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Abstract

Emerging-market economies have become increasingly important in driving global GDP growth over the past 10 to 15 years. This has made timely and accurate assessment of current and future economic activity in emerging markets important for policy-makers not only in these countries but also in advanced economies. This paper uses state-of-the-art dynamic factor models (DFMs) to nowcast real GDP growth in five major emerging markets—Brazil, Russia, India, China and Mexico ("BRIC+M"). The DFM framework allows us to efficiently handle data series characterized by different publication lags, frequencies and sample lengths. This framework is particularly suitable for emerging markets for which many indicators are subject to significant publication lags and/or have been compiled only recently. The methodology also allows us to extract model-based "news" from a data release and assess the impact of this news on nowcast revisions. Results show that the DFMs generally outperform simple univariate benchmark models for the BRIC+M. Overall, our results suggest that the DFM framework provides reliable nowcasts for GDP growth for the emerging markets under consideration.

JEL classification: C33, C53, E37
Bank classification: Econometric and statistical methods; International topics

Résumé

Au cours des dix à quinze dernières années, les économies de marché émergentes ont pris une place grandissante dans la croissance du PIB mondial. C'est pourquoi il est important que les responsables des politiques publiques de ces pays, mais également ceux des économies avancées, disposent de prévisions rapides et exactes de l'activité économique actuelle et future dans les marchés émergents. Dans la présente étude, les auteurs ont recours à des modèles à facteurs dynamiques avancés pour prévoir, pour un horizon allant du passé récent au futur proche, le taux de croissance du PIB réel de cinq grands marchés émergents, soit le Brésil, la Russie, l'Inde, la Chine et le Mexique (pays du BRIC+M). Ces modèles permettent de traiter efficacement des séries de données dont les délais et la fréquence de parution ainsi que la longueur de la période d'observation sont différents, et ils conviennent particulièrement bien aux marchés émergents pour lesquels de nombreux indicateurs sont publiés après un long délai ou sont compilés depuis peu de temps seulement. De plus, la méthode utilisée permet aux auteurs d'extraire à l'aide des modèles de « nouveaux éléments d'information » à partir de la publication de nouvelles données, et d'évaluer l'incidence de cette information sur les révisions des prévisions pour la période en cours. Les résultats montrent que les modèles à facteurs dynamiques ont généralement un pouvoir prédictif supérieur aux modèles de référence univariés simples pour les pays du BRIC+M. Dans l'ensemble, les résultats indiquent que les modèles à facteurs dynamiques fournissent des prévisions fiables de la croissance du PIB pour la période en cours dans les marchés émergents à l'étude.

Classification JEL : C33, C53, E37
Classification de la Banque : Méthodes économétriques et statistiques; Questions internationales

Non-Technical Summary

Emerging-market economies (EMEs) have become increasingly important in driving global GDP growth over the past 10 to 15 years. EMEs such as Brazil, Russia, India, China and Mexico (henceforth "BRIC+M") have seen their collective share of global GDP increase from 21 per cent in 2000 to 32 per cent in 2014 in terms of purchasing power parity. This has made timely and accurate assessment of current and future economic activity in emerging markets important for policy-makers not only in these countries but also in advanced economies. The practice of assessing and predicting economic activity in the very recent past, the present and the near future is commonly referred to as nowcasting. Long and varied publication delays, different data-reporting formats (such as growth rates instead of levels) and limited availability of historical data in many cases make this practice particularly challenging for emerging markets.

The aim of this paper is to nowcast real GDP growth for each country in the BRIC+M grouping. Our nowcasting procedure relies on the dynamic factor model (DFM) framework developed by Giannone et al. (2008). We build and estimate individual DFMs for Brazil, Russia, India, China and Mexico using a variety of monthly economic indicators for each economy. We examine the real-time performance of the individual models by creating bimonthly pseudo real-time data sets for each country using data release dates from previous years to create a standardized bimonthly release calendar for each variable. We use the DFM framework to nowcast GDP growth and to evaluate the marginal impact of each new data release (i.e., "news") on the nowcast, which in turn allows the nowcaster to identify the likely sources of the nowcast revisions.

The predictive accuracy of the five DFMs is evaluated by means of a pseudo out-of-sample exercise conducted at a bimonthly frequency from 2008Q1 to 2014Q1. In this evaluation procedure, the historical data set is intentionally restricted to produce a forecast of a previous period that is subsequently evaluated against a realized outcome. We refer to this exercise as "pseudo" since we do not control for the presence of historical revisions in the data. Results show that the DFMs provide reliable nowcasts for GDP growth for the BRIC+M. The models display good directional accuracy and generally outperform simple statistical forecasting tools such as the autoregressive model. Further, we compute and evaluate the impact of "news"—defined as the difference between the expected and realized data—as well as parameter re-estimation on nowcast revisions. Results show that while the impact of re-estimation on nowcast revisions is generally very small, the contribution of "news" to the nowcast revision varies across countries and indicator groups.

1 Introduction

Since the turn of the century the global economic landscape has changed considerably with the share of major emerging-market economies, namely Brazil, Russia, India, China and Mexico (henceforth "BRIC+M"), growing from about 21 per cent of global GDP in 2000 to nearly 32 per cent of global GDP in 2014 in purchasing power parity (PPP) terms (Figure 1). Trade and financial linkages between advanced economies and emerging-market economies (EMEs) have also become much stronger, and the notion that advanced economies have become more dependent on demand from relatively fast-growing EMEs has gained ground. Thus, timely and accurate assessment of economic activity for the BRIC+M group is of great importance for policy-makers not only in these economies but also in advanced economies.

At the same time, nowcasting GDP growth - defined here as predictions of GDP growth in the very recent past, the present and the very near future - is more relevant for EMEs where GDP data are released with a longer lag than for most advanced economies. For example, the first flash estimates of GDP for the United Kingdom and the United States are available 4 weeks after the end of the quarter, compared with 13 weeks for Russia and more than 8 weeks for Brazil, India and Mexico. In addition to the delay in data releases, a number of data challenges further underscore the need to develop nowcasting tools for EMEs that are tailored to addressing these issues. These challenges include (1) data published at different frequencies (weekly, monthly or quarterly); (2) unbalanced data patterns at the end of the sample due to non-synchronous data releases ("ragged edge");[1](3) missing data at the beginning of the sample since many macro indicators for EMEs are available relatively recently; (4) varying data formats (such as year-over-year versus quarter-over-quarter growth rates); and (5) substantial data revisions. While these peculiarities of the data are not unique to EMEs, they are more pronounced for these countries relative to advanced economies.

The aim of this paper is to nowcast real GDP growth for the BRIC+M. We use state-of-the-art dynamic factor models (henceforth DFMs) based on Giannone et al. (2008) combined with the estimation methodology of Banbura and Modugno (2014), since this setup is well suited to overcome the data challenges highlighted above. Specifically, we build separate DFMs for Brazil, Russia, India, China and Mexico that utilize a variety of monthly indicators for each economy. We

[1] "Ragged edge" generally arises in real-time applications when there is a varying number of missing observations at the end of the sample since different series are released at different points in time and are subject to different publication lags.

assess the real-time performance of the individual country models by creating bimonthly pseudo real-time data sets for each country since real-time data are not available. To create these pseudo real-time data vintages, we use data release dates from previous years to create a standardized bimonthly release calendar for each variable in the data set. Together this provides data release patterns for 132 variables across the five EMEs. These data sets mimic precisely the data available to the nowcaster at the middle and end of the month (hence "real time") but do not incorporate the possibility of revisions (hence "pseudo"). Further, we use the DFM framework not only to nowcast GDP growth but also to evaluate the marginal impact of each new data release on the nowcast. Given the volatile nature of emerging-market data, the latter feature is particularly valuable since it allows the nowcaster or decision maker to identify the sources of the nowcast revisions.

Our paper contributes to the extant and growing literature on nowcasting with DFMs pioneered by Giannone et al. (2008). Although their DFM framework has become the workhorse model for forecasters at central banks and other institutions, the majority of applications are focused on advanced economies while EMEs have received very little attention. The methodology has been applied for several advanced economies, such as the euro area (Angelini et al. 2011; Banbura and Runstler 2011; and Runstler et al. 2009), France (Barhoumi et al. 2010), Ireland (D'Agostino et al. 2012), New Zealand (Matheson 2010), Norway (Astveit and Trovik 2012), and Switzerland (Siliverstovs and Kholodilin 2010).[2] Generally speaking, this literature has shown that nowcasts based on DFMs tend to be superior than those based on random walk models, autoregressive models and bridge models, and they perform at least as well as institutional forecasts. The literature has further shown that predictions based on DFMs can be efficiently revised as new data for the current quarter become available. Another robust finding in this literature is that the exploitation of early releases improves nowcast accuracy, or, in other words, the timeliness of data matters.

With regard to the literature focusing on EMEs, Liu et al. (2012) evaluate forecasts and nowcasts of real GDP growth using five different models for 10 Latin American countries. Their results show that the DFM consistently outperforms other model specifications in terms of forecast accuracy across most of the countries under consideration. In another recent application using Brazilian data, Bragoli et al. (2014) compare forecasts for Brazilian GDP growth from a DFM with the Central Bank of Brazil Survey. They find that the survey-based forecasts perform as well as DFM-based

[2] Banbura et al. (2013) provide a review of the literature on applications of factor models for nowcasting.

forecasts.

Our paper differs from these studies in three dimensions. First, the distinguishing contribution of our study is the creation of bimonthly pseudo real-time data vintages for the BRIC+M group, which allows us to evaluate the real-time performance of the DFMs for each country. Although Liu et al. (2012) also compile pseudo real-time data sets for Brazil and Mexico (along with other Latin American countries), to the best of our knowledge this paper is the first to do so at the bimonthly frequency, thus mimicking real-time data more closely. This feature of our framework could be particularly appealing for policy-makers as it allows for a more timely assessment of economic activity in EMEs. Second, our framework allows us to evaluate the marginal impact of each new data release on the nowcast, which is not the case for Liu et al. (2012). Finally, our country coverage and estimation samples are different from the existing studies that focus on EMEs.

Our results show that the DFM framework provides reliable nowcasts for GDP growth for the BRIC+M. We find that nowcasts based on DFMs generally outperform those based on univariate benchmark models. Generally speaking, the models display good directional accuracy and perform reasonably well in terms of capturing GDP dynamics during the global financial crisis of 2008-09 for most countries under consideration. Finally, we compute and evaluate the impact of "news," which is the difference between the expected and realized data, as well as parameter re-estimation on nowcast revisions. We find that the impact of re-estimation on nowcast revisions is generally very small. Further, the contribution of "news" to the nowcast revisions varies considerably across countries as well as indicator groups. However, one common finding is that data releases for exogenous (i.e., global and U.S.) variables do not play a major role in explaining nowcast revisions.

The remainder of the paper is organized as follows. Section 2 describes the econometric framework in detail. Section 3 describes the data and the nowcasting exercise, while section 4 presents the results. Finally, section 5 provides a concluding discussion.

2 Econometric framework

2.1 The dynamic factor model

In this paper, we use the modeling framework proposed by Giannone et al. (2008). We first describe the dynamics of the monthly data. Let $x_t = (x_{1,t}, x_{2,t}, ...x_{n,t})', t = 1, ...T$ denote the n-dimensional vector of monthly variables that have been transformed to achieve stationarity. We assume that x_t has the following factor model representation:

$$x_t = \mu + \Lambda f_t + \epsilon_t, \tag{1}$$

where f_t is a $r \times 1$ vector of (unobserved) common factors and Λ is an $n \times r$ matrix of factor loadings for the monthly variables. ϵ_t is a vector of idiosyncratic components. The common factors and the idiosyncratic components are assumed to have a mean of zero, implying that μ is a vector of unconditional means.

Regarding the dynamics of the idiosyncratic component of monthly variables, ϵ_t, we consider two alternative cases. First, we allow it to be serially uncorrelated, i.e., $\epsilon_t \sim i.i.dN(0, R)$. Second, following Banbura and Modugno (2014), we allow ϵ_t to follow an AR(1) process:

$$\epsilon_{i,t} = \alpha_i \epsilon_{i,t-1} + e_{i,t}, \qquad e_{i,t} \sim i.i.dN(0, \sigma_i^2), \tag{2}$$

with $E[e_{i,t}e_{j,s}] = 0$ for $i \neq j$. For each of the five EMEs under consideration, we choose between these two alternative cases based on the out-of-sample evaluation exercise.[3]

The common factors are modeled as a stationary vector autoregressive (VAR) process of order p:

$$f_t = A_1 f_{t-1} + ... + A_p f_{t-p} + u_t, \qquad u_t \sim i.i.dN(0, Q), \tag{3}$$

where $A_1, ..., A_p$ are $r \times r$ matrices of autoregressive coefficients. The DFM can then be easily cast into state-space form (see Section 2.3).

[3]Section 3.3 describes the out-of-sample evaluation exercise in detail.

