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Real-time Forecasts of Economic Activity for Latin American Economies

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Real-time Forecasts of Economic Activity for Latin American Economies

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Abstract

Macroeconomic policy decisions in real-time are based the assessment of current and future economic conditions. These assessments are made difficult by the presence of incomplete and noisy data. The problem is more acute for emerging market economies, where most economic data are released infrequently with a (sometimes substantial) lag. This paper evaluates "nowcasts" and forecasts of real GDP growth using five alternative models for ten Latin American countries. The results indicate that the flow of monthly data helps to improve forecast accuracy, and the dynamic factor model consistently produces more accurate nowcasts and forecasts relative to other model specifications, across most of the countries we consider.

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I. INTRODUCTION

Macroeconomic policy decisions in real-time are based on incomplete and noisy data. This problem is more acute for emerging market economies, where most economic data are released infrequently with a (sometimes substantial) lag. The construction of timely economic indicators and short-term forecasts are crucial steps in the decision-making process. Many central banks use these forecasts as inputs for longer-term projections of the economy, and these projections are then the main focus of policy deliberations.

This paper evaluates nowcasts and forecasts of real GDP growth using five alternative models for each of the ten Latin American countries: Argentina, Brazil, Chile, Colombia, Ecuador, Dominican Republic, Mexico, Peru, Uruguay, and Venezuela.[2] We focus on model specifications that are particularly suitable for dealing with large real-time data sets. A number of studies for advanced economies conclude that these models are useful for improving the assessment of the current and short-term economic outlook. Barhourni et al. (2008) find that for the Euro area countries, models that exploit timely monthly releases fare better than quarterly models. Among the set of models they considered, factors models, which exploit a large number of releases, do generally better than other models based on small information sets. Similarly, Giannone et al (2008) and Matheson (2010) find that the dynamic factor model provides better out-of-sample forecasts relative to several benchmarks for the U.S. and New Zealand. Despite its usefulness, the application of these models to emerging market economies remains limited. Given the growing influence of emerging markets in the world economy, obtaining timely and accurate assessments of current economic conditions in these economies is not only a crucial task for domestic policy makers, but also for policy makers in advanced countries.

Macroeconomic indicators are subject to important differences in publication lags. Quarterly GDP data, for instance, is usually released months after the quarter has finished. On the other hand, monthly industrial production, survey and financial data are available more frequently and in a much more timely manner. The publication lag is generally even longer for emerging markets. For example, the first flash estimate of GDP is available in the U.S. four weeks after the quarter ends, while the GDP for Brazil is not released until 10 weeks after the end of the quarter. This paper examines the usefulness of data releases within the quarter for forecasting current and one-step ahead GDP growth. A key feature that we take into account is the real-time nature of the data flow when evaluating the forecast performance of the selected models.

We consider five alternative model specifications for the forecast evaluation exercise: an autoregressive model, a dynamic factor model, bridge equations, bivariate vector autoregressive models, and Bayesian vector autoregressive models. A number of results emerge from the real-time forecast evaluation exercise. First, models that use monthly data generally outperform the AR model that use only quarterly data, and the forecasts become more accurate as more information arrives within each quarter, despite the higher amount of

[2]The ten selected Latin American countries account for 94 percent of the regional GDP for Latin America.

noise in monthly data. This highlights the importance of exploiting the flow of monthly data releases. Second, the dynamic factor model consistently produces more accurate nowcasts and forecasts relative to other model specifications across most the countries we consider. This result is consistent with other advanced economy studies that conclude the dynamic factor model generally performs well for nowcasting/forecasting quarterly GDP. Third, we find that external indicators, such as commodity prices and U.S. variables, are useful in improving forecast accuracy for most Latin American countries.

The paper proceeds as follows. Section (II) outlines the five competing models and estimation methodology. Section (III) describes the real-time data set for the ten Latin American countries. Section (IV) discusses the real-time forecast experiment. Section (V) presents the results of the real-time forecasting exercise, and section (VI) concludes with the main findings.

II. MODELS SPECIFICATION AND ESTIMATION

This section briefly describes the set of models that we include for the forecast evaluation experiment. We focus the selection of models on those that are particularly suitable for dealing with large data sets. The models range from a simple autoregressive process to a more sophisticated dynamic factor model. The five models we consider here is only a small subset of the range of methods available, but these represent the standard set of tools used in many policy making institutions, such as central banks. See Eklund and Kapetanios (2008) for a more complete review of the current forecasting techniques using large data sets.

A. Baseline quarterly autoregressive model

As a benchmark, we use an univariate AR model of order *p* for quarterly GDP growth (y_t^Q):

$$y_t^Q = c + \sum_{i=1}^{p} \beta_i y_{t-i}^Q + \epsilon_t^Q \tag{1}$$

where c is a constant, ϵ_t^Q is a quarterly white noise term such that $\epsilon_t^Q \sim N(0, \sigma_\epsilon^2)$, and the lag length p is selected using the Schwartz Information Criterion (SIC). Note that the baseline AR(p) model does not exploit monthly data releases, thus it does not take into account the non-synchronous flow of the data over the monitoring quarter. The forecasting performance of the AR model will serve as a reference point for the forecast evaluation across different model specifications. This relative measure is also useful for comparison across different countries.

B. Pooled bridge equations

The bridge equation is perhaps the most widely used method for forecasting quarterly GDP using monthly indicators. Bridge equation forecasts are constructed following these three steps:

1. We consider a set of monthly indicators $\{x_{1,t}, x_{2,t}, \ldots, x_{k,t}\}$, and forecast the individual indicators $x_{i,k}$ over the relevant horizon using an univariate AR(p) model:

$$x_{i,t} = \mu_i + \sum_{s=1}^{p_i} \beta_s x_{i,t-s} + \epsilon_{i,t}, \quad i = 1, \ldots, k \tag{2}$$

2. Each indicator (including forecasts) is converted to the quarterly frequency, $x^Q_{i,t} = x_{i,t} + x_{i,t-1} + x_{i,t-2}$, and we estimate the following bridge equation,

$$y^Q_{i,t} = c_i + \sum_{s=1}^{q_i} \beta_s x^Q_{i,t-s} + \epsilon^Q_{i,t} \tag{3}$$

   which relates quarterly GDP growth to the quarterly aggregate of the monthly indicator.[3] The lag lengths p_i and q_i are determined using the SIC. The forecast of GDP growth $y^Q_{i,t+h|t}$ is obtained by inserting the monthly indicator forecast of $x^Q_{i,t+h|t}$ from equation 2 into 3.

