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Real-time fiscal forecasting using mixed frequency data*

Stylianos Asimakopoulos† Joan Paredes‡ Thomas Warmedinger§

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Abstract

The sovereign debt crisis has increased the importance of monitoring budgetary execution. We employ real-time data using a Mixed Data Sampling (MiDaS) methodology to demonstrate how budgetary slippages can be detected early on. We show that inspite of using real-time data, the year-end forecast errors diminish significantly when incorporating intra-annual information. Our results show the benefits of forecasting aggregates via subcomponents, in this case total government revenue and expenditure. Our methodology could significantly improve fiscal surveillance and could therefore be an important part of the European Commission's model toolkit.

Keywords: real-time data, fiscal policy, mixed-frequency data, short-term forecasting

JEL Classification: C22, C53, E62,H68

Corresponding author: s.asimakopoulos@bath.ac.uk

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†Department of Economics, University of Bath, email: s.asimakopoulos@bath.ac.uk

‡European Central Bank, Frankfurt, Germany; email: joan.paredes@ecb.europa.eu.

§European Central Bank, Frankfurt, Germany; email: thomas.warmedinger@ecb.europa.eu.

1 Introduction

The sovereign debt crisis has highlighted the importance of fiscal surveillance. In the context of the European Semester it is indeed important to assess the implications of incoming intra-annual data for annual budgetary outturns. The usefulness of intra-annual fiscal data has been shown in many recent studies, e.g. Pérez (2007), Onorante *et al.* (2010), Pedregal and Pérez (2010), Paredes *et al.* (2014) and Ghysels and Ozkan (2015).[1] The focus of that existing literature was mainly on the usefulness of high frequency data to monitor the current-year government balance (total revenue minus total expenditure). This is useful as such and can be used to signal risks to budgetary executions. Hughes Hallett *et al.* (2012) show how those signals should be used to design the necessary fiscal corrections and the gains that can be achieved by such interventions.

The Mixed Data Sampling (MiDaS) technique has been developed to accurately project lower frequency data with higher frequency regressors.[2] Using this technique, the aim of this paper is to utilize many disaggregated real-time quarterly fiscal data to forecast annual data. We also examine the differences between direct forecasts of aggregate fiscal variables and indirect forecasts via their subcomponents, and find that the latter works better.

MiDaS has been used in volatility predictions for financial sector data (e.g. Ghysels *et al.* (2006) and Forsberg and Ghysels (2007)) and in forecasting macroeconomic variables using intra-annual data (see for example Bai *et al.* (2013), Clements and Galvao (2008, 2009) and Kuzin *et al.* (2011) who use monthly data to improve the quarterly forecast of macroeconomic time series). Moreover, Asimakopoulos *et al.* (2017) have incorporated MiDaS for the analysis of the predictability of dividend growth via a time-disaggregated

[1] The latter with data for the U.S., while the previous ones for the euro area.

[2] It should be noted that the purpose of this paper is not to compare exhaustively and find the best model for forecasting fiscal policy variables. For that reason we do not assess all possible approaches that can deal with mixed frequency data. Nevertheless, we show that MiDaS is a suitable tool for assessing mixed frequency data in the context of fiscal policy. The advantage of this approach compared to alternative ones, such as State Space and mixed frequency VAR models, which make use of the Kalman filter, is that MiDaS is more parsimonious and less sensitive to specification errors due to the use of non-linear lag polynomials (i.e. Bai *et al.* (2013)).

dividend-price ratio. Finally, Andreou *et al.* (2010) and Ghysels and Wright (2009) use daily financial data to nowcast macroeconomic data of monthly or quarterly frequency.

Our major advancement compared to the papers in the field of intra-annual fiscal data mentioned above is that we use unrevised vintage data ("real time"), which allows us to perform a real-time forecast.[3] This real-time approach confirms the information content of quarterly fiscal data: in particular, the year-end forecast errors diminish when incorporating intra-annual information. Additionally, following Aruoba (2008), we present some stylized facts of fiscal data revisions. Finally, following de Castro *et al.* (2013), we also extend the analysis incorporating macroeconomic indicators to assess the rationality of those revisions.

Various strands of the literature highlight the benefit of forecasting aggregates indirectly via their subcomponents. Lütkepohl (2010) indicates that an indirect disaggregated forecast of subcomponents can lead to better forecasts for the aggregate than a direct forecast of the aggregate variables. This is mainly due to the richer information contained in the subcomponents. The aggregated versus disaggregated approach has also been assessed in the context of GDP forecasting. For instance, Baffigi *et al.* (2004) find that the aggregated forecast of the total GDP is more accurate than aggregating the forecast of its components. However, Perevalov and Maier (2010) find that forecasting economic activity in the U.S. indirectly through the expenditure components may improve the forecast for the aggregate. Similarly, Marcellino *et al.* (2003) show that it is better to forecast the euro area GDP via aggregating the forecast of individual countries (disaggregated approach).

In order to bring our work into a policy context, we compare our model with the forecast reported by the European Commission (EC). As it turns out, even though our method is relatively simple, it can still improve upon the far more sophisticated EC forecast. Timmermann (2006) points to the fact that it is not possible for an individual model to outperform all others at each point in time because such forecasting models are thought of as local approximations. Stock and Watson (2004) also suggest that a combination of forecasts using

[3] In doing so, we avoid the potential issue of having misleading conclusions, as highlighted by Orphanides (2001) and Cimadomo (2012)

many different variables and models can result in a much more accurate and robust forecast than an individual model. Therefore, the above results indicate that MiDaS could usefully complement the EC forecast models, with a particular view to improving fiscal surveillance within the year.

The paper is organized as follows. Section 2 describes the data and the importance of using real-time vintages. Section 3 provides a description of the econometric models. Section 4 describes the forecasting exercise. Section 5 shows the results and section 6 concludes the paper.

2 Data

The data are formed by a very disaggregated set of annual and quarterly fiscal variables. Specifically, the fiscal data used for all the case studies are the quarterly vintages of the Government Finance Statistics (GFS) database as compiled by Eurostat and the vintages of the DG-ECFIN AMECO database, which includes annual data and forecasts. In particular, we follow Paredes *et al.* (2014) when selecting fiscal variables, trying to cover as many as possible of the subcomponents of total revenue and total expenditure. Data include total revenue (TOR) and its subcomponents: direct taxes (DTX), indirect taxes (TIN), social security contributions (SCT); and total expenditure (TOE) and its subcomponents: social benefits other than in kind (THN), interest payments (INP), subsidies (SIN), compensation of employees (COE) and government investment (GIN).[4]

The data sample period depends on the countries. For Belgium and France fiscal data are available from 1991q1 to 2013q4 and for the rest of the countries the data sample is smaller, from 1999q1 to 2013q4.[5] We stop in 2013q4 due to the introduction of the 2010 European System of Accounts (ESA) at that time. The substitution of the previous ESA 1995 introduced a discontinuity in some fiscal series, i.e. it shortened their length and

[4]Note that all the data are stationary by applying the differences of their natural logarithms.

[5]The other countries are: Austria, Finland, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, Slovenia and Spain.

changed their dynamics.