2.2 Modeling of quarterly series

Following Mariano and Murasawa (2003) and Banbura et al. (2010a), we incorporate quarterly variables into the framework by expressing each variable in terms of a partially observed monthly counterpart. For example, let us denote the level of quarterly GDP by GDP_t^Q $(t = 3, 6, 9, ...)$, which in turn can be expressed as the sum of contributions from its unobserved monthly counterparts (GDP_t^M):

$$GDP_t^Q = GDP_t^M + GDP_{t-1}^M + GDP_{t-2}^M, \qquad t = 3, 6, 9, ... \tag{4}$$

Let $Y_t^Q = 100 \times log(GDP_t^Q)$ and $Y_t^M = 100 \times log(GDP_t^M)$. We assume that the (unobserved) monthly growth rate of GDP, $y_t = \Delta Y_t^M$, follows the same factor model representation as the real monthly variables:

$$y_t = \mu_Q + \Lambda_Q f_t + \epsilon_t^Q \tag{5}$$

In working with data from emerging markets, we need to take into account two alternative data formats - namely quarter-over-quarter and year-over-year growth rates. Generally speaking, most national statistical agencies publish their GDP series in levels and the common practice among researchers and policy-making organizations is to nowcast the quarter-over-quarter GDP growth rate. This is indeed the case for Brazil, Russia, India and Mexico. However, the National Bureau of Statistics of China does not publish the Chinese GDP series in levels but only as year-over-year growth rates, thus requiring nowcasts for GDP growth in year-over-year terms. In what follows, we describe our approach to incorporating quarterly series expressed in different data formats into the monthly factor model.

2.2.1 Quarter-over-quarter growth rate

We link y_t with the observed GDP data by constructing a partially observed monthly (3-month-over-3-month) GDP growth rate:

$$y_t^Q = \begin{cases} Y_t^Q - Y_{t-3}^Q, & \text{t = 3,6,9,...} \\ unobserved, & \text{otherwise} \end{cases}$$

Therefore, quarterly observations are assigned to the third month of a given quarter. Applying the approximation developed by Mariano and Murasawa (2003), we obtain

$$\begin{aligned} y_t^Q &= Y_t^Q - Y_{t-3}^Q \approx (Y_t^M + Y_{t-1}^M + Y_{t-2}^M) - (Y_{t-3}^M + Y_{t-4}^M + Y_{t-5}^M) \\ &= y_t + 2y_{t-1} + 3y_{t-2} + 2y_{t-3} + y_{t-4} \end{aligned} \tag{6}$$

To ensure that the sequential (i.e., monthly) GDP growth series, y_t, remains consistent with the observed quarterly growth rate, we add a set of restrictions on the factor loadings for the monthly GDP growth rate.

2.2.2 Year-over-year growth rate

In the case of year-over-year growth rates at the quarterly frequency, we follow Giannone et al. (2013) and define the partially observed monthly GDP growth rate (year-over-year) as follows:

$$y_t^Q = \begin{cases} Y_t^Q - Y_{t-12}^Q, & \text{t = 3,6,9,...} \\ unobserved, & \text{otherwise.} \end{cases}$$

Then, the monthly unobserved year-over-year GDP growth, denoted by $y_t = \Delta_{12} Y_t^M$, can be linked to the partially observed GDP growth rate using the following approximation:

$$\begin{aligned} y_t^Q &= Y_t^Q - Y_{t-12}^Q \approx (1 - L^{12})(1 + L + L^2) Y_t^M \\ &= y_t + y_{t-1} + y_{t-2} \end{aligned} \tag{7}$$

As in the case of sequential GDP growth rates, another distinct set of restrictions needs to be applied to the loadings of the monthly GDP series when using year-over-year growth of Chinese GDP. In particular, y_t^Q is required to load equally on the current and lagged values of the unobserved monthly factors, f_t.

2.3 Estimation

Dynamic factor models can be estimated in a number of different ways. Since the focus of this paper is on EMEs for which several macroeconomic indicators are available only recently, our data sets include series of different sample lengths and are relatively small in size compared with usual DFM applications. Therefore, we prefer the methodology of Banbura and Modugno (2014), which applies quasi-maximum likelihood estimation by using the Expectations Maximization (EM) algorithm and the Kalman smoother over alternatives. The maximum likelihood approach is appealing since it is more efficient in small samples and is straightforward to apply to mixed-frequency data sets with an arbitrary pattern of data availability.[4]

Since the factors f_t in equation (1) are unobserved, the maximum likelihood estimates of the parameters of equations (1) and (2) are generally not available in closed form. Moreover, a direct numerical maximization of the likelihood would be computationally challenging, especially in the case of a large number of variables, because of the large number of parameters. Thus, following Banbura and Modugno (2014), the DFM is represented in state-space form, where the vector of states includes the common factors and the idiosyncratic components. Considering quarterly variables expressed in quarter-over-quarter growth rates, we have the following state-space form in the case of $p = 1$ and the idiosyncratic component modeled as an $i.i.d$ process:

$$\begin{pmatrix} x_t \\ y_t^Q \end{pmatrix} = \begin{pmatrix} \Lambda & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \Lambda_Q & 2\Lambda_Q & 3\Lambda_Q & 2\Lambda_Q & \Lambda_Q & 1 & 2 & 3 & 2 & 1 \end{pmatrix} \times \begin{pmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ \epsilon_t^Q \\ \epsilon_{t-1}^Q \\ \epsilon_{t-2}^Q \\ \epsilon_{t-3}^Q \\ \epsilon_{t-4}^Q \end{pmatrix} + \begin{pmatrix} \epsilon_t \\ \xi_t^Q \end{pmatrix} \tag{8}$$

[4] The methodology of Banbura and Modugno (2014) is based on the EM algorithm that was originally developed by Dempster et al. (1977) as a general approach in cases where incomplete or latent data make the likelihood intractable or difficult to deal with.

$$
\begin{pmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ \epsilon_t^Q \\ \epsilon_{t-1}^Q \\ \epsilon_{t-2}^Q \\ \epsilon_{t-3}^Q \\ \epsilon_{t-4}^Q \end{pmatrix} = \begin{pmatrix} A_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \times \begin{pmatrix} f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ f_{t-5} \\ \epsilon_{t-1}^Q \\ \epsilon_{t-2}^Q \\ \epsilon_{t-3}^Q \\ \epsilon_{t-4}^Q \\ \epsilon_{t-5}^Q \end{pmatrix} + \begin{pmatrix} u_t \\ 0 \\ 0 \\ 0 \\ 0 \\ \epsilon_t^Q \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \tag{9}
$$

The model is then estimated by maximum likelihood using the EM algorithm. The methodology involves two steps. In the first step, expectation of the log-likelihood is calculated conditional on the estimates from the previous iteration. In the second step, the parameters are re-estimated using the expected likelihood from the previous step. The maximum likelihood estimation allows us to deal with certain characteristics of the data set, such as missing data, restrictions on the parameters and serial correlation of the idiosyncratic component. For technical details on the EM iterations, we refer the reader to Banbura and Modugno (2014).

2.4 Impact of new data releases

Nowcasters are often interested in not just a single nowcast but rather a series of nowcasts that are updated as new data arrive. The modeling framework of Banbura and Modugno (2014) described in the previous section allows us to obtain the so-called "news" component of nowcast revisions following data releases. Since the DFM naturally generates nowcasts for all the variables in the data set, revisions to GDP nowcasts can be associated with the model's forecast errors corresponding to each data release. Therefore, we can extract model-based news as the unexpected part of each new data release, thereby providing a meaningful interpretation to each revision of GDP growth nowcasts.

Following Banbura and Modugno (2014), let us denote Ω_v as the information set at release v and B_v the set of estimated parameters obtained from using the information in Ω_v. At time $v+1$, new data for a single or a group of variables are released, $\{x_{j,T_j,v+1}, j \in \mathbb{J}_{v+1}\}$, where j denotes the variable for which data are released and $\mathbb{J}$ the set of data released. Then $\Omega_v \subset \Omega_{v+1}$ and $\Omega_v \setminus \Omega_{v+1} = \{x_{j,T_j,v+1}, j \in \mathbb{J}_{v+1}\}$. The effect of news, i.e., the unexpected part of the released data, is given by

$$\mathbb{E}(y_t^Q|\Omega_{v+1}, B_{v+1}) - \mathbb{E}(y_t^Q|\Omega_v, B_{v+1}) = \sum_{j \in \mathbb{J}_{v+1}} \delta_{j,t,v+1} \left[x_{j,T_j,v+1} - \mathbb{E}(x_{j,T_j,v+1}|\Omega_v)\right], \tag{10}$$

where $\delta_{j,t,v+1}$ are weights obtained from the model estimation. Hence, the nowcast revision is a weighted average of the news associated with the data release for each variable. This allows us to calculate the contribution(s) of news pertaining to a single variable or a group of variables to the GDP growth nowcast revision.

In addition to the news component, a change in the nowcast of GDP can also be driven by the effects of re-estimation and/or data revisions. However, in this paper, we abstract from the effect of data revisions since real-time data are unavailable for the BRIC+M group and focus only on the effect of re-estimation. The latter is defined as the difference between the nowcast obtained using the old information set, Ω_v, and the old parameter estimates, B_v, and the nowcast using the old information set, Ω_v, and the new parameter estimates, B_{v+1}. That is,

$$\mathbb{E}(y_t^Q|\Omega_v, B_v) - \mathbb{E}(y_t^Q|\Omega_v, B_{v+1}). \tag{11}$$

3 Data and nowcasting framework

3.1 Data

We use dynamic factor models to nowcast real GDP growth for five major EMEs: Brazil, Russia, India, China and Mexico. Our models include a large number of monthly indicators that can be grouped into nine categories, although the coverage within these categories differs across countries:[5]

- Purchasing managers' indexes (PMIs): We include PMI series for all EMEs except Mexico, since the PMI series for that country are available only since 2011.

[5]We convert variables available at daily frequency, such as oil prices and most financial variables, into monthly frequency by taking the average over the month.

- Soft indicators (ind): These indicators include series like index of consumer expectations, as well as indexes of manufacturing, business and consumer confidence, etc. No soft indicators are available for India.
- Industrial production (IP): We use the headline index of industrial production for all countries, as well as sector-specific indexes, including those for metals (India), electricity (China, India, Mexico), utilities (Mexico), etc.
- Vehicle production and sales (vehicle): We include series under this category for all countries except India, for which data were not available.
- Balance of payments (BoP): We include merchandise exports and imports for all EMEs except Russia. We also include non-petroleum exports and worker remittances for Mexico.
- Financial indicators (financial): This category includes measures of money supply, stock market indexes, exchange rates, government bond yields, etc.
- Labor market indicators (labor): We include the unemployment rate as well as some sector-specific labor market indicators, where available. We do not include any series under this category for China and India.
- Prices: Under this category, we generally include the headline CPI as well as some disaggregated price indexes depending on data availability. For Russia, we include the producer price index (PPI) instead. We also use the wholesale price index for India since it is more closely watched than the headline CPI.
- Exogenous variables (exog): We incorporate some global variables (oil prices and a global commodity price index) and U.S. variables (industrial production, the Federal funds rate, ISM composite index, and S&P 500), which are common across Brazil, India, Mexico and Russia. One exception is Russia where we include the trend of German industrial production (excluding construction) instead of U.S. industrial production, given the importance of manufacturing conditions in Western Europe for the Russian economy. In the case of China, we follow Giannone et al. (2013) and include the OECD industrial production index (excluding construction) instead of U.S. industrial production.

The final selection of variables for each country used for the results reported in the paper is determined as follows. First, we consider the series of indicators available for each economy from Bloomberg and Haver Analytics, focusing on the ones closely followed by market participants. We then refine this set of available indicators by using economic judgment to select variables relevant to forming expectations of current GDP for the particular country (Banbura et al. (2010a) and Banbura et al. (2010b)). For example, we include worker remittances for Mexico and the trend of German industrial production for Russia. Following this approach, we end up with a relatively small number of variables compared with what is typically used in factor model applications. However, Banbura et al. (2010a) and Banbura et al. (2010b) have shown that medium-sized models (i.e., 20 to 40 variables) perform equally well in terms of forecast accuracy as large-sized models (with 100 or more variables). Further, Luciani (2014) shows that when the goal is to forecast a disaggregated variable, it is useful to capture the dynamics of sectoral/disggregated data, whereas aggregate data are good enough to forecast an aggregate variable, which is the objective of this paper. Finally, we fine-tune the selection of variables by comparing the out-of-sample performance of the DFMs based on different combinations of variables.[6]

Table 1 shows the final number of series under each category as well as the total number of series for each country. The number of indicators used for the BRIC+M ranges from 13 to 41. We use 13 series for China and 14 for Russia since these smaller variable sets are better than larger data sets in terms of the out-of-sample performance of the respective DFMs. This finding for the Chinese data is in line with that in Giannone et al. (2013) who also suggest that a smaller set of indicators performs well for nowcasting Chinese GDP growth.

All indicators are differenced or log-differenced where appropriate to achieve stationarity. In the case of Brazil, India, Mexico and Russia, we transform all level series into sequential month-over-month growth rates. For China, we transform the level series to year-over-year growth rates since many series, including GDP growth, are available only in the form of year-over-year growth rates.[7] Tables 2-6 provide detailed descriptions of the data, including lists of series for each of the five countries considered, their availability and applied transformations. It is important to note that the DFM can be applied in both quarter-over-quarter and year-over-year growth formats in all cases as long as the underlying indicator and GDP growth data are available.

