Analysis and synthesis assignment

Should Macroeconomic Forecasters Use Daily Financial Data and How?

Léo Renault · Nicolas Annon · Théo Verdelhan · Arthur Le Net

January 31, 2026

Quantitative Management

Master 2 272 – Economic and Financial Engineering
Quantitative Finance Track
Paris-Dauphine University–PSL

Contents

Preamble

Purpose of the document. This document presents a reading, analysis, and summary work based on the research article entitled *Should Macroeconomic Forecasters Use Daily Financial Data and How?*. We synthesize the authors' methodological contribution, in particular the use of MIDAS approaches and how to exploit daily financial data for macroeconomic forecasting.

Elena Andreou
Department of Economics, University of Cyprus, CY 1678 Nicosia, Cyprus
`elena.andreou@ucy.ac.cy`

Eric Ghysels
Department of Economics, University of North Carolina, Chapel Hill, NC 27599–3305,
and Department of Finance, Kenan–Flagler Business School, Chapel Hill, NC 27599
`eghysels@unc.edu`

Andros Kourtellos
Department of Economics, University of Cyprus, CY 1678 Nicosia, Cyprus
`andros@ucy.ac.cy`

1 Introduction

This work proposes a replication of the article *Should Macroeconomic Forecasters Use Daily Financial Data and How?* by Andreou, Ghysels and Kourtellos (2013). The study fits into the macroeconomic forecasting literature and questions the relevance of using daily financial data to anticipate variables observed at lower frequency, in particular quarterly GDP growth.

The central argument is that asset prices quickly incorporate information and agents' expectations, which can provide a useful signal for forecasting real activity. The challenge, however, is to integrate this high-frequency information properly without losing intra-period dynamics through overly naive aggregation. The article highlights two main difficulties: on the one hand, the management of mixed frequencies (daily vs quarterly); on the other hand, summarizing the information contained in a large number of financial series covering several asset classes.

The authors propose to address this using MIDAS (*Mixed Data Sampling*) regressions, which link a quarterly variable to daily observations without imposing uniform weighting. In this approach, a parametric weighting scheme summarizes high-frequency information parsimoniously. The article also discusses nowcasting-type extensions through the introduction of leads (*leads*), in order to mobilize the information available within the current quarter while respecting the information calendar.

Our replication has three objectives. First, to reproduce the main empirical results of the article, following the sample periods and the out-of-sample evaluation logic. Second, to make explicit the operational choices required for implementation (factor construction, parametrization, pseudo out-of-sample protocol and metrics). Third, to propose and test a simple extension of the initial framework, in order to assess whether a slight relaxation of the weighting structure can improve performance in certain configurations.

2 Context, motivation and contribution of the study

2.1 Research question and context

Macroeconomic forecasting generally relies on models using variables observed at monthly or quarterly frequency, even though financial markets continuously generate abundant daily information. This gap raises a central issue: how to efficiently exploit the information contained in daily financial data to improve the forecasting of aggregated economic activity, without introducing biases related to temporal aggregation or parameter proliferation? This question is particularly important in a context where asset prices are reputed to rapidly incorporate expectations and informational shocks, such as during periods of high macro-financial instability since the election of the President of the United States, Donald Trump.

From a methodological standpoint, classic solutions to link high-frequency variables with low-frequency variables consisted in aggregating high-frequency financial data:

(1) Temporal aggregation (for example average, sum, last value, etc.): We transform the high-frequency data $x_{t,i}$ (for example daily) into a low-frequency variable X_t (for example quarterly) by the average for example:

$$X_t = \frac{1}{m}\sum_{i=1}^{m} x_{t,i}, \tag{1}$$

where m denotes the number of high-frequency observations contained in period t, about 60 for a quarter. Then, we estimate a standard linear regression linking the aggregated variable X_t to the low-frequency target variable:

$$Y_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}. \tag{2}$$

Result: loss of information on intra-period dynamics, all data have the same weight. There is no economic justification for older data to be as informative as more recent data.

(2) Naive regression with all high-frequency data: aims to include directly the high-frequency observations in the regression linking the low-frequency target variable to its predictors. the estimated relationship can be written as:

$$Y_{t+1} = \alpha + \sum_{i=1}^{m} \beta_i x_{t,i} + \varepsilon_{t+1}, \tag{3}$$

where $x_{t,i}$ denotes the i-th high-frequency observation (for example daily) within period t, and m corresponds to the total number of high-frequency observations contained in this period. Although this specification fully exploits the available high-frequency information, it presents several major econometric limitations.

1. *Explosion in the number of parameters.* when m is large (for example $m \approx 60$ trading days per quarter), the model requires estimating a large number of coefficients. Given the small size of the low-frequency sample, this leads to severe over-parameterization.
2. *Extreme multicollinearity.* if the observations $x_{t,i}$ are highly autocorrelated, which induces strong collinearity between regressors and leads to a very high variance of the coefficient estimators β_i.
3. *Overfitting.* the model fits the in-sample data excessively, producing lower forecasting performance out of sample.

   Result: impractical in practice because the number of parameters explodes

The conventional approach to predict a variable observed at a low frequency with high-frequency financial series consists in using an augmented distributed-lag regression model, ADL (p_Y^Q, q_X^Q). ADL regressions rely on aggregated high-frequency variables, which amounts to imposing a fixed, uniform weighting scheme. This aggregation choice is not econometrically neutral, as it assumes that intra-period information is homogeneous and independent of the horizon (does not depreciate over time).

Yet, in financial series, information is temporally ranked: the most recent data are more relevant (information diffuses gradually into the asset price). The central problem lies in the exogenous and non-adaptive nature of the weights imposed relative to the data and the forecasting objective.

Moreover, previous research attempts to address this problem through the nowcasting process. According to the authors, nowcasting addresses two major structural difficulties of real-time macroeconomic forecasting:

1. The asynchronous availability over time of a large heterogeneous sample of model variables (the so-called irregular boundary or jagged/ragged edge problem).

2. The inadequacy of standard real-time models: unsuitable for sequential updates.

Nunes (2005) and Giannone, Reichlin and Small (2008), among others, formalized nowcasting, which aims to exploit all information partially available at a given point in time. This process updates a forecast of the low-frequency variable (for example quarterly GDP), even before this variable is officially released, as new high-frequency data become available (estimating the current state of the target variable) while taking into account uncertainty related to missing data. The Kalman filter nowcasting approach can be interpreted as a probabilistic generalization of temporal aggregation, in which the implicit weights applied to high-frequency observations are endogenous and determined by a state–space model. But they are burdensome to specify, sensitive to modeling errors when the number of daily series is high. Unlike ADL regressions with flat aggregation, these weights result from the estimated dynamics of latent factors and the publication calendar.

Andreou, Ghysels and Kourtellos propose an extension of ADL regressions without arbitrary aggregation when integrating high-frequency data, while offering a reduced-form alternative to Kalman filter nowcasting. Their approach avoids the parametric burden and dependence on latent states specific to state–space models but retains the informational flexibility of nowcasting.

2.2 Objectives and contribution of the study

The main objective of the study is to assess the informational contribution of daily financial data for forecasting quarterly real GDP growth, by proposing a forecasting approach based on mixed-frequency (MIDAS) regressions. The analysis aims to go beyond the use of aggregated financial indicators by exploiting directly their daily dynamics, while avoiding the complexity inherent in structural state–space models. Although effective in some contexts, the latter require estimating a large number of parameters and become difficult to apply when the information set includes hundreds of daily financial series. On the empirical side, the study tries to highlight robust forecasting gains and to identify the most informative financial asset classes for forecasting real activity.

3 MIDAS regression models

Introduced in the 2000s by Ghysels, Santa-Clara and Valkanov, the MIDAS model is a mixed-frequency regression that links a low-frequency dependent variable (for example quarterly GDP) to high-frequency explanatory variables (daily financial data), without arbitrarily aggregating these data.

