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Alberto Caruso
SBS-EM, ECARES, Université libre de Bruxelles

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Abstract

In this paper I study the flow of conjunctural data relevant to assess the state of the Mexican economy. I reconstruct the flow of releases that are most frequently monitored by market participants, economic commentators and policy makers. Given the close linkages with the US economy, I take into account both US and Mexican data. Following the literature on nowcasting, I jointly analyse these data in a model that is continuously updated as new data get released. The model can be used to assess the current macroeconomic conditions (predicting the present) of the Mexican economy and to evaluate the importance of each macroeconomic data release. I find that the model produces forecasts whose accuracy is similar to that of institutional and judgemental forecasts, and I document the importance of considering US data.

Keywords: Nowcasting, Dynamic Factor Model, Mexico.
JEL Classification: C32, C53, E37.

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1 Introduction

In this paper I reconstruct and interpret the macroeconomic information flow relevant to assess the state of the Mexican economy. Due to the significant publication delay of GDP, released several weeks after the end of the reference quarter, it is important to interpret the flow of macroeconomic indicators that are available at higher frequency, in order to have reliable short-term forecasts of the state of GDP that are constantly updated as new information is available. Policy makers, for example, make and implement decisions on the basis of the current state on the economy, and market participants take it into account in making their investment decisions. Private and institutional sources provide a flow of macroeconomic data almost every day: the challenge is to interpret properly the new information, in a process of signal extraction that copes with its complexity. To this aim, I analyse the data flow through the lens of a model of short-term forecasting based on dynamic factor models, following the developments in the "nowcasting" approach.

Factor models permit us to summarize the information of many indicators that are more timely than GDP, without incurring in a "curse of dimensionality". The idea is to estimate a few common factors that drive the co-movements among a large number of variables (Forni, Hallin, Lippi and Reichlin, 2000; Stock and Watson, 2002*a*). Based on factor models and Kalman filtering techniques, the nowcasting approach (for a review see Banbura et al., 2011, 2013) can deal with the ragged edge characteristics of an expanding dataset, since the variables are released in a non synchronous way. The approach permits us to efficiently estimate the latent factors and to update the forecasts in real-time, whenever new macroeconomic data is released (Giannone, Reichlin and Small, 2008; Doz, Giannone and Reichlin, 2011, 2012; Bańbura and Modugno, 2014). Moreover, it allows us to gauge the marginal contribution given by any single macroeconomic release, estimating its real-time information content. This methodology has been proven to be effective in many empirical applications, being to applied to many countries.[1] Following this strand of literature, I construct a nowcasting model for the Mexican real GDP, taking into account Mexican as well as US macroeconomic releases. I decide the dataset using a market-oriented approach, choosing the

[1]Among the others Rünstler, Barhoumi, Benk, Cristadoro, Den Reijer, Jakaitiene, Jelonek, Rua, Ruth and Van Nieuwenhuyze (2009), Angelini, Camba-Mendez, Giannone, Reichlin and Rünstler (2011) for the Euro Area, D'Agostino, McQuinn and Derry (2008) and Liebermann (2012) for Ireland, Matheson (2010) for New Zealand, Marcellino and Schumacher (2010) for Germany, Barhoumi, Darné and Ferrara (2010) for France, Aastveit and Trovik (2012) and Luciani and Ricci (2014) for Norway, Bragoli, Metelli and Modugno (2014) for Brasil.

indicators which are closely followed by the markets and policy makers. The model is estimated using quasi-maximum likelihood and Kalman filtering techniques, and I conduct a pseudo-real time evaluation of its forecasting performance from 2006 to 2013.

Some recent papers have the objective of producing a short-term forecasting model of Mexican GDP. Coutino (2005) presents a model based on several Mexican monthly indicators, but his technique does not allow either real-time updating or an evaluation of the impact of the different indicators. The VAR-based model presented in Guerrero, C. and Esperanza (2013) allows one to make an estimate of GDP that is more timely than the official release, but it can be only estimated at least 15 days after the end of the reference quarter, so it is not a "nowcast" but a "back-cast". The use of indicators external to the country is a practice rarely used in the nowcasting literature.[2] However, the empirical evidence of spillovers and synchronization between Mexican and US business cycles suggests that a forecasting model of the Mexican economy should take the relationship with the US into account. Among others, Torres and Vela (2003) document the synchronization of the US and Mexican business cycles and the role of trade, while Cuevas, Messmacher and Werner (2002), Kose, Towe and Meredith (2004), Chiquiar and Ramos-Francia (2005), Lederman, Maloney, Maloney and Serven (2005), Bayoumi and Swiston (2008) and Miles and Vijverberg (2011) evaluate the impact of NAFTA on the synchronization, documenting evidence of its importance. Hernández (2004) finds evidence of a common trend and a common cycle between Mexican and US GDP, and the correlation of business cycles is confirmed in later work by Mejía-Reyes and Campos-Chávez (2011). Regarding possible spillovers from the US to Mexican economy, Sosa (2008) finds a high impact of US shocks on Mexico in the post-NAFTA period, with a major role played by US Industrial Production and by the indicators relating to the automotive sector.

The closest paper to the present work is Liu, Matheson and Romeu (2012), in which they nowcast the GDP of several Latin American countries, including Mexico, using a dynamic factor model based on Giannone, Reichlin and Small (2008). They use a panel of 129 variables referring to the Mexican economy and 8 indicators from the US, compare their results with other model-based forecasts, and they show that the use of external indicators (the US variables plus

[2] Among the exceptions, see de Antonio Liedo (2014) on nowcasting Belgian GDP.

also 11 commodity prices and 8 US variables) does not help improve the accuracy of the nowcast in the sample 2005-2010, a result defined as "surprising" by the authors themselves.[3] There are some differences between their approach and the one of the present work, apart from the time span of the sample and the macroeconomic indicators that have been used in the analysis. First, they estimate the dynamic factor model with the two-step procedure described in Giannone, Reichlin and Small (2008) and Doz, Giannone and Reichlin (2011), that consists in estimating the factors in a balanced panel using principal components, and then exploiting the information contained in the end of the sample using a Kalman smoother. My estimation approach is different, being based on a Maximum Likelihood estimation in an Expectation-Maximization algorithm, following Doz, Giannone and Reichlin (2012) and Bańbura and Modugno (2014). Moreover, Liu, Matheson and Romeu (2012) do not measure directly the relevance of the US variables, while I explicitly evaluate the impact of the information coming from the US on the nowcast updates. The possibility given by the most recent nowcasting methodology to evaluate the marginal contribution of macroeconomic releases is essential to gauge which indicators help to better assess the state of the economy, and in my case also to evaluate the relevance of the information coming from the United States.

The main contributions of the present work can be summarized as follows: first, interpreting the Mexican and US macroeconomic data flow, I evaluate the importance of each data release and the relevance of the information accessible to markets participants and policy makers in order to assess the state of the Mexican economy. Second, I find that the information coming from US indicators helps in reducing the forecast errors and has an important role in the updating process of a nowcasting model for Mexican GDP. This a reasonable result, given the strong relationship between Mexican and US business cycle that has been documented in the literature. Finally, I find that a nowcasting model constructed using a medium-scale dataset of real macroeconomic indicators from Mexico and from the US performs well out of sample with respect to judgemental benchmarks. The latter result confirms the usefulness of model-based nowcasting based on

[3] They compare the performance of a forecast based on dynamic factor models to the performance of forecasts based on quarterly autoregressive model, pooled bridge equations, bivariate VARs and Bayesian VAR, documenting that the nowcast based on dynamic factor models has the best performance among the techniques considered.

dynamic factor models in tracking the state of the economy, filtering the signals and interpreting the relevant information contained in the flow of macroeconomic releases.