3. The forecast for GDP growth ($y^Q_{t+h|t}$) is a weighted average of the k forecasts ($y^Q_{i,t+h|t}$) from the individual indicators. The weights are based on the inverse of the root mean squared errors (RMSE) of the individual indicators:

$$y^Q_{t+h|t} = \sum_{i=1}^{k} \frac{RMSE_{i,h}}{\sum_{j=1}^{k} RMSE_{j,h}} y^Q_{i,t+h|t} \tag{4}$$

C. Pooled bivariate VARs

Similar to the bridge equation, the bivariate VAR model exploits the information content of monthly indicators. However, while the bridge equation relies on the autoregressive forecasts in step 1, it may be that information in real GDP growth itself can produce more efficient forecasts of the indicators and better forecasts of real GDP growth. To capture some of the dynamics between each of the monthly indicators and GDP, we let y^I_t denote interpolated quarterly GDP growth at the monthly frequency, $y^Q_t = y^I_{t-2} + y^I_{t-1} + y^I_t$.[4] We then estimate

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[3]Note that a more general specification would allow for lags of $y^Q_{i,t}$ on the right hand side of this equation. In our application, however, we found that allowing for such lags generally led to a deterioration in forecast accuracy.

[4]All quarterly series used in this paper are converted to the monthly frequency using linear interpolation. The results are robust to more sophisticated interpolation methods.

the following bivariate VAR model on GDP growth (y_t^I) and each of the monthly indicators,$\{x_{1,t}, x_{2,t}, \ldots, x_{k,t}\}$,

$$Z_{i,t} = c_i + \sum_{s=1}^{p_i} \beta_s Z_{i,t-s} + \epsilon_{i,t} \tag{5}$$

where $Z_{i,t} = [y_t^I \; x_{i,t}]'$. As with the other forecasting methods discussed, the lag length p_i is determined using the SIC. Relative to the bridge equations, this methodology loses some information by interpolating GDP, but it also may produce some efficiency gains by better capturing the dynamics between GDP growth and each of the monthly indicators. We use the estimated VAR in equation 5 to forecast the monthly GDP growth rates $y_{t+h|t}^I$, conditional on the latest monthly indicators available using the Kalman filter.[5] Finally, the forecast for GDP growth is formed using the k bivariate VAR forecasts as in step 3 in section (II.B).

D. Bayesian VAR

One extension of the bivariate VAR is to include a potentially large number of monthly indicators. Using the same notation as above, Z_t now includes a large set of monthly indicators, as well as the interpolated monthly GDP growth,

$$Z_t = c + \sum_{s=1}^{p} \beta_s Z_{t-s} + \epsilon_t \tag{6}$$

where the constant term c is an $k \times 1$ vector, β_s is an $k \times k$ autoregressive matrix, and ϵ_t is an $k \times 1$ white noise process with covariance matrix Ψ. To overcome the "curse of dimensionality" problem, we estimate the VAR using Bayesian shrinkage methods by imposing prior beliefs on the parameters. In setting the prior distributions, we follow the procedure developed by Doan, Litterman, and Sims (1984) and Litterman (1986).

The basic principle of the Litterman (1986) prior (often referred to as the Minnesota prior) is that all equations are "centered" around a random walk with drift. This amounts to shrinking the diagonal elements of β_1 towards one and all other coefficients in $\beta_2, \ldots, \beta_p$ towards zero. In the extreme case, the VAR becomes:

$$Z_t = c + Z_{t-1} + \epsilon_t \tag{7}$$

This embodies the belief that the more recent lags provide more useful information than the more distant ones. More formally, these priors can be imposed by setting the following moments for the prior distribution of the coefficients:

$$\mathrm{E}[(\beta_k)_{ij}] = \begin{cases} \delta_i, & j = i, k = 1 \\ 0, & \text{otherwise} \end{cases} \qquad \text{and} \qquad \mathrm{V}[(\beta_k)_{ij}] = \left(\frac{1}{\mu_1} \frac{1}{k^\lambda} \frac{\sigma_i}{\sigma_j} \right)^2 \tag{8}$$

[5] The monthly indicators are usually available ahead of the quarterly GDP release. The conditional forecast is constructed by imposing the latest observations of the monthly indicators on the VAR.

where $\delta_i = 1, \forall i$ reflects the random walk prior. However, the researcher can also incorporate priors where some variables are characterized by a degree of mean-reversion, $0 \leq \delta_i < 1$. In our application, we estimate BVARs on stationary data, so we set $\delta_i = 0, \forall i$. The hyper-parameter μ_1 controls the overall tightness of the prior distribution around δ_i, and the factor $1/k^{\lambda}$ is the rate at which the prior standard deviation decreases with the lag length of the VAR. If $\mu_1 = \infty$, the prior is imposed exactly so the data do not influence the parameter estimates, while $\mu_1 = 0$ removes the influence of the prior altogether.[6]

The Minnesota prior is implemented using dummy observations. Intuitively, this amounts to adding extra "data" to the sample that reflect the prior beliefs about the parameters. The posterior parameters can be computed with a simple ordinary least square (OLS) regression by augmenting the VAR in equation 6 with the dummy observations (see Banbura et al. (2010) for more detail). As with the bivariate VAR model, we include interpolated GDP in the Bayesian VAR, and the resulting model is used to produce conditional forecast of monthly real GDP growth using the Kalman filter.

E. Dynamic factor model

The final model we consider is the dynamic factor model (DFM). The DFM assumes that a panel of macroeconomic data can be decomposed into two orthogonal unobserved components: a common component and a idiosyncratic component. The common component captures the bulk of the covariation between the series in the panel and is driven by a small number of shocks, while the idiosyncratic component affects a limited number of series in the panel. The model can be described as:

$$X_t = \Lambda F_t + \epsilon_t, \text{ where } \epsilon_t \sim N(0, \Psi) \tag{9}$$

$$F_t = \sum_{s=1}^{p} A_s F_{t-s} + B u_t, \text{ where } u_t \sim N(0, \Sigma) \tag{10}$$

Equation 9 relates the $k \times 1$ vector of monthly indicators X_t (including interpolated real GDP growth) to the $r \times 1$ vector of common (static) factors F_t via the factor loadings Λ and the idiosyncratic component ϵ_t. Equation 10 assumes that the common factors follow a VAR(p) process driven by an $q \times 1$ vector of pervasive shocks u_t.The number of static and dynamic factors (r and q, respectively) are chosen according to a selection criteria that balances the "fit" of the common component with respect to quarterly GDP against the problem of over-parameterization.

We estimate the DFM using the two-step procedure described in Doz et al. (2007):

[6]The coefficients $\beta_1, \ldots, \beta_p$ are assumed to be independent and normally distributed. Following Sims and Zha (1998), the covariance matrix of the residuals Ψ is assumed to follow an inverse Wishart distribution.

