Which One Predicts Better? Comparing Different GDP Nowcasting Methods Using Brazilian Data

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Abstract

The objective of this paper is to develop a basic framework for the implementation of a GDP nowcasting strategy using Brazilian data. Our goal is to identify a scalable strategy that allows us to project the Brazilian GDP in real time at any point during the current quarter. In the paper we detail the survey of classical techniques and also of techniques usually known by market practitioners as "machine learning methods". We survey the literature since the first work on estimating business cycles and document the evolution of this literature until the insertion of machine learning methods. Additionally, we perform backtesting exercises, estimate several candidate models for GDP nowcasting. Finally, we evaluate the forecasting power of all models against a naive model and a market expecta-tions model. We demonstrate that a combination of machine learning models based on the distance of forecasts to the average market expectations defeats the fully informed market expectations, while the same is not possible for selected classical nowcasting models.

JEL Classification: C53; C45; E17.
Keywords: macroeconometrics; machine learning; Forecasting: Nowcasting; GDP; Brazil.

1 Introduction

Monitoring economic activity is no easy task. A country's economy features an immeasurable number of different activities. Obtaining a thermometer for the value produced in each of these activities is a problem that has intrigued economists of different strands since the conception of economic science. Although it is a Homeric task, the well-being of a country is impacted by the quality of its economic policies, which in turn depend on economic monitoring. To corroborate this statement, we can look at recent episodes of relevant economic crises, that is, even if it were not possible to avoid them, a more detailed economic monitoring of economic activity could have guided an early effort to mitigate their effects, saving jobs and directly affecting people's lives. In the absence of a bulwark that configures the objective measure of the active state of the national economy, methodologies for calculating the value added were developed and also, national accounting tautologies were synthesized to develop a variable that performs this task, the GDP.

By evaluating the economy using GDP, economic authorities can reach a consensus on the productive state of a country, being able to assess its growth and formulate plans. In addition, it is possible to create metrics of social inequality and look at economic development in a more objective way. In most countries, the statistical bureau publishes the GDP result in a quarterly period. Generally, this disclosure takes place several weeks after the reporting period. It is a consensus among economists that some of the macroeconomic variables have "memory"; in fact, often the best prediction of a macroeconomic variable is its lagged value. Even taking this fact into account, it is not possible to make economic policies having as the main measure of economic activity a variable that presents a quarterly interval of disclosure, with the aggravating factor of being a measure lagged months when disclosed.

Within this context, economists seek to produce monthly indicators of GDP designated coincident indicators. These indicators of economic activity and inflation present less temporality and are crucial to understand the evolution of the economy, yet these indicators suffer from the same problem as GDP – built "from the bottom up", they leave us lacking data on economic activity over a relatively long period.

To deal with these uncertainties about the future, the nowcasting literature build a statistical apparatus, guided by the econometric theory in its "state of the art", that plays the role of a real-time thermometer of the economy in a relevant way. The objective of this paper is to develop a basic framework for the implementation of a GDP nowcasting strategy in Brazil. We perform backtesting exercises with an updated Brazilian database, estimate several candidate models for GDP nowcasting, implementing the division of classical models and machine learning models. Finally, we evaluate the forecasting power of all models against a naive model and market expectations. The results show that that a combination of machine learning models based on the distance of forecasts to the average market expectations defeats the fully informed market expectations, while the same is not possible for selected classical nowcasting models.

The paper is divided into 5 sections besides this introduction. In Section 2, we review the nowcasting literature presenting the main methods adopted by researchers. Section 3 shows the dataset. Section 4 discusses the methodology used in the nowcasting exercise. Section 5 shows the main results. Section 6 concludes.

2 Literature Review

As stated by Giannone et al. (2011), the term nowcasting refers to the future, past and present at the same time, having been first used in meteorology and brought to economics for the first time by Giannone et al. (2008). The nowcasting economic activity has evolved quickly in the last years.[1]

2.1 Regime Switching Models

The use of markov switching models in nowcasting is viewed as ideal to detect turning points in GDP performance. Regime-switching models characterize data as falling into different, recurring "regimes" or "states". These models enable the characteristics of time series data, including means, variances, and model parameters to change across regimes. The regime switching literature has evolved to address mixed frequency variables, mixed frequency regime switching models.[2] For each one of these models, there are different approaches to deal with the jagged edge problem of the database (inherent to the nowcasting problem), an important contribution to deal with this problem in this literature was proposed in Mariano & Murasawa (2003). There are two main models that we want to highlight in this branch, MS-DFM (Markov switching dynamic factor models) and MS-MIDAS (Markov switching mixed data sampling regressions), in the next sections we see in detail MIDAS and DFM models.

2.2 Bridge Equations

If the goal is to predict a quarterly variable using monthly ones, the bridge equation *per se* would be a partial model, a simple regression to predict GDP used as a step in many estimation strategies of more complicated *full models*.

[1] The paper tries to organize an extensive review of the literature, yet there are several other works associated with this literature that are left out, configuring some important points and branches of the real-time monitoring discussion, they are: BVAR's, early selection of regressors in the base of nowcasting, sparsity discussion (Giannone (2021)) among others

[2] There are several contributions in this branch of the literature. Hamilton (19990 as the sinal work, Diebold & Rudebusch (1996) for a survey and theoretical contribution, Barsoum & Stankiewicz (2013), Carstensen et al. (2017) for a work to detect Turning Points and Camacho et al. (2012).

2.2.1 Bridge Equation - Standard Formulation

Take an activity indicator in quarterly frequency, given by its interanual quarter rate YQoQ (%), referred here as $y_\tau^q = y_t$, if we only use a monthly indicator on the basis of dependent variables (for simplicity), we have the standard regression that defines a bridge equation is as follows:

$$y_t = \beta_0 + \lambda y_{t-1} + \beta(L)x_t^q + \epsilon_t$$

Where $\epsilon_t \sim WN$, $\beta(L)$ is a polynomial of lags, L is the lag operator. In our case, the database has a higher frequency than that of the dependent variable, an aggregation is performed on this database to then estimate the regression. Suppose we take the simple average of the three months of the quarter on a monthly basis and then do a regression with that data. So, the idea is that you do some kind of aggregation using the monthly data and then you do the following projection:

$$y_{T+1|T+\nu} = \widehat{\beta}_0 + \widehat{\lambda} y_T + \widehat{\beta}(L)x_{T+1|T+\nu}^q + \epsilon_{T+1}$$

In this case, the subscript ν refers to intra-quarter months.

