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Mixed frequency models with MA components

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Décembre 2017

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Mixed frequency models with MA components ^{*}

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Abstract

Temporal aggregation in general introduces a moving average (MA) component in the aggregated model. A similar feature emerges when not all but only a few variables are aggregated, which generates a mixed frequency model. The MA component is generally neglected, likely to preserve the possibility of OLS estimation, but the consequences have never been properly studied in the mixed frequency context. In this paper, we show, analytically, in Monte Carlo simulations and in a forecasting application on U.S. macroeconomic variables, the relevance of considering the MA component in mixed-frequency MIDAS and UMIDAS models (MIDAS-ARMA and UMIDAS-ARMA). Specifically, the simulation results indicate that the short-term forecasting performance of MIDAS-ARMA and UMIDAS-ARMA is better than that of, respectively, MIDAS and UMIDAS. The empirical applications on nowcasting U.S. GDP growth, investment growth and GDP deflator inflation confirm this ranking. Moreover, in both simulation and empirical results, MIDAS-ARMA is better than UMIDAS-ARMA.

Keywords: Temporal aggregation, MIDAS models, ARMA models.

JEL Classification Code: E37, C53.

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1 Introduction

The use of mixed-frequency models has become increasingly popular among academics and practitioners. It is in fact by now well recognized that a good nowcast or short-term forecast for a low frequency variable, such as GDP growth and its components, requires to exploit the timely information contained in higher frequency macroeconomic or financial indicators, such as surveys or spreads. A growing literature has flourished proposing different methods to deal with the mixed-frequency feature. In particular, models cast in state-space form, such as vector autoregressions (VAR) and factor models, can deal with mixed-frequency data, taking advantage of the Kalman filter to interpolate the missing observations of the series only available at low frequency (see, among many others, Mariano and Murasawa (2010) and Giannone et al. (2008) in a classical context, and Chiu et al. (2011) and Schorfheide and Song (2015) in a Bayesian context). A second approach has been proposed by Ghysels (2016). He introduces a different class of mixed-frequency VAR models, in which the vector of endogenous variables includes both high and low frequency variables, with the former stacked according to the timing of the data releases. A third approach is the mixed-data sampling (MIDAS) regression, introduced by Ghysels et al. (2006), and its unrestricted version (UMIDAS) by Forni et al. (2015). MIDAS models are tightly parameterized, parsimonious models, which allow for the inclusion of many lags of the explanatory variables. Given their non-linear form, MIDAS models need to be estimated by non-linear least squares (NLS). UMIDAS models are the unrestricted counterpart of MIDAS models, which can be estimated by simple ordinary least squares (OLS), but work well only when the frequency mismatch is small.¹

In this paper, we start from the observation that temporal aggregation generally introduces a moving average (MA) component in the model for the aggregate variable (see, e.g., Marcellino (1999) and the references therein). A similar feature should be present in the mixed frequency models, and indeed we show formally that this is in general the case. The MA component is often neglected, both in same frequency and in mixed frequency

¹The literature on mixed-frequency approaches is vast. The papers cited in the text are a non-exhaustive list of key contributions to the field. For a review of the mixed-frequency literature, see Bai et al. (2013) and Forni and Marcellino (2013) among many others.

models, likely to preserve the possibility of OLS estimation and on the grounds that it can be approximated by a sufficiently long autoregressive (AR) component.

The effects of neglecting the MA component have been rarely explicitly considered. In a single frequency context, Lutkepohl (2006) showed that VARMA models are especially appropriate in forecasting, since they can capture the dynamic relations between time series with a small number of parameters. Further, Dufour and Stevanovic (2013) showed that a VARMA instead of VAR model for the factors provides better forecasts for several key macroeconomic aggregates relative to standard factor models, as well as producing a more precise representation of the effects and transmission of monetary policy. Leroux et al. (2017) found that ARMA(1,1) models predict well the inflation change and outperform many data-rich models, confirming the evidence on forecasting inflation by Stock and Watson (2007), Faust and Wright (2013) and Marcellino et al. (2006). Finally, VARMA models are often the correct reduced form representation of DSGE models (see, for example, Ravenna (2007)). For mixed frequency models, there are no results available.

We close this gap and analyze the relevance of the inclusion of an MA component in MIDAS and UMIDAS models, with the resulting specifications labeled, respectively, MIDAS-ARMA and UMIDAS-ARMA. We first compare the forecasting performance of the mixed frequency models with and without the MA component in a set of Monte Carlo experiments, using a variety of Data Generating Processes (DGPs). It turns out that the short-term forecasting performance is better when including the MA component, and the gains are higher the more persistent is the series. Moreover, in general the MIDAS-ARMA specifications are slightly better than the UMIDAS-ARMA specifications, though the differences are minor. This pattern is in contrast with the findings in Foroni et al. (2015), and suggests that adding the MA component to the MIDAS model helps somewhat in reducing the potential misspecification due to imposing a specific lag polynomial structure.

Next, we carry out an empirical investigation, where we predict several quarterly macroeconomic variables using timely monthly indicators. In particular, we forecast three relevant quarterly U.S. macroeconomic variables: real GDP growth, real private non residential fixed investment (PNFI) growth and GDP deflator inflation. The latter variable is particularly relevant, as Stock and Watson (2007) show that the MA component for US inflation is important, especially after 1984. In fact, while during the 1970s the inflation process could be very well approximated by a low order AR, after the 1980s this has become less accurate and the inclusion of an MA component more relevant. Evidence on the importance of the

MA component for the U.S. inflation is also found by Ng and Perron (2001) and Perron and Ng (1996). As monthly explanatory variables, we consider industrial production and employment for the real GDP growth and the PNFPI growth, CPI inflation and personal consumption expenditures (PCE) inflation for the GDP deflator. The inclusion of an MA component generally improves the forecasting performance substantially. In particular, adding the MA part to forecast GDP growth one-year ahead ameliorates the MSE up to 10%, while for PNFPI we obtain even bigger gains, up to 30% one-year ahead. Also in the case of GDP deflator we obtain robust improvements, which go up to 15%. For all variables, and in line with the simulation results, MIDAS-ARMA is better than UMIDAS-ARMA. Lastly, full sample estimates of MA coefficients are significant and important in most of MIDAS-ARMA and UMIDAS-ARMA specifications.

The remainder of the paper proceeds as follows. In Section 2 we show that temporal aggregation generally creates an MA component also in mixed frequency models. In Section 3 we describe parameter estimators for the MIDAS-ARMA and UMIDAS-ARMA models. In Section 4 we present the design and results of the simulation exercises. In Section 5 we develop the empirical applications on forecasting U.S. quarterly variables with monthly indicators. In Section 6 we summarize our main results and conclude.

2 The rationale for an MA component in mixed frequency models

The UMIDAS regression approach can be derived by aggregation of a general dynamic linear model in high frequency, as shown by Forni et al. (2015), while the MIDAS model imposes specific restrictions on the UMIDAS coefficients in order to reduce their number, which is particularly relevant when the frequency mismatch is large (for example, with daily and quarterly series). In Section 2.1, we briefly review the derivation of the UMIDAS model, highlighting that, in general, there should be an MA component, even though it is generally disregarded. In Section 2.2, we provide two simple analytical examples in which, starting from a high-frequency model without MA term, we end up with a mixed frequency model in which the MA component is present. We discuss estimation of mixed frequency models with an MA component in a separate section.

2.1 UMIDAS regressions and dynamic linear models

Let us assume that the Data Generating Process (DGP) for the variable y and the N variables x is an $ARDL(p, q)$ process, as in Foroni et al. (2015):

$$a(L)y_{t_m} = b_1(L)x_{1t_m} + \dots + b_N(L)x_{Nt_m} + e_{yt_m} \quad (1)$$

where $a(L) = 1 - a_1L - \dots - a_pL^p$, $b_j(L) = b_{j1}L + \dots + b_{jq}L^q$, $j = 1, \dots, N$, and the error e_{yt_m} is white noise. We assume, for simplicity, that $p = q$ and the starting values y_{-p}, \dots, y_0 and x_{-p}, \dots, x_0 are all fixed and equal to zero.

We then assume that x can be observed for each period t_m , while y can be only observed every m periods. We define $t = 1, \dots, T$ as the low frequency (LF) time unit and $t_m = 1, \dots, T_m$ as the high frequency (HF) time unit. The HF time unit is observed m times in the LF time unit. As an example, if we are working with quarterly (LF) and monthly (HF) data, it is $m = 3$ (i.e., three months in a quarter). Moreover, L indicates the lag operator at t_m frequency, while L^m is the lag operator at t frequency.

We also introduce the aggregation operator

$$\omega(L) = \omega_0 + \omega_1L + \dots + \omega_{m-1}L^{m-1}, \quad (2)$$

which characterizes the temporal aggregation scheme. For example, $\omega(L) = 1 + L + \dots + L^{m-1}$ indicates the sum of the high-frequency observations over the low-frequency period, typically used in the case of flow variables, while $\omega(L) = 1$ corresponds to point-in-time sampling and is typically used for stock variables. As we will see, different aggregation schemes will play a role in generating MA components.

To derive the generating mechanism for y at mixed frequency (MF), we introduce a polynomial in the lag operator, $\beta(L)$, whose degree in L is at most equal to $pm - p$ and which is such that the product $h(L) = \beta(L)a(L)$ only contains powers of L^m , so that $h(L) = h(L^m)$. It can be shown that such a polynomial always exists, and its coefficients depend on those of $a(L)$, see Marcellino (1999) for details.

In order to determine the AR component of the MF process, we then multiply both sides of (1) by $\omega(L)$ and $\beta(L)$ to get

$$h(L^m)\omega(L)y_{t_m} = \beta(L)b_1(L)\omega(L)x_{1t_m} + \dots + \beta(L)b_N(L)\omega(L)x_{Nt_m} + \beta(L)\omega(L)e_{yt_m}. \quad (3)$$

Hence, the autoregressive component only depends on LF values of y . Let us consider now the x variables, which are observable at high frequency t_m . Each HF x_{it_m} influences the LF variable y via a polynomial $\beta(L)b_j(L)\omega(L) = b_j(L)\beta(L)\omega(L)$, $j = 1, \dots, N$. We see that it is a particular combination of high-frequency values of x_j , equal to $\beta(L)\omega(L)x_{jt_m}$, that affects the low-frequency values of y .