Suppose we want to forecast a variable observed at low frequency (e.g., quarterly) denoted $Y_{t+h}^{Q,h}$ using daily financial series considered as useful predictors. Let $X_{m-j,t}^{D}$ be the j-th daily observation counted backward during quarter t. the last day of the quarter corresponds to j = 0 (so the day before last j = 1). Then $X_{m,t}^{D}$ the j-th daily observation where m denotes the number of daily lags, or equivalently the number of trading days per quarter, assumed constant for simplicity.

Let the ADL–MIDAS(p_Y^Q, q_X^D) regression model be defined by:

$$Y_{t+h}^{Q,h} = \mu^h + \sum_{j=0}^{p_Y^Q-1} \rho_{j+1}^h Y_{t-j}^Q + \beta^h \sum_{j=0}^{q_X^D-1} \sum_{i=0}^{m-1} w_{i+jm}^h X_{m-i,t-j}^D + u_{t+h}^h. \tag{4}$$

In this model, the weighting scheme w_{i+jm}^h depends on a low-dimensional vector of unknown hyperparameters θ, which avoids the parameter proliferation problem.

The fundamental principle of MIDAS models is to approximate the full linear projection linking the low-frequency variable to the whole set of high-frequency observations using a low-dimensional parametric weighting structure. Rather than estimating a distinct coefficient for each high-frequency lag (observation), MIDAS models impose that coefficients follow a functional form depending on a small number of hyperparameters (parameter proliferation), which greatly reduces the dimension of the estimation problem.

Andreou, Ghysels and Kourtellos (2013) choose to use an exponential Almon lag polynomial. Let $x_{t,j}$ be the j-th high-frequency observation (for example daily) available within period t, with $j = 1, \ldots, m$. The exponential Almon weighting defines the weights $w_j(\theta)$ associated with each observation as:

$$w_j(\theta) = \frac{\exp\left(\theta j^2\right)}{\sum_{k=1}^{m} \exp\left(\theta k^2\right)}, \tag{5}$$

where $\theta \in R$ is a hyperparameter to estimate.

By construction, this specification imposes two essential constraints:

1. The weights are strictly positive, i.e. $w_j(\theta) > 0$ for all j ;
2. The weights are normalized, i.e. $\sum_{j=1}^{m} w_j(\theta) = 1$;

These constraints ensure identification of the associated slope coefficient (β^h) for the aggregated predictor and interpret it as an overall marginal effect of high-frequency data on the low-frequency variable. The exponential function can generate linear and decreasing weighting profiles, capturing a decreasing-memory mechanism in which more recent observations are more informative (relative importance). Thus, instead of estimating m distinct coefficients for each observation, exponential Almon weighting in MIDAS regressions allows summarizing the information contained in the m high-frequency observations using a single hyperparameter (θ^h) in order to obtain a linear projection of daily data onto the quarterly variable. This hyperparameter ensures strong parsimony in the coefficients associated with lags while retaining sufficient flexibility. If $\theta^h < 0$, the weights decrease with j, recent observations receive more weight, which is economically justified. This weighting scheme is particularly useful in our context given the small size of our data sample. By imposing a single hyperparameter, we reduce the variance of estimators (which can be high with quarterly data), improving the stability of optimization and out-of-sample robustness as a consequence.

In unreported exercises, the authors indicate having experimented with a two-parameter exponential Almon lag polynomial without observing an improvement in forecasting performance. First, the limited size of the low-frequency sample makes any over-parameterization particularly costly in terms of estimator variance. Then, the assumption of a monotone and decreasing weighting structure is economically coherent in a macroeconomic forecasting context, where the most recent financial information is assumed to contain more signals about future activity.

Note nevertheless that the authors estimate the parameters $(\mu^h, \rho_1^h, \rho_2^h, \ldots, \rho_{p_Q}^h, \beta^h, \theta^h)$ of the MIDAS regression model in equation (4) by nonlinear least squares.

In summary, unlike uniform temporal aggregation, exponential Almon weighting allows the data to determine endogenously the relative contribution of each intra-period observation, thus avoiding information loss and arbitrary weight specification.

Moreover, compared to a naive regression, Almon weighting imposes strong structural regularization that reduces the number of parameters to estimate. This constraint limits multicollinearity induced by high autocorrelation in high-frequency data and reduces the risk of overfitting, thereby improving out-of-sample forecasting performance.

3.1 Temporal aggregation issues

Data-driven parametric aggregation (MIDAS) can be linked to the temporal aggregation literature and to the ADL model by considering the following filtered low-frequency variable, determined by the parameters:

$$X_t^Q(\tilde{\theta}) = \sum_{i=0}^{m-1} w_i(\tilde{\theta})\, X_{m-i,t}^D \tag{6}$$

This equation (6) shows that the MIDAS approach remains a form of aggregation of high-frequency data. MIDAS models can be interpreted as a flexible extension of classic ADL models, in which the intra-period weighting structure is determined endogenously (parametrically). The shape of the weighting scheme is estimated from the data to better reflect the informational dynamics of high-frequency series. This approach captures decreasing-memory profiles, more consistent with the dynamics of financial series, while maintaining a parsimonious structure suited to limited sample sizes.

We can then define the ADL–MIDAS–M(p_Y^Q, q_X^Q) model, where M refers to the multiplicative weighting scheme of the model, namely:

$$Y_{t+h}^{Q,h} = \mu^h + \sum_{k=0}^{p_Y^Q-1} \rho_k^h Y_{t-k}^Q + \sum_{k=0}^{q_X^Q-1} \beta_k^h X_{t-k}^Q(\tilde{\theta}^h) + u_{t+h}^h. \tag{7}$$

A question arises as to how the regression in equation (4) relates to the more traditional approach involving the Kalman filter. In these models, the macroeconomic variable of interest is generally interpreted as a latent component, observed imperfectly through a set of high-frequency signals. The Kalman filter then allows combining these signals optimally, taking into account their dynamics and relative precision. Although the Kalman filter is optimal in a Gaussian framework, it is sensitive to specification errors and requires estimating a large number of parameters, especially when the number of high-frequency series is high.

Conversely, the MIDAS approach does not rely on introducing a latent variable nor on fully specifying a state model. It adopts a reduced-form representation, in which the low-frequency variable is directly linked to a weighted aggregation of observed high-frequency data. The weights play a role analogous to the filtering mechanism in state–space models, by determining the relative contribution of different intra-period observations to the forecast. It is an approximation of an optimal filtering process.

This approach has the advantage of being simpler to estimate, more robust in limited samples, and particularly suited to out-of-sample forecasting objectives, which motivates its use over Kalman-filter-based methods only.

3.2 Nowcasting and leads

The authors of the paper propose an alternative reduced-form strategy, based on MIDAS regressions with leads. They rely on exploiting high-frequency observations available between dates t and $t+1$, before the official release of the low-frequency macroeconomic variable. Imagine we are two months into quarter $t+1$, i.e., at the end of November 2025, and our objective is to forecast quarterly economic activity at the end of December 2025. We therefore have the equivalent of at least 44 trading days (two months) of daily financial data.

Let $X^D_{m-i,t+1}$ be the i-th day counted backward in quarter $t+1$ and consider J^D_X daily leads for the daily predictor in terms of multiples of months (number of months of lead used), with $J^D_X = 2. Then, X^D_{2m/3,t+1}$ corresponds to 44 leads, while $X^D_{1,t+1}$ corresponds to one lead for the daily predictor (3 months minus 2 months).

