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Nowcasting the Costa Rican Quarterly Output Growth

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Fotografía de portada: “Presentes”, conjunto escultórico en bronce, año 1983, del artista costarricense Fernando Calvo Sánchez. Colección del Banco Central de Costa Rica.

Pronóstico en tiempo real del crecimiento trimestral del PIB para Costa Rica

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Resumen

El siguiente documento implementa diversos modelos econométricos (Bridge, MIDAS, versiones aumentadas por factores, MF-VAR Bayesiano y la respectiva combinación de pronósticos) para pronosticar el crecimiento inter-trimestral del PIB costarricense en tiempo real. Con el uso de un conjunto comprehensivo de indicadores macroeconómicos, se concluye que los modelos ARIMA, Factor-VAR, MIDAS no restringido y Bridge consistentemente producen mayor precisión que otras especificaciones con técnicas alternativas. Asimismo, se observa que los índices de producción poseen mayor poder predictivo (principalmente el IMAE), que controlar por estacionalidad introduce sesgos adicionales en el pronóstico y que los quiebres estructurales presentes en las series no representan problemas. Se recomienda el uso de estos modelos y su combinación para contar con información para la toma de decisiones de política.

Palabras clave: Modelos univariados y multivariados de series de tiempo, métodos de pronóstico.

Clasificación JEL: C22, C32, C53.

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Nowcasting the Costa Rican Quarterly Output Growth

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The ideas expressed here belong to the author and do not necessarily represent those of the Central Bank of Costa Rica.

Summary

This paper implements different econometric models (Bridge, MIDAS, factor-augmented versions, MF-BVAR models and their combination) to nowcast Costa Rican quarter-to-quarter GDP growth. I exploit a comprehensive set of macroeconomic indicators to conclude that models ARIMA, Factor-VAR, unrestricted MIDAS and Bridge are consistently more precise than other specifications. Furthermore, I find that production-related variables have higher predictive power (mainly the IMAE), controlling for seasonality adds biases to the model's forecasts, and structural breaks in the series do not affect the nowcasts. I recommend to use these models and their combination in order to have up to date information for policy making decisions.

Key words: Univariate and Multivariate Time-Series Models, Forecasting and Prediction Methods.

JEL Codes: C22, C32, C53.

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1 Introduction

Nowcasting is the forecast of the present, the very near future, or the recent past. Recently, we use this approach in economics to forecast macroeconomic variables as the GDP or trade (Giannone et al., 2008).

It is relevant since almost all the economic information necessary to make decisions is not timely available due to the difficulty in collecting information. Particularly in Costa Rica, GDP data is published a quarter after the reference period. Hence, policymakers and other economic agents need an accurate estimation of the present and the very recent past state of key economic indicators to incorporate them into the decision-making process. More precisely, GDP nowcasting means to use higher temporal frequency indicators such as monthly production indexes, international trade data, monthly inflation rates or policy changes in order to track the aggregate production at the quarter or annual frequency (Bańbura et al., 2013).

For the BCCR, it is utterly relevant to have accurate estimations of present and near past GDP behavior. Such a variable is central to anticipate inflationary pressures and calibrate the monetary policy instruments.

At the beginning of nowcasting in economics, expert judgement was used combined with simple models called Bridge (Baffigi et al., 2004). Bridge equations are essentially regressions relating GDP growth to one or few monthly variables aggregated to quarterly frequency mainly through simple averages.

MIDAS models arise as an alternative to Bridge ones, with a higher flexibility by allowing the use of data in their original frequency. An example is Andreou et al. (2013) who developed a method with MIDAS regressions to predict quarterly real economic activity, with daily financial data and forecast combination for the United States.

More recently Mixed Frequency VAR models (MF-VAR) were incorporated in the nowcasting literature. However, these models suffer from dimensionality problems. Schorfheide and Song (2015) developed a solution with a MF-VAR model using monthly and quarterly data. It is estimated with Bayesian methods under the Minnesota prior (MF-BVAR). With real time data, they generated and evaluated the MF-VAR forecasts with those from a VAR with quarterly aggregated data. They concluded that the use of monthly data improves the forecasting. Other applications of MF-VAR models are Giannone et al. (2009), Kuzin et al. (2011), and Brave et al. (2016).

For the Costa Rican case, Rodríguez-Vargas (2014) nowcast the quarterly GDP growth. The author focused on ARIMA, Bridge, and MIDAS models and found MIDAS with 9 and 12 lags to have the best accuracy and unbiaseness out-of-sample properties. Nonetheless, these methods use only the GDP growth and other single monthly indicator: the IMAE (monthly production index).

Therefore, I extend the analysis with methods that allow multiple variables as Factor-Augmented versions of MIDAS and Bridge models, as well as MF-VAR, and MF-BVARS. The focus is on nowcasting the last unobserved quarter-to-quarter real GDP growth. The goal is to assess which method has higher accuracy and better statistical properties. Also, I want to define which variables seem to nowcast better. I use a comprehensive macroeconomic dataset of 83 different variables from all the sectors of the economy. It includes three indexes build from surveys about economic future prospects (confidence indexes).[1] Among all model types and parametrizations, I estimate 217 different models.

The results suggest the production index variables, and in particular the IMAE, perform better as nowcasters relative to the other variables. Controlling for seasonality seems to bias the model's out-of-sample forecasts. Also, the coefficients associated with structural breaks in the series are not statistically significant in the estimations, maybe as the period of interest is far away from the last structural break in 2008.

I find that additional information inside the quarter is better. Also, that the confidence indexes could be used to compute an easy nowcast, but the best models proposed here are far superior in accuracy and statistical properties.[2] In particular, the optimal combination (with weights minimizing forecast RMSE) of only the best models has the best nowcasting capacity (higher accuracy and statistical properties).

I check that the nowcasting procedure proposed performs relatively well for the 2008 financial crisis and the beginning of the COVID-19 pandemic. For the COVID-19 pandemic, the nowcast are stable and similar when using data until 2019 for estimation relative to using data from the COVID-19's period.

Thus, I conclude it is possible to obtain forecasts with one-known month of IMAE 18 days before the current quarter finishes, and with three-known months of IMAE 48 days before the official quarterly GDP information is

[1] Economic Agent Confidence Index ("Índice de confianza del agente económico" in Spanish or ICAE) computed by the BCCR; Consumer Confidence Index ("Índice de confianza del consumidor" or ICC) measure by the University of Costa Rica; and Business Perceptions Index ("Índice empresarial de percepción", IEP) measure by a business private union in Costa Rica ("Unión Costarricense de Cámaras y Asociaciones del Sector Empresarial Privado", UCCAEP).

[2] The best models are: i) ARIMA of GDP growth with four lags in the quarterly data; ii) Factor-VAR with all the 83 variables, with two factors, two lags in the quarterly data, and 12 lags in monthly data; iii) Unrestricted MIDAS with the IMAE and GDP growth, with six lags in monthly data, three-known months of the IMAE, and four lags in the quarterly data; iv) MF-BVAR with data from 2005 and sample 4, (production indexes data, look Appendix 7.3) with 12 lags in monthly data, and 4 lags in quarterly data; v) Bridge with the IMAE and GDP growth, with one-known month of the IMAE, and for lags in the quarterly data; and v) Factor Bridge with all the 83 variables, with one factor and one lag in the quarterly data, and 12 lags in the monthly data.

published (usually with a quarter lag). I recommend to use these models and their combination in order to have up to date information for policy making decisions.

The next section 2 presents the empirical methodology followed for nowcasting and the models used. A general description of the models is in Appendix 7.1. Section 3 reviews all the variables included and their sources. It also addresses briefly the mismatch issue on the release of new information between the monthly and quarterly data. Section 4 summarizes the results for the best performing models. Also, I assess, in section 5, whether the nowcasting procedure is robust to crisis periods and the associated uncertainty, namely the 2008 financial crisis and the COVID-19 pandemic. Finally, section 6 concludes and recommends the use of the proposed models for nowcasting the quarterly GDP growth in Costa Rica.

2 Empirical methodology

The variable to nowcast is the most recent non-officially-published quarter-to-quarter real GDP growth without any seasonal adjustment. As I want to forecast the ongoing economic activity, the seasonal patterns are important to asses the level and not a measure of trend and cycle obtained after seasonal adjustment of the series (adjustment that could also contain errors).

At first during the research, observed data on quarterly growth were available until the third quarter 2019, meaning the last nowcast is for the third quarter of 2019 in the first part of the paper. Also, I compute a one-step-ahead nowcast for the growth of the fourth quarter of 2019 with daily information until November 2019, and monthly information until September 2019 (meaning there are zero-known months of the IMAE for this forecast).

Nonetheless, periods of crisis are associated with high uncertainty which undermines the reliance on forecasts. Therefore, I add a new section 5 where I check how robust is the nowcasting procedure for the 2008 financial crisis and the COVID-19 pandemic. For the pandemic, I update the data until June 2020. The goal in this section is to nowcast the year-to-year GDP growth (easily done with the quarter-to-quarter nowcast obtained with the procedure proposed here).

For the 2008 financial crisis, I nowcast the fourth quarter of 2008 until the first quarter of 2010. For the COVID-19 pandemic, I nowcast the fourth quarter of 2019 until the second quarter of 2020. For this last period, I extend and change a little the approach. Based on Schorfheide and Song (2020), I perform nowcasts both with and without the most recent observations in the estimates. The two sets computed are: (i) a sequence of nowcasts based on a fixed sample that ends in 2019; (ii) a sequence of nowcasts based on the most recent data that ends with the last observation available, including those from the pandemic.

Here, nowcasting is done on a expanding window basis. I begin the estimation from the first quarter of 1991 to the first quarter of 2015 and include the available monthly and daily information for the second quarter of 2015, then I compute a forecast for the second quarter of 2015 (the "unobserved" quarter for GDP here). Then, I add information for the second quarter of 2015, include monthly and daily information for the third quarter, and compute the forecast for this third quarter. I do this process recursively until nowcast of the fourth quarter of 2019. The same procedure applies to section 5 with the respective sample until the second quarter of 2020. This is done in this way to compare nowcasts with zero-, one-, two-, and three-known months of monthly variables in the sample.

As mentioned previously, the goal of this nowcasting exercise is to approximate the quarter-to-quarter GDP growth for the last unobserved quarter. I take advantage of know information inside that quarter (monthly and daily data) for that purpose. The expanding procedure allowed me to compute a series of nowcasting values from the second quarter of 2015 to the fourth quarter of 2019. I use these nowcasts series to measure which model performed better. In section 5, I only compare how close are the nowcasts with the observed year-to-year growth rates in both periods: the 2008 financial crisis and the beginning of the COVID-19 pandemic.

For comparison purposes, some models are estimated with 0-, 1-, 2- and 3-known months of the IMAE for the quarter to nowcast. The unknown months of IMAE are computed with ARIMA models (TRAMO-SEATS methodology) in order to have data for all the months inside each quarter, i.e. to balance the sample between the monthly and quarterly frequencies. This is needed to avoid singularity problems.

I use the following specifications for nowcasting:

- ARIMA: includes only the quarter-to-quarter GDP growth and I use the TRAMO-SEATS methodology. It includes four lags as the data is quarterly. This gives a complex naive forecast for comparison.

- Bridge: includes the quarterly GDP growth and the IMAE growth with 0-, 1-, 2- and 3-known months of the IMAE. The remaining unknown months inside each quarter are computed with TRAMO-SEATS. There are specifications with 3, 6, 9, and 12 lags in the monthly data, and all of them with four lags in the quarterly data.

- MIDAS: includes the quarterly GDP growth and the IMAE month-to-month growth with 0-, 1-, 2- and 3-known months of the IMAE. The remaining unknown months inside each quarter are computed with TRAMO-SEATS. There are specifications with 3, 6, 9, and 12 lags in the monthly data, and all of them with four lags in the quarterly data. I use several methods to match the monthly information with the quarterly output: i) unrestricted coefficients, ii) beta normalized probability density function, iii) exponentially normalized Almon lag polynomial, iv) non-normalized order-P Almon lag polynomial, and v) polynomial with step functions non-normalized. The detail of each one is in Appendix 7.1.

- Factor Bridge, Factor MIDAS and Factor VAR: all include the whole data set (83 variables). Factor Bridge and Factor VAR estimations use the transformed variables to quarterly frequency with the averages, while the Factor MIDAS estimation uses monthly frequency with the same five methods outlined before. There are specifications with 3, 6, 9, and 12 lags in the monthly data, and all of them with four lags in the quarterly data. I use the the Kalman filter to project unknown values inside each quarter for each of the variables. Afterwards, the factors are computed with Principal Components and there are models with 2, 3, and 4 factors as variables for estimation.

- Blocking MF-VAR: only includes IMAE month-to-month growth with 0-, 1-, 2- and 3-known months. The unknown months inside each quarter are computed with TRAMO-SEATS. As it is a transformation to quarterly data, there are only four lags.

- MF-BVAR: includes all the 83 variables. There are specifications with 3, 6, 9, and 12 lags in the monthly data, and all of them with four lags in the quarterly data. Due to different appearance dates (when the variable was registered for the first time) and to avoid exhaustion of the degrees of freedom, I estimate the models with nearly ten variables given their economic group (monetary, external sector, etc.), and several samples given by the jointly appearance of more variables (1991, 1992, 1998, 2000, 2005, and 2009). The several groups of data I use for the MF-BVAR estimation are described in the appendix 7.3. I use the Minnesota prior for the Bayesian procedure.

Each type of model outlined here has many differences with the others.

More information about each of the models is in the Appendix 7.1.

Other exercise I want to address is the forecasting performance of the confidence indexes for Costa Rica. This indexes could be good nowcasters as they measure current and forward-looking information: the perception of key economic agents (consumers and firms) about the current and future economic prospects. Thus, I estimate VAR models between them and the quarterly GDP growth. In total, they are four models: one with the three indexes, and the other three with just one index each. Then, I compare which index is the best nowcaster, and also how they perform relative to the models used here.

I include these indexes as additional variables in the Factor and BVAR models in order to capture forward looking information for Costa Rica. They are part of the 83 variables used.

As a robustness check I include seasonal dummies but found that the associated nowcasts do not pass the simple unbiasness test. Moreover, the coefficients for the two common structural breaks in the data - 1996 and from 2008 onwards - are not statistically significant in the models for nowcasting the quarterly growth. Maybe the periods for nowcasting are far enough from this structural breaks and the new information already incorporates them. At last, most of the predictors possess evidence of unit root presence, thus I use them in first differences.

The combination of forecast could also be useful (Stock and Watson, 2004). Here, I perform some combinations but only for the best models: the simple average, the simple median, and an optimal combination giving weights that minimize the root mean squared error (RMSE) for the out-of-sample observations. The next subsection 2.1 defines the procedure to obtain the best models here.

2.1 Nowcasting evaluation

I use several accuracy measures: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (SMAPE), and two Theil U formulations. All those are complemented with forecasting capacity statistical tests, namely Diebold-Mariano (Diebold and Mariano, 1995) with the Harvey, Leyboune and Newbold (Harvey et al., 1998) correction. Also, I compute simple unbiasedness tests as well as the ability to forecast the direction of changes in the GDP quarter-to-quarter growth rate.[3]

As usual, the lower the accuracy measure the better the forecast. Additionally, Theil U_1 statistic says the closer to zero the lower is the forecasting error, whereas Theil U_2 statistic says values lower than 1 means the model's forecast improves over the naive forecast $\hat{Y}_t = Y_{t-1}$.

The unbiasedness null hypothesis is tested with the following equation:

$$y_t = c + \beta \hat{y}_t + \epsilon$$

where y is the observed quarter-to-quarter growth, and $\hat{y}_t$ the expected out-of-sample one. Then a simple Wald test with null hypothesis $c = 0$ and $\beta = 1$ brings statistical evidence for biased forecasts.

I obtain a set of the best models with the following procedure:

1. Compute the nowcast with the expanding window procedure. Series of nowcast are created for each of the models and parametrizations.

2. Test the null hypothesis of unbiasedness. Discard all specifications that reject the null.

[3] As the quarterly growth is not seasonally adjusted, it could be easier to forecast correctly the direction of changes, hence this computation would result in overly optimistic results. Nonetheless, it is still useful to discriminate between competing models. The seasonality is also implicitly present in the monthly data, and it helps to forecast the quarter-to-quarter growth level and not a trend-cycle measure.

3. Compute the Theil U_2 statistic. Discard all specifications that do not perform better than the naive forecast (statistic is more than 1).

4. Compute the porcentage of times each model forecasts correctly the changes in the quarter-to-quarter GDP growth rate. Discard all specifications with less than 90%.

5. Take the models with the lowest RMSE and MAE among this final set.

Afterwards, I compute the combinations with the best models. Also, Diebold-Mariano test are computed between each of the best models and combinations with respect to the ARIMA specification (also one of the best models here). With this test, I want to asses which models or combinations perform statistically better than this (complex) naive forecast.

3 Data

Most of the variables used come from the Central Bank of Costa Rica (BCCR)'s web page.[4] The inflation and the industrial production index of the United States (principal Costa Rica's trade partner) are from the FRED,[5] and the oil barrel WTI price from Bloomberg.

The perception indexes that try to measure the agent's sentiment about current and future economic prospects (forward-looking information) are the following:

- Economic Agent Confidence Index ("Índice de confianza del agente económico" in spanish or ICAE) computed by the BCCR.
- Consumer Confidence Index ("Índice de confianza del consumidor" or ICC) measured by the University of Costa Rica.

[4]https://www.bccr.fi.cr/indicadores-economicos.
[5]https://fred.stlouisfed.org/.

- Business Perceptions Index ("Índice empresarial de percepción", IEP) measured by a business private union in Costa Rica ("Unión Costarricense de Cámaras y Asociaciones del Sector Empresarial Privado", UCCAEP).

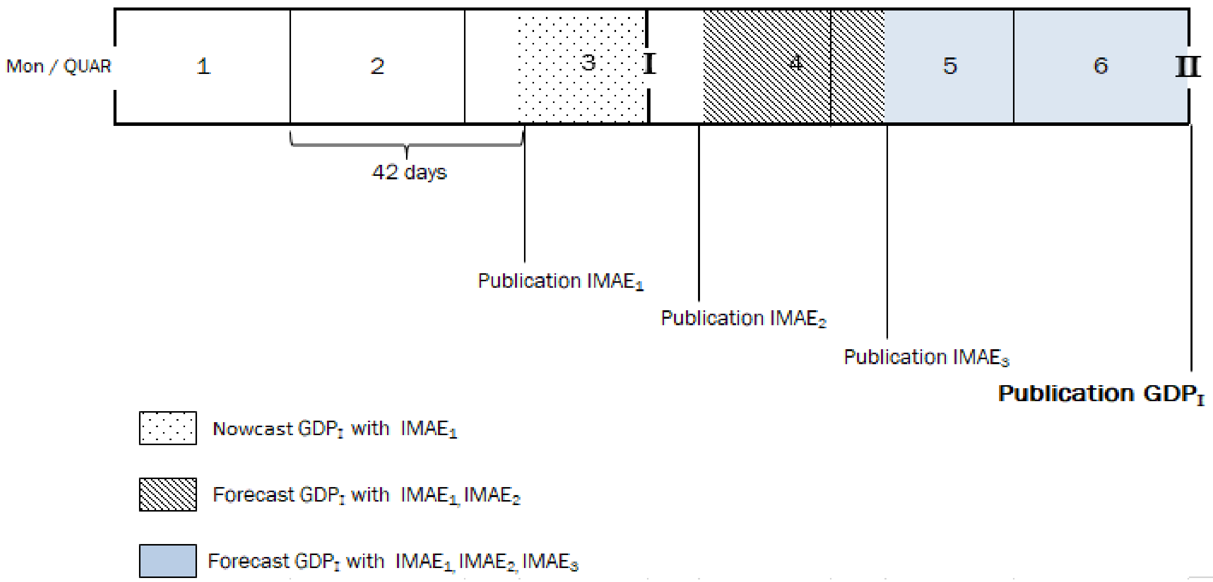
All these indexes are available at quarterly frequency from 2002 to the present. Additionally, I use a Financial Conditions Index measured by the BCCR at a monthly frequency. Models with and without these indexes are used for compare its forecasting capabilities. As a result, I find there are no important differences when including or not these indexes in the best models, meaning the nowcasting procedure perform well in incorporate forward-looking information with the other variables.

The detailed list of variables, available frequency and temporal horizon could be consulted in the appendix 7.2. In total there are 83 variables comprising the overall economy: external sector, monetary and financial sector, production, interest rates, negotiation markets (exchange rates), public sector and employment.

It is relevant to note that the nowcasting process has a matching problem between the data availability in higher frequency, for the explanatory variables, and the publication of the quarterly GDP growth. Figure 1 presents an overview of the publication lag issue for the IMAE and the GDP in Costa Rica.

For example, the official release for the GDP information of the first quarter is done at the end of the second quarter, whereas the IMAE's lag is 42 days in each month, meaning there is one month known of the IMAE 18 days before the first quarter finishes. Moreover, the first three months of IMAE are known 48 days before the first quarter GDP information is officially released. This implies there is information available to potentially nowcast the quarterly growth before its publication: 18 days before the current quarter ends using one-known month of the IMAE, and 48 days before the official release with three-known months of the IMAE.

Figure 1: Data publication lag (example)



Source: Taken from Rodríguez-Vargas (2014)

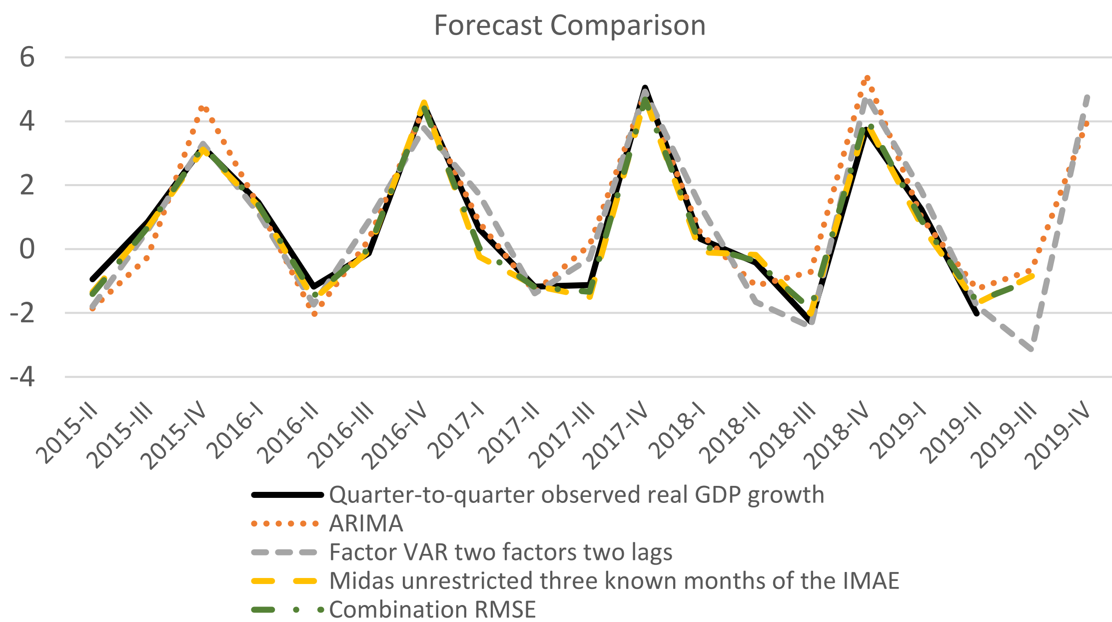
4 Results

Figure 2 presents a comparison between the best models and the observed quarter-to-quarter real GDP growth they tried to nowcast. Figure 3 shows the equivalent for models with only the economic perception indexes as predictors.

