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# AUTOREGRESSIVE AUGMENTATION OF MIDAS REGRESSIONS

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# Autoregressive augmentation of MIDAS regressions*

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**Abstract**

Focusing on the MI(xed) DA(ta) S(ampling) regressions for handling different sampling frequencies and asynchronous releases of information, alternative techniques for the autoregressive augmentation of these regressions are presented and discussed. For forecasting quarterly euro area GDP growth using a small set of selected indicators, the results obtained suggest that no specific kind of MIDAS regressions clearly dominates in terms of forecast accuracy. Nevertheless, alternatives to common-factor MIDAS regressions with autoregressive terms perform well and in some cases are the best performing regressions.

Keywords: MIDAS regressions, High-frequency data, Autoregressive terms, Forecasting

JEL Codes: C53, E37

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# 1 Introduction

Inspired in the distributed lag models, the MI(xed) DA(ta) S(ampling) framework, proposed by Ghysels et al. (2004), is a very flexible tool for dealing with different time frequencies, asynchronous releases of information, different aggregation polynomials and different forecast horizons (for a brief overview of the main topics related with MIDAS regressions see Andreou et al., 2011).

MIDAS regressions were originally associated with empirical applications to financial series, focusing on volatility predictions; see Ghysels et al. (2004, 2006, 2007). However, MIDAS regressions have also been used in typical macroeconomic forecasting applications (see, among others, Clements and Galvão, 2008 and Bai et al., 2013 for US GDP growth, Armesto et al., 2009 for the predictive content of the Beige Book, Kuzin et al., 2011 for euro area GDP, Marcellino and Schumacher, 2010 for German GDP, Monteforte and Moretti, 2013 for euro area inflation, and Asimakopoulos et al., 2013 for fiscal variables of a set of European countries).

The inclusion of autoregressive dynamics is an important feature of forecasting models, especially for macroeconomic applications. Ghysels et al. (2007) and Andreou et al. (2011) pointed out that the autoregressive distributed lag MIDAS regression entails an undesirable property - discontinuities in the impulse response function of the regressor ($x_t^{(m)}$) on the variable of interest ($Y_t$). To tackle this issue, Clements and Galvão (2008) suggested interpreting the dynamics on $Y_t$ as a common factor (Hendry and Mizon, 1978). This assumption rests on the hypothesis that $Y_t$ and $x_t^{(m)}$ share the same autoregressive dynamics, though, as Hendry and Mizon (1978) pointed out, a common factor may not always be found.

The main aim of this article is to discuss alternative techniques for introducing autoregressive terms in MIDAS regressions. The initial contributions on this issue are reassessed and an alternative approach is proposed. It is claimed that standard MIDAS regressions (no common factor restriction) are able to deal with autoregressive terms, without jeopardising the pattern of the impulse response functions from $x_t^{(m)}$ on $Y_t$. The sequence of coefficients associated with lags of $x_t^{(m)}$, retrieved from the distributed lag representation of MIDAS regressions, is not the relevant impulse response function. Inspired by the periodic model framework (see Hansen and Sargent (2013) and Ghysels (2012), among others), one can say that there are several impulse response functions, one for each high-frequency period within a low-frequency observation. The observed low-frequency impulse response functions do not exhibit discontinuities, regardless of the lags of $x_t^{(m)}$ or $Y_t$ included in the regression.

Furthermore, the empirical performance of alternative MIDAS regressions with autoregressive terms is evaluated through a forecasting exercise. For forecasting quarterly euro area GDP growth, the performance of an extended set of MIDAS regressions, in terms of root mean squared forecast error (RMSFE), is assessed through a horse race. Simple AR and traditional low-frequency models are used as benchmarks. MIDAS regressions without autoregressive terms are also included for comparison reasons. As the evidence in favour of using large information sets is not clear-cut (see, for example, Banerjee and Marcellino, 2006), this article focuses on a small set of selected indicators.

The forecasts are obtained through a recursive out-of-sample exercise, which takes into account the ragged-edges of the high-frequency data and the publication delay of GDP. To assess whether the gains in terms of forecast accuracy from taking on board high-frequency data are short-lived, past high-frequency data is combined to obtain nowcasts (current period forecasts) and direct forecasts for different horizons, up to 4 quarters ahead. The results obtained suggest that alternatives to common-factor MIDAS regressions with autoregressive terms perform well, being in some cases the best performing regressions.

The remainder of this paper is organised as follows. Section 2 describes the main topics related with MIDAS modelling and discusses in detail the different techniques for the autoregressive augmentation of MIDAS regressions. The design of the now- and forecasting exercise is presented in section 3, while section 4 focuses on the results. Finally, section 5 concludes.

## 2 MIDAS modelling

In this section, after presenting some theoretical motivation and notation (section 2.1), the MIDAS approach is discussed in section 2.2. Then, in section 2.3 the initial contributions on introducing autoregressive terms in MIDAS regressions are reviewed and an alternative perspective on this issue is proposed.

### 2.1 Background

Consider the traditional low frequency regression,

$$Y_{t+h} = \alpha + \beta Q_t + \varepsilon_{t+h} \tag{1}$$

where $h$ denotes the forecast horizon (when $h = 0$ the model delivers nowcasts) and both $Y_{t+h}$ and $Q_t$ are sampled at a low frequency, e.g., quarterly. All the parameters of the model depend on the forecast horizon and forecasts are computed directly, i.e., no additional forecasts of the explanatory variables are needed in order to obtain forecasts for the variable of interest. Equation 1 can be extended to include lags of the $Y$ and $Q$ variables, as well as additional regressors and respective lags.

Now, assume that $Y_{t+h}$ and $Q_t$ are temporal aggregates of higher frequency disaggregated series, e.g., monthly series ($y_{t+h}$ and $x_t$, respectively). For each low-frequency (quarterly) observation of $Y_{t+h}$ and $Q_t$ there are $m$ (3) observations of the high-frequency (monthly) $y_{t+h}$ and $x_t$ series. The low-frequency variables are characterised by an aggregation scheme $\Gamma(L^{1/m})$. There are different schemes, e.g., stock variables or flow variables with equal weights. In the following analysis an unrestricted linear combination of $\gamma_i$ weights will be considered.

In time series analysis, observed time series are often temporal aggregates of unobserved disaggregated series. As before, assume for instance that $Q_t$ is observed monthly ($x_t$), while $Y_{t+h}$ is only observed quarterly - meaning that $y_{t+h}$ is not observed (flow variable) or has missing observations (stock variable). Although regression analysis would ideally try to approximate the original data generating process (DGP) by using high-frequency samples, as in the following equation

$$g(L^{1/m})y_{t+h} = a + \sum_{i=1}^{N} b_i(L^{1/m})x_{i,t} + e_{t+h} \tag{2}$$

where $g(L^{1/m})$ and $b_i(L^{1/m})$ are finite order lag polynomials, this is not always possible.

The mixed-frequency approaches suggest mixing a low-frequency dependent variable on the left-hand side with high-frequency regressors on the right-hand side. Assuming that high-frequency $y_{t+h}$ would be well represented by equation 2, there is a $\phi(L^{1/m})$ polynomial such that $h(L) = g(L^{1/m})\phi(L^{1/m})$. Multiplying both sides of equation 2 by $\phi(L^{1/m})$ and the aggregation scheme $\Gamma(L^{1/m})$ one obtains

$$\begin{aligned}\phi(L^{1/m})g(L^{1/m})\Gamma(L^{1/m})y_{t+h} &= \ddot{a} + \sum_{i=1}^{N} b_i(L^{1/m})\phi(L^{1/m})\Gamma(L^{1/m})x_{i,t} \\ &\quad + \phi(L^{1/m})\Gamma(L^{1/m})e_{t+h} \\ h(L)Y_{t+h} &= \ddot{a} + \sum_{i=1}^{N} b_i(L^{1/m})z_{i,t} + \xi_{t+h} \qquad (3)\end{aligned}$$

where $\ddot{a} = \phi(L^{1/m})\Gamma(L^{1/m})a$, $z_{i,t} = \phi(L^{1/m})\Gamma(L^{1/m})x_{i,t}$, $\xi_{t+h} = \phi(L^{1/m})\Gamma(L^{1/m})e_{t+h}$ and $t = m, 2m, 3m, ....$ Equation 3 is the exact mixed-frequency model associated with the high-frequency model in equation 2, relating the low-frequency $Y_{t+h}$ dependent variable with the high-frequency $x_{i,t}$ regressors.

As discussed in Wei and Stram, 1990, Marcellino, 1998 and Marcellino, 1999, among others, in general it is not possible to uniquely identify $\phi(L^{1/m})$ in this single-equation framework and, so, neither the $g(L^{1/m})$ and $b_i(L^{1/m})$ polynomials. This means that, in general, one can only approximate the mixed-frequency model, as follows

$$\tilde{h}(L)Y_{t+h} = \tilde{a} + \sum_{i=1}^{N} \tilde{b}_i(L^{1/m})x_{i,t}^{(3)} + u_{t+h} \tag{4}$$

where $x_{i,t}^{(3)}$ is the skip-sampled version of the high-frequency $x_{i,t}$ and the orders of the polynomials $\tilde{h}(L)$ and $\tilde{b}_i(L^{1/m})$ are data-driven (e.g., selected from information criteria). Furthermore, since one cannot recover the high-frequency $g(L^{1/m})$ and $b_i(L^{1/m})$ polynomials, it is also not possible to identify the high-frequency impulse response function of $x_{i,t}$ on $y_t$. Hence, the approximate mixed-frequency model implies an observable quarterly impulse response function of $x_{i,t}^{(3)}$ on $Y_t$. Underlying this observable impulse response function are the latent monthly impulse response functions of $x_{i,t}$ on $y_t$.