Formally, we can specify an ADL–MIDAS(p^Q_Y, q^D_X, J^D_X) model with leads of the form:

$$\begin{aligned} Y^{Q,h}_{t+h} &= \mu^h + \sum_{k=0}^{p^Q_Y-1} \rho^h_k Y^Q_{t-k} \\ &\quad + \beta^h \left[\sum_{i=(3-J^D_X)m/3}^{m-1} w^{\theta^h}_{i-m} X^D_{m-i,t+1} + \sum_{j=0}^{q^D_X-1} \sum_{i=0}^{m-1} w^{\theta^h}_{i+jm} X^D_{m-i,t-j} \right] + u^h_{t+h}. \end{aligned} \tag{8}$$

In this equation, $Y^{Q,h}_{t+h}$ denotes the quarterly macroeconomic variable to forecast at horizon h, while the first summation term captures the autoregressive dynamics of the low-frequency variable. The central term corresponds to a weighted aggregation of daily financial data, where MIDAS weights w^{θ^h} summarize high-frequency information using a small number of parameters. Note that there are various ways to hyperparameterize MIDAS polynomials for leads and lags.

$$\beta^h \left[\underbrace{\sum_{i=(3-J^D_X)m/3}^{m-1} w^{\theta^h}_{i-m} X^D_{m-i,t+1}}_{\text{(1) component with leads}} + \underbrace{\sum_{j=0}^{q^D_X-1} \sum_{i=0}^{m-1} w^{\theta^h}_{i+jm} X^D_{m-i,t-j}}_{\text{(2) component without leads (past)}} \right]. \tag{9}$$

The first component of this aggregation exploits daily observations available before the end of the quarter in quarter $t+1$, this is the notion of a lead (nowcasting with the term $X^D_{m-i,t+1}$). The second component integrates daily data from previous quarters, ensuring temporal continuity of the predictor and thus a form of memory with the term $X^D_{m-i,t-j}$.

MIDAS weights play a static filtering role, determining the relative contribution of the most recent daily observations compared to older ones. This approach addresses the ragged edge problem without explicitly modeling latent factors, allowing for parsimonious and robust estimation.

There are two important differences between nowcasting (using the Kalman filter) and MIDAS models with leads:

(1) Nature of forecasts: intra-period updates vs direct multi-horizon forecasts. *Nowcasting* typically refers to frequent updates of forecasts within the current period (for example forecasts of real GDP growth for the current quarter). MIDAS models with leads can also play this role, but also forecast real GDP at a future horizon (over several quarters). Above all, an important difference is that MIDAS regressions allow obtaining direct forecasts h steps ahead (a regression estimated specifically for each horizon), as opposed to iterative approaches that rely on the implicit dynamics of the model.

Kalman-filter-based nowcasting state–space models and MIDAS regressions share the ability to produce forecasts at multiple horizons. However, a key methodological difference is that state–space models generally rely on iterative forecasts, whereas MIDAS regressions allow estimating direct forecasts at horizon h. In an iterative approach, the model is estimated for a one-step-ahead forecast, then predicted values are recursively fed back in order to obtain an h-step forecast. This procedure exploits the implicit dynamics of the estimated model, but any specification error is transmitted and amplified over iterations. As a result, forecast quality tends to deteriorate as the forecast horizon lengthens. Conversely, MIDAS regressions rely on a direct forecasting strategy. For each horizon h, a specific equation is estimated, directly relating the variable of interest $Y_{t+h}^{Q,h}$ to the entire information set available at the forecast date. This approach avoids error propagation inherent to iterative forecasts and gives MIDAS models greater robustness to specification errors.

(2) Explicit treatment of the *ragged edge* and the role of the publication calendar. The second difference concerns the jagged/ragged edge nature of real-time macroeconomic databases. Kalman filter nowcasting explicitly addresses this problem, since the publication calendar and the structure of missing data play an important role in specifying the measurement equations of the state–space model. In addition, the Kalman filter allows missing observations in the measurement equations and permits ex post data revisions (a source of additional uncertainty). The MIDAS approach with leads models neither publication processes, nor latent dynamics of variables (Kalman filter), nor their joint distribution. The core idea is to reformulate the nowcasting problem by directly exploiting, in a regression, all the information effectively available at the forecasting date. Data asynchrony is no longer treated as a missing-observation problem, but as a lead structure, allowing integration of high-frequency data belonging to the current or next period. the authors rely on the idea that with the MIDAS approach new information is quickly incorporated into asset prices. Thus, real-time information flow is captured via high-frequency financial variables (fundamentally forward-looking nature of financial asset prices), which allows producing forecast updates and dispenses with continuous updating of low-frequency macroeconomic series and explicit modeling of the publication calendar. Unlike macroeconomic indicators, these financial variables are observed without significant measurement error and are not revised, which strengthens the empirical reliability of forecasts. Finally, the Kalman filter, in the nowcasting context, facilitates studying the impact of macroeconomic announcements, "shocks", on forecasts. MIDAS regressions with leads can also handle the irregular nature of series and provide similar tools. Indeed, MIDAS regressions allow estimating regressions around announcement dates (financial data before and after announcements) and analyzing induced forecast variations.

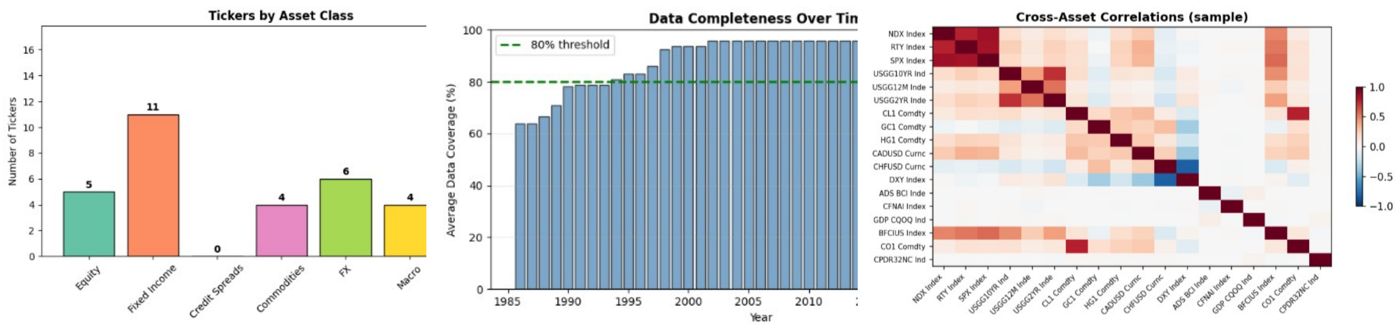
4 Data and preprocessing

This section describes (i) the series used, (ii) the transformations applied before factor extraction and MIDAS estimation, and (iii) the main difficulties encountered when ensuring consistency across multi-frequency data. Our protocol follows the approach of Andreou, Ghysels and Kourtellos (2013) (MIDAS + daily financial factors), while adapting it to a more restricted data universe than that of the paper.

4.1 Sources, frequencies and sample scopes

All financial and macroeconomic series are extracted from Bloomberg (Excel export), then restructured into a *date* × *ticker* panel. Financial data are observed at daily frequency (trading days), while the target variable is quarterly. Our database contains 47 daily tickers, covering the period from 02/01/1986 to 31/12/2025 (14 631 dates), i.e. a $14\,631 \times 47$ (dates × tickers) matrix. The series cover several asset classes (rates/sovereigns, credit/spreads, equities/volatility, FX, commodities), consistent with the paper's typology. The variable to forecast is quarterly U.S. real GDP growth (`GDP CQOQ Index`, in %), available for 161 quarters from 31/03/1986 to 31/12/2025. Over the sample, the mean is 2.71, the standard deviation is 4.22, with a minimum of -28.0 and a maximum of 34.9, reflecting in particular break episodes (COVID-19 crisis).

The authors work on two windows (1986–2008 and 1999–2008) and a much larger daily universe (up to ∼991 daily series). Our replication keeps the methodological logic (MIDAS regression, daily factor extraction, pseudo out-of-sample evaluation), but relies on a smaller ticker universe and an extended period up to end-2025 (data availability), which can modify certain stability properties (structural breaks, extreme volatility, etc.).



(a) Breakdown of tickers by asset class.

(b) Average data completeness (daily) over time.

(c) Cross correlations (panel excerpt).

Figure 1: Composition, coverage and dependence structure of the Bloomberg database used in the study.