Overall, the models with economic activity perception indexes as predictors perform well in following the quarter-to-quarter growth. None of them seem to outperform the others.

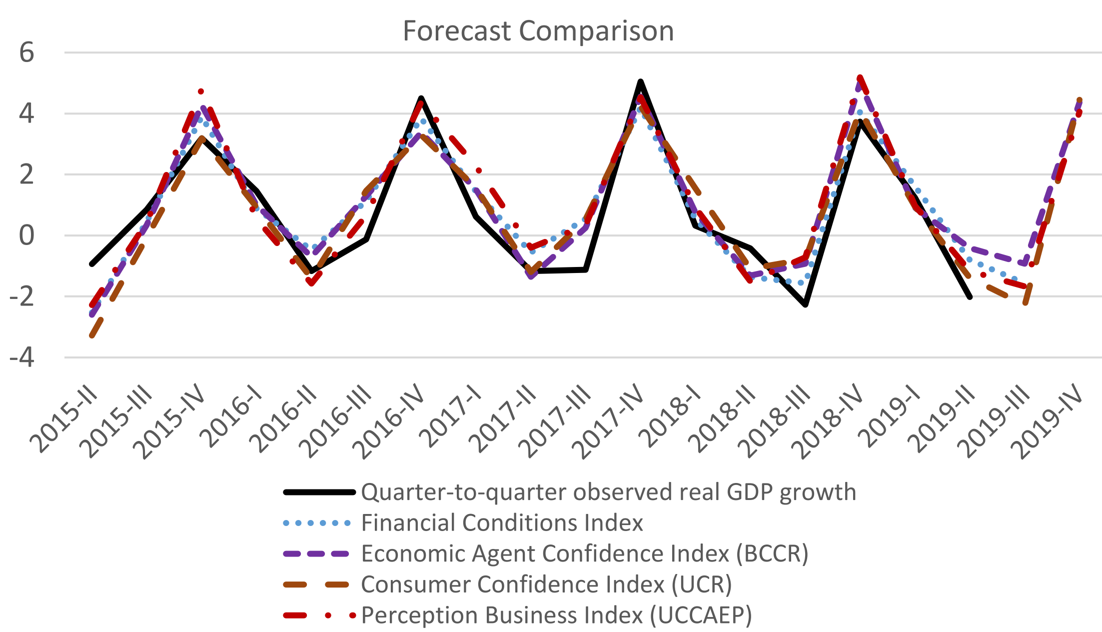
Nonetheless, the best models did a great job at following the changes. The Combination RMSE of the best models as well as the unrestricted MIDAS with three-known months of the IMAE are the best performers. This result tell us that the indexes could be used to easily compute forecasts of the economic activity. But, at a first glance, the models and nowcasting approach here outperform these "naive" forecasts.

Figure 2: Nowcasting comparison between best ARIMA, Factor-VAR, MIDAS, and RMSE Combination



Source: Own elaboration.

Figure 3: Nowcasting comparison between economic activiy perception indexes



Source: Own elaboration.

The actual numbers of nowcasts are in Table 1. It shows the observed quarter-to-quarter real GDP growth jointly with the respective nowcast from the three best models, and the combination of the best models named RMSE combination. Also, there is a comparison between the forecast from the several confidence indexes and the financial conditions index. With these nowcasts, it is possible to compute the GDP level and then the year-to-year growth which could be useful for policy makers.

As mentioned before, in order to evaluate the nowcasting capacity, several error measures and statistical tests were performed. Table 2 shows the RMSE for the three best models, the ones with indexes, and the RMSE combination. The unrestricted MIDAS with six lags and three-known months together with the RMSE combination have the lowest RMSE.

The RMSE combination with the full set of models (217) was not the best in terms of RMSE even relative to individual models, but the combination with just the best models (6) got the lowest forecasting errors. This implies the procedure used to select models for nowcasting the quarterly GDP growth effectively removed noise and resulted in a better nowcast.

Additionally, the unrestricted MIDAS result suggests the following: i) half a year (six lags of predictors) is the relevant information for short term forecast in Costa Rica, and ii) more information about the quarter to forecast (more known months inside the quarter) is better for that purpose.

Confidence indexes and the financial conditions index seem to be good short term forecasters, both given their models do not reject the unbiaseness null hypothesis, and the high accuracy in sign change. However, these models got higher RMSE measures relative to the best models, which implies they incur in more errors. In fact, when comparing the results from all the models with and without these indexes as additional forecasters, there where no differences in their results meaning the indexes do not provide further information regarding the variables already used.

Table 1: Quarter to quarter growth nowcasts

Period	Quarter to quarter observed real GDP growth	ARIMA	Factor VAR two factors two lags	MIDAS unrestricted, three-known months of the IMAE	Combination RMSE
2015-II	-0.94	-1.86	-1.80	-1.34	-1.41
2015-III	0.85	-0.25	0.59	0.67	0.68
2015-IV	3.19	4.56	3.29	3.11	3.21
2016-I	1.46	1.35	1.13	1.36	1.38
2016-II	-1.17	-2.06	-1.74	-1.58	-1.47
2016-III	-0.13	0.29	0.87	-0.06	0.01
2016-IV	4.50	4.43	3.79	4.59	4.43
2017-I	0.62	0.83	1.70	-0.24	0.03
2017-II	-1.17	-1.34	-1.38	-1.14	-1.19
2017-III	-1.12	0.13	-0.29	-1.50	-1.33
2017-IV	5.05	4.89	4.93	4.72	4.68
2018-I	0.32	0.50	1.35	-0.09	0.12
2018-II	-0.42	-1.14	-1.66	-0.18	-0.37
2018-III	-2.27	-0.71	-2.44	-2.02	-1.88
2018-IV	3.74	5.46	4.81	4.00	4.13
2019-I	1.24	0.99	1.81	0.74	0.90
2019-II	-2.02	-1.24	-1.78	-1.70	-1.64
2019-III	-0.17	-0.65	-3.15	-0.84	-0.96
2019-IV	4.13	4.00	4.75	NA	NA

Source: Own elaboration. Note: Period refers to the quater to be nowcasted. Column three is the nowcast of the best ARIMA model. Column four is the nowcast of the Factor-VAR model with two factor and two lags in the quarterly frequency. Fifth column is the nowcast of the MIDAS with unrestricted monthly and quarterly parameters with three-known months of the IMAE at the monthly frequency. Sixth column is the nowcast of the best models RMSE combination. In blue nowcasts before the official publication for the quarter. In red nowcasts before the end of the quarter.

Table 1: Quarter to quarter growth nowcasts (continuation)

Period	Quarter to quarter observed real GDP growth	Financial conditions index	Economic agent confidence index (BCCR)	Consumer confidence index (UCR)	Perception business index (UCCAEP)
2015-II	-0.94	-2.53	-2.60	-3.28	-2.28
2015-III	0.85	0.46	0.34	-0.06	0.43
2015-IV	3.19	3.89	4.27	3.19	4.80
2016-I	1.46	0.89	1.00	0.93	0.54
2016-II	-1.17	-0.47	-0.69	-1.41	-1.58
2016-III	-0.13	1.13	1.29	1.47	0.66
2016-IV	4.50	3.84	3.38	3.29	4.37
2017-I	0.62	1.45	1.51	1.56	2.28
2017-II	-1.17	-0.56	-1.36	-1.20	-0.40
2017-III	-1.12	0.54	0.25	0.53	0.33
2017-IV	5.05	4.20	4.55	4.24	4.53
2018-I	0.32	0.54	0.76	1.55	0.92
2018-II	-0.42	-1.37	-1.31	-1.09	-1.50
2018-III	-2.27	-1.57	-0.93	-0.78	-0.72
2018-IV	3.74	4.05	5.01	4.09	5.19
2019-I	1.24	1.60	0.91	0.94	0.97
2019-II	-2.02	-0.80	-0.41	-1.39	-1.17
2019-III	-0.17	-1.56	-0.93	-2.28	-1.67
2019-IV	4.13	NA	4.37	4.45	4.06

Source: Own elaboration. Note: Period refers to the quater to be nowcasted. Column three is the nowcast of the VAR with the Financial Conditions Index. Column four is the nowcast of the VAR with the Economic Agent Confidence Index. Fifth column is the nowcast of the VAR with the Consumer Confidence Index. Sixth column is the nowcast of the VAR with the Business Perception Index. In blue nowcasts before the official publication for the quarter. In red nowcasts before the end of the quarter.

Table 2: Test results summary

Model	RMSE	Percent of correct sign of the growth rate	Number of anticipation days to official release	Number of anticipation days to quarter's end
1. ARIMA	0.88	94	90	0
2. Factor VAR with two factors, two lags	0.72	100	108	18
3. U-MIDAS 6 lags, three-known months	0.35	100	48	0
4. RMSE combination	0.35	99	48	0
5. Bridge with ICF	0.90	100	60	0
6. VAR with IEP	1.05	94	NA	NA
7. VAR with ICC	1.08	94	120	30
8. VAR with ICAE	1.03	94	120	30

Source: Own elaboration. Note: The first column refers to the specification used. The second column is the Root Mean Square Error of the nowcast. The third column shows the percent of times the specification correctly followed the sign of the quarter-to-quarter real GDP growth. The fourth column is the number of days the specification could bring a nowcast before the official release of the new GDP observation. The fifth column is the number of days the specification could bring a nowcast before the end of the current quarter. Recall there is a quarter lag in the publication of GDP for Costa Rica.

In nowcasting, it is important to know by how many days it is possible to anticipate the official release of new information or even the quarter's end. Thus, Table 2 also present those days by model.

With the IEP exception (which publication dates are not known), the confidence indexes are published at the middle of each quarter. This means that these models have 30 days of anticipation to the quarter's end and 120 days to the official publication.

In contrast, the ARIMA model, in need of the previous quarter information, is not able to anticipate the quarter's end. However, given the official release is done a quarter later, this model could forecast the GDP growth 90 days before.

In the meantime the IMAE information is available 42 days after the reference month. Hence for the three-known months MIDAS model there is no anticipation to the quarter's end, but 48 days to the official publication.

Lastly, the Factor VAR relies on the Kalman filter to balance the missing values in any variable at the end of the sample. Therefore, this model is able to anticipate the quarter's end by 18 days (the time when the first month of the IMAE within the quarter is released) and by 108 days the official publication.

There are some other results from the nowcasting exercise. When comparing the accuracy for the several mixed frequency BVAR models, the ones with production indexes variables got the best performance, meaning monthly production information is better for short term forecast relative to any other economic variable. This conclusion was supported with the Diebold-Mariano test (not presented here).

I wanted to forecast the original growth series without any seasonally adjustment, as the seasonal patterns, their timing, and their magnitudes are important to assess the current state of the economy. Nevertheless, it is a common practice in forecasting to seasonally adjust the series to model a clean stationary process and to avoid undesired properties in the error term. Even though the nowcast was done for the original series, the best models have the desire properties of a white noise for the error term. This could be due to forecast the quarter-to-quarter growth rate instead of the year-to-year one. As a robustness check, I performed the nowcast including seasonal dummies in each of the models, but I found almost all the models, even the best ones, rejected the null hypothesis for unbiaseness.

With respect to the relative accuracy among models, the Diebold-Mariano (DM) test brings statistical evidence of which could be the best performer. Nonetheless, to compute the test across all the 217 models and permutations would be unfeasible. For simplicity, I focus in Table 3 on the comparison between best models, the models with economic activity perception indexes, and the ARIMA model used as a benchmark (complex naive forecast). I obtained suggestive evidence in favor of the RMSE combination and the Unrestricted MIDAS model with 6 lags and three-known months of the IMAE, both being superior than the ARIMA model for nowcasting. The best Factor Var model and the indexes model, with the IEP exception, were equivalent to the ARIMA in nowcasting capacity.

Table 3: Diebold-Mariano tests summary

Model	Surpass ARIMA	It is surpass by ARIMA
Factor VAR with factors, two lags	No	No
MIDAS unrestricted, six lags, three-known months	Yes	No
Root Mean Squared Error Combination	Yes	No
VAR with IEP	No	Yes
VAR with ICC	No	No
VAR with ICAE	No	No
Bridge with financial conditions index	No	No

Source: Own elaboration. Diebold-Mariano test results. Note: The first column is the specification which predictive accuracy would be compared with that of the ARIMA model. The overall null hypothesis is that both specifications have the same predictive accuracy. The second column shows whether the null hypothesis was rejected in favor of a greater accuracy of the specification in the first column. The third column shows whether the null hypothesis was rejected in favor of a greater accuracy of the ARIMA model.

Finally, it is easy to go from the quarter to quarter growth rate to the year-to-year real GDP growth. Thus table 4 shows the equivalent transformation to year-to-year quarterly growth. Only the best model, namely the RMSE combination, is presented there for simplicity.

Table 4: Year-to-year quarterly real GDP growth

Period	Year-to-year quarterly real GDP growth	Nowcasts RMSE combination
2017-IV	3.28	2.92
2018-I	2.98	2.77
2018-II	3.76	3.82
2018-III	2.56	2.97
2018-IV	1.28	1.67
2019-I	2.22	1.87
2019-II	0.57	0.97
2019-III	2.50	1.92
2019-IV	3.30	2.55

Source: Own elaboration. In blue the nowcast of the last unobserved quarter with the RMSE combination. In red a "one-period-ahead" forecast after the last unobserved quarter. This last forecast is computed with the median combination of the best models available: Factor Bridge, Factor VAR, and ARIMA.

The nowcast for the 2019's third quarter is in blue as it was the last unobserved quarter at the beginning of this research.[6] In red, there is a "one step ahead" forecast for the fourth quarter of 2019 as the monthly variables where not available for this quarter, only daily variables.

Another reason for this value to be in red is the RMSE could not be

[6]Although it is possible to forecast growth by any step ahead, I preferred to avoid that practice here as the main focus was the very short term forecast. Further steps ahead would need to forecast also several or even all the predictors, implying any forecast error there would be translated into a forecast error in the variable of interest in an unknown form. Also, it means losing the spirit of using the already available information of higher frequency.

computed as some models do not have any information for this quarter. Thus, I computed the median combination between the best Factor Bridge, the best Factor VAR and the ARIMA (all included in the RMSE combination). It was possible as these models automatically forecast the missing values at the end of the sample.

I strongly recommend not to perform one or more steps ahead for nowcasting, as the predictor would need to be also forecast and any error would be included in the resulting growth. I include the median combination mentioned previously just to show the one-step-ahead forecast in Table 4.

5 Nowcast robustness: the 2008 financial crisis and the COVID-19 pandemic

The Great Recession, also called subprime mortgage crisis, was a severe contraction of liquidity in global financial markets that started in the U.S. in 2008, as a result of the collapse of the U.S. housing market. It caused the failure or near-failure of several major investment and commercial banks, among other financial institutions. Its effects spread widely to all the global economic environment. Costa Rica was not an exception as the country experienced negative year-to-year growth rates for the first time in decades.

Also, the COVID-19 pandemic has had a deep impact on the global economic activity. Throughout 2020 and 2021, Costa Rica implemented several mobility restrictions to minimize the number of new contagious. As a result, the economic activity suffered a severe and unequally distributed downturn. The lack of consensus on how long it will take to end the current pandemic intrinsically introduces great complexity to forecast models. Past information could have low predictive power to infer short-term GDP behavior.

Central banks and international organizations require accurate information to track how the economy recovers from crisis in general. In particular, for the COVID-19 pandemic it is also important to keep track of the effects that the restrictions and policies implemented by the governments would have on the economic activity.

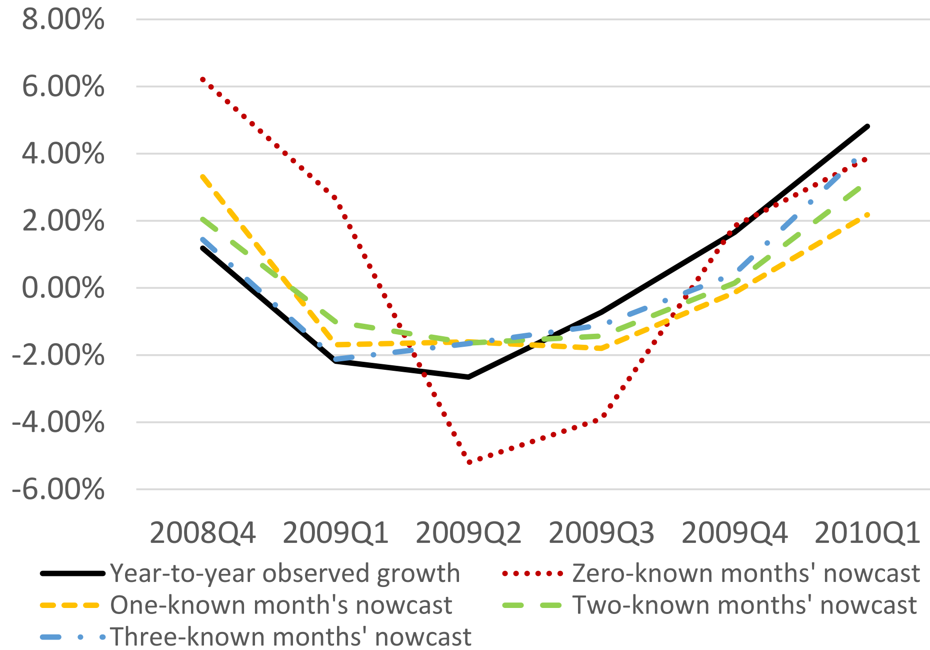
Therefore, I check how robust is the nowcasting procedure proposed when nowcasting growth in crisis periods. For the 2008 financial crisis, I estimate the model and nowcasts with the most recent available information previous to the official publication of the growth rate for the quarter to nowcast. I use the period from the fourth quarter of 2008 to the first quarter of 2010 to see how well the nowcast performs.

For the COVID-19 pandemic, I extend and change a little the approach. Based on Schorfheide and Song (2020), I perform nowcasts both with and without the most recent observations in the estimates. The two sets computed are: (i) a sequence of nowcasts based on a fixed sample that ends in 2019; (ii) a sequence of nowcasts based on the most recent data that ends with the last observation available, including those from the pandemic. Here, I use the first quarter of 2020 to the third quarter of 2020 as forecasting period.

Figures 4 and 5 show the results of the nowcasting procedure for these two periods of economic crisis. In these figures the results are from those models that use all the available information within the period, but restricts the estimation from zero-known months of information inside the quarter to one-, two-, and three-known months of information.

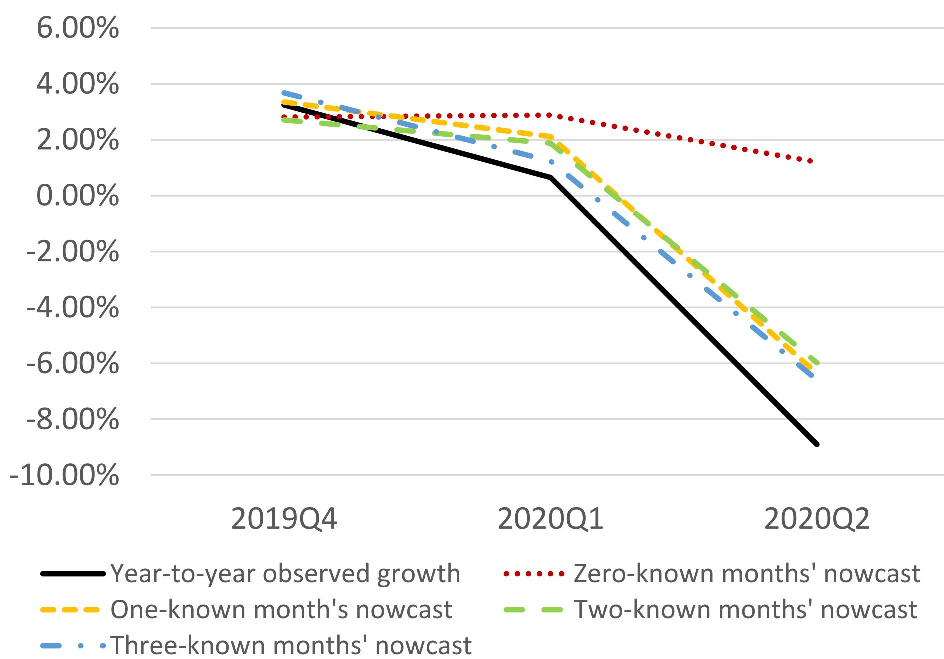
Figure 4 shows the downturn due to the 2008 financial crisis. It triggered negative year-to-year growth rates for the first, second, and third quarters of 2009, with a recovery in the last quarter of 2009 and first quarter of 2010. The nowcast with zero-known months inside each quarter performs poorly at the beginning of the downturn. It shows positive rates for the first two quarters in this sample (2008Q4 and 2009Q1). Afterwards, it adjust downwards, but overestimates the negative growth rates in 2009Q2 and 2009Q3.

Figure 4: Nowcast 2008 Financial Crisis Growth Rate Same Period, Previous Year, Quarterly



Source: Own elaboration.

Figure 5: Nowcast COVID-19 pandemic Growth Rate Same Period, Previous Year, Quarterly



Source: Own elaboration.

The other nowcasts performed better. The best, as expected, is the one with three-known months inside the quarter to nowcast. This closeness to the observed value could be explained mainly by the availability of information about the monthly production index (IMAE). As showed previously, monitoring the monthly response is key to approximate the level of the quarterly GDP growth, and this seems to be also true in times of economic distress.