2 The model

The main objective of the nowcasting approach is to extract the relevant information about the state of the economy contained in indicators that are more timely than the target variable (here the quarterly GDP growth), and to funnel it into an estimate that can be updated at every data release. The technique allows us to interpret the flow of macroeconomic information at any point in time, and, since the variables are jointly modelled, also allows us to have forecasts for any indicator of interest.

A first challenge to tackle is dealing with a large number of variables, capturing the relevant information of macroeconomic data in a parsimonious way. Factor models exploit the information of very rich datasets without incurring the "curse of dimensionality". The main idea is that the variables are linked to some unobserved factors that can be consistently estimated. It is indeed possible to express the behaviour of many macroeconomic variables through a few factors that drive their co-movements (Forni, Hallin, Lippi and Reichlin, 2000; Stock and Watson, 2002*a*). A second issue is dealing with the ragged edge of an expanding dataset, given that macroeconomic releases are available in a non-synchronous way. A dynamic factor model, and the use of Kalman filters and smoothers are natural techniques to handle these two main features of the data.

In the present work I rely on the nowcasting methodology further developed in Bańbura and Modugno (2014) to handle missing data, using Maximum Likelihood estimation in an Expectation-Maximization algorithm, whose desirable properties of consistency and robustness in this framework have been proven in Doz, Giannone and Reichlin (2012).

The dynamic factor model used in this work can be described as follows. The variables are assumed to have a factor structure:

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

Where x_t is a vector of standardized stationary monthly variables, f_t are unobserved common factors with zero mean and unit variance, Λ are the factor loadings, ϵ_t a vector of idiosyncratic components of dimension N and μ is a constant.

The dynamics of the factors are modelled as a stationary Vector Autoregressive process with p lags, in which $A_1, ..., A_p$ are $r \times r$ matrices of autoregressive coefficients, and ϵ_t follows an $AR(1)$ process uncorrelated with f_t at any leads and lags:

$$f_t = A_t f_{t-1} + ... + A_p f_{t-p} + u_t;\ u_t\ i.i.d. \sim \mathcal{N}(0, Q) \tag{2}$$

The idiosyncratic component is modelled as following:

$$\epsilon_{i,t} = \tilde{\epsilon}_{i,t} + \xi_{i,t}; \qquad \xi_{i,t} \sim \text{i.i.d. } \mathcal{N}(0, \kappa) \tag{3}$$

$$\tilde{\epsilon}_{i,t} = \alpha_i \tilde{\epsilon}_{i,t-1} + e_{i,t}; \qquad e_{i,t} \sim \text{i.i.d. } \mathcal{N}(0, \sigma_i^2) \tag{4}$$

To deal with the mixed frequency of macroeconomic data, given that I use only monthly indicators plus quarterly GDP, I follow the approximation of Mariano and Murasawa (2003), including the quarterly variable in the model as a monthly partially-unobserved variable. For any variable y_t, defined at the highest frequency present in the model, define y_t^k its "counterpart" which is observed every k periods. That means that the observations of the lower frequency variables are periodically missing. In the case of the present work y_t is the difference of natural logarithm of GDP, and since the highest frequency of the model is monthly, we have that its counterpart is y_t^3. Define as z_t the non-transformed series corresponding to y_t, in our example the level of GDP. The approximation is the following:

$$y_t^3 = log(z_t^3) - log(z_{t-3}^3) \approx y_t + 2y_{t-1} + 3y_{t-2} + 2y_{t-3} + y_{t-4} \tag{5}$$

with $t = 3, 6, 9, ...$

The model is estimated using Maximum Likelihood. To initialize the estimation, the factors are estimated using principal components analysis; then, the estimation is performed using Quasi-Maximum Likelihood and Kalman filtering techniques within an Expectation-Maximization (EM) algorithm. The EM algorithm has been proposed in order to estimate a model with latent data, and then has been extensively applied to factor estimation (see Dempster, Laird and Rubin, 1977; Shumway and Stoffer, 1982; Watson and Engle, 1983). The algorithm consists in the iteration of two steps: In the first step, the expectation of the conditional log-likelihood is calculated using the estimated values coming from the previous iteration; in the second step the resulting expected log-likelihood is maximized to obtain the estimates of the parameters to be used in the following iteration. The conditional moments of the factors in the first step can be retrieved using the Kalman smoother. The iteration is performed until convergence is achieved, depending on the stopping rule used. Even if the model does not allow for cross-correlation in the idiosyncratic component, the consistency of a Quasi-Maximum Likelihood estimator with an EM algorithm is proven in Doz, Giannone and Reichlin (2012), who show that it is also feasible for large cross-sections.

The Maximum Likelihood estimation of the dynamic factor model is performed once a year, and the updates of the factors, the forecast and the construction of the news are performed at every new release. The number of lags p is set to two.[4] Determining the number of factors is still a debated question in the literature; I fix the number of factors to one, as being the simplest choice, since previous works have shown that a small number of factors is sufficient for forecasting purposes (Stock and Watson, 2002*b*). The results are qualitatively the same with two factors. Actually the forecasting performance improves using two factors but I use the simplest possible specification, since their interpretation might be controversial and the magnitude of the gain could not justify the increase in the parametrization of the model. As a stopping rule for the iteration in the Expectation-Maximization algorithm, if ℓ_i is the conditional log-likelihood at iteration i, I stop when $\frac{\ell_{i+1} - \ell_i}{(|\ell_{i+1}| + |\ell_i|)/2} < 10^{-4}$.

[4] The results are robust to a change the number of lags, and available on request.

3 Data

I decide which variables to include in the model following a market-oriented approach.[5] I consider only surveys and real variables, since financial variables have been proven to be not effective in improving the precision of short-term forecasts of GDP in this framework (Banbura, Giannone, Modugno and Reichlin, 2013). I take into consideration what market operators, statistical agencies, and the specialized press consider to be the key variables for assessing the condition of the Mexican economy. As a starting point, I choose the variables reported on Bloomberg, one of the major sources of information for investors, traders and market operators. I also include some variables that were commented in Bloomberg in the past, given the importance they might have had, in the eyes of market operators, to assess the condition of the Mexican economy (e.g. Truck Sales). For each variable Bloomberg reports a "relevance index", that is the ratio of alerts requested for new releases of that variables to the total number of alerts. The index could be seen as a measure of the importance assigned by financial market operators to that indicator. Moreover, I also take into consideration the variables that are considered as "high impact" in ForexFactory.com, the most viewed forex-related website in the world. Finally, I consider the indicators that frequently appear in the public debate about Mexican economy in the main local media, and some variables that should be taken into account given their relevance in the analysis of the latest statistical reports of the INEGI (Instituto Nacional de Estadística y Geografía) and of the Bank of Mexico. The dataset is composed of 28 monthly variables plus quarterly Mexican GDP, and is described in Table 1. The dimension of the dataset is consistent with the results of Bańbura and Modugno (2014), who show that in the nowcasting framework small and medium scale models perform better than large scale ones.

