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A daily indicator of economic growth for the euro area*

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Abstract

In this paper we study alternative methods to construct a daily indicator of growth for the euro area. We aim for an indicator that (i) provides reliable predictions, (ii) can be easily updated at the daily frequency, (iii) gives interpretable signals, and (iv) it is linear. Using a large panel of daily and monthly data for the euro area we explore the performance of two classes of models: bridge and U-MIDAS models, and different forecast combination strategies. Forecasts obtained from U-MIDAS models, combined with the inverse MSE weights, best satisfy the required criteria.

JEL classification: C51, C53, E27.

Keywords: Nowcasting, mixed-frequency data.

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1 Introduction

EEEconomic agents need to assess the current state of the economy and its expected developments in real-time on a daily basis. From an economic perspective, a selection of the most relevant indicators is needed, together with a method to combine the various indicators into a summary measure that can be easily communicated to (and understood by) the general public. From a statistical point of view, the task of constructing and monitoring in real time a daily indicator is complicated by the unbalancedness of the data, which is due to the different sampling frequency. Publication delays cause missing values for some of the variables at the end of the sample, the so-called "ragged-edge" problem (see Wallis, 1986). There is therefore the need of statistical and econometric methods that can handle rich and "problematic" datasets.

While econometric techniques for mixing low and high frequency information are nowadays well established, daily indicators of economic activity are usually not published by institutions or by private analysts, even when daily data are used in the estimation. This is probably due to the fact that the use of daily information poses not only econometric but also communication challenges. Depending on the statistical treatment, the volatility of the daily series could in fact spill over to the final indicator posing a dilemma on whether to communicate frequent changes of view on the state of the economy. Two examples of prominent business cycle indicators that are based on the high frequency data, and which could in principle be updated on a daily basis, are the Eurocoin indicator, developed by Altissimo et al. (2010), and the Aruoba-Diebold-Scotti Business Conditions Index proposed by Aruoba, Diebold, and Scotti (2009). The Eurocoin indicator estimates the medium-term euro area GDP growth rate by using a wealth of data: stock market performance, commodity and finished product prices, industrial production and turnover, economic agents' opinions of the state of their markets and of the economy in general. Although the presence of daily indicators (like stock prices and interest rate spreads) makes the index suitable for daily updates, the underlying methodology is not explicitly designed to deal with mixed frequencies, so that monthly averages of the daily indicators need to be computed prior to estimation. The index is therefore made available only at the end of each month, when the data flow for at least the first three weeks of the month has accumulated and the most important survey series for the current month are available. A different approach is taken by the Philadelphia Fed with the Aruoba-Diebold-Scotti Business Conditions Index, which gauges the state of the business cycle in the U.S.. The index is based on a dynamic factor model which flexibly incorporates information from daily up to quarterly information, see Aruoba, Diebold, and Scotti (2009). In the official version made available by the Fed, however, the highest frequency considered is weekly. Due to asynchronous data releases, this means that on average the indicator is updated 7/8 times a month.[1] Apart from the indicators of economic activity, in the wake of the recent financial crisis, real time high frequency Financial Indicators, aiming at capturing early signs of distress in financial markets, have gained popularity. Some popular indicators are the National Financial Conditions Index (NFCI), published by the Chicago Fed, and the St. Louis

[1]For further details, see http://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index/schedule-history.cfm

Fed Financial Stress Index (STLFSI). In both cases, even though daily series are employed, weekly averaging is used to partially smooth out the economic series that are available on a daily basis.

In this paper we study alternative methods for constructing a daily indicator of growth that, drawing on a potentially large number of predictors available at the daily/monthly frequency, (i) provides reliable predictions (ii), can be easily updated at the daily frequency, (iii) gives interpretable and stable signals, and (iv) it is linear. Given these desired requirements, we select two alternative methodologies from the large pool of available techniques. The first and the simplest is bridge equations, i.e. linear regressions that link ("bridge") high frequency variables to low frequency ones. The second is the Unrestricted MIDAS (U-MIDAS), linear variant to the Mixed-Data Sampling (MIDAS) introduced by Ghysels, Santa-Clara, and Valkanov (2004), where low and high frequency variables are linked through highly parsimonious distributed lag polynomials (see Foroni, Marcellino, and Schumacher, 2013, and Carriero, Clark, and Marcellino, 2013, for a complete description of the U-MIDAS approach). As a target variable we adopt GDP growth, which, due to its broad coverage of the economy, is generally accepted as the key economic indicator of economic activity.

Our analysis proceeds as follows. We start with a preliminary screening of the available indicators using single regressors. This first step allows us to select a limited number of variables that we indicate as the ones that have information content for our forecast target. We then proceed by estimating multi-indicator models. In this setup we find that, due to collinearity of the regressors, the coefficients have no clear interpretation, therefore failing one of the desirable features that we require for our indicator. We therefore turn to forecast pooling, as an alternative way to exploit information on multiple indicators. It turns out that averaging the forecasts produced by single indicators provides accurate estimates of GDP growth, in the context of models that have interpretable and stable coefficients. Accuracy is improved by a step dummy that allows for a break in the average rate of growth of GDP after the crisis. Our preferred specification for the daily indicator is then based on the U-MIDAS approach, which represents the best compromise between parsimony, simplicity and accuracy.

The paper is structured as follows. Section 2 introduces alternative methods for estimation and prediction and provides a justification for the choice of the two methods discussed above. Section 3 describes data availability, and data treatment. We also present technical complications we have encountered for setting-up a real time daily database, and the solutions we propose. Section 4 presents the results. Section 5 concludes the paper.

2 The choice of the econometric models

In this section we briefly discuss the chosen econometric techniques and justify their choice with respect to alternative methodologies. The technical details on the different estimation methods will be introduced in Section 4, so as to tailor the discussion to the specific empirical exercise that we conduct.

2.1 Unrestricted MIDAS (U-MIDAS)

In order to take into account mixed-frequency data, Ghysels, Santa-Clara, and Valkanov (2004) introduce the Mixed-Data Sampling (MIDAS) approach, which is closely related to the classical distributed lag (DL) model. In MIDAS regressions the response to the higher-frequency explanatory variable is modelled using highly parsimonious distributed lag polynomials, to prevent the possible proliferation of parameters and the issues related to lag-order selection.

In this paper we follow the variant proposed by Foroni, Marcellino, and Schumacher (2013), who study the performance of a MIDAS which does not resort to functional distributed lag polynomials (U-MIDAS). In an empirical application to out-of-sample nowcasting GDP in the Euro area and the US using monthly predictors, the authors find a good performance for a number of indicators, albeit the results depend on the evaluation sample. Since it strikes a good balance between simplicity and accuracy this method is a good candidate for our purpose.[2]

2.2 Bridge equations

Bridge equations are linear regressions that link ("bridge") high frequency variables, such as industrial production or retail sales, to the low frequency ones, e.g. the quarterly real GDP growth, providing some estimates of current and short-term developments in advance of the release. In our context, we are interested in a nowcast of GDP, using indicators available at the daily and monthly frequency. When using bridge models we aggregate the daily indicators at the monthly frequency by averaging. In order to forecast the missing observations of the monthly indicators which are then aggregated to obtain a quarterly value of x_{it_q}, it is common practice to use autoregressive models, where the choice of the lag length is based on information criteria. As an alternative, direct estimation could be also used (see e.g. Marcellino, Stock and Watson, 2006).

Empirical applications, see Barhoumi et al. (2011), Baffigi, Golinelli, and Parigi (2004), Diron (2008), generally demonstrate that short-term forecasts based on bridge equations are informative, although a certain degree of discretion is usually applied in selecting the predictors.

2.3 Alternative methods

Other methods proposed in the literature could be used for producing a forecast of a quarterly variable on the basis of a daily data flow. Here, we briefly motivate the choice of U-MIDAS and bridge models within this pool of econometric techniques.