Figure 5 shows a similar result for the nowcast of the COVID-19 pandemic. Here, I compare the nowcasts from 2019Q4 to 2020Q2. Again, the nowcast with zero-known months of information fails in forecasting the negative growth rate in 2020Q2. However, the nowcasts with some information known inside the quarter (one-, two-, or three-known months) seem to track effectively the downturn.

As mentioned previously, I extend more on the nowcast for the COVID-19 pandemic. Tables 5 and 6 summarize the respective results with and without the most recent observations.

Nowcasts seem to not vary much among both exercises. As expected, for the first quarter of 2020 the closest were models with three-known months. However, they do not capture the full extend of the downturn.

For data until April 2020, there was an important decrease for the IMAE (-8.5% in year-to-year terms), which led to the unstable forecast near -17% in both approaches with one-known month. This result was quickly corrected with the next IMAE data available, namely May's IMAE (which still presented an important year-to-year decrease of -9.9%), resulting in forecast near -6% for either one- and two-known months. The correction with May's information is intuitive given more data availability.

Recall that when the IMAE of May 2020 is available, the GDP of the first quarter of the year is observed, thus the method still forecast the second quarter, but now it starts the respective for the third quarter. The inclusion of a new quarter to forecast implies three new monthly slots are to be filled,

Table 5: All sample available in estimates

Quarter to forecast	Observed year-to-year growth	Date for last observed IMAE data	Forecast zero known months	Forecast one known month	Forecast two known months	Forecast three known months	Alternative forecast for one or two known months
2020Q1	0.6%	December 2019	2.5%	NA	NA	NA	NA
2020Q1	0.6%	January 2020	2.5%	-0.3%	NA	NA	2.6%
2020Q1	0.6%	February 2020	2.9%	2.1%	1.8%	NA	2.6%
2020Q1	0.6%	March 2020	2.9%	2.6%	3.9%	1.2%	2.2%
2020Q1	0.6%	April 2020	2.9%	2.6%	3.9%	1.2%	2.2%
2020Q2	-8.9%	February 2020	3.5%	NA	NA	NA	NA
2020Q2	-8.9%	March 2020	3.7%	NA	NA	NA	NA
2020Q2	-8.9%	April 2020	3.7%	-17.3%	NA	NA	-2.4%
2020Q2	-8.9%	May 2020	2.2%	-6.5%	-5.9%	NA	-2.9%
2020Q2	-8.9%	June 2020	2.2%	-5.7%	-5.0%	-6.7%	-1.2%
2020Q3	-7.2%	May 2020	1.3%	NA	NA	NA	NA
2020Q3	-7.2%	June 2020	1.2%	NA	NA	NA	NA

Source: Own elaboration. Note: Alternative forecast for one- or two-known months is based on Factor-Bridge.

Table 6: Sample until 2019 in estimates

Quarter to forecast	Observed year-to-year growth	Date for last observed IMAE data	Forecast zero known months	Forecast one known month	Forecast two known months	Forecast three known months	Alternative forecast for one or two known months	Alternative forecast for zero-known months
2020Q1	0.6%	December 2019	2.4%	NA	NA	NA	NA	2.9%
2020Q1	0.6%	January 2020	2.4%	-0.3%	NA	NA	3.2%	2.9%
2020Q1	0.6%	February 2020	2.9%	2.1%	1.9%	NA	2.9%	2.2%
2020Q1	0.6%	March 2020	2.9%	2.7%	3.8%	1.2%	2.3%	2.4%
2020Q1	0.6%	April 2020	2.9%	2.7%	3.8%	1.2%	2.3%	2.4%
2020Q2	-8.9%	February 2020	3.4%	NA	NA	NA	NA	2.9%
2020Q2	-8.9%	March 2020	3.4%	NA	NA	NA	NA	2.9%
2020Q2	-8.9%	April 2020	3.4%	-17.1%	NA	NA	-3.2%	2.9%
2020Q2	-8.9%	May 2020	1.2%	-6.4%	-6.0%	NA	-3.7%	1.1%
2020Q2	-8.9%	June 2020	1.2%	-5.6%	-4.9%	-6.6%	-1.8%	-2.0%
2020Q3	-7.2%	May 2020	0.8%	NA	NA	NA	NA	0.3%
2020Q3	-7.2%	June 2020	0.8%	NA	NA	NA	NA	-3.9%

Source: Own elaboration. Note: Alternative forecast for one- or two-known months is based on Factor-Bridge. Alternative forecast for zero-known months is based on MIDAS.

meaning the TRAMO-SEATS result will vary even for one-known month. Therefore, even when the data observed is the same, the forecast changes as the effectively used IMAE for estimation and forecast is different. Overall, it seems to be stability for the nowcasts with or without the correction in the sample use for estimation. This is good news as we could update the data without the need for any correction in the sample.

6 Conclusions

Any Central Bank as a policy maker is in need of real time information about the state of the economy to anticipate inflationary pressures or to make decisions about economic activity stabilization. However, data on key variables is officially presented with an important lag, specially for the quarterly real GDP growth. The nowcasting principle emerge as a solution. Exploiting information available before the official growth data release, which also possess higher temporal frequency, allows to obtain sooner estimates.

The Central Bank of Costa Rica had previously implemented a methodology for nowcasting in Rodríguez-Vargas (2014). Here my pretension was to improve the short run forecast by updating and extending this methodology. Not only I estimate Bridge and MIDAS models, but also include Factor Bridge, Factor MIDAS, Factor VAR, blocking VAR, Mixed Frequency Bayesian VAR, and ARIMA as a benchmark, for a total of 217 models and 83 variables containing all the sectors of the economy. Moreover, I evaluate the nowcasting capacity of the three confidence indexes measure in Costa Rica, and a financial conditions index, as well as the combination of all and only the best models.

The best models do not reject the unbiased null hypothesis and have the lowest RMSE by model's type. Also they got a correct prediction for the change sign at least 90% of the time. This models where used for the RMSE and median combination and they are the following:

- ARIMA with four lags.
- Factor-VAR with two factors and two lags.
- Unrestricted MIDAS with six lags and three-known months of the IMAE.
- Mixed frequency Bayesian VAR with data from 2005 and sample 4 (production indexes data).
- Bridge with one-known month of the IMAE (equivalent by the Diebold-Mariano test to the three-known months Bridge model).
- Factor Bridge with one factor and one lag.

The unrestricted MIDAS with six lags and three-known months together with the RMSE combination have the lowest RMSE. Also, the RMSE combination with the full set of models (217) was not the best in terms of RMSE, but the combination with just the best models by type (6) got the lowest forecasting errors, implying the procedure used to select models for nowcasting the quarterly GDP growth effectively removed noise and resulted in a better nowcast. It is worth mentioning the two best models (unrestricted MIDAS and the RMSE combination) outperformed the benchmark ARIMA model according to the Diebold-Mariano tests.

That the unrestricted MIDAS resulted in the the best individual performer suggests half a year is the relevant information for short term forecast; and more information about the quarter to forecast is better for that purpose. Additionally, there is strong evidence that the monthly production indexes are the best nowcasters relative to any other economic variables.

Confidence indexes and the financial conditions index seem to be good short term forecasters, both given their models do not reject the unbiaseness null hypothesis, and the high accuracy in sign change. However, these models got higher RMSE measures relative to the best models, which implies they incur in more errors. Moreover, they do not seem to provide additional information as the for from models with and without the indexes as forecasters were equivalent.

I wanted to forecast the original growth series without any seasonally adjustment to account for any seasonal pattern, aspect important to assess the current state of the economy. It was a good decision as the nowcast including seasonal dummies in each of the models resulted in almost all the models, even the best ones, rejecting the null hypothesis for unbiaseness.

In general, periods of economic distress, as the 2008 financial crisis or the current COVID-19 pandemic, increase the degree of uncertainty posing a tremendous challenge for macroeconomic forecasting. I checked and confirmed that the nowcasting procedure is robust to these periods of crisis. Furthermore, for the COVID-19 pandemic, I performed a sequence of nowcasts based on a fixed sample that ends in 2019, and a sequence of nowcasts based on the most recent data that ends with the last observation available, including those from the pandemic. Overall, it seems to be stability for the nowcasts with or without the correction in the sample use for estimation. These are good news as the data could be updated and used without the need of adjustments.

As a policy recommendation, the nowcasting procedure, the best models here, and their combination could be used to forecast the quarterly output growth in the very short term, even under high uncertainty periods. This research showed it is not only possible but convenient as nowcasts could be available even 18 days before the quarter's end, or 108 days before the official data publication with accuracy. This would help to improve the informational set at disposal of the policy makers.

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7 Appendix

7.1 Description of models for nowcasting

I assume the publication intervals for the quarterly data are constant through time. In other words, the quarterly GDP has a constant number of months equal to three.

Next, I describe the models used for nowcasting. The main goal is not to fully present the Bridge, MIDAS, Factor-Bridge, Factor-MIDAS, MF-VAR and MF-Bvar models used here but a general specification. The explicit specifications are described in section 2. More details on each of these models could be consulted in Bańbura et al. (2013) and Foroni and Marcellino (2013).

7.1.1 Bridge models

Nowcasting the quarter-to-quarter GDP growth Y with a monthly indicator y uses the following regression:

$$Y_t = \alpha + \sum_{k=1}^{K} \beta_k * Y_{t-k} + \sum_{s=0}^{S} \gamma_s * \bar{y}_{t-s,i} + e_t, \quad i = 0, 1, 2, 3 \tag{1}$$

where Y_{t-k} are lags of the quarter-to-quarter GDP growth and $\bar{y}_t$ is the quarterly-frequency average of the monthly indicator in quarter t. I include lags of this transformed monthly indicator, as well as its contemporaneous values given the monthly information inside the quarter of interest. Note that $\bar{y}_{t,i}$ means the quarterly average of the monthly variable is computed with i-known months inside the quarter. In other words, $i = 0$ means we don't know any information of the monthly variable for the quarter of interest, whereas $i = 3$ means we do know the information for all the months inside this quarter.

Hence, the mixed frequency problem is solved in Bridge models by the temporal aggregation of the predictors from the higher to the lower frequency.

To manage the existence of missing data at the end of the sample, I use ARIMA models to project the unknown months of the monthly indicator and then compute $\bar{y}_{t-s,i}$ for $s = 0, \ldots, S$ in order to balance the sample. Recall we are interested in forecasting only the last quarter, meaning the lags $\bar{y}_{t-s,i}$ always have the information of all the months inside each quarter.

According to Bańbura et al. (2013), this is the traditional nowcasting tool popularly used by the central banks to obtain early estimation for the GDP and its components. The predictors are generally at monthly frequency and the estimation is made through ordinary least squares (Kitchen and Monaco, 2003; Baffigi et al., 2004). It could be extended to include lags of the relevant variable or exogenous variables. When the informational set is big, combination of forecast (Kitchen and Monaco, 2003; Diron, 2008; Angelini et al., 2011; Rünstler et al., 2009) or factors (Giannone et al., 2008) has been used in the literature. Here, I estimate simple Bridge models and factor augmented ones with autoregressive components.

7.1.2 MIDAS models

In contrast with the previous model, MIDAS uses the predictor's original monthly frequency and the regression is as follows:

$$Y_t = \alpha + \sum_{k=1}^{K} \beta_k * Y_{t-k} + \sum_{s=0}^{S} \gamma_s * \Gamma(L, \theta) * y_{t-s,i} + e_t, \quad i = 0, 1, 2, 3 \tag{2}$$

where $\Gamma(L, \theta)$ is a lag polynomial or a function that transforms the monthly information to quarterly frequency, s is the lag of the transformed predictor in the quarterly frequency, and i again represents the monthly information known inside the quarter to nowcast. As with Bridge models, I use ARIMA models to project the unknown months of the monthly indicator in order to balance the sample.

The lag polynomial $\Gamma(L, \theta)$ needs to be estimated as an additional step. It relates the monthly information to the quarterly variable of interest meaning each value of $\Gamma(L, \theta)$ is the weight assigned to that particular monthly variable and its lag in relation to its nowcasting ability of the quarterly variable. Therefore, L is the monthly lag and θ the associated monthly coefficient which then are used inside the function Γ. To not exhaust the degrees of freedom, $\Gamma(L, \theta)$ needs to be parameterized in a parsimonious way. Multiple settings have been proposed in the literature to compute $\Gamma(L, \theta)$ (Ghysels et al., 2004; Ghysels, 2014). I use the following:

- Unrestricted MIDAS (U-MIDAS): the coefficients of the polynomial are estimated without restriction. This approach has shown to work well for specifications that do not have a bigger difference between the higher and lower frequencies of the variables. This is the case with monthly/quarterly frameworks.

- Beta normalized probability density function: could be computed restricted or unrestricted versions, with final lag zero or non-zero.

- Exponentially normalized Almon lag polynomial: it has the following form:

$$\Gamma(L, \theta) = \sum_{m=1}^{M} \delta(m, \theta) L^m$$

  for N lags, with weights $\Gamma(m, \theta)$ both restricted or unrestricted, with sum equal to one, being parameter functions to estimate $\theta = (\theta_1, \theta_2)$ with the form

$$\delta(m, \theta) = \frac{\exp \theta_1 m + \theta_2 m^2}{\sum_{m=1}^{M} \exp \theta_1 m + \theta_2 m^2}$$

- Non-normalized, order-P Almon lag polynomial: $\gamma\Gamma(L, \theta)$ is jointly estimated, thus

$$\gamma\delta(m, \theta_0, ..., \theta_p) = \sum_{p=0}^{P} \theta_p m^p$$

weights are computed by ordinary least squares with a data transformation to high frequency and then they could be re-scaled to obtain the coefficient γ (Ghysels, 2014).

- Polynomial specification with step functions non-normalized.

7.1.3 Factor models (Bridge and MIDAS)

According to Bańbura et al. (2013), the most common version in nowcasting specifies that the high frequency variables, y_t, have a factor structure, and that the factors, F_t, follow a VAR process:

$$y_t = \mu + \Lambda F_t + E_t, E_t \sim \ i.i.d.\ N(0, \Sigma_E) \tag{3}$$

$$F_t = \Phi(L) F_t + U_t, U_t \sim \ i.i.d.\ N(0, \Sigma_U) \tag{4}$$

I follow Giannone et al. (2008)'s approach and thus y_t contains only observed monthly variables, for which equations 3 and 4 constitute a state-space representation. Then, the Kalman filter is used to obtain the unobserved monthly values inside each quarter as well as factor estimates. The factors comprise all the monthly information in few indicators. After their computation, nowcasting is achieved through OLS regression of the quarter-to-quater GDP growth on its lags, another quarterly frequency exogenous variables, and the factors aggregated to the quarterly frequency. If the aggregation of this factors is by the simple average, then it is a Factor-Bridge model, if it is by one of the MIDAS methods outlined before, then it is a Factor-MIDAS model.

7.1.4 Mixed frequency VAR and BVAR

In the present work I use three types of MF-VAR: i) blocking VAR; ii) Factor-Augmented VAR; and iii) MF-BVAR. The selection is due to their use in the nowcasting literature. All three models are estimated at the lowest (quarterly) frequency. Next, I mention some approaches for MF-VAR including the ones used here.

There exists a classical approach for MF-VAR. Mariano and Murasawa (2010) is an example. The approach is based on the treatment of low frequency variables as high frequency, with periodically missing observations. Their estimation is commonly done with maximum likelihood techniques as the Expectation Maximization mentioned. Also it is possible to obtain the missing data with the Kalman filter or smoother. I did not follow this technique.

For the simple MF-VAR I followed Chen et al. (2012). The authors came up with other solution referred as the Blocking Framework. It consists in specifying the model at low frequency and the high frequency information is separated in multiple series. For example, in a system with monthly and quarterly variables, this method will create three series per monthly variable, one for each of the months in each quarter. McCracken et al. (2015) has also employed this framework with a big mixed frequency Bayesian VAR.

VAR models are a less parsimonious representation than the factor models. For big informational sets, according to Bańbura et al. (2013); Koop (2013) and Bańbura and Modugno (2014), three solutions could be adopted for the dimensionality problem: i) forecast combination of smaller systems, ii) factor augmented VAR as in Bernanke et al. (2005) -although is application is not to forecasting-, or iii) Bayesian shrinkage also called Mixed Frequency Bayesian VAR (MF-BVAR).

Some of the first works with MF-BVAR models are Chiu et al. (2011) and Schorfheide and Song (2015). In the former the authors developed a Gibbs sample style to estimate the VAR with mixed and irregular sample data. In the second study, the authors used Monte Carlo Markov Chain (MCMC) to do Bayesian inference for the model's parameters and unobserved variables.

7.2 Data characteristics

Group	Variable name	Available sample	Frequency
External sector	United States Industrial Production Index	1919-2019	Monthly
External sector	United States inflation	1947-2019	Monthly
Prices	Consumer price index	1976-2019	Monthly
Prices	Annual inflation rate	1977-2019	Monthly
Prices	Services producer price index	1980-2019	Monthly
Interest rates	Passive basic rate	1981-2019	Daily
Interest rates	Real passive basic rate	1981-2019	Daily
Prices	Agricultural real minimum wage index	1984-2019	Monthly
Prices	Index of minimum real wages in exploitation of mines and quarries	1984-2019	Monthly
Prices	Index of real minimum wages manufacturing in industry	1984-2019	Monthly
Prices	Index of real minimum wages in construction	1984-2019	Monthly
Prices	Index of real minimum wages in electricity	1984-2019	Monthly
Prices	Index of minimum real wages in commerce	1984-2019	Monthly
Prices	Index of minimum real wages in transport, storage and communications	1984-2019	Monthly
Prices	Index of minimum wages real in services	1984-2019	Monthly
Monetary and financial	Monetary base	1987-2019	Monthly
Monetary and financial	Monetary emission	1987-2019	Monthly
Monetary and financial	Monetary multiplier M1	1987-2019	Monthly
Trading market	Dow Jones industrial average index	1990-2019	Daily
Trading market	Nasdaq Composite Index	1990-2019	Daily
Trading market	NYSE Composite Index	1990-2019	Daily
Trading market	Standard & Poor's 500 Index	1990-2019	Daily
Prices	Minimum nominal wage index	1991-2019	Monthly
Prices	Price of the hydrocarbon cocktail	1991-2019	Monthly
Prices	WTI oil barrel price	1991-2019	Monthly
Prices	Prices index to the manufacturing producer	1991-2019	Monthly
Production	Real state activities monthly index	1991-2019	Monthly
Production	Professional, scientific, technical, administrative, and support services activities monthly index	1991-2019	Monthly

Source: own elaboration.

Table A.1: Data characteristics (continuation)

Group	Variable name	Available sample	Frequency
Production	Public administration and social security plans monthly index	1991-2019	Monthly
Production	Financial and insurance activities monthly index	1991-2019	Monthly
Production	Agriculture forestry and fishing monthly index	1991-2019	Monthly
Production	Economic activity monthly index gap	1991-2019	Monthly
Production	Commerce monthly index	1991-2019	Monthly
Production	Information and communications monthly index	1991-2019	Monthly
Production	Construction monthly index	1991-2019	Monthly
Production	Electricity, water and sanitation services monthly index	1991-2019	Monthly
Production	Mining and quarrying monthly index	1991-2019	Monthly
Production	Teaching and human health activities monthly index	1991-2019	Monthly
Production	Accommodation and food service activities monthly index	1991-2019	Monthly
Production	Economic activity monthly index	1991-2019	Monthly
Production	Manufacture activity monthly index	1991-2019	Monthly
Production	Other activities monthly index	1991-2019	Monthly
Production	Transport and storage monthly index	1991-2019	Monthly
External sector	Net reserves of the Central Bank	1991-2019	Monthly
External sector	Real Multilateral Effective Exchange Rate with Mobile Weights	1991-2019	Monthly
Public sector	Central Government tax revenue accrued base	1991-2019	Monthly
Public sector	Current expenditure Central Government accrued base	1991-2019	Monthly
Public sector	Capital expenditure Central Government accrued base	1991-2019	Monthly
Production	Gross domestic product, volume to prices of the previous year chained	1991-2019	Quarterly
Production	Annual real GDP growth	1992-2019	Quarterly
Prices	Generic real minimum wage index	1995-2019	Monthly
Trading market	Costa Rica Stock Exchange Index	1995-2019	Daily
Prices	Index of real minimum wages	1995-2019	Monthly
External sector	FOB exports accumulated	1995-2019	Monthly
External sector	Cumulative CIF import	1995-2019	Monthly
Employment	Employment without entrepreneurship	1996-2019	Quarterly and Monthly
Interest rates	6 month Libor Rate	1996-2019	Daily

Source: own elaboration.

Table A.1: Data characteristics (continuation)

Group	Variable name	Available sample	Frequency
Monetary and financial	Circulating medium M1 measured at the level of the financial system	1998-2019	Monthly
Monetary and financial	Credit from the financial system to the total private sector	1998-2019	Monthly
Monetary and financial	Credit of the financial system to the agriculture sector	1998-2019	Monthly
Monetary and financial	Credit of the financial system to the livestock sector	1998-2019	Monthly
Monetary and financial	Credit of the financial system to the fishing sector	1998-2019	Monthly
Monetary and financial	Credit of the financial system to the industry sector	1998-2019	Monthly
Monetary and financial	Credit of the financial system to the housing sector	1998-2019	Monthly
Monetary and financial	Credit of the financial system to the construction sector	1998-2019	Monthly
Monetary and financial	Credit of the financial system to the tourism sector	1998-2019	Monthly
Monetary and financial	Credit of the financial system to the commerce sector	1998-2019	Monthly
Monetary and financial	Credit of the financial system to the services sector	1998-2019	Monthly
Monetary and financial	Credit of the financial system to the consumer sector	1998-2019	Monthly
Monetary and financial	Credit of the financial system to the electricity sector	1998-2019	Monthly
Monetary and financial	Credit of the financial system to the transport sector	1998-2019	Monthly
Monetary and financial	Credit of the financial system to the deposits and storage sector	1998-2019	Monthly
Monetary and financial	Credit of the financial system to the sector other activities	1998-2019	Monthly
Monetary and financial	Total liquidity maintained in the financial system	1998-2019	Monthly
Interest rates	Money Market Rate	1999-2019	Daily
External sector	Trade Partner Inflation Indicator	2004-2019	Monthly
Interest rates	United States Treasury Rates	2005-2019	Daily
Interest rates	Monetary policy rate indicator	2006-2019	Daily and Monthly
External sector	Foreign currency market average exchange rate	2006-2019	Daily and Monthly
Prices	Inflation expectations	2006-2019	Monthly
Prices	Truncated Average Price Index	2006-2019	Monthly
Prices	Truncated Average Price Index Inflation	2007-2019	Monthly
Interest rates	Rate in Integrated Liquidity Market	2009-2019	Daily
Expectations surveys	Economic agent confidence index, built by the Central Bank of Costa Rica	2002-2019	Quarterly
Expectations surveys	Consumer confidence index built with a survey from the University of Costa Rica	2002-2019	Quarterly
Expectations surveys	Perception Business Index built by UCCAEP surveys	2002-2019	Quarterly
Monetary and financial	Financial Conditions Index	2001-2019	Quarterly

Source: own elaboration.