Only under certain, rather strict conditions, it is possible to recover the polynomials $a(L)$ and $b_j(L)$ that appear in the HF model for y from the MF model, and in these cases also $\beta(L)$ can be identified. Therefore, when $\beta(L)$ cannot be identified, we can estimate a model as

$$\begin{aligned} c(L^k)\omega(L)y_{t_m} &= \delta_1(L)x_{1t_m-1} + \dots + \delta_N(L)x_{Nt_m-1} + \epsilon_{t_m}, \\ t_m &= m, 2m, 3m, \dots \end{aligned} \quad (4)$$

where $c(L^m) = (1 - c_1L^m - \dots - c_cL^{mc})$, $\delta_j(L) = (\delta_{j,0} + \delta_{j,1}L + \dots + \delta_{j,v}L^v)$, $j = 1, \dots, N$.

We can focus now on the error term of equation (3). In general, there is an MA component in the MF model, $q(L^m)u_{yt_m}$, with $q(L^m) = (1 + q_1L^m + \dots + q_qL^{mq})$. The order of $q(L^m)$, q , coincides with the highest multiple of m non zero lag in the autocovariance function of $\beta(L)\omega(L)e_{yt_m}$. The coefficients of the MA component have to be such that the implied autocovariances of $q(L^m)u_{yt_m}$ coincide with those of $\beta(L)\omega(L)e_{yt_m}$ evaluated at all multiples of m . Consequently, also the error term ϵ_{t_m} in the approximate mixed frequency model (4), which is the UMIDAS model, in general has an MA structure. It can be shown that the maximum order of the MA structure is p for average sampling and $p-1$ for point-in-time sampling, where p is the order of the AR component in the high frequency model for y_{t_m} (see, e.g., Marcellino (1999) for a derivation of this results).

2.2 Two analytical examples

In this section, we consider two simple DGPs and show that, even in these basic cases, an MA component appears in the mixed frequency model. In the first example, we consider an ARDL(1,1) with average sampling, in the second one an ARDL(2,2) with point-in-time sampling. In both cases, we work with monthly and quarterly variables, therefore $m = 3$, as in the empirical applications that will be presented later on. The examples could be easily generalized to consider higher order models and different frequency mismatches m .

ARDL(1,1) with average sampling

Let us assume an ARDL(1,1) as HF DGP:

$$y_{t_m} = ay_{t_m-1} + bx_{t_m-1} + e_{yt_m}, \quad (5)$$

where y_{t_m} is a variable unobservable at HF, x_{t_m} is the high-frequency variable, e_{yt_m} is white noise, and t_m is the high-frequency time index. Although we do not observe y_{t_m} , we observe the quarterly aggregated values of the series.

In order to obtain the model for the quarterly aggregated series, let us write (5) as

$$(1 - aL) y_{t_m} = bLx_{t_m} + e_{yt_m}. \quad (6)$$

We consider average sampling, and therefore we define the aggregation operator $\omega(L) = 1 + L + L^2$. Then, we first introduce a polynomial in the lag operator, $\beta(L)$, which is such that the product $h(L) = \beta(L)(1 - aL)$ only contains powers of L^3 . This polynomial exists and it is equal to $(1 + aL + a^2L^2)$. We then multiply both sides of equation (6) by $\omega(L)$ and $\beta(L)$ and we obtain:

$$(1 + aL + a^2L^2)(1 - aL)(1 + L + L^2)y_{t_m} = (1 + aL + a^2L^2)bL(1 + L + L^2)x_{t_m} + (1 + aL + a^2L^2)(1 + L + L^2)e_{yt_m}, \quad (7)$$

or equivalently:

$$(1 - a^3L^3)\tilde{y}_{t_m} = (1 + aL + a^2L^2)bL(1 + L + L^2)x_{t_m} + (1 + (a + 1)L + (a^2 + a + 1)L^2 + (a^2 + a)L^3 + a^2L^4)e_{yt_m}, \quad (8)$$

where $\tilde{y}_{t_m} = (1 + L + L^2)y_{t_m}$ and $t_m = 3, 6, 9, \dots$.

As we saw it in Section 2.1, the order of the MA component coincides with the highest multiple of 3 non zero lag in the autocovariance function of the error term in equation (8), and it is bounded above by the AR order of the model for y_{t_m} .

Eq. (8) is then estimated at quarterly frequency, but making use of all the information available in the HF variable x_{t_m} , and including the MA component, which is of order 1 in this case (being the relevant lag for the quarterly model L^3). The model in eq. (8) is therefore a UMIDAS-AR with an MA(1) component.

ARDL(2,2) with point-in-time sampling

Let us now assume an ARDL(2,2) as HF DGP:

$$y_{t_m} = a_1 y_{t_m-1} + a_2 y_{t_m-2} + b_1 x_{t_m-1} + b_2 x_{t_m-2} + e_{yt_m}, \quad (9)$$

or, equivalently,

$$(1 - a_1 L - a_2 L^2) y_{t_m} = (b_1 L + b_2 L^2) x_{t_m} + e_{yt_m}, \quad (10)$$

where y_{t_m} , x_{t_m} , e_{yt_m} and t_m are defined as in the previous example.

We consider point-in-time sampling, and therefore $\omega(L) = 1$. Next, we need to multiply both sides of equation (9) by $\omega(L)$ and find a polynomial $\beta(L)$ such that the product $h(L) = \beta(L)(1 - a_1 L - a_2 L^2)$ only contains powers of L^3 . It can be easily shown that $\beta(L)$ exists and it is equal to

$$(1 + a_1 L + (a_1^2 + a_2) L^2 - a_1 a_2 L^3 + a_2^2 L^4).$$

The resulting mixed frequency model for the low-frequency variable is:

$$(1 - (a_1^3 + 3a_2 a_1) L^3 - a_2^3 L^6) y_{t_m} = (1 + a_1 L + (a_1^2 + a_2) L^2 - a_1 a_2 L^3 + a_2^2 L^4) (b_1 L + b_2 L^2) x_{t_m} + (1 + a_1 L + (a_1^2 + a_2) L^2 - a_1 a_2 L^3 + a_2^2 L^4) e_{yt_m}, \quad (11)$$

with $t_m = 3, 6, 9, \dots$. Hence, also in this case there is an MA component in the mixed frequency model for y . Its order coincides with the highest multiple of 3 non zero lag in the autocovariance function of $(1 + a_1 L + (a_1^2 + a_2) L^2 - a_1 a_2 L^3 + a_2^2 L^4) e_{yt_m}$, and it is bounded above by the AR order of the model for y_{t_m} minus one, which is 1 in this example. Following the same line of reasoning as in the previous example, the MA component is of order 1.

3 UMIDAS-ARMA and MIDAS-ARMA: forecasting specifications and estimation

We describe now in more detail the model specifications we consider for forecasting, and the estimation details. We first recall the main features of the standard MIDAS

regression, introduced by Ghysels et al. (2006), and its unrestricted version, as in Foroni et al. (2015). Then, we discuss their extensions to allow for an MA component and we discuss the estimation of the models.

The starting point for our MF models is equation (4). In order to simplify the notation, we assume $\omega(L) = 1$ and one explanatory variable x_{t_m} ². Further, we allow for incorporating leads of the high frequency variable in the projections, which captures asynchronous releases.

The equation we are going to estimate to generate an h_m -step ahead forecast is the following:

$$y_{t_m} = \tilde{c}(L^m)y_{t_m-h_m} + \delta(L)x_{t_m-h_m+w} + \epsilon_{t_m}, \quad (12)$$

where $\tilde{c}(L^m)$ is a modified lag structure of equation (4) to obtain a direct forecast and w is the number of months with which x is leading y .

If ϵ_{t_m} is serially uncorrelated, equation (12) represents the UMIDAS-AR model. Given that the model is linear, the UMIDAS-AR regression can be estimated by simple OLS. Empirically, the lag length of the high frequency variable x is often selected by means of an information criterion, such as the BIC.

Adding an MA component to the UMIDAS-AR yields the UMIDAS-ARMA model:

$$y_{t_m} = \tilde{c}(L^m)y_{t_m-h_m} + \delta(L)x_{t_m-h_m+w} + u_{t_m} + q(L^m)u_{t_m-h_m}, \quad (13)$$

where u_{t_m} is a (weak) white noise with $E(u_{t_m}) = 0$ and $E(u_{t_m}u'_{t_m}) = \sigma_u^2 < \infty$, and all the remaining terms stay the same as in equation (12). Given that MIDAS models are direct forecasting tools, we decided to follow a direct approach also when modelling the MA component.

OLS estimation of the UMIDAS-ARMA model is no longer possible, because of the MA component in the residuals. We then estimate the model as in the standard ARMA literature, by maximum likelihood or, as we will actually do to be coherent with the MIDAS literature, by non-linear least squares (NLS).

²This is an innocuous simplification, as with a generic aggregation scheme $\omega(L) \neq 1$ we could just work with the redefined variable $\tilde{y}_{t_m} = \omega(L)y_{t_m}$.

The MIDAS-AR specification is a restricted version of the UMIDAS-AR. The MIDAS-AR model as in Ghysels et al. (2006), specified for forecasting h_m periods ahead, can be written as follows:

$$y_{t_m} = \tilde{c}(L^m)y_{t_m-h_m} + \beta B(L, \theta)x_{t_m-h_m+w} + \epsilon_{t_m}, \quad (14)$$

where

$$B(L, \theta) = \sum_{j=0}^K b(j, \theta)L^j,$$

$$b(j, \theta) = \frac{\exp(\theta_1 j + \theta_2 j^2)}{\sum_{j=0}^K \exp(\theta_1 j + \theta_2 j^2)},$$

and K is the maximum number of lags included of the explanatory variable.

As it is clear by comparing equation (12) and equation (14), the MIDAS model is nested into the UMIDAS model.