The main focus of this paper is the forecast of the end-of-year fiscal variables (year-end forecast), taking into account higher frequency data for the same period. In other words, quarterly fiscal data will be used as they become available in each quarter to perform nowcasting of the annual fiscal series. Nowcasting in the literature refers mostly to forecast updates using high frequency data. For example, if the aim is to forecast the annual growth rate of total revenue (TOR) using quarterly data, the nowcasting approach updates the 2012 forecast for TOR growth rate using data of the explanatory variables of either the first and/or the second and/or the third quarter in 2012. The MiDaS approach incorporates available higher frequency data within the forecast period to nowcast.

There are some specific features that should be borne in mind about the fiscal data. The available annual and quarterly data are revised every 6 months. This is related to the semi-annual (April-October) reporting obligation of annual GFS by Member States to Eurostat, as stated within the context of the Excessive Deficit Procedure (EDP). Revisions have not been subject to benchmark revisions, i.e. due to changes in statistical variable definitions during this period, but they are subject to revisions occurring after EDP audits. An example would be that Eurostat, in its role of auditing government accounts, requests a re-classification of a government transaction in a different manner (timing or item) to the national statistics authorities. These data are usually revised backwards up to three years. For example, when new data become available in 2011q3, the data could be revised backwards approximately until 2008q3. When performing forecasts, only information available at that point in time is used. These data are called end-of-sample vintage data (EndVint) and include a combination of first announcements and revised data. This is the type of data included throughout our analysis.[6]

[6] Koening *et al.* (2003) suggest that real-time vintage data (RTVin) are better because they are not revised. However, fiscal data are only available in RTVin format from 2005q2. Therefore, it is not possible to construct the RTVin database using only data without any revision and having at the same time a sufficiently large sample for the econometric analysis.

2.1 The importance of real-time data

In this section we assess the unconditional properties of our dataset. An economist will use all information available at each point in time when forecasting. Therefore, before analyzing if MiDaS is useful as a forecasting tool, we take a look at the properties of the data we use. In the words of Aruoba (2008), ideally data revisions are "well behaved" if three properties are fulfilled. First, the mean of the revisions is statistically different from zero, which would mean that the initial announcement is an unbiased estimate of the final value. Second, the volatility of these revisions should ideally be small in comparison to the volatility of the series themselves. Third, it is expected that the final revision is unpredictable.

In Tables 1a-1d we present the summary statistics of the final revisions for the big-4 euro area countries,[7] which will help us in the assessment of the properties discussed above. We assess revisions in terms of year-on-year growth rates to eliminate the effect of seasonality. The first column reports the number of observations for each variable. We always take into account more than 30 revisions, with 45 being the maximum number of available vintages for direct taxes (DTX) and indirect taxes (TIN), which, in turn, corresponds approximately to the first and last vintages dated in July 2002 and April 2014, respectively. The next column reports the mean of the final revision and we indicate with an asterisk which values are significant different from zero at the 10% level using the Newey-West (Newey and West, 1987) standard errors to account for the possible autocorrelated structure of the revisions. When statistically significant, we always find positive means, which implies that countries tend to under report both revenue and expenditure. For example, Germany presents five out of ten variables with a significant revision mean. This would violate the first desired property, i.e. the revisions do not have a zero mean.

In the next two columns we show the minimum and maximum of the final revision. We can see that fiscal data seem to be volatile and subject to very large revisions. For example, focusing on the aggregates, we can see that revisions on total revenue and expenditure

[7] The summary statistics for the remaining countries are available upon request.

year-on-year growth rates can fluctuate from -12.9% to 5.3% and from -11.6% to 9.8%, respectively. The next two columns report the standard deviation and the noise-to-signal ratio for the final revisions. The noise-to-signal ratio is calculated as a ratio of the standard deviation of revisions divided by the standard deviation of the initially reported value. This indicator measures the magnitude of the final revisions relative to the size of the original values. The reported values range from 0.14 to 1.22. In particular, a number above one implies that the standard deviation of the revision is larger than the standard deviation of the original series, which would indicate that the revision in that specific case is relatively large compared to their original values. This statistic, together with the minimum and maximum final revisions, gives us an idea about the size of the final revisions.

Finally, the second to last column reports the correlation of the final revision with the initial announcement. The values are mostly negative, reaching values as high as -0.88 for France. Those negative values would indicate in this case that for some variables and countries, the statistical agencies might use estimations instead of hard data in their initial announcements. When additional information becomes available a negative correlation means that the initial growth rate is corrected towards zero. The last column reports the first order autocorrelation coefficient of final revisions. Statistically significant positive persistence is mostly observable on the expenditure side, which indicates that new information collected by statisticians affect revisions in the same direction for a number of consecutive periods. In terms of revenue, we find some significant negative first order autocorrelation coefficients. This suggests that revisions within the year could be due to a reallocation of the timing when those payments are booked in government accounts. The final two columns of the tables would therefore indicate that final revisions are predictable.

[Tables 1a-1d here]

To reinforce this last point, we follow de Castro *et al.* (2013) and test if one can find variables with explanatory power on future revisions. We postulate the following equation for each single fiscal variable:

$$fr_t^Q = \beta_0 + \beta_1 iv_t^Q + \beta_2 GDP_t^A + \beta_2 INF_t^A \tag{1}$$

where fr_t^Q is the final revision for each quarter, while iv_t^Q is the first release, both expressed in year-on-year growth rates, GDP_t^A and INF_t^A are the annual growth rate of real GDP and GDP deflator forecasted at that moment for the end of the current year.

[Table 2 here]

Table 2 shows the estimation corresponding to equation (1). All equations have been estimated by pooled generalized least squares (GLS). Our results show that final revisions are negatively correlated with the initial published figure. In addition, we find that a higher expected output growth helps in forecasting an upcoming upward revision for revenue items, while a higher expected inflation helps in forecasting an upward revision for expenditure items. These results are also in line with de Castro *et al.* (2013).

Taking all the previous points into consideration, one could conclude that revisions are not "well-behaved".

3 Model specification

This section provides an overview of the various models that will be used in the empirical analysis. The first model is the simple aggregation approach in which the high frequency variables are transformed to low frequency by simply taking their average. The second model is the unrestricted mixed frequency data analysis. Using this model requires no assumption regarding the high frequency variables. However, other issues may arise, like the parameter proliferation issue.[8] The benchmark model is MiDaS, that makes use of a distributed lag polynomial, which is data driven and non-linear, in order to transform the high-frequency data into low frequency.

3.1 Flat-weight aggregation approach

The most simple case of dealing with mixed frequency data is to aggregate the high frequency data and then take their average. This approach implies equal weights on each quarter. However, if the true weighting scheme is not that of equal weights, the average estimation will lead to biased estimators.

In more detail, assuming that Y_{t+1}^A is the annual time series and that X_t^Q is the quarterly time series, the distributed lag regression applied is the following:

$$Y_{t+1}^A = \beta_0 + \beta_1 X_t^A + u_{t+1}^A \tag{2}$$

where $X_t^A = \sum_{i=1}^{N_Q} \frac{1}{N_Q} X_{i,t}^Q = \left(X_{N_Q,t}^Q + X_{N_Q-1,t}^Q + X_{N_Q-2,t}^Q + X_{N_Q-3,t}^Q \right) / N_Q$ is the annual time series obtained from the quarterly data. N_Q denotes the number of quarters within a year, u_{t+1}^A denotes the residuals.