Regarding Mexican surveys, I include Consumer Confidence, Producer Confidence, and a survey about Manufacturing Orders, all of which are very timely indicators. Moreover, I include two surveys about Business Climate conducted by the Instituto Mexicano de Ejecutivos de Finanzas (IMEF). Even though their Bloomberg relevance index is low, these two indicators (Manufacturing and Non-Manufacturing) are widely followed by economic commentators, in newspapers and specialized websites. They are the Mexican version of the "Purchasing Managers Index" published by

[5] An approach already followed in Luciani and Ricci (2014) and in Bragoli, Metelli and Modugno (2014).

	Series	Source	Start date	Unit	Transf.	Lag
Mexico	IMEF Bus.Clim. Index: Mfg	IIEEM	Jan-04	INDEX	Level	3
Mexico	IMEF Bus.Clim. Index: Nonmfg	IIEEM	Jan-04	INDEX	Level	3
Mexico	Consumer Confidence	INEGI	Apr-01	INDEX	Level	4
Mexico	Producer Confidence Index	INEGI	Jan-04	Units	YoY	4
Mexico	Opinion Survey: Mfg. Orders	INEGI	Jan-04	INDEX	Level	4
Mexico	Total Vehicle Production	AMIA	Jan-91	Units	YoY	10
Mexico	Industrial Production	INEGI	Jan-91	INDEX	MoM	13
Mexico	Total Vehicle Exports	AMIA	Jan-91	Units	YoY	13
Mexico	Unemployment Rate	INEGI	Apr-00	%	M diff	22
Mexico	Petroleum Exports: Crude	INEGI	Jan-91	US$	MoM	24
Mexico	Imports	INEGI	Jan-91	US$	MoM	24
Mexico	Exports	INEGI	Jan-91	US$	MoM	24
Mexico	Production of Crude Petroleum	INEGI	Jan-91	Units	MoM	26
Mexico	Automobile Sales	AMIA	Jan-91	Units	MoM	37
Mexico	Truck Sales: Total	AMIA	Jan-95	Units	YoY	37
Mexico	Retail Sales	INEGI	Jan-94	INDEX	MoM	52
Mexico	Gross Domestic Product	INEGI	Jan-91	Mil.Pesos	QoQ	55
Mexico	Trade Balance: United States	INEGI	Jan-93	US$	YoY	57
US	UoM: Cons. Sentiment	Un. of Mich.	Jan-91	INDEX	Level	-3
US	Conference Board: Cons. Conf.	CB	Jan-91	INDEX	Level	-3
US	ISM Mfg: PMI Composite Index	ISM	Jan-91	INDEX	Level	1
US	Employees on Nonfarm Payrolls	BLS	Jan-91	Units	M diff	5
US	Retail Sales	CENSUS	Jan-91	US$	MoM	13
US	Industrial Production	FRB	Jan-91	INDEX	MoM	16
US	Capacity Utilization	FRB	Jan-91	%	M diff	16
US	Housing Starts	CENSUS	Jan-91	Units	MoM	18
US	Wholesalers: Sales: Automotive	CENSUS	Jan-92	US$	MoM	40
US	Car Imports	CENSUS	Jan-91	US$	YoY	41
US	Truck Imports	CENSUS	Jan-91	US$	YoY	41

Table 1: The table describes the variables included in the model, the sources, the starting dates if their availability, the transformations and the units of measure. The "Lag" column indicates the average number of days between the macroeconomic announcement and the end of the reference period. IIEEM stands for "Indicador IMEF del Entorno Empresarial Mexicano", INEGI for "Instituto Nacional de Estadística Geografía e Informática", AMIA for "Asociación Mexicana de Industria Automotriz", CB for "The Conference Board", ISM for "Institute for Supply Management ", CENSUS for "Census Bureau", FRB for "Federal Reserve Board".

the Institute for Supply Management in the US, as their construction explicitly follows the same methodology.

As for standard macroeconomic indicators about Mexican production and internal demand I consider Industrial Production and Retail Sales. It is worth noting that Industrial Production has a Bloomberg relevance index even higher than GDP. I include two indicators related to the automotive sector (Automobile Sales and Truck Sales), given the importance of the automotive sector for the Mexican economy and Mexican exports.[6] The trade sector is particularly important: The trade balance historically fluctuates around zero, but trade has a major role in the economy since exports represents 31.7% of GDP.[7] The main trade partner is the United States, which absorbs

[6]Mexico is the 7th world producer of vehicles, 6th for commercial vehicles.
[7]Data relative to 2010-2014, World Bank.

79% of Mexican exports: the trade surplus with the US amounts to 53,8 Billions of USD.[8] The largest shares of exports are represented by vehicles, electronic and mechanical components (often linked to the automotive sector), and oil. However, the trade balance relative to the first two categories is almost neutral. Therefore, in addition to Imports and Exports, I include in the model indicators for oil production and exports, vehicle production and exports, and the trade balance with the United States. The final list of Mexican variables consists of 18 indicators.

Regarding US data, I look at a set of variables considered standard in the forecasting literature and by practitioners assessing the behaviour of the US economy. As regards real variables I include Industrial Production, Capacity Utilization, Retail Sales, Housing Starts, Personal Consumption Expenditure in Durable Goods and Employees on Non-Farm Payrolls. As regards surveys, I take the Purchasing Managers Index (Manufacturing), Consumer Confidence, and the Consumer Sentiment from the University of Michigan. Moreover, given the high importance of the automotive sector in the trade activity between Mexico and US, I include three automotive-related variables that are commented on Bloomberg (Automotive Wholesale Sales, Car Imports and Truck Imports).

[8]Source: www.census.gov.

Date	Country	Series	Average delay	Ref. Period	Bloomberg relevance
01-May	US	ISM Mfg: PMI Composite Index	1	April	94.7
02-May	Mexico	IMEF Index: Mfg	3	April	17.5
02-May	Mexico	IMEF Index: Nonmfg	3	April	12.5
02-May	US	Car Imports	41	March	
02-May	US	Truck Imports	41	March	
03-May	Mexico	Producer Confidence Index	4	April	
03-May	Mexico	Manufacturing Orders	4	April	
03-May	US	Employees on Nonfarm Payrolls	5	April	99.1
06-May	Mexico	Consumer Confidence	4	April	82.5
07-May	Mexico	Total Vehicle Production	10	April	37.5
07-May	Mexico	Total Vehicle Exports	13	April	30
08-May	Mexico	Automobile Sales	37	March	
08-May	Mexico	Truck Sales	37	March	
09-May	US	Automobile Sales	40	March	
10-May	Mexico	Industrial Production	43	March	92.5
13-May	US	Retail Sales	13	April	89.4
15-May	US	Industrial Production	16	April	86.7
15-May	US	Capacity Utilization	16	April	60.71
16-May	US	Housing Starts	18	April	88.5
24-May	Mexico	Unemployment rate	22	March	77.5
22-May	Mexico	Retail Sales	52	March	80
23-May	Mexico	Gross Domestic Product	55	2013 Q1	87.5
26-May	Mexico	Imports	24	April	75*
26-May	Mexico	Exports	24	April	75*
26-May	Mexico	Trade Balance: United States	57	March	
26-May	Mexico	Oil Exports	24	April	
26-May	Mexico	Oil Production	26	April	
28-May	US	Consumer Confidence	-3	May	95.6
31-May	US	Univ. of Michigan: Cons. Sentiment	-3	May	92.9

Table 2: Calendar overview.
* Refers to Trade Balance.

