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Nowcasting Mexico's Short-Term GDP Growth in Real-Time: A Factor Model versus Professional Forecasters

ABSTRACT We introduce a novel real-time database for the Mexican economy and propose a small-scale mixed-frequency dynamic factor model for nowcasting Mexico's short-term GDP growth in real-time. We compare our factor-based backcasts, nowcasts, and forecasts with those of the consensus of the survey of professional forecasters during the period from the second quarter of 2008 through the second quarter of 2014. Our results suggest that our factor-based backcasts, nowcasts, and forecasts outperform those of the consensus of professional forecasters in real-time comparisons despite some structural instability during the 2008–09 crisis and its aftermath in 2010.

Keywords: factor model; Mexico; nowcasting; real-time; short-term GDP growth
JEL Classification: C53, E27, E37.

Market analysts, investors, and policymakers often face a severe lack of information and thus must make decisions based on delayed and incomplete—perhaps noisy—pieces of economic information. For instance, a country's gross domestic product (GDP), which is considered the most important indicator for the economy as a whole, is published with a quarterly frequency and a substantial delay. In contrast, data on employment, sales, and industrial production, which are highly correlated with GDP, are published more frequently and with a shorter lag. Clearly, the more information the decisionmaker has, the better the decision will be. It is therefore

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crucial to develop different approaches to combining GDP with some of the available economic indicators to provide timely forecasts of GDP, as well as an evaluation of those forecasts.

We present a novel real-time database for the Mexican economy and propose a small-scale mixed-frequency dynamic factor model (MF-DFM) to backcast, nowcast, and forecast Mexico's short-term GDP growth in real-time.[1] To evaluate those forecasts, we compare the mean squared error (MSE) obtained from the MF-DFM with that of the consensus of Mexico's survey of professional forecasters (SPF) for the period from the second quarter of 2008 through the second quarter of 2014.[2] We also apply some statistical tests of the forecasts' predictive ability and encompassing between forecasts. We also report some empirical evidence on the robustness of the MF-DFM short-term forecasts in the presence of structural instability.

The MF-DFM is an effective approach to predict short-term GDP growth in real-time in the euro area and the United States. Despite its increasing popularity, only a few papers apply the approach to Latin American or Caribbean countries. A further limitation of the Latin American literature is that the results rely on pseudo-real-time forecasts, where both the publication schedule and data revision effects are ignored. Moreover, some of the papers evaluate only one or two forecasting horizons, rather than backcasts, nowcasts, and forecasts, inclusive.

The paper is organized as follows. The next section presents a review of the related literature. The paper then describes the econometric model and presents our empirical implementation for the Mexican economy. The final section concludes.

Related Literature

The basic assumption in the literature on dynamic factor models is that it is possible to extract an unobserved factor that is common to a small set of economic indicators.[3] For example, Mariano and Murasawa propose a procedure to extract the common factor in the presence of missing data and, simultaneously, in the presence of indicators with different frequencies: namely,

1. We sometimes use the term *forecast* as a generic term including backcasts, nowcasts, and forecasts.

2. The survey is the *Encuesta sobre Expectativas de los Especialistas en Economía del Sector Privado,* which is available at Bank of Mexico's website (www.banxico.org.mx).

3. See Stock and Watson (1989, 1991).

quarterly indicators, like GDP, and monthly indicators.[4] The extracted monthly factor is then interpreted as an index that represents the state of the economy. Recent applications of the mixed-frequency dynamic factor model (MF-DFM) are offered by Aruoba and Diebold for the United Sates; and Aruoba and others for the G-7.[5]

For forecasting purposes, Camacho and Pérez-Quirós extend Mariano and Murasawa's MF-DFM to provide forecasts of the euro area's short-term GDP growth in real-time.[6] They show that the MF-DFM forecast is at least as good as, and usually better than, projections by professional forecasters. Similar results are reported by Camacho, Dal Bianco, and Martínez-Martín for the United States.[7] However, only a few authors apply this approach to developing economies, particularly for Latin American or Caribbean economies. These economies typically face more volatile short-term GDP growth than advanced economies, and most economic indicators are published with a substantial lag.[8]