### 2.2 From the approximate mixed-frequency regression to MIDAS regressions

Equation 4 is a MIDAS regression. More precisely, equation 4 as been referred to in the literature as an *unrestricted* MIDAS regression; see e.g. Marcellino and Schumacher (2010), Foroni and Marcellino (2012) and Foroni et al. (2011). This regression is one of the particular cases covered by the general MIDAS framework. Introduced by Ghysels et al. (2004) and initially presented in Ghysels et al. (2006) or Ghysels et al. (2007), the MIDAS approach provides simple, reduced-form models to approximate more elaborate, though unknown, high-frequency models. Original MIDAS regressions assume that the coefficients of $\tilde{b}_i(L^{1/m})$ in equation 4 are captured by a known weight function $B(j;\theta)$,

$$Y_{t+h} = \beta_0 + \beta_1 B(L^{1/m};\theta)x_t^{(3)} + u_{t+h} \tag{5}$$

where $B(L^{1/m};\theta) = \sum_{j=0}^{J} B(j;\theta)L^{j/m}$ is a polynomial of length $J$ in the $L^{1/m}$ operator, $B(j;\theta)$ represents the weighting scheme used for the aggregation, which is assumed to be normalised to sum to 1, $\beta_1$ is the slope coefficient, $\beta_0$ is a constant, $L^{j/m}x_t^{(m)} = x_{t-j/m}^{(m)}$ and $u_{t+h}$ is a standard iid error term.

Although the order of the polynomial $B(L^{1/m};\theta)$, i.e. $J$, is potentially infinite, some restrictions must be imposed for the sake of tractability. The restrictions result from the need of a balance between the gains in terms of additional information (more lags) and the costs of parameter proliferation. Information criteria, such as AIC and BIC, can be used to guide this choice. In the original MIDAS regressions, the coefficients of $B(L^{1/m};\theta)$ are captured by a known weighting function $B(j;\theta)$, which depends on a few parameters summarised in vector $\theta$.

For example, Ghysels et al. (2007) considered two alternatives for the weighting function, both assuming that the weights are determined by a few hyperparameters $\theta$: the exponential Almon lag

$$B(j;\theta_1,\theta_2) = \frac{e^{(\theta_1 j+\theta_2 j^2)}}{\sum_{i=1}^{J} e^{(\theta_1 i+\theta_2 i^2)}} \tag{6}$$

and the beta polynomial

$$B(j;\theta_1,\theta_2) = \frac{f(\frac{j}{J},\theta_1,\theta_2)}{\sum_{i=1}^{J} f(\frac{i}{J},\theta_1,\theta_2)} \tag{7}$$

where $f(q,\theta_1,\theta_2) = (q^{\theta_1-1}(1-q)^{\theta_2-1}\Gamma(\theta_1+\theta_2))/(\Gamma(\theta_1)\Gamma(\theta_2))$ and $\Gamma(\theta) = \int_0^\infty e^{-k}k^{\theta-1}dk$. Given that exponential Almon and beta polynomials have nonlinear functional specifications, in both cases MIDAS regressions have to be estimated using nonlinear methods, namely nonlinear least squares.

Chen and Ghysels (2010) discussed a multiplicative MIDAS framework, which is closer to traditional aggregation. Instead of aggregating all lags in the high frequency variable to a single aggregate, multiplicative MIDAS regressions include $m$-aggregates of high-frequency data and their lags,

$$Y_{t+h} = \beta_0 + \sum_{i=1}^{p} \beta_{i+1} x_{t-i}^{mult} + u_{t+h} \tag{8}$$

where $x_t^{mult} = \sum_{j=0}^{m-1} B(j;\theta)L^{j/m}x_t^{(m)}$.

Another aggregation scheme is the one underlying the above-mentioned unrestricted MIDAS regressions, resulting in MIDAS regressions that can be estimated by OLS.

$$\begin{aligned} Y_{t+h} &= \beta_0 + B_u(L^{1/m})x_t^{(m)} + u_{t+h} \\ &= \beta_0 + \sum_{j=0}^{J} \beta_{j+1} L^{j/m} x_t^{(m)} + u_{t+h} \\ &= \beta_0 + \beta_1 x_t^{(m)} + \beta_2 x_{t-1/m}^{(m)} + \ldots + \beta_{J+1} x_{t-J/m}^{(m)} + u_{t+h}. \end{aligned} \tag{9}$$

When the difference between the low and the high frequency is large, estimating a regression such as equation 9 can involve a large number of parameters. In this case, large differences in sampling frequencies between the variables considered are readily penalised in terms of parsimony. For instance, if $Y_{t+h}$ is sampled quarterly and $x_t$

refers to daily data, then estimating a mixed-frequency regression can easily involve estimating more than 60 parameters.

Summing up, MIDAS regressions allow more flexible weighting structure than traditional low-frequency models and can also be more parsimonious. Moreover, the MIDAS framework can easily accommodate the timely releases of high-frequency data. In (5), where $Y_{t+h}$ and $x_t^{(m)}$ are contemporaneously related, it is assumed that all high-frequency observations over the current low-frequency period are known. Considering quarterly and monthly data, this means that the three months in the quarter are already available. If instead of a full-quarter, say, only the first month is available, then the MIDAS regression can be rewritten as

$$Y_{t+h} = \beta_0 + \beta_1 B(L^{1/3}; \theta) x_{t-2/3}^{(3)} + u_{t+h}. \tag{10}$$

### 2.3 Autoregressive augmentation of MIDAS regressions

In section 2.3.1 initial contributions to the literature regarding the introduction of autoregressive terms in MIDAS regressions are reviewed, while an alternative perspective on this subject is presented in section 2.3.2. For the sake of simplicity and unless otherwise stated, a first order autoregression and $h = 0$ are assumed. Notwithstanding, the notation can be easily extended.

#### 2.3.1 Initial contributions

Ghysels et al. (2007) discussed the implications of introducing autoregressive terms in MIDAS regressions and suggested two possible ways of doing this, noting that both solutions had caveats. In the first case, a polynomial in $L^{1/m}$ is considered,

$$Y_t = \beta_0 + \beta_1 B(L^{1/m}; \theta) x_t^{(m)} + \gamma Y_{t-(1/m)} + u_t \tag{11}$$

which implicitly assumes that $Y_{t-(1/m)}$ is available. This solution may not be very appealing because if high-frequency lags of $Y_t$ were available then probably it would be possible to set up a high-frequency regression. Moreover, Ghysels et al. (2007) remarked that estimating (11) is more challenging because including the term $Y_{t-(1/m)}$ forces one to deal with endogenous regressors and with instrumental variable estimation.

In the second case, a polynomial in $L$ is considered, i.e.

$$\begin{aligned} Y_t &= \beta_0 + \beta_1 B(L^{1/m}; \theta) x_t^{(m)} + \gamma Y_{t-1} + u_t \\ Y_t &= \beta_0^* + \beta_1 \frac{B(L^{1/m}; \theta)}{(1-\gamma L)} x_t^{(m)} + u_t^* \end{aligned} \tag{12}$$

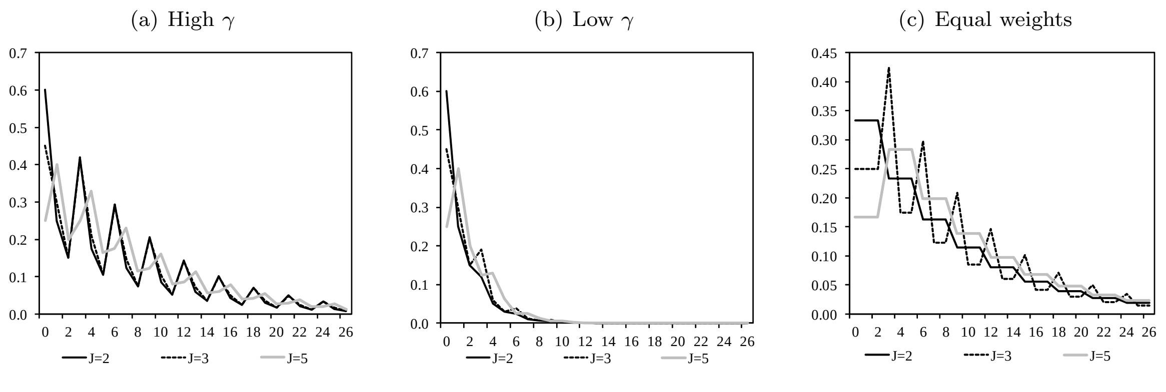
where $B(L^{1/m};\theta) = \sum_{j=0}^{J} B(j;\theta)L^{j/m}$, $\beta_0^* = \beta_0/(1-\gamma)$ and $u_t^* = u_t/(1-\gamma L)$. Considering the distributed lag representation, instead of a polynomial in $L^{1/m}$ one obtains a mixture $\frac{B(L^{1/m};\theta)}{(1-\gamma L)}$. Equation 13 shows more clearly the shape of the polynomial, for example assuming $J = m-1 = 2$ for the sake of simplicity, we can see that

$$\begin{aligned} Y_t \;=\; & \beta_0^* + \beta_1(B_0 x_t^{(3)} + B_1 x_{t-1/3}^{(3)} + B_2 x_{t-2/3}^{(3)} + \gamma B_0 x_{t-1}^{(3)} + \gamma B_1 x_{t-4/3}^{(3)} + \gamma B_2 x_{t-5/3}^{(3)} \\ & + \gamma^2 B_0 x_{t-2}^{(3)} + \gamma^2 B_1 x_{t-7/3}^{(3)} + \gamma^2 B_2 x_{t-8/3}^{(3)} + ...) + u_t^* \end{aligned} \tag{13}$$

Ghysels et al. (2007) and Andreou et al. (2011) pointed out that the autoregressive distributed lag MIDAS regression in equation 12 entails an undesirable property - the $\frac{B(L^{1/m};\theta)}{(1-\gamma L)}$ polynomial displays geometrically declining spikes at distance $m$, mimicking a seasonal pattern. This autoregressive augmentation of MIDAS regressions should be used if a seasonal pattern in $x_t^{(m)}$ is detected (Ghysels et al., 2007).