7.3 Variables included in each BVAR models' sample

Sample 1:

- United States Industrial Production Index.
- United States inflation.
- Consumer price index.
- Annual inflation rate.
- Services producer price index.
- Passive basic rate.
- Real passive basic rate.
- Agricultural real minimum wage index.
- Index of minimum real wages in exploitation of mines and quarries.
- Index of real minimum wages manufacturing in industry.
- Index of real minimum wages in construction.

Sample 2:

- Index of real minimum wages in electricity.
- Index of minimum real wages in commerce.
- Index of minimum real wages in transport, storage and communications.
- Index of minimum wages real in services.
- Monetary base.
- Monetary emission.
- Monetary multiplier M1.

- Dow Jones industrial average index.
- Nasdaq Composite Index.
- NYSE Composite Index.
- Standard & Poor's 500 Index.
- Generic real minimum wage index.

Sample 3:

- Minimum nominal wage index.
- Price of the hydrocarbon cocktail.
- WTI oil barrel price.
- Prices index to the manufacturing producer.
- Real state activities monthly index.
- Professional, scientific, technical, administrative, and support services activities monthly index.
- Public administration and social security plans monthly index.
- Financial and insurance activities monthly index.
- Agriculture forestry and fishing monthly index.
- Economic activity monthly index gap.

Sample 4:

- Commerce monthly index
- Information and communications monthly index.
- Construction monthly index.

- Electricity, water and sanitation services monthly index.
- Mining and quarrying monthly index.
- Teaching and human health activities monthly index.
- Accommodation and food service activities monthly index.
- Economic activity monthly index.
- Manufacture activity monthly index.
- Other activities monthly index.

Sample 5:

- Transport and storage monthly index.
- Net reserves of the Central Bank.
- Real Multilateral Effective.
- Exchange Rate with Mobile Weights.
- Central Government tax revenue accrued base.
- Current expenditure Central Government accrued base.
- Capital expenditure Central Government accrued base.
- Gross domestic product, volume to prices of the previous year chained.
- Annual real GDP growth.

Sample 6:

- Costa Rica Stock Exchange Index.
- Index of real minimum wages.
- FOB exports accumulated.

- Cumulative CIF import.
- Employment without entrepreneurship.
- 6 month Libor Rate.
- Circulating medium M1 measured at the level of the financial system.
- Credit from the financial system to the total private sector.
- Credit of the financial system to the agriculture sector.
- Credit of the financial system to the livestock sector.

Sample 7:

- Credit of the financial system to the fishing sector.
- Credit of the financial system to the industry sector.
- Credit of the financial system to the housing sector.
- Credit of the financial system to the construction sector.
- Credit of the financial system to the tourism sector.
- Credit of the financial system to the commerce sector.
- Credit of the financial system to the services sector.
- Credit of the financial system to the consumer sector.
- Credit of the financial system to the electricity sector.
- Credit of the financial system to the transport sector.
- Credit of the financial system to the deposits and storage sector.

Sample 8:

- Credit of the financial system to the sector other activities.

- Total liquidity maintained in the financial system.
- Money Market Rate.
- Trade Partner Inflation Indicator.
- United States Treasury Rates.
- Monetary policy rate indicator.
- Foreign currency market average exchange rate.
- Inflation expectations.
- Truncated Average Price Index.
- Truncated Average Price Index Inflation.
- Rate in Integrated Liquidity Market.

7.4 Tests' results

Table A.4: Simple unbiased test results

Model estimated	Wald test's p-value (without seasonal dummies)	Wald test's p-value (with seasonal dummies)
Bridge with IMAE, 0-known months	0.6684	0.145
Bridge with IMAE, 1-known month	0.1663	0.0116
Bridge with IMAE, 2-known months	0.0017	0.0003
Bridge with IMAE, 3-known months	0.1793	0.0209
ARIMA of GDP quarterly growth	0.1333	0.1531
Factor Bridge with one factor zero lags	0.9527	0
Factor Bridge with one factor one lag	0.3786	0
Factor Bridge with one factor two lags	0.0852	0
Factor Bridge with one factor three lags	0.0721	0
Factor Bridge with two factors zero lags	0.0405	0
Factor Bridge with two factors one lag	0.199	0
Factor Bridge with two factors two lags	0.0347	0
Factor Bridge with two factors three lags	0.0152	0
Factor MIDAS with one factor zero lags, Almon polynomial with 12 lags	0.1773	0
Factor MIDAS with one factor zero lags, Almon polynomial with 6 lags	0.0213	0
Factor MIDAS with one factor zero lags, Almon polynomial with 9 lags	0.1284	0

Source: own elaboration. Null hypothesis: the nowcast is unbiased, i.e constant equals zero, and $\beta = 1$.

Table A.4: Simple unbiased test results (continuation)

Model estimated	Wald test's p-value (without seasonal dummies)	Wald test's p-value (with seasonal dummies)
Factor MIDAS with one factor zero lags, step function polynomial with 12 lags	0.9421	0
Factor MIDAS with one factor zero lags, step function polynomial with 6 lags	0.0007	0
Factor MIDAS with one factor zero lags, step function polynomial with 9 lags	0.2489	0
Factor MIDAS with one factor zero lags, unrestricted polynomial with 12 lags	0	0
Factor MIDAS with one factor zero lags, unrestricted polynomial with 6 lags	0	0
Factor MIDAS with one factor zero lags, unrestricted polynomial with 9 lags	0	0
Factor MIDAS with one factor one lag, Almon polynomial with 12 lags	0	0
Factor MIDAS with one factor one lag, Almon polynomial with 6 lags	0.7189	0
Factor MIDAS with one factor one lag, Almon polynomial with 9 lags	0.7754	0
Factor MIDAS with one factor one lag, step function polynomial with 12 lags	0.0032	0
Factor MIDAS with one factor one lag, step function polynomial with 6 lags	0	0

Source: own elaboration. Null hypothesis: the nowcast is unbiased, i.e constant equals zero, and $\beta = 1$.

Table A.4: Simple unbiased test results (continuation)

Model estimated	Wald test's p-value (without seasonal dummies)	Wald test's p-value (with seasonal dummies)
Factor MIDAS with one factor one lag, step function polynomial with 9 lags	0.0099	0
Factor MIDAS with one factor one lag, unrestricted polynomial with 12 lags	0	0
Factor MIDAS with one factor one lag, unrestricted polynomial with 6 lags	0	0
Factor MIDAS with one factor one lag, unrestricted polynomial with 9 lags	0	0
Factor MIDAS with one factor two lags, Almon polynomial with 12 lags	0.2347	0
Factor MIDAS with one factor two lags, Almon polynomial with 6 lags	0.0235	0
Factor MIDAS with one factor two lags, Almon polynomial with 9 lags	0.1164	0
Factor MIDAS with one factor two lags, step function polynomial with 12 lags	0.5093	0
Factor MIDAS with one factor two lags, step function polynomial with 6 lags	0.1701	0
Factor MIDAS with one factor two lags, step function polynomial with 9 lags	0.6522	0
Factor MIDAS with one factor two lags, unrestricted polynomial with 12 lags	0	0

Source: own elaboration. Null hypothesis: the nowcast is unbiased, i.e constant equals zero, and $\beta = 1$.

Table A.4: Simple unbiased test results (continuation)

Model estimated	Wald test's p-value (without seasonal dummies)	Wald test's p-value (with seasonal dummies)
Factor MIDAS with one factor two lags, unrestricted polynomial with 6 lags	0.0001	0
Factor MIDAS with one factor two lags, unrestricted polynomial with 9 lags	0	0
Factor MIDAS with one factor three lags, Almon polynomial with 12 lags	0.7912	0
Factor MIDAS with one factor three lags, Almon polynomial with 6 lags	0.2684	0
Factor MIDAS with one factor three lags, Almon polynomial with 9 lags	0.0055	0
Factor MIDAS with one factor three lags, step function polynomial with 12 lags	0.9271	0
Factor MIDAS with one factor three lags, step function polynomial with 6 lags	0.7278	0
Factor MIDAS with one factor three lags, step function polynomial with 9 lags	0.0044	0
Factor MIDAS with one factor three lags, unrestricted polynomial with 12 lags	0.0005	0
Factor MIDAS with one factor three lags, unrestricted polynomial with 6 lags	0.153	0
Factor MIDAS with one factor three lags, unrestricted polynomial with 9 lags	0	0

Source: own elaboration. Null hypothesis: the nowcast is unbiased, i.e constant equals zero, and $\beta = 1$.

Table A.4: Simple unbiased test results (continuation)

Model estimated	Wald test's p-value (without seasonal dummies)	Wald test's p-value (with seasonal dummies)
Factor MIDAS with two factors zero lags, Almon polynomial with 12 lags	0.5225	0
Factor MIDAS with two factors zero lags, Almon polynomial with 6 lags	0.0863	0
Factor MIDAS with two factors zero lags, Almon polynomial with 9 lags	0.062	0
Factor MIDAS with two factors zero lags, step function polynomial with 12 lags	0.4526	0
Factor MIDAS with two factors zero lags, step function polynomial with 6 lags	0.1365	0
Factor MIDAS with two factors zero lags, step function polynomial with 9 lags	0.0684	0
Factor MIDAS with two factors zero lags, unrestricted polynomial with 12 lags	0.0493	0
Factor MIDAS with two factors zero lags, unrestricted polynomial with 6 lags	0.011	0
Factor MIDAS with two factors zero lags, unrestricted polynomial with 9 lags	0.0038	0
Factor MIDAS with two factors one lag, Almon polynomial with 12 lags	0.8318	0
Factor MIDAS with two factors one lag, Almon polynomial with 6 lags	0.048	0

Source: own elaboration. Null hypothesis: the nowcast is unbiased, i.e constant equals zero, and $\beta = 1$.

Table A.4: Simple unbiased test results (continuation)

Model estimated	Wald test's p-value (without seasonal dummies)	Wald test's p-value (with seasonal dummies)
Factor MIDAS with two factors one lag, Almon polynomial with 9 lags	0.1617	0
Factor MIDAS with two factors one lag, step function polynomial with 12 lags	0.8257	0
Factor MIDAS with two factors one lag, step function polynomial with 6 lags	0.0463	0
Factor MIDAS with two factors one lag, step function polynomial with 9 lags	0.1412	0
Factor MIDAS with two factors one lag, unrestricted polynomial with 12 lags	0.0629	0
Factor MIDAS with two factors one lag, unrestricted polynomial with 6 lags	0.0044	0
Factor MIDAS with two factors one lag, unrestricted polynomial with 9 lags	0.0237	0
Factor MIDAS with two factors two lags, Almon polynomial with 12 lags	0.9769	0
Factor MIDAS with two factors two lags, Almon polynomial with 6 lags	0.0687	0
Factor MIDAS with two factors two lags, Almon polynomial with 9 lags	0.4191	0
Factor MIDAS with two factors two lags, step function polynomial with 12 lags	0.7964	0

Source: own elaboration. Null hypothesis: the nowcast is unbiased, i.e constant equals zero, and $\beta = 1$.

Table A.4: Simple unbiased test results (continuation)

Model estimated	Wald test's p-value (without seasonal dummies)	Wald test's p-value (with seasonal dummies)
Factor MIDAS with two factors two lags, step function polynomial with 6 lags	0.1059	0
Factor MIDAS with two factors two lags, step function polynomial with 9 lags	0.2166	0
Factor MIDAS with two factors two lags, unrestricted polynomial with 12 lags	0.0974	0
Factor MIDAS with two factors two lags, unrestricted polynomial with 6 lags	0.0021	0
Factor MIDAS with two factors two lags, unrestricted polynomial with 9 lags	0.0352	0
Factor MIDAS with two factors three lags, Almon polynomial with 12 lags	0.299	0
Factor MIDAS with two factors three lags, Almon polynomial with 6 lags	0.113	0
Factor MIDAS with two factors three lags, Almon polynomial with 9 lags	0.5608	0
Factor MIDAS with two factors three lags, step function polynomial with 12 lags	0.2903	0
Factor MIDAS with two factors three lags, step function polynomial with 6 lags	0.0319	0
Factor MIDAS with two factors three lags, step function polynomial with 9 lags	0.323	0

Source: own elaboration. Null hypothesis: the nowcast is unbiased, i.e constant equals zero, and $\beta = 1$.

Table A.4: Simple unbiased test results (continuation)

Model estimated	Wald test's p-value (without seasonal dummies)	Wald test's p-value (with seasonal dummies)
Factor MIDAS with two factors three lags, unrestricted polynomial with 12 lags	0.8855	0
Factor MIDAS with two factors three lags, unrestricted polynomial with 6 lags	0.0005	0
Factor MIDAS with two factors three lags, unrestricted polynomial with 9 lags	0.9711	0
Factor VAR with one factor zero lags	0.977	0.0024
Factor VAR with one factor one lag	0.7512	0.0029
Factor VAR with one factor two lags	0.3241	0.0007
Factor VAR with two factors zero lags	0.5928	0.0024
Factor VAR with two factors one lag	0.3947	0.0039
Factor VAR with two factors two lags	0.2843	0.0013
MIDAS with IMAE zero known months, Almon polynomial with 12 lags	0.1539	0
MIDAS with IMAE zero known months, Almon polynomial with 6 lags	0.5051	0.0427
MIDAS with IMAE zero known months, Almon polynomial with 9 lags	0.4345	0.007
MIDAS with IMAE zero known months, step function polynomial with 12 lags	0.7586	0.0108
MIDAS with IMAE zero known months, step function polynomial with 6 lags	0.4954	0.0109

Source: own elaboration. Null hypothesis: the nowcast is unbiased, i.e constant equals zero, and $\beta = 1$.

Table A.4: Simple unbiased test results (continuation)

Model estimated	Wald test's p-value (without seasonal dummies)	Wald test's p-value (with seasonal dummies)
MIDAS with IMAE zero known months, step function polynomial with 9 lags	0.6273	0.0125
MIDAS with IMAE zero known months, unrestricted polynomial with 12 lags	0.2942	0.034
MIDAS with IMAE zero known months, unrestricted polynomial with 6 lags	0.5514	0.029
MIDAS with IMAE zero known months, unrestricted polynomial with 9 lags	0.3637	0.0161
MIDAS with IMAE one known month, Almon polynomial with 12 lags	0.1054	0
MIDAS with IMAE one known month, Almon polynomial with 6 lags	0	0.0007
MIDAS with IMAE one known month, Almon polynomial with 9 lags	0.1468	0.0005
MIDAS with IMAE one known month, step function polynomial with 12 lags	0.5861	0.0002
MIDAS with IMAE one known month, step function polynomial with 6 lags	0.4676	0.0009
MIDAS with IMAE one known month, step function polynomial with 9 lags	0.463	0.0022
MIDAS with IMAE one known month, unrestricted polynomial with 12 lags	0.0518	0

Source: own elaboration. Null hypothesis: the nowcast is unbiased, i.e constant equals zero, and $\beta = 1$.

Table A.4: Simple unbiased test results (continuation)

Model estimated	Wald test's p-value (without seasonal dummies)	Wald test's p-value (with seasonal dummies)
MIDAS with IMAE one known month, unrestricted polynomial with 6 lags	0.2109	0
MIDAS with IMAE one known month, unrestricted polynomial with 9 lags	0.4269	0
MIDAS with IMAE two known months, Almon polynomial with 12 lags	0.055	0
MIDAS with IMAE two known months, Almon polynomial with 6 lags	0.0004	0
MIDAS with IMAE two known months, Almon polynomial with 9 lags	0.0237	0
MIDAS with IMAE two known months, step function polynomial with 12 lags	0.2141	0
MIDAS with IMAE two known months, step function polynomial with 6 lags	0.2714	0.0002
MIDAS with IMAE two known months, step function polynomial with 9 lags	0.1722	0.0004
MIDAS with IMAE two known months, unrestricted polynomial with 12 lags	0.0036	0
MIDAS with IMAE two known months, unrestricted polynomial with 6 lags	0.3617	0
MIDAS with IMAE two known months, unrestricted polynomial with 9 lags	0.104	0

Source: own elaboration. Null hypothesis: the nowcast is unbiased, i.e constant equals zero, and $\beta = 1$.

Table A.4: Simple unbiased test results (continuation)

Model estimated	Wald test's p-value (without seasonal dummies)	Wald test's p-value (with seasonal dummies)
MIDAS with IMAE three known months, Almon polynomial with 12 lags	0.3605	0
MIDAS with IMAE three known months, Almon polynomial with 6 lags	0	0.0001
MIDAS with IMAE three known months, Almon polynomial with 9 lags	0.0062	0.0002
MIDAS with IMAE three known months, step function polynomial with 12 lags	0.6676	0.0002
MIDAS with IMAE three known months, step function polynomial with 6 lags	0.6158	0.0011
MIDAS with IMAE three known months, step function polynomial with 9 lags	0.5063	0.003
MIDAS with IMAE three known months, unrestricted polynomial with 12 lags	0.017	0
MIDAS with IMAE three known months, unrestricted polynomial with 6 lags	0.2157	0
MIDAS with IMAE three known months, unrestricted polynomial with 9 lags	0.3742	0
Blocking mixed frequency VAR with IMAE zero-known months	0.2676	0.3118
Blocking mixed frequency VAR with IMAE one-known month	0.2676	0.3118

Source: own elaboration. Null hypothesis: the nowcast is unbiased, i.e constant equals zero, and $\beta = 1$.

Table A.4: Simple unbiased test results (continuation)

Model estimated	Wald test's p-value (without seasonal dummies)	Wald test's p-value (with seasonal dummies)
Blocking mixed frequency VAR with IMAE two-known months	0.2676	0.3118
Blocking mixed frequency VAR with IMAE three-known months	0.2676	0.3118
Bayesian VAR with sample one from 1991	0.004	0
Bayesian VAR with sample two from 1991	0.0202	0
Bayesian VAR with sample three from 1991	0.0019	0.0001
Bayesian VAR with sample four from 1991	0.1322	0.0052
Bayesian VAR with sample five from 1991	0.1407	0
Bayesian VAR with sample one from 1992	0.004	0
Bayesian VAR with sample two from 1992	0.0202	0
Bayesian VAR with sample three from 1992	0.0019	0.0001
Bayesian VAR with sample four from 1992	0.1322	0.0052
Bayesian VAR with sample five from 1992	0.0816	0
Bayesian VAR with sample one from 1995	0.004	0
Bayesian VAR with sample two from 1995	0.1731	0
Bayesian VAR with sample three from 1995	0.0071	0.0001
Bayesian VAR with sample four from 1995	0.0454	0.008
Bayesian VAR with sample five from 1995	0.0873	0.0071
Bayesian VAR with sample one from 1998	0.004	0
Bayesian VAR with sample two from 1998	0.1731	0
Bayesian VAR with sample three from 1998	0.0019	0.0001

Source: own elaboration. Null hypothesis: the nowcast is unbiased, i.e constant equals zero, and $\beta = 1$.

Table A.4: Simple unbiased test results (continuation)

Model estimated	Wald test's p-value (without seasonal dummies)	Wald test's p-value (with seasonal dummies)
Bayesian VAR with sample four from 1998	0.1322	0.0054
Bayesian VAR with sample five from 1998	0.239	0.0012
Bayesian VAR with sample six from 1998	0.0091	0.0021
Bayesian VAR with sample seven from 1998	0.0197	0.0008
Bayesian VAR with sample one from 2000	0.004	0
Bayesian VAR with sample two from 2000	0.1731	0
Bayesian VAR with sample three from 2000	0.0007	0.0002
Bayesian VAR with sample four from 2000	0.1355	0.0055
Bayesian VAR with sample five from 2000	0.239	0.0012
Bayesian VAR with sample six from 2000	0.0091	0.0021
Bayesian VAR with sample seven from 2000	0.0197	0.0008
Bayesian VAR with sample one from 2005	0.004	0
Bayesian VAR with sample two from 2005	0.1731	0
Bayesian VAR with sample three from 2005	0.0019	0.0001
Bayesian VAR with sample four from 2005	0.1322	0.0054
Bayesian VAR with sample five from 2005	0.0003	0.2567
Bayesian VAR with sample six from 2005	0.0501	0.0039
Bayesian VAR with sample seven from 2005	0.0252	0.0004
Bayesian VAR with sample eight from 2005	0	0.2998
Bayesian VAR with sample one from 2009	0.004	0
Bayesian VAR with sample two from 2009	0.1731	0
Bayesian VAR with sample three from 2009	0.0019	0.0001

Source: own elaboration. Null hypothesis: the nowcast is unbiased, i.e constant equals zero, and $\beta = 1$.

Table A.4: Simple unbiased test results (continuation)

Model estimated	Wald test's p-value (without seasonal dummies)	Wald test's p-value (with seasonal dummies)
Bayesian VAR with sample four from 2009	0.1322	0.0013
Bayesian VAR with sample five from 2009	0.0003	0.2954
Bayesian VAR with sample six from 2009	0.0151	0.0035
Bayesian VAR with sample seven from 2009	0.0397	0.001
Bayesian VAR with sample eight from 2009	0	0.0028
Bridge with Financial Conditions Index	0.6476	0.0176
VAR with Perception Business Index	0.1353	0.0026
VAR with Consumer Confidence Index	0.8103	0.2124
VAR with Economic Agent Confidence Index	0.4431	0.1310

Source: own elaboration. Null hypothesis: the nowcast is unbiased, i.e constant equals zero, and $\beta = 1$.