Among the few authors who apply the MF-DFM approach in Latin America or the Caribbean are Camacho, Dal Bianco, and Martínez-Martín, who conclude that the model can produce accurate forecasts of short-term GDP growth in Argentina, despite significant volatility.[9] Similar results are found for Colombia, Chile, and Uruguay.[10] Additional papers that estimate a large-scale factor model to forecast short-term GDP growth include Caruso for Mexico; D'Amato, Garegnani, and Blanco for Argentina; Liu, Matheson, and Romeu for ten Latin American economies, including Mexico; and Liu and Romeu for Cuba and the Bahamas.[11] Nevertheless, one limitation in the literature of factor-based forecasts for Latin America and the Caribbean is that forecasts are evaluated in pseudo-, or quasi-, real-time, which ignores both the calendar and data revision effects.[12] Another limitation is that some of these papers evaluate only one or two forecast horizons, rather than covering

4. Mariano and Murasawa (2003).
5. Aruoba and Diebold (2010); Aruoba and others (2011).
6. Camacho and Pérez-Quirós (2010); Mariano and Murasawa (2003).
7. Camacho, Dal Bianco, and Martínez-Martín (2015).
8. Aguiar and Gopinath (2007); Liu, Matheson, and Romeu (2012).
9. Camacho, Dal Bianco, and Martínez-Martín (2015).
10. See Cristiano, Hernández, and Pulido (2012) for Colombia; Echavarría and González (2011) for Chile; and Rodríguez (2014) for Uruguay.
11. Caruso (2015); D'Amato, Garegnani, and Blanco (2011); Liu, Matheson, and Romeu (2012); Liu and Romeu (2012).
12. Pincheira (2010) provides a real-time comparison of two different sources of forecasts, but none of those forecasts is explicitly from a factor model.

backcasts, nowcasts, and forecasts. For instance, D'Amato, Garegnani, and Blanco only provide nowcasts and forecasts, but not backcasts.[13]

Econometric Model

The aim of this section is to specify the econometric model: a mixed-frequency dynamic factor model (MF-DFM) that allows the inclusion of both missing data and mixed frequency indicators.[14] The MF-DFM extracts the variations that are common among the low-frequency indicator (namely, quarterly GDP, denoted by $y_{1,t}$) and the monthly indicators ($y_{h,t}$, for $h = 2, \ldots N$). The model separates the comovement among all the indicators captured by the unobservable factor, f_t, from the idiosyncratic movement in each indicator captured by the unobservable idiosyncratic factors, $\upsilon_{n,t}$, for $n = 1, \ldots N$. Thus, we estimate a model of the following form:

$$
\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \\ \vdots \\ y_{N,t} \end{bmatrix} = \begin{bmatrix} \gamma_1\left(\frac{1}{3}f_t + \frac{2}{3}f_{t-1} + f_{t-2} + \frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4}\right) \\ \gamma_2 \sum_{j=0}^{11} f_{t-j} \\ \gamma_3 \sum_{j=0}^{11} f_{t-j} \\ \vdots \\ \gamma_N \sum_{j=0}^{11} f_{t-j} \end{bmatrix} + \begin{bmatrix} \frac{1}{3}\upsilon_{1,t} + \frac{2}{3}\upsilon_{1,t-1} + \upsilon_{1,t-2} + \frac{2}{3}\upsilon_{1,t-3} + \frac{1}{3}\upsilon_{1,t-4} \\ \upsilon_{2,t} \\ \upsilon_{3,t} \\ \vdots \\ \upsilon_{N,t} \end{bmatrix}, \tag{1}
$$

where γ_n are the factor loadings that measure the variations in the factor f_t due to variations in the respective indicator. The dynamics of the factors are modeled as autoregressive processes:

13. D'Amato, Garegnani, and Blanco (2011).

14. The proposed specification is very close to the one presented in Aruoba and Diebold (2010); Camacho and Pérez-Quirós (2010); Cristiano, Hernández, and Pulido (2012); and Rodríguez (2014).