To illustrate these so-called spikes, Figure 1 plots simulated sequences of the coefficients associated with $x_t^{(3)}$ and its lags (up to 26 lags). The solid black line refers to equation 13, with $J = m-1 = 2$, meaning that the high-frequency terms cover a full low-frequency period ($m = 3$). The dashed black line represents the case where $J = 3$ and the solid grey line is for $J = 5$ (two low-frequency periods). Two alternatives for the autoregressive $\gamma$ coefficient are considered: in panels 1(a) and 1(c) $\gamma = 0.7$, while in panel 1(b) $\gamma = 0.2$. Moreover, different weighting schemes are also assessed, as in Ghysels et al. (2007). Panels 1(a) and 1(b) display rapidly declining weights for $J = 2$, slower declining weights for $J = 3$ and hump-shaped weights for $J = 5$. Panel 1(c) plots the equal-weight case.

Figure 1: Simulated sequences of the coefficients associated with $x_t^{(3)}$ and its lags




Note: In panels 1(a) and 1(b) the assumptions for the $B_i$ coefficients are the following: if $J = 2$, $B_0 = 0.60$, $B_1 = 0.25$ and $B_2 = 0.15$; if $J = 3$, $B_0 = 0.45$, $B_1 = 0.30$, $B_2 = 0.15$ and $B_3 = 0.10$; finally, if $J = 5$, $B_0 = 0.25$, $B_1 = 0.40$, $B_2 = 0.20$, $B_3 = 0.075$, $B_4 = 0.05$ and $B_5 = 0.025$. In panels 1(a) and 1(c) $\gamma = 0.7$, while in panel 1(b) $\gamma = 0.2$. In all cases, $\beta_1 = 1$ and $\sum_{i=0}^{J} B_i = 1$.

By looking at Figure 1 one can see that all three simple sets of weights that try to mimic the polynomial weighting schemes display a *spiky* pattern and, as expected, this pattern is softened with smaller $\gamma$. Note that with unrestricted MIDAS the pattern could be even more irregular, as the weights/coefficients are estimated unrestrictedly, not obeying to a known polynomial function. In the traditional case of equal-weight schemes, the sequence of coefficients have a stepwise pattern, except when the number of high-frequency terms do not fully cover low-frequency periods (e.g. when $J = 3$), which also exhibits spikes.

Clements and Galvão (2008) suggested an alternative way of introducing autoregressive dynamics in MIDAS regressions. The authors proposed interpreting the dynamics on $Y_t$ as a common factor (Hendry and Mizon, 1978). This assumption rests on the hypothesis that $Y_t$ and $x_t^{(m)}$ share the same autoregressive dynamics, though, as Hendry and Mizon (1978) pointed out, a common factor may not always be found. Hence, considering

$$\begin{aligned} Y_t &= \beta_0 + \beta_1 B(L^{1/m};\theta)x_t^{(m)} + u_t \\ u_t &= \gamma u_{t-1} + \varepsilon_t \end{aligned} \tag{14}$$

and replacing $u_t$ in (14) it follows that

$$(1-\gamma L)Y_t = \beta_0(1-\gamma) + \beta_1(1-\gamma L)B(L^{1/m};\theta)x_t^{(m)} + \varepsilon_t \tag{15}$$

When writing (15) in the distributed lag representation, the polynomial in $L$ cancels out, leaving the polynomial in $L^{1/m}$. The coefficients $\beta_0$, $\beta_1$, $\theta$ and $\gamma$ are estimated together, using nonlinear least squares in a two-step approach. First, the initial value for $\gamma$ can be estimated as

$$\hat{u}_t = \gamma\hat{u}_{t-1} + \varepsilon_t \tag{16}$$

where $\hat{u}_t$ are the residuals from a static MIDAS regression (without autoregressive terms) and $\varepsilon_t$ is an error term iid $(0,\sigma^2)$. The estimates for $\gamma$ are used to filter the original $Y_t$ and $x_t^{(m)}$ variables. Second, the filtered variables are used to estimate $\beta_0$, $\beta_1$ and $\theta$ in a static MIDAS regression. Although the initial work by Clements and Galvão (2008) and subsequent empirical applications (see, for example, Marcellino and Schumacher, 2010, Kuzin et al., 2011, Foroni and Marcellino, 2012, Jansen et al., 2012, Monteforte and Moretti, 2013 and Kuzin et al., 2013) only consider a single autoregressive term, in this paper this technique was extended to allow for more autoregressive terms. This can be done by including the additional lags of the residuals $\hat{u}$ in (16), as follows

$$\hat{u}_t = \sum_{i=1}^{p}\gamma_i\hat{u}_{t-i} + \varepsilon_t. \tag{17}$$

### 2.3.2 Alternative perspective

The literature presented so far suggests that adding autoregressive terms to MIDAS regressions in such a way that generates a $\frac{B(L^{1/m};\theta)}{(1-\gamma L)}$ polynomial implies declining spikes at distance $m$ in the infinite sequence of coefficients associated with $x_t^{(m)}$ and its lags. However, should this sequence be perceived as the relevant impulse response function from the high-frequency variable on the low-frequency variable?

To answer this question let us start by assuming that $x_t$ and $y_t$ are both observed at the high frequency, say monthly. Furthermore, assume that the DGP is known and resumes to an autoregressive term of order one, the contemporaneous variable $x_t$ and two lags ($x_{t-1/3}$ and $x_{t-2/3}$). To ease the exposition, the time index remains unaltered, so that the monthly time index is expressed by $t = 0, 1/3, 2/3, 1, 4/3, \dots, T$.

$$y_t = \alpha + b_0 x_t + b_1 x_{t-1/3} + b_2 x_{t-2/3} + \lambda y_{t-1/3} + u_t \tag{18}$$

The distributed lag version of this equation can be written as

$$y_t = \alpha^* + b_0 x_t + (b_1 + \lambda b_0) x_{t-1/3} + \sum_{i=0}^{\infty} \lambda^i (b_2 + \lambda b_1 + \lambda^2 b_0) x_{t-(2+i)/3} + u_t^* \tag{19}$$

where $\alpha^* = \alpha/(1 - \lambda L^{1/3})$ and $u_t^* = u_t/(1 - \lambda L^{1/3})$. Consider a shock equal to 1 in $x$ in January 2012. The response on the $y$ variable in January 2012 is equal to $b_0$. The responses in February and March are $b_1 + \lambda b_0$ and $b_2 + \lambda b_1 + \lambda^2 b_0$, respectively. So, considering a generic aggregation scheme $\Gamma(L^{1/m})$, the response in the first quarter is equal to $b_0\gamma_0 + (b_1 + \lambda b_0)\gamma_1 + (b_2 + \lambda b_1 + \lambda^2 b_0)\gamma_2$. Similarly, the monthly responses in April, May and June are $\lambda(b_2 + \lambda b_1 + \lambda^2 b_0)$, $\lambda^2(b_2 + \lambda b_1 + \lambda^2 b_0)$ and $\lambda^3(b_2 + \lambda b_1 + \lambda^2 b_0)$, respectively, resulting in a response of $(\lambda^3\beta_0 + \lambda^2\beta_1 + \lambda\beta_2)(\gamma_0 + \gamma_1\lambda + \gamma_2\lambda^2)$ in the second quarter.

The exact mixed-frequency regression can be obtained by pre-multiplying (18) by the finite order polynomials $\phi(L^{1/3})$ and $\Gamma(L^{1/3})$. Assume that the autoregressive order in the low/quarterly frequency is also one. In this case, $\phi(L^{1/3}) = (1 + \lambda L^{1/3} + \lambda^2 L^{2/3})$, i.e., $\phi(L^{1/3})(1 - \lambda L^{1/3}) = 1 - \lambda^3 L$. So, applying both polynomials one obtains the following mixed-frequency regression

$$(1-\lambda^3 L)Y_t = \hat{\alpha} + \delta_0 x_t + \delta_1 x_{t-1/3} + \delta_2 x_{t-2/3} + \delta_3 x_{t-1} + \delta_4 x_{t-4/3} + \delta_5 x_{t-5/3} + \delta_6 x_{t-2} + \hat{u}_t \tag{20}$$

where $\delta_0 = b_0\gamma_2$, $\delta_1 = b_0(\gamma_1 + \lambda\gamma_2) + b_1\gamma_2$, $\delta_2 = b_0(\gamma_0 + \lambda\gamma_1 + \lambda^2\gamma_2) + b_1(\gamma_1 + \lambda\gamma_2) + b_2\gamma_2$, $\delta_3 = b_0(\lambda\gamma_0 + \lambda^2\gamma_1) + b_1(\gamma_0 + \lambda\gamma_1 + \lambda^2\gamma_2) + b_2(\gamma_1 + \lambda\gamma_2)$, $\delta_4 = b_0\lambda^2\gamma_0 + b_1(\lambda\gamma_0 + \lambda^2\gamma_1) + b_2(\gamma_0 + \lambda\gamma_1 + \lambda^2\gamma_2)$, $\delta_5 = b_1\lambda^2\gamma_0 + b_2(\lambda\gamma_0 + \lambda^2\gamma_1)$ and $\delta_6 = b_2\lambda^2\gamma_0$.