2.3 MIDAS - Mixed Data Sampling Regressions

The problem with Bridge equations models is that they require the estimation of a large number of parameters, to solve this, Ghysels, Santa Clara & Valkanov (2004) propose the MIDAS model. To control the curse of dimensionality, the MIDAS model places a restriction on the parameters of the polynomial lag structure using an aggregation function according to the following specification.

$$y_{t+h} = \beta_0 + \lambda y_t + \beta_1 B(L^{\frac{1}{3}};\theta)x_{t+\omega}^m + \epsilon_{t+h}$$

Where $\omega = T_y - T_x$, the ends of the samples of y and x and represents the lead of the highest frequency indicator. Additionally, $B(L^{\frac{1}{3}};\theta) = \sum_{k=0}^{K} b(k;\theta)L^{\frac{k}{3}}$ is the polynomial of lags and $b(k;\theta) = \frac{exp(\theta_1 k + \theta_2 k^2)}{\sum_{j=0}^{K} exp(\theta_1 j + \theta_2 j^2))}$, known as Almon's exponential polynomial. An important example of application it's Laine & Lindblad (2020) in a study by the Bank of Finland (Helsinky), used MIDAS to nowcast the Finnish GDP using financial variables with different frequencies.

2.4 Factor Models

Assume that a reasonable number of indicators are somehow related to economic conditions. According to Stock & Watson (1991), suppose that each variable can be written as the sum of two mutually uncorrelated stochastic components, the first component f_t is assumed to be common to all series in the base, the second component u_{it} refers to the idiosyncratic dynamics of each indicator in the base. Thus, the latent states of monthly GDP growth and monthly base indicators are assumed to follow the following dynamics. In this way, each series in this base can be translated as being composed of an element that measures the *business cycle overall* and the idiosyncratic component of each specific time series indicator.

$$y_t^m = \beta_0 f_t + u_{it}$$
$$x_{it}^m = \beta_i f_t + u_{it}$$

Where $i \in I_N$ and N is the number of monthly indicators used in the analysis. In the first works of Stock & Watson related to factor models we found the specification above, the literature evolved and today we find dynamic factor models, whose specification will be detailed later.

2.4.1 Dynamic Factor Model (DFM) Literature

In a factor model, the relationships between n variables $x_1, x_2, ..., x_n$, for which T observations are available, are due to a small number of latent variables called factors, assumed in quantity $r < n$. The link between the observed variables and the factors is assumed to be linear. In this way, each observation x_{it} can be decomposed in the following way:

$$x_{it} = \mu_i + \lambda_i' f_t + e_{it}$$

Where μ_i is the average of x_i, λ_i is a vector $r \cdot 1$ and e_{it} and f_t are two uncorrelated processes. Thus, $\forall t \in I_T$ and $\forall i \in I_N$, x_{it} can be decomposed into a sum of two unobserved orthogonal components: The common component, $\chi_{it} = \lambda_i' f_t$ and the idiosyncratic component, $\epsilon_{it} = \mu_i + e_{it}$.

2.4.2 Dynamic form

In the literature we find different ways of representing the DFM's, their exact form, their dynamic form, their approximate form. Different modes of interpretation lead to different estimation methods according to Stock & Watson (2016). Below its dynamic form.

$$X_t = \lambda(L) f_t + e_t$$
$$f_t = \psi(L) f_{t-1} + \eta_t$$

where X_t is a matrix of observed time series and f_t are the latent factors that will be estimated from this basis, $\lambda(L)$ and $\psi(L)$ are matrices $N \cdot q$ and $q \cdot q$ respectively, η_t is a vector $q \cdot 1$ of serially uncorrelated factor innovations, e_t are idiosyncratic shocks in the observed series. For estimation purposes it is necessary to specify a dynamics for e_t series... In this case: $e_{it} = \delta_i(L) e_{it-1} + \nu_{it}$, with ν_{it} being a white noise.

2.4.3 DFM Literature

The DFM literature is extensive, there are works focused on forecasting different macroeconomic variables, such as American and European GDP (Banbura et. al. (2013)), Giannone et al. (2008) and Giannone et al. (2017), GDP of China (Yiu & Chow (2011)), GDP of Norway (Aastvei & Trovik (2010)) and Thorstud (2016), GDP of Turkey Modugno et al. (2016), American annual inflation Giannone et al. (2006) and forecast for global economic growth (Ferrara & Marsilli (2014)). Liu et al. (2011) develop five GDP nowcasting models using the DFM literature for ten Latin American countries. Dahlhaus et al. (2015) made projections of the GDP of the countries Brazil, Russia, India, China and Mexico (BRIC + M).

2.5 DFM's Estimation

Stock & Watson (2010) document the evolution of factor models according to their estimation methods, divided into three generations:

- i) First generation: time domain maximum likelihood via the kalman filter - In this procedure the EM method is used to estimate the parameters via Maximum Likelihood and then, given the parameters, the Kalman Filter can be used to compute the likelihood and estimate filtered values for F_t and hence f_t. Advantage: This method can handle data irregularities in a better way, Drawback: the number of parameters estimated is proportional to the number of series in the database, in this way, direct MLE is historically prohibitive.

- ii.1) Second generation: non-parametric averaging methods - the reason to consider cross-section averaging methods of X_t is that the idiosyncratic disturbances will converge to zero by the weak law of large numbers, in this case, only the linear combination of the factors will remain.

- ii.2) A specific method of Weighted average estimators is component analysis. Strenght: the second generation methods can handle large datasets very well. Drawback: The method cannot deal very well with missing data and jagged edge datasets.

- iii) Third generation: Hybrid principal components and state space methods - The third generation of methods for estimating the factors merges the statistical efficiency of the state space approach with the robustness and convenience of the principal components approach. This merged procedure occurs in two steps, which are described in more detail in works such as Giannone, Reichlin & Small (2008) and Doz, Giannone & Reichlin (2006).
  - First step: The factors are estimated by principal components
  - Second step: In the second step the estimated factors $\widehat{F}_t$ are used to estimate the unknown parameters of the state space representation.

2.6 Understanding Dynamic Factor Models

The Hybrid Method of the third generation is largely used in the literature after the seminal work of Giannone et al. (2008), the consistency properties of this method is studied by Doz et al (2011). To better understand this class of models, it is formulated a state space model as below:

$$x_{nt} = \begin{bmatrix} \lambda_n & 0_{nxr} & \dots & 0_{nxr} & 0_{nxr} \end{bmatrix} \begin{pmatrix} f_t \\ \dots \\ f_{t-p+2} \\ f_{t-p+1} \end{pmatrix} + \xi_{nt}$$

which is just the specification pointed out by Stock & Watson, a time series indicator can be decomposed into a factor component plus an idyosincratic therm. In space state form, this is called a measurement equation. Aditionally, the factors are suposed to follow a simple VAR(p) process:

$$F_t = AF_{t-1} + G\mu_t$$

2.7 Machine Learning methods

There are not many works that used Machine Learning for GDP projection before the 2000s, however, with all the discussion about the entry of machine learning methods in all sciences, machine learning methods are now being largely used in nowcasting. Specially in post covid times, where the uncertainty about economic activity raised and economic activity forecasting was requested.