1. Based on the latest available complete balanced data panel, estimate the common factors using principle components.[7] Given the common factors, estimate the factor loadings $\hat{\Lambda}$ and the covariance matrix $\hat{\Psi}$ associated with ϵ_t using OLS. In addition, estimate the VAR coefficients $\hat{A}_1, \ldots, \hat{A}_p$ and $\hat{\Sigma}$ using OLS, where the number of lags p is selected using SIC.[8]

2. Given the estimated parameters ($\hat{\Lambda}$, $\hat{\Psi}$, $\hat{A}_1, \ldots, \hat{A}_p$, and $\hat{\Sigma}$) in step 1, we apply the Kalman Smoother to the entire data panel (including missing observations) and re-estimate the factors. If $x_{i,t}$ has missing observations, the implicit signal extraction process of the filter will place no weight on the missing variable x_i in the computation of the factors at time t.

Doz et al. (2007) have shown that the two-step procedure outlined above gives consistent estimates of the factors.[9] Finally, we apply the Kalman filter forward recursion using the estimated factors in step 2 to obtain the h-step ahead forecast for GDP growth.

III. DATA

The ten countries selected for this study represent 94 percent of the Latin America and Caribbean (LAC) region's GDP in 2009, and cover geographically the entire region, which includes the Caribbean, Mexico and South America, with a combined population of over 480 million. Table 1 gives a summary of selected set of economic indicators and shows the heterogeneity present within the region. For example, some countries show double digit average inflation rates over the past decade, while others have stable inflation that is comparable with the U.S. Generally, the degree of uncertainty (proxied by the volatility) for Latin America data is much greater than that for advanced economies. Annual declines in real GDP exceeding five percent are not uncommon (figure 1), and hence nowcasts in these economies must contend with greater fundamental variation.

There are hundreds of published economic indicators at the monthly or quarterly frequency for many of the Latin American economies studied here. Nonetheless, coverage is uneven relative to advanced economy data sets. Table 2 breaks down the selected indicators for each of the ten countries. Activity surveys are only available for Argentina, Brazil, Chile, and Mexico. On the other hand, there is good coverage for trade and financial conditions indicators across most of the countries. The total number of selected indicators ranges from 81 for the Dominican Republic to 149 for Chile.

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[7] We de-mean and standardized the data series prior to estimation, see Appendix I for more details on data transformation.

[8] The matrix $\hat{B} = MP^{1/2}$, where P is an $q \times q$ diagonal matrix with the entries given by the largest q eigenvalues of $\hat{\Sigma}$ and M is the $r \times q$ matrix of the corresponding eigenvectors.

[9] In a separate paper Doz et al. (2006) show that by iterating steps 1 and 2, a quasi-maximum likelihood estimator for the factors is obtained.

Table 1. Summary of country economic indicators

	GDP (US$B)	Regional GDP (%)	GDP per capita (US$)	Average GDP growth 2000-10	Average Inflation 2000-10
Argentina	310	7.8	7,780	3.8	10.0
Brazil	1,574	39.6	8,199	3.4	6.6
Chile	162	4.1	9,628	3.7	3.2
Colombia	229	5.8	5,084	3.9	5.5
Dom. Rep.	47	1.2	4,691	4.9	11.8
Ecuador	57	1.4	4,251	4.3	6.5
Mexico	875	22.0	8,060	1.6	4.5
Peru	127	3.2	4,396	5.4	2.2
Uruguay	36	0.9	10,755	3.0	8.7
Venezuela	337	8.5	11,994	2.9	23.2

Source: International Monetary Fund World Economic Outlook, 2010. GDP and regional shares are calculated using data for 2009.

Table 2. Summary of economic indicators by category

	Activity (survey)	Activity (hard data)	Trade	Financial conditions	Employment & income	Prices	Total
Argentina	17	15	28	16	17	13	106
Brazil	19	33	38	20	10	11	131
Chile	13	28	34	31	12	31	149
Colombia	...	43	20	19	21	18	121
Dom. Rep.	...	...	46	11	13	11	81
Ecuador	...	32	38	16	5	20	111
Mexico	19	42	15	17	17	16	126
Peru	...	56	5	23	16	20	120
Uruguay	...	21	20	18	29	35	123
Venezuela	...	25	3	43	...	31	102

Note: Table shows the number of monthly/quarterly indicators employed in forecasting. Series are drawn from Haver and are shown by type of economic indicator.

In addition to domestic indicators, we also include relevant commodity price series. The Latin America region as a whole is a net commodity exporter of fuels, metals and minerals, and agricultural products, and most countries produce a variety of primary commodities. Nevertheless, commodity endowments are heterogeneous within the region, so that increased commodity prices (especially fuels) can adversely affect some energy importing economies while benefitting others. We include 11 commodity price series covering prices of Petroleum, Copper, Soy Gold, Metals, Industrials, Food, Fats and oils, Coffee, Sugar, and Livestock. In addition, given the importance of trade and financial linkages with the U.S. economy for the region, we also include 8 U.S. indicators.[10]

An important problem with emerging market data is that samples for many of the monthly

[10]We include industrial production, 3 retail sales series, the ISM survey for manufacturing, the unemployment rate, employment, and consumer confidence (Conference Board).