One method is the mixed-frequency VARs (MF-VAR) introduced by Mariano and Murasawa (2010). The MF-VAR consists of the state-space representation of a VAR model, treating quarterly series as monthly series with missing observations. The observation equation of the state-space is

[2] Carriero, Clark, and Marcellino (2013) use Bayesian techniques to estimate specifications similar to U-MIDAS models with several regressors and stochastic volatility, which can easily produce not only point but also interval and density forecasts. This approach could be helpful in the present context, since the presence of daily/monthly/quarterly indicators substantially increases the number of regressors in U-MIDAS models. However, for the sake of simplicity, we estimate our model with classical methods.

an aggregation equation in which quarterly (observed) variables are linked to the latent monthly counterparts. The model can be estimated by maximum-likelihood techniques or the expectation-maximization algorithm. In a forecast exercise on euro area data Kuzin, Marcellino, and Schumacher (2011) compare the MF-VAR with the MIDAS approach. They tend to be more complementary than substitutes, since the MF-VAR performs better for longer horizons, whereas MIDAS for shorter horizons. Similar evidence is found by Foroni and Marcellino (2013) in now- and forecasting the quarterly growth rate of the Euro Area GDP and its components using a very large set of monthly indicators. Overall, given the better short-run performance of MIDAS type models in applications with European data and the computational time required for estimation of the MF-VAR (due to the presence of the missing observations), it seems that MIDAS type models could be preferred.

A second alternative is given by unobserved component models. Small scale factor models, for example, have been used for short term forecasting using mixed data sampling by Frale et al. (2011), Camacho, and Perez-Quiros (2010) and Marcellino, Porqueddu and Venditti (2015). Alternatively, large factor models like in Giannone, Reichlin, and Small (2008) could be used. The latter methodology, which relies on the two-step estimator by Doz, Giannone, and Reichlin (2011), combines principal components with the Kalman filter. The main drawback of these approaches is that it is not easy to interpret the estimated factors, which are liner combinations of all the indicators. This would make the explanation of the resulting daily economic indicator to the general public more difficult, failing in one of the three requirements that we have set.

3 Data and data treatment

The dataset is composed of quarterly, monthly and daily data. We will go through the different frequencies of the data and describe the problems encountered when dealing with such a heterogeneous dataset.

Our forecast target is the quarter on quarter growth rate of euro-area GDP, which is the only quarterly series in the dataset. In a pseudo real-time context we assume that the quarterly variable is released on the 15th of each second month of the quarter after the one under analysis (e.g. on the 15th of May, we can see the advanced release of Q1).

As monthly explanatory variables, we use a set of indicators commonly recognized to have a good forecasting performance. We consider variables such as industrial production, construction production index, unemployment rate, retail trade, expectations on employment next month, and the economic sentiment indicator. Since most of these variables are also released with a lag, we fix a stylized release calendar, to replicate the real-time data flow as closely as possible. Admittedly, the release date may vary depending on the month in which the forecast is computed, but for a pseudo real-time dataset, fixing a release date is the only feasible way to construct pseudo-vintages. The full list of the used monthly data is reported in Table 1, together with the transformations applied and the fictitious release date.

The daily dataset is composed of 47 daily series including exchange rates, interest rates at different maturities, spreads and equity indexes, see Table 2. Many issues arise when dealing with these series. First of all, the release calendar is extremely irregular, due to the presence of festive days and holidays. Since the econometric methods that we use are not suitable for treating missing values we keep the values of the daily series constant over holidays. This seems a good approximation and it is equivalent to saying that, for example, on Christmas day, when no new data are released, the forecast for GDP is unchanged with respect to the previous day. The second issue relates to the irregular number of days in each month, from 28 to 31. To handle this, we construct a stylized, fictitious, calendar in which we attribute 31 days to each month. In the case of daily data, in the fictitious days (say on the 30th of February) we keep daily observations constant to the last available data. Given the way we treat missing data over holidays, this is equivalent to saying that, for example, February has 31 days but we only observe the first 28. We then match the daily information with the available monthly indicators by keeping the monthly indicator constant in between releases. To clarify, taking as an example the case of the Industrial Production index, we fix its release in a stylized calendar on the 15th day of the month. From then on, industrial production remains constant for the following 30 days. This simplification of the information flow gives us the possibility to work with a fixed structure regardless of the number of working days within a given quarter/year and regardless of the frequency of the predictor, whether daily or monthly. Notice that this data treatment does not have any consequences for the empirical results but it greatly simplifies computation since it makes all the matrices in the system conformable, regardless of month in which the forecast is computed. The final issue is that daily series are extremely volatile, so that we need a way to extract a reliable signal useful for forecasting GDP growth. We therefore use moving averages of the daily series, such that each day we have the average of the previous 20 observations (20 is chosen as a good approximation of the number of working days in a month). This means that when we estimate U-MIDAS models we treat the daily data as rolling averages over the previous 20 days. To avoid overlapping information we adjust the lag structure of the model accordingly, see section 4.1. Finally, all the data are reduced to stationarity by an appropriate quarter on quarter transformation.

Our dataset starts in Q2-1999 (data are available from the beginning of 1999, but the first quarter is lost due to the data transformations). The last available quarter is Q2-2013. We start our evaluation sample on the 2nd of January, 2009. For each working day of the evaluation sample, we produce a prediction of quarter on quarter GDP. Depending on the period within the quarter we produce either a forecast (for the first 45 days of the quarter) or a nowcast (for the remaining days of the quarter). We use a recursive approach, meaning that the estimation sample is progressively increased.

4 Empirical analysis

We start our analysis by screening the indicators and shrinking the information set to a small number of variables that have relatively higher predictive content for GDP. Regardless of the model (U-MIDAS or bridge), the screening proceeds in the following way. For each of the 93 days of the quarter we estimate the model and forecast current quarter GDP growth. This procedure yields a forecast error for each day of the quarter and therefore allows us to compute (for each indicator) 93 daily specific RMSE. Next, for each of the 93 days of the quarter we rank the indicators in terms of RMSE. Finally we select the indicators that appear *more frequently* among the top five. In a second step we explore the performance of multi-indicator models based on the variables that survived the screening process in the first step and evaluate the relative merits of the different econometric approaches, including model averaging. Notice that the procedure that we use to reduce the dimension of the data set is quite different from other (regression based) data reduction techniques more popular in the literature, like for example the Least Angle Regression and its variants Lasso and Elastic Net (see Hastie et al., 2003). While these techniques have been shown to work well in a forecasting context (Bai and Ng, 2008 and Bulligan, Marcellino and Venditti, 2015), they are conceived to select regressors in balanced panels. With ragged edged datasets, they do not pick up timely indicators (financial and business surveys) whose information content is negligible once hard indicators are available, but could be quite useful before these are released. Our method, albeit more heuristic, tries instead to solve the problem of variable selection in a context that approximates as closely as possible the situation faced by a forecaster on a daily basis. Before moving to the results, we briefly describe in details the model specifications employed in the analysis.

4.1 The specification of U-MIDAS models

In the U-MIDAS models, the higher-frequency variables are decomposed into a larger set of lower frequency variables (e.g., a monthly indicator is turned into 3 quarterly indicators), and enter together with their lags as unrestricted explanatory variables. In terms of notation, $t_q = 1, ..., T_q$ indexes the basic time unit (e.g. quarters), and m is the number of times the higher sampling periods appear in the same basic time unit. For example, for quarterly GDP growth and monthly indicators as explanatory variables, $m = 3$. This is the basic case for us, since, as discussed in the previous section, we aggregate the daily indicators over the previous twenty days to have a sufficiently smooth regressor at the daily level and avoid excessive volatility of the resulting daily indicator. Given this aggregation scheme a higher m would yield regressors that are very correlated with each other and basically convey the same information. In other words, each day the daily regressors change only marginally, as 19 out of its 20 components remain the same, so that daily lags of the indicators would not add much information.

The lower-frequency variable can be expressed at the high frequency by setting $y_{t_m} = y_{t_q}, \forall t_m = mt_q$, where t_m is the time index at the high frequency.

The U-MIDAS model is based on a linear lag polynomial such as

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

where $c(L^m) = (1 - c_1 L^m - ... - c_c L^{mc})$, $\delta_j(L) = (\delta_{j,0} + \delta_{j,1}L + ... + \delta_{j,v}L^v)$, $j = 1, ..., N$.