Writing this equation in a distributed lag form one obtains

$$\begin{aligned}
Y_t = \tilde{\alpha} + & \quad \delta_0 x_t + \quad \delta_1 x_{t-1/3} + \quad \delta_2 x_{t-2/3} \\
+ & \quad (\delta_3 + \lambda^3\delta_0) x_{t-1} + (\delta_4 + \lambda^3\delta_1) x_{t-4/3} + (\delta_5 + \lambda^3\delta_2) x_{t-5/3} \\
+ & \quad (\delta_6 + \lambda^3\delta_3 + \lambda^6\delta_0) x_{t-2} + \lambda^3(\delta_4 + \lambda^3\delta_1) x_{t-7/3} + \lambda^3(\delta_5 + \lambda^3\delta_2) x_{t-8/3} \\
& + \lambda^3(\delta_6 + \lambda^3\delta_3 + \lambda^6\delta_0) x_{t-3} + \lambda^6(\delta_4 + \lambda^3\delta_1) x_{t-10/3} + \lambda^6(\delta_5 + \lambda^3\delta_2) x_{t-11/3} \\
& + \lambda^6(\delta_6 + \lambda^3\delta_3 + \lambda^6\delta_0) x_{t-4} + \lambda^9(\delta_4 + \lambda^3\delta_1) x_{t-13/3} + \lambda^9(\delta_5 + \lambda^3\delta_2) x_{t-14/3} + ... + \tilde{u}_t
\end{aligned} \tag{21}$$

where $\tilde{\alpha} = \hat{\alpha}/(1 - \lambda^3 L)$ and $\tilde{u}_t = \hat{u}_t/(1 - \lambda^3 L)$. Again, consider a shock equal to 1 in $x$ in January 2012. The response on the $Y$ variable in the first quarter of 2012 is equal to $\delta_2$, which corresponds to $b_0(\gamma_0 + \lambda\gamma_1 + \lambda^2\gamma_2) + b_1(\gamma_1 + \lambda\gamma_2) + b_2\gamma_2$. Rearranging the terms, this response equals the quarterly aggregate response underlying the monthly regression. A similar result is obtained for the following period - the response on the $Y$ variable in the second quarter of 2012 is $\delta_5 + \lambda^3\delta_2$, which also equals the quarterly aggregate of the monthly responses in April, May and June. The same reasoning is also valid if shocks in other months or combined shocks in more than one month were considered. These results can be extended to different specifications and to other forecast horizons.

As regards impulse response functions from $x_t^{(m)}$ on $Y_t$, sequentially assessing the coefficients in (21) does not seem to be very informative. The sequence $\delta_0$, $\delta_1$, $\delta_2$, $(\delta_3 + \lambda^3\delta_0)$, ... - with or without spikes - cannot be considered the relevant impulse response function because some of the coefficients (in this case, sets of three non-overlapping parameters) refer to the same time period in the low frequency, i.e., to the same quarter. Furthermore, recall that each coefficient in this sequence already covers the relevant latent monthly impulse responses on $y$ within each quarterly observation of $Y$, for each monthly shock in $x$.

Inspired by the periodic model framework (see Hansen and Sargent (2013) and Ghysels (2012), among others), one can say that there are several impulse response functions, one for each $m$ high-frequency period within a low-frequency observation. For example, in (21), the observed quarterly impulse response function from a shock in the first month of the quarter on the quarterly $Y_t$ variable is $\delta_2$, $\delta_5 + \lambda^3\delta_2$, $\lambda^3(\delta_5 + \lambda^3\delta_2)$, $\lambda^6(\delta_5 + \lambda^3\delta_2)$, and so on and so forth. Similarly, the observed quarterly impulse response function from a shock in the second month of the quarter on the quarterly $Y_t$ variable is $\delta_1$, $\delta_4 + \lambda^3\delta_1$, $\lambda^3(\delta_4 + \lambda^3\delta_1)$, $\lambda^6(\delta_4 + \lambda^3\delta_1)$, ..., and so on. Any of the observed quarterly impulse response functions do not exhibit spikes, regardless of the lags of $x_t^{(m)}$ or $Y_t$ included in the regression.

When the number of high-frequency lags in the mixed-frequency regressions is multiple of $m$ minus 1 (or lower than $m-1$) there is homogeneity in the shape of the impulse response functions on $Y_t$, regardless of the type of shock in $x_t^{(m)}$. This means that all impulse response functions share the same geometric decay pattern, i.e., the decay starts at the same time. In cases where the number of high-frequency lags is greater than $m-1$ but not its multiple, such as equation 20, the shape of the impulse response functions varies with the high-frequency timing of the shock in $x_t^{(m)}$ - for shocks in the first and second months of the quarter the geometric decay starts after two quarters, while for shocks in the third month of the quarter that decay only starts after three quarters.

Note that, as mentioned before, in a single-equation environment, one cannot recover the monthly impulse response functions of $x_t$ on $y_t$ departing from the mixed-frequency regression. Moreover, this framework only analyses the transmission of changes in one direction, from the high-frequency variables to the low-frequency variable, not taking into account the possible relation between the high-frequency variables nor the impact of changes in the low-frequency variable into the high-frequency variables.

In light of this discussion, alternatives to the common factor way of introducing autoregressive terms in MIDAS regressions can be considered. In particular, generalizing conventional ADL regressions, autoregressive terms are added to MIDAS regressions, without restrictions - not imposing the common factor, no restrictions on both the lag structure and the order of the autoregressive polynomial - see Andreou et al. (2013) and Guérin and Marcellino (2013). Moreover, no restrictions are imposed on the aggregation scheme - exponential Almon weight function, unrestricted (Foroni and Marcellino, 2012) and multiplicative (Francis et al., 2011).

Furthermore, in the same vein of multiplicative MIDAS regressions, which closely map the traditional low frequency model (i.e., reverse engineering the low frequency regressions, replacing the time aggregates by the underlying combinations of high-frequency lags, results in a mixed-frequency regression with a number of high-frequency lags that is always a multiple of $m$ minus 1) the performance of original and unrestricted MIDAS regressions with autoregressive terms and with high-frequency lags multiple of $m$ minus 1 is also analysed.

The latter regressions require full quarter information to be available, including for the current quarter. In order to implement these regressions when the $m$ current-period high-frequency observations have not been released, the series of the regressors with unbalanced $m$ periods were stacked with forecasts obtained from simple autoregressive regressions. Given that MIDAS regressions deliver direct forecasts, the autoregressive extrapolation of regressors is also based on direct forecasting. Note that this *bridge* approach to MIDAS regressions can be easily implemented for, say, monthly regressors. However, this procedure is less feasible when the regressors have time frequencies higher than monthly. This approach somehow mimics the state-space approach, with the simple autoregressive regressions acting as the state equation, and the MIDAS regression as the observation equation. Nevertheless, as in the traditional bridge model framework, this two-step approach is hindered by orthogonality issues, which can lead to biases in coefficient estimates.

Note that this latter version of MIDAS regressions ensures that the geometric decay pattern starts at the same time in all $m$ impulse response functions. Moreover, when new information becomes available within the current quarter, there is no need to change the forecasting regression in order to update the forecasts. This procedure only involves substituting the stacked regressor forecasts by the newly observed figures.

## 3 Design of the nowcasting and forecasting exercise

The aim of this exercise is to nowcast and forecast quarterly developments in euro area GDP growth, in real terms, using three different indicators: a hard-data series; a soft-data series; and a financial series. Thus, the dataset used contains a quarterly series on the real GDP from 1996$Q$1 to 2012$Q$4, the monthly industrial production and the monthly economic sentiment indicator from January 1996 to December 2012, and the Dow Jones Euro Stoxx index on a daily basis from 1 January 1996 to 31 December 2012. All series are seasonally adjusted except the stock market information. Apart from the economic sentiment indicator, the original series were transformed, using the rate of change (based on the first difference), in order to have stationary variables.

The data considered are final data, meaning that they refer to the latest release available when the database was built. While in the case of the economic sentiment indicator and the stock market index final data equal real-time data, as these series are not revised, revisions of GDP and industrial production are not taken into account in this analysis. However, evidence from previous work on data revisions suggests that revisions are typically small for euro area GDP (Marcellino and Musso, 2011).

The database is split in two, for the in-sample estimation and the out-of-sample forecasting exercise. From 1996$Q$1 to 2006$Q$4 the sample was used for in-sample model specification and estimation. Different types of MIDAS regressions were estimated - original, multiplicative, with and without autoregressive terms - based on different information sets.[1] Different lags were considered (up to 4 quarters), also for the

[1] The codes used to estimate and forecast using MIDAS regressions were written in Matlab. Some functions were

autoregressive terms. All regressions were recursively estimated and selected using information criteria, namely the BIC.

In the following analysis the original MIDAS regressions, as in equation 5, will be simply denoted as "MIDAS". Moreover, the multiplicative (equation 8) and unrestricted (equation 9) regressions are denoted as "M-MIDAS" and "U-MIDAS", respectively. The MIDAS specification with common factor autoregressive dynamics (equation 15) will be labelled "CF-MIDAS", while without that restriction the prefix "AR-" is added. The case of MIDAS regressions with autoregressive terms and with high-frequency lags multiple of $m$ minus 1 will have the prefix "Balanced". Apart from U-MIDAS regressions, all other MIDAS regressions were estimated using the exponential Almon polynomial defined as in equation 6.[2] Different initial parameter specifications (including the equal weight hypothesis, i.e. $\theta_1 = \theta_2 = 0$) were tested and the results do not differ significantly (for a discussion on the shapes of different weighting sets, see Ghysels et al., 2007). The hyperparameters $\theta$ of the exponential Almon function are restricted to $\theta_1 < 5$ and $\theta_2 < 0$.

The sample from $2007Q1$ to $2012Q4$ was used for the out-of-sample nowcasting and forecasting exercise. Although an out-of-sample forecast exercise with $P = 24$ quarters has limitations, using euro area data still bears an inevitable trade-off between sample sizes for in-sample and out-of-sample exercises and this forecasting exercise is no exception. For obtaining the forecasts, a recursive exercise was performed, so that throughout the out-of-sample period the estimation sample is recursively expanded by adding one observation at a time. As a new observation is added to the estimation sample, the regressions are re-estimated and, thus, the coefficients are allowed to change over time. Adding to nowcasts ($h = 0$) direct forecast for up to $h = 4$ quarters ahead are also presented. For each forecast horizon a different model is estimated.