The MIDAS-AR model in equation (14) is estimated by NLS. Given that it is h_m -dependent, as in the UMIDAS case it has to be re-estimated for each forecast horizon.

Exactly as for the UMIDAS, we extend the MIDAS-AR in equation (14) to incorporate an MA component:

$$y_{t_m} = \tilde{c}(L^m)y_{t_m-h_m} + \beta B(L, \theta)x_{t_m-h_m+w} + u_{t_m} + q(L^m)u_{t_m-h_m}, \quad (15)$$

where the error term is defined as in (13). Given the nonlinearity of the model, we estimate its parameters by NLS. Appendix A provides additional details on the NLS estimation procedures.

To conclude, it is worth briefly comparing the use for forecasting of UMIDAS-ARMA versus the Kalman filter. The latter is clearly optimal in the presence of mixed frequency data and linear models. However, UMIDAS-ARMA is equivalent if it is theoretically derived from a known high frequency linear dynamic model, as UMIDAS-ARMA coincides with the mixed frequency data generating process. The ranking of the two approaches is unclear if the high frequency model is mis-specified. Moreover, the Kalman filter can incur into computational problems when the frequency mismatch is large. Something similar happens to UMIDAS-ARMA, due to parameter proliferation, and in this case the parsimony of MIDAS-ARMA can be particularly helpful. Bai et al. (2013) propose a more detailed comparison of the Kalman filter and the MIDAS approach.

4 Monte Carlo evaluation

We now assess the forecasting relevance of including an MA component in MIDAS and UMIDAS models by means of simulation experiments. We use two designs, closely related to the two analytical examples described in Section 2.2. We present first the Monte Carlo designs and then the results.

4.1 Monte Carlo design

In the first design, the DGP is the HF ARDL(1,1):

$$y_{t_m} = \rho y_{t_m-1} + \delta_l x_{t_m-1} + e_{y,t_m}, \quad (16)$$

where y_{t_m} is unobservable at HF, but available at LF, while x_{t_m} is the HF variable, t_m is the HF time index, the aggregation frequency is $m = 3$ (as in the case of quarterly and monthly frequencies), and t is the LF time index, with $t = 3t_m$. We assume that $\omega(L) = 1 + L + L^2$, corresponding to average sampling.

The shocks e_{y,t_m} are independent and sampled from a normal distribution with zero mean and variance chosen such that the unconditional variance of y is equal to one. We consider different combinations of ρ and δ_l , representing different degrees of persistence and correlation between the HF and the LF variables. In detail, we evaluate the following parameter sets:

$$(\rho, \delta_l) = \{(0.1, 0.1), (0.5, 0.1), (0.9, 1), (0.94, 1)\}. \quad (17)$$

Finally, x_{t_m} is generated as an AR(1) with coefficient ρ .

In the second design, the DGP is the HF ARDL(2,2):

$$y_{t_m} = \rho_1 y_{t_m-1} + \rho_2 y_{t_m-2} + \delta_{l1} x_{t_m-1} + \delta_{l2} x_{t_m-2} + e_{y,t_m}. \quad (18)$$

We still assume $m = 3$ but now $\omega(L) = 1$, so that the LF variable is skip-sampled every $m = 3$ observations.

In this second DGP, we consider the following parameter combinations:

$$(\rho_1, \rho_2, \delta_{l1}, \delta_{l2}) = \{(0.05, 0.1, 0.5, 1), (0.125, 0.5, 0.125, 0.5), (0.25, 0.5, 0.5, 1)\}. \quad (19)$$

All the other design features are as in the first DGP.

We focus on typical sample sizes for the estimation sample, with $T = 50, 100$. The size of the evaluation sample is set to 50, and the estimation sample is recursively expanded as we progress in the recursive forecasting exercise. The number of replications is 500.

The competing forecasting models are the following:

1. A MIDAS-AR model, with 12 lags in the exogenous HF variable and 1 lag in the AR component;
2. A MIDAS-ARMA model, as in the previous point but with the addition of an MA component;
3. A MIDAS-ARMA model, with only 3 lags in the exogenous HF variable and 1 AR lag;
4. A UMIDAS-AR model, with lag length selected according to the BIC criterion, where the maximum lag length is set equal to 12;
5. A UMIDAS-ARMA model, as in the previous point, with the addition of an MA component;
6. A UMIDAS-ARMA, fixing at 3 the number of lags of the HF exogenous variable.

In all ARMA models there is an MA(1) component, in line with the theoretical results, but an higher order can be allowed.

We evaluate the competing one-step ahead forecasts on the basis of their associated mean square prediction error (MSE), assuming that information on the first two months of the quarter is available (as it is common in nowcasting exercises).

4.2 Results

In Tables 1 to 4 we report the mean relative MSE across simulations, and numbers smaller than one indicate that the model is better than the benchmark (model 1, the standard MIDAS). We also report the 10th, 25th, 50th, 75th and 90th percentiles, to provide a measure of the dispersion in the results.

Tables 1 and 2 present the results for the first DGP (the ARDL(1,1) with average sampling), using $T = 100$ in Table 1 and $T = 50$ in Table 2. The corresponding Tables 3 and 4 are based on the second DGP (the ARDL(2,2) with point-in-time sampling).

A few key findings emerge. First, adding an MA component to the MIDAS model generally helps. The gains are not very large but they are visible at all percentiles, with a few exceptions for the second DGP. The gains are larger either with substantial persistence ($\rho = 0.9$ or $\rho = 0.94$ in the first DGP and $\rho_1 = 0.25$, $\rho_2 = 0.5$ in the second DGP) or with low persistence in the first DGP ($\rho = 0.1$), but in the latter case the result is mainly due to a deterioration in the absolute performance of the standard MIDAS model. The more parsimonious specification with 3 lags only of the HF variable is generally better, except when $\rho = 0.5$.

Second, adding an MA component to the UMIDAS model is also generally helpful, though the gains remain small.

Third, in general the MIDAS-ARMA specifications are slightly better than the UMIDAS-ARMA specifications, though the differences are minor. This pattern is in contrast with the findings in Forni et al. (2015), and suggests that adding the MA component to the MIDAS model helps somewhat in reducing the potential misspecification due to imposing a specific lag polynomial structure.

Finally, results are consistent across sample sizes, and the models do not seem sensitive to short sample sizes.

5 Empirical applications

In this section, we look at the performance of our MA augmented mixed frequency models in forecasting exercises with actual data. The analysis focuses on forecasting quarterly U.S. variables.

In particular, we consider three relevant quarterly U.S. macroeconomic variables: real GDP growth, real private non residential fixed investment (PNFI) growth and GDP deflator inflation. As monthly explanatory variables, we consider industrial production and employment for the real GDP growth and the PNFI growth, while we consider CPI inflation and personal consumption inflation for the GDP deflator. A complete description of data sources and transformations is available in Table 5.

The total sample spans over 50 years of data, from the first quarter of 1960 to the end of 2015. The forecasts are computed in pseudo real time, with progressively expanding samples. The evaluation period goes from 1980Q1 to the end of the sample, covering roughly 35 years. As a robustness check, we will also analyze a shorter sample ending in 2007Q3, to assess the effects of the recent crisis. At each point in time, we compute forecasts from 1- up to 4-quarter ahead. The forecasting target is the annualized growth rate. Although the information contained in the monthly variables updates every month, we focus on the case in which the first two months of the quarter are already available.³

We consider the models (1) to (7) as described in Section 4.1, plus a simple low frequency AR(1) model as a further benchmark for the usefulness of the mixed-frequency data. In particular, we consider the direct forecast resulting from the model:

$$y_t = c + \rho y_{t-h} + e_t. \quad (20)$$

We evaluate the forecasts both in terms of mean squared errors (MSE) and in terms of mean absolute errors (MAE). We then compare the forecasting performance relative to a standard MIDAS model with an autoregressive component and 12 lags of the explanatory variable (as the model (1) in Section 4).

In Tables 6 to 8 we report the results for, respectively, the real GDP growth, the real PNFI growth and the GDP deflator inflation rate. Each table is organized in the same way: it reports the value of MSE and MAE for each model, the ratio of those criteria for each model relative to the MIDAS-AR, our benchmark model, and the p-value of the Diebold-Mariano test, to check the statistical significance of the differences in forecast measures with respect to the benchmark (see Diebold and Mariano (1995)).

³With the MIDAS setup, we could also report the results when no information or only one month of information is available. However, for the sake of conciseness we focus only on the case in which we are two months into the quarter, to have the shortest nowcast horizon. Given that our models are all mixed frequency, this choice does not bias the comparison.

The tables are broadly supportive of the inclusion of the MA component in the mixed frequency models, as the MSE and MAE ratios are often smaller than one for the MIDAS-ARMA and UMIDAS-ARMA models when compared with their versions without MA.⁴ More in detail: for forecasting GDP growth, adding the MA component does not provide substantial improvements with respect to standard mixed frequency models for $h = 1$, with industrial production being the best indicator. When $h = 2$, employment becomes better than industrial production, and adding an MA term matters, with gains of 8% for the MIDAS-ARMA model. A similar results holds for $h = 3$, with gains increasing to 20%. Four-quarter ahead, industrial production returns best, and MIDAS-ARMA leads to a decrease of 10% in the MSE. For PNFI growth, MIDAS-ARMA is best at all horizons, with employment preferred to industrial production except for $h = 1$. The gains are small for $h = 1, 2, 3$, in the range 1%-8%, but increase to 30% for $h = 4$. For GDP deflator, PCE inflation is systematically better than CPI, and MIDAS-ARMA yields gains for $h = 1$ and 2 of, respectively, 15% and 10%. It is also worth mentioning that MSE and MAE lead to the same rankings, and that the gains from adding the MA parts are generally statistically significant. Finally, the models perform well with respect to the AR benchmark. Confirming the widespread evidence in the literature, the mixed frequency models perform the best at short horizons. However, we get satisfactory results also up to $h = 4$.