2.7.1 Machine Learning Methods - Shrinkage Models

Shrinkage Models are a well-stablished alternative to factor models, the basic idea behind this modelling is to reduce the parameters that correspond to irrelevant variables towards zero. To quickly understand these models we can follow Maynard's specification (Maynard (2021)): Shrinkage models are based in the simple optimization problem:

$$\widehat{\beta} = \underset{\beta}{argmin} \sum_{t=1}^{T} (y_t - x_t'\beta)^2 + \lambda \left[\alpha \sum_{j=1}^{N} \frac{|\beta_j|}{\omega_j} + (1-\alpha) \sum_{j=1}^{N} \frac{|\beta_j|^2}{\omega_j} \right]$$

Setting the following vector of settings: $\psi = (\alpha, \lambda, \omega_j)$

- Ridge Regression: $\alpha = 0$ and $\omega_j = 1 \ \forall j \in I_N$ where N is the number of parameters in the regression model.
- LASSO: $\alpha = 1$ and $\omega_j = 1 \ \forall j \in I_N$
- Elastic Net: $\alpha \in (0, 1)$ and $\omega_j = 1 \ \forall j \in I_N$

In this branch of the machine learning literature we also use the adaptative LASSO, or adaLASSO, these models are an evolution of LASSO tecniques and they have the oracle properties for the choice of λ.

2.7.2 Machine Learning Methods - Neural Networks

A neural net is a method of artificial intelligence that allows computers to process data in a way that is somewhat linked to the way the human brain learns. It is a type of machine learning process more closely related to deep learning, the method uses neurons, interconnected in hidden layers, hence the analogy to the human brain. A neuron in a neural network takes one or more inputs, applies a mathematical function to the inputs, and produces an output. The mathematical operation performed by each neuron is called the activation function. Let x be the input vector of size n, w be the weight vector of size n, and b be the bias term. The output h of the neuron is given by the activation function f applied to the weighted sum of the inputs plus the bias term:

$$h = f(W^T x + b)$$

In a neural network with multiple layers, the output of one layer becomes the input to the next layer. Let $x^{(l)}$ denote the input to layer l, and $h^{(l)}$ denote the output of layer l for $l = 1, 2, \ldots, L$. Then the output of the entire network is given by:

$$h^{(L)} = f^{(L)}(W^{(L)} h^{(L-1)} + b^{(L)})$$

where $W^{(L)}$ is the weight matrix for layer L, $b^{(L)}$ is the bias vector for layer L, and $f^{(L)}$ is the activation function for layer L. During training, the network's parameters are updated using the backpropagation algorithm. The loss function $L(y, \hat{y})$ measures the difference between the predicted output $\hat{y}$ and the true output y, and the network's parameters are updated to minimize this loss function.

2.7.3 Machine Learning Methods - Bagging or Bootstrap Aggregating

Bagging is a type of ensemble method in machine learning algorithms that uses bootstrap and aggregating to form an ensembled model, where it's given a sample of data. Bootstrap samples are pulled, then a decision three is formed on each of the bootstrapped subsamples. After each subsample decision three has been formed; an algorithm is used to aggregate on the decision threes to form the most efficient predictors. The procedure used here is better described in Inoue, A., Kilian, L. (2008). This algorithm is largelly use to reduce variance and prevent from overtfitting. The basic idea behind bagging is to train multiple models on different subsets of the training data and then combine their predictions. The subsets are created by randomly sampling the training data with replacement, a process known as bootstrapping. This means that some instances may be sampled multiple times, while others may not be sampled at all.

Once the models have been trained, their predictions are combined using a simple averaging or voting scheme, depending on the problem being solved. This combination of models is known as an ensemble. Mathematically, let $(x_1, y_1), ..., (x_n, y_n)$ be the training dataset, where each x_i is a feature vector and y_i is the corresponding target value. We want to train T models $f_1(x), ..., f_T(x)$ on different subsets of the training data. To create each subset, we randomly sample n instances from the training dataset with replacement. This means that some instances may be sampled multiple times, while others may not be sampled at all. Let $D_1, ..., D_T$ be the T subsets of the training data. Next, we train T models $f_1(x), ..., f_T(x)$ on the T subsets of the training data, using the same learning algorithm for each model. Finally, to make predictions for a new instance x, we combine the predictions of the T models using a simple averaging or voting scheme. For regression problems, we can average the predictions:

$$y(\hat{x}) = \frac{1}{T} \sum_{t=1}^{T} f_i(x)$$

Bagging can improve the performance of high-variance algorithms, such as decision trees, by reducing overfitting and improving generalization. By training multiple models on different subsets of the training data, bagging reduces the variance of the ensemble and improves its stability.

2.7.4 Complete subset regression

Complete subset regression is a tecnique presented in Elliott, Gargano and Timmermann (2013), the rationale behind this method is that all the subsets of a given sample data are selected and the forecasts computed on these subsamples are then compared. [3] Suppose we have a response variable Y and p predictor variables denoted by $X_1, X_2, ..., X_p$. The complete subset regression problem involves fitting all possible linear regression models using different subsets of the predictor variables. There are 2^p possible subsets of predictor variables, which means there are 2^p possible models. The algorithm then fits a linear model on the selected subsample of regressors, using OLS. The best subset regression is the regression that minimizes information criterion AIC or BIC.

2.7.5 Random Forests

Random forest is a Supervised Machine Learning Algorithm that is used widely in Classification and Regression problems. It builds decision trees on different samples and takes their majority vote for classification and average in case of regression. As we mentioned before, the random forests algorithm of machine learning is closely related with that proposed by Inoue, A., Kilian, L. (2008) (bagging). The Random Forests methodology per se was first described

[3] for more information in using these methods to nowcast economic variables see: https://github.com/gabrielrvsc/HDeconometrics/blob/master/R/bagging.R

in Breiman (2001), as it's explained perfectly in Maynard (2021). Suppose we have a training dataset with n observations and p predictor variables. To construct a random forest, we first generate B bootstrap samples of the training data, each containing n observations randomly sampled with replacement from the original data. For each bootstrap sample[4], we construct a decision tree using a random subset of m predictor variables selected at each split.

To grow a decision tree, we recursively split the data into smaller and smaller subsets based on the values of the predictor variables. At each split, we select the best variable and split point that maximizes the reduction in variance or the information gain. After constructing all B decision trees, we obtain a prediction for a new observation by averaging the predictions from all the trees. For a regression problem, the prediction is simply the mean of the predicted values from each tree. For a classification problem, we use majority voting to determine the predicted class. The random forest algorithm also provides estimates of variable importance based on the decrease in node impurity or the reduction in mean squared error resulting from splits involving a given variable. These estimates can be used to identify the most important predictor variables for the response variable. Random forests are known to be robust to overfitting and it's also great at dealing with large number of predictor variables.