Although the database used is not a real-time database, the different publication lags of the indicators are taken into account when within-quarter information is used. So, in a single-variable framework, it is possible to have up to 3 different forecasts for a given quarter, for each quarterly forecast horizon, depending on the within-quarter information used - one month ($I$), two months ($II$), or full quarter ($III$).

To evaluate the forecasting performance of the different MIDAS regressions is used the root mean squared forecast error (RMSFE). Relative RMSFE are computed to compare the performance of the MIDAS approach with alternative, purely quarterly, benchmark models. Two benchmark models are considered. The first is an autoregressive (AR)

taken from the Econometrics Toolbox written by James P. LeSage (http://www.spatial-econometrics.com). The MIDAS toolbox used was greatly inspired in a code kindly provided by Arthur Sinko.

[2]The beta polynomial was also tested and the results were qualitatively similar. All results are available from the author upon request.

model, which is estimated recursively, using a general-to-specific approach, and the lag length (from 0 to 4 lags) is chosen according to information criteria, namely the BIC. The AR benchmark boils down to the sample average when, according to the BIC criterion, including positive lags leads to a worse performance than choosing the lag length equal to 0.

The second is a traditional quarterly single-equation multivariate model, with all the variables in the low frequency. This model includes autoregressive terms (from 0 to 4 lags) and is also estimated recursively, using a general-to-specific approach and the BIC. As different information sets are considered (different variables) the quarterly multivariate models are adjusted accordingly. Moreover, when full quarter information is not available, forecasts from the quarterly multivariate models are obtained through a bridge model framework, in this case with a direct forecasting approach, similarly to MIDAS approach. So, estimates for the missing monthly observations, obtained from univariate models, are plugged in the monthly data, which are transformed into quarterly series and, then, used for forecasting in the traditional quarterly model. To ensure consistency within all forecasts used, the missing monthly observations are also direct forecasts from autoregressive models.

In order to assess the statistical significance of the differences in the forecasting performance between the alternatives considered, the test of equal forecast accuracy on the population-level of direct multi-step forecasts from nested linear models proposed by Clark and McCracken (2005) is used. The null hypothesis is that the benchmark model forecasts (restricted model, denoted as model 1) are as accurate as those of the MIDAS regressions (unrestricted model, denoted as model 2) and the one-sided alternative hypothesis is that the unrestricted model forecasts are more accurate. Following the authors' notation, the test statistic used is

$$MSE - F = P\frac{MSE_1 - MSE_2}{MSE_2} \tag{22}$$

where $P$ is the number of forecasts and $MSE_i$ denotes the mean squared forecast error of model $i$, with $i = 1, 2$. Because this test has a non-standard limiting distribution, a bootstrap procedure was implemented to obtain the critical values. As suggested by Clark and McCracken (2005) and similarly to Kilian (1999), the bootstrap algorithm used starts with the estimation of a large set of simulated samples of the dependent variable (1000 samples), which are computed by drawing with replacement from the sample residuals under the null hypothesis (restricted model). Moreover, a bootstrap-after-bootstrap procedure, as proposed by Kilian (1998), is implemented to obtain small-sample bias-adjusted bootstrapped time series. Based on this simulated data, both restricted and unrestricted direct multi-step forecasts are calculated recursively and the test statistic is computed for each set of forecasts. The critical values are computed as quantiles of the bootstrapped series of test statistics.

## 4 Empirical results

Figures 2 and 3 summarise the results on the forecasting performance of different MIDAS regressions against an AR and traditional low-frequency quarterly benchmark, with a different regressor in each panel - panels (a), (b) and (c) display the results of industrial production, economic sentiment indicator and stock market index, respectively (more detailed results, as well as the significance levels for comparing forecast accuracy, can be found in Tables A.1 and A.2, in the Appendix). The figures reported refer to the relative RMSFE, so figures lesser than one mean that the forecasting performance of the MIDAS model is better, in terms of RMSFE, than the benchmark model - the naive AR or the traditional quarterly model, respectively.

Overall, although the best results are not always obtained from the same type of MIDAS weighting scheme, the best performing MIDAS regressions deliver better results than both benchmarks and the differences in terms of RMSFE are, in general, statistically significant. So, as in Clements and Galvão (2008), Clements and Galvão (2009) and Marcellino and Schumacher (2010), among others, it can be concluded that exploiting high-frequency data has a significant impact on forecasting performance and using MIDAS regressions contributes to increase forecast accuracy in terms of RMSFE.

Moreover, the use of MIDAS data-driven weighting schemes to aggregate the high-frequency data is advantageous for forecasting over horizons up to 4 quarters ahead, using either monthly or daily data. MIDAS regressions with the highest forecast accuracy also show a good performance when incomplete information for the current quarter is used, beating the results from traditional quarterly model that rely on monthly direct forecasts to construct missing quarterly observations (bridge model framework). Hence, MIDAS seems to be a good and simple tool for using within-quarter high-frequency information in order to improve forecast accuracy.

Looking into more detail at the different MIDAS regressions, there are five main conclusions that can be drawn from these results. First, as the forecast horizon increases, the differences in the forecasting performance between MIDAS regressions decrease, making the choice among alternative MIDAS weighting schemes less relevant. In contrast, the differences are higher for short-term forecasting, rendering this choice crucial for achieving the best performance.

Second, less parsimonious MIDAS weighting schemes - multiplicative and unrestricted

Figure 2: Relative RMSFE of MIDAS regressions compared to an AR benchmark

(a) Industrial production (b) Economic sentiment indicator (c) Dow Jones Euro Stoxx index

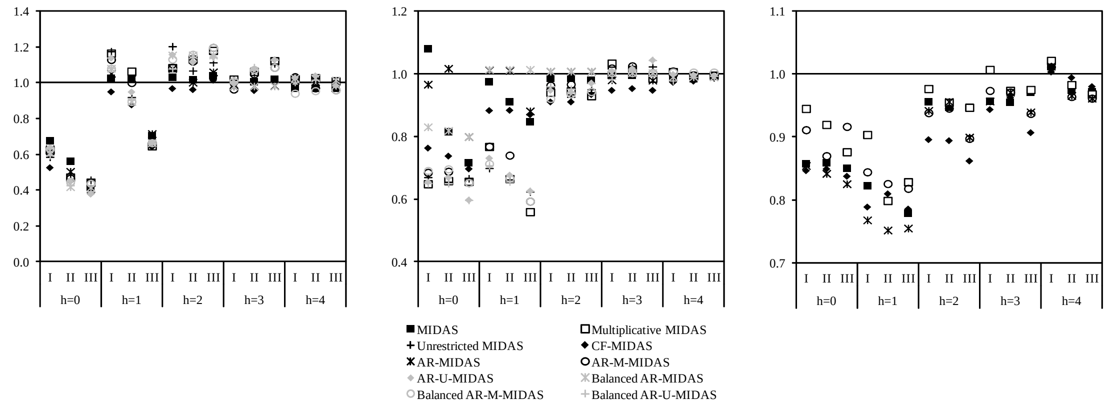
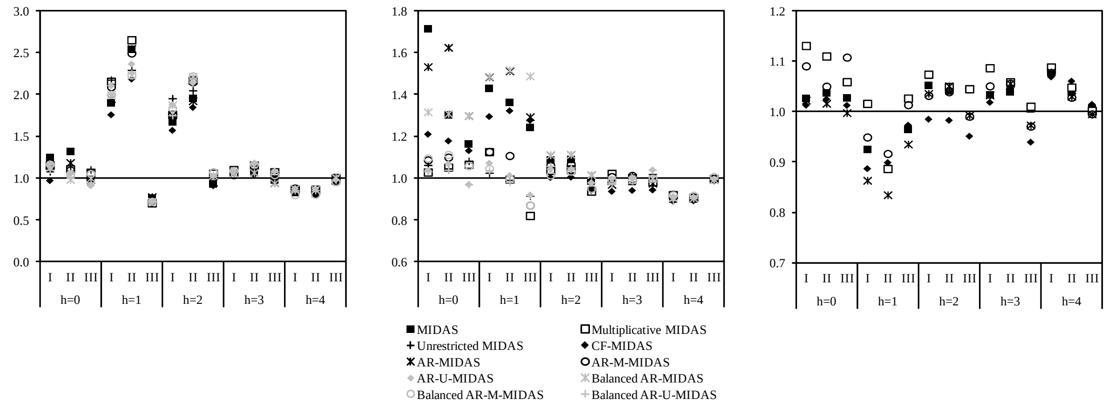



Figure 3: Relative RMSFE of MIDAS regressions compared to a quarterly benchmark

(a) Industrial production (b) Economic sentiment indicator (c) Dow Jones Euro Stoxx index




MIDAS - are often less accurate, in terms of RMSFE, than polynomial schemes. One exception are the short-term forecasts (up to 2 quarters ahead) using the economic sentiment indicator. In this case, multiplicative and unrestricted MIDAS regressions, with or without autoregressive terms display the best forecasting performances, either in comparison with the AR or the quarterly benchmark. This performance may be explained by the fact that the restrictions on the signs of the coefficients are less stringent in multiplicative or unrestricted MIDAS. As noted by Breitung et al. (2012), using exponential (or beta) polynomials to determine the shape of the lag distribution imposes that all $B(j;\theta_1,\theta_2)$ lag coefficients share their sign. Thus, in polynomial MIDAS regressions the sign of the relation between $Y_t$ and $x_t^{(m)}$ is determined by the sign of the $\beta_1$ coefficient. On the contrary, the multiplicative scheme allows different signs on the $\beta_i$ coefficients for each lag of the $m$-aggregates of the $x$ variables. Similarly, in the unrestricted regressions each high-frequency lag has its own coefficient.[3] The

[3] Using the traditional Almon polynomial, instead of exponential or beta polynomials, is another alternative to eliminate the restrictions on the signs of the coefficients.

estimation results from the traditional quarterly models confirm that changing signs in the lag coefficients is an important feature in the regressions using the economic sentiment indicator, for forecast horizons up to 2 quarter ahead.