We now decompose the MSE in bias and variance, as:

$$MSE = \underbrace{(E(e))^2}_{\text{Bias}} + \underbrace{Var(e)}_{\text{Variance}} \quad (21)$$

with $e = y - \hat{y}$. We find that the MA part helps especially in reducing the bias, suggesting that the MA part is important to well approximate the conditional mean of y (the optimal forecast under the quadratic loss). When the models with the MA component are not performing well, this is due especially to the variance term, instead. Detailed results on the bias/variance decomposition are presented in Table 9. In particular, in the table we report the ratio of the bias and of the variance of each model relative to the bias and variance of the MIDAS-AR model, which is taken as a benchmark.

The MSE and MAE are computed over the entire evaluation sample. To check whether the performance of our models remains good across the entire sample, in Figure 1 we report

⁴The models which include an MA component are indicated in bold in the tables, while the lowest MSE and MAE values are underlined.

the one-quarter ahead forecasts of the benchmark MIDAS-AR model and of one of the MA augmented models, together with the realized series. In Figure 2, instead, we report the 4-quarter ahead forecasts.⁵ It turns out that, on average, MIDAS models perform well throughout the sample, both with and without an MA component.

Tables 10 and 11 report the full-sample estimates of MA coefficients in MIDAS-ARMA and UMIDAS-ARMA models that have been used in the forecasting exercise. The corresponding t-statistics are shown in parentheses. We observe that many MA coefficients are significant. For instance, MA(1) coefficient in MIDAS-ARMA-3lags model on GDP growth equation with employment growth is precisely estimated at horizons $h = 1, 2, 3$. This MIDAS-ARMA model was also the best in out-of-sample forecasting exercise, see table 6. In case of PNFI, when forecasting one quarter ahead with industrial production as high frequency predictor, MA coefficient is significant in all models. Same result holds at longer horizons with employment growth. When it comes to GDP deflator prediction, an interesting finding is that the MA(2) component is highly strong and significant for most of the horizons and models.

Finally, to assess whether our results are robust to the exclusion of the recent crisis, we have rerun the forecast evaluation over a sample ending in 2007Q3. Results do not change substantially, and remain broadly supportive of the inclusion of the MA component in the mixed-frequency models. In most of the cases, the best performing model up to 2007 remains the best in the full sample. The magnitude of improvements is also very comparable. Detailed results are provided in Appendix B.

6 Conclusions

In this paper, we start from the observation that temporal aggregation in general introduces a moving average component in the aggregated model. We show that a similar feature also emerges when not all but only a few variables are aggregated, which generates a mixed frequency model. Hence, an MA component should be added to mixed frequency models, while this is generally neglected in the literature.

We illustrate in a set of Monte Carlo simulations that indeed adding an MA component to MIDAS and UMIDAS models further improves their nowcasting and forecasting

⁵Figures 1 and 2 focus only on a small portion of results that we have available. The same figures for other models, other forecast horizons and other explanatory variables are available upon request.

abilities, though in general the gains are limited and particularly evident in the presence of persistence. Interestingly, the relative performance of MIDAS versus UMIDAS further improves when adding an MA component, with the latter attenuating the effects of imposing a particular polynomial structure in the dynamic response of the low frequency to the high frequency variable.

A similar pattern emerges in an empirical exercise based on actual data. Specifically, we find that the inclusion of an MA component can substantially improve the forecasting performance of quarterly macroeconomic U.S. variables, as GDP growth, PNFII growth and GDP deflator inflation. MIDAS-ARMA models perform particularly well, suggesting that the addition of an MA component to the MIDAS model helps somewhat in reducing the potential misspecification due to imposing a specific lag polynomial structure. Finally, full sample estimates of MA coefficients are significant and important in most of MIDAS-ARMA and UMIDAS-ARMA specifications.

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Table 1: Monte Carlo simulations results: MSE(model) relative to MSE(MIDAS) - DGP: ARDL(1,1) with average sampling, $T = 100$.

PANEL (A): $\rho = 0.94, \delta_l = 1$						
	mean	10 prct	25 prct	median	75 prct	90 prct
MIDAS-ARMA-12 (2)	0.974	0.986	0.981	0.968	0.970	0.967
MIDAS-ARMA-3 (3)	0.966	0.981	0.969	0.962	0.959	0.966
UMIDAS-AR (4)	0.997	0.997	0.986	1.005	0.994	0.990
UMIDAS-ARMA (5)	0.969	0.983	0.974	0.970	0.961	0.973
UMIDAS-ARMA-3 (6)	0.971	0.977	0.974	0.971	0.964	0.975
PANEL (B): $\rho = 0.9, \delta_l = 1$						
	mean	10 prct	25 prct	median	75 prct	90 prct
MIDAS-ARMA-12 (2)	0.976	0.989	0.984	0.979	0.973	0.976
MIDAS-ARMA-3 (3)	0.975	0.983	0.988	0.969	0.978	0.971
UMIDAS-AR (4)	1.030	1.024	1.023	1.029	1.038	1.040
UMIDAS-ARMA (5)	1.019	1.018	1.023	1.012	1.024	1.028
UMIDAS-ARMA-3 (6)	0.976	0.979	0.984	0.977	0.977	0.981
PANEL (C): $\rho = 0.5, \delta_l = 0.1$						
	mean	10 prct	25 prct	median	75 prct	90 prct
MIDAS-ARMA-12 (2)	0.986	0.990	0.994	0.984	0.983	0.978
MIDAS-ARMA-3 (3)	1.184	1.197	1.178	1.174	1.202	1.176
UMIDAS-AR (4)	1.005	1.000	1.003	1.006	1.013	0.995
UMIDAS-ARMA (5)	1.000	1.005	0.992	0.998	0.993	0.992
UMIDAS-ARMA-3 (6)	1.182	1.212	1.185	1.175	1.198	1.179
PANEL (D): $\rho = 0.1, \delta_l = 0.1$						
	mean	10 prct	25 prct	median	75 prct	90 prct
MIDAS-ARMA-12 (2)	0.981	0.985	0.989	0.983	0.980	0.972
MIDAS-ARMA-3 (3)	0.833	0.848	0.846	0.834	0.827	0.828
UMIDAS-AR (4)	0.825	0.837	0.834	0.823	0.824	0.819
UMIDAS-ARMA (5)	0.832	0.841	0.844	0.833	0.831	0.836
UMIDAS-ARMA-3 (6)	0.833	0.846	0.846	0.834	0.829	0.829

Note: The four panels report the results for four different DGPs for 1-quarter ahead horizon (with the information of the first two months of the quarter available). The numbers (2) to (6) refer to the corresponding models described in Section 4. The results reported are the average, median and the 10th, 25th, 75th, 90th percentiles of the MSE of the indicated model relative to the average, median and the 10th, 25th, 75th, 90th percentiles of the MSE of the benchmark MIDAS (model (1) in Section 4) computed over 500 replications.

Table 2: Monte Carlo simulations results: MSE(model) relative to MSE(MIDAS) - DGP: ARDL(1,1) with average sampling, $T = 50$

PANEL (A): $\rho = 0.94, \delta_l = 1$						
	mean	10 prct	25 prct	median	75 prct	90 prct
MIDAS-ARMA-12 (2)	0.985	0.975	0.996	0.983	0.990	0.968
MIDAS-ARMA-3 (3)	0.957	0.949	0.982	0.947	0.957	0.944
UMIDAS-AR (4)	0.982	0.984	0.998	0.968	0.986	0.979
UMIDAS-ARMA (5)	0.957	0.950	0.984	0.954	0.965	0.939
UMIDAS-ARMA-3 (6)	0.968	0.950	1.003	0.962	0.975	0.955
PANEL (B): $\rho = 0.9, \delta_l = 1$						
	mean	10 prct	25 prct	median	75 prct	90 prct
MIDAS-ARMA-12 (2)	0.997	1.001	1.012	0.994	0.986	0.982
MIDAS-ARMA-3 (3)	0.973	0.978	1.006	0.964	0.961	0.977
UMIDAS-AR (4)	1.033	1.074	1.041	1.025	1.034	1.013
UMIDAS-ARMA (5)	1.020	1.041	1.040	1.018	1.019	1.016
UMIDAS-ARMA-3 (6)	0.981	0.982	1.023	0.968	0.971	0.983
PANEL (C): $\rho = 0.5, \delta_l = 0.1$						
	mean	10 prct	25 prct	median	75 prct	90 prct
MIDAS-ARMA-12 (2)	1.013	1.007	1.010	1.022	0.999	1.014
MIDAS-ARMA-3 (3)	1.188	1.182	1.172	1.179	1.168	1.249
UMIDAS-AR (4)	1.038	1.056	1.054	1.026	1.046	1.064
UMIDAS-ARMA (5)	1.061	1.089	1.059	1.049	1.049	1.062
UMIDAS-ARMA-3 (6)	1.197	1.186	1.181	1.181	1.173	1.241
PANEL (D): $\rho = 0.1, \delta_l = 0.1$						
	mean	10 prct	25 prct	median	75 prct	90 prct
MIDAS-ARMA-12 (2)	0.984	0.987	0.989	0.983	0.989	0.973
MIDAS-ARMA-3 (3)	0.824	0.809	0.807	0.825	0.830	0.846
UMIDAS-AR (4)	0.810	0.791	0.814	0.819	0.814	0.820
UMIDAS-ARMA (5)	0.834	0.824	0.826	0.831	0.834	0.853
UMIDAS-ARMA-3 (6)	0.830	0.826	0.816	0.827	0.832	0.859

Note: See Table 2.

