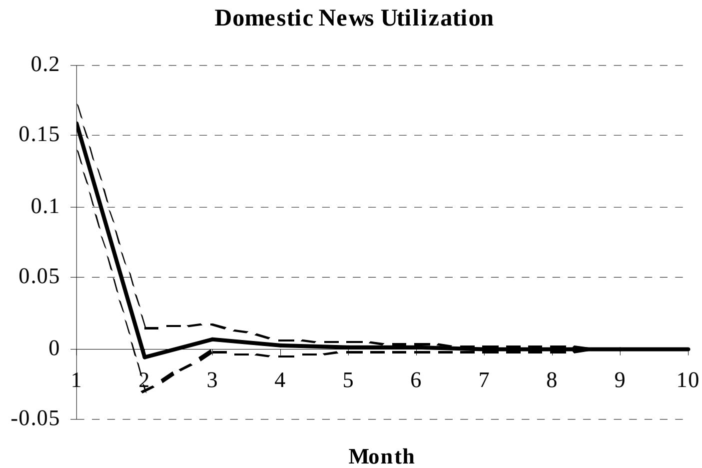
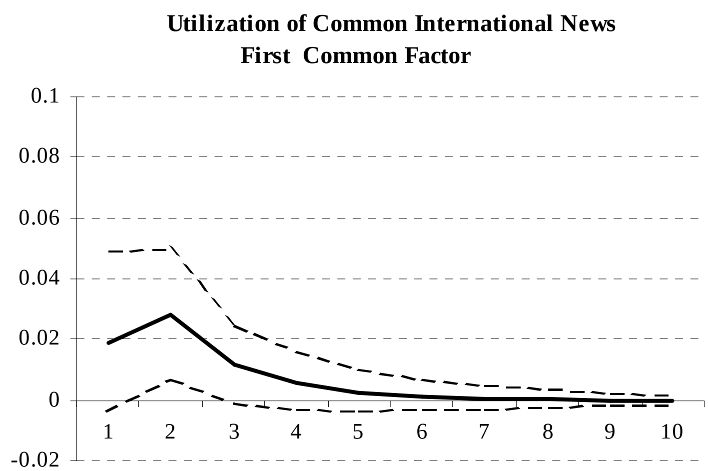


**Figure 7 Impulse Responses of India from FSVAR(1) model- Domestic News and Common International News**



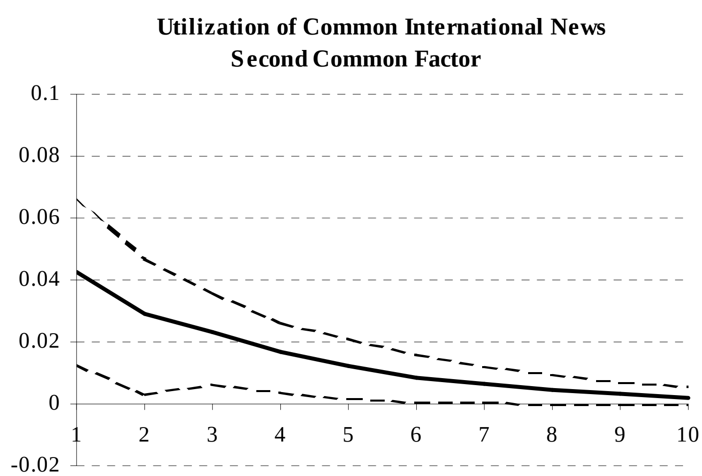



**Figure 8 Intertemporal Variance Decompositions of India from FSVAR(1) ±2SE - Total (Cumulative, %)**

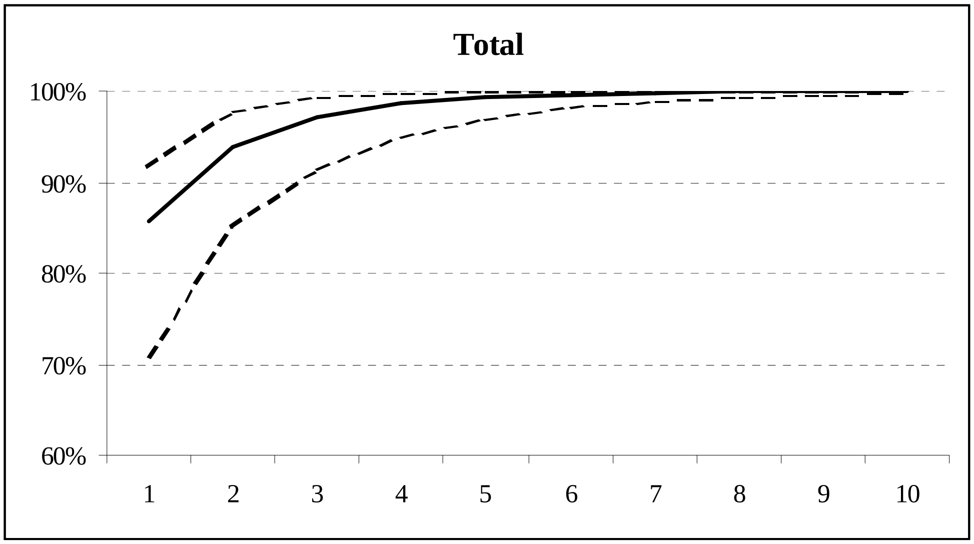



**Figure 9 Intertemporal Variance Decompositions of India ±2SE - International Common Factors (Cumulative, %)**