Note that if we assume that the lag orders c and v are large enough to make the error term ϵ_{t_m} uncorrelated all the parameters in the U-MIDAS model can be estimated by simple OLS (while the aggregation scheme $\omega(L)$ is supposed to be known). From a practical point of view, the lag order v could differ across variables, and v_j and c could be selected by an information criterion such as BIC.

In our case, we select the number of lags chosen according to the BIC criterion, where the maximum lag is fixed at 12 (a year of monthly information).

We use a form of direct (OLS) estimation and construct the nowcasts as

$$\widetilde{y}_{T_q m+m|T_q m} = \widetilde{c}(L^m) y_{T_q m} + \widetilde{\delta}_1(L) x_{1T_q m} + ... + \widetilde{\delta}_N(L) x_{NT_q m}, \tag{2}$$

where the polynomials $\widetilde{c}(L^m) = \widetilde{c}_1 L^m + ... + \widetilde{c}_c L^{mc}$ and $\widetilde{\delta}_i(L)$ are obtained by projecting y_{t_m} on information dated $t_m - m$ or earlier, for $t_m = m, 2m, ..., T_q m$.

4.2 The specification of bridge models

The basic bridge setup is described in the following system of linear regressions, where we link GDP in a given quarter with the 93 observations of the daily/monthly indicator that we use as predictor (for simplicity we omit the autoregressive term and the intercept from this representation):

$$\underbrace{\begin{bmatrix} y_1^{99.Q2} & \cdots & y_{93}^{99.Q2} \\ y_1^{99.Q3} & \cdots & y_{93}^{99.Q3} \\ \vdots & \ddots & \vdots \\ \vdots & \cdots & \vdots \\ y_1^{13.Q2} & \cdots & y_{93}^{13.Q2} \end{bmatrix}}_{N_q \times 93} = \underbrace{\begin{bmatrix} x_{93}^{99.Q1} & x_1^{99.Q2} & \cdots & x_{92}^{99.Q2} \\ x_{93}^{99.Q2} & x_1^{99.Q3} & \cdots & x_{92}^{99.Q3} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ x_{93}^{13.Q1} & x_1^{13.Q2} & \cdots & x_{92}^{13.Q2} \end{bmatrix}}_{N_q \times 93} \times \underbrace{\begin{bmatrix} \beta_1 & 0 & 0 & 0 \\ 0 & \beta_2 & \vdots & \vdots \\ \vdots & 0 & \ddots & \vdots \\ 0 & \cdots & \cdots & \beta_{93} \end{bmatrix}}_{93 \times 93} + \underbrace{\begin{bmatrix} e_1^{99.Q2} & \cdots & e_{93}^{99.Q2} \\ e_1^{99.Q3} & \cdots & e_{93}^{99.Q3} \\ \vdots & \vdots & \vdots \\ \vdots & \ddots & \vdots \\ e_1^{13.Q2} & \cdots & e_{93}^{13.Q2} \end{bmatrix}}_{N_q \times 93} \tag{3}$$

The matrix in the left hand side collects GDP data as available in each of the 93 days of a given quarter. Each row corresponds to a different quarter, running from the first to the last available, for a total of N_q available quarter, while the 93 columns correspond to the 93 days. The X matrix collects a single daily indicator from the first to the last day of the quarter. Since daily data in our dataset have one day of publication lag (i.e. each day we observe the release of the previous day), we have ordered the daily indicators column wise from the last day of the previous quarter to the second-to-last day of the current one. This system allows us to estimate a *day-specific* relationship between GDP and a given predictor, summarized in a *day-specific* coefficient ($\beta_d, d = 1, 2, ..., 93$). In real time we then use these *day-specific* coefficients to produce direct GDP forecasts on a daily basis.

4.3 Indicators selection

Starting from U-MIDAS models, we find that the best performing indicators change frequently over time (not surprisingly) reflecting the lack of synchrony in data releases and the different informational content of the various indicators. In table 3 we report the five indicators appearing among the five best performing models. Among daily indicators, the U-MIDAS models select financial indicators typically correlated with the business cycle, that is long-term interest rates, the nominal exchange rate and a measure of interest rate spreads (the difference between the lowest and the highest yield, in 10 year bonds within the euro area). Among monthly indicators that appear most often among the five best performers we find widely used soft indicators (the Economic Sentiment Indicator and the Employment expectations for the months ahead) together with the Industrial Production Index. When using bridge models we find that the best daily indicators are rather stable across the days of the quarter. Furthermore, the best performing daily variables, reported in table 4, are similar to those obtained on the basis of U-MIDAS models, i.e. interest rates, effective exchange rates and credit default swaps among daily data. Among monthly data, on the other hand, bridge models also select the unemployment rate and the retail trade index.

4.4 Multiple indicator models

The U-MIDAS specification leads to a multiplication in the number of regressors as each monthly indicator (either monthly variable or monthly average of daily variable) is transformed into three quarterly indicators. This feature, combined with the rather short sample available, suggests to work with rather parsimonious specifications. Bridge models also suffer from similar limitations. Given these constraints, we proceed to specifying multiple indicator models using a subset of the predictors shown in tables 1 and 2. Specifically, we consider three monthly variables (the Industrial Production Index, IPI, the Economic Sentiment Indicator, ESI, the Employment Expectations index, EMPEXP) together with three daily indicators (the 10 year interest rate on government bonds, 10y, the euro/US dollar exchange rate[3], USD, and the 10 year lowest/highest yield spread, SPREAD). Moreover, out of these six indicators we select four *core* indicators (IPI, ESI, 10y and USD), which are more commonly monitored by private and Institutional forecasters. We start our evaluation sample on 1st of July, 2011.

4.4.1 Multi indicator U-MIDAS

U-MIDAS model based on IP, ESI, 10y and USD in general produces better (lower) RMSE than most of the underlying single indicator models.[4] However, due to collinearity, there are substantial problems in the interpretation of its coefficients. The estimated coefficients (the sum of the U-MIDAS coefficients for each variable) for each day in the quarter are reported in Figure 1. In the figure there are 8 lines for each parameter, as we have also re-estimated the 93 daily models for each of the last 8 quarters of the sample, in order to assess parameter stability not only intra-quarter but also across quarters. The figure highlights that the weights of the indicators change on a daily basis during the quarter, which is natural as the relative importance of each indicator changes as new data are released. For example, the ESI should matter more until IP is released. However,

[3] This is highly correlated with the effective exchange rates, but more readily available.

[4] We have considered U-MIDAS versions with and without AR component, but the former is generally better in economic terms (interpretability of the coefficients) and comparable in statistical terms (very similar RMSE). Hence, we only present results for U-MIDAS models without AR (those with AR are also available if of interest).

the indicators are also collinear, and this creates problems in the economic interpretation of their associated coefficients. In particular, the coefficient on ESI is negative for most of the quarter while other coefficients switch sign. A solution to this problem could be to pool forecasts from single indicator models. In the next subsection we explore such possibility.

4.4.2 Pooling of selected single indicator U-MIDAS

Figure 2 has a similar structure as Figure 1. It reports the estimated coefficients (sums of the U-MIDAS coefficients) of the (93 daily) 6 single indicator U-MIDAS models (based on IP, ESI, USD, 10y, SPREAD and EMPEXP). The models are again re-estimated for the last 8 quarters to assess parameter stability. Three main comments can be made. First, with the exception of the SPREAD, the coefficients are rather stable across quarters. Second, the coefficients change within the quarter, on a daily basis for the daily indicators and on a monthly basis only for the monthly indicators (since here there is no interaction between monthly and daily indicators). Finally, all the coefficients have the proper sign from an economic point of view. In particular, IPI and ESI have positive coefficients (increasing during the quarter), USD and 10y also have positive coefficients, reflecting the fact that financial markets react to good news on growth prospects by pricing higher long term rates and a stronger exchange rate. Employment expectation has a positive though small coefficient over the entire quarter. Finally, in the case of SPREAD the sign is negative (as this variable captures turbulence in financial markets and debt concerns) but the size of the coefficients varies substantially over the quarters.