In Table 2 I report an example of the flow of macroeconomic releases included in the model for May 2013. In the first days of the month three surveys are released: the Mexican IMEF (manufacturing and non-manufacturing) and the US PMI Manufactuting. On the same day of the IMEF surveys data about Car and Trucks Imports in the United States are released, but they refer to the month of March. This is an example of the ragged edge feature of the dataset, and of the importance of taking all available information into account: using a balanced panel the forecaster would have neglected the information relative to April about US PMI, an indicator which has a very high average impact on the nowcast of Mexican GDP (see section 4.2). Data has been downloaded from Haver Analytics on 30th November 2014. All the variables apart from the surveys have been transformed to have monthly growth rates (or monthly differences when not applicable and in the case of Employment variables), and a linear filter has been used to transform non-seasonally adjusted variables.

As benchmarks for the forecasting accuracy of the calendar year GDP growth rate I use some institutional forecasts.[9] In particular, I use the forecasts published in the World Economic Outlook by the International Monetary Fund in April and October of the reference year, and the projections published in the OECD Economic Outlook in June and December of the reference year. As a benchmark for the year-on-year growth rate, I use the Surveys of Professional Forecasters conducted monthly by the Bank of Mexico. Capistrán and López-Moctezuma (2014) have analysed the properties of these forecasts, finding that they have neither weak nor strong efficiency properties. Forecasters, in particular, do not efficiently incorporate the available information in updating their assessments. This is indeed a strong motivation to use a model that could update the forecast in real-time, exploiting the relevant information embedded in the data flow of macroeconomic indicators.

[9] An example of a calendar year growth rate is the growth rate of GDP in 2013 with respect to GDP in 2012.

4 Results

4.1 Out of sample evaluation

In this section I present the result of the out of sample evaluation of the model, performing a pseudo real-time historical evaluation. It is called "pseudo" because it abstracts from data revisions, but in this framework the estimates are robust to data revisions if the revision errors are weakly cross-correlated (Giannone, Reichlin and Small, 2008). The estimation sample starts in January 1991, and the sample of the out of sample evaluation goes from the first quarter of 2006 to the fourth quarter of 2013. At each release after 1st January 2006, the forecast (1-quarter ahead), nowcast (same quarter) and back-cast (last quarter) are updated.[10] It is worth remarking that, since the variables are jointly modelled, the model produces a forecast for each variable in the dataset. If a data release brings new information (i.e. different from the model's expectation) the model is updated. I evaluate two versions of the model: one in which I include all the variables and one in which I use just Mexican variables. I compare the forecasts of the two models to three benchmarks: an AR(1), the nowcast of the Survey of Professional Forecasters reported monthly by the Bank of Mexico, and the surveys conducted among Professional Forecasters by Bloomberg.[11]

Figure 1 shows a comparison between the nowcast of the YoY growth rate of Mexican GDP and the actual values. The nowcast tracks well the large crisis of 2009, the recovery, as well as more tranquil periods. The model also performs very well in comparison to the nowcasts from the surveys of Professional Forecasters. Similar qualitative results hold for the nowcast of the QoQ growth rate, in Figure 2, and for the forecast of the calendar year growth rate, in Figure 3, compared with the performance of institutional forecasts coming from the IMF World Economic Outlook and the OECD Economic Outlook. In the QoQ case, we can note that the model that includes US variables captures the crisis of 2008-2009 and the recovery more rapidly than the model with just Mexican variables, showing the importance of taking into account possible shocks from the US.

In Figures 4 and 5 I present the reduction in the Root Mean Squared Forecast Errors of the nowcast of the QoQ and the YoY growth rate during the forecast period (from -90 to 0 days to the

[10]The estimation is performed recursively.

[11]The comparison gives an idea of the performance of the model but it should be taken with caution, since the model works with revised data and professional forecasters operate in real time.

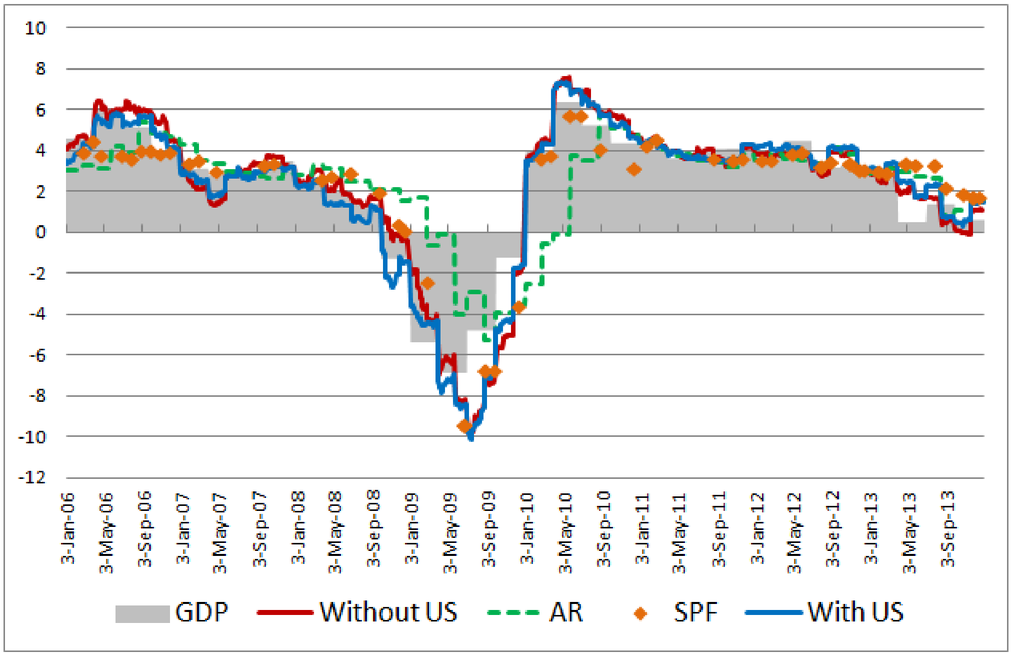

Figure 1: Now-cast of the YoY growth rate of GDP of the model that includes US variables (With US) and the one that includes just Mexican variables (Without US), compared with the actual value and forecast from an AR(1) model and of the surveys of Professional Forecasters conducted by the Bank of Mexico.

start of the reference quarter), the nowcast period (from day 0 to day 90) and the back-cast period (from day 90 onwards). The figure shows the results of the two versions of the model: including the US variables, and with just Mexican ones. I also compare the performance of these models to the same benchmarks: the forecast from an AR(1), surveys of Professional Forecasters interviewed by the Bank of Mexico, and the surveys of Professional Forecasters reported by Bloomberg.