Figure 1. Latin America Ten Countries, normalized Real GDP (IMF WEO), 1980-2010

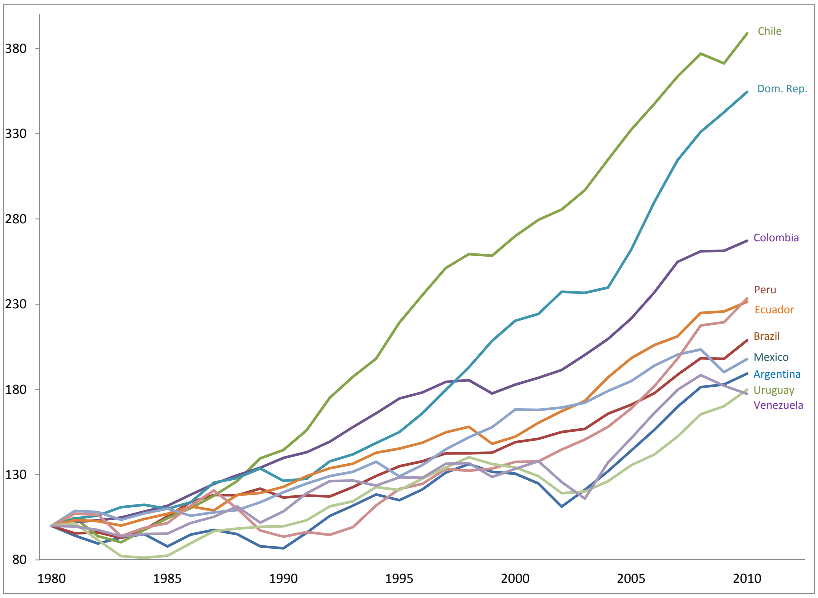


Table 3. Estimation and forecast evaluation sample

	Sample starts	Sample ends	Forecast evaluation	n.o series$^{(1)}$
Brazil	1995Q1	2010Q1	2000Q1	148
Mexico	2000Q1	2010Q1	2005Q1	129
Argentina	2003Q1	2010Q1	2008Q1	102
Chile	2000Q1	2010Q1	2005Q1	150
Colombia	2000Q1	2010Q1	2005Q1	141
Peru	2000Q1	2010Q1	2005Q1	124
Ecuador	2000Q1	2010Q1	2005Q1	108
Uruguay	2001Q1	2010Q1	2006Q1	134
Venezuela	2004Q2	2010Q1	2008Q1	117
Dom. Rep.	2000Q1	2010Q1	2005Q1	147

(1) This represents the effective number of series used for the forecast evaluation.

indicators are very short, and some series include missing values and/or outliers within the sample period. As such, we employ an extensive pre-filtering process to transform and clean the data prior to the empirical analysis, including seasonal adjustment, removal of series with very short samples, backdating of series with missing values at the beginning of the sample, and outlier correction.[11] After pre-filtering, all data are measured at the monthly frequency. The sample periods, evaluation periods, and the effective sample sizes after pre-filtering are displayed in table 3.

As part of the pre-filtering process, we transform all data to be stationary. Log quarterly differences are taken of the non-stationary series, $\ln(x_t) - \ln(x_{t-3})$, except those that are measured in percentages or can take negative values; these series are differenced, $x_{i,t} - x_{i,t-3}$.

[11] Appendix I provides a more detail description of the pre-filtering process.

IV. Real-time forecast experiment

This section briefly describes the real-time forecasting problem in a very stylized way, and the general principles underlying the forecast evaluation experiment. The aim is to evaluate the current quarter nowcast and the one-step ahead forecast of the annualized quarterly real GDP growth, using the five model specifications across the ten Latin American countries.

A. The real-time problem

Within each quarter, contemporaneous values of key macroeconomic variables such as GDP are not available. In the case of our sample countries, the first estimate of GDP is only available in the third month after the end of the quarter. However, they can be estimated using more timely, higher-frequency indicators.

At an arbitrary point in each quarter ν, e.g.: ν is the end of the month 1, 2, and 3 of the monitoring quarter, the data available are represented by the information set Ω_ν^n, which includes the most recent data for n monthly time series. The forecaster's task is to project GDP growth $y_{\nu+h}$ for $h = 0, \ldots, H$ based on the information set available at ν:

$$\hat{y}_{\nu+h} = \text{Proj}[\text{GDP}|\Omega_\nu^n],\ h = 0, \ldots, H \tag{11}$$

Assume that Ω_ν^n composes of two blocks $[\Omega_\nu^{n1}\ \Omega_\nu^{n2}]$. The variables in Ω_ν^{n2}, say industrial production, are released a month later than those in Ω_ν^{n1}, say asset prices. This implies that variables in Ω_ν^{n1} are available up to month ν, while variables in Ω_ν^{n2} are only available up month $\nu - 1$. Table 4 illustrates a stylized data panel for different classes of variables. The forecaster needs to project on the basis of this unbalanced panel of data.

Table 4. Stylized data panel for different classes of variable(1)

Month	Activity	Surveys	Asset prices	Foreign	GDP(2)
$\nu - 2$	X	X	X	X	O
$\nu - 1$	O	X	X	X	O
ν	O	O	X	O	O

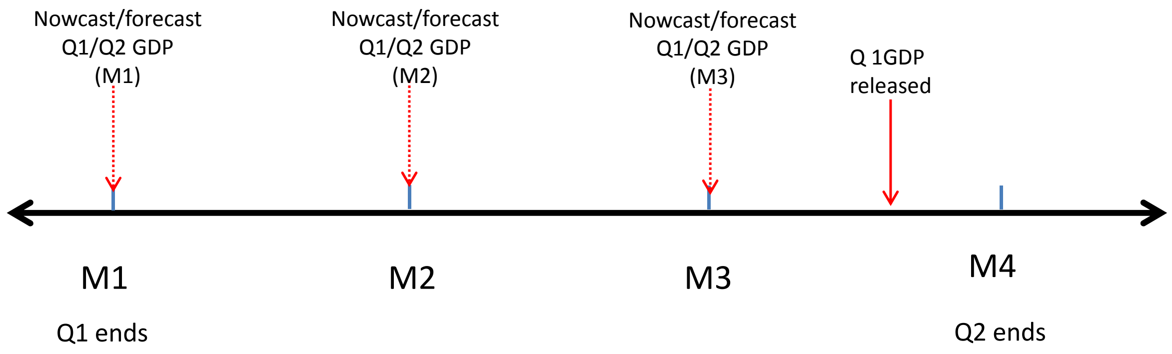
(1) X indicates data are available at the end of the month, and O indicates data that is missing from the panel.

(2) GDP data are usually released in month $\nu + 3$.

B. Real-time forecasting experiment

In the forecasting experiment, we aim to replicate the real-time application of the models as closely as possible. However, we do not have real-time datasets for the ten Latin America countries. Instead, we rely on data release dates recorded by Haver Analytics to compile quasi-real-time data sets by manipulating the most recent vintages of data. These data sets mimic *exactly* the data available to the forecaster at the beginning of each month, but it does not account for the possibility of data revisions. The first estimates of GDP for the previous quarter are released in the third month after the quarter ends. We compute the nowcast of previous quarter GDP growth and the one-step-ahead forecast using information available up to the first day of each month of the quarter: we compute three nowcasts and three one-step ahead forecasts of GDP growth in each quarter. Figure 2 illustrates the timing of nowcasts/forecast for an arbitrary quarter.

Figure 2. Timing of nowcasts for an arbitrary quarter



We compare the nowcast/forecast of annualized quarterly real GDP growth in each month with the latest final published GDP outturn and compute the RMSE for each of the five models.

C. Variable selection and model parameters

This section outlines the variable selection procedure and the choice of parameters for each model. In each month of the forecast evaluation period, we re-estimate all model parameters, re-select all lag lengths and hyperparmeters, and re-run all variable-selection algorithms, given the available quasi-real time dataset.