2.7.6 Support Vector Machines

Support vector machines or simply SVM's is a supervised machine learning model that uses classification algorithms. In high dimensional data, what the SVM algorithm does is simply try to separate or classify a pre selected class of data using a hyperplane. For time series forecasting, the use of SVM is promising, as it's shown in Kyoung-Jae Kim (2003). One approach to using SVMs for time series prediction is to convert the time series into a supervised learning problem by framing it as a regression task. This involves selecting a window of past observations as input features, and using the next observation in the time series as the target variable.

For example, suppose we want to predict the next value in a time series based on the previous three values. We can frame this as a supervised learning problem by using the first three observations as input features and the fourth observation as the target variable. We can then use an SVM regression model to learn the relationship between the input features and the target variable. Another approach to using SVMs for time series prediction is to treat the time series as a sequence of data points and use an SVM-based sequence prediction model. This involves training an SVM to predict the next value in the sequence based on the previous values, similar to recurrent neural networks (RNNs). Overall, SVMs can be a useful tool for time series prediction tasks, particularly for data with short-term dependencies and where interpretability is important. However, selecting appropriate input features and tuning the model parameters can be challenging, and more complex models such as RNNs may be necessary for certain types

[4] A bootstrap sample is a sample of data that is drawn from the original dataset by sampling with replacement. In other words, a bootstrap sample is obtained by randomly selecting observations from the original dataset, with replacement, until a sample of the desired size is obtained.

of time series data.

2.8 Dealing with mixed frequencies

MF MIDAS regression models, MF-VAR's and other models use the aggregation proposed by Mariano & Murasawa (2004) in order to deal with the mixed frequency problem inherent to GDP nowcast. The authors demonstrated that if the sample mean of the three months of a quarter can be well approximated by the geometric mean then the quarterly growth rate can be decomposed into moving averages of the monthly rates, in particular, the quarterly growth rate can be expressed as:

$$y_\tau^q = \frac{2}{3}y_t^m + \frac{1}{3}y_{t-1}^m + y_{t-2}^m + \frac{1}{3}y_{t-3}^m + \frac{2}{3}y_{t-4}^m$$

As we shall see, the dynamic factor model, with agregation on it's factors is one notable example of the aplicability of this relation.

In recent work, IMF (2022) compared machine learning models with factor-calculated models using out of sample-sized error measurements. In another work Maynard (2020) also compared Machine Learning models with simulated factor models. Neither of these works used the dynamic factor model with the aggregation of Mariano & Murasawa in the factors, Valk et al. (2017) and Martins (2020) showed that this aggregation improves the GDP nowcast of dynamic factor models. Maynard (2021) discusses that Ridge Regressions together with DFM's are a powerfull tool for nowcasting, but also don't make use of the Mariano & Murasawa aggregation.

3 Database

The main idea of the paper is to create a scalable approach to implement nowcasting of economic activity using real time data using a database of Brazilian economic activity indicators of several sorts and frequencies shown in table 1. Concerning the database used in our exercise, the nowcasting main algorithm may or may not have all the series here described, as we're constantly trying new configurations of regressors in order to better nowcast GDP.

Table 1: Description of the variables

Data ID	Series Explained	Frequency/type
PIM_IG	Industrial Production General Index	Monthly/Industry
PIM_EXT	Industrial Production Extractive Index	Monthly/Industry
PIM_TRANS	Industrial Production Transformation Index	Monthly/Industry
PIM_BK	Industrial Production Capital Goods	Monthly/Industry
PIM_BC	Industrial Production Consu Goods	Monthly/Industry
PIM_BCD	Industrial Production Durable Cons Goods	Monthly/Industry
PIM_BI	Industrial Production Intermediary Goods	Monthly/Industry
PIM_ITCC	Industrial Production Typical Build.	Monthly/Industry
PMC_IG_VA	Retail Sales - General enlarged volume	Monthly/Retail
PMC_IG_VR	Retail Sales - General enlarged volume	Monthly/Retail
CS_FGV	Services Confidence Indicator (FGV)	Monthly/Sentiment
IBC_BR	Economic Activity Monthly Indicator	Monthly/General
ABCR	Tolled Vehicle Flow Index	Monthly/leading
ABPO	Corrugated Paper Index	Monthly/leading
Abraciclo	Motorcycle License Plate Index	Monthly/leading
anfavea2	motor vehicle financed index 2	Monthly/leading
anfavea3	motor vehicle financed index 3	Monthly/leading
Fenabrave...19	License Plate Vehicles Index	Monthly/leading
CNI...20	Industry Indicator Index (hours worked)	Monthly/leading
ABAL	Produced Aluminum Index	Monthly/leading
funcex1	External sector data (Exports)	Monthly/leading
funcex2	External sector data (Imports)	Monthly/leading
funcex3	External sector data (Therms of trade)	Monthly/leading
funcex4	External sector data (Therms of trade)	Monthly/leading
fgv1	Confidence Consumer index 1	Monthly/Sentiment
fgv2	Idleness index	Monthly/Sentiment
IAB	Steel Production Index	Monthly/leading
ONS	Electric Charging Index	Qtly/General
rf1	Families Income 1	Qtly/General
rf2	Families Income 2	Qtly/General
rf3	Families Income 2	Qtly/General
Abras	Supermarket Sales Index	Qtly/General
CNI	Industrial Production Volume produced cni	Monthly/leading

Data ID	Series Explained	Frequency/type
Fecomércio	Sentiment Index business indicator	Monthly/leading
Fenabrave	Vehicles Distributed Index	Monthly/leading
Serasa	Credit Default Indicator Index 1	Monthly/leading
ANP1	Oil Produced Index 1	Monthly/leading
ANP2	Oil Produced Index 2	Monthly/leading
ANP3	Oil Produced Index 3	Monthly/leading
SPC	Credit Default Indicator Index 2	Monthly/leading
Usecheque	Payment Indicator (Checks)	Monthly/leading
IPEA_FBCF1	IPEA gross fixed capital formation 1	Monthly/Coincident
IPEA_FBCF2	IPEA gross fixed capital formation 2	Monthly/Coincident
IPEA_FBCF3	IPEA gross fixed capital formation 3	Monthly/Coincident
IPEA_FBCF4	IPEA gross fixed capital formation 4	Monthly/Coincident
LSPA1	Agricultural production 1	Monthly/Agric.
LSPA2	Agricultural production 2	Monthly/Agric
ICI - FGV	Confidence Industry indicator 1	Monthly/Sentiment
ISA - FGV	Actual Conjuncture Confidence Indicator	Monthly/Sentiment
est_termo	Therm Structure of interest rate	Monthly/Financial
IBOVESPA	number of operations in BR Stock Ex.	Monthly/Financial
IE - FGV	Expectations Indicator	Monthly/Sentiment
NUCI - FGV	Idleness Indicator	Monthly/coincident
PIB(1)	First Difference of GDP	Qtly/General
PIB(2)	Second Difference of GDP	Qtly/General
RNB	Gross Domestic Income	Qtly/General
CONS_CNT	Families Consumption	Qtly/General
FBKF_CNT	Gross Fixed Capital Formation	Monthly/Industry
cambio_real	Dolar/BRL Currency	Monthly/International
usa_atividade	USA Economic Activity	Qtly/International
gtrends	google searches - unemployment	Monthly/General
cdi_eua	American inter-bank deposit rate	Monthly/Financial
jobs_survey	American employment survey	Monthly/Financial