Table 3: Monte Carlo simulations results: MSE(model) relative to MSE(MIDAS) - DGP: ARDL(2,2) with point-in-time sampling, $T = 100$

PANEL (A):						
$\rho_1 = 0.05, \rho_2 = 0.1, \delta_{l1} = 0.5, \delta_{l2} = 1$						
	mean	10 prct	25 prct	median	75 prct	90 prct
MIDAS-ARMA-12 (2)	1.007	1.010	1.003	1.007	1.010	1.025
MIDAS-ARMA-3 (3)	1.006	1.006	0.997	1.003	1.014	1.018
UMIDAS-AR (4)	1.014	1.007	1.016	1.005	1.006	1.030
UMIDAS-ARMA (5)	1.015	1.000	1.014	1.007	1.014	1.026
UMIDAS-ARMA-3 (6)	1.007	0.998	1.004	1.006	1.016	1.023
PANEL (B):						
$\rho_1 = 0.125, \rho_2 = 0.5, \delta_{l1} = 0.125, \delta_{l2} = 0.5$						
	mean	10 prct	25 prct	median	75 prct	90 prct
MIDAS-ARMA-12 (2)	0.956	0.955	0.960	0.963	0.949	0.959
MIDAS-ARMA-3 (3)	0.940	0.932	0.950	0.950	0.931	0.943
UMIDAS-AR (4)	0.938	0.921	0.938	0.945	0.929	0.946
UMIDAS-ARMA (5)	0.921	0.927	0.922	0.926	0.908	0.939
UMIDAS-ARMA-3 (6)	0.943	0.921	0.950	0.947	0.932	0.948
PANEL (C):						
$\rho_1 = 0.25, \rho_2 = 0.5, \delta_{l1} = 0.5, \delta_{l2} = 1$						
	mean	10 prct	25 prct	median	75 prct	90 prct
MIDAS-ARMA-12 (2)	0.984	0.968	0.981	0.985	0.991	0.998
MIDAS-ARMA-3 (3)	0.980	0.981	0.982	0.968	0.981	0.999
UMIDAS-AR (4)	1.021	1.032	1.020	1.006	1.032	1.036
UMIDAS-ARMA (5)	0.992	0.987	0.986	0.988	1.001	1.004
UMIDAS-ARMA-3 (6)	0.983	0.978	0.979	0.980	0.985	0.998

Note: The four panels report the results for three different DGPs. The numbers (2) to (6) refer to the corresponding models described in Section 4. The results reported are the average, median and the 10th, 25th, 75th, 90th percentiles of the MSE of the indicated model relative to the average, median and the 10th, 25th, 75th, 90th percentiles of the MSE of the benchmark MIDAS (model (1) in Section 4) computed over 500 replications.

Table 4: Monte Carlo simulations results: MSE(model) relative to MSE(MIDAS) - DGP: ARDL(2,2) with point-in-time sampling, $T = 50$

PANEL (A):						
$\rho_1 = 0.05, \rho_2 = 0.1, \delta_{l_1} = 0.5, \delta_{l_2} = 1$						
	mean	10 prct	25 prct	median	75 prct	90 prct
MIDAS-ARMA-12 (2)	1.020	1.003	1.024	1.021	1.009	1.017
MIDAS-ARMA-3 (3)	1.003	0.990	1.015	1.014	0.986	0.994
UMIDAS-AR (4)	1.006	0.982	1.036	1.019	1.011	0.988
UMIDAS-ARMA (5)	1.018	0.955	1.033	1.037	1.023	1.030
UMIDAS-ARMA-3 (6)	1.018	1.000	1.024	1.028	1.021	1.010
PANEL (B):						
$\rho_1 = 0.125, \rho_2 = 0.5, \delta_{l_1} = 0.125, \delta_{l_2} = 0.5$						
	mean	10 prct	25 prct	median	75 prct	90 prct
MIDAS-ARMA-12 (2)	1.017	0.980	1.006	1.004	1.019	1.042
MIDAS-ARMA-3 (3)	0.967	0.934	0.970	0.995	0.953	0.991
UMIDAS-AR (4)	0.971	0.973	0.979	0.979	0.961	0.997
UMIDAS-ARMA (5)	0.983	0.983	0.977	1.000	0.958	0.980
UMIDAS-ARMA-3 (6)	1.009	0.970	1.002	1.016	1.000	1.023
PANEL (C):						
$\rho_1 = 0.25, \rho_2 = 0.5, \delta_{l_1} = 0.5, \delta_{l_2} = 1$						
	mean	10 prct	25 prct	median	75 prct	90 prct
MIDAS-ARMA-12 (2)	1.016	1.003	0.991	1.005	1.012	1.010
MIDAS-ARMA-3 (3)	0.990	0.993	0.965	0.984	0.988	0.979
UMIDAS-AR (4)	1.046	1.024	1.016	1.047	1.059	1.039
UMIDAS-ARMA (5)	1.041	1.051	1.035	1.018	1.045	1.038
UMIDAS-ARMA-3 (6)	1.016	1.008	1.014	0.991	1.024	1.018

Note: see Table 3.

Table 5: Data description

Series	Source	Source Code	Transformation	Frequency
US data				
GDP Deflator	FRED	GDPDEF	Log-difference	Quarterly
Real GDP	FRED	GDP	Log-difference	Quarterly
Private Nonresidential Fixed Investment	FRED	PNFI	Level	Quarterly
Nonresidential (implicit price deflator)	FRED	A08RD3Q086SBEA	Level	Quarterly
Real Private Nonresidential Fixed Investment	FRED	PNFI / A08RD3Q086SBEA	Log-difference	Quarterly
Consumer Price Index (CPI)	FRED	CPIAUCSL	Log-difference	Monthly
Personal Consumption Expenditures: Price Index (PCE)	FRED	PCEPI	Log-difference	Monthly
Employment	FRED	PAYEMS	Log-difference	Monthly
Industrial Production	FRED	INDPRO	Log-difference	Monthly

Table 8: Forecasting U.S. GDP Deflator

	Explanatory variable: CPI inflation						Explanatory variable: PCE inflation						
	h=1			h=1			h=1			h=1			
	MSE		DM	MAE		DM	MSE		DM	MAE		DM	
	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	DM
MIDAS-AR-12	0.65	1.00	NaN	0.61	1.00	NaN	0.51	1.00	NaN	0.52	1.00	NaN	
MIDAS-ARMA-12	0.65	0.99	0.42	0.61	1.00	0.45	0.50	0.98	0.37	0.51	0.99	0.28	
MIDAS-ARMA-3	0.61	0.94	0.09	0.59	0.97	0.17	<u>0.43</u>	0.85	0.07	<u>0.49</u>	0.95	0.20	
UMIDAS-biclags	0.65	0.99	0.42	0.60	0.98	0.22	0.53	1.04	0.24	0.52	1.00	0.47	
UMIDAS-ARMA-biclags	0.61	0.94	0.09	0.59	0.97	0.17	0.51	1.01	0.44	0.52	1.00	0.47	
UMIDAS-ARMA-3	0.61	0.94	0.09	0.59	0.97	0.17	0.49	0.96	0.11	0.51	0.98	0.14	
AR	0.79	1.20	0.11	0.68	1.11	0.07	0.79	1.55	0.00	0.68	1.32	0.00	
	h=2						h=2						
	MSE		DM	MAE		DM	MSE		DM	MAE		DM	
	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	DM
MIDAS-AR-12	0.79	1.00	NaN	0.67	1.00	NaN	0.55	1.00	NaN	0.55	1.00	NaN	
MIDAS-ARMA-12	0.68	0.86	0.08	0.64	0.95	0.09	0.56	1.01	0.38	0.55	1.01	0.36	
MIDAS-ARMA-3	0.68	0.86	0.13	0.64	0.96	0.16	<u>0.50</u>	0.90	0.14	<u>0.53</u>	0.96	0.24	
UMIDAS-biclags	0.74	0.94	0.31	0.66	0.99	0.38	0.55	1.00	0.49	0.56	1.01	0.44	
UMIDAS-ARMA-biclags	0.70	0.89	0.15	0.67	1.00	0.46	0.52	0.95	0.30	0.55	1.00	0.47	
UMIDAS-ARMA-3	0.68	0.87	0.13	0.64	0.96	0.16	<u>0.50</u>	0.90	0.14	<u>0.53</u>	0.96	0.24	
AR	0.82	1.04	0.43	0.71	1.05	0.27	0.82	1.48	0.00	0.71	1.28	0.00	
	h=3						h=3						
	MSE		DM	MAE		DM	MSE		DM	MAE		DM	
	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	DM
MIDAS-AR-12	0.80	1.00	NaN	0.69	1.00	NaN	<u>0.57</u>	1.00	NaN	<u>0.57</u>	1.00	NaN	
MIDAS-ARMA-12	0.87	1.08	0.29	0.73	1.07	0.15	0.64	1.13	0.04	0.61	1.06	0.07	
MIDAS-ARMA-3	0.73	0.91	0.23	0.68	0.99	0.42	0.60	1.05	0.28	0.58	1.01	0.46	
UMIDAS-biclags	0.84	1.05	0.31	0.72	1.05	0.17	0.71	1.24	0.05	0.63	1.10	0.03	
UMIDAS-ARMA-biclags	0.84	1.05	0.36	0.74	1.07	0.15	0.76	1.33	0.00	0.66	1.15	0.01	
UMIDAS-ARMA-3	0.75	0.93	0.25	0.68	0.99	0.43	0.60	1.05	0.27	0.58	1.01	0.45	
AR	0.85	1.05	0.39	0.73	1.05	0.26	0.85	1.49	0.00	0.73	1.27	0.00	
	h=4						h=4						
	MSE		DM	MAE		DM	MSE		DM	MAE		DM	
	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	DM
MIDAS-AR-12	0.86	1.00	NaN	0.74	1.00	NaN	<u>0.63</u>	1.00	NaN	<u>0.61</u>	1.00	NaN	
MIDAS-ARMA-12	1.08	1.25	0.00	0.84	1.13	0.00	0.81	1.27	0.00	0.70	1.16	0.00	
MIDAS-ARMA-3	0.85	0.98	0.42	0.73	0.99	0.36	0.69	1.09	0.09	0.63	1.04	0.14	
UMIDAS-biclags	1.00	1.16	0.00	0.80	1.07	0.01	0.74	1.17	0.01	0.65	1.08	0.02	
UMIDAS-ARMA-biclags	1.06	1.23	0.01	0.81	1.09	0.02	0.83	1.31	0.00	0.70	1.15	0.00	
UMIDAS-ARMA-3	0.98	1.13	0.06	0.77	1.03	0.20	0.73	1.15	0.02	0.65	1.07	0.05	
AR	0.89	1.03	0.41	0.76	1.01	0.41	0.89	1.41	0.00	0.76	1.25	0.00	

Note: See Table 6.