Table A.5: Models' precision in nowcasting sign change

Model	Percentage
Bridge with IMAE, 0-known months	93.75%
Bridge with IMAE, 1-known month	100.00%
Bridge with IMAE, 2-known months	93.75%
Bridge with IMAE, 3-known months	93.75%
ARIMA of GDP quarterly growth	93.75%
Factor Bridge with one factor zero lags	93.75%
Factor Bridge with one factor one lag	93.75%
Factor Bridge with one factor two lags	93.75%
Factor Bridge with one factor three lags	93.75%
Factor Bridge with two factors zero lags	93.75%
Factor Bridge with two factors one lag	93.75%
Factor Bridge with two factors two lags	93.75%
Factor Bridge with two factors three lags	100.00%
Factor MIDAS with one factor zero lags, Almon polynomial with 12 lags	93.75%
Factor MIDAS with one factor zero lags, Almon polynomial with 6 lags	75.00%
Factor MIDAS with one factor zero lags, Almon polynomial with 9 lags	93.75%
Factor MIDAS with one factor zero lags, step function polynomial with 12 lags	93.75%
Factor MIDAS with one factor zero lags, step function polynomial with 6 lags	87.50%

Source: own elaboration.

Table A.5: Models' precision in nowcasting sign change (continuation)

Model	Percentage
Factor MIDAS with one factor zero lags, step function polynomial with 9 lags	87.50%
Factor MIDAS with one factor zero lags, unrestricted polynomial with 12 lags	93.75%
Factor MIDAS with one factor zero lags, unrestricted polynomial with 6 lags	68.75%
Factor MIDAS with one factor zero lags, unrestricted polynomial with 9 lags	87.50%
Factor MIDAS with one factor one lag, Almon polynomial with 12 lags	100.00%
Factor MIDAS with one factor one lag, Almon polynomial with 6 lags	68.75%
Factor MIDAS with one factor one lag, Almon polynomial with 9 lags	93.75%
Factor MIDAS with one factor one lag, step function polynomial with 12 lags	93.75%
Factor MIDAS with one factor one lag, step function polynomial with 6 lags	87.50%
Factor MIDAS with one factor one lag, step function polynomial with 9 lags	93.75%
Factor MIDAS with one factor one lag, unrestricted polynomial with 12 lags	93.75%

Source: own elaboration.

Table A.5: Models' precision in nowcasting sign change (continuation)

Model	Percentage
Factor MIDAS with one factor one lag, unrestricted polynomial with 6 lags	68.75%
Factor MIDAS with one factor one lag, unrestricted polynomial with 9 lags	93.75%
Factor MIDAS with one factor two lags, Almon polynomial with 12 lags	75.00%
Factor MIDAS with one factor two lags, Almon polynomial with 6 lags	68.75%
Factor MIDAS with one factor two lags, Almon polynomial with 9 lags	93.75%
Factor MIDAS with one factor two lags, step function polynomial with 12 lags	62.50%
Factor MIDAS with one factor two lags, step function polynomial with 6 lags	68.75%
Factor MIDAS with one factor two lags, step function polynomial with 9 lags	75.00%
Factor MIDAS with one factor two lags, unrestricted polynomial with 12 lags	93.75%
Factor MIDAS with one factor two lags, unrestricted polynomial with 6 lags	81.25%
Factor MIDAS with one factor two lags, unrestricted polynomial with 9 lags	93.75%

Source: own elaboration.

Table A.5: Models' precision in nowcasting sign change (continuation)

Model	Percentage
Factor MIDAS with one factor three lags, Almon polynomial with 12 lags	75.00%
Factor MIDAS with one factor three lags, Almon polynomial with 6 lags	75.00%
Factor MIDAS with one factor three lags, Almon polynomial with 9 lags	93.75%
Factor MIDAS with one factor three lags, step function polynomial with 12 lags	87.50%
Factor MIDAS with one factor three lags, step function polynomial with 6 lags	56.25%
Factor MIDAS with one factor three lags, step function polynomial with 9 lags	93.75%
Factor MIDAS with one factor three lags, unrestricted polynomial with 12 lags	93.75%
Factor MIDAS with one factor three lags, unrestricted polynomial with 6 lags	50.00%
Factor MIDAS with one factor three lags, unrestricted polynomial with 9 lags	68.75%
Factor MIDAS with two factors zero lags, Almon polynomial with 12 lags	68.75%
Factor MIDAS with two factors zero lags, Almon polynomial with 6 lags	68.75%

Source: own elaboration.

Table A.5: Models' precision in nowcasting sign change (continuation)

Model	Percentage
Factor MIDAS with two factors zero lags, Almon polynomial with 9 lags	68.75%
Factor MIDAS with two factors zero lags, step function polynomial with 12 lags	68.75%
Factor MIDAS with two factors zero lags, step function polynomial with 6 lags	56.25%
Factor MIDAS with two factors zero lags, step function polynomial with 9 lags	62.50%
Factor MIDAS with two factors zero lags, unrestricted polynomial with 12 lags	68.75%
Factor MIDAS with two factors zero lags, unrestricted polynomial with 6 lags	75.00%
Factor MIDAS with two factors zero lags, unrestricted polynomial with 9 lags	75.00%
Factor MIDAS with two factors one lag, Almon polynomial with 12 lags	75.00%
Factor MIDAS with two factors one lag, Almon polynomial with 6 lags	56.25%
Factor MIDAS with two factors one lag, Almon polynomial with 9 lags	62.50%
Factor MIDAS with two factors one lag, step function polynomial with 12 lags	75.00%

Source: own elaboration.

Table A.5: Models' precision in nowcasting sign change (continuation)

Model	Percentage
Factor MIDAS with two factors one lag, step function polynomial with 6 lags	75.00%
Factor MIDAS with two factors one lag, step function polynomial with 9 lags	62.50%
Factor MIDAS with two factors one lag, unrestricted polynomial with 12 lags	93.75%
Factor MIDAS with two factors one lag, unrestricted polynomial with 6 lags	81.25%
Factor MIDAS with two factors one lag, unrestricted polynomial with 9 lags	75.00%
Factor MIDAS with two factors two lags, Almon polynomial with 12 lags	62.50%
Factor MIDAS with two factors two lags, Almon polynomial with 6 lags	62.50%
Factor MIDAS with two factors two lags, Almon polynomial with 9 lags	62.50%
Factor MIDAS with two factors two lags, step function polynomial with 12 lags	62.50%
Factor MIDAS with two factors two lags, step function polynomial with 6 lags	68.75%
Factor MIDAS with two factors two lags, step function polynomial with 9 lags	68.75%

Source: own elaboration.

Table A.5: Models' precision in nowcasting sign change (continuation)

Model	Percentage
Factor MIDAS with two factors two lags, unrestricted polynomial with 12 lags	93.75%
Factor MIDAS with two factors two lags, unrestricted polynomial with 6 lags	75.00%
Factor MIDAS with two factors two lags, unrestricted polynomial with 9 lags	68.75%
Factor MIDAS with two factors three lags, Almon polynomial with 12 lags	68.75%
Factor MIDAS with two factors three lags, Almon polynomial with 6 lags	68.75%
Factor MIDAS with two factors three lags, Almon polynomial with 9 lags	62.50%
Factor MIDAS with two factors three lags, step function polynomial with 12 lags	68.75%
Factor MIDAS with two factors three lags, step function polynomial with 6 lags	68.75%
Factor MIDAS with two factors three lags, step function polynomial with 9 lags	62.50%
Factor MIDAS with two factors three lags, unrestricted polynomial with 12 lags	87.50%
Factor MIDAS with two factors three lags, unrestricted polynomial with 6 lags	75.00%

Source: own elaboration.

Table A.5: Models' precision in nowcasting sign change (continuation)

Model	Percentage
Factor MIDAS with two factors three lags, unrestricted polynomial with 9 lags	75.00%
Factor VAR with one factor zero lags	93.75%
Factor VAR with one factor one lag	93.75%
Factor VAR with one factor two lags	100.00%
Factor VAR with two factors zero lags	93.75%
Factor VAR with two factors one lag	100.00%
Factor VAR with two factors two lags	100.00%
MIDAS with IMAE zero known months, Almon polynomial with 12 lags	93.75%
MIDAS with IMAE zero known months, Almon polynomial with 6 lags	93.75%
MIDAS with IMAE zero known months, Almon polynomial with 9 lags	93.75%
MIDAS with IMAE zero known months, step function polynomial with 12 lags	87.50%
MIDAS with IMAE zero known months, step function polynomial with 6 lags	100.00%
MIDAS with IMAE zero known months, step function polynomial with 9 lags	87.50%
MIDAS with IMAE zero known months, unrestricted polynomial with 12 lags	93.75%

Source: own elaboration.

Table A.5: Models' precision in nowcasting sign change (continuation)

Model	Percentage
MIDAS with IMAE zero known months, unrestricted polynomial with 6 lags	93.75%
MIDAS with IMAE zero known months, unrestricted polynomial with 9 lags	93.75%
MIDAS with IMAE one known month, Almon polynomial with 12 lags	81.25%
MIDAS with IMAE one known month, Almon polynomial with 6 lags	93.75%
MIDAS with IMAE one known month, Almon polynomial with 9 lags	93.75%
MIDAS with IMAE one known month, step function polynomial with 12 lags	81.25%
MIDAS with IMAE one known month, step function polynomial with 6 lags	81.25%
MIDAS with IMAE one known month, step function polynomial with 9 lags	87.50%
MIDAS with IMAE one known month, unrestricted polynomial with 12 lags	100.00%
MIDAS with IMAE one known month, unrestricted polynomial with 6 lags	100.00%
MIDAS with IMAE one known month, unrestricted polynomial with 9 lags	100.00%

Source: own elaboration.

Table A.5: Models' precision in nowcasting sign change (continuation)

Model	Percentage
MIDAS with IMAE two known months, Almon polynomial with 12 lags	75.00%
MIDAS with IMAE two known months, Almon polynomial with 6 lags	81.25%
MIDAS with IMAE two known months, Almon polynomial with 9 lags	93.75%
MIDAS with IMAE two known months, step function polynomial with 12 lags	87.50%
MIDAS with IMAE two known months, step function polynomial with 6 lags	87.50%
MIDAS with IMAE two known months, step function polynomial with 9 lags	87.50%
MIDAS with IMAE two known months, unrestricted polynomial with 12 lags	87.50%
MIDAS with IMAE two known months, unrestricted polynomial with 6 lags	87.50%
MIDAS with IMAE two known months, unrestricted polynomial with 9 lags	100.00%
MIDAS with IMAE three known months, Almon polynomial with 12 lags	81.25%
MIDAS with IMAE three known months, Almon polynomial with 6 lags	93.75%

Source: own elaboration.

Table A.5: Models' precision in nowcasting sign change (continuation)

Model	Percentage
MIDAS with IMAE three known months, Almon polynomial with 9 lags	100.00%
MIDAS with IMAE three known months, step function polynomial with 12 lags	93.75%
MIDAS with IMAE three known months, step function polynomial with 6 lags	87.50%
MIDAS with IMAE three known months, step function polynomial with 9 lags	93.75%
MIDAS with IMAE three known months, unrestricted polynomial with 12 lags	87.50%
MIDAS with IMAE three known months, unrestricted polynomial with 6 lags	93.75%
MIDAS with IMAE three known months, unrestricted polynomial with 9 lags	100.00%
Blocking mixed frequency VAR with IMAE zero-known months	93.75%
Blocking mixed frequency VAR with IMAE one-known month	93.75%
Blocking mixed frequency VAR with IMAE two-known months	93.75%
Blocking mixed frequency VAR with IMAE-three known months	93.75%

Source: own elaboration.

Table A.5: Models' precision in nowcasting sign change (continuation)

Model	Percentage
Bayesian VAR with sample one from 1991	93.75%
Bayesian VAR with sample two from 1991	93.75%
Bayesian VAR with sample three from 1991	93.75%
Bayesian VAR with sample four from 1991	93.75%
Bayesian VAR with sample five from 1991	93.75%
Bayesian VAR with sample one from 1992	93.75%
Bayesian VAR with sample two from 1992	93.75%
Bayesian VAR with sample three from 1992	93.75%
Bayesian VAR with sample four from 1992	93.75%
Bayesian VAR with sample five from 1992	93.75%
Bayesian VAR with sample one from 1995	93.75%
Bayesian VAR with sample two from 1995	93.75%
Bayesian VAR with sample three from 1995	93.75%
Bayesian VAR with sample four from 1995	93.75%
Bayesian VAR with sample five from 1995	87.50%
Bayesian VAR with sample one from 1998	93.75%
Bayesian VAR with sample two from 1998	93.75%
Bayesian VAR with sample three from 1998	93.75%
Bayesian VAR with sample four from 1998	93.75%
Bayesian VAR with sample five from 1998	93.75%
Bayesian VAR with sample six from 1998	93.75%
Bayesian VAR with sample seven from 1998	93.75%

Source: own elaboration.

Table A.5: Models’ precision in nowcasting sign change (continuation)

Model	Percentage
Bayesian VAR with sample one from 2000	93.75%
Bayesian VAR with sample two from 2000	93.75%
Bayesian VAR with sample three from 2000	93.75%
Bayesian VAR with sample four from 2000	93.75%
Bayesian VAR with sample five from 2000	93.75%
Bayesian VAR with sample six from 2000	93.75%
Bayesian VAR with sample seven from 2000	93.75%
Bayesian VAR with sample one from 2005	93.75%
Bayesian VAR with sample two from 2005	93.75%
Bayesian VAR with sample three from 2005	93.75%
Bayesian VAR with sample four from 2005	93.75%
Bayesian VAR with sample five from 2005	93.75%
Bayesian VAR with sample six from 2005	93.75%
Bayesian VAR with sample seven from 2005	93.75%
Bayesian VAR with sample eight from 2005	93.75%
Bayesian VAR with sample one from 2009	93.75%
Bayesian VAR with sample two from 2009	93.75%
Bayesian VAR with sample three from 2009	93.75%
Bayesian VAR with sample four from 2009	93.75%
Bayesian VAR with sample five from 2009	93.75%
Bayesian VAR with sample six from 2009	93.75%
Bayesian VAR with sample seven from 2009	93.75%
Bayesian VAR with sample eight from 2009	93.75%

Source: own elaboration.

Table A.5: Models' precision in nowcasting sign change (continuation)

Model	Percentage
Bridge with Financial Conditions Index	100.00%
VAR with Perceptions Business Index	93.75%
VAR with Consumer Confidence Index	93.75%
VAR with Economic Agent Confidence Index	93.75%

Source: own elaboration.

Table A.6: Models' nowcasting error measures

Model	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
Bridge with IMAE, 0-known months	0.986	0.809	94.053	72.535	0.222	0.160
Bridge with IMAE, 1-known month	0.574	0.504	51.113	47.512	0.126	0.158
Bridge with IMAE, 2-known months	0.537	0.436	41.710	40.283	0.115	0.104
Bridge with IMAE, 3-known months	0.593	0.486	85.431	52.460	0.132	0.129
ARIMA of GDP quarterly growth	0.882	0.700	73.619	68.416	0.182	0.136
Factor Bridge with one factor zero lags	0.928	0.776	93.266	71.498	0.212	0.330
Factor Bridge with one factor one lag	0.883	0.731	91.450	64.167	0.194	0.295
Factor Bridge with one factor two lags	0.900	0.757	95.088	77.483	0.193	0.263
Factor Bridge with one factor three lags	0.910	0.774	97.039	81.772	0.194	0.219
Factor Bridge with two factors zero lags	1.007	0.851	131.628	74.907	0.219	0.193
Factor Bridge with two factors one lag	0.915	0.758	116.847	65.646	0.191	0.184
Factor Bridge with two factors two lags	1.021	0.812	102.536	77.887	0.211	0.195
Factor Bridge with two factors three lags	1.122	0.806	84.887	64.678	0.233	0.273
Factor MIDAS with one factor zero lags, Almon polynomial with 12 lags	1.142	0.912	116.701	88.978	0.295	0.427
Factor MIDAS with one factor zero lags, Almon polynomial with 6 lags	1.442	1.284	125.118	130.952	0.405	0.540
Factor MIDAS with one factor zero lags, Almon polynomial with 9 lags	1.361	1.166	129.527	113.652	0.376	0.533
Factor MIDAS with one factor zero lags, step function polynomial with 12 lags	1.137	0.904	130.920	79.203	0.272	0.402
Factor MIDAS with one factor zero lags, step function polynomial with 6 lags	1.571	1.278	113.773	124.121	0.483	0.652
Factor MIDAS with one factor zero lags, step function polynomial with 9 lags	1.453	1.241	137.196	126.798	0.405	0.578

Source: own elaboration.

Table A.6: Models' nowcasting error measures (continuation)

Model	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
Factor MIDAS with one factor zero lags, unrestricted polynomial with 12 lags	2.672	2.002	220.879	86.150	0.393	0.458
Factor MIDAS with one factor zero lags, unrestricted polynomial with 6 lags	1.939	1.447	205.335	98.078	0.372	0.339
Factor MIDAS with one factor zero lags, unrestricted polynomial with 9 lags	1.945	1.494	189.745	91.272	0.370	0.396
Factor MIDAS with one factor one lag, Almon polynomial with 12 lags	1.508	1.272	134.430	119.276	0.416	0.536
Factor MIDAS with one factor one lag, Almon polynomial with 6 lags	1.607	1.379	161.072	125.653	0.409	0.513
Factor MIDAS with one factor one lag, Almon polynomial with 9 lags	1.287	0.945	136.587	73.003	0.321	0.479
Factor MIDAS with one factor one lag, step function polynomial with 12 lags	1.590	1.281	139.689	115.622	0.453	0.595
Factor MIDAS with one factor one lag, step function polynomial with 6 lags	1.951	1.597	121.665	145.029	0.689	0.770
Factor MIDAS with one factor one lag, step function polynomial with 9 lags	1.703	1.391	142.082	120.978	0.505	0.653
Factor MIDAS with one factor one lag, unrestricted polynomial with 12 lags	2.719	1.791	213.684	70.168	0.412	0.487
Factor MIDAS with one factor one lag, unrestricted polynomial with 6 lags	2.042	1.549	221.230	98.874	0.385	0.328
Factor MIDAS with one factor one lag, unrestricted polynomial with 9 lags	2.415	1.868	262.110	87.747	0.381	0.426

Source: own elaboration.

Table A.6: Models' nowcasting error measures (continuation)

Model	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
Factor MIDAS with one factor two lags, Almon polynomial with 12 lags	2.074	1.747	173.337	127.942	0.606	0.747
Factor MIDAS with one factor two lags, Almon polynomial with 6 lags	1.794	1.530	141.359	137.077	0.562	0.715
Factor MIDAS with one factor two lags, Almon polynomial with 9 lags	1.641	1.340	173.519	106.972	0.441	0.597
Factor MIDAS with one factor two lags, step function polynomial with 12 lags	2.042	1.526	220.867	85.534	0.514	0.775
Factor MIDAS with one factor two lags, step function polynomial with 6 lags	2.106	1.748	142.149	138.018	0.700	0.804
Factor MIDAS with one factor two lags, step function polynomial with 9 lags	1.753	1.399	187.134	92.297	0.458	0.623
Factor MIDAS with one factor two lags, unrestricted polynomial with 12 lags	2.558	2.024	248.472	91.501	0.397	0.457
Factor MIDAS with one factor two lags, unrestricted polynomial with 6 lags	2.250	1.735	139.502	89.657	0.493	0.898
Factor MIDAS with one factor two lags, unrestricted polynomial with 9 lags	2.666	2.382	393.755	109.922	0.419	0.461
Factor MIDAS with one factor three lags, Almon polynomial with 12 lags	1.979	1.669	165.939	141.365	0.574	0.770
Factor MIDAS with one factor three lags, Almon polynomial with 6 lags	1.993	1.613	153.413	128.953	0.611	0.739
Factor MIDAS with one factor three lags, Almon polynomial with 9 lags	1.862	1.565	177.866	122.270	0.512	0.646

Source: own elaboration.

Table A.6: Models' nowcasting error measures (continuation)

Model	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
Factor MIDAS with one factor three lags, step function polynomial with 12 lags	1.712	1.343	170.353	109.470	0.463	0.704
Factor MIDAS with one factor three lags, step function polynomial with 6 lags	2.110	1.803	170.093	135.816	0.636	0.779
Factor MIDAS with one factor three lags, step function polynomial with 9 lags	1.794	1.521	185.585	122.401	0.480	0.614
Factor MIDAS with one factor three lags, unrestricted polynomial with 12 lags	1.980	1.620	277.289	92.685	0.360	0.390
Factor MIDAS with one factor three lags, unrestricted polynomial with 6 lags	2.308	1.903	191.112	122.193	0.587	0.902
Factor MIDAS with one factor three lags, unrestricted polynomial with 9 lags	2.448	2.078	389.295	98.997	0.424	0.382
Factor MIDAS with two factors zero lags, Almon polynomial with 12 lags	2.148	1.815	210.220	135.308	0.559	0.623
Factor MIDAS with two factors zero lags, Almon polynomial with 6 lags	2.344	2.037	268.322	130.632	0.548	0.552
Factor MIDAS with two factors zero lags, Almon polynomial with 9 lags	2.294	2.007	268.879	127.223	0.544	0.543
Factor MIDAS with two factors zero lags, step function polynomial with 12 lags	2.170	1.822	219.056	133.420	0.554	0.622
Factor MIDAS with two factors zero lags, step function polynomial with 6 lags	2.311	1.999	256.499	128.988	0.558	0.575
Factor MIDAS with two factors zero lags, step function polynomial with 9 lags	2.338	2.035	273.718	128.397	0.546	0.539

Source: own elaboration.

Table A.6: Models' nowcasting error measures (continuation)

Model	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
Factor MIDAS with two factors zero lags, unrestricted polynomial with 12 lags	2.200	1.819	275.186	136.221	0.459	0.605
Factor MIDAS with two factors zero lags, unrestricted polynomial with 6 lags	2.447	1.939	295.115	117.292	0.504	0.527
Factor MIDAS with two factors zero lags, unrestricted polynomial with 9 lags	2.400	1.968	299.658	119.103	0.480	0.480
Factor MIDAS with two factors one lag, Almon polynomial with 12 lags	1.948	1.528	163.412	125.461	0.512	0.615
Factor MIDAS with two factors one lag, Almon polynomial with 6 lags	2.353	2.043	279.739	128.034	0.541	0.529
Factor MIDAS with two factors one lag, Almon polynomial with 9 lags	2.285	1.978	257.885	134.963	0.548	0.565
Factor MIDAS with two factors one lag, step function polynomial with 12 lags	1.954	1.571	169.515	129.782	0.523	0.638
Factor MIDAS with two factors one lag, step function polynomial with 6 lags	2.348	2.050	280.694	128.424	0.541	0.526
Factor MIDAS with two factors one lag, step function polynomial with 9 lags	2.301	2.019	258.757	136.157	0.551	0.554
Factor MIDAS with two factors one lag, unrestricted polynomial with 12 lags	1.905	1.531	205.243	112.063	0.390	0.559
Factor MIDAS with two factors one lag, unrestricted polynomial with 6 lags	2.492	1.949	309.017	111.307	0.497	0.485
Factor MIDAS with two factors one lag, unrestricted polynomial with 9 lags	2.245	1.809	272.801	121.804	0.453	0.574

Source: own elaboration.