One of the main problems in Nowcasting Economic Activity is the fact that in general, along the dates defining the *vintages*, the database becomes unbalanced, that is, as if it were not enough for the variable of interest to have a frequency different from that in which the data are observed, the nature of the intra-quarter releases causes the database to present the characteristic that the literature calls *jagged-edge*. Due to the large number of models estimated, we will not present a unique solution to this problem, for the simple reason that each model requires a different solution. For example, in the case of the MIDAS model the balancing of the base must follow a "frequency alignment", whereas in the case of machine learning algorithms and dynamic factor models the balancing can be done in the same way. In general, to set the database in the real-time exercises using the entire surveyed database, when necessary, we will use machine learning models to fill in the *missing values*, thus dealing with the Jagged-Edge problem.

4 Methodology - Nowcasting Strategy

A GDP Nowcasting Strategy is a method used to predict the current level of a country's Gross Domestic Product (GDP) in real-time or near-real-time using the most recent available data.

4.1 Unbalanced Panel

Updating the time series matrix in real time results in a razor tooth or "jagged edge" database, the strategy used to deal with this problem requires a panel balancing method, some works use as a balancing method the simple naive forecast (from a well calibrated autoregressive model) applied on each column of the observations matrix. In our case, we use the following procedure to deal with the unbalanced basis problem.

- **Step 1**: Select the column of the updated series (or series) on each day of nowcasting.
- **Step 2:** Using the date of the update of these series as the projection horizon for the most lagged series select the machine learning algorithm that performed best (according to the metrics used (RMSE, MAE)) in the past vintages.
- **Step 3:** Make out-of-sample projections up to the selected horizon for each of the series with missing values.

Following these steps one should have a balanced time series panel, the only missing values should be the values of the GDP to nowcast at the quarter of concern.[5]

4.2 Estimation and Performance Tests

To evaluate the accuracy of the models used in our nowcasting algorithm, we formulated the following Backtesting Strategy:

[5]The only model used in our strategy that does not fit in this procedure is the MIDAS model, because the structure of the model requires a separate frequency alignment. Therefore for the MIDAS model the Nowcasting strategy is done separately, in this case we emphasize that the number of rows of the matrix must be equal to three times the number of observations of the lower frequency series (in this case GDP), in some vintages this rule will not be respected, to estimate MIDAS we will then need to use some of the machine learning models to make the frequency alignment satisfied. In this topic we follow Ghysels et al. (2016), addressing the frequency alignment issue by aggregating the high-frequency data to match the low-frequency data. This is done by using weighted averages of the high-frequency data, where the weights are estimated as part of the model. Specifically, the authors use polynomial weighting schemes, such as the Almon lag polynomial, the Beta lag polynomial, and the Exponential Almon lag polynomial.

- 1) Make pseudo real-time databases in final quarters of each year, in this way we set different training samples and one step ahead test samples.
- 2) Separate the database into training set and test set, as we noticed, a general interest of the scientific community was to interpret the behavior of these models after the COVID-19 event, knowing this, we used a pertinent first time window for the backtesting, for the first nowcast then, the training set is the entire pre covid period, i.e., 1996 (year of the first YQoQ(%) release of Brazilian GDP) until March 2020 (vintage of first estimation), thus we will have the out-of-sample estimations after the COVID-19 period, starting from march 2020, always using end of quarter data[6]. That is, we put ourselves in a period in time that from which all data for Q2 2020 GDP was available except the own GDP (Hence the name fully informed expectations). After that, we repeated this procedure by re-estimating the models up to August 2022 and computing the pertinent metrics.
- 3) After separating the base into training set and test set, we estimate all models as if we were on the eve of the covid 19 events, i.e., the first vintage used in the exercise is that of February 28, 2020. This procedure is done only to evaluate the accuracy of the models, the main code of work will allow the selection of any vintage anywhere in time in order to get backtesting out-of-sample results. The only caveat here is the fact that all the series are prone to revisions, our main algorithm deals with this problem updating all the series in each nowcast, but this exercise it's not revision proof.
- 4) Calculation of selected error metrics (RMSE, MAE) to evaluate the predictive potential of these nowcasts against two different benchmarks.
- 5) Perform Diebold-Mariano tests. In the paper, we evaluate projections h = 10 steps ahead using the Diebold Mariano test using the standard error computation method to compute the loss function. For the framework of the test, we will use the null hypothesis that the forecast of the model is less accurate than that of the benchmark , a Well specified ARIMA or Central Bank FOCUS market expectations. Thus, if the p-value is smaller than a certain predetermined value, we can vouch for the quality of the model projection. In this case, we attest that the model projections beat a benchmark model.

4.3 Classical vs Machine Learning Methods

The exercises done are in the sense of estimating models traditionally classified as "machine learning" methods and methods that, in some classifications, may also fall under this nickname but are estimated in the classical nowcasting literature, that is, we will classify these methods as "classical models". In our classification these models are classical in the sense that they have been part of the nowcasting literature, both for inflation and GDP, for much longer than the techniques under the "Machine Learning" umbrella. In the classification of classical models, we estimate MIDAS (Mixed Data Sampling Regression), Dynamic Factor Model (two

[6] This is done in order to compare performances with what we call fully informed market expectations.

step) and Dynamic Factor Model (two step - Mariano & Murasawa factor aggregation). Under the ML classification, we estiamte LASSO, adaLASSO, Ridge, Elastic Net, Neural Networks, Bagging & Bootstrapping methods, Complete Subset Regression, Random Forests and Support Vector Machines.