$$f_t = \phi_1 f_{t-1} + \cdots + \phi_P f_{t-P} + e_t, e_t \sim \text{i.i.d. } N(0,1); \tag{2}$$

$$\upsilon_{n,t} = \phi_{n1}\upsilon_{n,t-1} + \cdots + \phi_{nQn}\upsilon_{n,t-Qn} + \epsilon_{n,t}, \epsilon_t \sim \text{i.i.d. } N(0, \sigma^2_{\epsilon_n}), \quad \text{for } n = 1, 2, \ldots, N. \tag{3}$$

The model assumes that f_t and υ_{nt} are mutually independent at all leads and lags for all N.

To obtain optimal estimates of the factors f_t and υ_{nt}, the system of equations 1–3 is rewritten in state-space form and estimated by the Kalman filter:

$$y_t = \mathbf{HF}_t + \xi_t, \xi_t \sim \text{i.i.d. } N(0, \mathbf{R}) \tag{4}$$

$$\mathbf{F}_t = \mathbf{TF}_{t-1} + \zeta_t, \zeta_t \sim \text{i.i.d. } N(0, \mathbf{Q}). \tag{5}$$

The measurement equation (equation 4) relates the observed indicators to the factors, while the transition equation (equation 5) specifies the dynamics of the factors.

Following Camacho and Pérez-Quirós, we modify the state-space model (equations 4 and 5) to incorporate missing data into the system.[15] The modification consists in substituting each missing datum with a random draw, υ_t, from a $N(0, \sigma^2_\upsilon)$. This modification keeps all the matrices conformable with no effect on the model's estimation. The elements of the model are modified depending on whether or not $y_{n,t}$ is observed:

$$y_{n,t} = y_{n,t} \text{ if } y_{n,t} \text{ observed; } \upsilon_t \text{ otherwise,}$$

$$H^*_{n,t} = H_n \text{ if } y_{n,t} \text{ observed; } 0_{1k} \text{ otherwise,}$$

$$\xi^*_{n,t} = 0 \text{ if } y_{n,t} \text{ observed; } \upsilon_t \text{ otherwise,}$$

$$R^*_{n,t} = 0 \text{ if } y_{n,t} \text{ observed; } \sigma^2_\upsilon \text{ otherwise,}$$

where $H^*_{n,t}$ is the nth row of the matrix $\mathbf{H}$, which has k columns, and 0_{1k} is a k-row vector of zeros.

15. Camacho and Pérez-Quirós (2010).

Therefore, in the modified model, the measurement equation 4 is replaced by

$$y_t = \mathbf{H}_t^* \mathbf{F}_t + \xi_t^*,\ \xi_t^* \sim \text{i.i.d. } N\left(0, \mathbf{R}_t^*\right). \tag{6}$$

The Kalman filter is then applied to the state-space model (equations 5 and 6) to obtain optimal estimates for all the model's parameters and the matrix $\mathbf{F}_t$, which contains the dynamic factor f_t. The filter tracks the factor f_t, which is calculated using only observations on $y_{n,t}$. It also computes recursively one-step-ahead predictions and updates equations on the conditional expectation of the factors and the associated mean-squared-error matrices. The resulting factor f_t is an optimal estimation as a linear combination of the $y_{i,t}$ economic indicators. When new information is published, the filter is applied to update the matrix $\mathbf{F}_t$. A by-product of the filter is the conditional likelihood of the indicators. The filter simultaneously evaluates the likelihood function, which is maximized with respect to the parameters of the model through an optimization algorithm. With both the parameters and the indicators $y_{n,t}$, the filter extracts the optimal factors based on maximum likelihood estimates.

Empirical Results

In this section, we describe the data used to estimate the mixed-frequency dynamic factor model (MF-DFM) and show its results. We also explain how the model is used to produce backcasts, nowcasts, and forecasts in real-time and to evaluate those forecasts. Finally, we show evidence of robustness despite some structural instability during the forecasting exercise.