Table A.6: Models' nowcasting error measures (continuation)

Model	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
Factor MIDAS with two factors two lags, Almon polynomial with 12 lags	1.802	1.380	126.368	116.472	0.499	0.654
Factor MIDAS with two factors two lags, Almon polynomial with 6 lags	2.388	2.079	277.481	134.737	0.548	0.527
Factor MIDAS with two factors two lags, Almon polynomial with 9 lags	2.114	1.814	219.525	128.704	0.547	0.628
Factor MIDAS with two factors two lags, step function polynomial with 12 lags	1.762	1.371	114.232	116.158	0.505	0.670
Factor MIDAS with two factors two lags, step function polynomial with 6 lags	2.165	1.896	232.137	128.355	0.558	0.613
Factor MIDAS with two factors two lags, step function polynomial with 9 lags	2.117	1.844	216.038	130.254	0.565	0.639
Factor MIDAS with two factors two lags, unrestricted polynomial with 12 lags	1.761	1.405	174.474	109.449	0.364	0.529
Factor MIDAS with two factors two lags, unrestricted polynomial with 6 lags	2.642	2.149	344.410	122.366	0.527	0.517
Factor MIDAS with two factors two lags, unrestricted polynomial with 9 lags	2.258	1.767	276.499	138.493	0.467	0.598
Factor MIDAS with two factors three lags, Almon polynomial with 12 lags	1.871	1.473	105.643	136.268	0.603	0.828
Factor MIDAS with two factors three lags, Almon polynomial with 6 lags	2.113	1.819	203.067	128.578	0.581	0.667
Factor MIDAS with two factors three lags, Almon polynomial with 9 lags	1.969	1.567	140.196	123.275	0.602	0.751

Source: own elaboration.

Table A.6: Models' nowcasting error measures (continuation)

Model	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
Factor MIDAS with two factors three lags, step function polynomial with 12 lags	1.795	1.385	100.410	123.050	0.559	0.798
Factor MIDAS with two factors three lags, step function polynomial with 6 lags	2.094	1.796	198.277	127.467	0.581	0.675
Factor MIDAS with two factors three lags, step function polynomial with 9 lags	1.990	1.606	146.140	125.347	0.615	0.763
Factor MIDAS with two factors three lags, unrestricted polynomial with 12 lags	1.184	0.969	93.326	98.433	0.270	0.427
Factor MIDAS with two factors three lags, unrestricted polynomial with 6 lags	2.202	1.851	248.016	119.315	0.497	0.462
Factor MIDAS with two factors three lags, unrestricted polynomial with 9 lags	1.412	1.219	109.844	140.681	0.351	0.557
Factor VAR with one factor zero lags	0.939	0.811	104.288	73.416	0.215	0.357
Factor VAR with one factor one lag	0.905	0.843	111.438	73.605	0.201	0.308
Factor VAR with one factor two lags	1.032	0.913	148.674	68.908	0.220	0.366
Factor VAR with two factors zero lags	0.864	0.731	131.123	61.347	0.191	0.243
Factor VAR with two factors one lag	0.730	0.664	112.097	67.729	0.155	0.167
Factor VAR with two factors two lags	0.722	0.612	116.583	55.274	0.152	0.185
MIDAS with IMAE zero known months, Almon polynomial with 12 lags	1.279	1.041	106.425	94.112	0.308	0.266
MIDAS with IMAE zero known months, Almon polynomial with 6 lags	1.376	1.050	97.726	92.105	0.343	0.219
MIDAS with IMAE zero known months, Almon polynomial with 9 lags	1.453	1.062	109.119	80.745	0.321	0.252

Source: own elaboration.

Table A.6: Models' nowcasting error measures (continuation)

Model	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
MIDAS with IMAE zero known months, step function polynomial with 12 lags	1.201	0.927	88.408	64.105	0.283	0.163
MIDAS with IMAE zero known months, step function polynomial with 6 lags	1.194	0.916	80.705	65.723	0.292	0.186
MIDAS with IMAE zero known months, step function polynomial with 9 lags	1.212	0.959	96.269	72.616	0.285	0.177
MIDAS with IMAE zero known months, unrestricted polynomial with 12 lags	1.210	0.973	81.438	91.896	0.258	0.200
MIDAS with IMAE zero known months, unrestricted polynomial with 6 lags	1.207	0.968	82.694	92.509	0.273	0.162
MIDAS with IMAE zero known months, unrestricted polynomial with 9 lags	1.277	1.042	103.380	95.997	0.275	0.209
MIDAS with IMAE one known month, Almon polynomial with 12 lags	1.055	0.831	109.649	78.244	0.240	0.354
MIDAS with IMAE one known month, Almon polynomial with 6 lags	0.845	0.722	62.360	66.896	0.208	0.252
MIDAS with IMAE one known month, Almon polynomial with 9 lags	0.868	0.551	53.383	49.487	0.193	0.213
MIDAS with IMAE one known month, step function polynomial with 12 lags	0.921	0.722	83.821	54.476	0.208	0.187
MIDAS with IMAE one known month, step function polynomial with 6 lags	0.960	0.796	88.076	69.914	0.224	0.244
MIDAS with IMAE one known month, step function polynomial with 9 lags	0.969	0.748	82.354	54.908	0.219	0.208

Source: own elaboration.

Table A.6: Models' nowcasting error measures (continuation)

Model	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
MIDAS with IMAE one known month, unrestricted polynomial with 12 lags	0.567	0.447	51.501	47.611	0.118	0.061
MIDAS with IMAE one known month, unrestricted polynomial with 6 lags	0.488	0.396	42.609	40.423	0.108	0.108
MIDAS with IMAE one known month, unrestricted polynomial with 9 lags	0.537	0.396	36.629	37.602	0.114	0.081
MIDAS with IMAE two known months, Almon polynomial with 12 lags	1.186	0.809	109.442	73.538	0.255	0.257
MIDAS with IMAE two known months, Almon polynomial with 6 lags	0.869	0.718	66.649	74.802	0.204	0.160
MIDAS with IMAE two known months, Almon polynomial with 9 lags	0.837	0.516	50.459	58.732	0.182	0.177
MIDAS with IMAE two known months, step function polynomial with 12 lags	0.910	0.674	72.235	54.077	0.198	0.115
MIDAS with IMAE two known months, step function polynomial with 6 lags	0.939	0.750	79.790	62.035	0.211	0.118
MIDAS with IMAE two known months, step function polynomial with 9 lags	0.930	0.680	71.729	54.404	0.204	0.098
MIDAS with IMAE two known months, unrestricted polynomial with 12 lags	0.653	0.578	67.685	62.469	0.132	0.183
MIDAS with IMAE two known months, unrestricted polynomial with 6 lags	0.461	0.400	50.484	52.651	0.100	0.095
MIDAS with IMAE two known months, unrestricted polynomial with 9 lags	0.537	0.443	48.044	58.038	0.112	0.140

Source: own elaboration.

Table A.6: Models' nowcasting error measures (continuation)

Model	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
MIDAS with IMAE three known months, Almon polynomial with 12 lags	1.267	0.980	119.807	91.964	0.286	0.365
MIDAS with IMAE three known months, Almon polynomial with 6 lags	0.860	0.763	91.104	80.955	0.210	0.188
MIDAS with IMAE three known months, Almon polynomial with 9 lags	0.730	0.508	68.125	58.348	0.163	0.145
MIDAS with IMAE three known months, step function polynomial with 12 lags	0.982	0.837	106.994	79.111	0.224	0.171
MIDAS with IMAE three known months, step function polynomial with 6 lags	1.049	0.935	108.718	90.932	0.246	0.233
MIDAS with IMAE three known months, step function polynomial with 9 lags	1.002	0.817	106.972	76.842	0.229	0.188
MIDAS with IMAE three known months, unrestricted polynomial with 12 lags	0.469	0.377	41.127	57.709	0.097	0.088
MIDAS with IMAE three known months, unrestricted polynomial with 6 lags	0.351	0.290	35.692	45.751	0.077	0.036
MIDAS with IMAE three known months, unrestricted polynomial with 9 lags	0.391	0.331	43.341	43.446	0.083	0.061
Blocking mixed frequency VAR with IMAE zero-known months	0.985	0.852	82.590	75.381	0.227	0.366
Blocking mixed frequency VAR with IMAE one-known month	0.985	0.852	82.590	75.381	0.227	0.366
Blocking mixed frequency VAR with IMAE two-known months	0.985	0.852	82.590	75.381	0.227	0.366

Source: own elaboration.

Table A.6: Models' nowcasting error measures (continuation)

Model	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
Blocking mixed frequency VAR with IMAE three-known months	0.985	0.852	82.590	75.381	0.227	0.366
Bayesian VAR with sample one from 1991	1.695	1.415	141.760	122.817	0.494	0.581
Bayesian VAR with sample two from 1991	1.662	1.228	63.435	92.682	0.520	0.684
Bayesian VAR with sample three from 1991	1.425	1.000	61.129	64.845	0.408	0.569
Bayesian VAR with sample four from 1991	1.167	0.903	75.206	74.978	0.299	0.332
Bayesian VAR with sample five from 1991	1.361	1.056	104.675	77.183	0.363	0.511
Bayesian VAR with sample one from 1992	1.695	1.415	141.760	122.817	0.494	0.581
Bayesian VAR with sample two from 1992	1.662	1.228	63.435	92.682	0.520	0.684
Bayesian VAR with sample three from 1992	1.425	1.000	61.129	64.845	0.408	0.569
Bayesian VAR with sample four from 1992	1.167	0.903	75.206	74.978	0.299	0.332
Bayesian VAR with sample five from 1992	1.320	1.012	98.532	75.227	0.352	0.495
Bayesian VAR with sample one from 1995	1.695	1.415	141.760	122.817	0.494	0.581
Bayesian VAR with sample two from 1995	1.772	1.397	106.255	118.646	0.537	0.743
Bayesian VAR with sample three from 1995	1.279	0.926	53.580	58.697	0.353	0.499
Bayesian VAR with sample four from 1995	1.165	0.954	79.986	67.638	0.296	0.342
Bayesian VAR with sample five from 1995	1.388	1.057	92.133	84.140	0.388	0.521
Bayesian VAR with sample one from 1998	1.695	1.415	141.760	122.817	0.494	0.581
Bayesian VAR with sample two from 1998	1.772	1.397	106.255	118.646	0.537	0.743
Bayesian VAR with sample three from 1998	1.425	1.000	61.129	64.845	0.408	0.569
Bayesian VAR with sample four from 1998	1.167	0.903	75.206	74.978	0.299	0.332
Bayesian VAR with sample five from 1998	1.327	1.024	126.606	79.247	0.343	0.429
Bayesian VAR with sample six from 1998	1.447	1.200	153.485	102.644	0.354	0.391
Bayesian VAR with sample seven from 1998	1.482	1.262	143.161	108.593	0.404	0.478

Source: own elaboration.

Table A.6: Models' nowcasting error measures (continuation)

Model	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
Bayesian VAR with sample one from 2000	1.695	1.415	141.760	122.817	0.494	0.581
Bayesian VAR with sample two from 2000	1.772	1.397	106.255	118.646	0.537	0.743
Bayesian VAR with sample three from 2000	1.458	0.994	59.519	62.486	0.420	0.577
Bayesian VAR with sample four from 2000	1.164	0.902	75.449	75.212	0.298	0.332
Bayesian VAR with sample five from 2000	1.327	1.024	126.606	79.247	0.343	0.429
Bayesian VAR with sample six from 2000	1.447	1.200	153.485	102.644	0.354	0.391
Bayesian VAR with sample seven from 2000	1.482	1.262	143.161	108.593	0.404	0.478
Bayesian VAR with sample one from 2005	1.695	1.415	141.760	122.817	0.494	0.581
Bayesian VAR with sample two from 2005	1.772	1.397	106.255	118.646	0.537	0.743
Bayesian VAR with sample three from 2005	1.425	1.000	61.129	64.845	0.408	0.569
Bayesian VAR with sample four from 2005	1.167	0.903	75.206	74.978	0.299	0.332
Bayesian VAR with sample five from 2005	1.551	1.208	98.830	101.622	0.473	0.619
Bayesian VAR with sample six from 2005	1.460	1.060	92.398	91.507	0.413	0.600
Bayesian VAR with sample seven from 2005	1.464	1.241	159.921	98.176	0.375	0.411
Bayesian VAR with sample eight from 2005	1.611	1.349	118.017	123.735	0.477	0.586
Bayesian VAR with sample one from 2009	1.695	1.415	141.760	122.817	0.494	0.581
Bayesian VAR with sample two from 2009	1.772	1.397	106.255	118.646	0.537	0.743
Bayesian VAR with sample three from 2009	1.425	1.000	61.129	64.845	0.408	0.569
Bayesian VAR with sample four from 2009	1.167	0.903	75.206	74.978	0.299	0.332
Bayesian VAR with sample five from 2009	1.551	1.208	98.830	101.622	0.473	0.619
Bayesian VAR with sample six from 2009	1.421	1.029	88.296	88.629	0.404	0.574
Bayesian VAR with sample seven from 2009	1.395	1.144	143.784	91.808	0.363	0.412
Bayesian VAR with sample eight from 2009	1.475	1.151	79.253	102.180	0.450	0.612

Source: own elaboration.

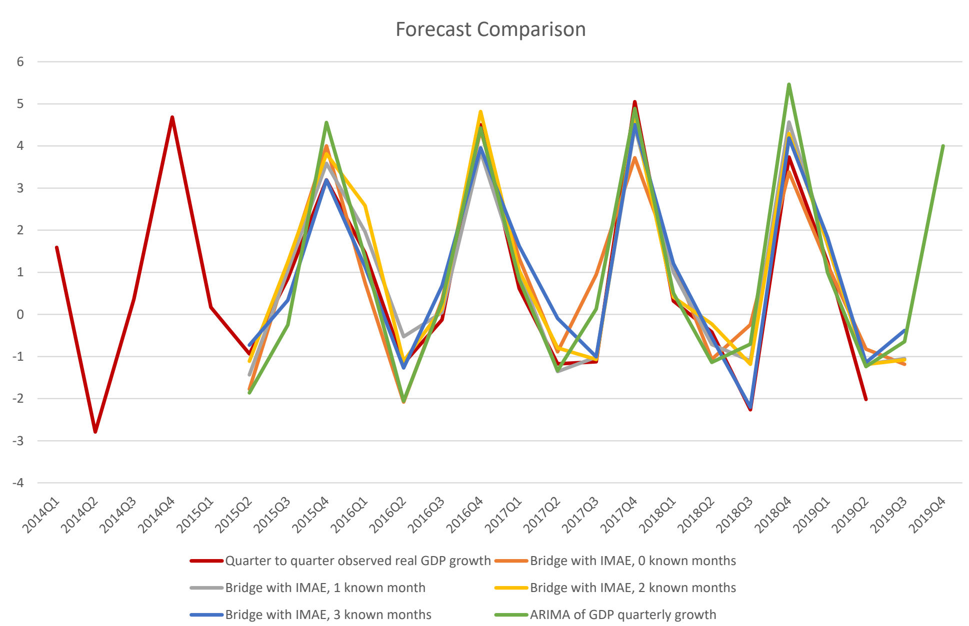
Table A.6: Models' nowcasting error measures (continuation)

Model	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
Bridge with Financial Conditions Index	0.898	0.799	124.158	70.882	0.199	0.180
VAR with Perceptions Business Index	1.052	0.933	121.103	80.286	0.218	0.158
VAR with Consumer Confidence Index	1.079	0.881	158.256	76.750	0.240	0.284
VAR with Economic Agent Confidence Index	1.029	0.916	136.793	76.218	0.222	0.269
Simple mean of best models	0.550	0.489	60.661	46.241	0.123	0.166
Simple median of best models	0.583	0.494	58.919	48.604	0.128	0.180
Mean square error combination of best models	0.349	0.304	35.168	32.776	0.077	0.084

Source: own elaboration.

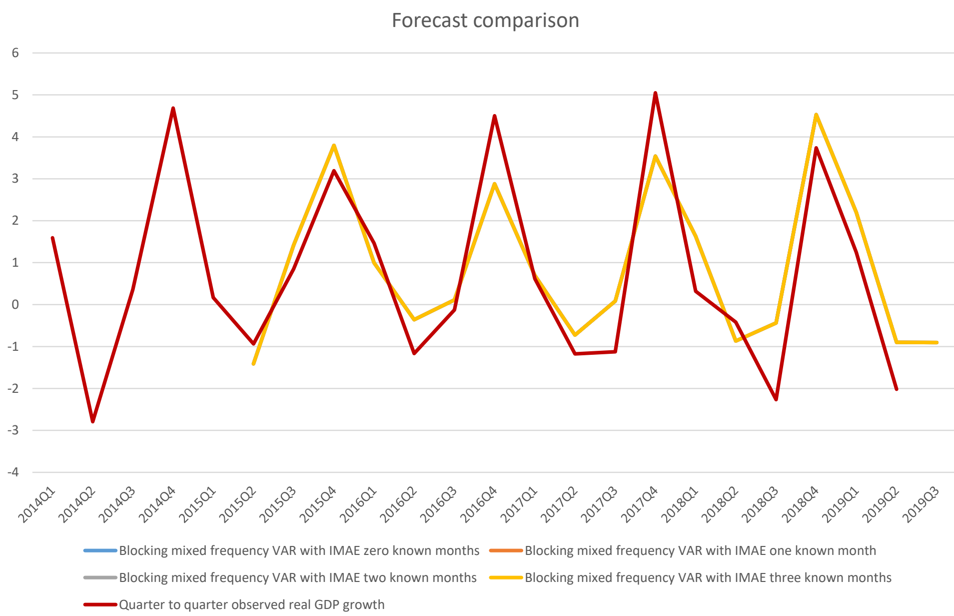
7.5 Nowcast from all models

Figure 6: Bridge and ARIMA Models



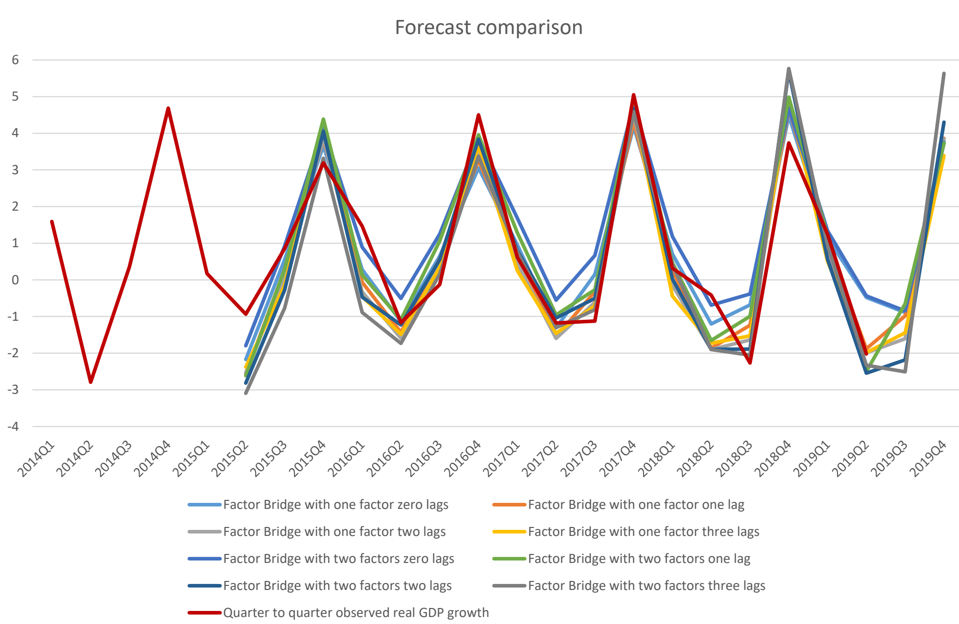
Source: Own elaboration.

Figure 7: Blocking Mixed Frequency VAR



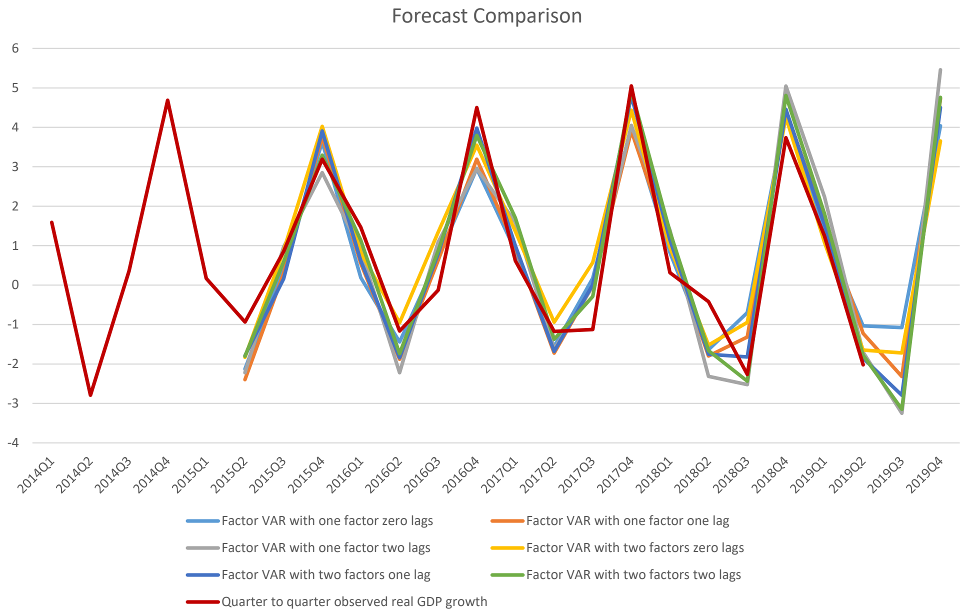
Source: Own elaboration.