5 Estimation and Forecasting Results

5.1 Classical Models

5.1.1 MIDAS

To estimate the MIDAS model we follow Ghysels et al. (2016), the main challenge is to adjust the database according to the required "frequency alignment". It is interesting to note that the real-time data update procedure is much simpler for this model than all the other estimated models. As we have pointed out, we used the base described above and the result for the projections was not satisfactory, for the MIDAS model we then decided to test a more sparse database in the follow-up and updating of the Brazilian GDP, in this case we opted for the following regression:

$$PIB_t^Q = \alpha + \beta_1 PIB_{t-1}^Q + \beta_2 PIM_t^M + \beta_3 PMC_t^M + \beta_4 IBCBR_t^M + \epsilon_t$$

This would be a regression with simple time series in the way it was put, however it should be understood that in all variables within the model it was used the aggregation with the Almon polynomial explained earlier, this aggregation allows to map variables of different frequencies in the same simple regression, the estimation of the MIDAS model is done by non-linear least squares. The superscripts Q and M mean that the series have quarterly and monthly frequencies respectively. Table 2 shows the summary of our MIDAS regression results.

Table 2: MIDAS Model Regression Results

Variable	**Estimate**	**Standard Error**	**t-statistic**
Intercept	0.5485***	0.15882	3.468
lag(GDP)	0.1211***	0.0324	3.725
Industrial Prod. (IBGE)	-0.174643***	0.02559	-6.824
Retail Sales (IBGE)	0.0686**	0.0231	2.992
IBC Br (Central Bank)	59.1823***	2.9312	20.190

Signif. Codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' '

Regarding the choice of regressors, the industrial production measured by the monthly industrial survey is remarkably one of the variables that most explains the Brazilian GDP, being on a par with the monthly trade survey. We have included the IBC-BR, the Central Bank Activity Index.

5.1.2 Dynamic Factor Models

In order to estimate Dynamic Factor Models, first, using the full base described above, we selected the number of factors via information criteria. As we can see, the information criteria point to three, two, and seven factors to extract, to preserve degrees of freedom in our estimation we selected two factors only. Remember that estimating dynamic factor models involves specifying a VAR, whose degrees of freedom are lost depending on the number of independent variables included and the number of lags required in the model structure. For example, take a VAR(3) on a database with 3 variables, then each VAR equation will have $3 \cdot 3 + 1 = 10$ parameters including the constant, this number is acceptable with a small series like GDP, however if we consider 7 extracted factors, as pointed out by the third criterion, we will have in a VAR(7) $7 \cdot 7 + 1 = 22$ parameters, if we understand that the GDP series within the sample considered in this estimation presents a little more than 85 observations we realize the size of the problem[7]. First we estimate Dynamic factor models using two factors and then three factors extracted, using the two steps method, and then, we estimate the same models using two steps aggregating the factors extracted by using Mariano Murasawa aggregation. Figure 6 shows information criteria for dynamic factor model with three dynamic and static factors extracted. Using these criteria, we estimated factor models with 3 lags and 3 dynamic factors extracted and also with 2 lags and 2 dynamic factors only. As we can notice at a first glance, the dynamic factor model with 3 extracted factors and 3 lags did not perform so well in our vintages, the same behavior observed in the previous model occurs, that is, right after the pandemic the model performs poorly and then becomes better, however it is notable that this estimation does not beats the fully informed expectations. On the statistical significance side, our bridge equation presented stastically significant results for this estimation. However, the significance remains at optimal level as we can see in the table below.

Table 3: DFM (3,3) Bridge Equation Summary

Variable	**Estimate**	**Standard Error**	**t-statistic**
Intercept	0.02227***	0.00084	26.6
Factor 1	0.00510***	0.00016	30.5
Factor 2	0.00185***	0.00038	4.8
Factor 3	-0.00342**	0.00044	-7.7

Signif. Codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' '

With this, we set out to estimate the DFM(2,2) model as the information criteria pointed out. At a first glance there doesn't seem to be a very satisfactory performance either. However, we need statistical evaluation to determine whether the models perform well or not.

[7]More at: https://kevinkotze.github.io/ts-7-var/

Table 4: DFM (2,2) Bridge Equation Summary

Variable	Estimate	Standard Error	t-statistic
Intercept	0.02227***	0.00091	24.3
Factor 1	0.00510***	0.00016	30.5
Factor 2	0.00508***	0.00018	28.1

Signif. Codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' '

After estimating these models we can compare them with the Naive model using Mariano Murasawa test. The test rejects the Null hypothesis that DFM's are less accurate than the naive model in forecasting the Year - Quarterly GDP Growth at 1% significance However, Diebold Mariano tests point out that both DFM(2,2) and DFM(3,3) are unable to defeat fully informed market expectations.

5.1.3 Dynamic Factor Models with Factor Aggregation

The classic literature of dynamic factor models has used Mariano and Murasawa's aggregation on factors to improve the quality of nowcasting models [8], here we use the same method in order to evaluate these nowcasts compared. We used the Mariano & Murasawa aggregation as we highlighted in section 2.8. The results are a little different when we look at statistical significance, after aggregating the factors extracted the bridge equation regression became less significant, but still the coefficients are statistically significant at maximum of 1%.

Table 5: Significance DFM(3,3) with Mariano Murasawa Aggregation on it's factors

Variable	Estimate	Standard Error	t-statistic
Intercept	0.0219***	0.000816	25.2
Factor 1 agg	0.00062***	0.00002	27.8
Factor 2 agg	0.00125**	0.00004	2.7
Factor 3 agg	0.00008*	0.00008	-2.3

Signif. Codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' '

5.2 Machine Learning Methods

For machine learning methods we will skip some details regarding estimation, the packages used in R for estimating these models are in general very standard.

[8] Stock & Watson, 2016

5.2.1 LASSO

The LASSO (Least Absolute Shrinkage and Selection Operator) is a popular shrinkage method for selecting relevant economic variables in forecasting and nowcasting models. It combines regularization with variable selection, resulting in a more interpretable and parsimonious model.

LASSO works by adding a penalty term to the ordinary least squares (OLS) objective function, which forces the sum of the absolute values of the coefficients to be less than a predetermined value. The penalty term shrinks the coefficients of less important variables towards zero and sets the coefficients of irrelevant variables to exactly zero. This process effectively removes them from the model, leading to automatic variable selection.

In the context of nowcasting economic variables, LASSO can be particularly useful due to the following reasons:

- High-dimensional data: Economic datasets often contain a large number of potential predictors. LASSO helps to navigate this high-dimensionality by identifying a subset of relevant variables, leading to more accurate and interpretable models.
- Multicollinearity: Economic variables often exhibit multicollinearity, with high correlations between predictors. LASSO helps to mitigate multicollinearity issues by generating stable and unique coefficient estimates.
- Overfitting: By shrinking the coefficients of less important variables, LASSO prevents overfitting, leading to better out-of-sample forecasting performance.