Data and In-Sample Estimation

To estimate the model, we consider a small data set of six economic indicators, which are considered as coincident with short-term economic growth in Mexico by the National Institute of Geography and Statistics (INEGI): GDP; the global indicator of economic activity (IGAE), an approximation of monthly GDP published by INEGI; the industrial production index (IPI); retail sales; permanent employees enrolled in social security; and the value of total imports, including oil. A concise description of the small set of indicators

TABLE 1. Data Description[a]

Indicator	*Frequency*	*Sample*	*Observations*	*Lag*[b]
GDP	Quarterly	1993:1–2014:2	086	55 days
IGAE	Monthly	1993:1–2014:6	258	55 days
Sales	Monthly	2001:1–2014:8	161	55 days
IPI	Monthly	1993:1–2014:6	258	40 days
Imports	Monthly	1993:1–2014:6	258	25 days
Employment	Monthly	1997:7–2014:7	205	10 days

a. The table describes the data for the sample ending on 21 August 2014. The variables are defined as follows: GDP: gross domestic product; IGAE: global indicator of economic activity, an approximation of monthly GDP published by INEGI; IPI: industrial production index; Sales: retail sales; Employment: permanent employees enrolled in social security; and Imports: value of total imports, including oil. All indicators are from INEGI.

b. Approximate.

TABLE 2. Estimated Factor Loadings[a]

GDP	*IGAE*	*Sales*	*IPI*	*Imports*	*Employment*
0.22	0.22	0.17	0.21	0.16	0.13
(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)

a. The estimated factor loadings are based on data as of 21 August 2014. Standard errors are in parentheses.

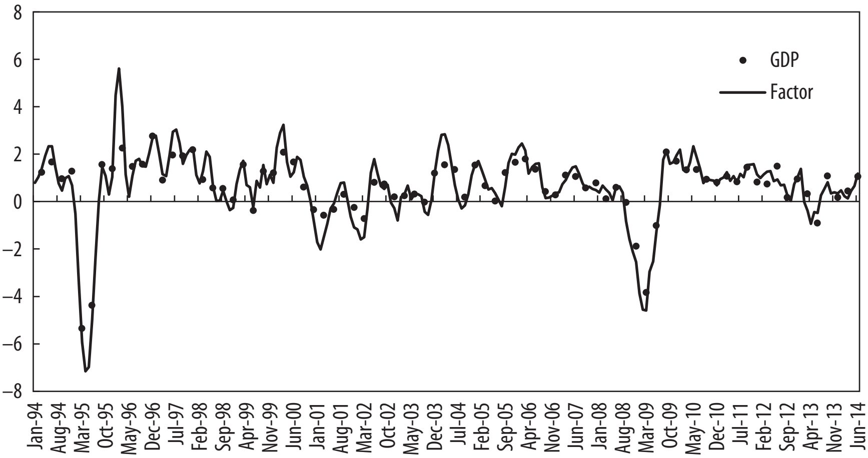
is provided in table 1.[16] One characteristic of the set is that it contains indicators with different frequencies (namely, quarterly and monthly), and missing data due to the different sample sizes or the different publication lags (that is, the ragged edge problem).

We perform the in-sample estimation with the latest available data described above. All the indicators are transformed into interannual growth rates, with the exception of GDP, which is transformed into quarter-on-quarter growth rates. All the indicators are available with seasonal adjustment, except employment. Finally, we standardized the mean and the standard deviation of all the indicators before estimating the model.

Table 2 shows the estimated factor loadings (that is, the model's parameters) from equation 6, with standard errors in parentheses. A factor loading measures the degree to which variations in a given indicator contribute to variations in the common factor. All the estimated factor loadings are positive and statistically different from zero. GDP and IGAE have the highest load on the common factor, while employment has the lowest.

16. In the next section, we try to enlarge the set of indicators.

FIGURE 1. Extracted Common Factor[a]



a. The figure shows the quarter-on-quarter growth rates of the factor extracted from the latest available data on economic indicators (21 August 2014).