We combine predictions from these individual models using weights that reflect their out of sample predictive ability. More specifically, let us assume that we have n nowcasts, $\widehat{y}^i_{t_q}$, with associated MSE^i. We use inverse MSE weights for the combination:

$$w_i = \left(\frac{1/MSE^i}{\sum_{i=1}^{n} 1/MSE^i} \right),$$

and consider combining either all the 6 single indicator U-MIDAS models, or only the 4 main ones.[5]

The results are reported in Figure 3. The upper panel of the figure presents the day by day evolution of the weights of each model. First, we observe that SPREAD has systematically the lowest weight. Second, the weight of ESI increases during the quarter, while the importance of long term rates wanes as more information on hard data is available. The medium panel of the figure presents the same information when combining only the four main indicators. The size and pattern over time of the weights is overall similar to those reported in the upper panel. Finally, the lower panel of Figure 3 presents the daily evolution of the RMSE of the 6- and 4-combined GDP nowcasts. We see that the RMSE values are very similar but the core 4-variable nowcast is slightly better for most of the sample. The RMSE is rather stable in the first part of the quarter while it clearly declines around day 60 and then day 80, when new ESI and IPI data are released.

[5]Equal weights give very similar results. Also pooling across all possible indicators worsened the results.

The indicator resulting from this approach is graphed, together with actual GDP growth in Figure 4, for the last 8 quarters of the evaluation sample. Unfortunately, the figure suggests that there is some systematic bias in the daily forecasts. This is likely due to the presence in our estimation sample of the deep recession associated with the financial crisis. A Bai-Perron break test indeed reveals a break in the intercept around 2008Q2. To account for this structural break we have allowed for a breaking intercept in all the daily U-MIDAS models and rerun the entire exercise. The RMSEs are lowered substantially by the introduction of the dummy, and indeed the bias is greatly reduced, see Figures 5 and 6, respectively.[6] In summary, the analysis conducted in this subsection supports the use of an inverted MSE combination of four single U-MIDAS models (without AR and with a step dummy from 2008Q2), based on monthly IP and ESI and daily 10y and USD, to construct the daily indicator of economic conditions for the euro area.

4.4.3 Pooling of selected single indicator bridge models

Bridge models with multiple indicators present similar problems of interpretability of the coefficients as U-MIDAS models, and their RMSE is similar to that of pooled single indicator bridge models. Hence, we here focus on model combination forecasts, where each single indicator bridge model has also a 2008 step dummy and no AR term.[7] Forecast accuracy results are reported in Figure 7. Looking at model weights we see that 10y has the highest weight in the first part of the quarter but decreases later on, accompanied by an increase in the weight of IP and ESI. The results obtained combining only the four main indicators display a similar pattern. Finally, in terms of forecast accuracy, the core 4-variable nowcast is slightly better for most of the sample. The results are overall comparable with those obtained with the U-MIDAS approach, though the fact that the sign of some coefficients is counter-intuitive (the coefficient on SPREAD in bridge models is always positive, for example) supports the use of the pooled U-MIDAS.

4.5 A longer evaluation sample

To assess whether the quality and relative ranking of the pooled U-MIDAS and bridge are stable over time, we have repeated the evaluation over a longer sample starting in 2009Q3. The lower panels of Figures 8 and 9 presents the daily evolution of the RMSE of the 6- and 4-combined GDP nowcasts from the pooled U-MIDAS and bridge approaches, respectively. We see that the RMSE values are very similar across methods, and the core 4-variable nowcast is slightly better than the 6-variable combination for both methods. The RMSEs are now larger than before, since more crisis quarters are included in the evaluation period, but nicely decline over the quarter, as more and more information is available.

[6] The fact that the RMSE in Figure 5 do not decline monotonically is likely due to the short evaluation sample. When in Section 4.5 we repeat the analysis for a longer sample period indeed we find that the accrual of new information improves forecast accuracy.

[7] Results with AR terms, available upon request, are slightly worse but overall similar.

5 Conclusions

In this paper we construct an indicator of growth for the euro area that (i) provides reliable predictions, (ii) can be easily updated at the daily frequency, (iii) gives interpretable signals, and (iv) it is linear. First, using a large panel of daily and monthly data for the euro area and two classes of econometric models (bridge and U-MIDAS models) we have selected a number of candidate predictors to be used in the composite indicator. The best monthly indicators emerging from this analysis are the Economic Sentiment Indicator, Industrial Production, employment expectations for the months ahead, and the exchange rate. Among the best daily indicators we find long term bond yields and the spreads between the lowest and highest long term government bond yield within the euro area. Second, we have implemented multi indicator U-MIDAS and bridge models, based on the best single monthly and daily indicators resulting from the preliminary analysis. Although the RMSEs are satisfactory, the indicators are collinear and this creates problems in the economic interpretation of their associated coefficients. Given the need to use all the best available information, we have combined the best performing single indicator models using weights based on predictive accuracy. The analysis supports the use of an inverted MSE combination of four single U-MIDAS models (without AR and with a step dummy from 2008Q2), based on monthly IP and ESI and daily 10 year bond yield and exchange rate, to construct the daily indicator of economic conditions for the euro area. The proposed method features all the desired properties since it is easy to implement (based on OLS estimation) and it is based on well known and generally accepted indicators, available and comparable also across countries. Furthermore it produces results that have an economic interpretation (all the indicators have the proper sign), gives increasing weight to the monthly indicators as time passes within the quarter and properly takes into account daily information.

MONTHLY INDICATORS	Release day	Publication lag	Transformation
Euro-area trade volumes	16th of the month	2 months	level
Current account position	16th of the month	2 months	level
Harmonized Index of Consumer Prices	16th of the month	1 month	log-diff
Harmonised Unemployment Rate	1st of the month	2 months	level
Industrial Production	12th of the month	2 months	log-diff
Construction Production Index	18th of the month	2 months	log-diff
Retail Trade	5th of the month	2 months	log-diff
Economic Sentiment Indicator	30th of the month	0 months	level
Long Term Government Bond yields	10th of the month	2 months	level
Eur/USD exchange rate	30th of the month	0 months	level
Employment expectations	30th of the month	0 months	level

Table 1: Monthly data description. Data sources: Eurostat and ECB.

DAILY INDICATORS	Transformation
ECB reference exchange rate, UK pound sterling/Euro	log-diff
ECB reference exchange rate, US dollar/Euro	log-diff
EER20	log-diff
EER40	log-diff
Euro area 10year Government Benchmark bond yield Yield Euro	diff
Euro area 10year Government Benchmark bond yield, GDP weighted Yield Euro	diff
Benchmark bond Euro area 2year Government Benchmark bond yield Yield Euro	diff
Benchmark bond Euro area 30year Government Benchmark bond yield Yield Euro	diff
Euro area 3year Government Benchmark bond yield Yield Euro	diff
Benchmark bond Euro area 5year Government Benchmark bond yield Yield Euro	diff
Euro area 7year Government Benchmark bond yield Yield Euro	diff
EMU Banks Equity Index Price earning ratio Euro	log-diff
EMU Financials Index Price earning ratio Euro, provided by ECB'	log-diff
EMU Insurance Index Price earning ratio Euro, provided by ECB'	log-diff
EMU NonFinancial Index Price earning ratio Euro, provided by ECB'	log-diff
EMU Market Index Price earning ratio Euro, provided by ECB'	log-diff
Spread highest/lowest 10y bond yield Euro area countries	diff
10year bond yield differential. Spain/Euro area	diff
10year bond yield differential. Greece/Euro area	diff
10year bond yield differential. Ireland/Euro area	diff
10year bond yield differential.Italy/Euro area	diff
Spread corporte/government bond 10y	diff
10year bond yield differential Portugal/Euro area Spread	diff
Spread swaps 6month Euribor and benchmark bonds of 10year maturity	diff
Spread swaps Euribor/bonds of 2year maturity	diff
Spread swaps Euribor/bonds of 3year maturity	diff
Spread swaps Euribor/bonds of 5year maturity	diff
Spread swaps Euribor/bonds of 7year maturity	diff
Financial Times Stock Exchange (FTSE) Eurofirst 100 Index Historical close	log-diff
Financial Times Stock Exchange (FTSE) Eurofirst 300 Index Historical close	log-diff
Deutsche Borse HDAX Index. Historical close	log-diff
Dow Jones Eurostoxx 50 Index. Historical close	log-diff
Dow Jones Euro Stoxx Broad Stock Exchange Index. Historical close	log-diff
Wheat Price	log-diff
UNITED KINGDOM MONEY AND BANKING GOLD PRICE	log-diff
Brent prices	log-diff
DAX 30 INDEX - GERMANY - IHS Economics	log-diff
Frankfurt Stock Exchange: DAX Volatility Index (VDAX) - Germany, Unit: Index	level
STOCK MARKET INDEX - CAC 40 INDEX - FRANCE - IHS Economics	log-diff
Dow Jones STOXX: 600 Index - EUR Price Index Value	log-diff
Dow Jones STOXX: 50 Index - EUR Price Index Value	log-diff
Dow Jones EURO STOXX: 50 Index - EUR Price Index Value	log-diff
LIBOR 1 month	diff
LIBOR 3 month	diff
EURIBOR 6 months	diff
EONIA	diff