1. The baseline AR(p) model is only based on quarterly GDP growth. This implies that the AR(p) forecasts will remain fixed for three consecutive months until new quarterly GDP data arrives.

2. For the pooled bridge equation (BRIDGE), we select a set of 10 monthly indicators that have the highest contemporaneous correlation with quarterly GDP growth and that are available prior to the release of the GDP data.[12]

3. For the pooled bivariate VAR (BIVAR) model, we use the same set of monthly indicators as the pooled bridge equation.

[12] We found that including more than 10 variables generally led to a deterioration in forecast accuracy for both the pooled bridged equations and bivariate VAR forecasts.

4. We consider two Bayesian VAR specifications: a small BVAR (BVAR) and a large BVAR (LBVAR). The small BVAR contains real GDP growth, inflation, terms of trade, short-term interest rates, and stock prices.[13] The large BVAR includes the entire set of monthly indicators. Following Banbura et al. (2010), the overall tightness of the priors μ_1 is set such that the average R^2 across all equations is fixed at 0.6 to avoid the problem of "over-fitting".[14]

5. For the dynamic factor model (DFM), we select the number of static factors (r) such that the marginal improvement in the R^2 of the regression of real GDP growth and the common component (measured at the quarterly frequency) is less than 0.025. In initial work, we found that the Bai and Ng (2002) criteria for selecting r generally choses too many factors, leading to poor forecasting performance.[15] Given r, we determine the number of dynamic factors using the information criteria described in Bai and Ng (2007).[16] Table 5 summarizes the parameters for the DFM estimated with the final vintage of data across the different countries and the percentage variation explained by the common component (for GDP growth and the entire data set).

Table 5. Parameter specification for DFM

	% of GDP$^{(1)}$	% of data set$^{(2)}$	r	q	p
Brazil	66	38	4	3	1
Mexico	61	27	1	1	3
Argentina	57	23	1	1	2
Chile	43	18	1	1	3
Colombia	58	17	1	1	2
Peru	63	30	3	3	1
Ecuador	27	28	2	2	3
Uruguay	62	40	3	2	2
Venezuela	72	56	5	2	1
Dom. Rep.	47	18	2	2	1

(1) Percentage variation of GDP explained by the common component.

(2) Percentage variation of the entire data set explained by the common component.

[13] For some countries, due to a lack of available data, we replaced one or more of these series with series that have a similar economic interpretation.

[14] The BVARs contains 6 lags with λ set to 1, and the prior standard deviations on the autoregressive parameters are selected using error standard deviations from a AR(6) process.

[15] Likewise, the ad-hoc criterion (of choosing the number of static factors to explain a certain proportion of the variation in key series, including GDP alone) used by Giannone, Reichlin, and Sala (2005) and Matheson (2010) greatly deteriorated forecast accuracy for some countries.

[16] We use the parameters as suggested by Bai and Ng (2007).

V. RESULTS

For each country, we consider five alternative model specifications: the AR model; the pooled bridge equation; the pooled bivariate VAR; the large and small BVARs; and the dynamic factor model. We also compute two weighted-average forecasts based on the five models. The first uses the recursively computed inverse RMSEs of each model as weights; the second is a simple average across the six models.

A. Nowcast accuracy

Table 6 presents the RMSEs of the nowcasts for each of the eight specifications (including the weighted-average forecasts) across the ten countries for annualized quarterly real GDP growth. The month indicates the timing of the forecast within each quarter, e.g., month 1 corresponds to the nowcast of GDP for the previous quarter on the first day of the month. The first column reports the RMSE of the benchmark quarterly AR model. The size of the forecast error is similar for most countries except for Mexico, Venezuela and the Dominican Republic where the errors are much larger. The size of the forecast errors are generally larger compared with results reported in other studies for advanced countries, consistent with the higher volatility of GDP for Latin American countries.

To simplify comparison across different countries, the rest of the table presents the RMSEs of the other specifications as a ratio to the AR model. The main findings can be summarized as follows:

1. Models that use monthly data generally outperform the quarterly AR model.

2. The nowcast becomes more accurate as more information arrives within the quarter, i.e., the RMSE for the third month is smaller than the first month. This highlights the importance of exploiting the flow of monthly data releases.

3. The DFM consistently produces more accurate nowcasts relative to other model specifications, with the exception of Argentina and Peru. For Argentina, the pooled bivariate VAR is preferred, while for Peru the pooled bridge equation fared slightly better.

4. The large BVAR is generally the worst performer, despite using the same complete dataset as the DFM model.

5. The weighted-average nowcasts generally perform well, but the errors are sometimes larger than the best performing model.

Table 6. RMSE of GDP nowcast across different models

	Month	AR(1)	DFM	BRIDGE	BIVAR	BVAR	LBVAR	INVMSE	MEAN
Brazil	1	4.97	0.74	0.84	0.90	0.92	1.77	0.80	0.83
	2		0.72	0.77	0.84	0.87	2.96	0.78	0.93
	3		0.67	0.62	0.68	0.73	2.40	0.67	0.82
Mexico	1	8.24	0.68	0.77	0.82	0.73	1.19	0.80	0.78
	2		0.69	0.78	0.74	0.72	1.33	0.78	0.78
	3		0.69	0.72	0.71	0.73	0.93	0.74	0.74
Argentina	1	4.81	1.15	1.04	0.91	1.05	1.01	0.98	0.76
	2		1.18	1.12	0.91	1.06	1.30	1.05	0.98
	3		1.18	1.20	0.93	1.18	1.29	1.09	1.00
Chile	1	5.18	0.74	0.89	0.89	0.92	1.41	0.83	0.81
	2		0.71	0.88	0.86	0.84	1.32	0.79	0.75
	3		0.70	0.85	0.85	0.77	1.78	0.77	0.75
Colombia	1	5.29	0.77	0.79	0.92	0.99	0.99	0.79	0.74
	2		0.72	0.72	0.81	1.03	1.20	0.74	0.72
	3		0.73	0.64	0.66	0.80	0.91	0.66	0.65
Peru	1	4.26	0.93	1.01	1.05	1.04	2.39	0.84	0.91
	2		0.99	0.83	1.03	1.08	3.56	0.84	0.95
	3		1.01	0.82	1.02	1.11	1.76	0.84	0.84
Ecuador	1	4.67	0.90	0.99	1.57	1.11	4.74	1.02	1.36
	2		0.89	0.95	1.49	1.07	4.95	1.02	1.42
	3		0.87	0.92	1.45	1.10	5.05	1.00	1.46
Uruguay	1	5.60	0.77	0.82	0.72	0.94	0.98	0.79	0.77
	2		0.76	0.89	0.66	0.95	1.40	0.81	0.79
	3		0.80	0.87	0.65	1.04	1.13	0.77	0.78
Venezuela	1	10.91	0.75	0.89	0.85	0.84	1.53	0.85	0.85
	2		0.47	0.95	1.03	0.84	1.10	0.73	0.79
	3		0.49	0.87	0.56	0.84	1.01	0.66	0.68
Dom. Rep.	1	7.93	0.86	0.95	1.03	1.11	20.18	1.00	2.31
	2		0.87	0.94	1.02	1.11	1.29	0.95	0.88
	3		0.87	0.95	1.02	1.11	1.15	0.94	0.89

(1) Absolute value of the RMSE.