4.2 Series construction and alignment

Series are aligned on a common time index (`DatetimeIndex`) and pivoted into wide format (columns = tickers). Infinite values are treated as missing and no interpolation is performed to avoid introducing artificial information. The quarterly GDP variable is aligned to quarter ends. In our implementation, quarterly GDP is reconstructed by taking the last available observation of `GDP CQOQ Index` within each quarter (end of period). Daily predictors are then used via blocks of m days preceding each quarterly date (see §4.3).

4.3 Transformations of daily data

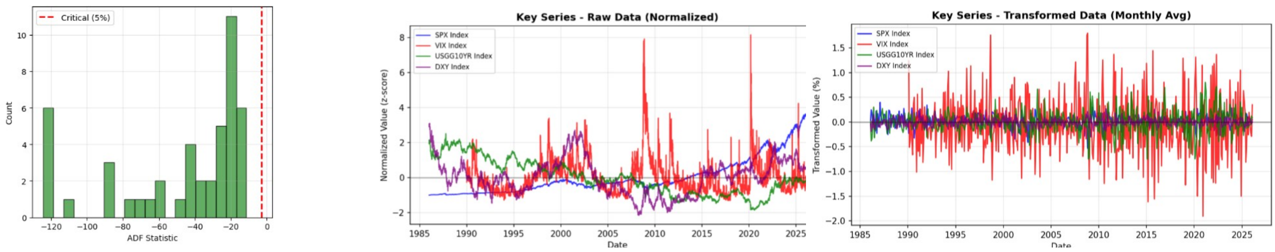
Financial series are transformed into stationary series before factor extraction and MIDAS estimation, in line with standard practices in empirical finance and the spirit of the paper (returns/differences, robustness to extremes). For strictly positive series (prices/indices), we use log-returns $x_t = 100\big(\ln X_t - \ln X_{t-1}\big)$. For series that can be zero or negative (rates, spreads), we use first differences $x_t = 100(X_t - X_{t-1})$. This rule avoids logarithm issues and standardizes units in percentage points.

Data Type	Transformation	Formula	Rationale
Prices/Indices	Log-returns	$r_t = \ln(P_t) - \ln(P_{t-1})$	Prices are I(1), returns are I(0)
Interest Rates	First differences	$\Delta x_t = x_t - x_{t-1}$	Rates can be ≤0, so log impossible
Spreads	First differences	$\Delta x_t = x_t - x_{t-1}$	Already in % but often I(1)
GDP Growth	None (kept in levels)	—	Already a growth rate, stationary

Figure 2: Transformation rules applied to the main series categories (prices/indices, rates, spreads, GDP).

After transformation, each series is winsorized at the 1% and 99% percentiles (capping extremes without removing observations). This choice limits the influence of atypical episodes (crises, quote errors) while preserving sample size.

Two series are not included in the extraction of daily financial factors: (i) the target variable `GDP CQOQ Index` (quarterly frequency), and (ii) a monthly macro series `NFP TCH Index` (non-daily frequency). These series can be used separately as macro indicators (benchmark FAR/FADL), but must not enter a daily PCA.



(a) ADF statistics (5% threshold). (b) Key series (raw data, normalized). (c) Key series (after transformation).

Figure 3: Transformation diagnostics: stationarity (ADF) and illustration on representative series before/after treatment.

4.4 Extraction of daily financial factors

We build daily financial factors by applying PCA to the panel of transformed daily series. The objective is to summarize the common information contained in the cross-section of series, while avoiding over-parameterization. Before PCA, series are standardized (mean-centering and scaling) so that no variable mechanically dominates component extraction because of its variance.

Let $X_t \in R^N$ be the vector of the N transformed and standardized series on day t. PCA constructs factors F_t as linear combinations

$$F_t = W^\top X_t,$$

where the columns of W are chosen to maximize explained variance, under orthogonality constraints. In our case, we retain $K = 5$ daily factors $\{DF1, \dots, DF5\}$.

Concretely, PCA is estimated over the period 03/01/1998–31/12/2025, which produces a factor matrix of dimension $10\,247 \times 5$. The factors explain a total of 57.5% of panel variance (DF1: 20.0%, DF2: 16.5%, DF3: 8.6%, DF4: 8.0%, DF5: 4.4%). To ensure stable extraction, only series with sufficient coverage (at least 70% non-missing observations) are retained for PCA.

Finally, in a strictly pseudo out-of-sample replication, PCA should ideally be recomputed recursively (expanding or rolling window) to avoid any look-ahead bias. In our pipeline, this point is treated as a limitation and discussed in §4.6.

4.5 PCA factor analysis

To verify that the extracted factors adequately summarize the macro-financial information contained in our panel, we analyze two elements: (i) the share of variance explained by each factor, and (ii) the average correlation of factors with the main asset classes (equities, rates, commodities, FX). This step allows relating our factors to the usual interpretations proposed in the reference article, without prejudging forecasting performance.

Factor	**Explained variance (%)**	**Corr. with GDP (CQOQ)**
DF1	20.0	0.165
DF2	16.5	-0.050
DF3	8.6	-0.034
DF4	8.0	0.067
DF5	4.4	0.186
Cumulative (DF1–DF5)	**57.5**	

Table 1: Variance explained by PCA factors and contemporaneous correlation with GDP.

Table 1 shows that the first two factors concentrate a significant share of common information (36.5% explained variance), while subsequent factors capture more specific dimensions. Contemporaneous correlation with GDP is overall moderate, consistent with the idea that financial factors are not direct proxies for real activity but may contain a useful signal for forecasting. In our sample, DF5 has the highest correlation with GDP (0.186).

Asset class	**DF1**	**DF2**	**DF3**	**DF4**	**DF5**
Equity	0.405	-0.084	0.373	-0.117	-0.024
Fixed Income	0.558	0.252	-0.135	0.187	0.041
Commodities	0.262	-0.247	-0.138	-0.148	0.020
FX	-0.080	-0.339	0.025	0.221	0.016

Table 2: Average correlation of factors with series in each asset class.

Table 2 suggests that DF1 is a "global" factor: it is positively correlated with equities, interest rates and, to a lesser extent, commodities. This corresponds to a common market component (*risk-on/risk-off*) that spans several asset classes. DF2 appears more closely related to foreign exchange, with a marked negative average correlation for the FX class (-0.339), and a component linked to interest rates (positive correlation with Fixed Income). Factors DF3 and DF4 capture more specific dimensions (for instance an additional equity component for DF3 or a rates/FX component for DF4), while DF5 exhibits weak correlations by asset class but remains the factor most correlated with GDP in our sample.

4.6 Difficulties encountered and data limitations

Building a dataset suitable for MIDAS raises several practical difficulties. First, the multi-frequency nature of the problem imposes alignment choices between daily data (trading days) and the quarterly target variable: one must fix an anchor date (quarter-end), define a window size m, and decide how to handle missing days. In the paper, m is assumed constant for simplicity; in practice, it should rather be viewed as an order of magnitude (for example $m = 63$ days $\approx$ one trading quarter).

Second, the series do not all share the same historical depth. Some start later, while others contain more missing values. This reduces the effective sample size as soon as long windows are used (for example $m = 189$ or $m = 252$) and makes performance comparisons more delicate if not all models generate forecasts on exactly the same dates.

Another important issue concerns the presence of extreme episodes. Crises (2008–2009, COVID-19) generate very atypical movements in the target variable and may trigger over-reactions when weights become highly concentrated. Winsorization helps limit the impact of extreme values on predictors, but it does not "correct" the breaks observed in GDP itself.

In addition, the task of mapping Bloomberg tickers is not always straightforward. Some series require adjustments (renaming, proxies, substitute series) to match as closely as possible the categories used in the paper. This introduces a degree of uncertainty in the correspondence (*matching*) between variables, especially when the exact series is not available over the same period or under the same code.

Finally, implementing MIDAS weights (exponential Almon polynomial) requires particular attention to the time convention and to the alignment of available information. In particular, the introduction of leads (*leads*) must strictly respect a real-time logic: only observations effectively available at the information date should be used to forecast the target quarter. These points are carefully checked in our pipeline and discussed in the results section.