Figure 8: Factor Bridge Models



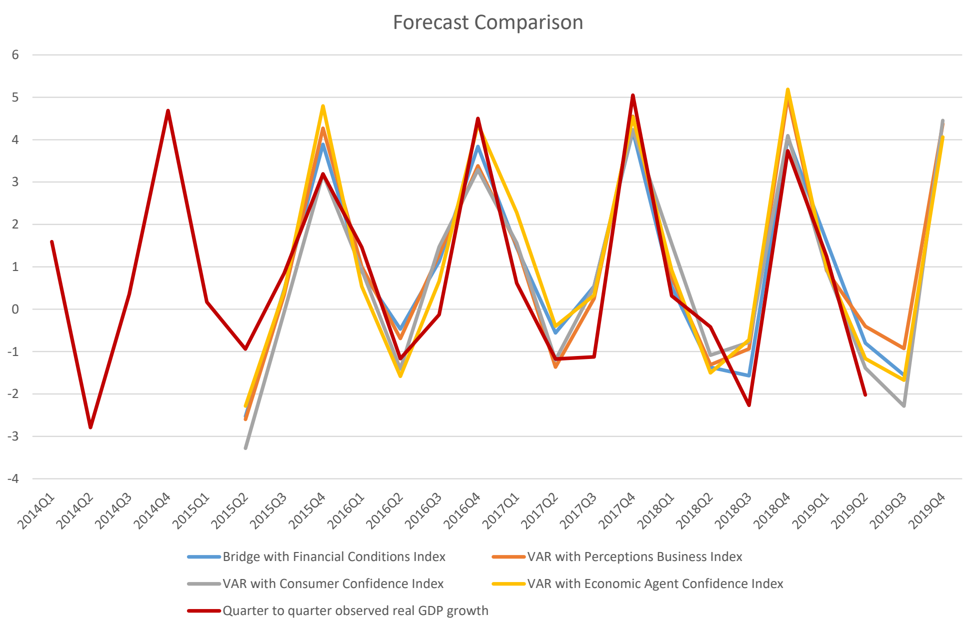
Source: Own elaboration.

Figure 9: Factor VAR Models



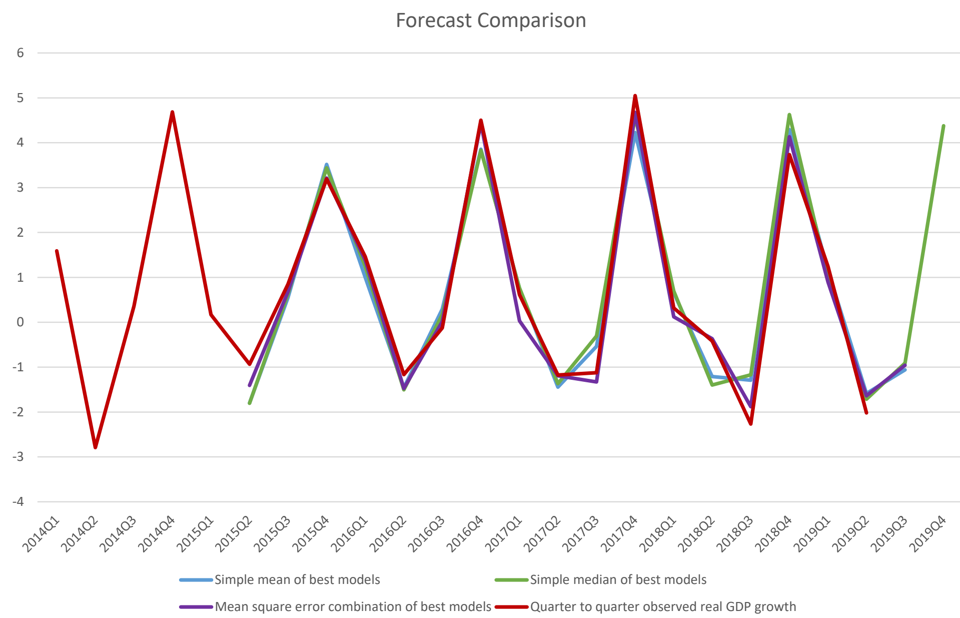
Source: Own elaboration.

Figure 10: Confidence and Financial Conditions Indexes Models



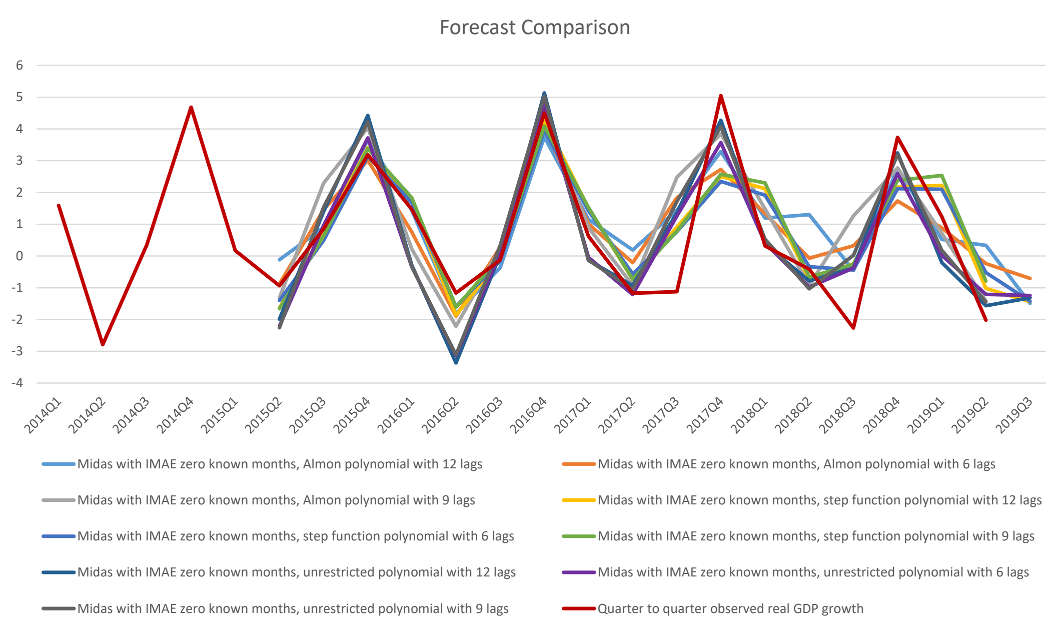
Source: Own elaboration.

Figure 11: Combinations of Forecasts



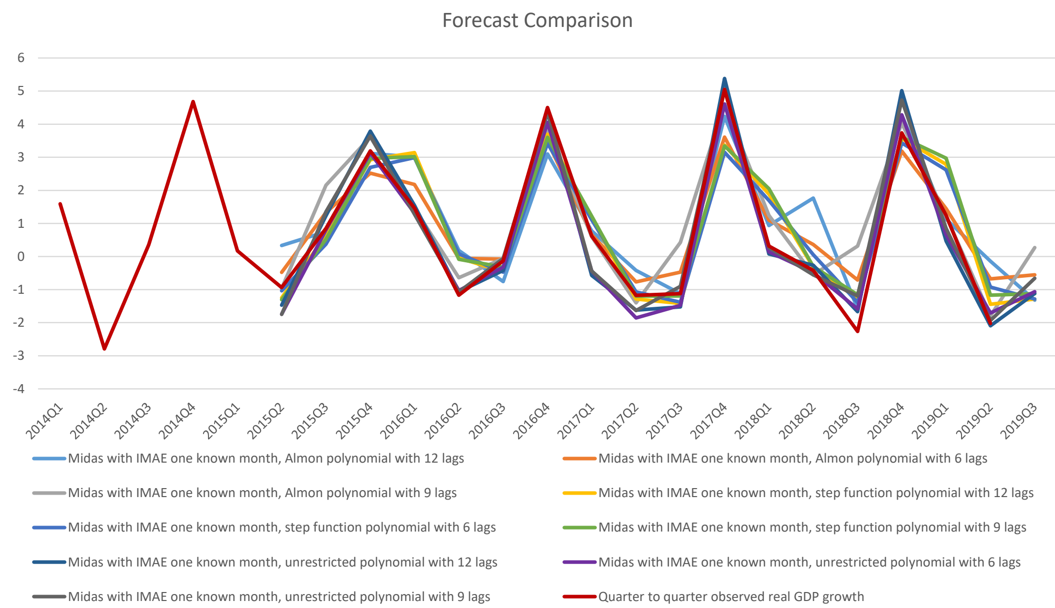
Source: Own elaboration.

Figure 12: MIDAS with IMAE zero-known months



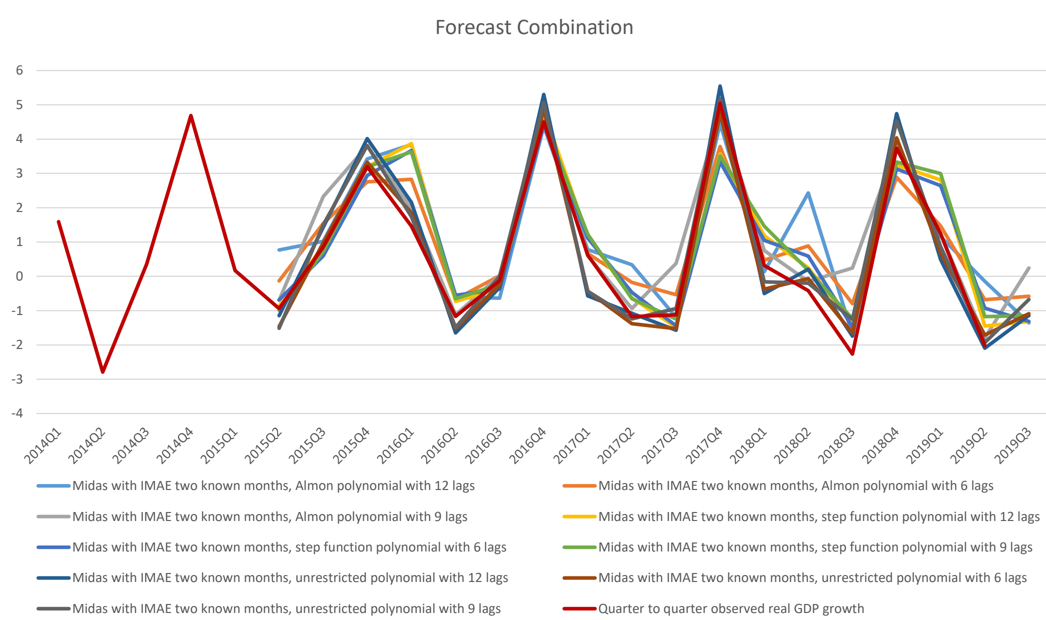
Source: Own elaboration.

Figure 13: MIDAS with IMAE one-known month



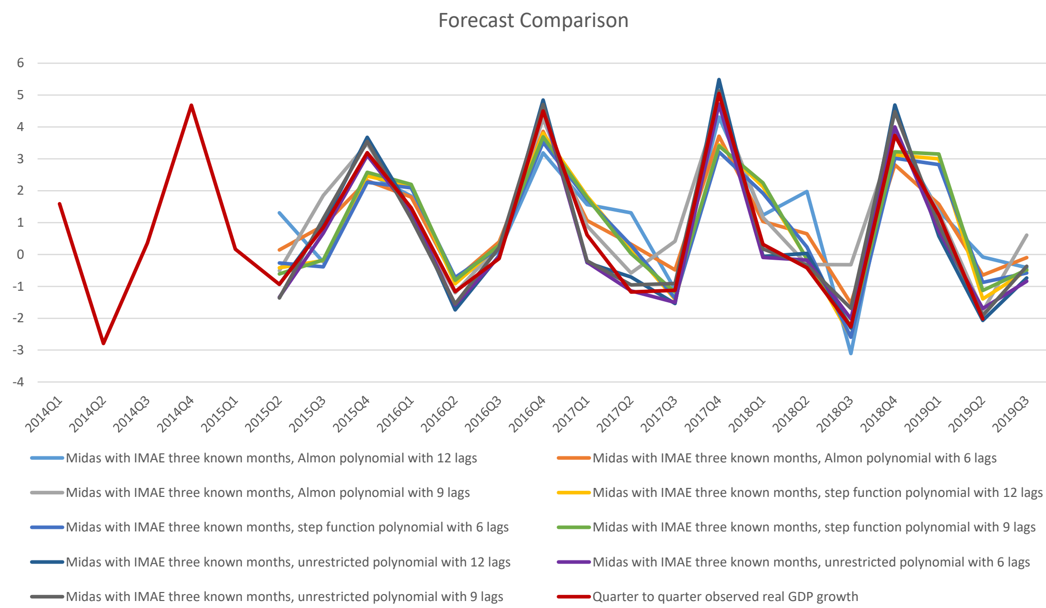
Source: Own elaboration.

Figure 14: MIDAS with IMAE two-known months



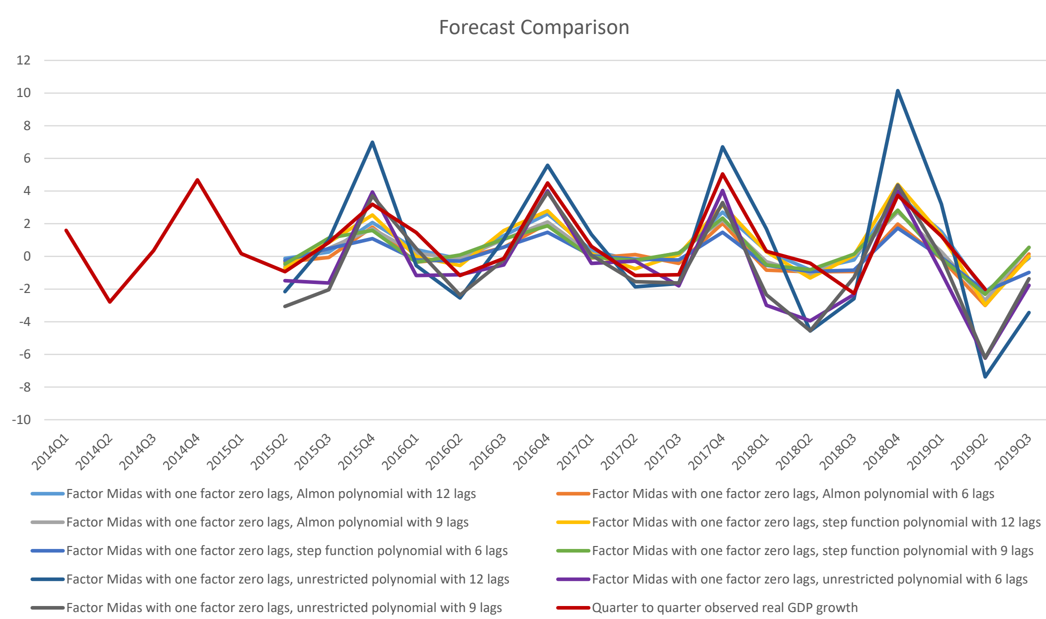
Source: Own elaboration.

Figure 15: MIDAS with IMAE three-known months



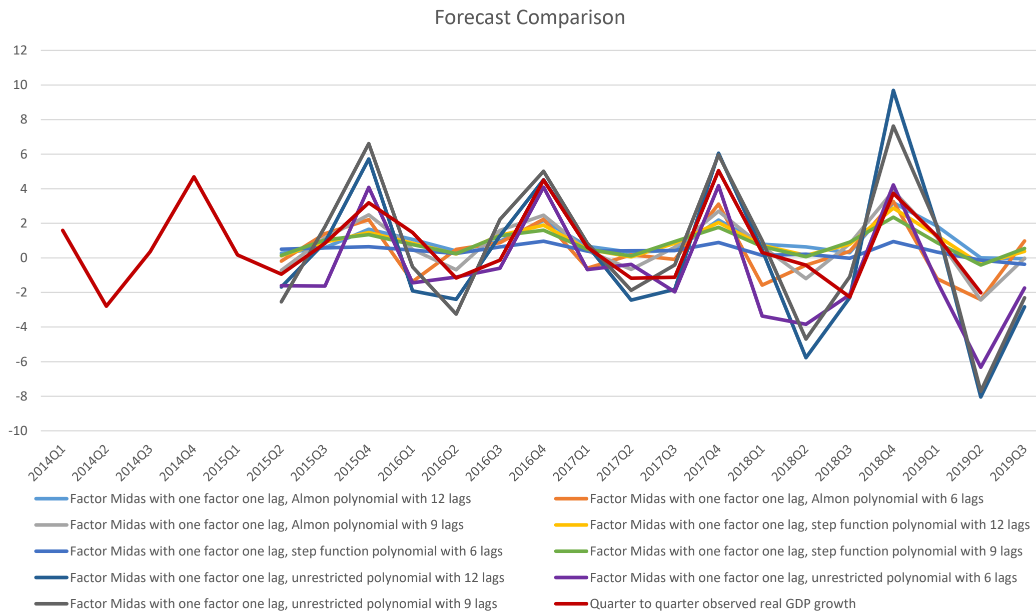
Source: Own elaboration.

Figure 16: Factor MIDAS with one factor, zero lags



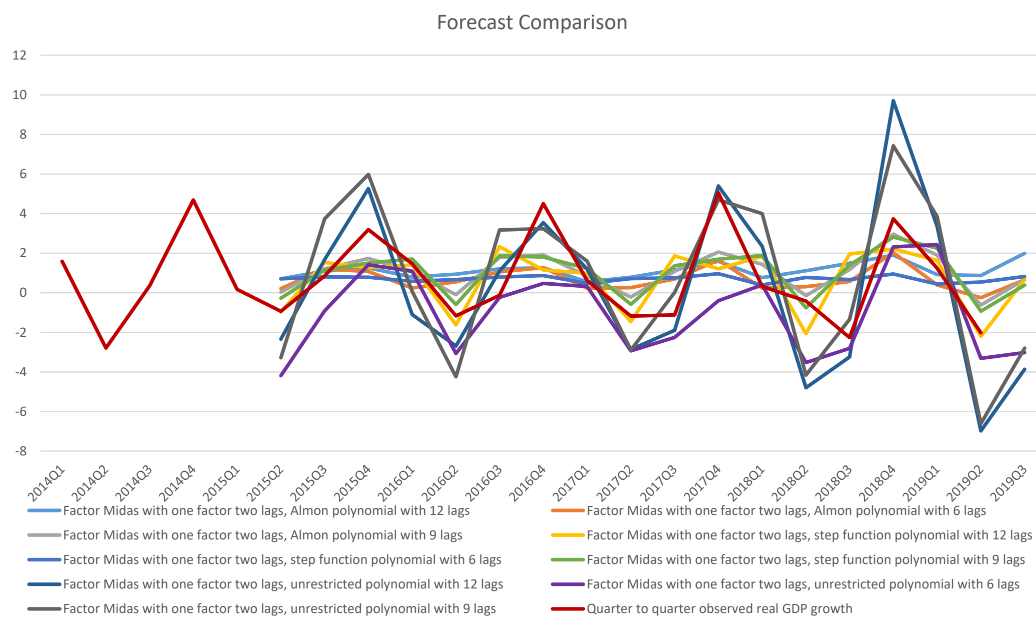
Source: Own elaboration.

Figure 17: Factor MIDAS with one factor, one lag



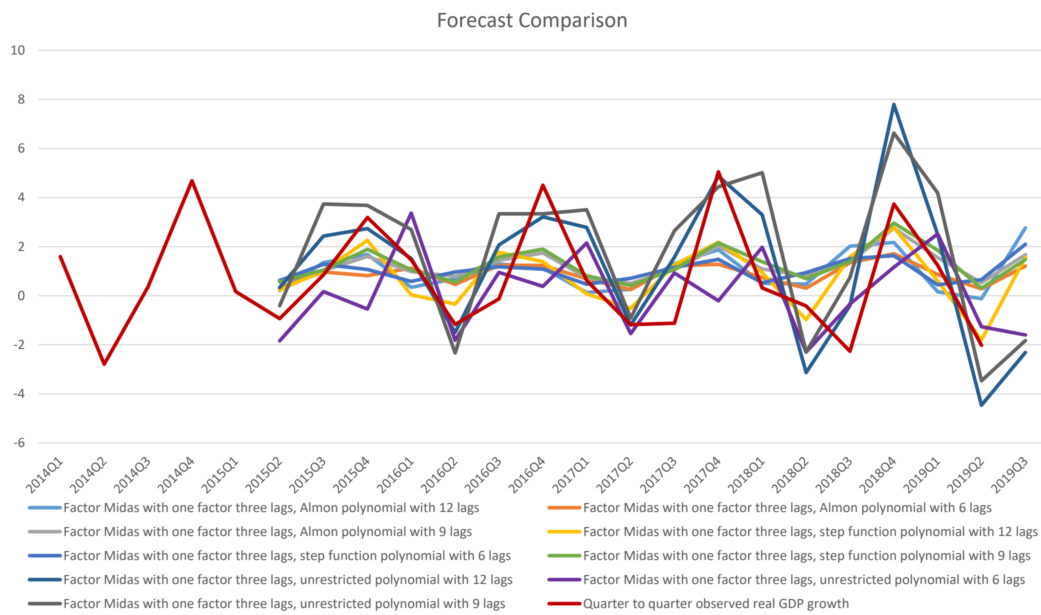
Source: Own elaboration.

Figure 18: Factor MIDAS with one factor, two lags



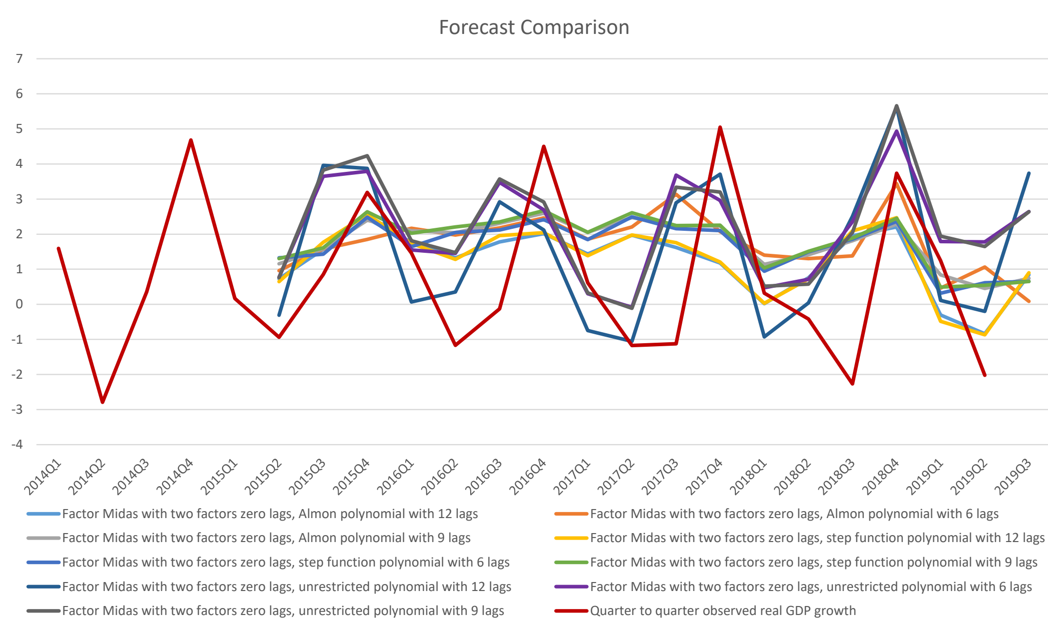
Source: Own elaboration.