Note, the table shows relative RMSEs for the DFM, BRIDGE, BIVAR, BVAR and LBVAR to the AR model.

Table 7. RMSE of one-step ahead GDP forecast cast across different models

	Month	AR(1)	DFM	BRIDGE	BIVAR	BVAR	LBVAR	INVMSE	MEAN
Brazil	1	4.91	0.91	1.01	1.02	0.86	1.00	0.96	0.91
	2		0.78	1.00	1.02	0.87	1.13	0.93	0.88
	3		0.76	0.99	1.01	0.88	2.84	0.87	0.99
Mexico	1	9.38	0.77	0.82	0.94	0.63	0.70	0.79	0.80
	2		0.71	0.83	0.91	0.61	0.66	0.77	0.77
	3		0.63	0.80	0.76	0.62	0.91	0.74	0.74
Argentina	1	6.30	1.09	1.07	0.97	1.64	1.54	1.14	1.16
	2		1.14	1.05	0.99	1.56	1.10	1.17	1.12
	3		1.15	1.05	0.85	1.06	1.26	0.84	0.83
Chile	1	5.81	0.76	0.88	0.93	0.97	0.85	0.91	0.84
	2		0.78	0.86	0.90	0.96	1.04	0.91	0.86
	3		0.68	0.82	0.83	0.99	1.13	0.84	0.78
Colombia	1	4.36	1.05	1.02	1.26	1.16	0.98	1.03	1.03
	2		0.99	1.00	1.31	1.15	1.03	1.03	1.02
	3		0.95	0.96	1.11	1.16	1.21	1.01	0.95
Peru	1	5.05	0.86	1.02	1.01	1.12	0.78	0.91	0.84
	2		0.71	0.95	0.98	1.13	1.15	0.90	0.83
	3		0.90	0.96	1.23	1.09	1.89	0.90	1.01
Ecuador	1	5.06	1.10	1.00	1.24	1.28	1.42	1.18	1.03
	2		1.02	1.00	1.21	1.26	1.41	1.19	1.02
	3		0.96	1.02	1.07	1.30	3.53	1.07	1.19
Uruguay	1	5.83	0.97	1.00	1.11	1.01	1.07	0.96	0.98
	2		0.99	0.99	1.07	0.97	1.11	0.93	0.97
	3		0.92	1.00	0.93	1.00	1.49	0.92	0.90
Venezuela	1	10.15	1.10	0.92	1.07	1.04	1.11	1.14	1.00
	2		0.97	0.92	1.31	1.04	1.62	1.39	1.07
	3		0.89	0.95	1.04	1.04	2.87	1.19	1.03
Dom. Rep.	1	7.77	1.00	1.01	1.04	1.11	20.83	1.31	1.51
	2		0.95	1.01	1.03	1.19	17.77	1.17	2.54
	3		0.93	1.00	0.97	1.23	12.45	1.07	2.01

(1) Absolute value of the RMSE.
Note, the table shows relative RMSEs for the DFM, BRIDGE, BIVAR, BVAR and LBVAR to the AR model.