5 Replication design and forecasting protocol

This section describes the empirical framework of the replication: definition of samples and horizons, estimated specifications, pseudo out-of-sample procedure, and evaluation criteria. The objective is to reproduce as closely as possible the spirit of the paper, while taking into account constraints related to our data universe (smaller number of series and extended period).

5.1 Samples, horizons and window m

The target variable is quarterly real GDP growth (`GDP CQOQ Index`). Financial predictors are observed at daily frequency and integrated into mixed-frequency regressions through blocks of m trading days. In what follows, m denotes the number of daily observations used to construct the high-frequency component within a quarter.

In line with the order of magnitude used in the MIDAS literature, we set $m = 63$ days by default (approximately one trading quarter). We also test longer windows (for example $m = 126$, $m = 189$, $m = 252$) in order to assess the sensitivity of performance to the choice of intra-quarter memory. Intuitively, longer windows increase the amount of information available, but may also introduce noise and reduce the effective sample size when some series are shorter.

Forecasts are produced at different horizons h (in quarters) depending on the configurations. The short horizon $h = 1$ corresponds to a one-quarter-ahead forecast, while longer horizons (for example $h = 4$) allow assessing whether financial factors carry a more structural signal. When multiple horizons are studied, we estimate a distinct equation for each h (direct forecasting).

5.2 Estimated models and benchmarks

We compare several families of models, organized around an autoregressive benchmark and MIDAS variants.

- Univariate benchmark (AR): The main point of comparison is a quarterly autoregressive model, typically an AR(1):
$$y_{t+h} = \alpha + \rho\, y_t + u_{t+h},$$
where y_t denotes quarterly GDP growth and h the forecasting horizon. This benchmark captures persistence in the target variable without financial information.

- ADL–MIDAS model: We estimate MIDAS regressions augmented with lags of the target variable, of the form:
$$y_{t+h} = \alpha^h + \sum_{j=0}^{p_y-1} \rho_{j+1}^h\, y_{t-j} + \beta^h \sum_{i=0}^{m-1} w_i(\theta^h)\, x_{t,i} + u_{t+h},$$
where $x_{t,i}$ is the (transformed) daily observation associated with the i-th lag in the window, and $w_i(\theta^h)$ is a low-dimensional parametric weighting function (exponential Almon polynomial). In our replication, predictors x can be individual series or daily factors extracted via PCA (DF1–DF5).

- MIDAS with leads: For intra-quarter nowcasting, we consider an extension with leads, which incorporates daily observations available during the current quarter (for example two months of information available before the end of the quarter). This variant allows studying the contribution of the most recent financial information in a real-time updating framework.

- Forecast combination: When several models/factors are available, we also consider forecast combinations (weights based on past performance), in order to reduce dependence on a particular factor and improve out-of-sample robustness.

The choice of the number of quarterly lags p_y can be fixed a priori (often small) or selected using an information criterion (AIC/BIC) on a restricted grid, in order to avoid over-parameterization.

Forecast combination (MSFE-weighted): When multiple predictors/models are available, we construct a combined forecast at horizon h as a weighted average of the M individual forecasts:

$$\widehat{Y}^{Q,h}_{c,t+h|t} = \sum_{i=1}^{M} \omega^h_{i,t}\, \widehat{Y}^{Q,h}_{i,t+h|t},$$

where $\omega^h_{i,t}$ denotes the (time-varying) weight assigned to model i.

Weight construction: Weights are determined from a discounted MSFE:

$$\omega^h_{i,t} = \frac{\left(\lambda^{-1}_{i,t}\right)^{\kappa}}{\sum_{j=1}^{M}\left(\lambda^{-1}_{j,t}\right)^{\kappa}}, \qquad \lambda_{i,t} = \sum_{\tau=T_0}^{t-h} \delta^{\,t-h-\tau}\left(Y^Q_{\tau+h} - \widehat{Y}^{Q,h}_{i,\tau+h|\tau}\right)^2.$$

In this construction, $\delta \in (0,1)$ is the discount factor (in our tests, $\delta = 0.9$): the higher δ, the more recent errors weigh in $\lambda_{i,t}$. The parameter $\kappa > 0$ (here $\kappa = 2$) controls weight concentration: the larger κ, the more the combination favors models with the smallest past errors.

5.3 Pseudo out-of-sample procedure (expanding/rolling)

Performance is evaluated in a pseudo out-of-sample framework. An out-of-sample start date T_0 is fixed: models are estimated on an initial in-sample period, and forecasts are generated sequentially as new observations become available.

We primarily use an expanding (recursive) window: at each date t, the estimation sample includes all observations available from the origin up to t. Parameters are re-estimated at each iteration, and a forecast $\widehat{y}_{t+h|t}$ is produced. This procedure closely resembles a real-time forecasting exercise, while remaining reproducible.

In some sensitivity analyses, a rolling (fixed-size) window can also be used to test coefficient stability when structural breaks are likely to affect the relationship between financial factors and real activity. In that case, only the last L quarters are kept at each iteration.

5.4 Evaluation metrics

Forecast quality is measured using the forecast error $e_{t+h} = y_{t+h} - \widehat{y}_{t+h|t}$ and two standard metrics:

- **RMSFE** (*Root Mean Squared Forecast Error*) :

$$\text{RMSFE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T} e^2_{t+h}},$$

- **MAE** (*Mean Absolute Error*) :

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T} |e_{t+h}|.$$

When we report performance gains, we express them relative to the AR(1) benchmark. For instance, a gain in RMSFE can be summarized as a percentage:

$$\text{Gain}(\%) = 100 \times \left(1 - \frac{\text{RMSFE}_{\text{model}}}{\text{RMSFE}_{\text{AR}}}\right).$$

A positive gain indicates that the model improves performance relative to AR(1).

Finally, to ensure a fair comparison across models, metrics should ideally be computed on a common set of forecast dates (same out-of-sample period). This precaution is important when some models generate fewer forecasts due to missing data or longer m windows.

6 Replication results

This section presents (i) the replication of the main empirical tables from the paper (Tables 1, 3 and 5) on the *Long sample* and (ii) an application of the methodology over a recent period (2024–2025). Replication tables report RMSFE ratios relative to the Random Walk (RW) benchmark: a value below 1 indicates an improvement relative to RW. For the recent period, we report RMSFEs in levels as well as RMSFEs relative to RW.

6.1 Replication of the paper results: *Long sample* (1988–2008)

Table 1 – Models without leads (no leads): RW is reported as an absolute RMSFE (2.69 at $h = 1$ and 3.18 at $h = 4$) and all other models are expressed as ratios to RW.

Model	**Long** $h = 1$	**Long** $h = 4$
Univariate models		
RW (absolute)	2.69	3.18
AR	1.01	0.91
Models with macro data		
FAR (CFNAI)	0.91	0.90
Models with financial data (5 DF)		
ADL (5 DF)	1.09	1.12
ADL-MIDAS (5 DF) `ADL-MIDAS(`$J_X^D = 0$`)`	1.11	1.11
Models with macro and financial data (CFNAI, 5 DF)		
FADL (CFNAI, 5 DF)	0.96	1.12
FADL-MIDAS (CFNAI, 5 DF) `FADL-MIDAS(`$J_X^D = 0$`)`	1.07	0.86

Table 3: Table 1 (replication) – RMSFE without leads (Long sample): RW is reported as an absolute RMSFE; other values are ratios to RW (values $<$ 1: improvement vs RW).

Table 3 – Models with leads: $J_X^D = 2$ corresponds to two months of daily leads; $J_M = 1$ corresponds to one month of lead for the monthly macro indicator.