Figure 19: Factor MIDAS with one factor, three lags



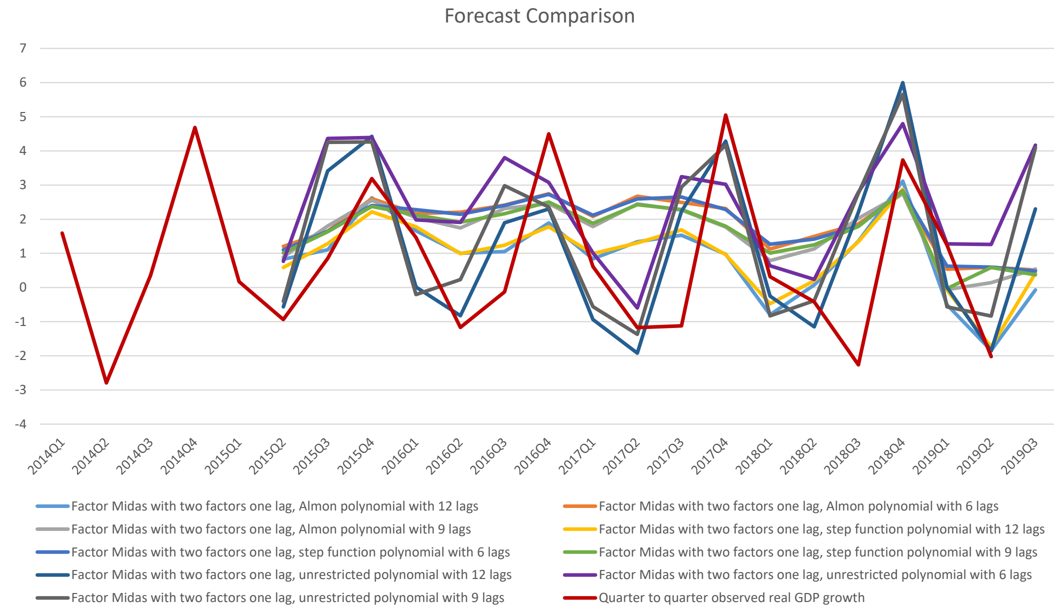
Source: Own elaboration.

Figure 20: Factor MIDAS with two factors, zero lags



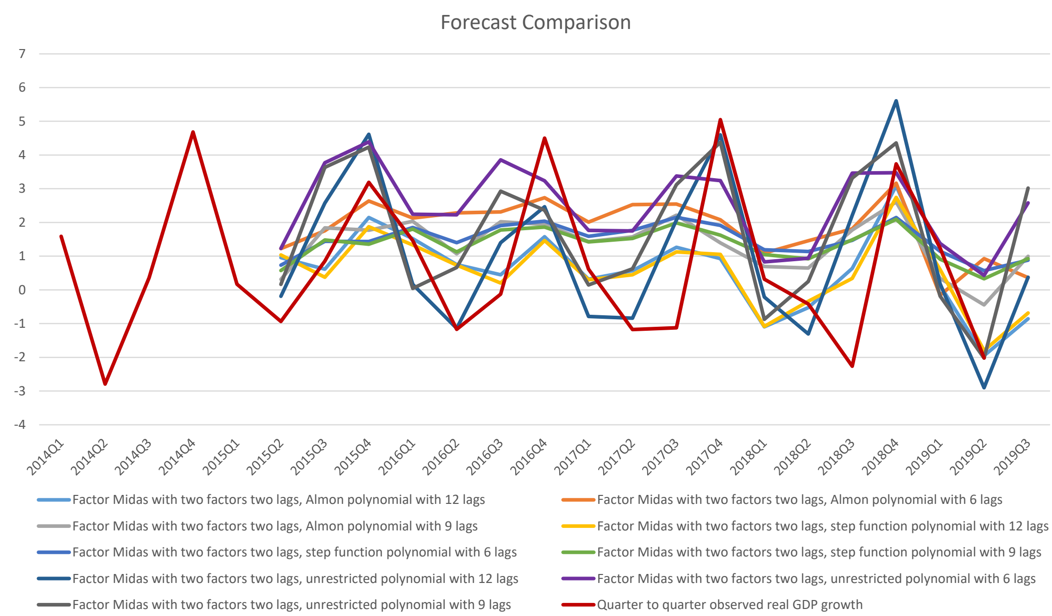
Source: Own elaboration.

Figure 21: Factor MIDAS with two factors, one lag



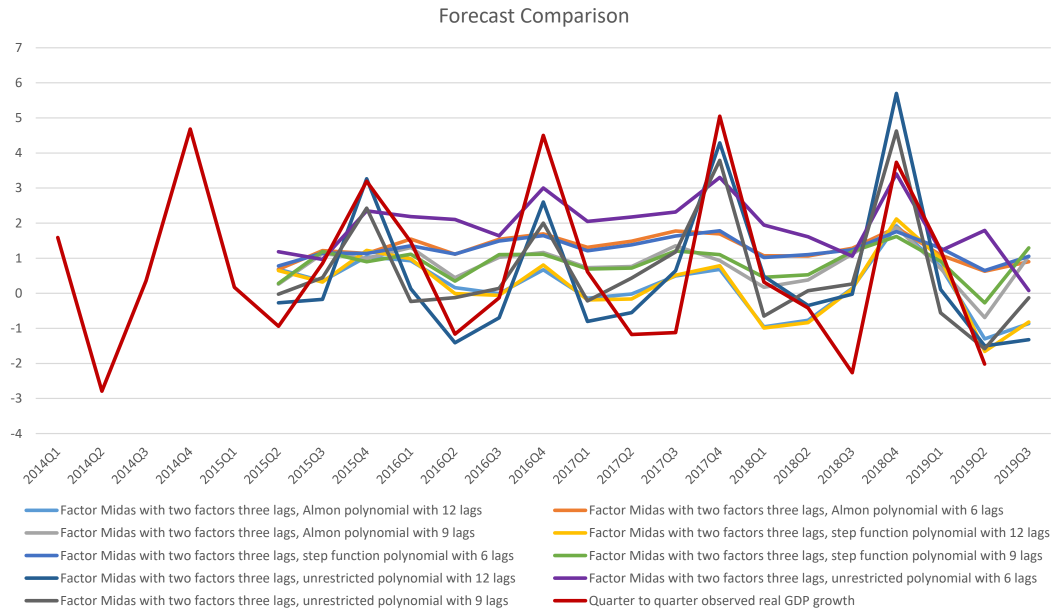
Source: Own elaboration.

Figure 22: Factor MIDAS with two factors, two lags



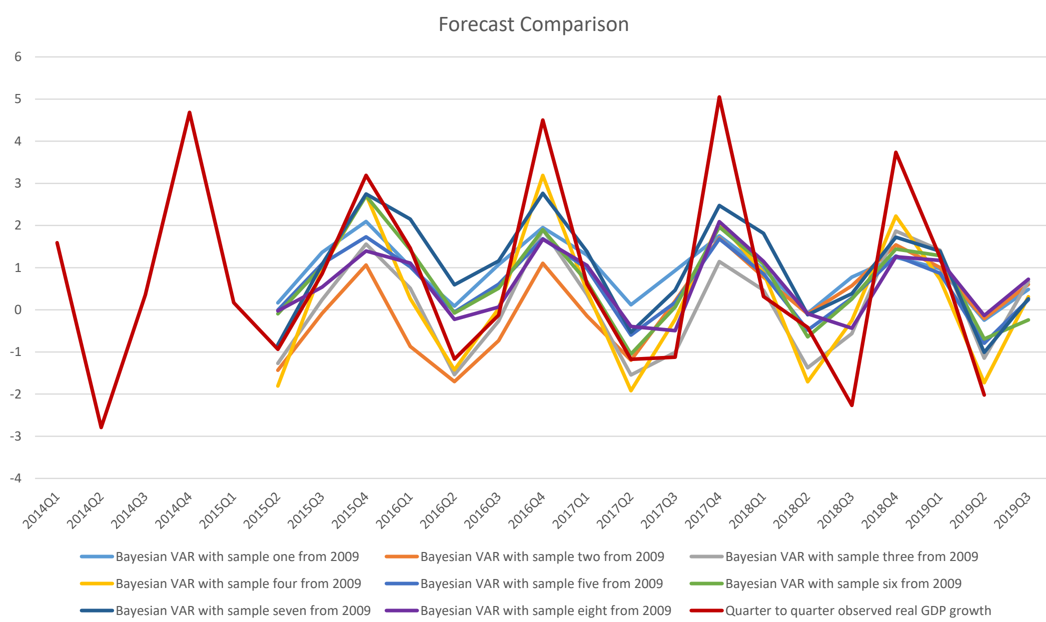
Source: Own elaboration.

Figure 23: Factor MIDAS with two factors, three lags



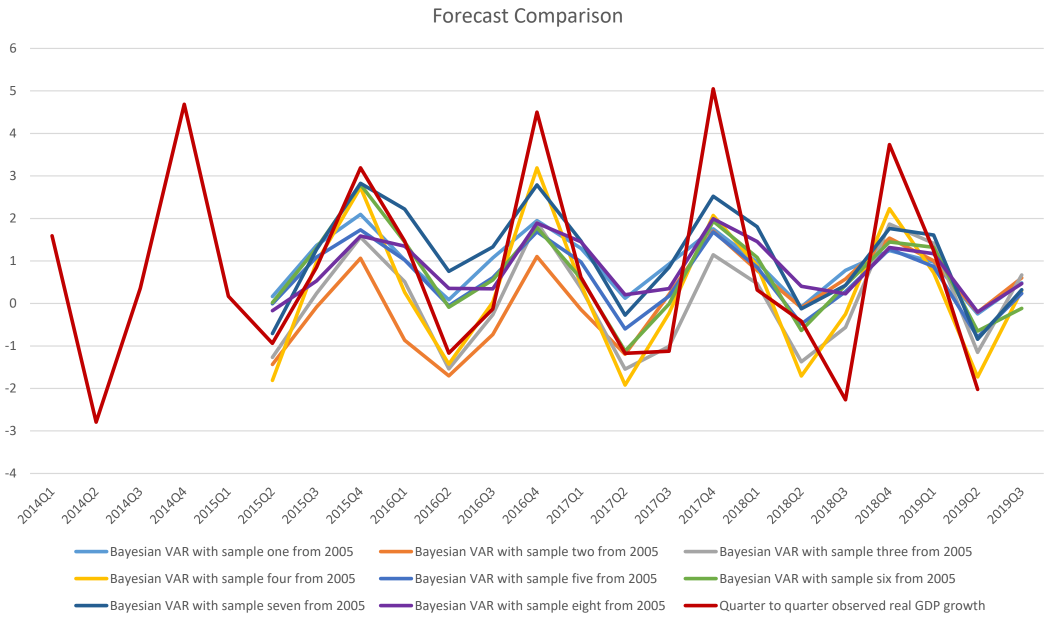
Source: Own elaboration.

Figure 24: Bayesian Mixed Frequency VAR, samples of 2009



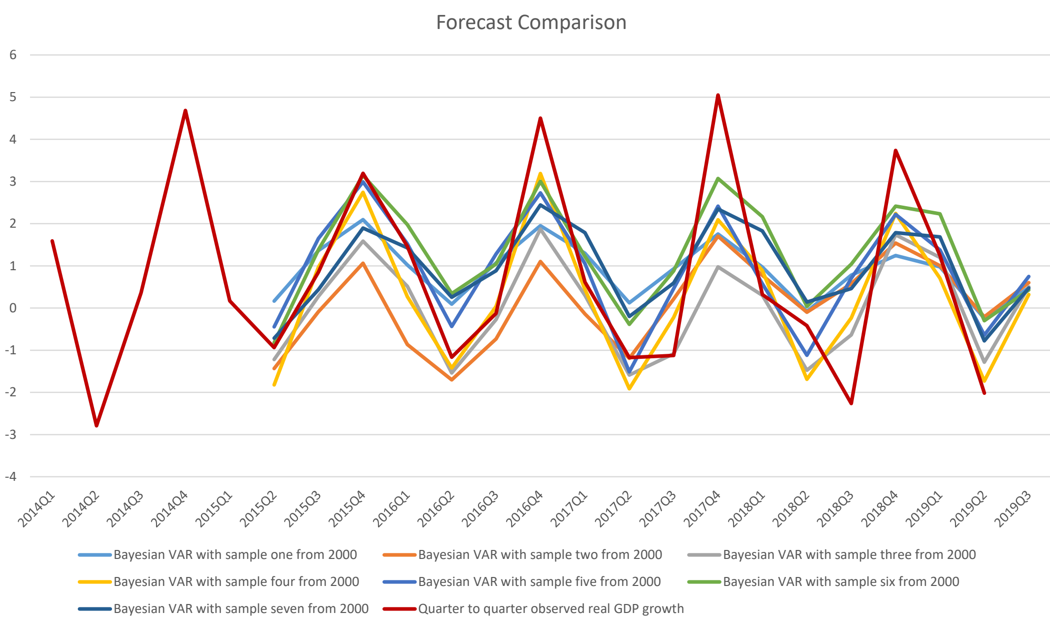
Source: Own elaboration.

Figure 25: Bayesian Mixed Frequency VAR, samples of 2005



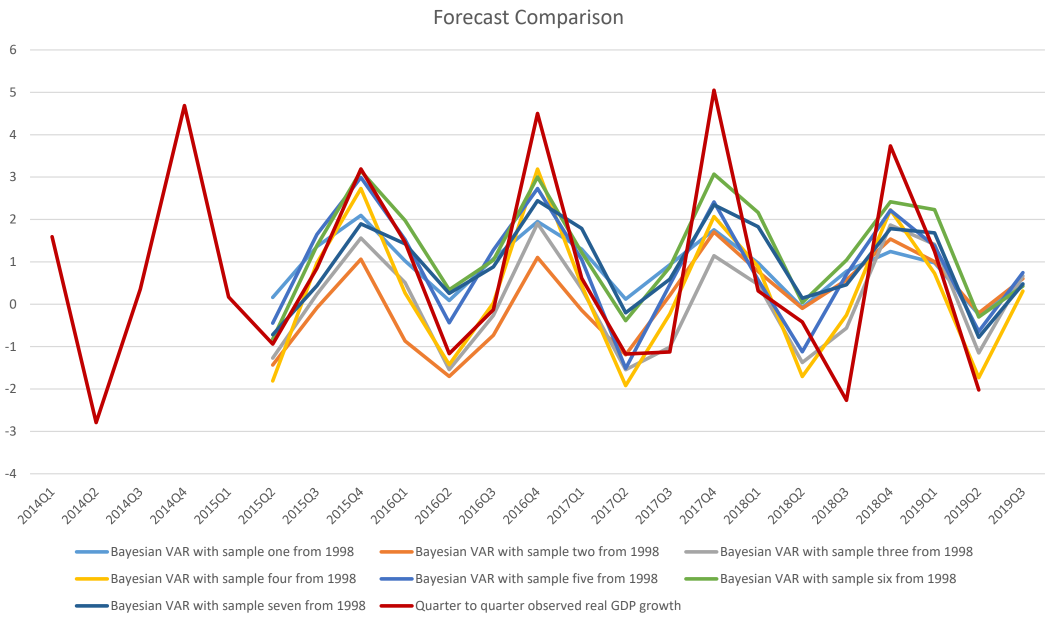
Source: Own elaboration.

Figure 26: Bayesian Mixed Frequency VAR, samples of 2000



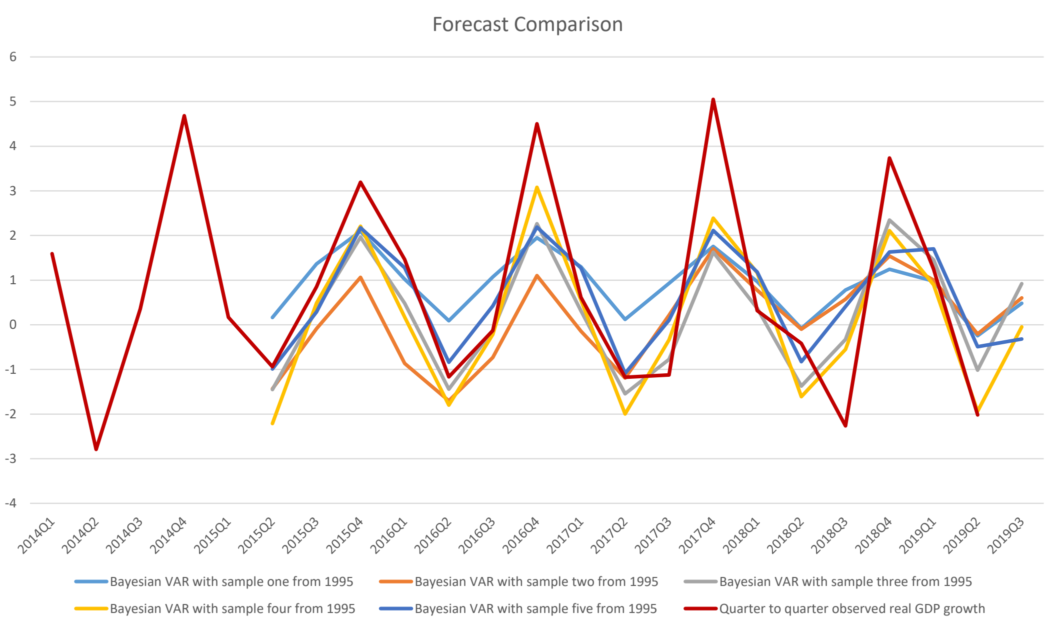
Source: Own elaboration.

Figure 27: Bayesian Mixed Frequency VAR, samples of 1998



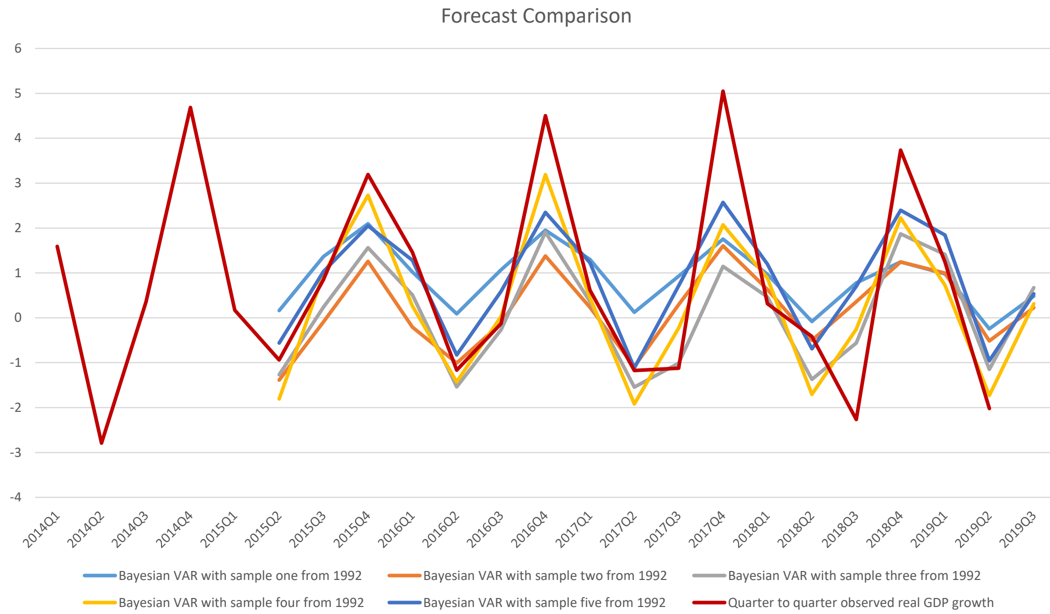
Source: Own elaboration.

Figure 28: Bayesian Mixed Frequency VAR, samples of 1995



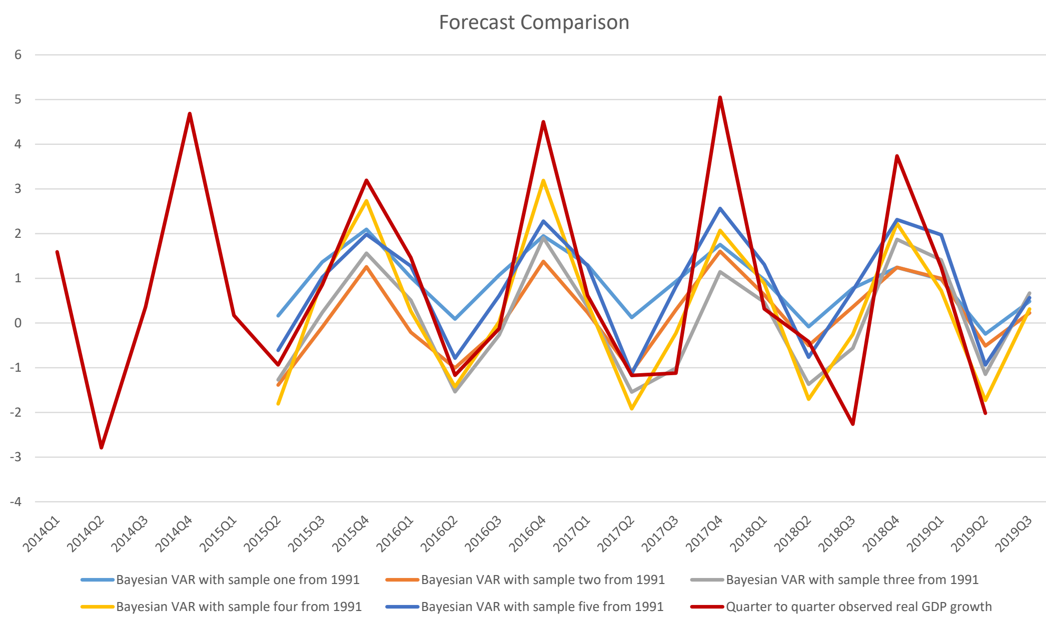
Source: Own elaboration.

Figure 29: Bayesian Mixed Frequency VAR, samples of 1992



Source: Own elaboration.

Figure 30: Bayesian Mixed Frequency VAR, samples of 1991



Source: Own elaboration.