Figure 1 graphs the quarter-on-quarter growth rates of the estimated monthly factor from equation 5. For comparison purposes, we also plot the observed quarter-on-quarter GDP growth rates as of 21 August 2014. The factor is a monthly index that summarizes the state of the economy as a whole. It explains 94 percent of the variance of GDP.

To enlarge the model, we consider some other economic indicators, such as nonoil exports and industrial production in the United States, and financial indicators, such as the short-term interest rate or the stock exchange. In all the cases, however, the indicators were not statistically significant or did not increase the explained variance of GDP. We attribute this finding to the fact that the explained variance of GDP is already very high. Finally, we consider some soft variables such as the business confidence survey and the purchasing managers' index. These series are available only for a very small fraction of the whole sample, so we do not incorporate the soft variables in the final model.

Forecasting in Real-Time

Using the small set of economic indicators described in table 1, we create a novel real-time database for the Mexican economy, which is a collection of data vintages, each containing the data set as it would be available for anybody on any day from 22 May 2008, which is our first vintage, to 21 August 2014, which is the vintage that we used for the in-sample estimation in the preceding section. We end up with 2,283 vintages (that is, one vintage per day).[17] The construction of this database is an important step since measures of prediction error, like the mean squared error (MSE), may be misleadingly low when using the latest available data and only a limited number of out-of-sample observations rather than a real-time database.[18]

We use three horizons in the real-time forecasting exercise. Backcasts are estimations in a given quarter for GDP growth in the previous quarter, before it is officially announced. Nowcasts are estimations in a given quarter for GDP growth in that quarter. Finally, forecasts are estimations of GDP growth in the next quarter.

The survey of professional forecasters (SPF) is published on 03 May 2010, and, on that day, GDP is available up to the fourth quarter of 2009. We estimate the model with the available information on that day, backcasting GDP growth for 2010:1, nowcasting GDP growth for 2010:2 and forecasting GDP growth for 2010:3. GDP for 2010:1 is finally published on 20 May 2010. The SPF is updated on 01 June 2010. We then re-estimate our model with the available information on that day, including GDP for 2010:1, nowcasting GDP growth for the 2010:2 and forecasting GDP growth for 2010:3. The SPF is again updated on 01 July 2010. We re-estimate our model again using the available information on that day, producing backcasts of GDP growth for 2010:2, nowcast of GDP growth for 2010 Q3, and forecasts of GDP growth for 2010:4.

We repeat the recursive procedure described above to backcast, nowcast, and forecast Mexico's short-term GDP growth rate in real-time from 22 May 2008 to 21 August 2014. Lastly, because we estimate the model using standardized indicators, our backcasts, nowcasts, and forecasts are also in standardized form. We recover the mean and standard deviation of the indicators by multiplying the standardized forecasts by the standard deviation and adding the mean from the observed indicators.

Forecast Evaluation

Our main purpose is to compare, in real-time, the MF-DFM backcasts, nowcasts, and forecasts with the SPF consensus forecasts, which are published

17. The real-time database is available on request.
18. Stark and Croushore (2002).

on a monthly basis and practically in real-time. The first is a statistical model, while the latter is a combination of forecasts deriving from simple to state-of-the-art models and the judgment of the forecasters.

The SPF reports GDP growth in inter-annual growth rates. To make our factor-based forecasts comparable, we recover the level of the series and compute inter-annual growth rates, in addition to the original quarter-on-quarter growth rates. We calculate mean squared errors (MSE) for the real-time MF-DFM's backcasts, nowcasts, and forecasts and for the SPF consensus forecasts. MSEs are calculated with respect to the real-time GDP growth series officially announced by Mexico's National Institute of Statistics and Geography (INEGI) during the 2008:2–2014:2 period, which have a mean and standard deviation of 1.50 and 4.19 percent, respectively.