Third, the best performing MIDAS regressions tend to include autoregressive terms, which is an expected result given that this empirical application uses macroeconomic data (Clements and Galvão, 2008, Marcellino and Schumacher, 2010, Monteforte and Moretti, 2013, among others). Fourth, focusing on MIDAS regressions with autoregressive terms, the results suggest that it is possible to improve forecasting performance of MIDAS regressions by using weighting schemes alternative to CF-MIDAS. In particular, up to 1 quarter ahead, balanced AR-U-MIDAS consistently outperforms CF-MIDAS in the regressions using the economic sentiment indicator. Note that this performance is observed even when full-quarter information is not available, which suggests that combining balanced MIDAS regressions with autoregressive extrapolation of the regressor can deliver good results in terms of forecast accuracy in the short term. Also for short-term forecasting, AR-MIDAS regressions with the Dow Jones Euro Stoxx index have the best forecasting performance, being a good alternative for dealing with autoregressive augmentation. In the case of industrial production, the evidence is more mixed and no clear pattern is detected. Nevertheless, in 7 out of 15 cases the alternative models to CF-MIDAS show the best forecasting performance.

Finally, the existence of some degree of variability in the ranking of forecasting performance among alternative MIDAS regressions with autoregressive terms, especially in the short term, suggests that choosing is essentially an empirical question. It may be the case that in some empirical exercises imposing a common factor dynamics between $Y_t$ and $x_t^{(m)}$ can be less benign than using alternative ways of including autoregressive terms in MIDAS regressions. In other cases it may be the opposite.

## 5 Conclusion

Having started on the financial field, MIDAS regressions have been gaining an increasing attention in macroeconomic forecasting. This technique is a simple, flexible and potentially parsimonious way of taking into account timely releases of high-frequency data, in particular for forecasting a low-frequency series. Nevertheless, the autoregressive augmentation of MIDAS regressions has raised some concerns. In this paper, alternative ways of dealing with autoregressive augmentation of MIDAS regression are discussed. It is shown that standard MIDAS regressions (no common factor restriction) are able to deal with autoregressive terms.

Moreover, the forecasting performance, in terms of RMSFE, of several kinds of MIDAS regressions is assessed through a recursive forecasting exercise. The benchmarks used are a simple autoregressive model and traditional quarterly models. In the latter case, a bridge model framework was put in place whenever full-quarter information was not available. Corroborating previous evidence, the results obtained suggest that using MIDAS regressions contributes to increase forecast accuracy. The statistically significant benefits from this data-driven, and potentially more parsimonious, weighting scheme to aggregate the high-frequency data are obtained for forecast horizons up to 4 quarter ahead, regardless of having incomplete information for the current quarter and of the exact time frequency of the regressors.

The results also stress the importance of choosing the best MIDAS model for each specific situation, namely when the aim is short-term forecasting. The auxiliary choices of the forecaster when using MIDAS regressions are, thus, crucial for the success in nowcasting and forecasting exercises. Although there is no one-fits-all recipe, the results suggests that the multiplicative and unrestricted MIDAS seem to be a good alternative to the original (polynomial) MIDAS regressions when restrictions on signs of the coefficients play an important role. Furthermore, focusing on MIDAS regressions with autoregressive terms, imposing a common factor dynamics between the dependent variable and the regressors (CF-MIDAS) can be, in some cases, too strict. The other ways of introducing autoregressive terms in MIDAS regressions analysed in this paper - AR-MIDAS, AR-M-MIDAS, AR-U-MIDAS and the respective balanced versions - proved to be good alternatives and in some cases are the best performing MIDAS regression.

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# Appendix

Table A.1: Single-variable models: relative performance, in terms of RMSFE, against an AR benchmark, for forecast horizon h