[6] Section 3.2 describes the out-of-sample exercise in detail.
[7] All growth rates are approximated using log differences.

3.2 Pseudo out-of-sample design

Table 7 summarizes the design of the nowcasting exercise. For Brazil, India and Mexico the model is estimated over 1996Q1 to 2014Q1. In the case of China, official year-over-year GDP growth series are available only since 1999 and so 2000Q1 provides a natural starting point for estimation. For Russia, the estimation period starts in 2001Q1 in order to avoid the 1998 crisis.

The out-of-sample evaluation period is 2008Q1 to 2014Q1. Over this period, we evaluate the nowcasts at the bimonthly frequency at the middle and the end of the month for a period of 3 quarters, i.e., up to 18 bimonthly periods surrounding the quarter of interest. For example, nowcasts for 2014Q1 are computed at a bimonthly frequency from mid-October 2013 through 30 June 2014 or the release of 2014Q1 GDP, whichever occurs earlier. At each bimonthly point in time, more history is added to the unbalanced data panel, the model is re-estimated and the nowcasts are obtained. To generate the pseudo real-time data required for the out-of-sample evaluation, we construct a grid that tracks the publication lags of each indicator for each of the five EMEs. To do so, we use information from JPMorgan's data release calendars and/or country-specific sources such as the central bank to construct a data grid for each country. Let us use the grid for Mexico (Table 4) as an example. Let M10 and M11 refer to the beginning and end of the first month of a quarter. If we look at rows 14 and 15, we see that the exports and imports series are available with a lag of one to two months and are released in the middle of the month. So in the middle of January, only the November figures would be available. But by the end of January, the December data for exports and imports are released. Thus, the pseudo real-time data sets allow us to assess the contribution of data releases to nowcasts at the bimonthly frequency. We then overlay this completed grid onto our data set to reproduce the characteristic "ragged edge" or unbalanced panel at each point in time. We construct the unbalanced data panels for the other four countries in a similar fashion. These data sets mimic precisely the data available to the econometrician at the middle and the end of each month (i.e.,"real time"). But these data sets do not account for the possibility of revisions (i.e.,"pseudo").

3.3 Model selection

To select the optimal model for each economy, we compare the out-of-sample performance for every possible combination of model parameters, including the number of factors ($r = 1, 2, ..., 5$), the number of lags in the VAR ($p = 1, 2, ..., 5$), and the idiosyncratic component modeled as an autoregressive process of order 1 (i.e., AR(1)). We use the root mean squared forecast error (RMSE) as the measure of forecast accuracy. The state-space representation for the case with the idiosyncratic component modeled as an AR(1) process is shown in the appendix. With each additional parameter, such as an extra factor, the size of the state-space increases significantly, thus limiting the set of admissible factor model specifications. Table 7 shows the chosen model parameters for each economy. We find that simple model specifications with one or two factors and one lag often yield the best out-of-sample performance. Modeling the idiosyncratic component as an AR(1) process also improves the out-of-sample performance of the model in the case of Russia and China, but not for Brazil, India and Mexico.

4 Results

This section reports the monthly GDP tracking capabilities of our dynamic factor models, their out-of-sample performance, and the impact of the data releases or "news" on the model nowcast for each of the five EMEs.

4.1 In-sample properties

The DFMs can be used to produce smooth monthly GDP series or "GDP trackers." Figures 2-6 show the monthly estimates of quarter-over-quarter GDP growth rates (year-over-year growth rates in the case of China) along with the corresponding actual GDP growth rates for the five EMEs. These series represent the in-sample estimates (using the Kalman filter) of the partially observed monthly GDP series using data as of July 2014. The restrictions imposed on the factor loadings, described in section 2.2, ensure that the Kalman filter anchors monthly estimates to actual data whenever GDP is observed. Hence, the actual value of GDP growth and its estimates coincide for the months in which GDP growth is known.

4.2 Pseudo out-of-sample nowcasts

Figures 7-11 show the out-of-sample nowcasts for the five EMEs over the evaluation period. The blue bars represent the realized quarterly GDP growth (non-annualized). Let Q(0) refer to the quarter of interest, M1 refer to the first month of that quarter, and D30 refer to the end of the month. The red line shows the results of a nowcast performed early in the quarter of interest, i.e., at the end of the first month of the quarter being nowcasted. For example, if we are nowcasting 2013Q4, the red line would show the nowcast results as of 30 October 2014. At this point in the quarter of interest, very few data are usually available beyond the high-frequency financial indicators. The green line shows the results of a nowcast performed later in the monitoring period. Specifically, the green line represents the nowcasts performed at the end (D30) of the first month (M1) in the quarter following the quarter of interest, i.e., Q(+1). Again, if we were nowcasting 2013Q4, the green line would amount to the nowcast of 2013Q4 GDP growth at the end of January 2014. This nowcast would be based on a lot of data for the quarter of interest, including multiple releases of hard indicators, such as industrial production, and complete quarterly data for higher-frequency financial variables.

Considering the nowcast of Brazilian GDP growth as of Q(0) M1 D30 (Figure 7), we can see that the model tracks observed quarterly GDP growth relatively well, despite the lack of data at that point in time. Directional accuracy improves for the nowcast made later in the monitoring period, i.e., Q(+1) M1 D30, as more data are available. In particular, during the global financial crisis of 2008-09, the earlier nowcast seems to predict the trough with a lag of one quarter while the nowcast made later tracks it well.

A very similar picture arises in the case of China (Figure 8). Note that in this case we consider nowcasts as of Q(-1) M3 D30 (early nowcast) and Q(0) M3 D30 (late nowcast) since Chinese GDP has a shorter publication lag than that for the other countries. The nowcast as of Q(0) M3 D30 generally performs better than the one made earlier in the monitoring period. In particular, during the global financial crisis the green line captures the downturn and subsequent pickup in Chinese GDP growth more accurately and in a more timely manner than the red line. The nowcast as of Q(-1) M3 D30 generally appears to track the direction of GDP growth with a lag.

Similarly, the DFM performs well in nowcasting quarterly GDP growth for Mexico, India and Russia (Figures 9-11). Once again, by comparing the red and green lines for these countries, one can see that incorporating more information typically improves the performance of the nowcast. Generally speaking, the DFMs display good directional accuracy and perform well in capturing GDP dynamics in these countries during the global financial crisis, with the exception of India.

4.3 Forecast accuracy: Pseudo out-of-sample evaluation

In this section, we assess the forecast accuracy of the DFMs as measured by the RMSEs. We present the performance of the model relative to two standard benchmarks: AR(2) and MA(4). Figure 12 shows the ratio of the RMSEs from the dynamic factor model to the RMSEs from an AR(2) model on the y-axis. The x-axis shows each bimonthly nowcast evaluation period starting from the middle of the first month of the quarter immediately preceding the quarter of interest to the end of the last month of the quarter immediately following the quarter of interest. This amounts to 17 different nowcast origins. In the case of China, since GDP growth is published three weeks after the close of the quarter, the RMSE ratios can be obtained up to Q(+1) M1 D15. A number below 1 indicates that the dynamic factor model forecasts are more accurate than those produced by the AR(2) benchmark.

Two key results emerge from Figure 12. First, the RMSE of the DFM decreases as the actual GDP release date approaches for all the countries under consideration. The fact that the nowcast accuracy of the DFM tends to improve as more data become available is a standard finding in the literature (see, for example, Giannone et al. (2008) and Liu et al. (2012)). Second, the RMSE ratios are below 1 across all nowcast origins for Brazil, China, India and Mexico (except for Brazil at Q(-1) M1 D15). Therefore, the DFMs beat the naive AR(2) benchmark at very early nowcast origins, which suggests they are good at nowcasting GDP growth not only in the present and past, but in the future as well. In the case of Russia, the DFM nowcast improves upon the benchmark only in the quarter of interest (i.e., Q(0)). This is likely due to the long publication lags in Russian data.

Figure 13 shows the forecast accuracy of the DFMs relative to an MA(4) benchmark. The results are qualitatively very similar to those discussed above. However, the DFM for China beats the MA(4) benchmark one forecast origin later when compared with the AR(2) benchmark.

4.4 Contribution of news to forecasts

As discussed in section 2, an important feature of the methodology used here is its ability to decompose the sources of changes in the nowcast following new data releases. Since the DFM produces forecasts for all variables in the data set, the methodology allows us to precisely decompose the changes in the model outcomes into the contributions of individual and/or groups of indicators, or what we refer to as the "news," and the impact of parameter updates. Figures 14-23 show the evolution of the nowcast as new data become available. For ease of exposition, we group the "news" from individual releases into the groups discussed in section 3.1. We use the nowcast of 2014Q1 GDP growth to illustrate the contributions of "news" and re-estimation.

In the case of Brazil, Figure 14 shows that the impact of re-estimation on the nowcast revision is broadly negligible. If we abstract from the minor impact of the re-estimation and focus on the impact of the news, we can see the breakdown of the contributions across indicator groups (Figure 15). We find that the GDP nowcast responds in a roughly proportional manner to several indicator groups, with financial variables such as the stock market index, PMIs and soft indicators shifting the GDP nowcast with every release. Early in the monitoring period, i.e., 2013Q4, most of the changes in the GDP nowcast can be attributed to the release of financial indicators. The contribution of releases of soft indicators and PMIs seems to diminish as time evolves within the nowcast period. Further, we find that the contribution of GDP releases per se to the nowcast revision is relatively small.

As is the case for Brazil, re-estimation has only a small effect on the nowcast revisions for China (Figure 16). However, a slightly different picture emerges when we look at the contributions of the various groups of indicators. Figure 17 shows that the two GDP growth releases for 2013Q3 and 2013Q4 are the biggest contributors to the nowcast revisions of 2014Q1 GDP growth. The relatively short time lag in the release of Chinese GDP data probably explains why it contains important information for the nowcast of interest. Apart from the importance of news coming from GDP releases, we also find the releases of financial variables to have a significant effect on the GDP nowcast throughout the monitoring period. PMI releases seem to be of little importance for the nowcast of 2014Q1 Chinese GDP growth, which is somewhat surprising since this group of indicators is generally regarded as providing early signals of broad macroeconomic developments.

Figures 18 and 19 show the corresponding results for Mexico. Once again, re-estimation has only a very small impact on the nowcast revision. Furthermore, "news" related to the different indicator groups changes the 2014Q1 GDP nowcast in a similar and relatively proportional manner. Releases of financial indicators are not important contributors of nowcast revisions early in the monitoring period as in the case of Brazil. Further, GDP releases seem to be of very little importance for the nowcast of Mexican GDP. One interesting observation is that the DFM predicted 2014Q1 GDP growth well until the release of trade data in 2014Q1, which is a relatively volatile indicator. A large negative shock to trade pushed the nowcast into contractionary territory in February, only to have a large positive shock to trade offset this decline in March.

Looking at Figure 20, we find that re-estimation has a small impact on the nowcast revisions for India. The release of financial indicators plays a role in explaining nowcast revisions early in the monitoring period. The release of GDP growth data for 2013Q4 is also an important contributor to the nowcast revision. Lastly, Figures 22 and 23 show the nowcast revision for 2014Q1 Russian GDP and its decomposition into news and re-estimation, with the latter being negligible. News coming from soft indicators seems to be a robust contributor to 2014Q1 GDP nowcast revisions in this case. Further, earlier GDP releases do not change the nowcasts much. The results also highlight the volatile nature of Russian PMI data. The PMI release in early November 2013 contains large positive news pushing up the GDP nowcast to 1.6 per cent. The next release of the PMIs in December 2013 offsets this positive change with negative news of a similar magnitude. Finally, results indicate that data releases in the couple of months prior to the actual GDP release in late June do not change the nowcast much.

In sum, there seems to be considerable heterogeneity in how news pertaining to different indicators affects the 2014Q1 GDP nowcast across the BRIC+M. The ability of the DFM framework to assess the impact of news on the nowcast could be of immense value to policy-makers, especially given the volatile nature of emerging-market data (such as the trade release for Mexico and the PMI release for Russia). Finally, we also find that data releases for exogenous variables, such as the oil price and the S&P 500, play a relatively minor role in explaining nowcast revisions in general. While these variables usually move the nowcast slightly at every release, news pertaining to domestic indicators are by far the biggest contributor to nowcast revisions of 2014Q1 GDP growth in our sample.

5 Conclusion

This paper provides nowcasts for real GDP growth for the BRIC+M group based on state-of-the-art dynamic factor models along the lines of Giannone et al. (2008) and Banbura and Modugno (2014). While the usefulness of these models has been demonstrated by a number of studies focusing on advanced economies, this paper advances the nowcasting literature by applying these models to major emerging-market economies.