Table 2: Daily data description

Daily	Monthly
10 year Government Benchmark bond yields	Economic Sentiment Indicator
Wheat Prices	Employment Expectations
30 year Government Benchmark bond yields	Retail trade
10 year bond spread lowest/higest yield,	US/Euro Exchange rate
US/Euro Exchange rate	Industrial Production Index

Table 3: Selection from single indicator models, U-MIDAS models

Daily	Monthly
NEER - 40 trading partners	US/Euro Exchange rate
NEER - 20 trading partners	Long Term Interest rate
10 year Government Benchmark bond yields	Retail trade
EU - CDS Senior Debt 5year	Unemployment
10 year Government Benchmark bond yields	Industrial Production Index

Table 4: Selection from single indicator models, Bridge models

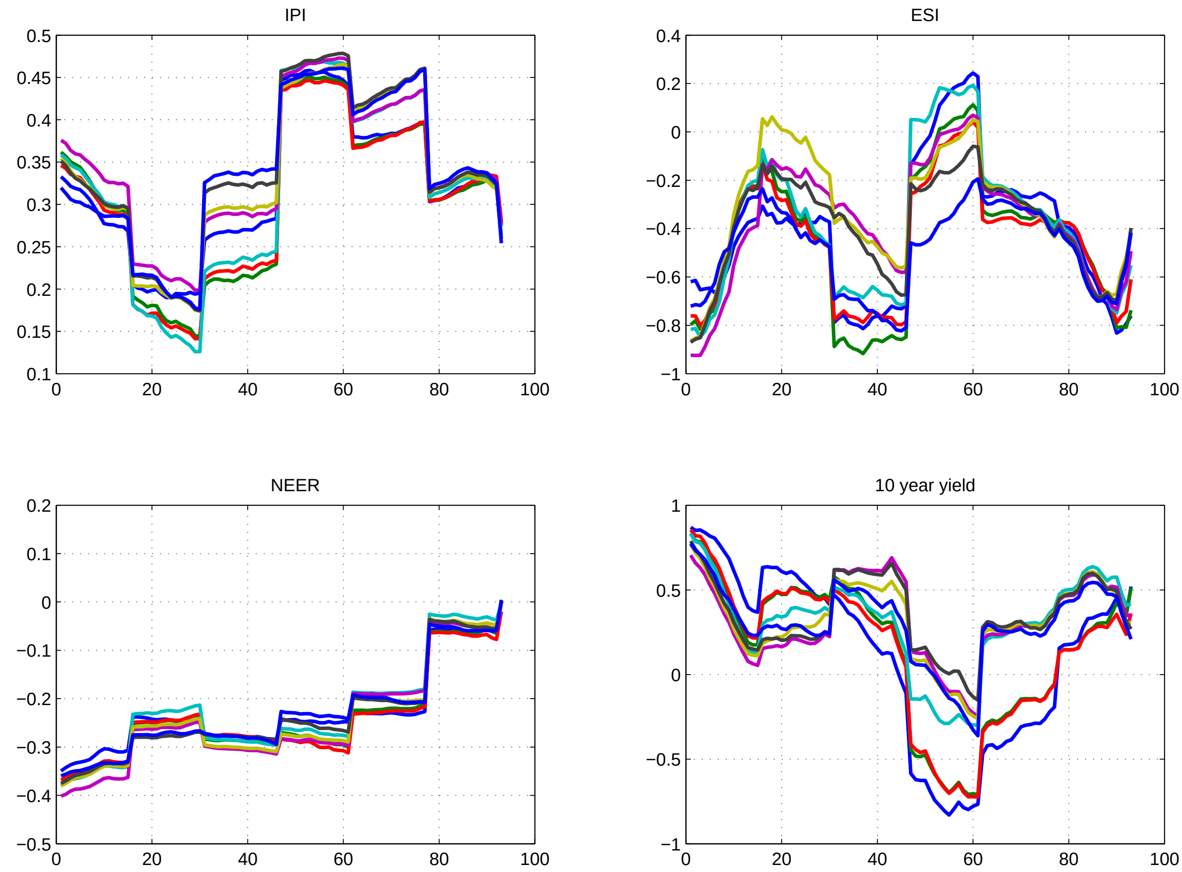

Figure 1: Estimated coefficients in multi indicator U-MIDAS model

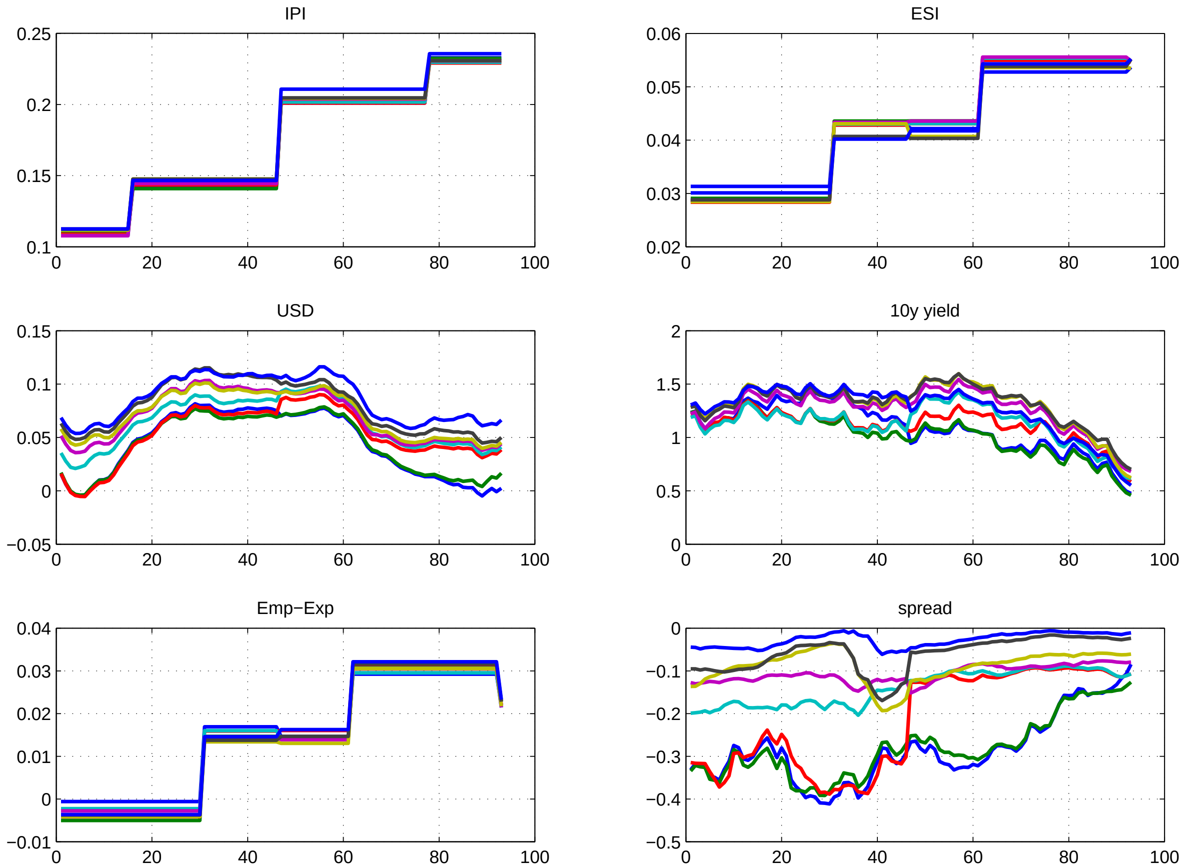

Figure 2: Estimated coefficients in best single indicator U-MIDAS models

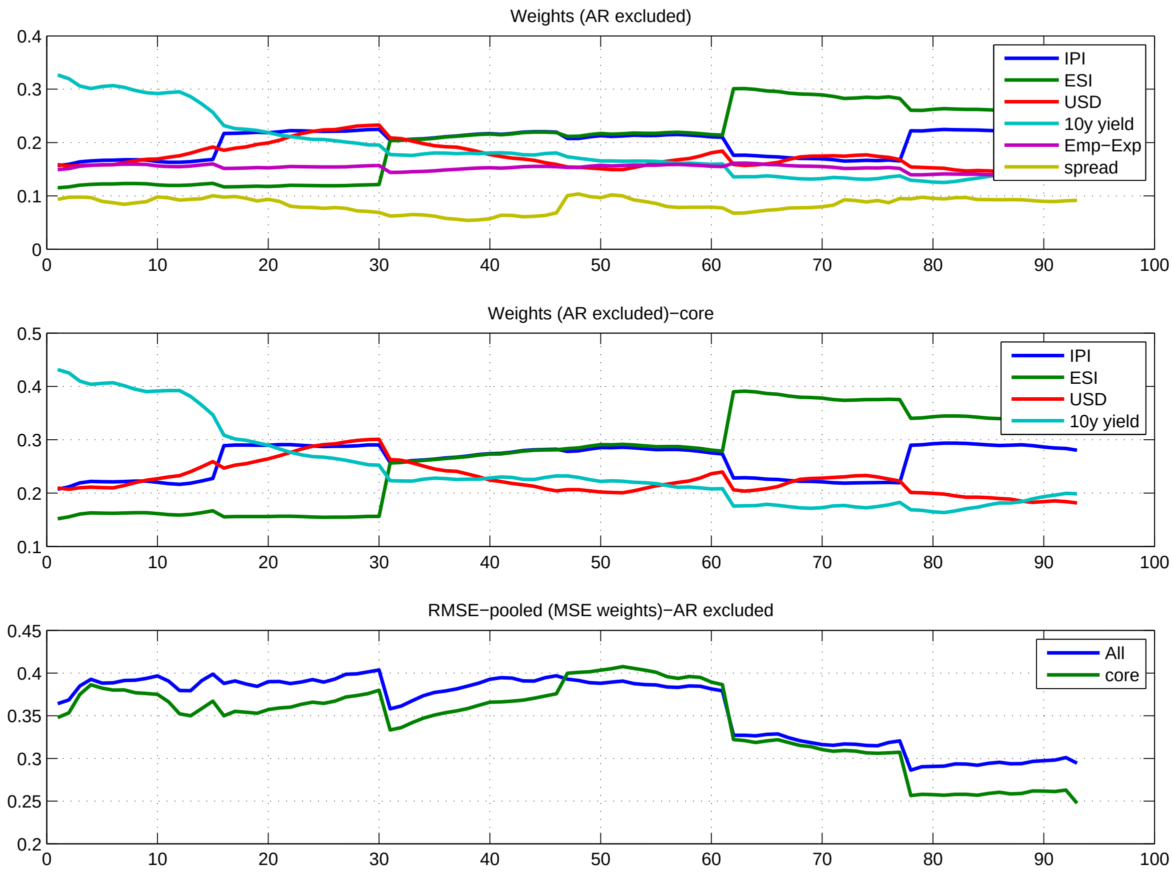

Figure 3: Weights and RMSE from pooled single indicator U-MIDAS models

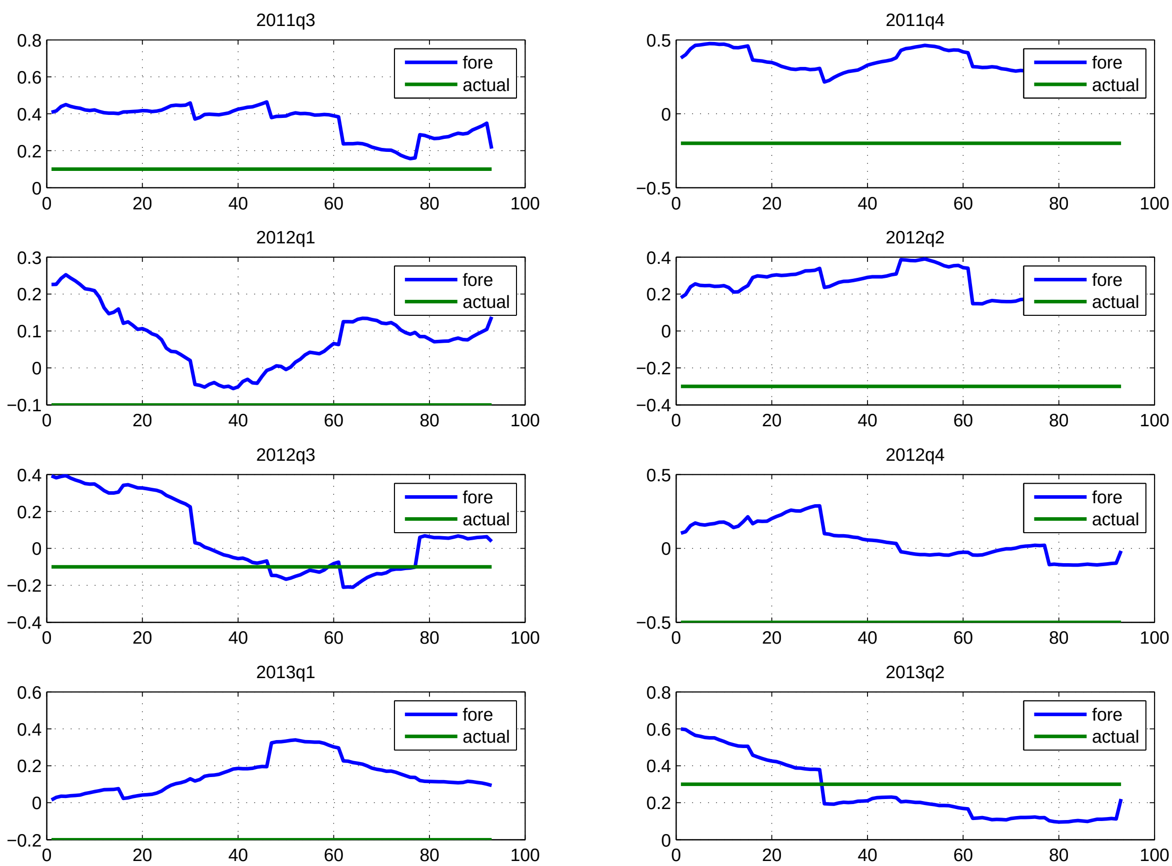

Figure 4: Best pooled U-MIDAS predictions and GDP growth

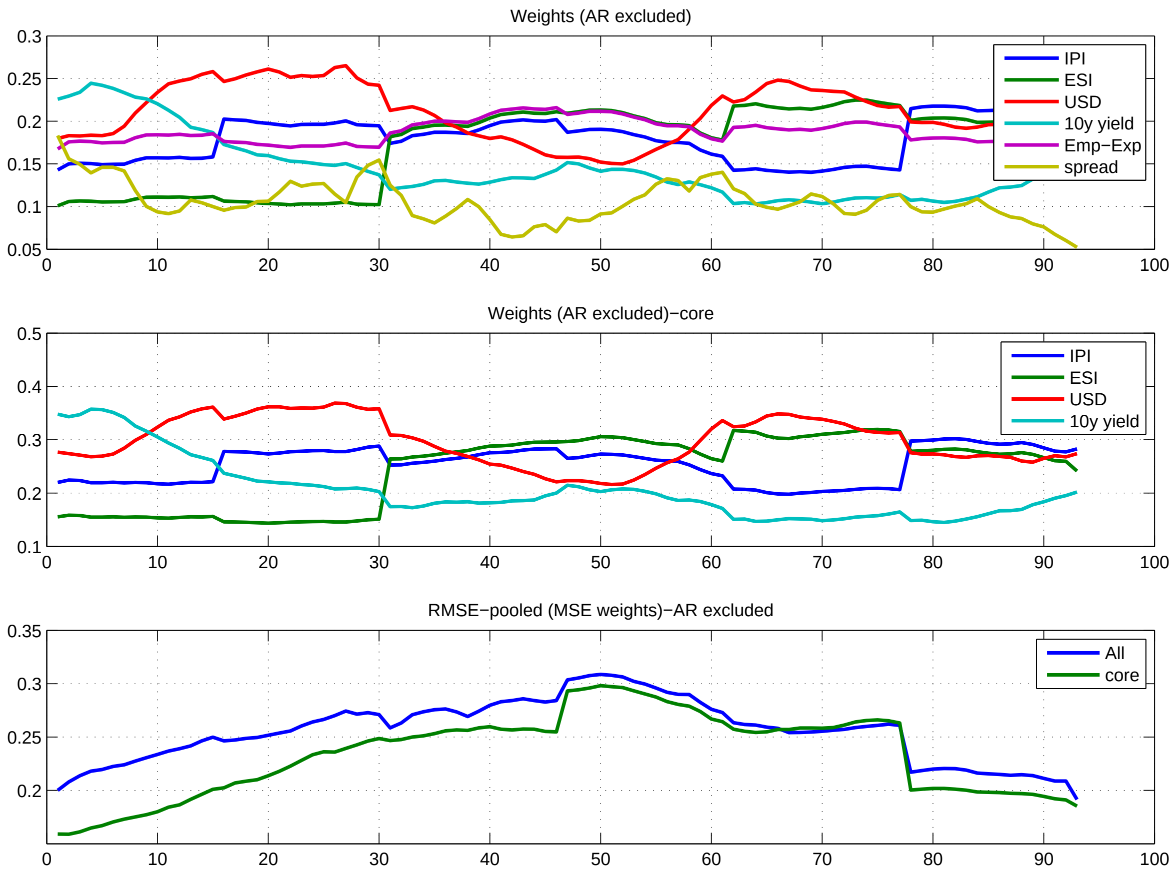

Figure 5: Weights and RMSE from pooled single indicator U-MIDAS models with dummy