Model	**Long** $h = 1$	**Long** $h = 4$
Models with leads in daily financial data		
ADL-MIDAS($J_X^D = 2$)	0.97	0.87
FADL-MIDAS($J_X^D = 2$)	0.77	0.73
Models with leads in monthly macro and daily financial data		
FADL-MIDAS($J_M = 1, J_X^D = 2$)	0.93	0.81
Models with leads in monthly macro data		
FAR($J_M = 1$)	0.87	0.73
FADL($J_M = 1$)	0.90	0.88
FADL-MIDAS($J_M = 1, J_X^D = 0$)	0.97	0.82

Table 4: Table 3 (replication) – RMSFE with leads (Long sample). Values reported as ratios to RW.

Table 5 – ADS case (daily macro index): Table 5: ADS is a daily macro indicator; values are RMSFE ratios vs RW.

Model	$h = 1$	$h = 4$
ADL-MIDAS($J_{ADS}^D = 2$)	0.57	0.48
FADL-MIDAS($J_M = 1, J_{ADS}^D = 2$)	0.60	0.52

Table 5: Table 5 (replication) – Comparisons with ADS. Values reported as ratios to RW.

6.2 Replication of the paper results: *Short sample* (1999–2008)

The *Short sample* corresponds to the exercise on a more recent and shorter window, which allows testing the robustness of the results when the estimation sample is more limited. As in the *Long sample*, RW is reported as an absolute RMSFE and other values are ratios to RW (values < 1: improvement vs RW).

Model	**Short** $h = 1$	**Short** $h = 4$
Univariate models		
RW (absolute)	3.46	4.66
AR	1.13	1.00
Models with macro data		
FAR (CFNAI)	0.94	0.98
Models with financial data (5 DF)		
ADL (5 DF)	1.20	1.14
ADL-MIDAS (5 DF) `ADL-MIDAS(`$J_X^D = 0$`)`	1.24	1.13
Models with macro and financial data (CFNAI, 5 DF)		
FADL (CFNAI, 5 DF)	1.00	1.14
FADL-MIDAS (CFNAI, 5 DF) `FADL-MIDAS(`$J_X^D = 0$`)`	1.02	1.00

Table 6: Table 1 (replication) – RMSFE without leads (*Short sample*). RW is reported as an absolute RMSFE; other values are ratios to RW (values < 1: improvement vs RW).

Model	**Short** $h = 1$	**Short** $h = 4$
Models with leads in daily financial data		
ADL-MIDAS($J_X^D = 2$)	0.94	0.89
FADL-MIDAS($J_X^D = 2$)	0.70	0.62
Models with leads in monthly macro and daily financial data		
FADL-MIDAS($J_M = 1, J_X^D = 2$)	0.86	0.82
Models with leads in monthly macro data		
FAR($J_M = 1$)	0.84	0.72
FADL($J_M = 1$)	0.92	0.86
FADL-MIDAS($J_M = 1, J_X^D = 0$)	0.92	0.86

Table 7: Table 3 (replication) – RMSFE with leads (*Short sample*). Values reported as ratios to RW.

Model	$h = 1$	$h = 4$
ADL-MIDAS($J_{ADS}^D = 2$)	0.56	0.42
FADL-MIDAS($J_M = 1, J_{ADS}^D = 2$)	0.60	0.46

Table 8: Table 5 (replication) – Comparisons with ADS (*Short sample*). Values reported as ratios to RW.

On the Short sample, models based only on financial factors (ADL, ADL-MIDAS with 5 DF) do not beat RW in the no-leads specification. By contrast, introducing leads markedly improves performance, especially for FADL-MIDAS($J_X^D = 2$), and the ADS indicator remains very strong, particularly at the longer horizon ($h = 4$).

6.3 Recent out-of-sample analysis (2024–2025)

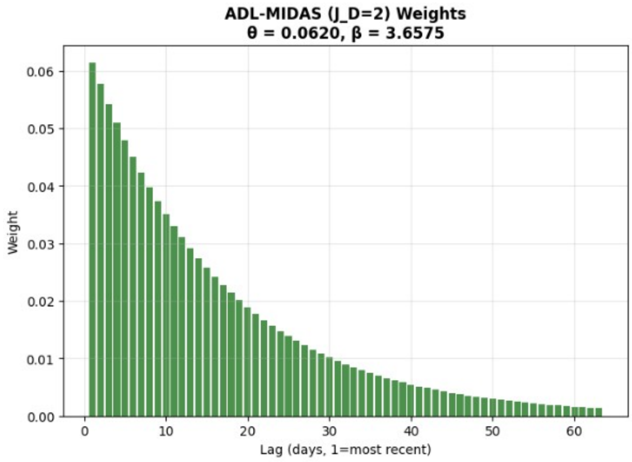
The training sample covers 2020Q1–2023Q4 and the out-of-sample evaluation focuses on 2024Q1–2025Q4. In practice, some specifications do not generate a forecast for the very first quarter, because the nowcast is constructed at an information date (end of the 2^{nd} month of the quarter). The RMSFEs reported below therefore correspond to the forecasts actually produced over the recent window.

Table 9 presents the ranking of models on the recent sample: four models beat RW (ADL(flat), FAR(CFNAI), AR, FADL($J_M = 1$)), whereas the MIDAS variants tested underperform over this period.

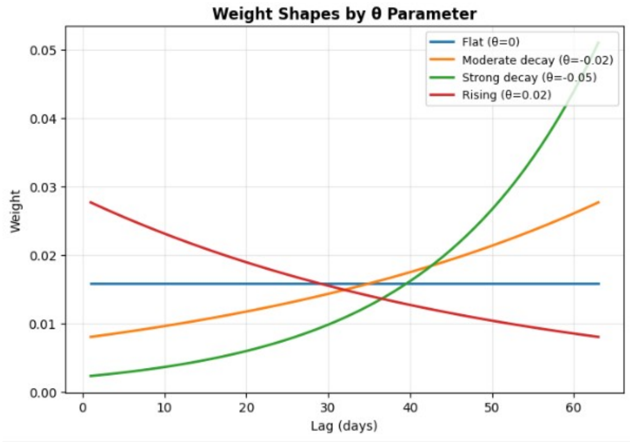
Rank	**Model**	**RMSFE**	**Rel. to RW**	**vs RW**
1	ADL(flat)	0.9511	0.449	+55.1%
2	FAR(CFNAI)	1.8016	0.851	+14.9%
3	AR	1.8844	0.890	+11.0%
4	FADL($J_M = 1$)	2.1136	0.998	+0.2%
5	RW	2.1172	1.000	Baseline
6	FAR($J_M = 1$)	2.2609	1.068	-6.8%
7	ADL-MIDAS($J_D = 2$)	3.2400	1.530	-53.0%
8	FADL-MIDAS($J_M = 1, J_D = 2$)	3.6527	1.725	-72.5%
9	FADL-MIDAS	3.7317	1.763	-76.3%

Table 9: Recent period (OOS 2024–2025, $h = 1$) – Model ranking.

6.4 Graphical illustrations (recent period)



(a) Estimated MIDAS weights (ADL–MIDAS, $J_D = 2$).



(b) Weight shapes as a function of θ.

Figure 4: Diagnostics on MIDAS weight shapes (recent period).