Assuming that ω_i are the weights assigned to each quarter (i), and using the quarterly lag operator L_Q^i we can re-write equation (2) as:

$$Y_{t+1}^A = \beta_0 + \bar{\beta}_1 \sum_{i=1}^{N_Q} \omega_i L_Q^i X_{i,t}^Q + u_{t+1}^A$$

Comparing this equation with equation (2), taking the aggregation scheme of the quarters into account, the following expression can be obtained:

$$Y_{t+1}^A = \beta_0 + \bar{\beta}_1 X_t^A + \bar{\beta}_1 \sum_{i=1}^{N_Q} \left(\omega_i - \frac{1}{N_Q} \right) L_Q^i X_{i,t}^Q + u_{t+1}^A$$

[8] For example, a model with six quarters of information, as in our analysis, requires seven parameters to be estimated compared to only three parameters in MiDaS.

Therefore, if the true weighting scheme is not the "equal/average" weighting scheme, the simple ordinary least squares (OLS) regression will have biased estimators because of the omitted regressor (the third term in the above equation). As a consequence, the slope coefficient will be biased because of the misspecified model.[9]

3.2 Mixed frequency data sampling approach (MiDaS)

Ghysels *et al.* (2004, 2005) proposed the MiDaS approach where the parameter proliferation issue can be avoided and no assumption is required regarding the attached weights to high frequency variables. There are only three parameters to be estimated in the single variable distributed lag model case, which is invariant with respect to the frequency or the lag length of the explanatory variable. This is because the MiDaS regression is based on distributed lag polynomials to ensure a parsimonious specification. However, the lag polynomials are not linear and the MiDaS regression is therefore estimated using non-linear least squares (NLS).

Denoting the high frequency data (quarterly data in this case) with X_t^Q and the low frequency data (annual data) with Y_t^A, the typical MiDaS regression is the following:

$$Y_{t+1}^A = \mu + \beta \sum_{j=0}^{q_X^Q - 1} W\left(L^{N_Q}; \theta\right) X_{t-j}^Q + \varepsilon_{t+1}$$

where $W\left(L^{N_Q}; \theta\right)$ are the weights attached to each lag of the quarterly data. L^{N_Q} is a simple quarterly lag operator and θ is a composition of two parameters that determine the curvature of the weighting scheme. q_X^Q denotes the number of quarterly lags and ε_{t+1} is the error term.

Specifically, the distributed lag polynomial is given by:

$$W\left(L^{N_Q}; \theta\right) X_t^Q = \sum_{j=0}^{N_Q - 1} \omega_j\left(\theta\right) X_{t-j}^Q$$

where ω_j denotes the weighting scheme.

[9] This does not mean that they would forecast badly. Indeed, biased estimators could forecast better if they have lower estimation uncertainty.

The lag polynomial determines the effect (weight) of the explanatory variable on the dependent variable. Ghysels *et al.* (2007) propose various weighting schemes. We use the exponential Almon lag polynomial, as it is very flexible and can take many shapes. This polynomial needs only two parameters, $\theta = (\theta_1, \theta_2)$, to be estimated using the data.[10] As a result, the weights are purely data driven and no prior assumption is required.

The following distributed lag (DL) model can be obtained using the MiDaS method and the exponential Almon lag polynomial.

$$Y_{t+1}^{A} = \beta_0 + \beta_1 \sum_{j=0}^{q_X^Q - 1} \sum_{i=0}^{N_Q - 1} \omega_{i+j*N_Q}(\theta) \, X_{N_Q - i, t-j}^{Q} + \varepsilon_{t+1} \tag{3}$$

This method is called DL-MiDaS(q_X^Q).[11] Note that q_X^Q denotes the number of lags of the high frequency variable after it has been transformed to low frequency using the lag polynomial.[12]

Another important characteristic of the MiDaS approach is that the slope coefficient β can be easily obtained from the regression as the weights attached to the high frequency data are normalized and sum to one. In addition, MiDaS is much more flexible than a flat-weighting scheme since it can nest the equal weighting scheme by setting $\theta_1 = \theta_2 = 0$. MiDaS can also take seasonality into account by attaching the appropriate weight to each lagged regressor.[13]

[10] See Ghysels *et al.* (2007) for more details regarding the specific expression of the exponential Almon lag polynomial.

[11] Note that throughout the paper we also refer to DL-MiDaS simply as MiDaS.

[12] It is possible to augment DL-MiDaS using an autoregressive term. However, in this paper we do not follow this approach because the high frequency variables are the disaggregated version of the low frequency variables. As a robustness check, though, we implemented an autoregressive distributed lag MiDaS and we find that the accuracy of the forecast does not improve with the inclusion of the autoregressive term.

[13] For verifying that seasonality is not an issue in the MiDaS regression the data have been de-seasonalized and then re-estimated with MiDaS. The forecast accuracy reported from this method is equivalent with the forecast reported when vintage data are used instead.

3.3 Nowcasting with MiDaS

Using high frequency data for forecasting low frequency data can lead to a more accurate forecast in the case where data from within the forecast period are utilized. Especially during periods of economic turmoil intra-annual data releases can improve forecast accuracy.

The MiDaS regression can take this new information into account and perform the nowcasting. In this case the DL-MiDaS presented in equation (3) becomes:

$$Y_{t+1}^{A} = \beta_0 + \beta_1 \sum_{j=0}^{q_X^Q - 1} \sum_{i=0}^{N_Q - 1} \omega_{i+j*N_Q}(\theta)\, X_{N_Q - i, t+1-j-s/4}^{Q} + \varepsilon_{t+1} \tag{4}$$

where s is the forecast horizon in quarters. Note that the time period for the high frequency variable, X_t^Q, is not t any longer but $t+1$ and depends on the quarterly information released within the year of forecast, determined by s.

When $s < 4$ the exercise becomes a nowcast based on information of the current year. For example, $s = 3$ denotes a forecast horizon equal to 3 quarters ahead. In this case the model will use data from the first quarter of the year to update the year-end forecast. The nowcasting exercise is restricted in using up to three quarters within the year of the forecast.[14]

3.4 Unrestricted regression

As an alternative model, the high frequency variable can be directly related to the low frequency variable without the need for aggregation (e.g. Foroni *et al.*, 2015):

$$Y_{t+1}^{A} = \beta_0 + \sum_{i=0}^{N_Q - 1} \beta_j X_{N_Q - i, t}^{Q} + u_{t+1} \tag{5}$$

Equation (5) is estimated using OLS. The advantage of this approach is that it does

[14] Note that when the weighting scheme multiplies the quarterly fiscal data the newly created low frequency vector is not the same as the actual low frequency fiscal variable (due to the weighting scheme).

not make any assumption on the weights that should be attached to each quarter (unrestricted). This estimation is called Unrestricted Mixed frequency Data Sampling (U-MiDaS) throughout the paper.