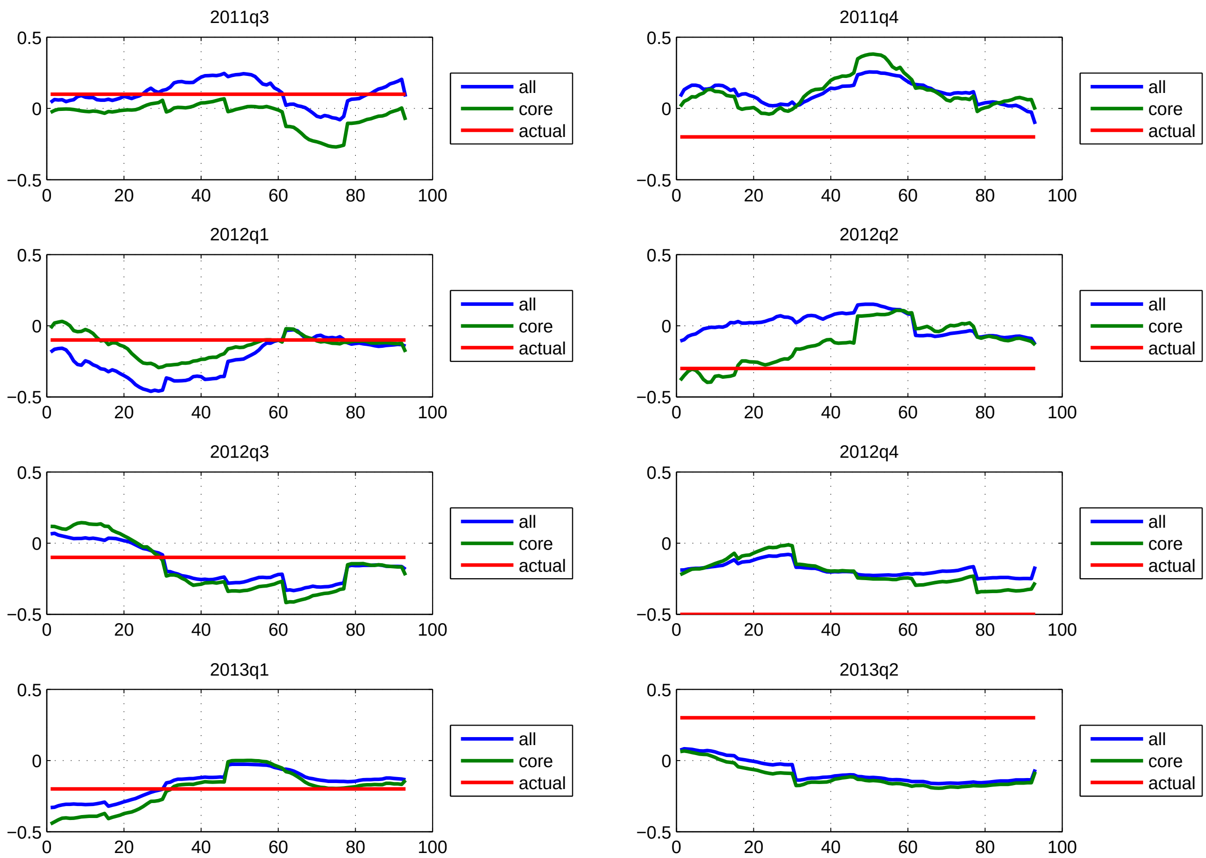

Figure 6: Best pooled U-MIDAS predictions with dummy and GDP growth

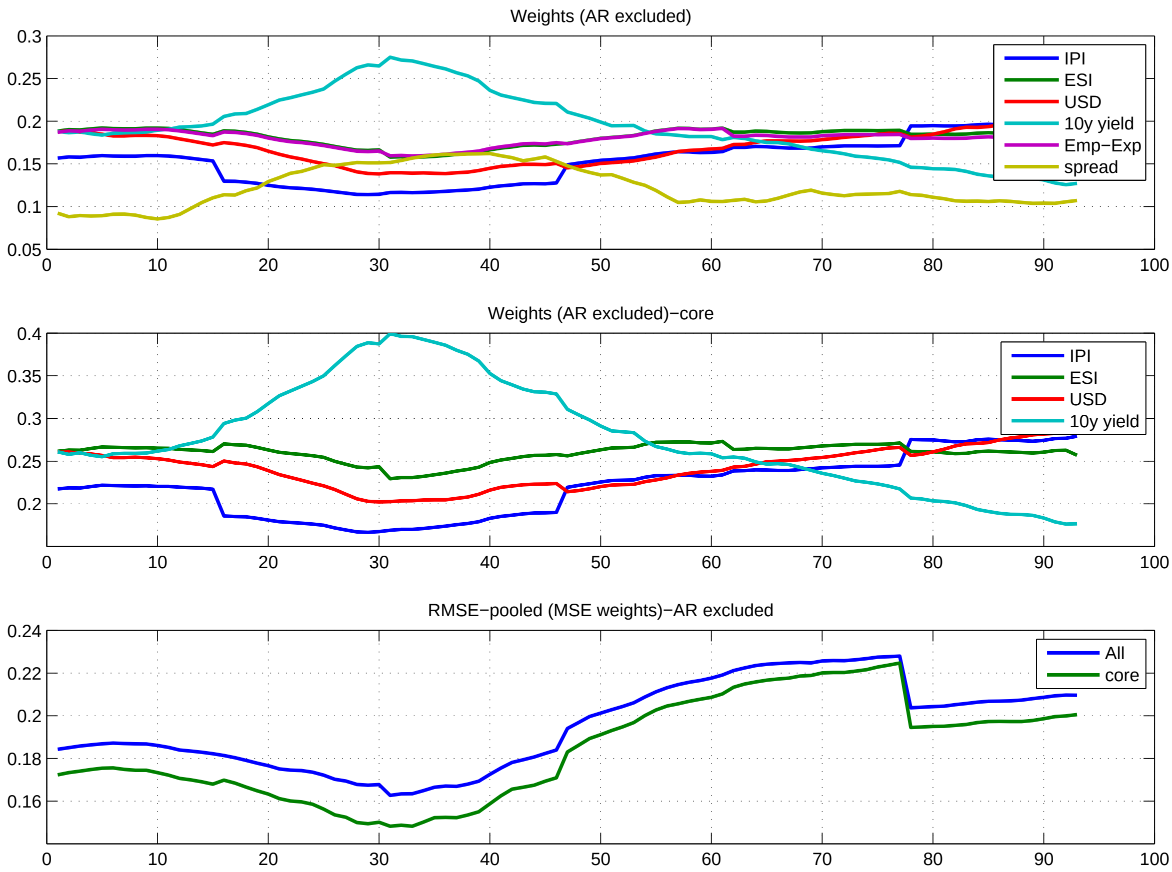

Figure 7: Weights and RMSE from pooled single indicator bridge models

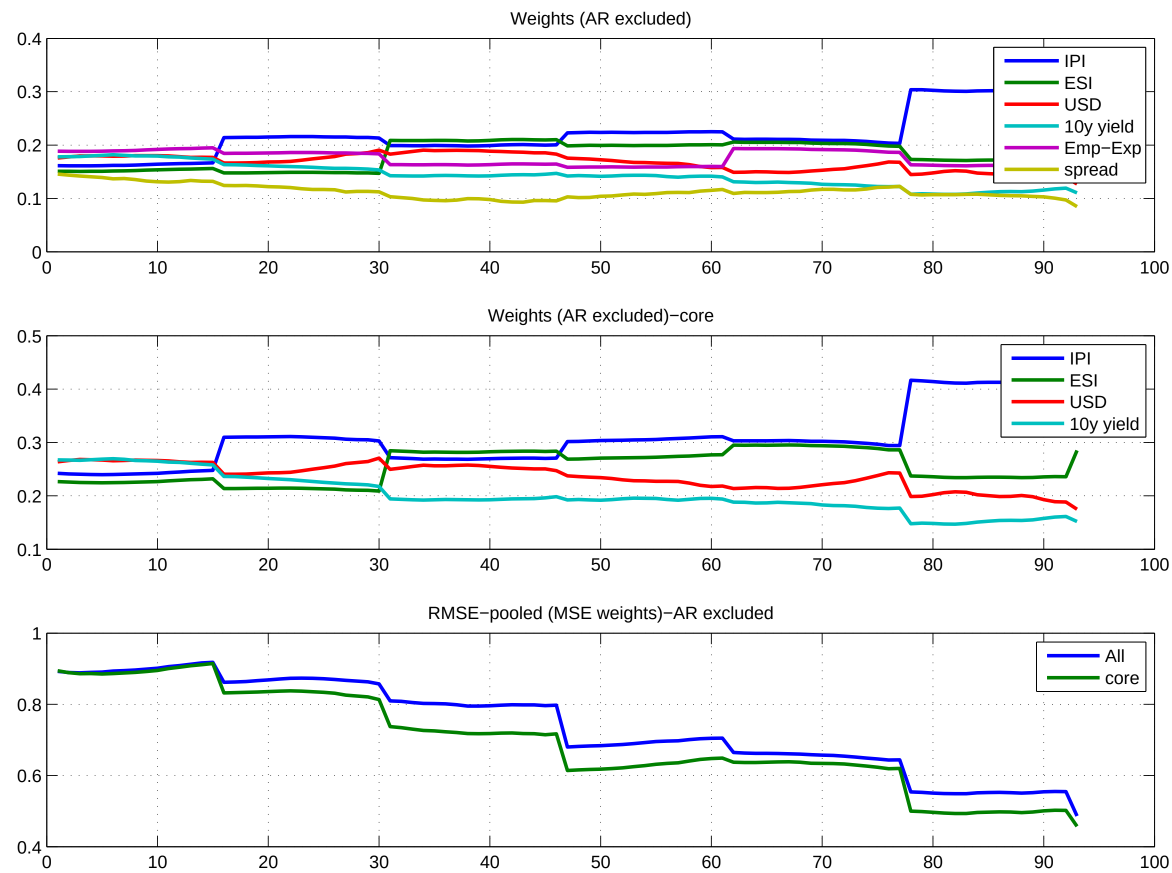