The chart shows three main results. First, the reduction in RMSFE shows how the information coming from macroeconomic releases is effectively incorporated into the estimates of the GDP growth rate. Second, it shows that in the QoQ case the model that includes the US indicators performs uniformly better than the model that excludes them, in the forecast period and in the nowcast period up to the 80th day after the start of the reference quarter. In the YoY case the RMSFE is lower only in the forecast period, and very similar in the nowcast and backcast periods. Third, the chart shows that the forecasts coming from such a mechanical model are comparable to those of professional forecasters, with the advantages that the model can be updated in real time

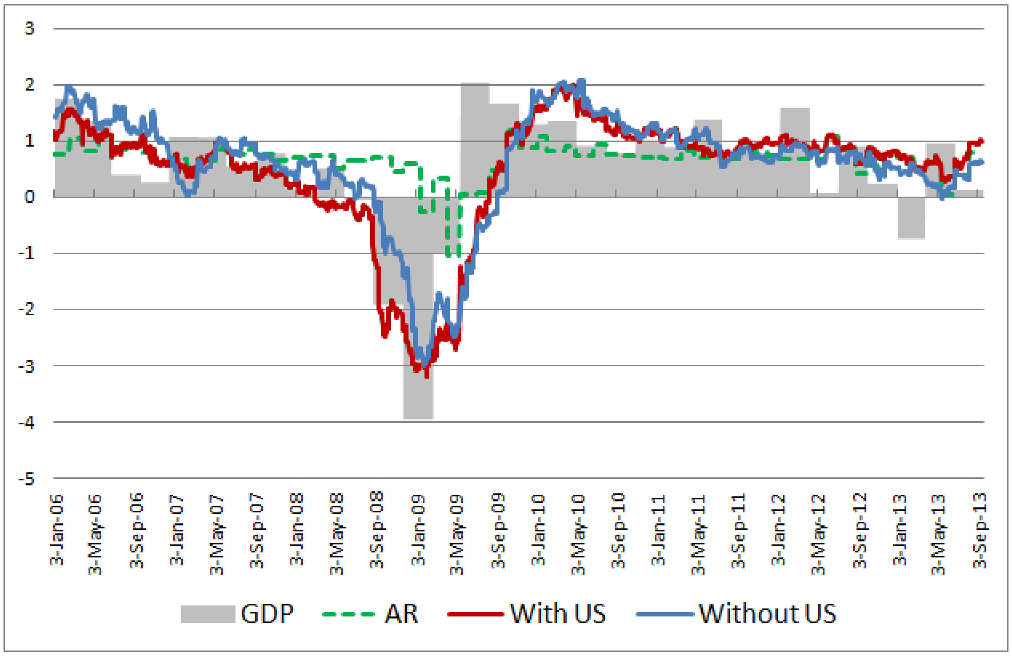

Figure 2: Now-cast of the QoQ growth rate of GDP of the model that includes US variables (With US) and the one that includes just Mexican variables (Without US), compared with the actual value and the forecast from an AR(1) model.

at any release and it is totally free of judgemental biases.

To test the performance of the models I perform a Diebold and Mariano (1995) test of equal predictive accuracy. Let us call the model that includes just Mexican variables "small", and the model that includes Mexican and US variables "large". I test the equal accuracy of the forecasts (i) from the small model with the ones from the large, (ii) from the large model with respect to the ones from the AR(1), (iii) from the small model with respect to the ones from the AR(1). The models are nested, but the higher estimation uncertainty of the parameters in finite samples, in the case of the large model, makes the test of Diebold-Mariano even more conservative if the test is designed to evaluate the greater forecasting accuracy of its forecasts with respect to the ones from the small model. I consider as the loss function the average squared differential of the forecast errors of the two competing models, taken in correspondence of the last release of each month. The null hypothesis is that the forecasts from the two models have the same predictive accuracy, the

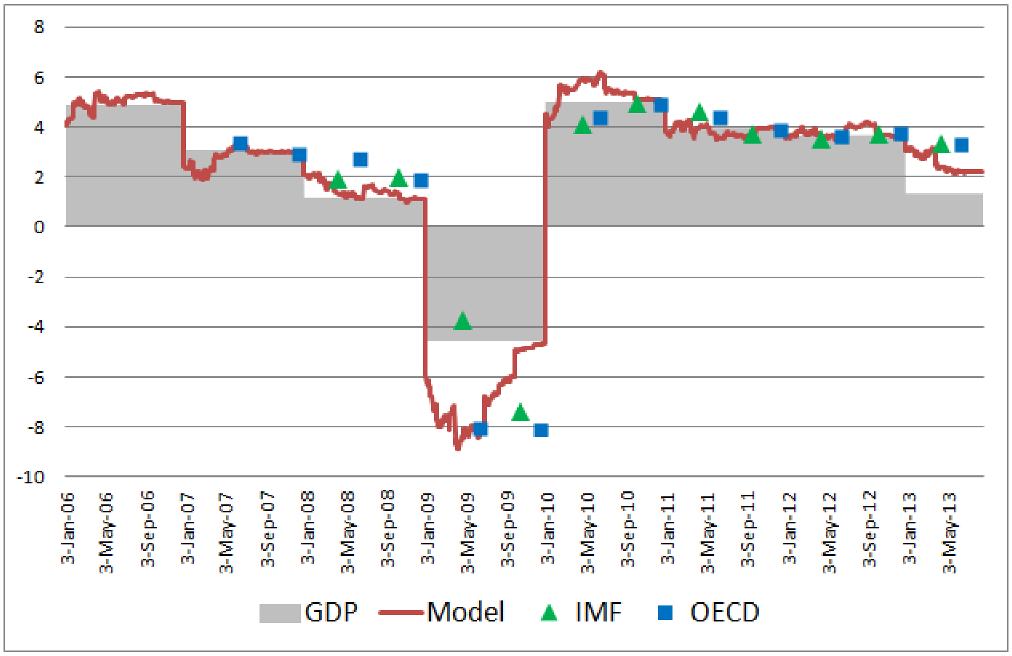

Figure 3: Now-cast of the calendar year growth rate of GDP using the model that includes US and Mexican variables, compared with the actual value of GDP growth rate and forecast produced by IMF and OECD.

alternative is that the forecast from the latter models in the couples specified above have higher predictive accuracy.

I first analyse the results relative to the YoY GDP growth rate. Regarding the comparison of nowcast and forecast of the nowcasting models with respect to the AR(1), the test rejects the null hypothesis at the 99% confidence level, and at 95% in the case of the backcast. When comparing the small and the large models, the null hypothesis is rejected at the 90% level in the case if the nowcast and at the 95% level in the case of the forecast. In comparison with the Surveys of Professional Forecasters, the null hypothesis is rejected for both nowcasting models at the 99% confidence level.

Considering the results relative to the target of the QoQ growth, there is no advantage of the nowcasting models with respect to the AR in forecasting one step ahead. However, in the backcast case there is evidence in favour of the small model at the 90% level and in favour of the large at 95% level, and for the nowcast the null hypothesis is rejected at 90% level for the small and at 95% level for the large. Comparing the two nowcasting models, the null hypothesis is rejected in favour of the large one at 95% for nowcast and forecast, and it is not rejected for the backcast.