| | h=0 | | | h=1 | | | h=2 | | | h=3 | | | h=4 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | I | II | III | I | II | III | I | II | III | I | II | III | I | II | III |
| Industrial Production | | | | | | | | | | | | | | | |
| MIDAS | 0.676 | 0.560 | 0.415 | 1.024 | 1.018 | 0.702 | 1.030 | 1.017 | 1.038 | 1.017 | 1.005 | 1.017 | 0.970 | 0.970 | 0.970 |
| | [0.000] | [0.000] | [0.000] | [0.188] | [0.147] | [0.000] | [0.244] | [0.139] | [0.225] | [0.096] | [0.125] | [0.091] | [0.010] | [0.008] | [0.008] |
| Multiplicative MIDAS | 0.624 | 0.472 | 0.443 | 1.164 | 1.063 | 0.646 | 1.083 | 1.131 | 1.179 | 1.019 | 1.062 | 1.121 | 1.022 | 1.027 | 1.010 |
| | [0.000] | [0.000] | [0.000] | [0.705] | [0.277] | [0.000] | [0.471] | [0.510] | [0.327] | [0.159] | [0.265] | [0.306] | [0.176] | [0.129] | [0.057] |
| Unrestricted MIDAS | 0.585 | 0.464 | 0.457 | 1.175 | 0.919 | 0.646 | 1.203 | 1.067 | 1.113 | 1.015 | 1.056 | 1.106 | 1.014 | 1.020 | 0.998 |
| | [0.000] | [0.000] | [0.000] | [0.824] | [0.008] | [0.000] | [0.863] | [0.535] | [0.646] | [0.162] | [0.444] | [0.644] | [0.143] | [0.124] | [0.086] |
| CF-MIDAS | **0.525** | 0.449 | 0.379 | **0.948** | **0.875** | **0.641** | **0.967** | **0.961** | **1.014** | 0.987 | **0.956** | 1.013 | 1.026 | 1.025 | 1.005 |
| | [0.000] | [0.000] | [0.000] | [0.018] | [0.004] | [0.000] | [0.025] | [0.021] | [0.119] | [0.037] | [0.013] | [0.071] | [0.166] | [0.162] | [0.086] |
| AR-MIDAS | 0.629 | 0.504 | 0.407 | 1.052 | 1.022 | 0.715 | 1.079 | 1.002 | 1.059 | 0.979 | 0.981 | 0.984 | 1.012 | 1.005 | 0.979 |
| | [0.000] | [0.000] | [0.000] | [0.307] | [0.182] | [0.000] | [0.477] | [0.050] | [0.293] | [0.024] | [0.026] | [0.022] | [0.103] | [0.057] | [0.026] |
| AR-M-MIDAS | 0.609 | 0.466 | 0.437 | 1.129 | 1.000 | 0.664 | 1.085 | 1.120 | 1.196 | **0.964** | 1.049 | 1.085 | 1.032 | 0.971 | 0.960 |
| | [0.000] | [0.000] | [0.000] | [0.243] | [0.215] | [0.000] | [0.232] | [0.252] | [0.338] | [0.006] | [0.065] | [0.296] | [0.168] | [0.011] | [0.018] |
| AR-U-MIDAS | 0.635 | 0.449 | **0.378** | 1.137 | 0.948 | 0.664 | 1.156 | 1.114 | 1.143 | 1.001 | 1.075 | 1.127 | 1.026 | 1.037 | 0.983 |
| | [0.000] | [0.000] | [0.000] | [0.583] | [0.024] | [0.000] | [0.635] | [0.651] | [0.668] | [0.439] | [0.471] | [0.644] | [0.174] | [0.167] | [0.012] |
| Balanced AR-MIDAS | 0.609 | **0.418** | 0.415 | 1.080 | 0.894 | 0.664 | 1.154 | 1.154 | 1.154 | 0.980 | 0.980 | **0.980** | 1.026 | 1.026 | 1.014 |
| | [0.000] | [0.000] | [0.000] | [0.744] | [0.007] | [0.000] | [0.623] | [0.600] | [0.542] | [0.035] | [0.022] | [0.019] | [0.234] | [0.188] | [0.107] |
| Balanced AR-M-MIDAS | 0.631 | 0.448 | 0.437 | 1.080 | 0.894 | 0.664 | 1.131 | 1.157 | 1.196 | 1.010 | 1.072 | 1.085 | **0.940** | **0.955** | **0.960** |
| | [0.000] | [0.000] | [0.000] | [0.744] | [0.007] | [0.000] | [0.267] | [0.304] | [0.338] | [0.125] | [0.313] | [0.296] | [0.010] | [0.017] | [0.018] |
| Balanced AR-U-MIDAS | 0.594 | 0.426 | 0.393 | 1.082 | 0.904 | 0.664 | 1.078 | 1.122 | 1.143 | 1.003 | 1.086 | 1.127 | 1.003 | 1.015 | 0.983 |
| | [0.000] | [0.000] | [0.000] | [0.779] | [0.011] | [0.000] | [0.716] | [0.749] | [0.668] | [0.191] | [0.636] | [0.644] | [0.207] | [0.205] | [0.012] |
| Economic Sentiment Indicator | | | | | | | | | | | | | | | |
| MIDAS | 1.080 | 0.815 | 0.716 | 0.975 | 0.910 | 0.846 | 0.986 | 0.986 | 0.979 | 0.995 | 0.995 | 0.986 | 0.985 | 0.984 | 0.993 |
| | [0.073] | [0.002] | [0.000] | [0.047] | [0.007] | [0.000] | [0.096] | [0.084] | [0.052] | [0.168] | [0.166] | [0.097] | [0.071] | [0.080] | [0.115] |
| Multiplicative MIDAS | **0.648** | 0.658 | 0.656 | 0.767 | 0.665 | **0.559** | 0.940 | 0.945 | **0.929** | 1.033 | 1.013 | 0.985 | 1.006 | 0.994 | 0.995 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.014] | [0.021] | [0.008] | [0.220] | [0.217] | [0.091] | [0.108] | [0.113] | [0.141] |
| Unrestricted MIDAS | 0.670 | 0.655 | 0.666 | **0.699** | 0.662 | 0.623 | 0.956 | 0.926 | 0.950 | 1.004 | 1.019 | 1.023 | 0.993 | 0.994 | 0.988 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.024] | [0.013] | [0.027] | [0.170] | [0.301] | [0.317] | [0.107] | [0.114] | [0.083] |
| CF-MIDAS | 0.763 | 0.737 | 0.696 | 0.882 | 0.883 | 0.869 | **0.910** | **0.910** | 0.934 | **0.947** | **0.952** | **0.947** | **0.973** | **0.976** | **0.987** |
| | [0.001] | [0.000] | [0.000] | [0.003] | [0.004] | [0.000] | [0.010] | [0.011] | [0.010] | [0.035] | [0.036] | [0.036] | [0.057] | [0.073] | [0.095] |
| AR-MIDAS | 0.966 | 1.017 | 0.799 | 1.012 | 1.010 | 0.881 | 1.007 | 1.007 | 1.007 | 0.980 | 1.003 | 0.979 | 0.990 | 0.990 | 0.990 |
| | [0.147] | [0.183] | [0.203] | [0.299] | [0.322] | [0.329] | [0.483] | [0.481] | [0.493] | [0.438] | [0.469] | [0.425] | [0.432] | [0.425] | [0.427] |
| AR-M-MIDAS | 0.685 | 0.688 | 0.652 | 0.768 | 0.740 | 0.593 | 0.963 | 0.966 | 0.942 | 1.018 | 1.025 | 1.003 | 1.008 | 0.996 | 0.995 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.031] | [0.029] | [0.010] | [0.155] | [0.175] | [0.205] | [0.094] | [0.090] | [0.079] |
| AR-U-MIDAS | 0.654 | 0.669 | 0.597 | 0.730 | 0.676 | 0.625 | 0.947 | 0.941 | 0.970 | 1.008 | 1.015 | 1.043 | 0.997 | 0.995 | 0.993 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.022] | [0.021] | [0.044] | [0.169] | [0.212] | [0.371] | [0.097] | [0.101] | [0.083] |
| Balanced AR-MIDAS | 0.830 | 0.819 | 0.799 | 1.013 | 1.013 | 1.013 | 1.007 | 1.007 | 1.007 | 1.003 | 1.003 | 1.003 | 0.990 | 0.990 | 0.990 |
| | [0.000] | [0.000] | [0.000] | [0.227] | [0.225] | [0.221] | [0.206] | [0.208] | [0.206] | [0.204] | [0.209] | [0.205] | [0.088] | [0.085] | [0.085] |
| Balanced AR-M-MIDAS | 0.691 | 0.696 | 0.652 | 0.713 | 0.666 | 0.593 | 0.921 | 0.935 | 0.942 | 1.003 | 1.003 | 1.003 | 1.005 | 1.005 | 1.005 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.005] | [0.010] | [0.010] | [0.204] | [0.209] | [0.205] | [0.179] | [0.173] | [0.173] |
| Balanced AR-U-MIDAS | 0.650 | **0.650** | **0.597** | 0.707 | **0.655** | 0.625 | 0.960 | 0.951 | 0.970 | 0.983 | 1.011 | 1.043 | 0.978 | 0.990 | 0.993 |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.039] | [0.023] | [0.044] | [0.112] | [0.221] | [0.371] | [0.063] | [0.092] | [0.083] |
| Dow Jones Euro Stoxx | | | | | | | | | | | | | | | |
| MIDAS | 0.857 | 0.859 | 0.850 | 0.822 | 0.799 | 0.778 | 0.956 | 0.947 | 0.947 | 0.957 | **0.955** | 0.970 | 1.013 | 0.974 | 0.972 |
| | [0.001] | [0.002] | [0.000] | [0.002] | [0.001] | [0.000] | [0.045] | [0.024] | [0.032] | [0.044] | [0.039] | [0.079] | [0.229] | [0.064] | [0.072] |
| Multiplicative MIDAS | 0.945 | 0.920 | 0.876 | 0.904 | 0.799 | 0.829 | 0.977 | 0.955 | 0.947 | 1.007 | 0.974 | 0.975 | 1.021 | 0.983 | 0.968 |
| | [0.009] | [0.001] | [0.000] | [0.008] | [0.000] | [0.000] | [0.081] | [0.036] | [0.035] | [0.246] | [0.070] | [0.091] | [0.317] | [0.074] | [0.056] |
| CF-MIDAS | **0.846** | 0.849 | 0.837 | 0.789 | 0.809 | 0.785 | **0.895** | **0.894** | **0.862** | **0.943** | 0.963 | **0.907** | **1.003** | 0.994 | 0.980 |
| | [0.004] | [0.000] | [0.005] | [0.000] | [0.000] | [0.000] | [0.006] | [0.007] | [0.001] | [0.025] | [0.046] | [0.012] | [0.173] | [0.119] | [0.084] |
| AR-MIDAS | 0.854 | **0.842** | **0.825** | **0.768** | **0.752** | **0.755** | 0.942 | 0.956 | 0.899 | 0.957 | 0.971 | 0.939 | 1.012 | 0.966 | 0.961 |
| | [0.004] | [0.001] | [0.001] | [0.000] | [0.000] | [0.000] | [0.026] | [0.035] | [0.006] | [0.033] | [0.063] | [0.031] | [0.189] | [0.047] | [0.042] |
| AR-M-MIDAS | 0.911 | 0.870 | 0.916 | 0.844 | 0.826 | 0.818 | 0.938 | 0.945 | 0.897 | 0.974 | 0.971 | 0.937 | 1.011 | **0.964** | **0.961** |
| | [0.002] | [0.003] | [0.006] | [0.000] | [0.000] | [0.000] | [0.023] | [0.034] | [0.006] | [0.050] | [0.037] | [0.029] | [0.168] | [0.053] | [0.042] |

Note: For each quarterly forecast horizon (h), depending on the within-quarter information used, "I" refers to one month, "II" to two months and "III" to a full quarter. The figures in bold denote the minimum relative RMSFE for each single-variable model. The figures shaded denote the minimum relative RMSFE for each forecast horizon, across the single-variable models. The figures in brackets denote the empirical rejection frequencies for the null hypothesis of equal RMSFE calculated using bootstrapped test statistics.

Table A.2: Single-variable models: relative performance, in terms of RMSFE, against a traditional low-frequency quarterly benchmark, for forecast horizon h