The number of parameters that need to be estimated in this approach increases significantly in comparison to the previous case. In particular, there are five parameters to be estimated when dealing with annual/quarterly data.[15] However, this number can further increase if monthly data are being used instead of quarterly data, or if several lags of each quarter are incorporated. Therefore, U-MiDaS suffers from the parameter proliferation issue.

4 Forecasting Exercise

Initially, the three models under consideration will be compared in terms of their average forecasting and nowcasting performance.[16] The comparison of the different models is based on their average Root Mean Squared Forecast Error (RMSFE). The estimation period ends in 2009q4 for all countries and we use data until 2013q4 for a rolling estimation of end-year forecasts for the period 2010q1-2013q4. The average RMSFE is obtained from each forecast/nowcast for each year and for each one of the 10 fiscal variables resulting in 40 different RMSFEs for each country and for each quarter.

Therefore, for each country we present four bar plots (see Figures 1-3). They are constructed to facilitate the comparison of all models' average forecasting performance. Each graph shows the average RMSFEs per country, per model and per quarter of observation. Every bar consists of the RMSFEs for the 10 fiscal variables and for 4 years (2010-2013). Values close to zero indicate better forecasts from that approach.[17]

The bar plot entitled "April (Q0)" includes only data as released in April, which is due to

[15] One coefficient for each quarter and one for the constant.

[16] The benchmark model is the distributed lag MiDaS regression, as in equation (3). The benchmark model will be compared with a simple aggregation scheme, also called flat-weighting scheme, as in equation (2) (named flat-weight) and with the Unrestricted-MiDaS, as in equation (5) (named U-MiDaS).

[17] Note that at this stage we only compare the overall forecast performance of each model at each point in time and not the individual time series.

the publication lag of data from the previous year. As a result there is no benefit from using quarterly data at that point in time, which means that the first bar plot of each country makes no use of quarterly information within the forecasted year. In contrast, the other three bar plots within the graph include the results of RMSFE from the nowcasting exercise. The bar plot "July (Q1)" includes the release of the first quarter of the current year, which will be taken into account when updating the annual forecast. Following the same concept, the other two bar plots, labeled as "Oct (Q2)" and "Jan (Q3)", take into account quarterly information from fiscal data up until the second and third quarter, respectively. Comparing the evolution of country specific bar plots illustrates the information content of data releases within the year. As can be expected, a clearly decreasing pattern becomes apparent as we incorporate new information within the year of forecast.

The RMSFE results, as shown in the bar charts, indicate that the MiDaS approach outperforms the flat-weighting and U-MiDaS approach in the majority of cases.[18] Therefore, we will use the MiDaS approach as our benchmark model.[19]

5 Results

5.1 Forecasting aggregates using subcomponents

We examine whether forecasting deficit, total revenue and total expenditure through a disaggregated approach using their subcomponents will result in a more accurate forecast of the aggregates compared to forecasting the aggregates directly. Timmerman (2006) finds that forecast combinations from several models can result in more accurate forecasts than using any single model due to the misspecification issues and measurement errors that arise from

[18] We have also performed a Giacomini-White test on the RMSFE results from the bar plots but we do not show them here to save space.

[19] Note that in MiDaS the lag-length is determined through the Bayesian Information Criteria (BIC), choosing between six and twelve quarterly lags. The flat-weight model has two annual lags included in the regression. The Unrestricted MiDaS has six quarterly lags included due to small sample and proliferation issues.

the use of a single model.

There are many ways to combine forecasts (see, for example, Timmerman (2006) for a survey). In our work we follow the approach of Stock and Watson (2004) and Andreou *et al.* (2013) and we focus on the squared discounted mean square forecast errors (dMSFE) combinations approach. Under this approach, each individual forecast from a fiscal variable is given a weight according to its historical performance. The discount factor places a higher weight on the recent predictive ability of the fiscal variables.[20]

The forecast combination in our paper involves two steps. First, we compute the forecasts for each annual fiscal variable using past quarterly information of the same variable. Second, we combine these forecasts using the dMSFE approach so as to forecast the aggregate fiscal variable, like total expenditure and revenue.

Tables 3-4 compare the aggregated and disaggregated approach through the RMSFEs and the Giacomini-White test in particular. A negative value of the test-statistic indicates that the RMSFEs of the aggregated approach are higher than that of the disaggregated approach. In other words, a negative sign indicates that the disaggregated approach performs better in forecasting the aggregate fiscal variables than the aggregated approach.

Table 3 indicates that for the majority of the countries there is a consistent improvement of the forecast if the disaggregated approach is implemented. In addition, this improvement in the forecast appears to be statistically significant at least in half of the case studies. In particular, when we use the disaggregated fiscal data to forecast deficits we find that in 11 out of the 12 countries the forecast improves (we get a lower RMSFE compared to the aggregated approach) and the improvement is statistically significant in 8 out of the 11 countries.

The information shown in Table 4 indicates that the main driver of the forecast improvement of the disaggregated approach is the expenditure side. We observe a statistically significant improvement in 9 out of the 12 countries, whereas on the revenue side we have a statistical significant improvement in half of the countries in our sample. This could be

[20]See alo Ghysels and Ozkan (2015) for a similar approach.

related to the fact that the expenditure side depends on discretionary government decisions and less on statistical profiles of the fiscal series.[21]

In this section, we showed that the indirect forecast of the aggregate fiscal variables through their subcomponents (disaggregated approach) can improve the accuracy of the forecast, similarly to the results of Marcellino *et al.* (2003) and Perevalov and Maier (2010), albeit on different setups and applications.

[Tables 3-4 here]

5.2 The improvement of forecast performance in real time

As shown, the MiDaS approach indicates that high frequency fiscal data (quarterly in this case) contain important information that should be taken into account when fiscal variables are forecasted. It is generally shown that the forecasts using the MiDaS approach improve in most of the cases when we incorporate new information to our nowcasting as the year advances. It could thus be concluded that when high frequency fiscal data become available within the forecast period they should be included to update the nowcast.

So far only the overall forecasting ability of MiDaS model has been assessed. In order to make this conclusion more robust, we now provide an analysis of the individual fiscal time series. The forecast/nowcast of each variable will be compared with the actual data. Table 5 illustrates the information contained in a new release of quarterly fiscal data. In particular, it examines whether the inclusion of one additional quarter will improve the forecast performance in terms of the RMSFE. For example, the inclusion of the first quarter will improve the forecast of TOR in 11 out of 12 countries (92% improvement). Moreover, the inclusion of the second quarter will further improve the forecast of TOR in 10 out of 12 countries (83% improvement) compared with the nowcast with only the first quarter.

There are very few countries in our sample where this was not the case. This could be

[21] We have also included additional explanatory factors (i.e. GDP and inflation forecasts) and the results remain unchanged.

due to a lack of quality in their quarterly GFS data.

[Table 5 here]

From Table 5 we can confirm that the inclusion of a new quarter systematically improves the forecast accuracy of individual fiscal variables on both the revenue and the expenditure side. This holds for most of the countries with the exception of the second quarter for subsidies (SIN). These results indicate clearly that quarterly data contain significant news and improve the year-end forecast.