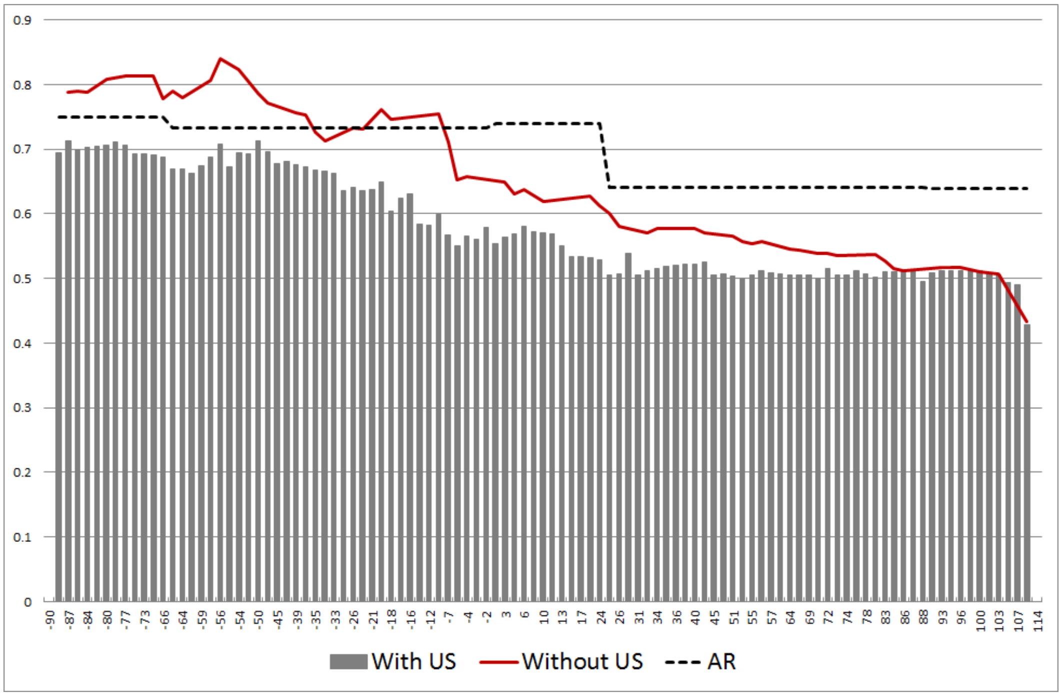

Figure 4: Root Mean Squared Forecast Errors of the two nowcast models of the QoQ growth rate of GDP during the forecast period (from -90 to 0 days to the start of the reference quarter), the nowcast period (from day 0 to day 90) and the back-cast period (from day 90 onwards). The days are on the horizontal axis.

To sum up, the test indicates a statistically significant advantage of the nowcasting models with respect to the AR(1), and an advantage of the large model with respect to the small one in nowcasting and forecasting. Moreover, the analysis shows that the nowcasting models produce nowcasts and forecasts that are more accurate than the ones of professional forecasters.[12] The worse performance in backcasting, also with respect to the AR, is a feature of a model that is designed to take advantage of the timeliness of some indicators that are referred to the reference quarter. It disregards indicators that might forecast some components included in GDP accounting (e.g. investment), and that might be useful only in the backcasting period. The inclusion of such indicators, and an improvement of the model in that direction, are left for future research.

[12]I express as an advantage the fact that H_0 is rejected at least at 90% confidence level.

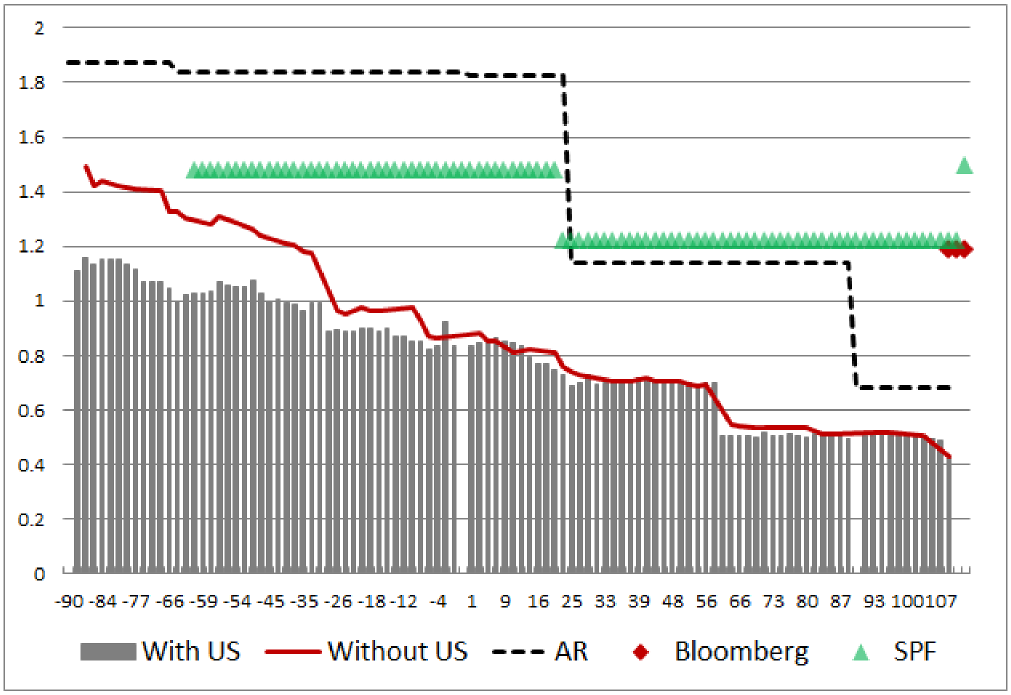

Figure 5: Root Mean Squared Forecast Errors of the two nowcast models of the YoY growth rate of GDP during the forecast period (from -90 to 0 days to the start of the reference quarter), the nowcast period (from day 0 to day 90) and the back-cast period (from day 90 onwards). The days are on the horizontal axis. The chart shows also the comparison with the RMSFE of the forecast of SPF from Bank of Mexico and of Bloomberg surveys.

	DM stat	Backcast	Nowcast	Forecast
QoQ	Mex vs (Mex+US)	0.479	2.048	1.693
	AR vs (Mex+US)	1.262	1.783	0.912
	AR vs Mex	1.299	1.541	0.256
YoY	Mex vs (Mex+US)	0.479	1.496	1.971
	AR vs (Mex+US)	2.271	3.403	3.379
	AR vs Mex	2.267	3.354	3.231
	SPF vs Mex		3.497	2.490
	SPF vs (Mex+US)		4.212	2.630

Table 3: In the table the results of a Diebold-Mariano (1995) test of equal predictive accuracy. The model written as the second is the one whose forecast are tested to be more accurate in the alternative hypothesis (e.g.: A vs B, H_1 is that forecasts from B are more accurate than forecasts from A). "Mex" refers to the model with just Mexican variables; "Mex+US" to the model with all the variables; "AR" to the AR(1); "SPF" to the survey of professional forecasters (Bank of Mexico).