| | h=0 | | | h=1 | | | h=2 | | | h=3 | | | h=4 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | I | II | III | I | II | III | I | II | III | I | II | III | I | II | III |
| Industrial Production | | | | | | | | | | | | | | | |
| MIDAS | 1.248 | 1.317 | 1.001 | 1.896 | 2.539 | 0.762 | 1.672 | 1.951 | 0.930 | 1.097 | 1.093 | 0.975 | 0.826 | 0.817 | 0.966 |
| | [0.784] | [0.839] | [0.197] | [1.000] | [1.000] | [0.002] | [1.000] | [1.000] | [0.037] | [0.774] | [0.892] | [0.086] | [0.095] | [0.093] | [0.079] |
| Multiplicative MIDAS | 1.152 | 1.110 | 1.068 | 2.156 | 2.651 | 0.702 | 1.758 | 2.170 | 1.056 | 1.100 | 1.154 | 1.075 | 0.871 | 0.866 | 1.005 |
| | [0.542] | [0.094] | [0.044] | [0.999] | [1.000] | [0.034] | [0.966] | [0.992] | [0.332] | [0.589] | [0.603] | [0.411] | [0.165] | [0.132] | [0.424] |
| Unrestricted MIDAS | 1.080 | 1.091 | 1.101 | 2.175 | 2.292 | 0.701 | 1.953 | 2.047 | 0.997 | 1.095 | 1.148 | 1.060 | 0.863 | 0.860 | 0.994 |
| | [0.698] | [0.647] | [0.609] | [1.000] | [1.000] | [0.000] | [1.000] | [1.000] | [0.272] | [0.845] | [0.936] | [0.696] | [0.063] | [0.049] | [0.203] |
| CF-MIDAS | **0.969** | 1.056 | 0.913 | **1.756** | **2.183** | **0.697** | **1.570** | **1.844** | **0.908** | 1.065 | **1.039** | 0.971 | 0.874 | 0.864 | 1.001 |
| | [0.025] | [0.265] | [0.021] | [0.998] | [1.000] | [0.001] | [1.000] | [1.000] | [0.030] | [0.655] | [0.583] | [0.087] | [0.046] | [0.058] | [0.307] |
| AR-MIDAS | 1.162 | 1.184 | 0.981 | 1.947 | 2.547 | 0.776 | 1.752 | 1.922 | 0.949 | 1.057 | 1.067 | 0.942 | 0.862 | 0.847 | 0.975 |
| | [0.838] | [0.747] | [0.100] | [1.000] | [1.000] | [0.002] | [1.000] | [1.000] | [0.051] | [0.627] | [0.665] | [0.029] | [0.033] | [0.085] | [0.081] |
| AR-M-MIDAS | 1.125 | 1.096 | 1.054 | 2.090 | 2.493 | 0.721 | 1.762 | 2.149 | 1.071 | **1.040** | 1.140 | 1.040 | 0.879 | 0.818 | 0.956 |
| | [0.158] | [0.271] | [0.103] | [0.999] | [1.000] | [0.000] | [0.999] | [1.000] | [0.132] | [0.288] | [0.483] | [0.250] | [0.075] | [0.043] | [0.041] |
| AR-U-MIDAS | 1.173 | 1.056 | **0.911** | 2.105 | 2.363 | 0.721 | 1.877 | 2.137 | 1.024 | 1.080 | 1.169 | 1.080 | 0.874 | 0.874 | 0.979 |
| | [0.894] | [0.368] | [0.003] | [1.000] | [1.000] | [0.000] | [1.000] | [1.000] | [0.332] | [0.518] | [0.929] | [0.678] | [0.177] | [0.136] | [0.029] |
| Balanced AR-MIDAS | 1.125 | **0.983** | 1.000 | 1.999 | 2.230 | 0.721 | 1.873 | 2.214 | 1.034 | 1.058 | 1.066 | **0.939** | 0.874 | 0.865 | 1.009 |
| | [0.737] | [0.140] | [0.147] | [1.000] | [1.000] | [0.000] | [0.999] | [1.000] | [0.221] | [0.683] | [0.674] | [0.028] | [0.129] | [0.099] | [0.352] |
| Balanced AR-M-MIDAS | 1.164 | 1.053 | 1.054 | 1.999 | 2.230 | 0.721 | 1.836 | 2.221 | 1.071 | 1.090 | 1.166 | 1.040 | **0.801** | **0.805** | **0.956** |
| | [0.346] | [0.103] | [0.103] | [1.000] | [1.000] | [0.000] | [0.996] | [1.000] | [0.132] | [0.793] | [0.862] | [0.250] | [0.013] | [0.009] | [0.041] |
| Balanced AR-U-MIDAS | 1.098 | 1.003 | 0.947 | 2.003 | 2.253 | 0.721 | 1.751 | 2.154 | 1.024 | 1.083 | 1.181 | 1.080 | 0.854 | 0.856 | 0.979 |
| | [0.731] | [0.095] | [0.016] | [1.000] | [1.000] | [0.000] | [1.000] | [1.000] | [0.332] | [0.916] | [0.953] | [0.678] | [0.025] | [0.025] | [0.029] |
| Economic Sentiment Indicator | | | | | | | | | | | | | | | |
| MIDAS | 1.713 | 1.303 | 1.164 | 1.430 | 1.362 | 1.242 | 1.087 | 1.089 | 0.987 | 0.984 | 0.983 | 0.982 | 0.900 | 0.899 | 0.996 |
| | [0.220] | [0.206] | [0.170] | [0.955] | [0.978] | [0.142] | [0.830] | [0.866] | [0.135] | [0.121] | [0.121] | [0.055] | [0.079] | [0.074] | [0.053] |
| Multiplicative MIDAS | **1.028** | 1.052 | 1.066 | 1.125 | 0.995 | **0.821** | 1.036 | 1.043 | **0.937** | 1.022 | 1.000 | 0.981 | 0.920 | 0.907 | 0.997 |
| | [0.462] | [0.717] | [0.824] | [0.992] | [0.981] | [0.002] | [0.710] | [0.660] | [0.040] | [0.245] | [0.275] | [0.076] | [0.092] | [0.077] | [0.212] |
| Unrestricted MIDAS | 1.062 | 1.046 | 1.082 | **1.025** | 0.991 | 0.915 | 1.054 | 1.022 | 0.958 | 0.992 | 1.007 | 1.019 | 0.908 | 0.907 | 0.990 |
| | [0.658] | [0.402] | [0.392] | [0.962] | [0.982] | [0.020] | [0.660] | [0.629] | [0.051] | [0.249] | [0.383] | [0.363] | [0.086] | [0.092] | [0.112] |
| CF-MIDAS | 1.209 | 1.177 | 1.131 | 1.294 | 1.321 | 1.276 | **1.003** | **1.004** | 0.941 | **0.936** | **0.941** | **0.943** | **0.889** | **0.891** | **0.990** |
| | [0.097] | [0.098] | [0.181] | [0.909] | [0.971] | [0.175] | [0.421] | [0.470] | [0.041] | [0.029] | [0.064] | [0.030] | [0.066] | [0.083] | [0.099] |
| AR-MIDAS | 1.532 | 1.624 | 1.298 | 1.484 | 1.512 | 1.293 | 1.110 | 1.112 | 1.016 | 0.969 | 0.991 | 0.975 | 0.906 | 0.904 | 0.993 |
| | [0.453] | [0.398] | [0.367] | [0.983] | [0.996] | [0.299] | [0.914] | [0.927] | [0.455] | [0.070] | [0.072] | [0.070] | [0.095] | [0.093] | [0.187] |
| AR-M-MIDAS | 1.086 | 1.100 | 1.060 | 1.126 | 1.107 | 0.870 | 1.061 | 1.067 | 0.950 | 1.006 | 1.012 | 0.999 | 0.922 | 0.909 | 0.997 |
| | [0.653] | [0.733] | [0.528] | [0.985] | [0.991] | [0.006] | [0.734] | [0.713] | [0.044] | [0.202] | [0.212] | [0.217] | [0.078] | [0.067] | [0.133] |
| AR-U-MIDAS | 1.037 | 1.068 | 0.970 | 1.071 | 1.012 | 0.918 | 1.043 | 1.039 | 0.978 | 0.997 | 1.003 | 1.039 | 0.912 | 0.909 | 0.995 |
| | [0.193] | [0.276] | [0.049] | [0.969] | [0.980] | [0.018] | [0.609] | [0.641] | [0.085] | [0.225] | [0.307] | [0.445] | [0.080] | [0.080] | [0.125] |
| Balanced AR-MIDAS | 1.316 | 1.308 | 1.298 | 1.486 | 1.517 | 1.488 | 1.110 | 1.112 | 1.016 | 0.992 | 0.990 | 0.999 | 0.906 | 0.904 | 0.993 |
| | [0.347] | [0.330] | [0.367] | [0.988] | [0.990] | [0.371] | [0.934] | [0.942] | [0.455] | [0.345] | [0.335] | [0.217] | [0.100] | [0.094] | [0.187] |
| Balanced AR-M-MIDAS | 1.095 | 1.112 | 1.060 | 1.046 | 0.997 | 0.870 | 1.015 | 1.033 | 0.950 | 0.992 | 0.990 | 0.999 | 0.919 | 0.917 | 1.007 |
| | [0.831] | [0.818] | [0.528] | [0.958] | [0.980] | [0.006] | [0.505] | [0.612] | [0.044] | [0.345] | [0.335] | [0.217] | [0.113] | [0.107] | [0.353] |
| Balanced AR-U-MIDAS | 1.032 | **1.039** | **0.970** | 1.037 | **0.981** | 0.918 | 1.058 | 1.051 | 0.978 | 0.972 | 0.999 | 1.039 | 0.894 | 0.903 | 0.995 |
| | [0.224] | [0.186] | [0.049] | [0.951] | [0.019] | [0.018] | [0.797] | [0.741] | [0.085] | [0.104] | [0.324] | [0.445] | [0.062] | [0.076] | [0.125] |
| Dow Jones Euro Stoxx | | | | | | | | | | | | | | | |
| MIDAS | 1.026 | 1.037 | 1.027 | 0.924 | 0.887 | 0.964 | 1.051 | 1.041 | 1.045 | 1.033 | **1.039** | 1.005 | 1.079 | 1.039 | 1.006 |
| | [0.118] | [0.145] | [0.146] | [0.070] | [0.068] | [0.073] | [0.925] | [0.931] | [0.336] | [0.739] | [0.784] | [0.243] | [0.905] | [0.858] | [0.336] |
| Multiplicative MIDAS | 1.131 | 1.110 | 1.059 | 1.016 | 0.887 | 1.026 | 1.074 | 1.049 | 1.045 | 1.087 | 1.059 | 1.010 | 1.088 | 1.048 | 1.002 |
| | [0.352] | [0.293] | [0.155] | [0.960] | [0.068] | [0.201] | [0.929] | [0.950] | [0.355] | [0.880] | [0.844] | [0.257] | [0.909] | [0.798] | [0.209] |
| CF-MIDAS | **1.013** | 1.025 | 1.012 | 0.887 | 0.899 | 0.973 | **0.985** | **0.983** | **0.951** | **1.018** | 1.047 | **0.939** | **1.069** | 1.060 | 1.014 |
| | [0.102] | [0.103] | [0.102] | [0.089] | [0.090] | [0.098] | [0.037] | [0.037] | [0.036] | [0.637] | [0.800] | [0.033] | [0.882] | [0.885] | [0.241] |
| AR-MIDAS | 1.022 | **1.016** | **0.998** | **0.863** | **0.835** | **0.935** | 1.036 | 1.051 | 0.993 | 1.033 | 1.056 | 0.973 | 1.079 | 1.030 | 0.995 |
| | [0.535] | [0.450] | [0.355] | [0.026] | [0.025] | [0.028] | [0.855] | [0.932] | [0.143] | [0.672] | [0.822] | [0.056] | [0.875] | [0.789] | [0.155] |
| AR-M-MIDAS | 1.090 | 1.050 | 1.108 | 0.949 | 0.917 | 1.013 | 1.032 | 1.039 | 0.990 | 1.051 | 1.056 | 0.971 | 1.077 | **1.028** | **0.995** |
| | [0.840] | [0.633] | [0.867] | [0.117] | [0.113] | [0.125] | [0.796] | [0.908] | [0.092] | [0.719] | [0.765] | [0.044] | [0.859] | [0.742] | [0.155] |

Note: For each quarterly forecast horizon (h), depending on the within-quarter information used, "I" refers to one month, "II" to two months and "III" to a full quarter. The figures in bold denote the minimum relative RMSFE for each single-variable model. The figures in brackets denote the empirical rejection frequencies for the null hypothesis of equal RMSFE calculated using bootstrapped test statistics.

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