Table 9: Bias/Variance decomposition of MSE

		Bias				Variance			
		h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
GDP with Industrial Production	MIDAS1-AR-12lags	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	MIDAS-ARMA-12lags	0.72	0.68	0.59	0.89	1.00	0.97	1.04	0.94
	MIDAS-ARMA-3lags	0.85	0.97	1.01	0.90	1.06	0.99	0.91	0.90
	UMIDAS-biclags	1.09	1.04	1.08	0.87	1.04	1.06	0.99	0.97
	UMIDAS-ARMA-biclags	0.96	1.03	1.13	1.06	1.03	1.03	1.50	0.97
	UMIDAS-ARMA-3lags	0.85	1.12	1.23	0.98	1.06	1.05	1.00	1.10
GDP with Employment	AR	3.06	1.02	1.23	1.01	1.84	1.17	1.07	0.95
	MIDAS1-AR-12lags	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	MIDAS-ARMA-12lags	0.26	0.70	2.22	1.69	0.98	0.92	0.95	0.93
	MIDAS-ARMA-3lags	0.18	1.44	0.51	0.65	0.98	0.94	0.82	0.94
	UMIDAS-biclags	5.60	1.00	0.51	0.74	0.97	1.00	0.89	0.95
	UMIDAS-ARMA-biclags	19.59	1.52	1.88	1.30	0.90	0.95	1.71	0.97
PNFI with Industrial Production	UMIDAS-ARMA-3lags	0.18	1.40	0.56	0.61	0.98	1.00	0.93	0.88
	AR	348.15	4.11	0.87	0.56	1.51	1.24	1.00	0.81
	MIDAS1-AR-12lags	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	MIDAS-ARMA-12lags	5.39	0.94	0.86	0.86	0.95	0.99	0.96	0.96
	MIDAS-ARMA-3lags	10.55	1.13	1.54	1.12	0.91	1.07	1.05	0.95
	UMIDAS-biclags	0.09	1.38	1.31	1.01	1.04	1.08	1.21	1.01
PNFI with Employment	UMIDAS-ARMA-biclags	1.52	1.50	1.65	1.20	0.95	1.15	1.08	1.04
	UMIDAS-ARMA-3lags	10.59	1.54	1.54	0.92	0.91	1.13	1.05	1.01
	AR	33.09	2.46	2.77	2.10	1.45	1.20	1.27	1.19
	MIDAS1-AR-12lags	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	MIDAS-ARMA-12lags	0.99	1.15	0.00	0.73	1.01	0.99	0.93	0.86
	MIDAS-ARMA-3lags	0.78	0.42	4.78	0.17	1.01	1.01	0.94	0.72
GDP Deflator with CPI inflation	UMIDAS-biclags	0.91	0.85	0.35	0.24	1.01	1.04	1.04	0.86
	UMIDAS-ARMA-biclags	0.81	0.32	7.20	0.23	1.04	1.06	0.97	0.84
	UMIDAS-ARMA-3lags	0.78	0.44	4.22	0.23	1.01	1.01	0.94	0.80
	AR	0.25	2.53	230.03	0.58	1.40	1.29	1.25	0.93
	MIDAS1-AR-12lags	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	MIDAS-ARMA-12lags	1.08	0.79	0.83	0.95	0.98	0.88	1.15	1.35
GDP Deflator with PCE inflation	MIDAS-ARMA-3lags	0.87	0.61	0.51	0.72	0.94	0.92	1.03	1.07
	UMIDAS-biclags	0.63	0.61	0.63	0.98	1.02	1.01	1.18	1.21
	UMIDAS-ARMA-biclags	0.87	0.64	0.59	0.76	0.94	0.95	1.19	1.37
	UMIDAS-ARMA-3lags	0.87	0.61	0.53	0.69	0.94	0.92	1.06	1.27
	AR	0.79	0.62	0.67	0.89	1.24	1.13	1.17	1.07
	MIDAS1-AR-12lags	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
GDP Deflator with PCE inflation	MIDAS-ARMA-12lags	1.23	1.00	0.88	1.04	0.97	1.01	1.19	1.33
	MIDAS-ARMA-3lags	0.45	0.58	0.62	0.77	0.87	0.95	1.15	1.17
	UMIDAS-biclags	0.70	0.58	0.60	0.87	1.06	1.07	1.39	1.24
	UMIDAS-ARMA-biclags	0.96	0.70	0.49	0.81	1.01	0.99	1.51	1.43
	UMIDAS-ARMA-3lags	0.90	0.58	0.62	0.73	0.96	0.95	1.15	1.26
	AR	2.09	1.16	1.24	1.45	1.52	1.53	1.54	1.40

Note: The table the decomposition of the MSE of the different models as presented in Section 4 into bias and variance, for different forecasting horizons. The forecasts are evaluated over the sample 1980Q1-2015Q4. The numbers reported are the ratio of the bias and of the variance of each model relative to the bias and variance of the MIDAS-AR model.

Table 10: Full-sample estimated MA coefficients

Forecasting U.S. GDP growth									
	Explanatory variable: Industrial Production					Explanatory variable: Employment			
	h=1	h=2	h=3	h=4		h=1	h=2	h=3	h=4
	MA(1)	MA(1)	MA(2)	MA(1)	MA(1)	MA(1)	MA(1)	MA(1)	MA(1)
MIDAS-ARMA-12lags	0.06 (0.45)	0.03 (0.46)	0.11 (0.72)	0.29 (1.33)	0.26 (0.78)	0.39 (3.59)	0.35 (2.26)	0.24 (1.18)	0.12 (0.42)
MIDAS-ARMA-3lags	-0.10 (-0.89)	0.05 (0.73)	0.17 (1.13)	0.31 (1.71)	0.32 (1.20)	0.41 (4.00)	0.44 (2.85)	0.37 (1.95)	0.26 (1.01)
UMIDAS-ARMA-biclags	0.01 (0.08)	0.06 (0.84)	0.19 (1.14)	0.11 (0.43)	0.25 (1.22)	0.05 (0.18)	0.42 (2.98)	0.25 (1.47)	0.28 (1.15)
UMIDAS-ARMA-3lags	-0.10 (-0.89)	0.05 (0.73)	0.17 (1.13)	0.31 (1.80)	0.16 (0.60)	0.41 (4.00)	0.45 (3.03)	0.33 (1.70)	0.27 (1.07)
Forecasting PNFI growth									
	Explanatory variable: Industrial Production				Explanatory variable: Employment				
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4	
	MA(1)	MA(1)	MA(1)	MA(1)	MA(1)	MA(1)	MA(1)	MA(1)	
MIDAS-ARMA-12lags	-0.33 (-3.82)	-0.14 (-1.15)	0.13 (0.65)	-0.03 (-0.13)	0.13 (1.27)	0.29 (2.22)	0.35 (2.37)	0.46 (2.67)	
MIDAS-ARMA-3lags	-0.39 (-5.83)	-0.14 (-1.54)	0.15 (1.14)	-0.07 (-0.43)	0.11 (1.23)	0.27 (2.86)	0.37 (2.65)	0.48 (2.94)	
UMIDAS-ARMA-biclags	-0.31 (-3.70)	0.05 (0.50)	0.17 (1.33)	-0.09 (-0.51)	-0.04 (-0.42)	0.26 (2.78)	0.35 (2.41)	0.48 (2.46)	
UMIDAS-ARMA-3lags	-0.39 (-5.83)	-0.12 (-1.24)	0.15 (1.14)	-0.07 (-0.43)	0.08 (0.83)	0.29 (3.00)	0.37 (2.65)	0.48 (2.98)	

Note: The table reports the estimated values of MA coefficients using the full sample 1960-2015. The values in parentheses are t-statistics calculated with Newey-West standard errors to take into account the serial autocorrelation of order $h - 1$, possibly induced by direct forecasting.

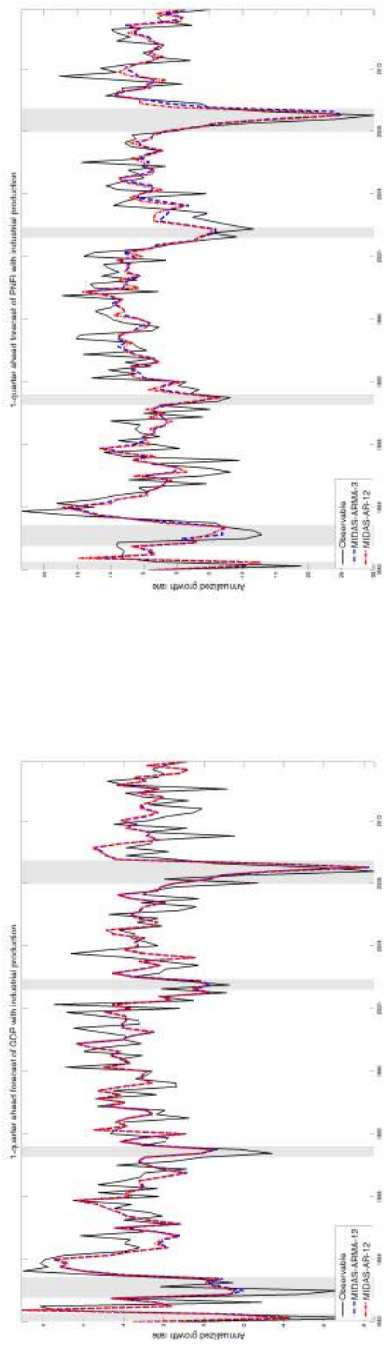
Table 11: Full-sample estimated MA coefficients