A number of key findings emerge from this study. First, we demonstrate how DFMs can be used to produce smooth monthly GDP series, which in turn can be a very useful current analysis tool for policy-makers. Second, the DFMs generally display good directional accuracy and perform well in terms of capturing GDP dynamics during the global financial crisis. Third, the accuracy of nowcasts obtained from the DFMs tends to improve as more data become available, a result that is consistent with the existing literature. Fourth, using 2014Q1 GDP as an example, we demonstrate the ability of DFMs to decompose the sources of nowcast revisions into the effects of parameter re-estimation and the impact of new data releases. Our results show considerable heterogeneity in how news pertaining to different indicator groups affects the nowcast of 2014Q1 GDP across the five EMEs in our sample. However, one common finding is that releases of domestic indicators are the main drivers of nowcast revisions, while the role of exogenous variables is relatively minor.

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Table 1: Number of indicators by type used for each economy

	PMI	Soft indicators	IP	Vehicle	BoP	Financial	Labour	Prices	Exogenous	Total
Brazil	7	7	1	1	2	5	3	3	6	35
China	2	1	2	1	2	2	0	1	2	13
Mexico	0	7	4	2	4	9	4	5	6	41
India	7	0	4	0	2	8	0	2	6	29
Russia	2	1	1	1	0	4	0	1	4	14

Notes: PMI refers to purchasing managers' index, IP refers to industrial production and BoP refers to the balance of payments.

Table 2: Data and publication lags for Brazil

No	Name	Group	Haver code	Trans (log)	Trans (diff)	M10	M11	M20	M21	M30	M31
1	Brazil PMI: Manufacturing Output (SA, 50+=Expansion)	PMI	S223MG@PMI	0	1	1	1	1	1	1	1
2	Brazil PMI: Manufacturing Stocks of Finished Goods (SA, 50+=Expansion)	PMI	S223MSF@PMI	0	1	1	1	1	1	1	1
3	Brazil PMI: Manufacturing Input Prices(SA, 50+=Expansion)	PMI	S223MPI@PMI	0	1	1	1	1	1	1	1
4	Brazil PMI: Manufacturing (SA, 50+=Expansion)	PMI	S223M@PMI	0	1	1	1	1	1	1	1
5	Brazil PMI: Manufacturing New Orders (SA, 50+=Expansion)	PMI	S223MO@PMI	0	1	1	1	1	1	1	1
6	Brazil PMI: Manufacturing Output Prices (SA, 50+=Expansion)	PMI	S223MPO@PMI	0	1	1	1	1	1	1	1
7	Brazil PMI: Manufacturing Stocks of Purchases (SA, 50+=Expansion)	PMI	S223MSP@PMI	0	1	1	1	1	1	1	1
8	Brazil: Manufacturing Confidence Index (SA, Points)	Ind	S223VM@EMERGELA	0	1	1	0	1	0	1	0
9	Brazil: ICEI: Business Confidence Index (50+=Growth)	Ind	N223VBC@EMERGELA	0	1	1	0	1	0	1	0
10	Brazil: Total Leading Indicator (NSA, Amplitude Adjusted)	Ind	C223LIAT@OECDMEI	0	1	2	2	2	2	2	2
11	Brazil: Economic Activity Indicator (SA)	Ind	S223GVI@EMERGELA	1	1	3	2	3	2	3	2
12	Brazil: Consumer Expectations Index (SA, Points)	Ind	S223VCEF@EMERGELA	0	1	1	0	1	0	1	0
13	Brazil: Consumer Confidence Index (SA, Points)	Ind	S223VCCF@EMERGELA	0	1	1	0	1	0	1	0
14	Brazil: Industrial Production (SA, 2002=100)	IP	S223D@EMERGELA	1	1	2	2	2	2	2	2
15	Brazil: Total Production of Vehicles (NSA, Units)	Vehicle	N223OMVU@EMERGELA	1	1	2	1	2	1	2	1
16	Brazil: Retail Trade: Volume of Sales (NSA, 2011=100)	Ind	C223SRV@EMERGELA	1	1	3	2	3	2	3	2
17	Brazil: Merchandise Exports (NSA, Mil.US$)	BoP	C223TXD@EMERGELA	1	1	1	1	1	1	1	1
18	Brazil: Merchandise Imports (NSA, Mil.US$)	BoP	C223TMD@EMERGELA	1	1	1	1	1	1	1	1
19	Brazil: Money Supply, M1 (EOP, NSA, Mil.Reais)	Financial	C223M1E@EMERGELA	1	1	2	1	2	1	2	1
20	Brazil: Money Supply, M2 (EOP, NSA, Mil.Reais)	Financial	C223M2E@EMERGELA	1	1	2	1	2	1	2	1
21	JPMorgan Broad REER Index: Brazil (2000=100)	Financial	N223XJRB@EMERGELA	1	1	1	0	1	0	1	0
22	Brazil: US$ Exchange Rate: Commercial rate (Reais/US$)	Financial	(C223XLDO@EMERGELA)/2	1	1	1	0	1	0	1	0
23	Brazil: Stock Price Index: Bovespa	Financial	C223KN@EMERGELA	1	1	1	1	1	1	1	1
24	Brazil: Unemployment Rate (NSA, %) [HEADLINE]	Labour	C223EURM@EMERGELA	0	0	2	1	2	1	2	1
25	Brazil: Emp: Mining & Mfg &(NSA, Thous)	Labour	N223ETXC@EMERGELA	1	1	2	1	2	1	2	1
26	Brazil: Nominal Salaries: Manufacturing (NSA, 2006=100)	Labour	C223EWC@EMERGELA	1	1	2	2	2	2	2	2
27	Brazil: Natl Consumer Price Index [INPC] (12/93=100)	Prices	C223PCN@EMERGELA	1	1	1	1	1	1	1	1
28	Brazil: National Core CPI [Extended, IPCA] (NSA, 12/95=100)	Prices	C223PCX@EMERGELA	1	1	1	1	1	1	1	1
29	Brazil: CPI: Food & Beverages [INPC] (NSA, Jul 2006=100)	Prices	N223CPFB@EMERGELA	1	1	1	1	1	1	1	1
30	Industrial Production Index (SA, 2007=100)	Exog	IP@USECON	1	1	2	1	2	1	2	1
31	Petroleum, Brent Spot Price (US$/Barrel)	Exog	C112CLPE@IFS	1	1	2	1	2	1	2	1
32	World: Commodity Price Index: All Commodities (2005=100)	Exog	C001CXAP@IFS	1	1	1	1	1	1	1	1
33	Federal Open Market Committee: Fed Funds Target Rate: Upper Limit (%)	Exog	FFEDTAH@USECON	0	0	1	0	1	0	1	0
34	ISM Composite Index (SA, > 50=Increasing)	Exog	ISMC@USECON	0	1	1	1	1	1	1	1
35	Stock Price Index: Standard & Poor's 500 Composite (1941-43=10)	Exog	SP500@USECON	1	1	1	0	1	0	1	0

Notes: 1. The columns 'trans log' and 'trans diff' show the transformations made to the raw data series to achieve stationarity. A '1' entry in the 'trans log' column means that the series is expressed in logs, while a '0' means otherwise. Similarly, the column 'trans diff' takes a value of 1 if the series are expressed in first differences, and 0 otherwise. Series that have '1' entries in both columns have been log-differenced.
2. 'M10' and 'M11' refer to the beginning and end of the *first* month of a quarter. 'M20' and 'M21' refer to the beginning and end of the *second* month of a quarter, and 'M30' and 'M31' refer to the beginning and end of the *third* month of a quarter.

Table 3: Data and publication lags for China

No	Name	Group	Haver code	Trans (log)	Trans (diff)	M10	M11	M20	M21	M30	M31
1	China: Purchasing Managers' Index (SA, 50+=Expansion)	PMI	CBAWLX@CHINA	0	1	1	1	1	1	1	1
2	China PMI: Manufacturing (SA, 50+=Expansion)	PMI	S924M@MKTPMI	0	1	1	0	1	0	1	0
3	China: Macroeconomic Climate Index: Leading Index (NSA, 1996=100)	Ind	N924VLD@EMERGEPR	0	1	2	1	2	1	2	1
4	China: Real Gross Value Added (NSA, yr/yr % change)	IP	n924gdxy@emergepr	0	0	1	1	1	1	1	1
5	China: Production of Energy: YoY: Electricity (%)	IP	CRBADJS@CHINA	0	0	1	1	1	1	1	1
6	CN: Freight Ton Kilometer Carried (Ton Km Mn)	Vehicle	CTCB@CHINA	1	1	2	1	2	1	2	1
7	China Exports fob (Mil.US$)	BoP	CJAA@CHINA	1	1	2	1	2	1	2	1
8	China Imports cif (Mil.US$)	BoP	CJAC@CHINA	1	1	2	1	2	1	2	1
9	China: JPMorgan Broad Real Effective Exchange Rate Index (2000=100)	Financial	N924XJRB@EMERGEPR	1	1	1	0	1	0	1	0
10	China: Index: Shanghai Stock Exchange: Composite (Dec-19-91=100)	Financial	aggany(CDIAA@CHINA)	1	1	1	0	1	0	1	0
11	CN: Consumer Price Index (PY=100)	Prices	CIEA@CHINA	0	0	1	1	1	1	1	1
12	OECD Total: Industrial Production ex Construction (SA, 2010=100)	Exog	C003IZ@OECDMEI	1	1	4	4	4	4	4	4
13	European Free Market Price: Brent Crude Oil ($/Barrel)	Exog	aggany(PZBRT@DAILY)	1	1	1	0	1	0	1	0

Notes: See notes to Table 2.

Table 4: Data and publication lags for Mexico

No	Name	Group	Haver code	Trans (log)	Trans (diff)	M10	M11	M20	M21	M30	M31
1	IMEF Business Climate Index: Manufacturing (SA, 50+=Econ Expand)	Ind	S273VM@EMERGELA	0	1	1	1	1	1	1	1
2	IMEF Business Climate Index: Mfg: Inventory (NSA, 50+=Econ Expand)	Ind	N273VMI@EMERGELA	0	1	1	1	1	1	1	1
3	IMEF Business Climate Index: Mfg: New Orders (SA, 50+=Econ Expand)	Ind	S273VMO@EMERGELA	0	1	1	1	1	1	1	1
4	Indicator of Global Economic Activity (SA, 2008=100)	Ind	S273AE@EMERGELA	1	1	3	2	3	2	3	2
5	Consumer Expectations (NSA, 01/03=100)	Ind	C273VCE@EMERGELA	1	1	1	1	1	1	1	1
6	Consumer Confidence (NSA, 01/03=100)	Ind	C273VCC@EMERGELA	1	1	1	1	1	1	1	1
7	Industrial Production (SA, 2008=100)	IP	S273DW@EMERGELA	1	1	2	2	2	2	2	2
8	Industrial Production: Primary Metal Manufacturing (SA, 2008=100)	IP	S273DMAB@EMERGELA	1	1	2	2	2	2	2	2
9	Industrial Production: Utilities (SA, 2008=100)	IP	S273DV@EMERGELA	1	1	2	2	2	2	2	2
10	IP: Electric Power Generation, Transmiss & Distribution (SA, 2008=100)	IP	S273DVE@EMERGELA	1	1	2	2	2	2	2	2
11	Total Vehicle Production (NSA, Units)	Vehicle	N273OMV@EMERGELA	1	1	1	1	1	1	1	1
12	Total Vehicle to Sales to Distributors (NSA, Units)	Vehicle	N273TSV@EMERGELA	1	1	1	1	1	1	1	1
13	Retail Sales (SA, 2003=100)	Ind	S273TRS@EMERGELA	1	1	2	1	2	1	2	1
14	Exports, fob (SA, USD)	BoP	S273TXD@EMERGELA	1	1	2	1	2	1	2	1
15	Imports, fob (SA, USD)	BoP	S273TMD@EMERGELA	1	1	2	1	2	1	2	1
16	Nonpetroleum Exports (SA, Mil.US$)	BoP	S273TXND@EMERGELA	1	1	2	1	2	1	2	1
17	Worker's Remittances: Total (NSA, Mil.US$)	BoP	N273BW@EMERGELA	1	1	2	2	2	2	2	2
18	Money Supply, M1 (NSA, Loc.Cur)	Financial	C273M1@EMERGELA	1	1	2	1	2	1	2	1
19	Money Supply, M2 (NSA, Loc.Cur)	Financial	C273M2@EMERGELA	1	1	2	1	2	1	2	1
20	Total Performing Commercial Bank Loans (EOP, NSA, Loc.Cur)	Financial	N273UCH@EMERGELA	1	1	2	1	2	1	2	1
21	JPMorgan Broad REER Index: Mexico (2000=100)	Financial	N273XJRB@EMERGELA	1	1	1	0	1	0	1	0
22	Exchange Rate (NewPeso/US$)	Financial	C273XLDV@EMERGELA	1	1	1	1	1	1	1	1
23	Stock Price Index: IPC (Avg, 11/78=0.78)	Financial	C273KNV@EMERGELA	1	1	1	1	1	1	1	1
24	91-Day Treasury Certificates (%)	Financial	C273RC91@EMERGELA	0	0	1	0	1	0	1	0
25	364-Day Treasury Certificates (%)	Financial	C273RC1Y@EMERGELA	0	0	1	0	1	0	1	0
26	10 Year Government Bond Yield	Financial	N273RG10@EMERGELA	0	0	1	0	1	0	1	0
27	Unemployment Rate (SA, %)	Labour	S273EUR@EMERGELA	0	0	2	1	2	1	2	1
28	Employed: Manufacturing (NSA, Persons)	Labour	N273ET@EMERGELA	1	1	3	2	3	2	3	2
29	Mfg Remunerations (NSA, Thous.Pesos)	Labour	N273EE@EMERGELA	1	1	3	2	3	2	3	2
30	Coincident Index: IMSS Insured Workers (NSA, Points)	Labour	N273VLC4@EMERGELA	0	0	2	2	2	2	2	2
31	Consumer Price Index (NSA, Dec 16-31, 2010=100)	Prices	N273PJ@EMERGELA	1	1	1	1	1	1	1	1
32	Consumer Price Index: Core (NSA, Dec 16-31, 2010=100)	Prices	N273PJXQ@EMERGELA	1	1	1	1	1	1	1	1
33	CPI: Food, Beverages & Tobacco (NSA, Dec 16-31, 2010=100)	Prices	N273PJF@EMERGELA	1	1	1	1	1	1	1	1
34	PPI: Total Production Incl oil & Services (NSA, Jun 2012=100)	Prices	N273PP@EMERGELA	1	1	1	1	1	1	1	1
35	PPI: Final Merchandise Domestic Demand (NSA, Jun 2012=100)	Prices	N273PDF@EMERGELA	1	1	1	1	1	1	1	1
36	Industrial Production Index (SA, 2007=100)	Exog	IP@USECON	1	1	2	1	2	1	2	1
37	Petroleum, Brent Spot Price (US$/Barrel)	Exog	C112CLPE@IFS	1	1	2	1	2	1	2	1
38	World: Commodity Price Index: All Commodities (2005=100)	Exog	C001CXAP@IFS	1	1	1	1	1	1	1	1
39	Federal Open Market Committee: Fed Funds Target Rate: Upper Limit (%)	Exog	FFEDTAH@USECON	0	0	1	0	1	0	1	0
40	ISM Composite Index (SA, > 50=Increasing)	Exog	ISMC@USECON	0	1	1	1	1	1	1	1
41	Stock Price Index: Standard & Poor's 500 Composite (1941-43=10)	Exog	SP500@USECON	1	1	1	0	1	0	1	0