4.2 News analysis

Bańbura and Modugno (2014) explain how to extract model-based news in the nowcasting framework. In our case, let y_t^Q be the GDP at time t, and Ω_ν the information set at time ν, where ν is a vintage of data. The nowcast is the projection of y_t^Q using the available data, $\mathbb{E}[y_t^Q|\Omega_\nu]$. At any release, the information set expands : $\Omega_\nu \subset \Omega_{\nu+1}$, and it is possible to decompose the new forecast in:

$$\underbrace{\mathbb{E}[y_t^Q|\Omega_{\nu+1}]}_{\text{new forecast}} = \underbrace{\mathbb{E}[y_t^Q|\Omega_\nu]}_{\text{old forecast}} + \underbrace{\mathbb{E}[y_t^Q|I_{\nu+1}]}_{revision} \tag{6}$$

Where $I_{\nu+1}$ is the information in $\Omega_{\nu+1}$ orthogonal to Ω_ν. Therefore, it is possible to express the revision as a weighted sum of news from the released variables, where b_{j,t,ν_+1} are the weights:

$$\underbrace{\mathbb{E}[y_t^Q|\Omega_{\nu+1}] - \mathbb{E}[y_t^Q|\Omega_\nu]}_{revision} = \sum_{j \in J_{\nu+1}} b_{j,t,\nu+1} \underbrace{(x_{i_j,t_j} - \mathbb{E}[(x_{i_j,t_j}|\Omega_\nu)]}_{news} \tag{7}$$

This methodology permits us to evaluate the marginal contribution of every release in the updating of the nowcast. In Figure 6 I report the average impact of the variables on the update of the nowcast, calculated as the average weight multiplied by the standard deviation of the model-based news. I have ordered the variables by the average distance of the releases from their reference period, expressed in days, to appreciate the effect of the timeliness (if any) on the variables' impacts. The main result of this analysis is that the now-casting model attributes a very high importance to the variables relative to the US economy. The release of the US PMI in the first month of the quarter has the second highest impact after Mexican GDP, followed by Mexican Producer Confidence, US Industrial Production and US Non Farm Payrolls. I find a high impact of both US soft and hard variables. As expected, the highest impacts are of the variables that are released on average in the first half of the first month, and this confirms that timeliness is indeed important. The ranking of the impacts is very similar if we look at the second month in the quarter, other than Mexican GDP. In the third month, US Industrial Production seems to be the most important variable according to the model. However, the informational content of the variables is also important, not just their timeliness: the high impact of US Car and Truck Imports, which are released with a significant delay, confirms the relevance of looking at the trade with the US, especially in the automotive sector, to gauge the state of the Mexican economy. Among Mexican variables, it is worth noticing the predominant role of the Producer Confidence Index, of Vehicle Production and Vehicle Exports, and of Imports and Exports. The analysis confirms the high importance of US variables in assessing the current state of the Mexican economy.

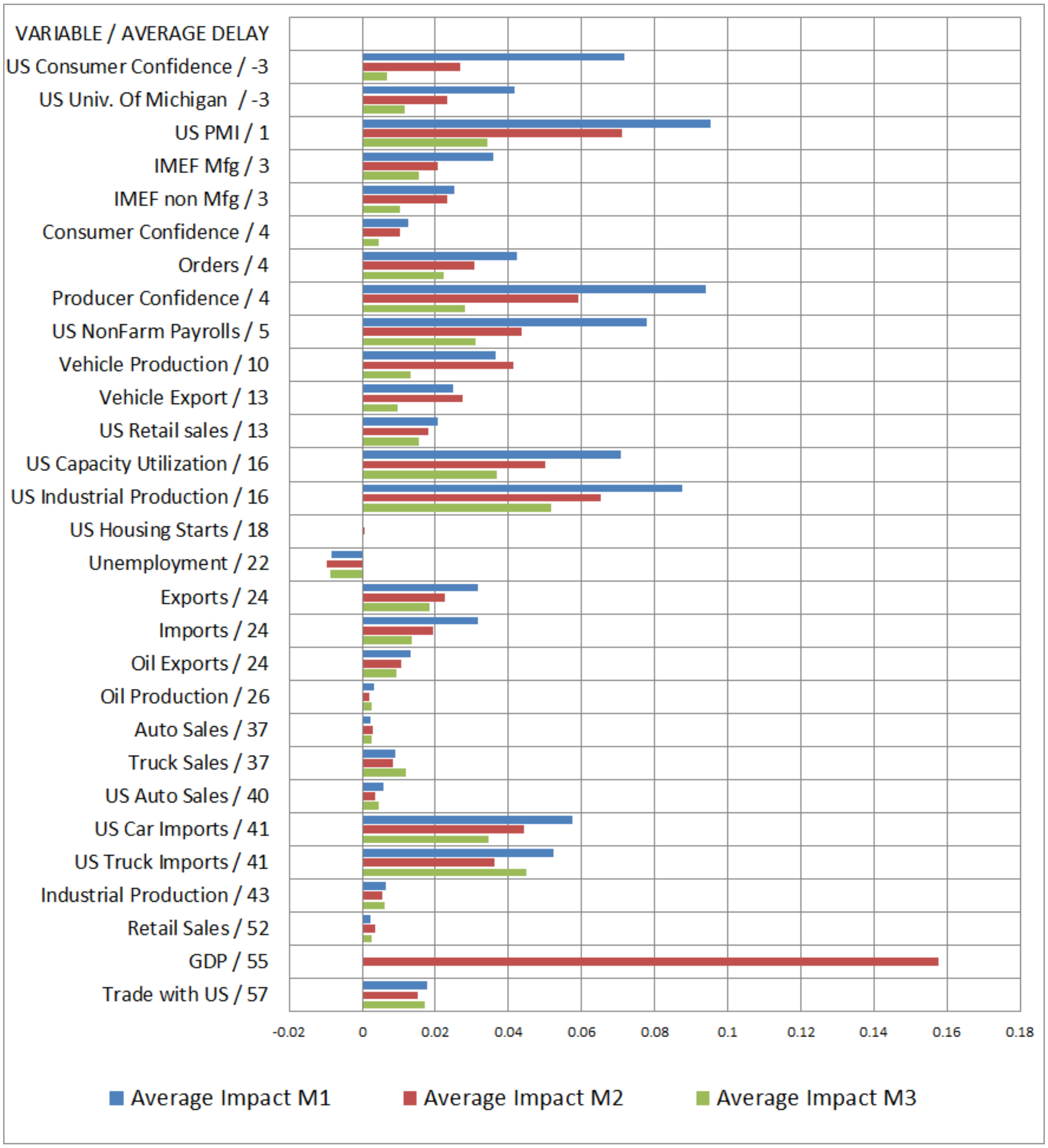

Figure 6: The chart shows the average impact of the variables in the 3 months of the nowcast (m1, m2, m3), where the impact is the product of the average model-based standardized news and the weight of the variable in the updating process. The variables are ordered by average release delay from the reference period, expressed in days after the name of the variable.