Forecasting U.S. GDP deflator								
Explanatory variable: Consumer Price Index								
	h=1		h=2		h=3		h=4	
	MA(1)	MA(2)	MA(1)	MA(2)	MA(1)	MA(2)	MA(1)	MA(2)
MIDAS-ARMA-12lags	-0.09 (-1.03)	-0.31 (-2.43)	0.18 (1.89)	-0.30 (-2.78)	0.29 (2.78)	-0.08 (-0.67)	0.19 (1.70)	0.14 (1.46)
MIDAS-ARMA-3lags	-0.09 (-1.13)	-0.36 (-4.65)	0.20 (2.09)	-0.34 (-4.48)	0.28 (2.99)	-0.10 (-0.93)	0.18 (1.76)	0.11 (1.08)
UMIDAS-ARMA-biclags	-0.09 (-1.13)	-0.36 (-4.65)	0.18 (1.78)	-0.35 (-4.58)	0.25 (2.62)	-0.12 (-1.09)	0.16 (1.58)	0.09 (0.91)
UMIDAS-ARMA-3lags	-0.09 (-1.13)	-0.36 (-4.65)	0.20 (2.06)	-0.34 (-4.44)	0.28 (2.99)	-0.10 (-0.93)	0.18 (1.76)	0.11 (1.08)

Explanatory variable: PCE Price Index								
	h=1		h=2		h=3		h=4	
	MA(1)	MA(2)	MA(1)	MA(2)	MA(1)	MA(2)	MA(1)	MA(2)
MIDAS-ARMA-12lags	-0.06 (-0.68)	0.09 (0.55)	0.13 (1.50)	-0.22 (-1.62)	0.25 (2.48)	-0.03 (-0.30)	0.19 (1.84)	0.19 (2.07)
MIDAS-ARMA-3lags	0.15 (1.97)	0.32 (3.25)	0.14 (1.56)	-0.30 (-3.86)	0.24 (2.95)	-0.05 (-0.53)	0.18 (1.91)	0.16 (1.53)
UMIDAS-ARMA-biclags	-0.13 (-1.84)	-0.29 (-3.60)	0.14 (1.56)	-0.30 (-3.86)	0.22 (2.63)	-0.06 (-0.63)	0.17 (1.82)	0.16 (1.51)
UMIDAS-ARMA-3lags	-0.13 (-1.84)	-0.29 (-3.60)	0.14 (1.56)	-0.30 (-3.86)	0.24 (2.95)	-0.05 (-0.53)	0.18 (1.91)	0.16 (1.53)

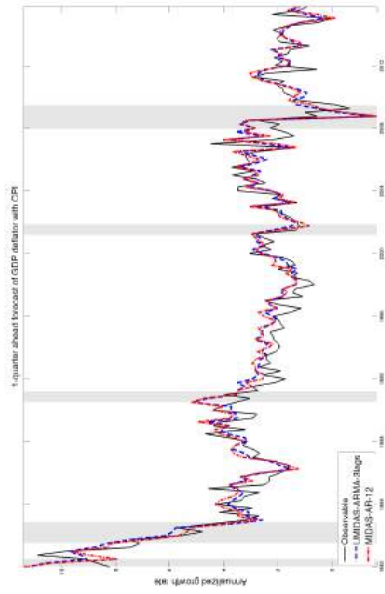
Note: The table reports the estimated values of MA coefficients using the full sample 1960-2015. The values in parentheses are t-statistics calculated with Newey-West standard errors to take into account the serial autocorrelation of order $h - 1$, possibly induced by direct forecasting.

Figure 1: Out-of-sample performance: one-quarter ahead

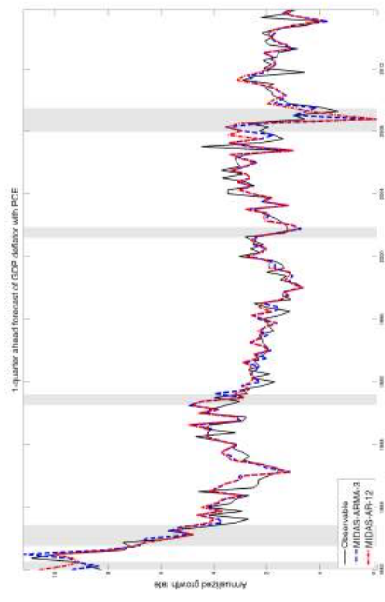


(a) GDP with monthly industrial production

(b) PNF with monthly industrial production

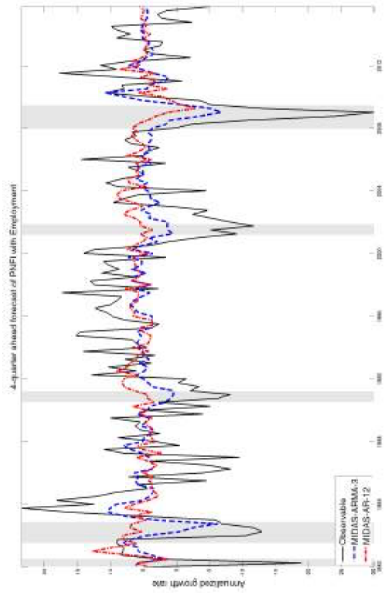


(c) GDP deflator with monthly CPI

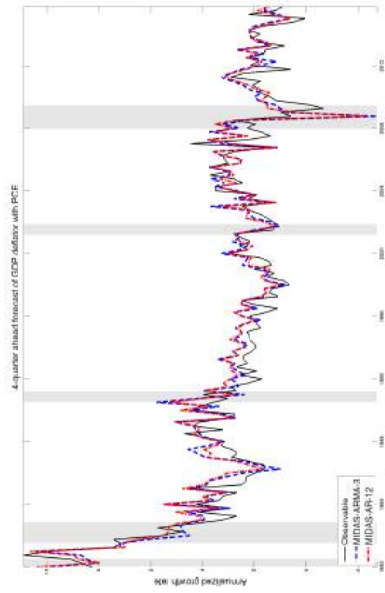


(d) GDP deflator with monthly PCE

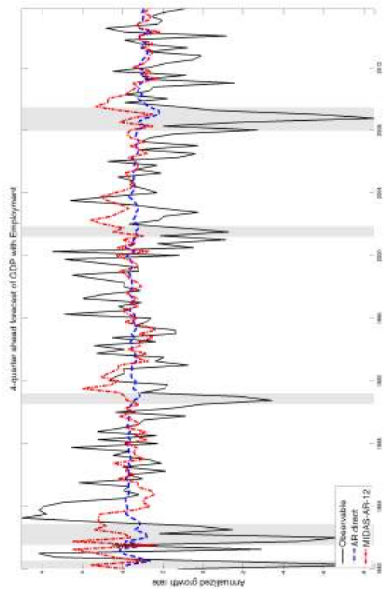
Figure 2: Out-of-sample performance: four-quarters ahead



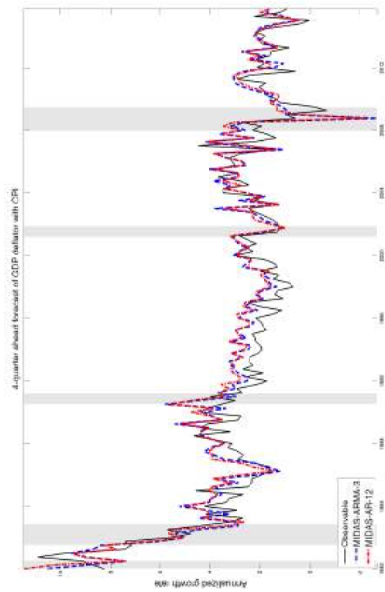
(b) PNF with monthly employment



(d) GDP deflator with monthly PCE



(a) GDP with monthly employment



(c) GDP deflator with monthly CPI

A Estimation of (U)MIDAS-ARMA models

In this section we detail the algorithm used to estimate the (U)MIDAS-ARMA models with non-linear least squares (NLS).

A.1 NLS estimation of MIDAS-ARMA

The MIDAS-ARMA specification is as in (15):

$$y_{t_m} = \tilde{c}(L^m)y_{t_m-h_m} + \beta B(L, \theta)x_{t_m-h_m+w} + u_{t_m} + q(L^m)u_{t_m-h_m}.$$

The estimation procedure, for given orders of the lag polynomials, consists of the following steps:

- Step 1 Get initial values for all the parameters but $q(L^m)$ following Foroni et al. (2015) (the starting values are chosen with a grid search over a set of values for θ , which minimize the residual sum of squares). Set the initial values for $q(L^m)$. We initialize the MA coefficients by a draw from the uniform $U(0.1, 0.5)$ distribution. In principle, it is possible to include the selection of initial value of $q(L^m)$ into the grid search.
- Step 2 Estimate all the parameters, including the weights in the Almon polynomial, simultaneously by NLS, numerically minimizing the residual sum of squares, starting from the initial values obtained in Step 1.

A.2 NLS estimation of UMIDAS-ARMA

The UMIDAS-ARMA specification is as in (13):

$$y_{t_m} = \tilde{c}(L^m)y_{t_m-h_m} + \delta(L)x_{t_m-h_m+w} + u_{t_m} + q(L^m)u_{t_m-h_m},$$

with p , d and r being the lag orders of $\tilde{c}(L^m)$, $\delta(L)$ and $q(L^m)$ respectively. The estimation procedure consists of the following steps:

- Step 1 Get the initial values for all the parameters but $q(L^m)$ by projecting y_{t_m} on $\sum_{j=0}^p y_{t_m-h_m-j}$ and $\sum_{j=0}^d x_{t_m-h_m+w-j}$. Set the initial value for $q(L^m)$. We initialize the MA coefficients by a draw from the uniform $U(0.1, 0.5)$ distribution. In principle, it is possible to perform a grid search and find a set of starting values of $q(L^m)$ which minimize the residual sum of squares.
- Step 2 Estimate all the parameters simultaneously by NLS, numerically minimizing the residual sum of squares, starting from the initial values obtained in Step 1.

B Evaluation excluding the Great Recession

To see whether our results are robust, and not driven by the Great Recession, we recompute the forecast evaluation stopping our evaluation sample in 2007Q3.

Tables 12 to 14 are the equivalent of Tables 6 to 8 for the full sample. Results do not change substantially, and remain broadly supportive of the inclusion of the MA component in the mixed-frequency models. In most of the cases, the best performing model up to 2007 stays the best in the full sample also. Also the magnitude of improvements is very comparable.