Notes: See notes to Table 2.

Table 5: Data and publication lags for India

No	Name	Group	Haver code	Trans (log)	Trans (diff)	M10	M11	M20	M21	M30	M31
1	India PMI: Manufacturing Output (SA, 50+=Expansion)	PMI	S534MG@PMI	0	1	1	1	1	1	1	1
2	India PMI: Manufacturing Stocks of Finished Goods (SA, 50+=Expansion)	PMI	S534MSF@PMI	0	1	1	1	1	1	1	1
3	India PMI: Manufacturing Input Prices(SA, 50+=Expansion)	PMI	S534MPI@PMI	0	1	1	1	1	1	1	1
4	India PMI: Manufacturing (SA, 50+=Expansion)	PMI	S534M@PMI	0	1	1	1	1	1	1	1
5	India PMI: Manufacturing New Orders (SA, 50+=Expansion)	PMI	S534MO@PMI	0	1	1	1	1	1	1	1
6	India PMI: Manufacturing Output Prices (SA, 50+=Expansion)	PMI	S534MPO@PMI	0	1	1	1	1	1	1	1
7	India PMI: Manufacturing Stocks of Purchases (SA, 50+=Expansion)	PMI	S534MSP@PMI	0	1	1	1	1	1	1	1
8	India: Industrial Production (SA, FY2004=100)	IP	N534D@EMERGEPR	1	1	2	2	2	2	2	2
9	India: Industrial Production: Manufacturing (SA, FY2004=100)	IP	N534DM@EMERGEPR	1	1	2	2	2	2	2	2
10	India: IP: Basic metals (NSA, FY2004=100)	IP	N534DMAB@EMERGEPR	1	1	2	2	2	2	2	2
11	India: IP: Electricity (NSA, FY2004=100)	IP	N534DVE@EMERGEPR	1	1	2	2	2	2	2	2
12	India: Exports, fob (NSA, USD)	BoP	N534IXD@EMERGEPR	1	1	2	1	2	1	2	1
13	India: Imports, fob (NSA, USD)	BoP	N534IMD@EMERGEPR	1	1	2	1	2	1	2	1
14	India: Money Supply: M1 (NSA, Bil.Rupees)	Financial	N534FM1@EMERGEPR	1	1	1	1	1	1	1	1
15	India: Money Supply: M2 (NSA, Bil.Rupees)	Financial	N534FM2@EMERGEPR	1	1	1	1	1	1	1	1
16	India: JPMorgan Broad Real Effective Exchange Rate Index (2000=100)	Financial	N534XJRB@EMERGEPR	1	1	1	0	1	0	1	0
17	India: Rupee/US$ Exchange Rate (AVG)	Financial	N534XUSV@EMERGEPR	1	1	1	0	1	0	1	0
18	India: Stock Price Index: NSE 500 (AVG, 1994=1000)	Financial	N534SK5@EMERGEPR	1	1	1	0	1	0	1	0
19	India: 91-Day Tresury Bill Implicit Cut-Off Yield (% per annum)	Financial	N534RJ3M@EMERGEPR	0	0	1	1	1	1	1	1
20	India: 364-Day Treasury Bill Implicit Cut-Off Yield (% per annum)	Financial	N534RJ1Y@EMERGEPR	0	0	1	1	1	1	1	1
21	India: 10-Year Government Bond Yield (% per annum)	Financial	N534RG10@EMERGEPR	0	0	2	1	2	1	2	1
22	India: Consumer Price Index: Food, Beverages, Tobacco (NSA, 2010=100)	Prices	N534PCF@EMERGEPR	1	1	1	1	1	1	1	1
23	India: Wholesale Price Index: All Items (NSA, FY04=100)	Prices	N534PW@EMERGEPR	1	1	1	1	1	1	1	1
24	Industrial Production Index (SA, 2007=100)	Exog	IP@USECON	1	1	2	1	2	1	2	1
25	Petroleum, Brent Spot Price (US$/Barrel)	Exog	C112CLPE@IFS	1	1	2	1	2	1	2	1
26	World: Commodity Price Index: All Commodities (2005=100)	Exog	C001CXAP@IFS	1	1	1	1	1	1	1	1
27	Federal Open Market Committee: Fed Funds Target Rate: Upper Limit (%)	Exog	FFEDTAH@USECON	0	0	1	0	1	0	1	0
28	ISM Composite Index (SA, > 50=Increasing)	Exog	ISMC@USECON	0	1	1	1	1	1	1	1
29	Stock Price Index: Standard & Poor's 500 Composite (1941-43=10)	Exog	SP500@USECON	1	1	1	0	1	0	1	0

Notes: See notes to Table 2.

Table 6: Data and publication lags for Russia

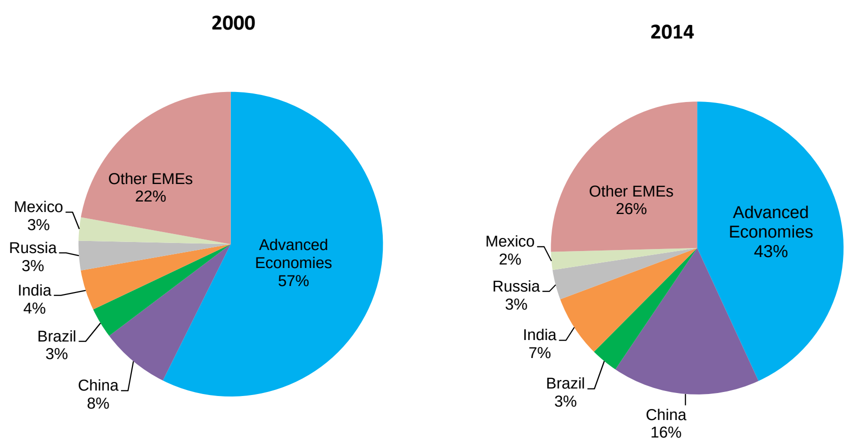
No	Name	Group	Haver code	Trans (log)	Trans (diff)	M10	M11	M20	M21	M30	M31
1	Russia PMI: Manufacturing (SA, 50+=Expansion)	PMI	S922M@MKTPMI	0	1	1	1	1	1	1	1
2	Russia PMI: Manufacturing New Orders (SA, 50+=Expansion)	PMI	S922MO@MKTPMI	0	1	1	1	1	1	1	1
3	Russia: Business Confidence: Manufacturing (NSA, %)	Ind	N922VBM@EMERGECW	0	1	1	0	1	0	1	0
4	Russia: Output: Industrial Production Index: Total (SA, 2011=100)	IP	S922D@EMERGECW	1	1	2	1	2	1	2	1
5	Russia: Passenger Car Sales Imported Plus Domestic (NSA, Units)	Vehicle	N922CVLF@EMERGECW	1	1	1	1	1	1	1	1
6	Russia: Money Supply: M2 (NSA, Loc.Cur)	Financial	N922FM2@EMERGECW	1	1	2	1	2	1	2	1
7	Russia: Stock Price Index: RTS (avg, Sep 1995=100)	Financial	N922FKRV@EMERGECW	1	1	1	0	1	0	1	0
8	Russia: Gov't Securities: Up to 90 Days AVG (%)	Financial	N922RGS@EMERGECW	0	0	1	1	1	1	1	1
9	Russia: Zero Coupon Yield Curve: 10-Year (AVG, %)	Financial	N922G10@EMERGECW	0	0	1	1	1	1	1	1
10	Russia: Producer Price Index: Total (NSA, 2000=100)	Prices	N922PP@EMERGECW	1	1	2	1	2	1	2	1
11	Industrial Production Index (SA, 2007=100)	Exog	IP@USECON	1	1	2	1	2	1	2	1
12	World: Commodity Price Index: All Commodities (2005=100)	Exog	C001CXAP@IFS	1	1	2	1	2	1	2	1
13	ISM Composite Index (SA, >50=Increasing)	Exog	ISMC@USECON	0	1	1	1	1	1	1	1
14	German IP ex construction (Trend)	Exog	T134D@G10	1	1	2	2	2	2	2	2

Notes: See notes to Table 2.

Table 7: Model set-up

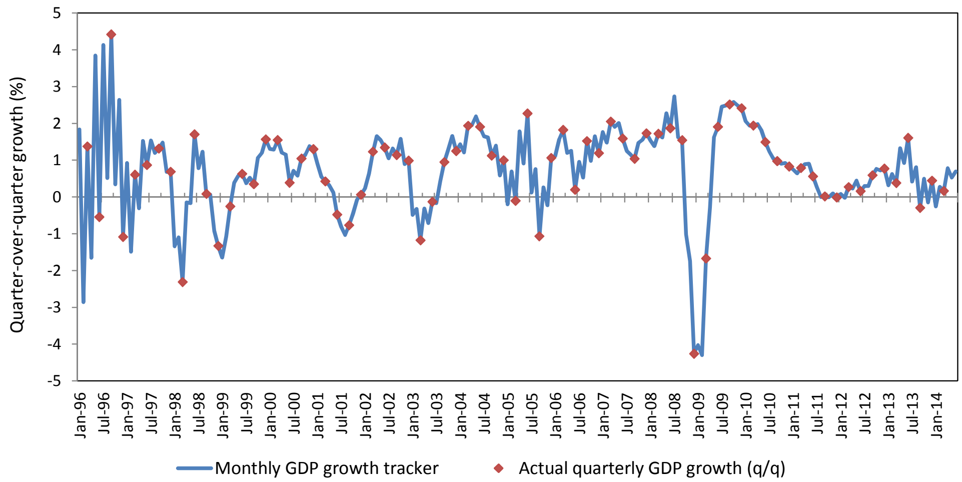
	Brazil	China	Mexico	India	Russia
Data Format	Q/Q	Y/Y	Q/Q	Q/Q	Q/Q
Estimation Period	96Q1 to 14Q1	00Q1 to 14Q1	96Q1 to 14Q1	96Q1 to 14Q1	2001Q1 to 14Q1
Specification	r=3, p=3	r=1, p=1	r=3, p=4	r=2, p=1	r=2, p=1
Idiosyncratic AR?	No	Yes	No	No	Yes

Figure 1: Shares of global GDP in PPP terms: 2000 vs. 2014



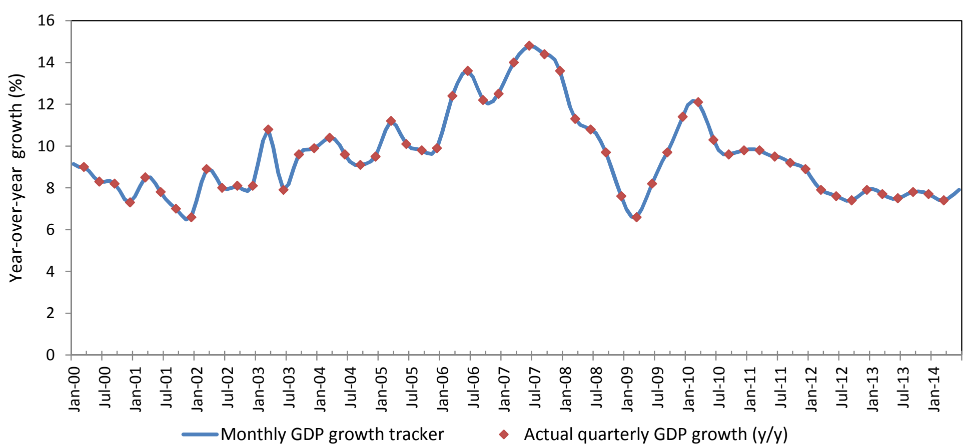
Sources: International Monetary Fund *World Economic Outlook* database and Haver Analytics