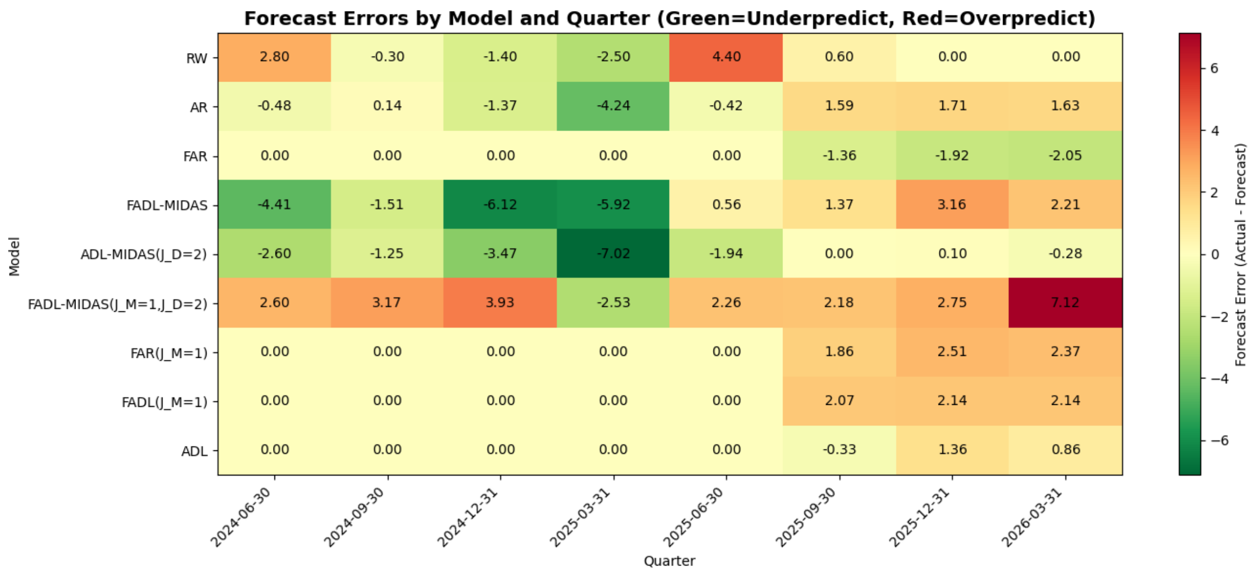


Figure 5: Forecast errors by model and by quarter (2024–2025).

7 Extension: Two-parameter MIDAS β (lags vs leads)

This section proposes a simple extension of the MIDAS model with leads. In the standard specification (Andreou, Ghysels and Kourtellos, 2013), a *single* parameter β determines the shape of the weights applied to the entire daily block used, i.e., both past data (lags) and nowcast data (leads). Our extension consists in splitting this parameter into two: β_{lag} to weight the lag block, and β_{lead} to weight the lead block. The objective is to relax a potentially strong constraint, while remaining in a parsimonious approach (we add only one parameter).

7.1 Motivation and economic intuition

In our replication, the nowcast is constructed at a fixed date at the end of the second month of the target quarter. Concretely, this amounts to using about two months of daily data "in advance," i.e., around 42–44 trading days. This convention respects the information calendar: the forecast for quarter t is constructed only from observations available at the information date, without using later data (no *look-ahead bias*).

The intuition behind the extension is as follows. If we impose a *single* β for the whole block (lags + leads), we force the same weighting dynamics for past information and for intra-quarter information. Yet the leads correspond to the beginning of the target quarter: they are the most recent data at the time the forecast is made, but they may end up relatively under-weighted if the weight shape is primarily driven by the lag block. Allowing $\beta_{\text{lag}} \neq \beta_{\text{lead}}$ therefore gives the model the possibility to treat historical information and nowcast information differently, which seems more economically coherent in a nowcasting exercise.

7.2 Model specification

We split the daily component into two MIDAS aggregates:

- a lag aggregate built on $m = 63$ days (about one trading quarter);
- a lead aggregate built on $m_L \approx 42$ days (about two months) within the target quarter.

At horizon $h = 1$, the regression can be written as:

$$y_{t+1} = \alpha + \rho\, y_t + \beta_{\text{lag}} \sum_{k=1}^{m} B(k;\theta_{\text{lag}})\, x_{t-k} + \beta_{\text{lead}} \sum_{j=1}^{m_L} B(j;\theta_{\text{lead}})\, x_{t+j} + \varepsilon_{t+1}, \tag{10}$$

where $B(\cdot;\theta)$ is a normalized exponential Almon weight:

$$B(k;\theta) = \frac{\exp(\theta k)}{\sum_{\ell} \exp(\theta \ell)}. \tag{11}$$

The single-β model is a special case when $\beta_{\text{lag}} = \beta_{\text{lead}}$ (and, implicitly, when the same weighting dynamics are imposed on both blocks).

7.3 Evaluation protocol (OOS) and configuration

The exercise is conducted in pseudo out-of-sample (OOS) with recursive estimation. The data window used for this extension covers 2015–2025, and the out-of-sample evaluation starts in 2024:Q1. The model is estimated at each forecast date using information available up to the information date (end of the 2^{nd} month of the target quarter), and then a forecast of y_{t+1} is produced. Under this configuration, we obtain 8 OOS forecasts.

The retained parameters are: $h = 1$, $p_y = 1$, $m = 63$, and 2 months of leads.

7.4 Results: performance and comparison to the single-β

Over the evaluation period (OOS 2024–2025), the two-β model yields an RMSFE of 2.7267, i.e., a ratio of 1.288 relative to the Random Walk (a deterioration of 28.8%). On average across forecasts, the estimated parameters are:

$$\theta_{\text{lag}} = 0.0266 \qquad \theta_{\text{lead}} = 0.0176 \qquad \beta_{\text{lag}} = 2.5252, \qquad \beta_{\text{lead}} = 3.6708.$$

These estimates suggest different weighting dynamics between past and nowcast information, which is precisely the objective of the extension.

The comparison with the single-β model with 2 months of leads is nevertheless instructive: although the two-β model does not beat RW on this recent window, it improves upon the standard MIDAS model (single-β). Table 10 shows a decrease in RMSFE from 3.2400 to 2.7267, i.e., a relative improvement of 15.8% compared to the single-β specification.

Model	**RMSFE**	**RMSFE / RW**	**vs RW**
Two-β MIDAS ($J_D = 2$)	2.7267	1.288	-28.8%
Single-β MIDAS ($J_D = 2$)	3.2400	1.530	-53.0%

Table 10: Comparison two-β vs single-β (OOS 2024–2025, leads = 2 months).

Table 11 reports the two-β forecasts and associated errors over the 8 out-of-sample quarters, in detail by quarter.

Quarter	**Realized**	**Forecast (two-β)**	**Error**	$\boldsymbol{\beta}_{\text{lag}}$	$\boldsymbol{\beta}_{\text{lead}}$
2024-Q2	3.600	5.595	-1.995	0.0145	0.5085
2024-Q3	3.300	0.947	2.353	0.0149	0.5205
2024-Q4	1.900	-0.251	2.151	0.0142	0.5358
2025-Q1	-0.600	4.171	-4.771	0.0130	0.5295
2025-Q2	3.800	0.932	2.868	0.0124	0.5295
2025-Q3	4.400	4.296	0.104	0.0130	0.5251
2025-Q4	4.400	1.734	2.666	0.0130	0.5248
					RMSFE: 2.7267

Table 11: Out-of-sample forecasts from the two-β model (OOS 2024–2025, $h = 1$). Error = Realized – Forecast.

7.5 Application to the paper samples (Long/Short sample)

In addition to the exercise on the recent period, we apply the same two-β extension to the two reference samples from the paper (*Long sample* and *Short sample*). The objective is to check whether the gain observed relative to the single-β specification is also present over the paper periods. As before, performance is reported in RMSFE (level), RMSFE relative to RW, and gain/loss relative to RW.

Sample	**Model**	**RMSFE**	**Rel. to RW**	**vs RW**
Long sample	Two-β MIDAS ($J_D = 2$)	2.3966	1.132	-13.2%
Long sample	Single-β MIDAS ($J_D = 2$)	3.2400	1.530	-53.0%
Short sample	Two-β MIDAS ($J_D = 2$)	2.8268	1.335	-33.5%
Short sample	Single-β MIDAS ($J_D = 2$)	3.2400	1.530	-53.0%

Table 12: Two-β vs single-β extension on the *Long* and *Short* paper samples (leads = 2 months). Reported values are RMSFE in level, RMSFE relative to RW, and gain/loss vs RW.

Reading the results. On both samples, the two-β extension systematically improves the single-β version: RMSFE decreases from 3.2400 to 2.3966 on the *Long sample* (relative improvement of 26.0%) and from 3.2400 to 2.8268 on the *Short sample* (relative improvement of 12.8%). However, both specifications remain above RW (RMSFE/RW > 1): the extension therefore corrects part of the weighting issue (lags vs leads) without being sufficient to make the strategy globally superior to the RW benchmark under these configurations.