Table 12: Forecasting U.S. GDP growth: evaluation sample 1980Q1- 2007Q3

	Explanatory variable: Industrial production growth						Explanatory variable: Employment growth						
	h=1			h=1			h=1			h=1			
	MSE		DM	MAE		DM	MSE		DM	MAE		DM	
	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	DM
MIDAS-AR-12	<u>3.81</u>	1.00	NaN	<u>1.51</u>	1.00	NaN	4.82	1.00	NaN	1.71	1.00	NaN	
MIDAS-ARMA-12	3.83	1.01	0.36	1.53	1.01	0.04	4.81	1.00	0.48	1.70	1.00	0.44	
MIDAS-ARMA-3	3.89	1.02	0.26	1.51	1.00	0.47	4.86	1.01	0.45	1.71	1.00	0.49	
UMIDAS-biclags	3.88	1.02	0.30	1.51	1.00	0.44	4.74	0.98	0.39	1.72	1.01	0.43	
UMIDAS-ARMA-biclags	3.86	1.01	0.35	1.52	1.01	0.36	4.43	0.92	0.10	1.66	0.97	0.24	
UMIDAS-ARMA-3	3.89	1.02	0.26	1.51	1.00	0.47	4.86	1.01	0.45	1.71	1.00	0.49	
AR	7.37	1.93	0.01	1.94	1.29	0.01	7.37	1.53	0.04	1.94	1.14	0.09	
	h=2						h=2						
	MSE		DM	MAE		DM	MSE		DM	MAE		DM	
	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	DM
MIDAS-AR-12	6.59	1.00	NaN	1.85	1.00	NaN	6.15	1.00	NaN	1.80	1.00	NaN	
MIDAS-ARMA-12	6.26	0.95	0.05	1.84	0.99	0.40	<u>5.63</u>	0.92	0.06	<u>1.76</u>	0.98	0.20	
MIDAS-ARMA-3	6.53	0.99	0.39	1.91	1.03	0.10	5.76	0.94	0.11	1.77	0.98	0.26	
UMIDAS-biclags	7.04	1.07	0.00	1.96	1.06	0.00	6.15	1.00	0.12	1.80	1.00	0.09	
UMIDAS-ARMA-biclags	6.74	1.02	0.22	1.92	1.04	0.03	5.76	0.94	0.12	1.77	0.98	0.26	
UMIDAS-ARMA-3	6.71	1.02	0.21	1.86	1.00	0.42	6.19	1.01	0.45	1.82	1.01	0.30	
AR	7.45	1.13	0.19	1.94	1.05	0.16	7.45	1.21	0.06	1.94	1.08	0.04	
	h=3						h=3						
	MSE		DM	MAE		DM	MSE		DM	MAE		DM	
	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	DM
MIDAS-AR-12	7.76	1.00	NaN	2.00	1.00	NaN	8.79	1.00	NaN	2.12	1.00	NaN	
MIDAS-ARMA-12	7.91	1.02	0.27	2.02	1.01	0.28	9.38	1.07	0.23	2.35	1.11	0.04	
MIDAS-ARMA-3	6.91	0.89	0.00	<u>1.85</u>	0.93	0.00	<u>6.88</u>	0.78	0.00	1.89	0.89	0.00	
UMIDAS-biclags	7.67	0.99	0.32	1.96	0.98	0.12	7.36	0.84	0.01	1.93	0.91	0.01	
UMIDAS-ARMA-biclags	11.40	1.47	0.02	2.44	1.22	0.02	16.27	1.85	0.00	3.35	1.58	0.00	
UMIDAS-ARMA-3	7.33	0.94	0.12	1.90	0.95	0.04	7.90	0.90	0.13	1.99	0.94	0.09	
AR	8.22	1.06	0.23	2.00	1.00	0.49	8.22	0.94	0.03	2.00	0.94	0.03	
	h=4						h=4						
	MSE		DM	MAE		DM	MSE		DM	MAE		DM	
	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	DM
MIDAS-AR-12	8.26	1.00	NaN	2.03	1.00	NaN	10.56	1.00	NaN	2.26	1.00	NaN	
MIDAS-ARMA-12	8.08	0.98	0.28	2.04	1.00	0.44	10.94	1.04	0.36	2.43	1.08	0.09	
MIDAS-ARMA-3	<u>7.73</u>	0.94	0.06	<u>1.97</u>	0.97	0.14	9.85	0.93	0.09	2.12	0.94	0.03	
UMIDAS-biclags	8.26	1.00	0.50	2.00	0.98	0.27	9.89	0.94	0.10	2.11	0.94	0.02	
UMIDAS-ARMA-biclags	7.04	0.85	0.04	1.96	0.96	0.26	11.10	1.05	0.31	2.39	1.06	0.18	
UMIDAS-ARMA-3	9.45	1.14	0.29	2.01	0.99	0.43	9.26	0.88	0.01	2.06	0.91	0.01	
AR	8.09	0.98	0.30	1.99	0.98	0.23	8.09	0.77	0.01	1.99	0.88	0.00	

Note: The table reports the results on the forecasting performance of the different models. In the columns "value" we report the MSE and the MAE respectively. In the columns "ratio" we report the MSE and MAE of each model relative to the MIDAS-AR benchmark. In the columns "DM" we report the p-value of the Diebold-Mariano test. The forecasts are evaluated over the sample 1980Q1-2007Q3. The lowest values for each variable are underlined.

Table 14: Forecasting U.S. GDP Deflator: evaluation sample 1980Q1- 2007Q3

	Explanatory variable: CPI inflation						Explanatory variable: PCE inflation						
	h=1			h=1			h=1			h=1			
	MSE		DM	MAE		DM	MSE		DM	MAE		DM	
	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	DM
MIDAS-AR-12	0.63	1.00	NaN	0.60	1.00	NaN	0.42	1.00	NaN	0.48	1.00	NaN	
MIDAS-ARMA-12	0.63	1.00	0.49	0.61	1.02	0.29	0.43	1.03	0.29	0.49	1.02	0.23	
MIDAS-ARMA-3	0.58	0.92	0.09	0.58	0.96	0.15	<u>0.39</u>	0.95	0.32	<u>0.48</u>	1.02	0.36	
UMIDAS-biclags	0.59	0.93	0.19	0.58	0.97	0.19	0.43	1.04	0.29	0.49	1.02	0.29	
UMIDAS-ARMA-biclags	0.58	0.92	0.09	0.58	0.96	0.15	0.45	1.08	0.18	0.49	1.03	0.19	
UMIDAS-ARMA-3	0.58	0.92	0.09	0.58	0.96	0.15	0.41	1.00	0.47	0.48	1.01	0.39	
AR	0.77	1.23	0.15	0.68	1.14	0.06	0.77	1.86	0.00	0.68	1.43	0.00	
	h=2						h=2						
	MSE		DM	MAE		DM	MSE		DM	MAE		DM	
	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	DM
MIDAS-AR-12	0.83	1.00	NaN	0.68	1.00	NaN	0.51	1.00	NaN	0.53	1.00	NaN	
MIDAS-ARMA-12	0.69	0.83	0.08	0.65	0.95	0.14	0.54	1.05	0.11	0.54	1.01	0.15	
MIDAS-ARMA-3	0.64	0.77	0.04	0.64	0.93	0.09	<u>0.43</u>	0.84	0.08	<u>0.52</u>	0.98	0.35	
UMIDAS-biclags	0.71	0.85	0.14	0.66	0.97	0.27	0.48	0.93	0.30	0.54	1.02	0.40	
UMIDAS-ARMA-biclags	0.66	0.80	0.04	0.64	0.94	0.12	0.44	0.85	0.08	0.52	0.98	0.40	
UMIDAS-ARMA-3	0.64	0.77	0.04	0.64	0.93	0.09	0.43	0.84	0.08	0.52	0.98	0.35	
AR	0.81	0.97	0.46	0.71	1.04	0.33	0.81	1.57	0.01	0.71	1.35	0.00	
	h=3						h=3						
	MSE		DM	MAE		DM	MSE		DM	MAE		DM	
	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	DM
MIDAS-AR-12	0.83	1.00	NaN	0.70	1.00	NaN	<u>0.51</u>	1.00	NaN	<u>0.54</u>	1.00	NaN	
MIDAS-ARMA-12	0.92	1.10	0.28	0.75	1.08	0.14	0.60	1.18	0.03	0.58	1.07	0.08	
MIDAS-ARMA-3	0.72	0.87	0.18	0.69	0.99	0.42	0.53	1.04	0.38	0.55	1.02	0.40	
UMIDAS-biclags	0.83	0.99	0.48	0.72	1.03	0.32	0.56	1.11	0.18	0.58	1.07	0.14	
UMIDAS-ARMA-biclags	0.85	1.01	0.46	0.74	1.06	0.25	0.64	1.26	0.03	0.61	1.13	0.06	
UMIDAS-ARMA-3	0.74	0.89	0.19	0.69	0.99	0.43	0.53	1.04	0.37	0.55	1.02	0.40	
AR	0.84	1.00	0.49	0.73	1.05	0.29	0.84	1.65	0.00	0.73	1.35	0.00	
	h=4						h=4						
	MSE		DM	MAE		DM	MSE		DM	MAE		DM	
	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	Value	Ratio	DM
MIDAS-AR-12	0.85	1.00	NaN	0.75	1.00	NaN	<u>0.55</u>	1.00	NaN	<u>0.59</u>	1.00	NaN	
MIDAS-ARMA-12	1.11	1.31	0.00	0.86	1.14	0.00	0.74	1.34	0.00	0.68	1.16	0.00	
MIDAS-ARMA-3	0.80	0.95	0.28	0.73	0.97	0.28	0.60	1.08	0.18	0.60	1.03	0.27	
UMIDAS-biclags	0.97	1.14	0.03	0.79	1.05	0.05	0.62	1.13	0.08	0.61	1.05	0.14	
UMIDAS-ARMA-biclags	1.02	1.21	0.04	0.80	1.06	0.11	0.68	1.23	0.01	0.65	1.11	0.01	
UMIDAS-ARMA-3	0.97	1.14	0.10	0.78	1.03	0.23	0.65	1.18	0.05	0.62	1.06	0.10	
AR	0.89	1.04	0.39	0.76	1.01	0.43	0.89	1.61	0.00	0.76	1.30	0.00	

Note: See Table 12.