Figure 2: Monthly GDP tracker for Brazil as of July 2014



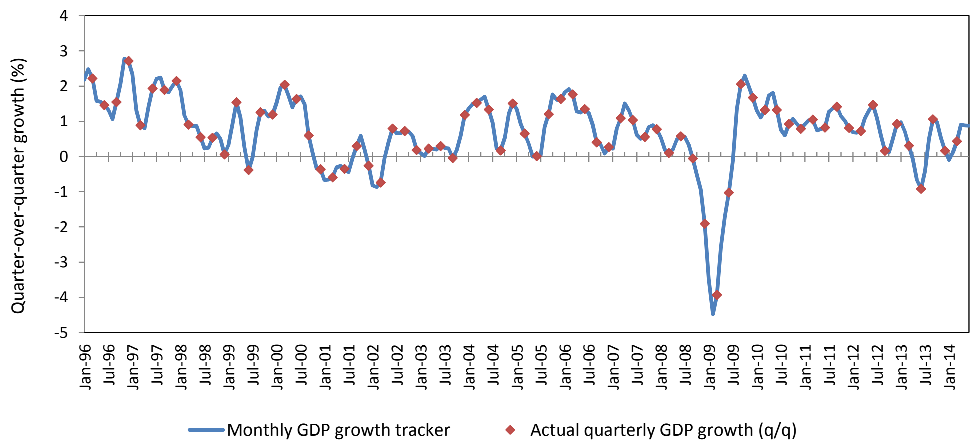
Sources: Haver Analytics and authors' calculations

Figure 3: Monthly GDP tracker for China as of July 2014



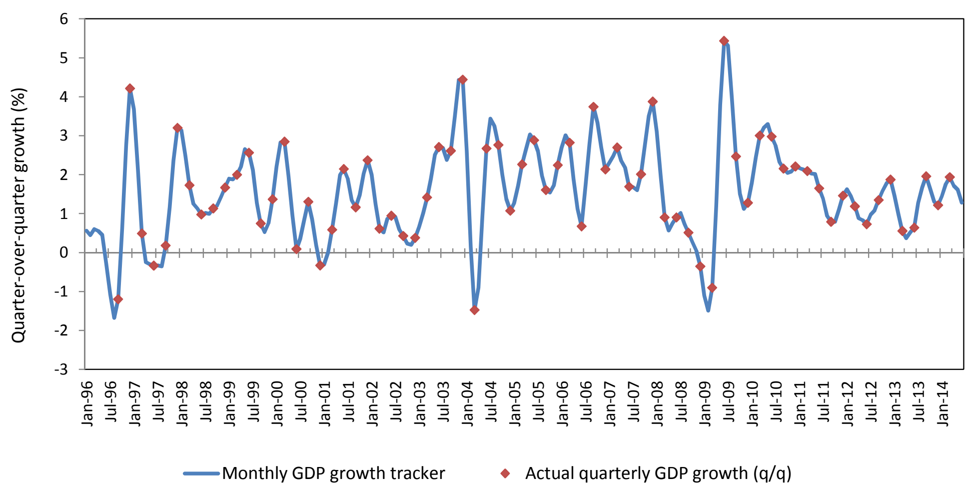
Sources: Haver Analytics and authors' calculations

Figure 4: Monthly GDP tracker for Mexico as of July 2014



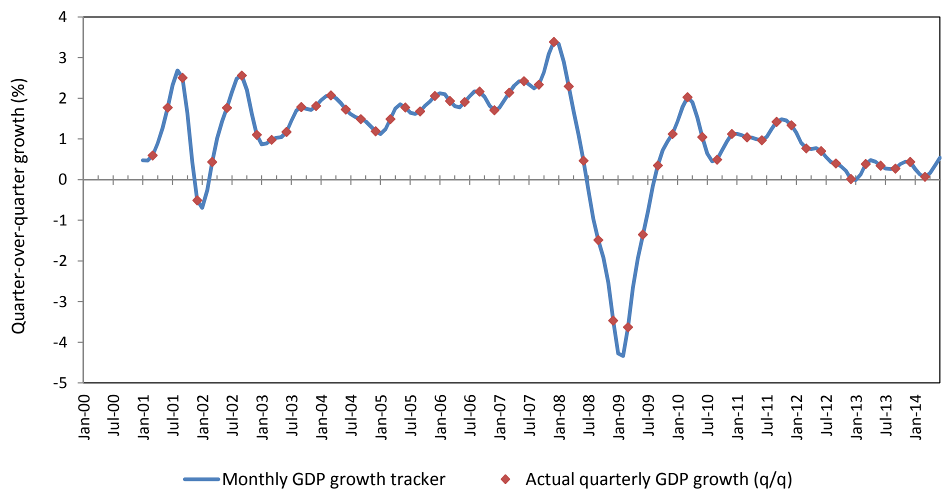
Sources: Haver Analytics and authors' calculations

Figure 5: Monthly GDP tracker for India as of July 2014



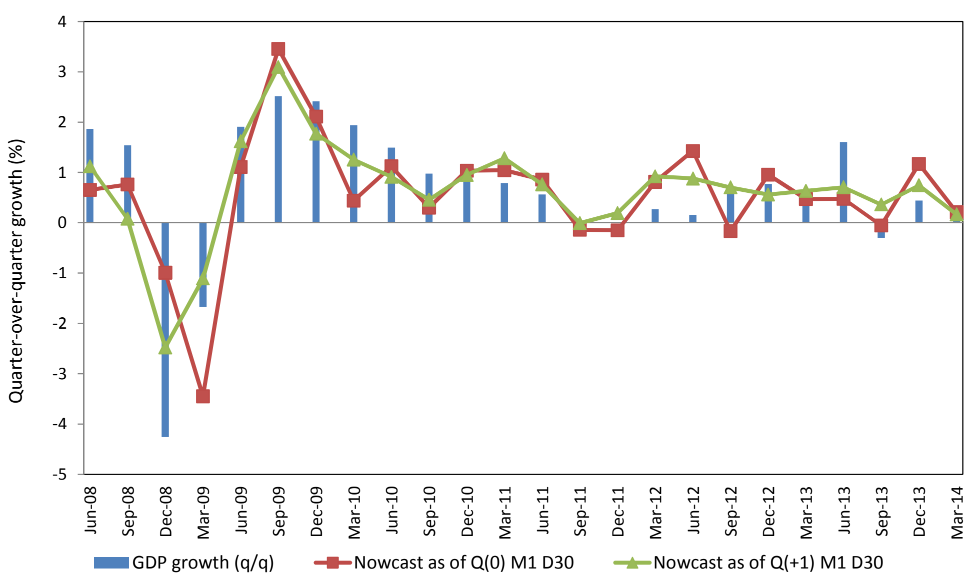
Sources: Haver Analytics and authors' calculations

Figure 6: Monthly GDP tracker for Russia as of July 2014



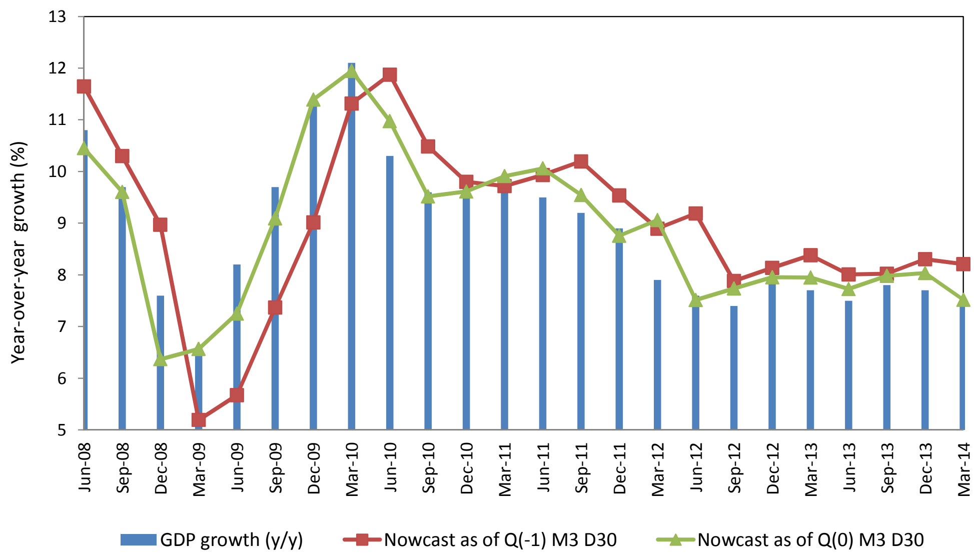
Sources: Haver Analytics and authors' calculations

Figure 7: Out-of-sample nowcasts for Brazil



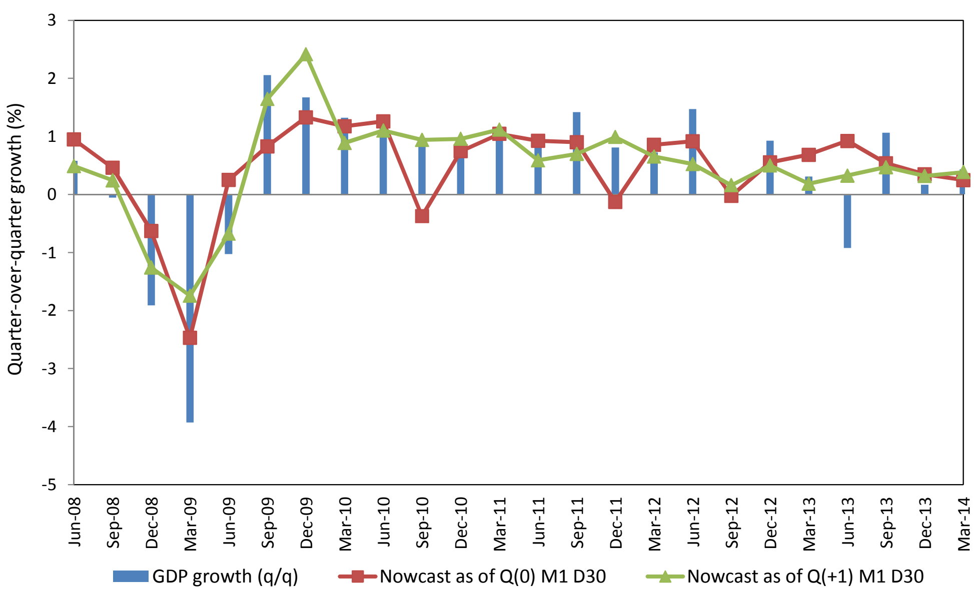
Notes: Q(0) refers to the quarter of interest, M1 refers to the first month of that quarter, and D30 refers to the end of the month. Q(+1) refers to the quarter following the quarter of interest.

Figure 8: Out-of-sample nowcasts for China



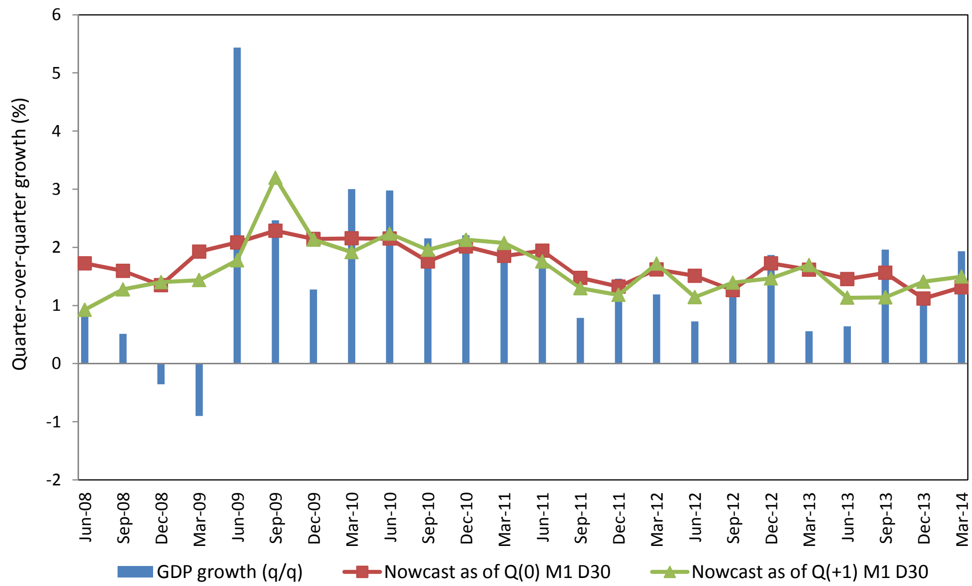
Notes: Q(0) refers to the quarter of interest, M3 refers to the third month of the quarter, and D30 refers to the end of the month. Q(-1) refers to the quarter preceding the quarter of interest.