Figure 2 shows the real-time GDP growth series and both the real-time MF-DFM forecasts and the consensus forecasts. Given the SPF publication schedule, backcasts are sometimes not of interest because the GDP growth series is already officially published, which in practice limits the number of backcasts available to calculate the MSE. Similarly, the SPF does not always report forecasts. Figure 2 reveals that real-time backcasts are more accurate than nowcasts or forecasts because backcasts are calculated immediately after the end of the quarter, exploiting a larger sample of observed economic indicators. Nowcasts and forecasts follow observed GDP with a lag, given that they both exploit a smaller sample of observed economic indicators.

To evaluate the predictive accuracy of the real-time forecasts, in table 3 we show the MSE calculated for the MF-DFM and SPF forecasts. The MF-DFM forecasts outperform the consensus forecasts, and the gains are of considerable magnitude: 37 percent ($[1 - 0.72/1.15] * 100$) for backcasting, 33 percent ($[1 - 2.23/3.32] * 100$) for nowcasting, and 10 percent ($[1 - 5.06/5.61] * 100$) for forecasting. For the backcasts and nowcasts, we are able to reject the null hypothesis of equal predictive ability according to the Diebold-Mariano-West test at the conventional levels of significance.[19] The standard errors in the Diebold-Mariano-West test are estimated using heteroskedasticity and autocorrelation consistent (HAC) standard errors [20]

Finally, we evaluate whether the SPF consensus contains additional information that is not incorporated in the MF-DFM nowcasts. Following Camacho