Figure 3. Estimated common component using DFM against quarterly GDP growth

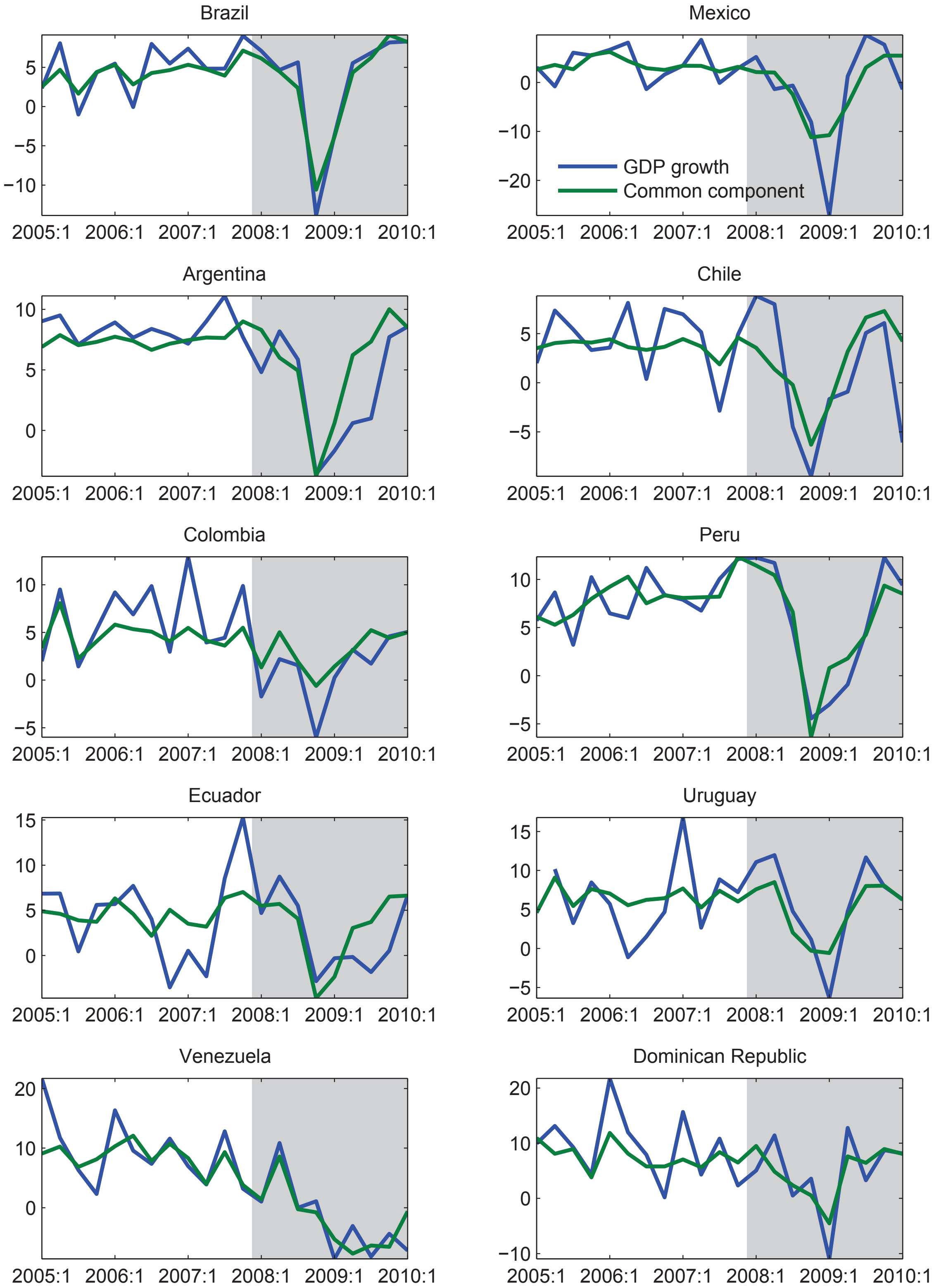
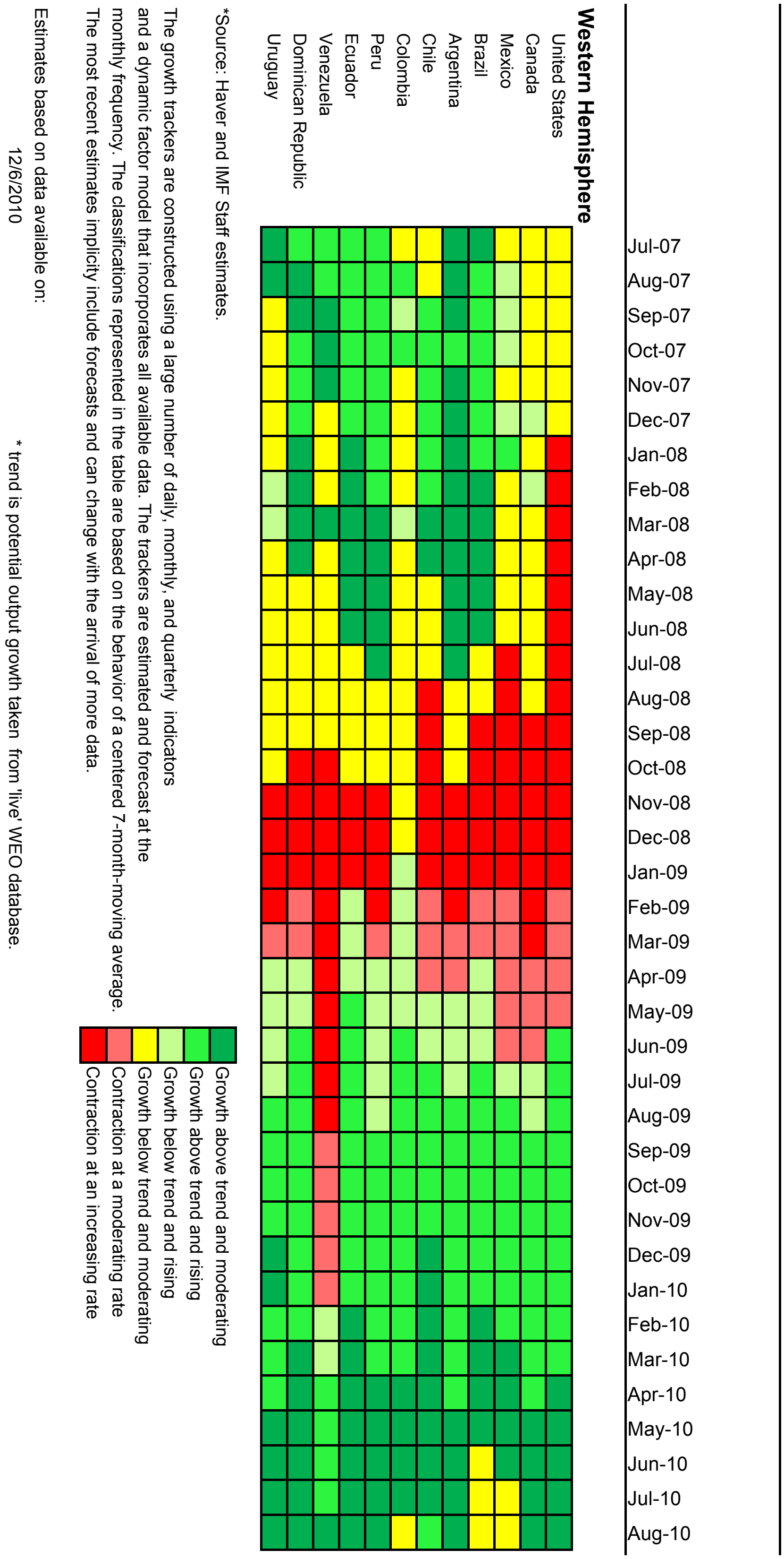


Figure 4. Monthly growth indicator for Latin America



B. One-step ahead forecast accuracy

Table 7 summarizes the RMSEs for the one-step ahead forecasts of annualized quarterly real GDP growth. Similar to the previous table, we present the RMSEs as a ratio to the RMSE of the relevant AR model. The main findings can be summarized as follows:

1. The forecast errors are larger for the one-step ahead forecast compared with the nowcast across all model specifications.
2. Additional monthly information is generally useful in improving the one-step ahead forecasts for most countries, with Argentina and Ecuador being the exceptions.
3. Across the models, the DFM again consistently produces more accurate one-step ahead forecasts for most countries. However, the BVARs tend to be more accurate for Mexico, and the bivariate VARs tend to be more accurate for Argentina.

For both the nowcast and one-step ahead forecast evaluation exercise, the DFM consistently produces smaller forecast errors relative to the other model specifications considered across most countries. The usefulness of the DFM comes down to its ability to extract timely information from a large set of indicators using a small handful of common factors. The use of a few factors avoids the "over-fitting" problem that usually exists for other time-series models. This result is consistent with other studies, mainly for advanced economies, that show that the DFM generally outperforms other model specifications for nowcasting and short-term forecasting, e.g., Barhourni et al. (2008) for the Euro area countries, Giannone et al. (2008) for the U.S., and Matheson (2010) for New Zealand.

Figure 3 plots the estimated common components using the DFM at the end of the sample alongside quarterly GDP growth for each country. The estimated common component generally tracks GDP growth quite closely, and captures the sharp contraction in economic activity over the crisis period.