Figure 9: Out-of-sample nowcasts for Mexico



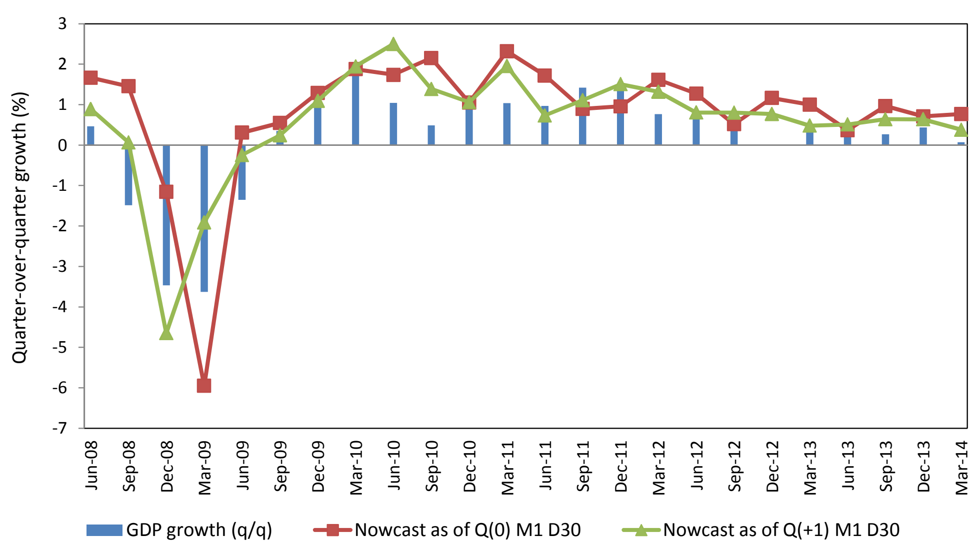
See notes to Figure 7.

Figure 10: Out-of-sample nowcasts for India



See notes to Figure 7.

Figure 11: Out-of-sample nowcasts for Russia



See notes to Figure 7.