5 Conclusions

In this paper I have presented a model to interpret the flow of Mexican macroeconomic data releases. In particular, I exploited the information embedded in macroeconomic news from Mexico and from the United States, in a model constructed to nowcast Mexican real GDP. I have used the nowcasting technique based on dynamic factor models and Kalman filters that has its grounds in Giannone, Reichlin and Small (2008), which permits us to evaluate the relevance of any single indicator used in the nowcast. The results confirm the good quality of the model if compared to institutional forecasts from the International Monetary Fund and the OECD, with the advantage that it is possible to update the nowcast at any macroeconomic release. Moreover, the model outperforms the judgemental forecast of professional forecasters of Bank of Mexico, both in nowcasting and in forecasting the GDP growth rate. Among the results, I have documented the importance of the variables related to the automotive sector and trade, and I have found an important role for indicators about the US economy. In particular, the model indicates the usefulness of a group of "core" US variables, given their high average impact in the nowcast updates, like the Manufacturing Purchasing Managers Index, Non-Farm Payrolls, Capacity Utilization and Industrial Production. These results confirm the findings of a literature on the important linkages between US and Mexican economy in the post-NAFTA period (e.g. Sosa, 2008; Miles and Vijverberg, 2011). Therefore, they encourage a more frequent use of external indicators in short-term GDP forecasting of countries whose business cycles are highly synchronized with other economies.

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Appendix

5.1 News - descriptive statistics

In Table 4 I present some descriptive statistics of the model-based news, from the out of sample evaluation presented in section 4.2.

Variable	Average News	News Standard Deviation
Auto Sales	0.249	4.404
Consumer Confidence	-0.320	1.840
Exports	0.139	3.286
GDP	0.094	0.648
IMEF Manufacturing	0.055	1.665
IMEF non Manufacturing	-0.630	2.350
Imports	0.045	3.164
Industrial Production	0.000	0.763
Oil Exports	-0.380	8.170
Oil Production	-0.251	1.966
Orders	0.076	1.119
Producer Confidence	0.069	2.292
Retail Sales	0.067	1.208
Trade with US	56829	807908
Truck Sales	-1.873	8.117
Unemployment	-0.017	0.200
Vehicle Export	1.093	17.598
Vehicle Production	1.864	15.790
US Auto Sales	0.005	12.071
US Capacity Utilization	0.111	0.557
US Car Imports	-0.104	4.666
US Consumer Confidence	-21.471	86.793
US Housing Starts	0.045	3.976
US Industrial Production	-0.022	0.730
US Change in NonFarm Payrolls	-24.559	117.208
US PMI Mfg.	0.188	1.633
US Retail sales	-0.082	1.104
US Truck Imports	-0.379	10.436
US Univ. Of Michigan	0.198	6.060

Table 4: The table shows the average and the standard deviation of the news, extracted as described in Section 4.2.

5.2 Robustness

In this section I present some results of the out of sample performance of the model with different specifications. In particular, in Figure 7 I present some results of the estimation performed using different lags and factors, for the model with Mexican and US variables, and in Figure 8 the results relative to the model with just Mexican variables.

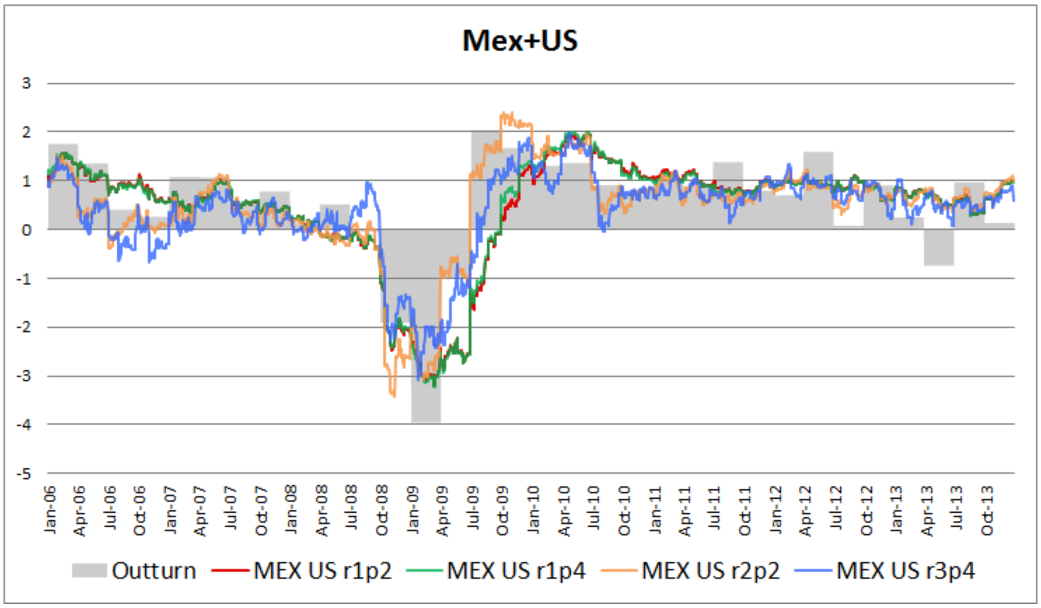

Figure 7: The figure shows the historical out of sample evaluation (QoQ) of different specifications of the model including Mexican and US variables. I indicate with r the number of factors, and with p the number of lags.

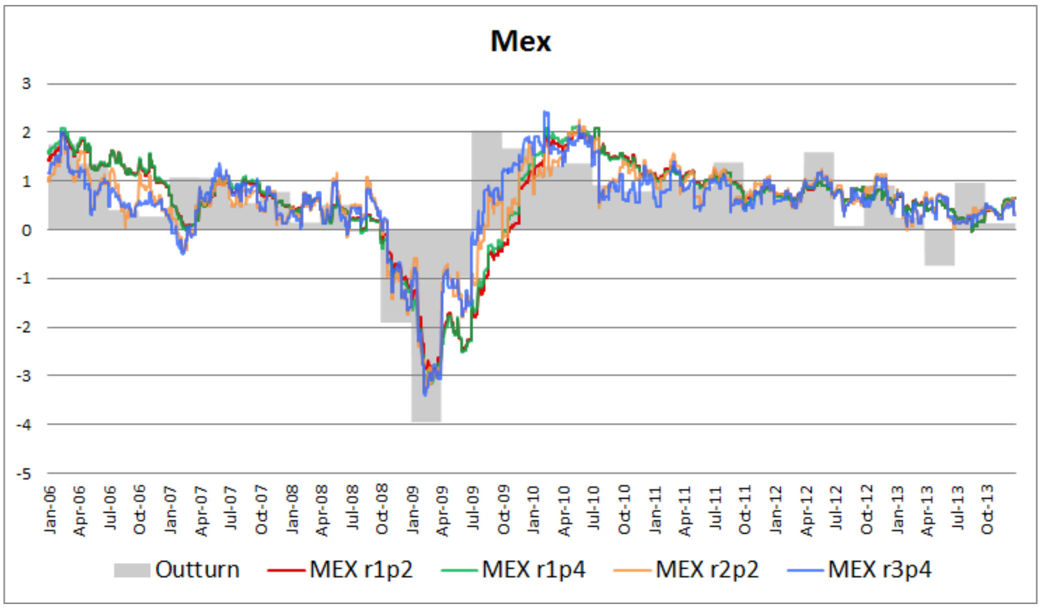

Figure 8: The figure shows the historical out of sample evaluation (QoQ) of different specifications of the model including just Mexican variables. I indicate with r the number of factors, and with p the number of lags.