19. Diebold and Mariano (1995); West (1996).

20. The result is confirmed by the modified Diebold-Mariano test specified by Harvey, Leybourne, and Newbold (1997).

FIGURE 2. Real-Time GDP Series and Real-Time Forecast Series

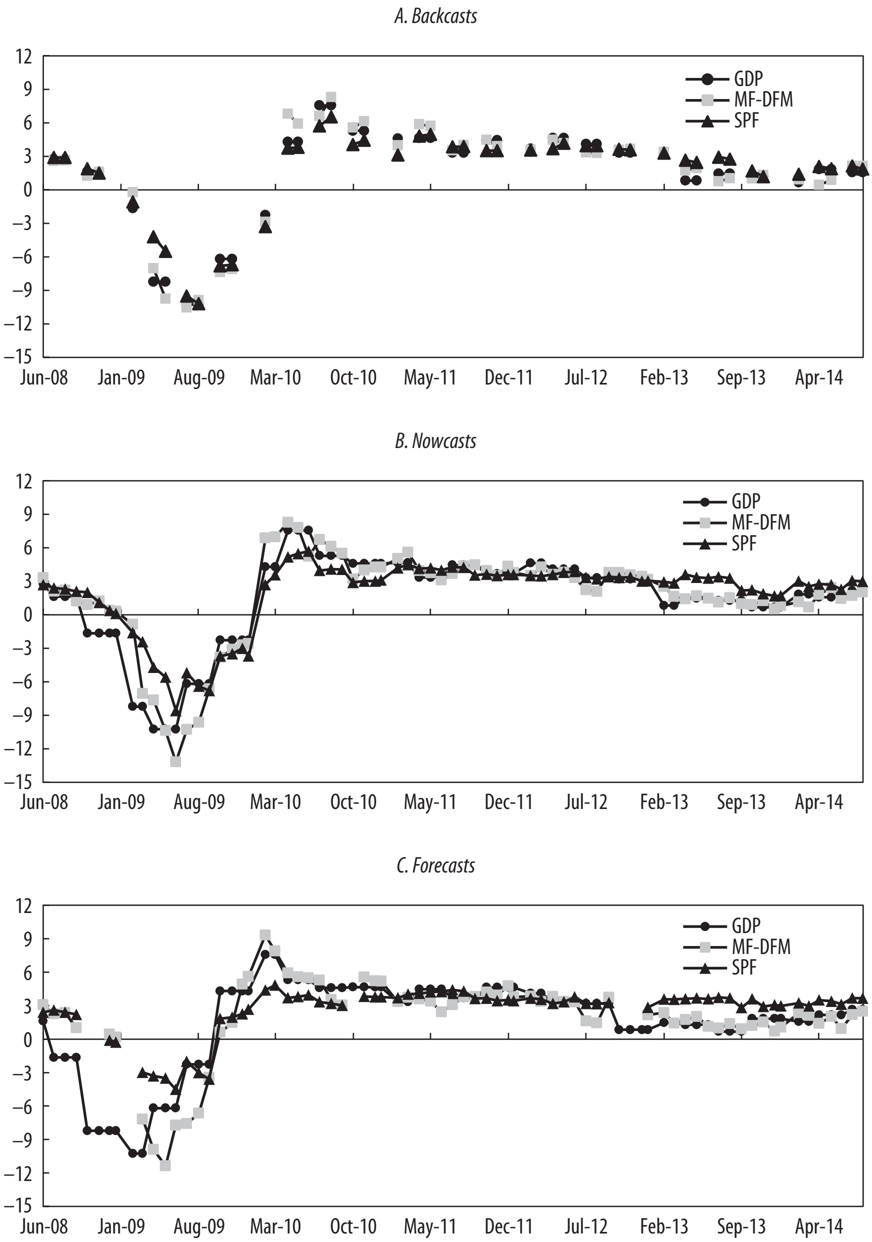


TABLE 3. Real-Time Forecast Evaluation

	Mean squared error		
Source of forecast	*Backcasting*	*Nowcasting*	*Forecasting*
MF-DFM	0.72	2.23	5.06
SPF	1.15	3.32	5.61
Summary statistic	*Backcasting*	*Nowcasting*	*Forecasting*
No. observations	44	75	68
Diebold-Mariano-West test (*p* value)	0.001	0.021	0.29

TABLE 4. Encompassing Test[a]

Coefficient	*HAC standard error*	*t statistic*	*Probability*
–0.08	0.12	–0.67	0.51

a. Parameter α_1 estimated from equation 7.

and Pérez-Quirós, we apply an encompassing test.[21] The test is based on the following OLS regression:

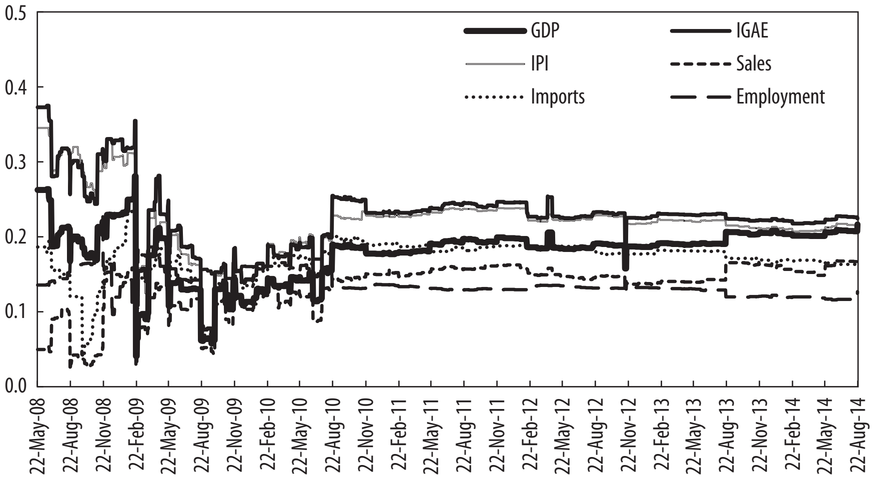
$$(7) \qquad y_t^{Real\text{-}time} - f_t^{Nowcasting}, \text{MF-DFM} = \alpha_0 + \alpha_1 f_t^{Nowcasting}, \text{Consensus} + \varepsilon_t,$$

where the left-hand side is the difference between GDP in real-time, y_t, and the MF-DFM nowcasts, and the right-hand side is the sum of a constant coefficient, α_0, a coefficient for the consensus nowcasts, α_1, and a residual, ε_t. If the coefficient α_1 is statistically different from zero, the consensus has some relevant information that is not considered in the MF-DFM.