5.3 Comparison between the benchmark model and the EC forecast

Since it has been concluded that quarterly fiscal data contain significant information, it is also important to compare our forecast with other forecasts. It has been shown in the literature (e.g. Keereman (1999) and Artis and Marcellino, (2001)) that the forecast reported by the EC is very accurate, so it can serve as a natural benchmark for the MiDaS forecast. The EC's fiscal forecasts take into account intra-annual information, macroeconomic variables and models, as well as experts' beliefs. They are therefore forecasts produced with many different variables and indicators, which one could expect to increase their accuracy. In contrast, the MiDaS model used here employs only historical information from the same variable under consideration, i.e. it is a very simple univariate model for the case of forecasting individual series. Nonetheless, to qualify the accuracy of MiDaS forecasts we will still compare them with the forecasts from the EC for those individual fiscal variables.[22] In particular, we are going to combine the EC forecasts with that of MiDaS and then we will compare the

[22] Timmermann (2006) points to the fact that it is not possible for an individual model to outperform all others at each point in time because such forecasting models are thought of as local approximations. Also, Stock and Watson (2004) suggest that a combination of forecasts using many different variables and models can result in a much more accurate and robust forecast than an individual model.

predictions of the combined forecast with the EC's predictions on its own.[23]

Table 6 shows the evolution of MiDaS-EC combination forecasts for each variable and quarter. For instance, for indirect taxes (TIN) in Q_0 (April) (without using any intra-annual information) 25% of the countries in our sample exhibit lower RMSFE from the MiDaS-EC combination forecast than that of the EC. Moreover, when the first quarterly data become available for Q_1 (July), 50% of the countries have on average a more accurate forecast when using a combination of the MiDaS univariate model and the EC forecast for the specific variable. However, this result is compared against the DG-ECFIN AMECO April release, which is not fully fair as it does not incorporate any new information from within the year of forecast.

If we compare forecast performances in October, Q2 data are included in both MiDaS and in the DG-ECFIN AMECO release, there is no information advantage. The univariate MiDaS-EC combination seem to be able to extract important news on the expenditure side that might not be fully exploited in the EC forecast. For that particular quarter, a MiDaS-EC combination results in more accurate forecasts on average for at least half of the countries. The importance of quarterly information is especially relevant on the expenditure side of fiscal forecasts, since there are often no clear macroeconomic variables to which expenditure items can be linked. This is less the case on the revenue side, where macroeconomic tax bases are clearly defined. For instance, indirect taxes can be expected to follow private consumption dynamics.

Finally, the most significant improvement comes in the last quarter (Q_3), released in January of the following year, where for most of the variables and for more than half of the countries, the MiDaS-EC combination can further improve the accuracy of the forecast compared to the EC on its own. However, the comparison here is again not fully fair as the

[23] We have also performed a forecasting comparison of MIDAS forecasts with EC forecasts and we found that the results do not differ substantially. These results are available upon request.

DG-ECFIN Autumn release does not incorporate the information from the last quarter.

[Table 6 here]

6 Conclusions

The sovereign debt crisis has increased the importance to monitoring and forecasting budgetary execution, particularly in EU countries. This paper has employed a MiDaS approach to utilize intra-annual fiscal data to forecast end-of-year budgetary outturns. MiDaS was developed and used for a number of other mixed-frequency modelling applications and we have used it in a fiscal policy context with direct application to fiscal surveillance in the EU. We used real time data to make our analysis credible for actual applications. Indeed, we find that employing MiDaS with real-time intra-annual data reduces the year-end forecast errors for budgetary outturns. A further finding of this paper relates to the literature on forecast performance of direct forecasts for the aggregate versus indirect forecasts for the aggregate via subcomponents. We find that the indirect disaggregate approach works significantly better, taking into account not only revenue and expenditure but also further subcomponents. Further, we find that this advantage of the disaggregate approach stems mainly from the expenditure side, which is typically more prone to discretionary policy choices compared to the revenue side of the budget. Above all, we confirmed the importance of quarterly fiscal data when forecasting annual outturns. Such intra-annual data should be taken into account as they become available throughout the year so as to update the year-end fiscal forecast (nowcasting). Finally, we put our analysis into the context of actual fiscal surveillance in the EU. The fiscal forecasts by the EC are prepared bottom-up via the various subcomponents. A comparison with the EC forecasts indicate that our MiDaS model can also improve the forecast performance for very specific individual fiscal series. And can thus be concluded that MiDaS would be an important addition to the European Commission toolkit of models to forecast fiscal variables.

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Table.1a: Data revision statistics for France

Variable	N	Mean	Min	Max	Std. Dev.	Noise/Signal	Corr. with initial	AC (1)
TOR	34	-0.30	-12.95	3.02	2.57	0.68	-0.50*	-0.14
		0.80					0.00	
DTX	45	-0.51	-18.15	5.08	3.48	0.45	0.12	0.02
		0.82					0.44	
TIN	45	0.29	-10.74	9.76	3.41	0.81	-0.67*	-0.29*
		0.24					0.00	
SCT	32	0.10	-0.61	0.96	0.44	0.34	-0.22	0.42*
		0.15					0.22	
TOE	34	0.06	-11.56	3.01	2.28	0.94	-0.88*	-0.22
		0.43					0.00	
THN	32	0.15	-0.84	1.75	0.59	0.64	0.32*	0.63*
		0.17					0.07	
INP	35	-0.15	-34.16	35.13	11.22	0.95	-0.53*	0.19
		0.53					0.00	
SIN	35	-0.25	-8.57	7.52	4.24	1.22	-0.37*	0.77*
		0.59					0.03	
COE	32	0.16	-3.24	2.48	1.04	0.91	-0.49*	0.16
		0.22					0.00	
GIN	35	3.01*	-5.40	20.79	6.40	1.00	-0.56*	0.63*
		0.04					0.00	

Table 1a shows the summary statistics of the final revisions for France. The first column reports the number of observations (N) for each variable. The next columns report the mean, minimum and maximum of the final revision. The next two columns report the standard deviation (s.d.) and the noise-to-signal ratio for the final revision. The second to last column reports the correlations of the final revision with the initial announcement. The last column reports the first order autocorrelation coefficient of final revisions. We indicate with an asterisk which values are significant different from zero at the 10% level using the Newey-West (Newey and West, 1987) standard errors in the case of the mean. The fiscal variables are the following: total revenue (TOR) and its subcomponents: direct taxes (DTX), indirect taxes (TIN), social security contributions (SCT); and total expenditure (TOE) and its subcomponents: social benefits other than in kind (THN), interest payments (INP), subsidies (SIN), compensation of employees (COE) and government investment (GIN).