Figure 8: Weights and RMSE from pooled single indicator bridge models

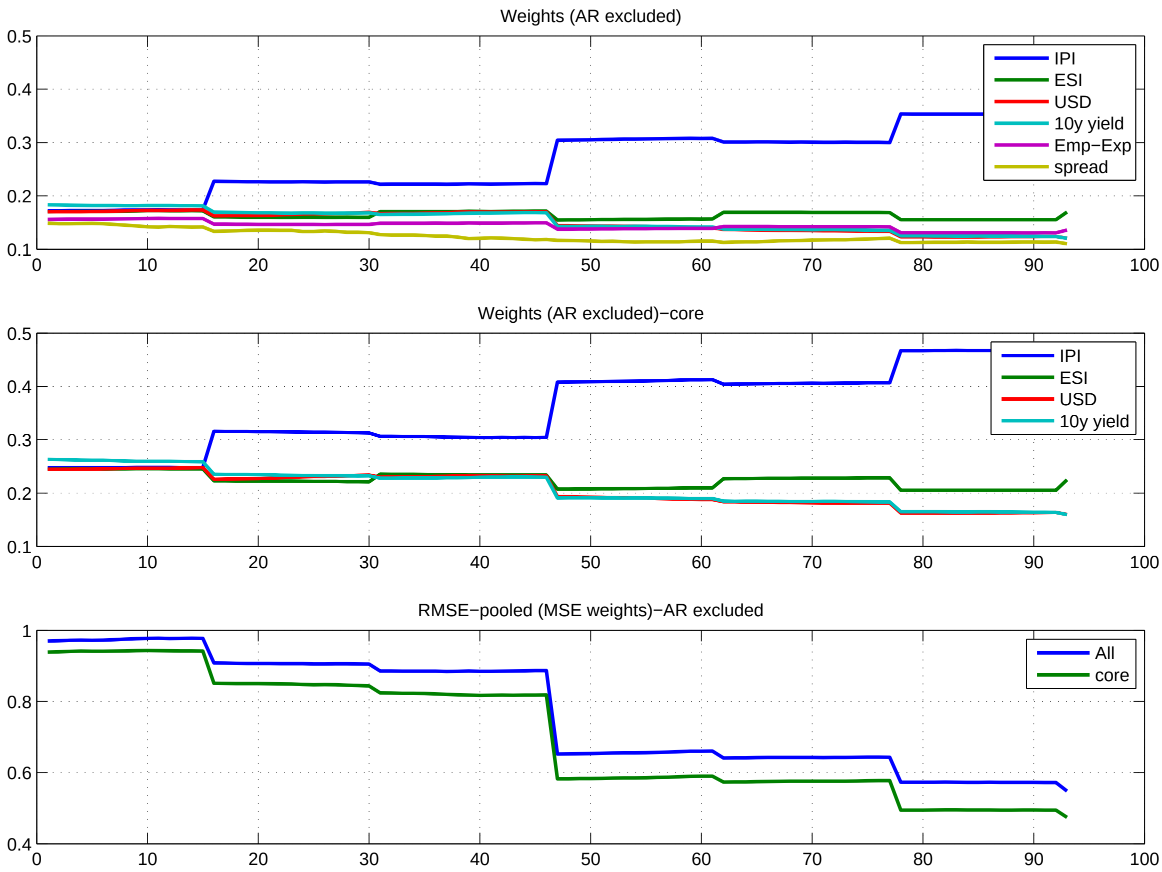

Figure 9: Weights and RMSE from pooled single indicator bridge models

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