Table 4 reports the coefficient, α_1, its standard error, *t* statistic, and probability as estimated from equation 7. We find that the coefficient for a constant, α_0, and the coefficient for the consensus forecast, α_1, are statistically indistinguishable from zero. We are not able to reject the null hypothesis associated with those coefficients at traditional significance levels. Specifically, given that the coefficient associated with the consensus nowcasts, α_1, is statistically equal to zero, the MF-DFM nowcasts "encompass" the consensus nowcasts. Therefore, we do not have statistical support to consider the consensus as an additional source of information that is not included in the MF-MFD nowcasts.

21. Camacho and Pérez-Quirós (2010).

FIGURE 3. Recursively Estimated Factor Loadings in Real-Time[a]



a. The figure graphs the factor loadings estimated in real-time from 22 May 2008, which is our first vintage, through 21 August 2014, which is our last vintage.

Forecasting under Structural (In)Stability?

Structural instability is one of the primary sources of forecast failure.[22] To address this issue, Stock and Watson suggest that when forecasts start to fail in practice, attention should to be focused on the instability of the forecasting equation and not on the factor estimation.[23]

To provide some empirical evidence on (in)stability from our empirical application, we graph the estimated factor loadings of the measurement equation (equation 6) in real-time (see figure 3). There is clearly some structural instability in the model from the beginning of the estimation, on 22 May 2008, to late 2010. This period roughly coincides with the 2008–09 economic crisis and its aftermath in 2010. Given the structural instability present in the model, it is at first surprising that the model's forecasts are still worthy. We attribute this finding to both the recursive procedure adopted to produce the forecasts, which might moderate the instability effects, and the fact that in our empirical application, the forecasts are provided only for a short-term horizon.

22. See Hendry and Clements (2004); Hendry and Mizon (2005).
23. Stock and Watson (2009).

Conclusions

Every day, economic agents make decisions on the basis of limited and delayed economic information. For the economy as a whole, the most relevant indicator is GDP; however, this information is published quarterly and with a considerable lag. Fortunately, other relevant economic indicators are published in a timely manner, with a less substantial delay. These can be exploited to produce short-term GDP growth backcasts, nowcasts, and forecasts.

One way to do so is through a factor model. The small-scale mixed-frequency dynamic factor model (MF-DFM) is successfully used, for instance, to provide short-term GDP growth estimates for the euro zone and the United States. This approach has not been applied extensively to Latin American and Caribbean economies. Notable exceptions are Camacho, Dal Bianco, and Martínez-Martín for Argentina; Cristiano, Hernández, and Pulido for Colombia; Echavarría and González for Chile; and Rodríguez for Uruguay.[24] However, their results rely on pseudo-real-time backcasts, nowcasts, and forecasts, which limits their usefulness.

We introduce a novel real-time data set for the Mexican economy and propose an MF-DFM to backcast, nowcast, and forecast Mexico's GDP growth in real-time. We then compare our factor-based estimates with the consensus forecasts published in Mexico's survey of professional forecasters (SPF). The results suggest that our factor-based backcasts, nowcasts, and forecasts outperform the SPF consensus forecasts in real-time comparisons during the evaluation period (2008:2 to 2014:2). The mean squared error (MSE) of our factor-based backcasts, nowcasts, and forecasts are 37, 33, and 10 percent lower than the consensus forecasts, respectively; these differences are statistically significant for the backcasts and nowcasts according to the Diebold-Mariano-West test of predictive ability. Furthermore, our evidence suggests that these results are robust to the presence of structural instability during the 2008–09 crisis and its aftermath in 2010.

The work started here could be continued in a number of fruitful directions. For example, our model could be extended to explicitly consider structural instability, as proposed by Barnett, Chauvet, and Leiva-León.[25]

24. Camacho, Dal Bianco, and Martínez-Martín (2015); Cristiano, Hernández, and Pulido (2012); Echavarría and González (2011); Rodríguez (2014).

25. Barnett, Chauvet, and Leiva-León (2016).

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