Table.1b: Data revision statistics for Germany

Variable	N	Mean	Min	Max	Std. Dev.	Noise/Signal	Corr. with initial	AC (1)
TOR	34	0.63*	-0.53	1.69	0.60	0.23	-0.03	0.28
		0.00					0.88	
DTX	45	0.57*	-3.40	4.33	1.92	0.31	0.36*	0.30*
		0.07					0.02	
TIN	45	0.40*	-2.61	4.35	1.50	0.42	-0.23	0.45*
		0.09					0.13	
SCT	32	-0.01	-1.12	0.79	0.53	0.33	-0.15	-0.01
		0.53					0.40	
TOE	34	0.54*	-1.21	9.84	1.81	0.74	0.01	-0.02
		0.04					0.96	
THN	32	-0.08	-2.02	0.89	0.66	0.29	0.07	0.27
		0.73					0.71	
INP	35	-0.56	-11.15	17.50	4.95	1.12	-0.36*	0.26
		0.72					0.03	
SIN	35	0.42	-6.10	8.84	3.52	0.37	-0.24	-0.01
		0.24					0.17	
COE	32	0.50*	-0.90	1.96	0.83	0.57	-0.19	0.50*
		0.02					0.29	
GIN	35	-0.46	-10.45	6.55	4.82	0.52	-0.25	0.11
		0.72					0.15	

Table 1b shows the summary statistics of the final revisions for Germany. The first column reports the number of observations (N) for each variable. The next columns report the mean, minimum and maximum of the final revision. The next two columns report the standard deviation (s.d.) and the noise-to-signal ratio for the final revision. The second to last column reports the correlations of the final revision with the initial announcement. The last column reports the first order autocorrelation coefficient of final revisions. We indicate with an asterisk which values are significant different from zero at the 10% level using the Newey-West (Newey and West, 1987) standard errors in the case of the mean. The fiscal variables are the following: total revenue (TOR) and its subcomponents: direct taxes (DTX), indirect taxes (TIN), social security contributions (SCT); and total expenditure (TOE) and its subcomponents: social benefits other than in kind (THN), interest payments (INP), subsidies (SIN), compensation of employees (COE) and government investment (GIN).

Table.1c: Data revision statistics for Italy

Variable	N	Mean	Min	Max	Std. Dev.	Noise/Signal	Corr. with initial	AC (1)
TOR	34	0.37*	-1.70	3.78	1.22	0.36	-0.15	0.26
		0.08					0.40	
DTX	45	0.40*	-1.09	6.09	1.36	0.20	-0.48*	0.22
		0.07					0.00	
TIN	45	0.61*	-3.92	8.00	2.44	0.69	0.01	0.11
		0.06					0.95	
SCT	32	0.11	-2.07	2.00	1.01	0.32	0.07	-0.25
		0.26					0.68	
TOE	34	0.02	-8.64	8.44	2.24	0.71	-0.63*	-0.10
		0.48					0.00	
THN	32	-0.08	-0.42	0.26	0.20	0.14	0.13	0.57*
		0.93					0.48	
INP	35	0.33	-6.06	6.27	2.65	0.30	-0.16	0.10
		0.23					0.36	
SIN	35	0.65	-14.73	14.60	6.07	0.58	-0.29*	-0.20
		0.24					0.10	
COE	32	0.04	-2.31	2.31	1.28	0.27	0.12	0.31*
		0.45					0.50	
GIN	35	2.45	-21.62	64.61	15.26	0.97	-0.46*	-0.26
		0.14					0.01	

Table 1c shows the summary statistics of the final revisions for Italy. The first column reports the number of observations (N) for each variable. The next columns report the mean, minimum and maximum of the final revision. The next two columns report the standard deviation (s.d.) and the noise-to-signal ratio for the final revision. The second to last column reports the correlations of the final revision with the initial announcement. The last column reports the first order autocorrelation coefficient of final revisions. We indicate with an asterisk which values are significant different from zero at the 10% level using the Newey-West (Newey and West, 1987) standard errors in the case of the mean. The fiscal variables are the following: total revenue (TOR) and its subcomponents: direct taxes (DTX), indirect taxes (TIN), social security contributions (SCT); and total expenditure (TOE) and its subcomponents: social benefits other than in kind (THN), interest payments (INP), subsidies (SIN), compensation of employees (COE) and government investment (GIN).

Table.1d: Data revision statistics for Spain

Variable	N	Mean	Min	Max	Std. Dev.	Noise/Signal	Corr. with initial	AC (1)
TOR	34	0.39*	-4.67	5.25	2.48	0.31	-0.11	-0.30*
		0.10					0.52	
DTX	45	0.10	-8.39	10.52	3.09	0.23	-0.32*	-0.25
		0.39					0.03	
TIN	45	0.33	-16.83	15.45	6.01	0.48	-0.20	-0.24
		0.29					0.20	
SCT	32	0.12	-1.53	1.59	0.70	0.15	0.21	0.06
		0.19					0.24	
TOE	34	0.24	-3.72	2.57	1.47	0.31	-0.16	0.05
		0.18					0.37	
THN	32	-0.09	-2.62	2.02	0.91	0.22	0.03	0.18
		0.70					0.87	
INP	35	0.19	-7.07	4.43	2.92	0.30	-0.09	0.46*
		0.40					0.60	
SIN	35	-2.74	-37.59	13.79	10.26	0.40	-0.31*	0.00
		0.93					0.07	
COE	32	0.58*	-1.89	2.77	1.17	0.19	-0.13	0.36*
		0.01					0.50	
GIN	35	1.74*	-20.25	16.54	7.63	0.62	-0.11	-0.18
		0.06					0.51	

Table 1d shows the summary statistics of the final revisions for Spain. The first column reports the number of observations (N) for each variable. The next columns report the mean, minimum and maximum of the final revision. The next two columns report the standard deviation (s.d.) and the noise-to-signal ratio for the final revision. The second to last column reports the correlations of the final revision with the initial announcement. The last column reports the first order autocorrelation coefficient of final revisions. We indicate with an asterisk which values are significant different from zero at the 10% level using the Newey-West (Newey and West, 1987) standard errors in the case of the mean. The fiscal variables are the following: total revenue (TOR) and its subcomponents: direct taxes (DTX), indirect taxes (TIN), social security contributions (SCT); and total expenditure (TOE) and its subcomponents: social benefits other than in kind (THN), interest payments (INP), subsidies (SIN), compensation of employees (COE) and government investment (GIN).