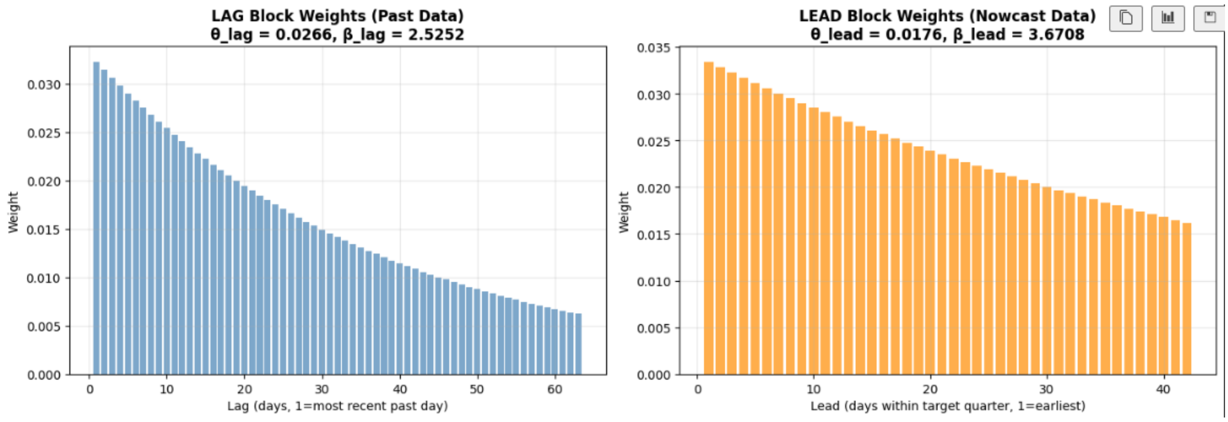


Figure 6: Two-β extension: estimated weights on the lag block (past) and on the lead block (nowcast).

Figure 6 illustrates the main contribution of the extension: instead of imposing a single weight shape on the entire block (past + nowcast), the model estimates two distinct profiles. The *lag* block (left) decreases smoothly over $m = 63$ days: the most recent information from the past receives more weight, consistent with a standard decreasing-memory pattern. The *lead* block (right), built on the days available in the target quarter ($m_L \approx 42$), displays its own dynamics: weights are not constrained to follow the same decay as the past. Concretely, this allows the model to adjust separately how it exploits (i) historical lags and (ii) intra-quarter information available at the information date, directly addressing the limitation of the single-β specification.

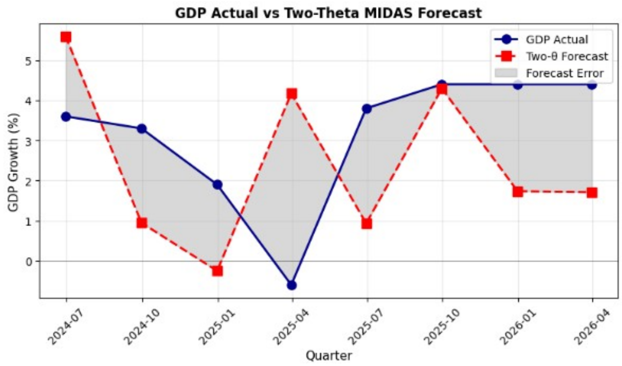
7.6 Positioning relative to other models (recent period)

To position this extension within the set of models tested on 2024–2025, Table 13 reproduces the full ranking. The two-β extension improves upon the single-β MIDAS (rank 7 versus rank 8), but does not outperform simple benchmarks over this recent window. This result is consistent with the previous analysis: over a short and relatively stable period, parsimonious models (ADL(flat), FAR(CFNAI), AR) can dominate richer specifications, and MIDAS models may suffer from instability in the relationship between factors and real activity.

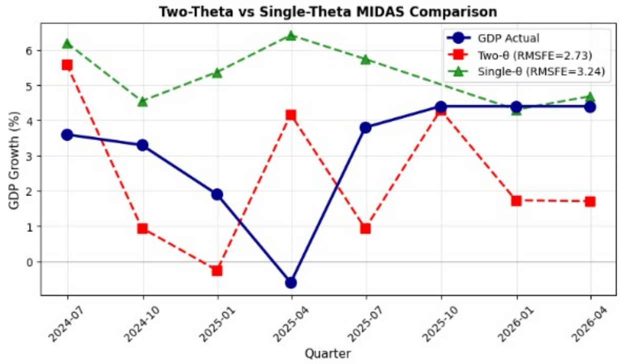
Rank	**Model**	**RMSFE**	**RMSFE / RW**	**vs RW**
1	ADL(flat)	0.9511	0.449	+55.1%
2	FAR(CFNAI)	1.8016	0.851	+14.9%
3	AR	1.8844	0.890	+11.0%
4	FADL($J_M = 1$)	2.1136	0.998	+0.2%
5	RW	2.1172	1.000	Baseline
6	FAR($J_M = 1$)	2.2609	1.068	-6.8%
7	$\star$MIDAS-2β($J_D = 2$)	2.7267	1.288	-28.8%
8	ADL–MIDAS($J_D = 2$)	3.2400	1.530	-53.0%
9	FADL–MIDAS($J_M = 1, J_D = 2$)	3.6527	1.725	-72.5%
10	FADL–MIDAS	3.7317	1.763	-76.3%

Table 13: Model ranking over the recent period (OOS 2024–2025, $h = 1$), including the two-β extension. $\star$ indicates our contribution.

7.7 Graphical illustrations



(a) Paths: realized vs forecast.



(b) Two-β vs single-β.

Figure 7: Additional visualizations of the two-β model (OOS 2024–2025).

7.8 Discussion and limitations

This extension increases model flexibility by explicitly distinguishing past information from nowcast information, without introducing latent states nor excessively complicating estimation. Over the recent period, it improves the standard MIDAS model with leads, suggesting that the single-β constraint may be too restrictive.

However, the extension does not beat RW over 2024–2025. Two main reasons seem plausible. First, the out-of-sample window is very short (8 quarters), making the RMSFE sensitive to a few large errors. Second, the post-COVID period may correspond to a regime in which the relationship between financial factors and quarterly GDP is less stable, penalizing more structured models.

8 Conclusion

This replication confirms the relevance of the MIDAS framework proposed by Andreou, Ghysels and Kourtellos (2013) to integrate daily data into the forecasting of quarterly macroeconomic variables, especially when the information calendar is strictly respected and models are evaluated out of sample. On the *Long sample*, the reproduced tables (Tables 1, 3 and 5) highlight that gains do not mechanically come from using high-frequency data: they strongly depend on the chosen specification, the introduction of leads, and the choice of indicators. The case of the daily ADS index notably illustrates that some daily macroeconomic signals can be highly informative.

Over the recent period (2024–2025), results are more mixed: simple and parsimonious models (flat ADL, FAR/AR) dominate the MIDAS variants tested. This suggests that the relationship between financial factors and GDP growth may be less stable in the post-COVID regime and that, over a short window, model rankings are highly sensitive to a few forecast errors. It also reminds that predictive performance depends on the macro-financial context and on the effective size of the out-of-sample window.

Finally, our two-β extension (distinct weights for lags and leads) goes in the direction of a natural relaxation of the single-β constraint. Over the recent window, it improves upon the standard MIDAS model with leads, without however exceeding the Random Walk benchmark. This result is consistent with the idea that the extension fixes a structural limitation, but is not sufficient on its own to make the model robust across all regimes. Immediate extensions would be (i) to test the extension over longer windows and across multiple horizons, (ii) to integrate a systematic selection of p_y as in the main protocol, and (iii) to extend the two-β approach to the FADL–MIDAS framework in order to explicitly combine macro and financial information in a single model.