The variable that presents the greatest weight in the GDP projection according to the LASSO selection was the FGV's idle capacity indicator, the NUCI. Also noteworthy is the negative impact on Brazilian GDP growth of the general government net debt. We also estimate a second LASSO model, the difference of this second estimation is only the pre-treatment of the data, in the former we used only the original database without lags, in the second estimation we used lags of the own nowcasting database. We did not have much change in the regressors selected for the final estimation between the first and the second estimations of LASSO.

5.3 AdaLASSO

LASSO (Least Absolute Shrinkage and Selection Operator) and adaLASSO (Adaptive LASSO) are both regularization methods for linear regression that aim to improve model accuracy and variable selection. The main difference between them lies in the penalty term applied to the coefficients. For a linear regression model, let $\mathbf{y}$ be the response variable, $\mathbf{X}$ be the predictor matrix, and $\boldsymbol{\beta}$ be the coefficient vector. The objective functions for LASSO and adaLASSO are as follows:

- LASSO:

$$\hat{\boldsymbol{\beta}}_{\text{LASSO}} = \arg\min_{\boldsymbol{\beta}} \left\{ \frac{1}{2n} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 + \lambda \|\boldsymbol{\beta}\|_1 \right\},$$

- adaLASSO:

$$\hat{\boldsymbol{\beta}}_{\text{adaLASSO}} = \arg\min_{\boldsymbol{\beta}} \left\{ \frac{1}{2n} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 + \lambda \sum_{j=1}^{p} w_j |\beta_j| \right\},$$

In the adaLASSO formula, w_j represents the adaptive weights for each coefficient, which are typically chosen based on some preliminary estimates of the coefficients, such as the OLS estimates. By introducing these adaptive weights, adaLASSO improves upon LASSO's variable selection consistency and estimation accuracy.

5.4 Ridge Regressions

Now we estimate a ridge regression, we use the cross validation method to obtain the optimal values for λ[9], taking the package default, we use 10 cross-validations to obtain this parameter. After the estimation we can look at the realized values against the estimated values in an out-of-sample exercise.

5.5 Neural Networks

In the case of neural networks we made three estimations, the difference between the estimations is the configuration of the neural network, in the first one we used a hidden layer and 2 neurons, in the second one we used a hidden layer and 3 neurons, and in the last estimation we used two hidden layers where the first presents 4 neurons and the second presents 2 neurons. We would like to point out that the determination of these parameters is the subject of a separate study, one direction in which we can advance in the quality of our projections is to improve the choice of these networks, additionally, it is interesting to note that there is a long way to go towards the use of *deep learning* techniques involving these networks.

5.6 Other models

We also estimated the BAGGING, Complete subset regression and Support Vector Machines models.

[9]The parameter λ, both in LASSO, ridge and elastic net, is the parameter that dictates the degree of penalty that the regression parameters will suffer. In the case of ridge, it is interesting to choose λ with some method, in our case we use cross-validation.

5.6.1 Selection Algorithm

Since we have the expectations beforehand, we can encompass them in the projection of the models in an algorithm, that is, we can select the models that are closest (above or below) the perfectly informed market projection, so we can somehow improve the projection in an automatic way, below we perform this experiment with the classical models and compare them with the perfectly informed projection. The selection algorithm takes into account a metric $d(\mathcal{M}, \mathcal{E})$ defined as follows: Let $\mathcal{M}, \mathcal{E}$ be respectively the set of model projections taken into account and perfectly informed market expectations respectivelly. Additionally define $\mathcal{FF}$ as the set of models selected at the final forecast. We detail the selection algorithm below:

- 1) Define a real value for α
- 2) Calculate $d(\mathcal{M}_i, \mathcal{E}) = |\mathcal{M}_i - \mathcal{E}|$, $\forall i \in I_j$, where I_j is the set of natural numbers that index all models encompassed in this algorithm.
- 3) If the signal of the forecast is different from the signal of the expectation discard that model from $\mathcal{FF}$ in this step.
- 4) If $d(\mathcal{M}_i, \mathcal{E}) > \alpha$, discard $\mathcal{M}_i$ from $\mathcal{FF}$, else, include $\mathcal{M}_i$ in $\mathcal{FF}$.
- 5) If no model succeed in the step 3 or 4, select only the expectation.
- 6) The final forecast is: $\hat{\mathcal{F}} = \frac{\sum_{i=1}^{k} M_i}{k}$, where k is the number of models selected.

We want to highlight the importance of selecting α according to your own expectations, if the policy-maker it's more confident that the market has the right call about economic activity, one should consider lower the value of α along the vintages, the opposite it's also true, if the policy-maker it's confident that the market expectations are completely wrong about the economic activity, it's desirable to set a higher value for alpha. One should expect the α values to be higher when there's no hard data concerning the current quarter available, as the time of the quarter goes by the value of α should lower, proportional to the increase of market expectations theoretical accuracy power. It's desirable that the minimum value of α it's closer to 2%, this value used here still preserves the idiosyncrasies of each nowcast from estimated models, if the numbers are not making any sense using α near to this value, the policy-maker should consider reestimate the models.

5.7 Results - Forecasting Exercises

Table 6 summarises the results. it is important to emphasize that we compare the models against two benchmarks: ARIMA and fully informed market expectations. The fully informed market ecpectations are used to perform a real test to decide whether the use of a model adds or does not add value in the projection of a macroeconomic variable is its comparison with the market projections. In Brazil these projections are carried out by the FOCUS survey. it is important to note that in many works, there is a mistaken notion of what market expectations are, that is, the time at which they are collected makes a lot of difference. In the case of GDP, the relevant data for the following quarter all come out around the second month after the reference quarter, so using expectations collected before that underestimates the power of market expectations. To emphasize that we deal with this problem by putting expectations on an equal base with our projections, we will call these expectations collected two months after the reference period fully informed expectations. Table 6 shows that none of the models alone were capable of defeating the fully informed market expectations, the only nowcast that does this it's the nowcast that arises from the selection algorithm using machine learning techniques. The nowcast from a combination of machine learning models defeats the fully informed market expectations.

Table 6: Forecasting Results - Error metrics of estimated models and DM test significance against Market and Naive model respectively.