Table 2: Final revision estimation: $fr_t^Q = \beta_0 + \beta_1 iv_t^Q + \beta_2 GDP_t^A + \beta_2 INF_t^A$

fr_t	TOR	DTX	TIN	SCT	TOE	THN	INP	SIN	COE	GIN
iv^Q	-0.14*	-0.01	-0.15*	-0.25*	-0.09*	-0.32*	-0.57*	-0.48*	-0.10*	-0.27*
	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)	(0.04)	(0.03)	(0.03)	(0.02)	(0.04)
GDP^A	0.29*	0.15*	0.11	0.28*	0.03	-0.11	0.40	0.10	0.03	0.45
	(0.05)	(0.06)	(0.08)	(0.06)	(0.07)	(0.07)	(0.23)	(0.26)	(0.04)	(0.34)
INF^A	0.13	-0.19	-0.06	0.35*	0.14	0.13	0.28	1.24*	0.24*	2.44*
	(0.11)	(0.12)	(0.14)	(0.13)	(0.16)	(0.15)	(0.49)	(0.58)	(0.10)	(0.78)
β_0	0.00	0.01*	0.01*	0.00	0.00	0.01*	0.02	-0.01	0.00	-0.05*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Obs	370	478	478	350	370	350	380	380	350	380
R^2	0.11	0.01	0.09	0.18	0.04	0.17	0.26	0.33	0.04	0.10

Notes: Standard errors are in parentheses. The symbol * denotes significance at the 10% level The no-fixed effects specification is shown in the table since the model with fixed-effects is rejected in all cases. fr denotes final revision of the fiscal variable, iv initial value of the fiscal variable, GDP^A and INF^A denote annual growth rate of output and inflation respectively

Table.3: Aggregated versus Disaggregated forecast of deficits

Austria	-4.835**	Italy	-2.758*
Belgium	-8.799***	Luxembourg	-3.842**
Finland	-5.954**	Netherlands	-5.328**
France	-9.905***	Portugal	-3.229*
Germany	0.319	Slovenia	-1.123
Ireland	-0.500	Spain	-0.562

A negative Giacomini-White test-statistic indicates that disaggregated approach performs better than the aggregated approach.
***, **, * indicate significant differences at the 1%, 5%, 10% level respectively.

Table.4: Aggregated versus Disaggregated forecast of revenue and expenditure

Revenue			
Austria	-1.219	Italy	-1.515
Belgium	-1.777	Luxembourg	-0.406
Finland	-3.610**	Netherlands	-2.631*
France	-4.490**	Portugal	-2.834*
Germany	-9.099***	Slovenia	-0.709
Ireland	-0.872	Spain	-2.728*
Expenditure			
Austria	-2.702*	Italy	-2.804*
Belgium	-2.827*	Luxembourg	-2.955*
Finland	-3.892**	Netherlands	-3.864**
France	-3.035*	Portugal	-2.706*
Germany	0.742	Slovenia	-2.701*
Ireland	0.006	Spain	-1.344

A negative Giacomini-White test-statistic indicates that disaggregated approach performs better than the aggregated approach.
***, **, * indicate significant differences at the 1%, 5%, 10% level respectively.

Table 5: Univariate MiDaS improvement

	TOR	DTX	TIN	SCT
Q_1	92%	75%	75%	92%
Q_2	83%	92%	75%	83%
Q_3	67%	67%	67%	75%

	TOE	THN	INP	SIN	COE	GIN
Q_1	92%	83%	67%	67%	75%	75%
Q_2	75%	83%	92%	50%	75%	67%
Q_3	75%	75%	67%	75%	75%	58%

This table shows the share of countries in our sample for which the fiscal forecast improves with the inclusion of one additional quarter in terms of the point RMSFE.

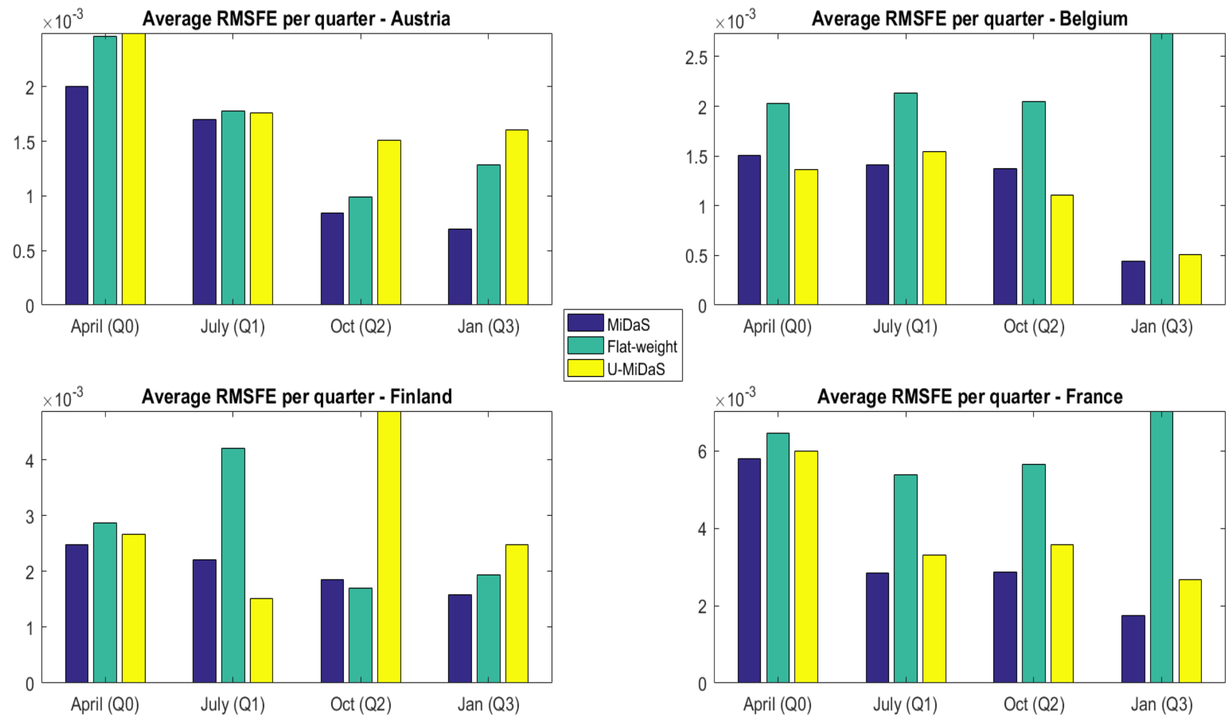
Table 6: Combination of MiDaS and EC versus EC

	TOR	DTX	TIN	SCT
Q_0	25%	25%	25%	33%
Q_1	33%	8%	50%	58%
Q_2	25%	33%	42%	50%
Q_3	33%	33%	67%	42%

	TOE	THN	INP	SIN	COE	GIN
Q_0	42%	42%	50%	42%	58%	50%
Q_1	58%	58%	42%	50%	50%	42%
Q_2	42%	50%	50%	58%	50%	25%
Q_3	67%	75%	58%	67%	58%	17%