Figure 12: DFM vs. AR(2) benchmark: Pseudo out-of-sample RMSEs

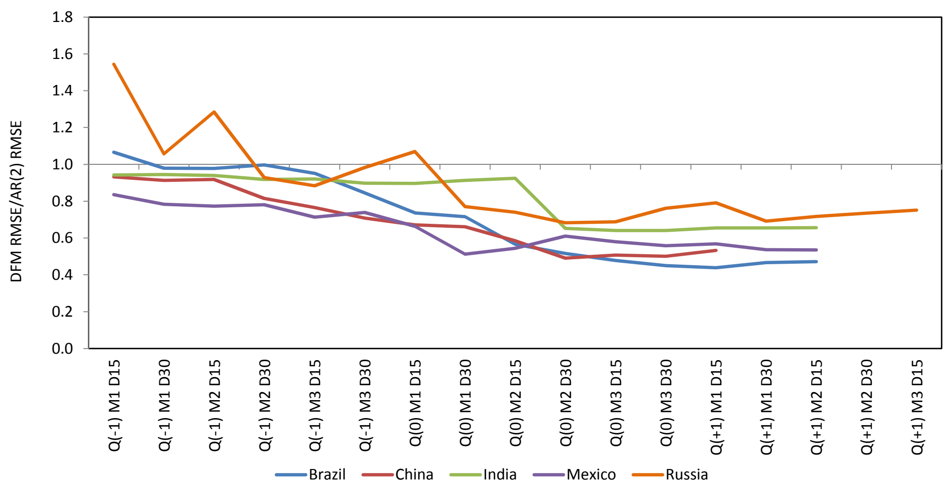


Figure 13: DFM vs. MA(4) benchmark: Pseudo out-of-sample RMSEs

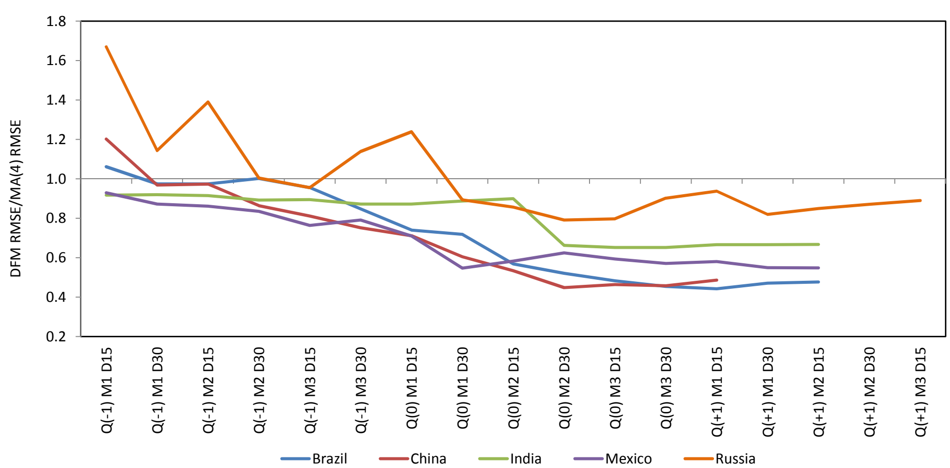


Figure 14: Impact of re-estimation and news: Brazil

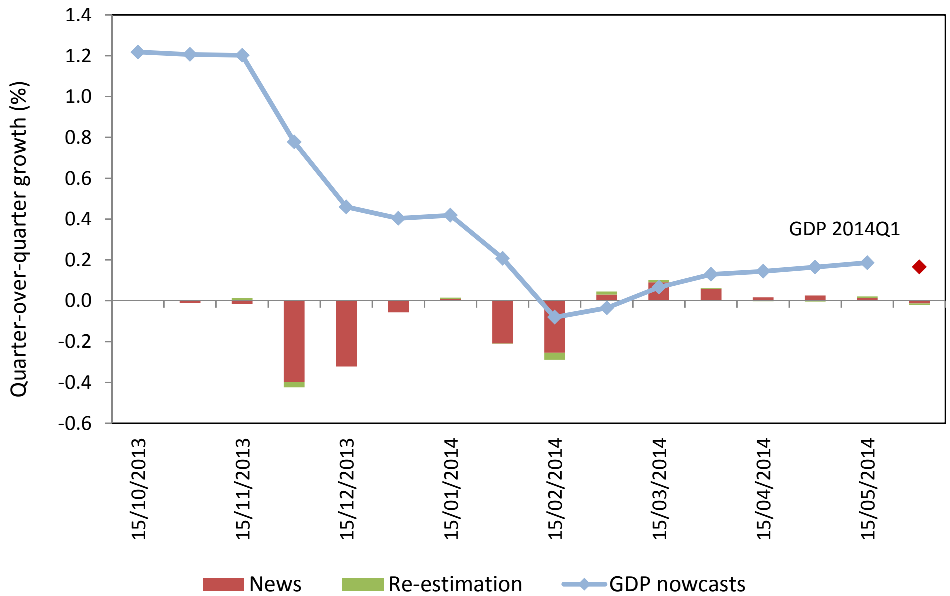


Figure 15: Decomposition of news: Brazil

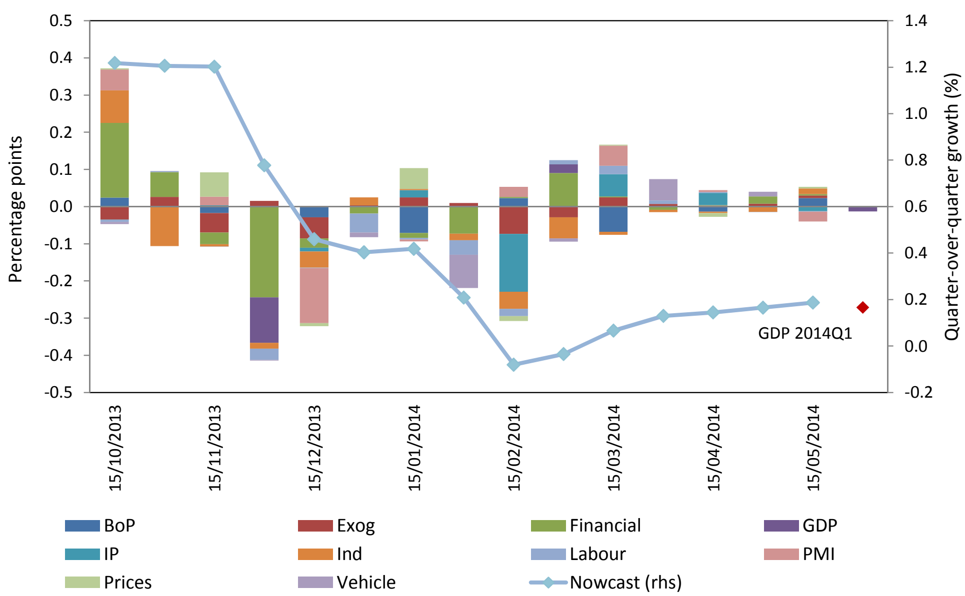


Figure 16: Impact of re-estimation and news for China

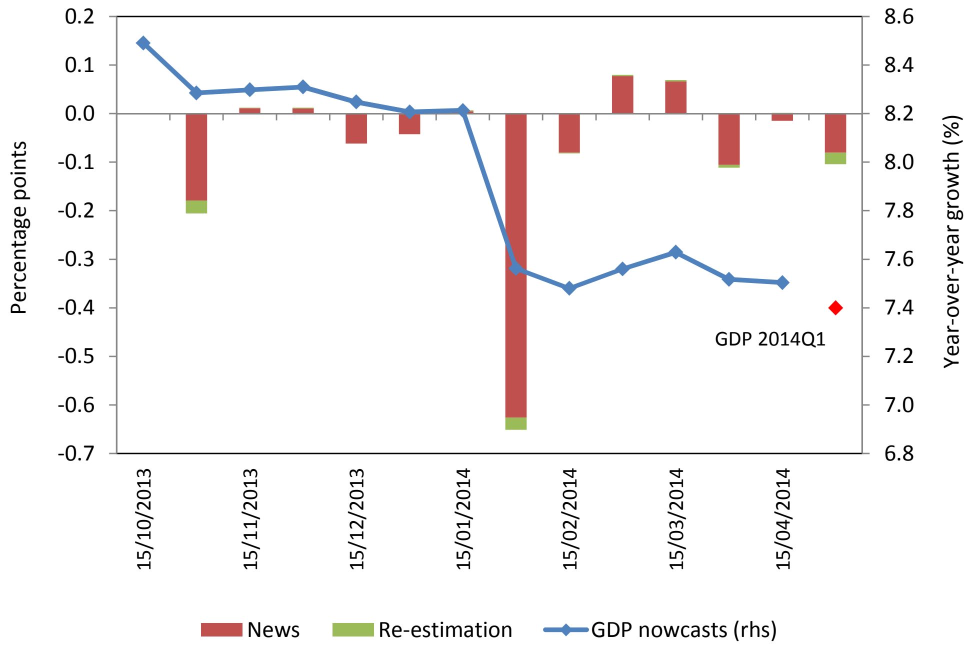


Figure 17: Decomposition of news for China

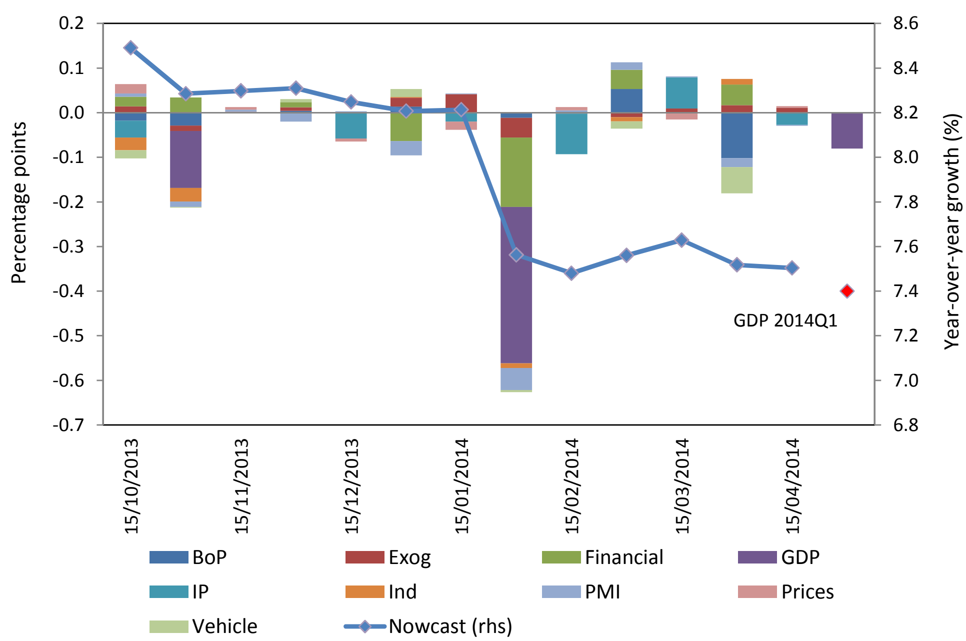


Figure 18: Impact of re-estimation and news for Mexico

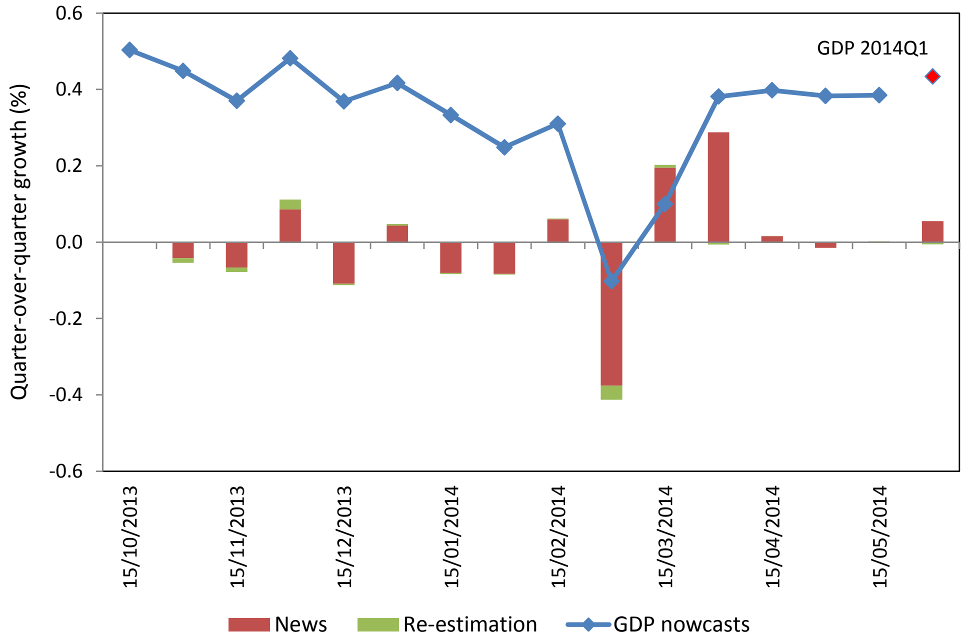


Figure 19: Decomposition of news for Mexico

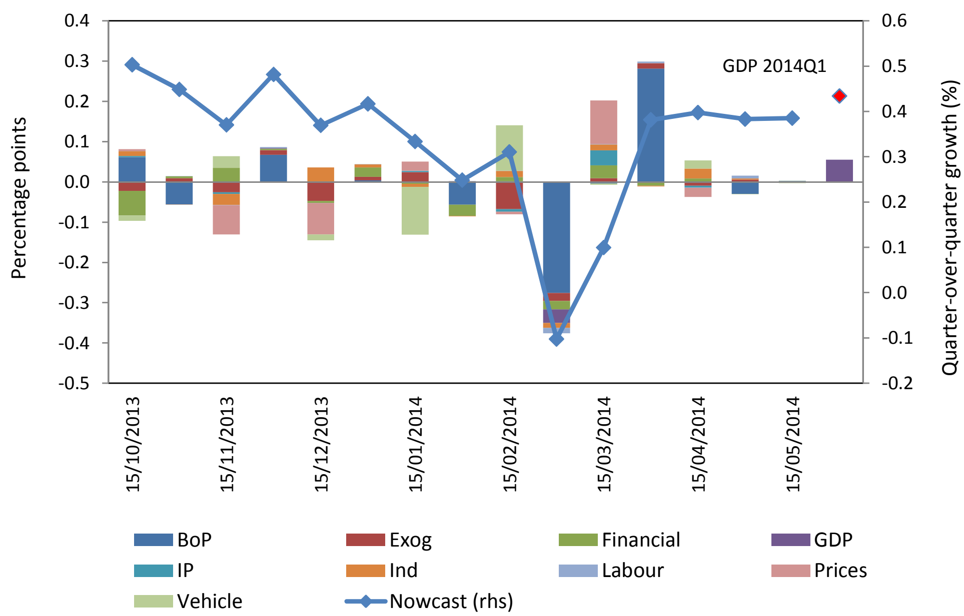


Figure 20: Impact of re-estimation and news for India

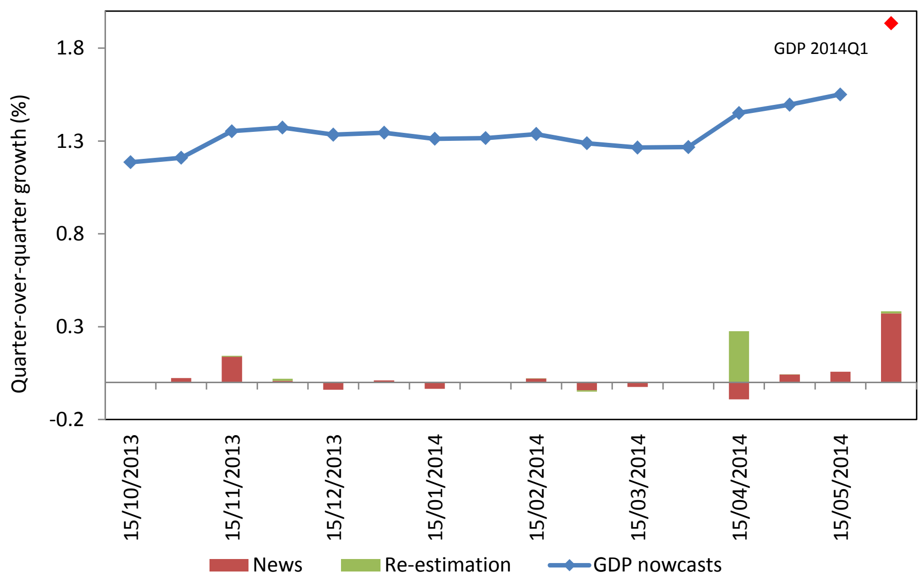


Figure 21: Decomposition of news for India

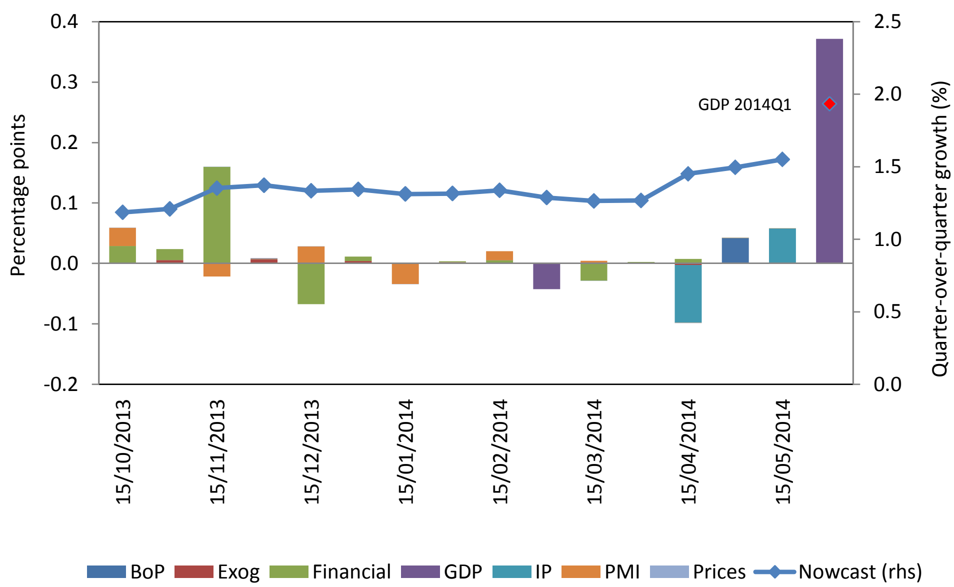


Figure 22: Impact of re-estimation and news for Russia

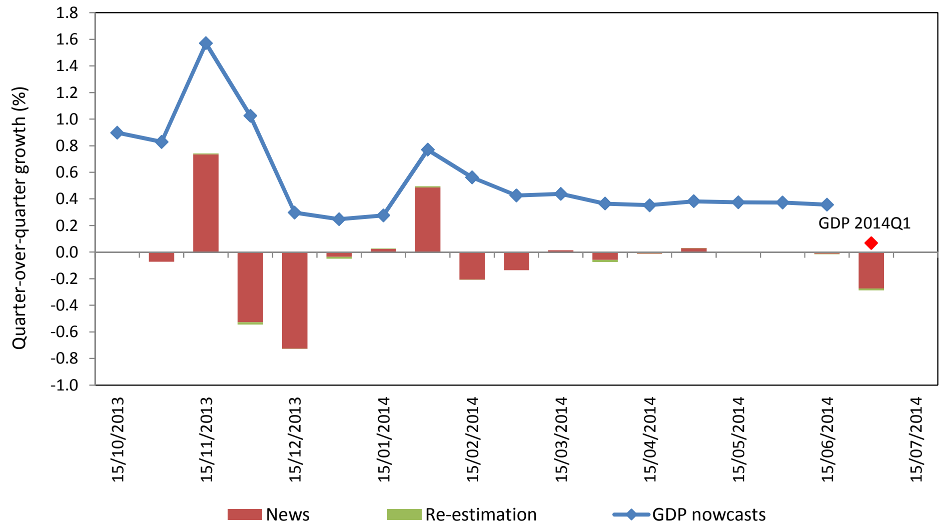
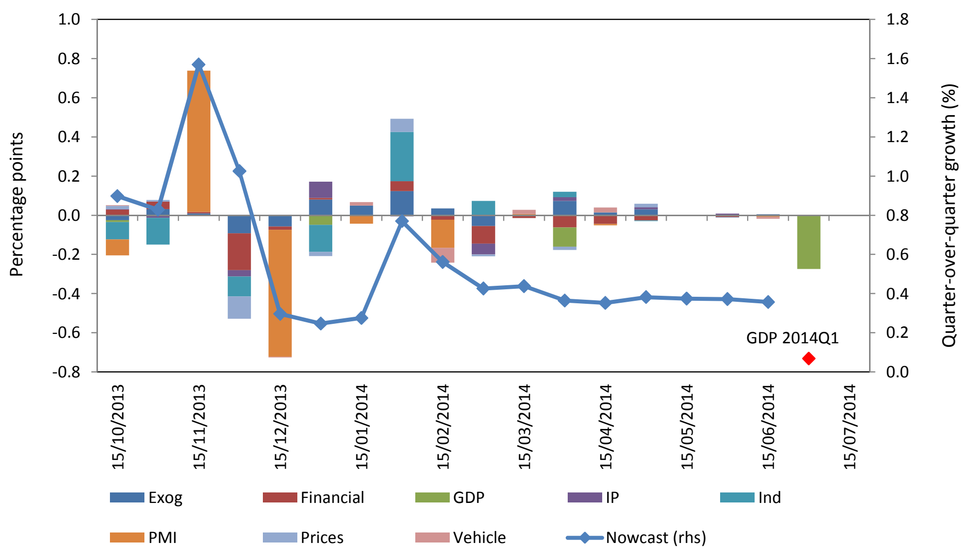


Figure 23: Decomposition of news for Russia



Appendix A State-space representation in case of AR(1) idiosyncratic component

Consider the case with the idiosyncratic component in equation 1 modeled as AR(1). Let $\alpha_M = diag(\alpha_{M,1}, ...\alpha_{M,n_M})$ and $\alpha_Q = diag(\alpha_{Q,1}, ...\alpha_{Q,n_Q})$ represent the AR(1) coefficients of the idiosyncratic component of the monthly and quarterly series, respectively. The resulting state-space representation is given by the following:

$$\begin{pmatrix} x_t \\ y_t^Q \end{pmatrix} = \begin{pmatrix} \Lambda & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \Lambda_Q & 2\Lambda_Q & 3\Lambda_Q & 2\Lambda_Q & \Lambda_Q & 0 & 1 & 2 & 3 & 2 & 1 \end{pmatrix} \times \begin{pmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ \epsilon_t^M \\ \epsilon_t^Q \\ \epsilon_{t-1}^Q \\ \epsilon_{t-2}^Q \\ \epsilon_{t-3}^Q \\ \epsilon_{t-4}^Q \end{pmatrix} + \begin{pmatrix} \xi_t^M \\ \xi_t^Q \end{pmatrix} \tag{12}$$

$$\begin{pmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ \epsilon_t^M \\ \epsilon_t^Q \\ \epsilon_{t-1}^Q \\ \epsilon_{t-2}^Q \\ \epsilon_{t-3}^Q \\ \epsilon_{t-4}^Q \end{pmatrix} = \begin{pmatrix} A_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \alpha_M & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \alpha_Q & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \times \begin{pmatrix} f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ f_{t-5} \\ \epsilon_{t-1}^M \\ \epsilon_{t-1}^Q \\ \epsilon_{t-2}^Q \\ \epsilon_{t-3}^Q \\ \epsilon_{t-4}^Q \\ \epsilon_{t-5}^Q \end{pmatrix} + \begin{pmatrix} u_t \\ 0 \\ 0 \\ 0 \\ 0 \\ e_t^M \\ e_t^Q \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \tag{13}$$