Figure 4 presents the monthly growth indicator using the DFM model for the ten Latin America countries at the end of August 2010.[17] The chart illustrates how outputs from the DFM model can be use to monitor economic activity for individual countries and to explore the synchronization of regional business cycles. The monthly indicator for the U.S. and Canada is added for relative comparison over the crisis period. The chart indicates a slowdown in the pace of economic expansion recently among the Latin American countries, in particular for the larger economies, such as Brazil, Mexico and Colombia . Over the crisis period, the growth indicator also indicates that the contraction in economic activity was well synchronized across the region, at around the third quarter of 2008, while the contraction in the U.S. economy started two quarters earlier. On the other hand, the recovery was much

[17] The monthly growth indicator is constructed based on a seven-month moving average of the estimated common component using the DFM model; the trend is the IMF World Economic Outlook estimate of the country's potential GDP growth rate.

more synchronized between Latin America and the North American economies, except for Venezuela.

C. Usefulness of external indicators

The baseline forecasting exercise includes many external indicators, such as commodity prices and a set of U.S. variables. In this section, we examine the importance of these indicators for the accuracy of the DFM nowcast. We re-run the real-time forecasting experiment, but this time excluding the external indicators from the analysis. Table 8 presents the ratios of RMSEs for the DFM from the two experiments (the RSMEs for the model without external indicators over the model with external indicators). A ratio greater than one indicates external indicators help to improve the accuracy of the nowcast. The table divides the set of countries into two columns, one where the RMSE ratio equals or exceeds 1 (deterioration in forecast accuracy without external indicators), and the other for countries with ratio below 1 (improvement in forecast accuracy without external indicators).

Table 8. Nowcast RMSE with and without external indicators for DFM

	Month	RMSE ratio(1)		Month	RMSE ratio(1)
Brazil	1	1.09	Argentina	1	0.91
	2	1.06		2	0.94
	3	1.04		3	0.94
Chile	1	0.99	Peru	1	0.94
	2	1.04		2	0.94
	3	1.08		3	0.81
Colombia	1	1.07	Venezuela	1	0.89
	2	1.08		2	1.23
	3	1.04		3	0.94
Ecuador	1	1.15			
	2	1.14			
	3	1.15			
Uruguay	1	1.01			
	2	1.03			
	3	1.05			
Mexico	1	1.00			
	2	1.00			
	3	1.01			
Dom. Rep.	1	1.05			
	2	1.03			
	3	1.04			

(1) The RMSE ratio is the RMSE for the model without external indicators over the model with external indicators. A ratio greater than one indicates external indicators help improve the accuracy of the nowcast.

For six of the ten countries, Brazil, Chile, Colombia , Ecuador, Uruguay, and Dominican Republic, removing the external indicators from the information set leads to a deterioration in the nowcast accuracy. This highlights the importance of links between these countries and the U.S. economy, and with the evolution of commodity prices. For Mexico, the size of the RMSE remains largely the same. This is somewhat surprising given the close trade links between Mexico and the U.S.; it could possibly reflect that the effects of developments in the U.S. economy and commodity prices are already well captured by the indicators included in the Mexican data set, the external indicators adds little information. For Argentina, Peru, and Venezuela, nowcasting performance improves by removing U.S. and commodity price indicators. This suggests developments in these economies are not as closely linked with the U.S. economy and/or developments in commodity prices than the other countries in our sample. However, these results should be interpreted with caution given the relatively short evaluation period, in particular for Argentina and Venezuela (see table 3).[18] For Peru, the bridge equations produce the most accurate forecast. Thus, the DFM may not be the best model to capture the additional information from external indicators for this country.

VI. Concluding Remarks

This paper evaluates the nowcasting and forecasting performance for quarterly real GDP growth using five types of models for ten Latin American countries. The selected countries include Argentina, Brazil, Chile, Colombia, Ecuador, Dominican Republic, Mexico, Peru, Uruguay, and Venezuela. We consider five model specifications for the evaluation exercise: an autoregressive model; a dynamic factor model; bridge equations; bivariate vector autoregressions; and Bayesian vector autoregressions. While a number of advanced economy studies have demonstrated the usefulness of some of these models for short-term forecasting, this paper is a first attempt (to our knowledge) to evaluate its performance for a large number of emerging market economies. A key feature that we took into account was the real-time nature of the data flow when evaluating the forecast performance of the selected models.

A number of results emerge from the evaluation exercise. First, models that use monthly data generally outperform the AR model that uses only quarterly data, and the forecasts become more accurate as more information arrive within quarter. This highlights the importance of exploiting the flow of monthly data releases. Second, the DFM produces more accurate nowcasts and forecasts relative to other model specifications considered. This result is consistent with other advanced economy studies that conclude that the DFM generally performs well for nowcasting/forecasting quarterly GDP growth. The superior nowcasting performance of the DFM models is in part because of the signal extraction process, implicit in the Kalman Filter, to efficiently separate out the "signal" from the large number of noisy monthly series. Third, external indicators, such as commodity prices and U.S. variables, are useful in improving the forecast accuracy for most Latin American countries.

The analysis presented in here assumes that the individual countries are independent of other countries in the region, except linkages to the global economy via external conditions.

[18]Private analysts estimates that real GDP growth for Argentina has been lower than the of official reports since the last quarter of 2008 (IMF WHD Regional Economic Outlook, October 2010), which could also distort the results of the analysis.

However, it is well documented in other studies that countries among the Latin America region are closely linked to each other, in particular, the risk of contagion during previous crises (though no evidence during the latest global crisis). Future studies could explore the usefulness of inter-regional dependence for short-term forecasting.

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Appendix I. Data transformation

We apply the following ten steps to each countries' data set:

1. All the series are taken from Haver Analytics for each of the ten countries and categorized into six areas; The six categories of data are:[19]
    - Surveys of economic activity,
    - Hard data indicators of economic activity (e.g. industrial production),
    - Indicators of trade (including trade prices and exchange rates),
    - Indicators of financial conditions,
    - Indicators of employment (including household income and wages),
    - Indicators of prices and inflation.
2. Missing values are linearly interpolated;
3. The seasonal series are adjusted using X11;
4. Quarterly series are interpolated into monthly by repeating the quarterly observation for each month; the daily series are averaged into monthly.
5. Log differences are taken of the non-stationary series (four quarter or twelve month) except those that are measured in percentages or can take negative values, where the difference is taken.
6. The series that only change 10 percent of the time are discarded.
7. The series with less than 3 years worth of data are discarded.
8. The series not released in the past year are discarded (possibly discontinued).
9. Outliers are removed - observations greater/less than 6 times the interquartile range are replaced with the next highest/lowest admissible value;
10. Missing observations at the beginning of the sample are backdated using a DFM, with the number factors set to explain 60 percent of the variation in the data.

[19] The results presented here are based on data downloaded from the Haver database on June 13, 2010.