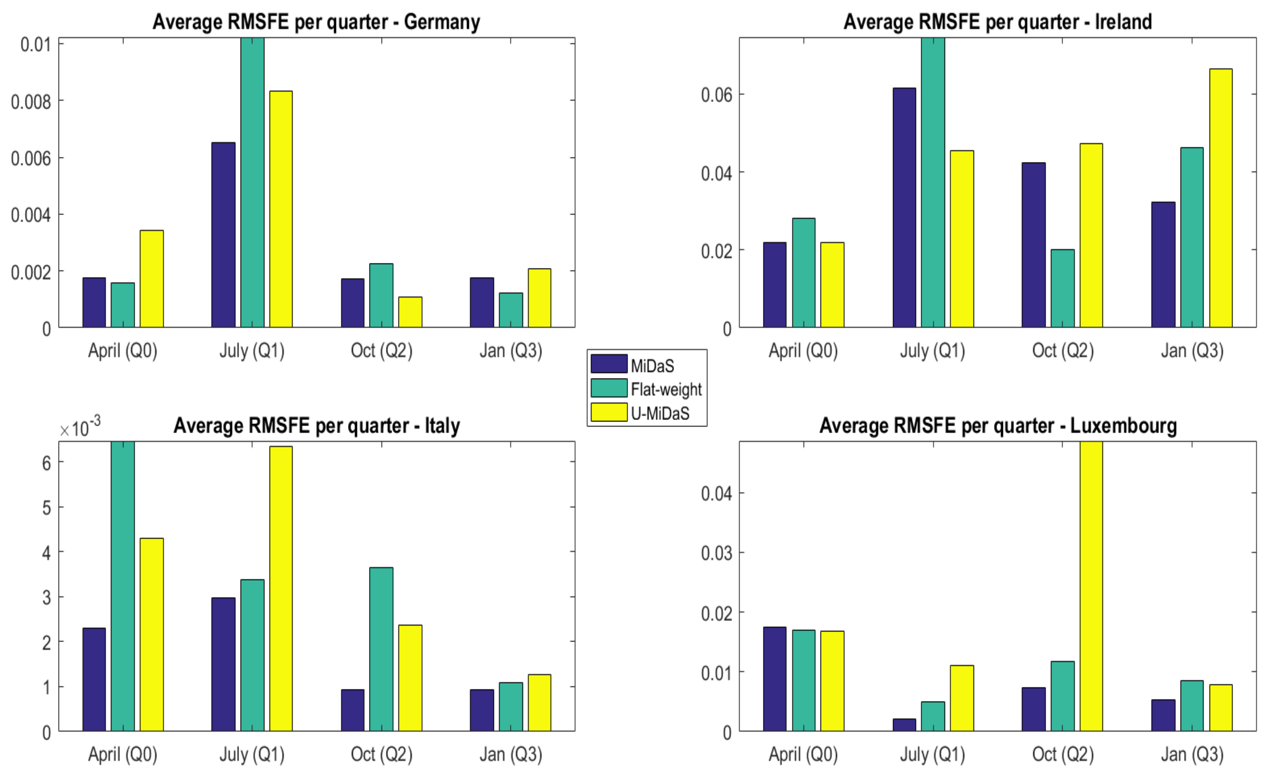
This table shows the share of countries in our sample for which the forecast accuracy of MiDaS with the EC is better on average compared to that of the EC for each quarter within the year using point RMSFEs.

Figure 1: Average RMSFEs for Austria, Belgium, Finland and France



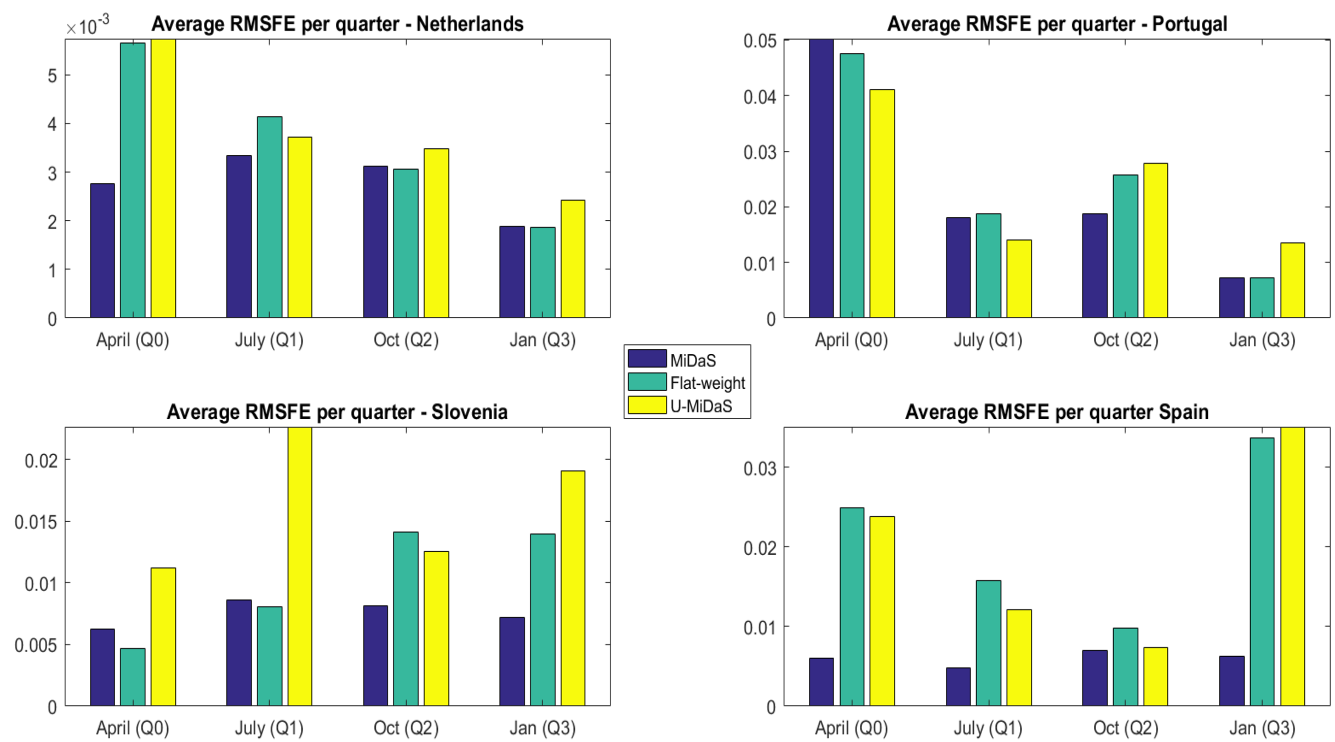
The graphs present the predictive abilities of three different approaches measured by the Root Mean Squared Forecast Errors (RMSFEs), for Austria, Belgium, Finland and France. The first column corresponds to the forecast of MiDaS, the second column to the forecast from a flat-weighting scheme and the last column to the forecast from the unrestricted MiDaS. Each set of bars presents the average RMSFEs in each quarter within the year for all the fiscal variables and for all the four years in the out-of-sample rolling window.

Figure 2: Average RMSFEs for Germany, Ireland, Italy and Luxembourg



The graphs present the predictive abilities of three different approaches measured by the Root Mean Squared Forecast Errors (RMSFEs), for Germany, Ireland, Italy and Luxembourg. The first column corresponds to the forecast of MiDaS, the second column to the forecast from a flat-weighting scheme and the last column to the forecast from the unrestricted MiDaS. Each set of bars presents the average RMSFEs in each quarter within the year for all the fiscal variables and for all the four years in the out-of-sample rolling window.

Figure 3: Average RMSFEs for Netherlands, Portugal, Slovenia and Spain



The graphs present the predictive abilities of three different approaches measured by the Root Mean Squared Forecast Errors (RMSFEs), for Netherlands, Portugal, Slovenia and Spain. The first column corresponds to the forecast of MiDaS, the second column to the forecast from a flat-weighting scheme and the last column to the forecast from the unrestricted MiDaS. Each set of bars presents the average RMSFEs in each quarter within the year for all the fiscal variables and for all the four years in the out-of-sample rolling window.