Model	**RMSE**	**DM stat. (Market)**	**MAE**	**DM stat. (Naive)**
FULLY INF. MKT.	0.95		0.88	
ARIMA	9.61		8.98	
MIDAS	3.38	4.37	2.99	-2.78*
DFM1	9.43	4.02	8.36	-3.53**
DFM2	7.86	3.70	6.97	-3.85**
DFM3	10.83	3.60	9.60	-4.68***
DFM4	10.21	3.52	9.05	-4.92***
BAGGING	2.03	4.07	1.80	-3.75**
RF	3.47	4.12	3.08	-3.59**
CSR	2.48	3.87	2.20	-3.76**
SVM	2.83	4.66	2.51	-3.58**
LASSO1	2.01	4.26	1.78	-3.73**
LASSO2	3.49	3.41	3.09	-2.79*
adaLASSO	1.76	5.43	1.56	-3.64**
RIDGE	1.67	3.50	1.48	-3.81**
ELASTIC NET	2.31	4.76	2.05	-3.68**
RNN1	2.74	3.74	2.43	-3.79**
RNN2	1.82	22.40	1.61	-3.50**
RNN3	2.51	6.30	2.22	-3.49**
COMBO CLASS.	1.19	4.36	1.01	-3.73**
COMBO ML.	0.54	6.21***	0.48	-3.81**

The application of the model selection algorithm brings satisfactory results for the machine learning model. The projection improves significantly. Note that some machine learning models are able to beat the perfectly informed market, yet only for brief periods. None model consistently beat the market expectations. However, the use of the algorithm improves the predictions, leading to more consistent results. As an example of this result, a visual analysis of Figure 1 shows that the MIDAS model estimated in these vintages, on average, does not beat the fully informed market, although in 2021 and 2022 it performs better than the market expectations model. The results indicate that the selection algorithm greatly improves the final forecast, pointing out that the combination of models is the best alternative to beat the market. The results are similar for a set of models. All models are superior to the naive one at 1% significance. On the other hand they are not superior, by themselves, to the perfectly informed market estimates, yet during some periods of times that are able to outperform the benchmark. In general, the results point out that machine learning models are superior to classical models. Moreover, there is no linear combination among the classical models' projections that can outperform the perfectly informed market's projections. In the case of machine learning models, the result is repeated, the models alone fail to beat the market projections. Yet, once we combine the models it is possible to beat the market. The difference is statistically significant as shown in table 6. Figure 2 shows graphically the predictions from the combination of the machine learning models and the fully informed market expectations. The prediction of the combination of machine learning models is consistently better than the market expectations model.

6 Concluding remarks

In this work we estimate several models used in nowcasting literature in order to show that a combination of machine learning models can beat the fully informed market expectations at the eve of GDP releases, this performance is reached once we include a selection algorithm with a proposed metric, below we highlight a list of results of our work.

- Machine learning methods perform better in this exercise, however, it's not the case that these models are unconditionally superior, we estimated a very large number of models from this literature. The combination of the projections outperform the market expectation model in a consistent manner. yet, individual models are better only in determined periods.

- The Diebold Mariano test between the combination of machine learning models and perfectly informed expectations reveals that the combination coming from our algorithm is superior to market expectations at 1% significance (p-value of the order of 10^{-5}).

- The model-matching algorithm improves the projection of the classical models but does not generate a projection that is better than the one made by the market on the eve of the GDP release.

- The aggregation of factors in dynamic models using Mariano & Murasawa's aggregation did not improve the projection of the models, contrary to evidence in the literature.

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7 Anexes

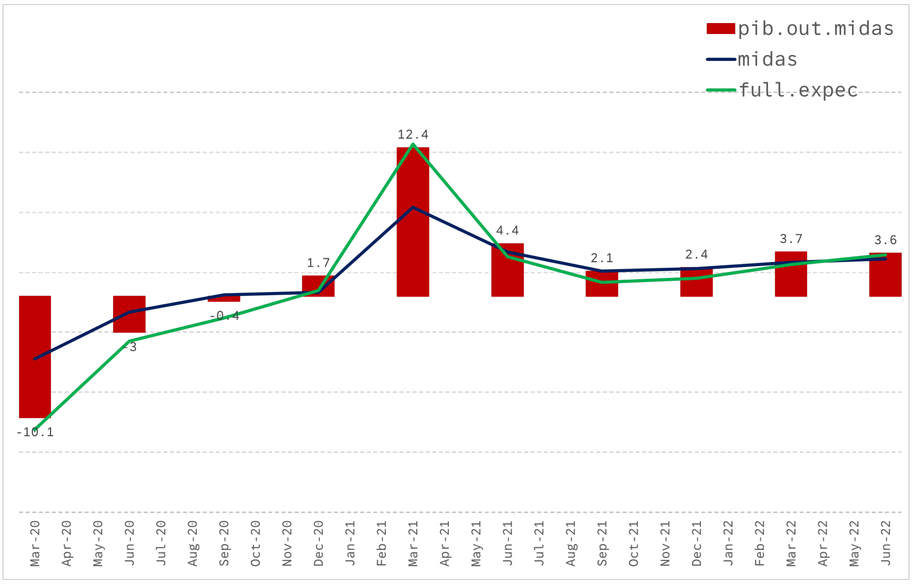

Figure 1: Out of sample forecast comparison MIDAS/fully informed market expectations

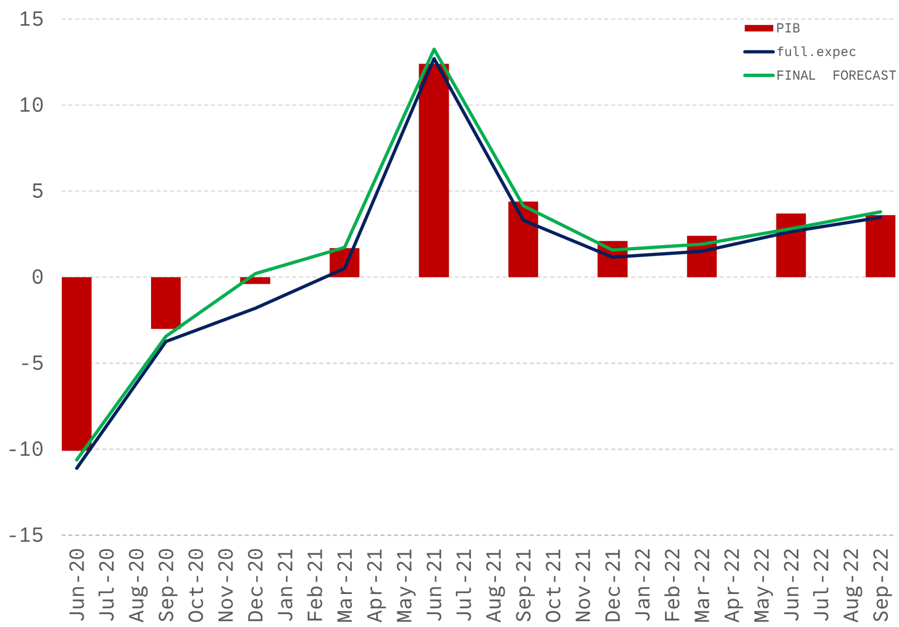

Figure 2: Out of sample comparison combination of machine learning models and fully informed market expectations