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Philipp an de Meulen

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Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI)
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Tobias Kitlinski and Philipp an de Meulen[1]

The Role of Targeted Predictors for Nowcasting GDP with Bridge Models: Application to the Euro Area

Abstract

Using factor models, it has recently been shown that a pre-selection of indicators improves GDP forecasts in the very short-term. The aim of this paper is to adopt this research to the methodology of bridge models in combination with pooling approaches. Focusing on Euro Area GDP between 2005 and 2013, we find that a selection of targeted predictors by means of soft- and hard-threshold algorithms improves the forecasting performance, especially during periods of economic crisis. While a critical number of indicators are needed to include all relevant information, adding additional indicators has a negative effect on forecasting performance, all the more, if the set of indicators becomes unbalanced.

JEL Classification: C53, E37

Keywords: Forecasting; bridge equations; pooling of forecasts

May 2015

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1 Introduction

Reliable information on the current macroeconomic situation is an essential ingredient of decision making within private enterprises, central banks and governments. It helps to identify the current stage of the business cycle and thereby builds an important starting point for assessing the future path of the economy. Unfortunately GDP - which is the most important indicator of economic activity - is released only quarterly and mostly with considerable delay.[1] To estimate GDP more timely, forecasters therefore refer to monthly economic indicators - of which a plethora is available.

To condense the information contained in these indicators into a single forecast, there are basically two strands of approaches. With the factor model (FM) approach, the information is pooled before the regressions are estimated. The numerous indicators are first combined in few common factors. Then, these factors jointly enter a regression equation to forecast GDP.[2] The alternative strand suggests to use indicators directly to produce different forecasts of GDP and to condense the information contained in the forecasts in a second step, e.g. by pooling techniques.

One approach in this field is Mixed-data sampling (MIDAS), which regresses quarterly GDP on monthly indicator observations.[3] Statistically less sophisticated, Bridge models (BM) regress quarterly GDP on quarterly aggregates of the monthly indicator values.[4] Generating forecasts by means of simple linear regressions, BM are a popular and widely used forecasting tool, which in general

[1]For the countries of the EU, the first official estimates are published six weeks after the end of the reference quarter.

[2]The literature on forecasting with FM is extensive, see (Diebold and Lopez, 1996; Giannone et al., 2008). Applications to forecasting Euro Area GDP can be found in Angelini et al. (2011), Banbura and Rünstler (2011), Marcellino et al. (2003) and Rünstler et al. (2009).

[3]See e.g. Clements and Galvão (2008), Clements and Galvao (2009), Kuzin et al. (2011), Ferrara et al. (2014) and Foroni et al. (2015).

[4]Among the papers which put their focus on forecasting Euro Area GDP with BM are Grassmann and Keereman (2001), Diron (2008), Hahn and Skudelny (2008) and Drechsel and Maurin (2011).

do not perform worse than MIDAS and FM in terms of forecast precision.[5]

Despite their differences, all forecast approaches have one problem in common: Which indicators should be taken into account in first place? In this regard, forecasters face a trade-off: Focusing on only a few indicators bears the risk of ignoring important information for forecasting, while considering too many indicators may lead to increased error variance. Moreover, if a certain group of predictors is overrepresented in the set of indicators, forecasts may be biased since different indicator groups may explain different parts of GDP. This trade-off generates the starting point of our paper, which poses the question, whether reducing large indicator sets toward fewer carefully chosen predictors in a first step can reduce forecast errors.

This question has recently become popular in the field of FM. Boivin and Ng (2006) show that a smaller set of indicators can enhance forecast accuracy if the influence of factors which provide high forecasting power declines with an increasing panel size. Bai and Ng (2008) show that if the set of indicators is not only small but restricted to those series which well explain the target variable, this also improves forecasts of FM. In the present paper we analyze if this line of reasoning can be adopted to the field of BM, which, to the best of our knowledge, has not been done before.[6]

If we follow the arguments of Boivin and Ng (2006) and Bai and Ng (2008), additional indicators (and thus additional forecasts) may harm forecast accuracy if they only add noise. Whether this materializes in the field of BM is however uncertain. Therefore, it is at the heart of our paper to investigate if a selection of indicators provides a better forecasting performance of BM than including

[5] See Angelini et al. (2011), Kitchen and Monaco (2003), Schumacher and Dreger (2004), Antipa et al. (2012) and Schumacher (2014).

[6] This is at least true if we focus on forecasting with many low-dimensional bridge equations. Alternatively, it can be set up one single bridge equation including a small representative set of indicators as regressors. In this strand, reducing the set of indicators is of course an important aspect to prevent overfitting. However, since it can only be handled a limited number of indicators, this strand is less suitable to investigate forecast accuracy with regard to the size of the indicator set.

all available information. On the one hand, like for FM, additional indicators may trigger overrepresentation of a certain group of indicators and thus bias forecasts of BM. On the other hand, adding as many indicators as possible to the BM should not harm forecast precision: Additional indicators mean additional forecasts and if these were useful in enhancing forecast accuracy, an appropriate pooling technique would account for them, while if not, they would simply be left out of consideration.

In focusing on the prediction of quarterly growth rates of Euro Area GDP between 2005 and 2013, we apply two different data reduction rules, soft- and hard-thresholding, to identify the so-called ”targeted predictors” from a large set of predetermined indicators. To analyze the sensitivity of forecast accuracy with regard to the set of targeted predictors, we test different thresholds. Constructing quarterly aggregates of the respective targeted predictors, we set up bridge equations, run one-step-ahead forecasts and pool them by means of different weighting schemes.

To mimic the ragged edge of the dataset a forecaster is faced with in real time, we account for the monthly release pattern of our indicators. In a first step we forecast the missing values by means of univariate autoregressive models. In a second step we compute the quarterly aggregates. Since new indicator information arrives every month, we run our forecasts monthly to correspond to the monthly frequency of indicator releases. As GDP is released only quarterly, this results in three successive forecast rounds on each quarterly GDP growth rate. To not mix up the different levels of information, we conduct separate analyses for forecasts made in the first, second and third forecasting round, respectively

It turns out that pre-selecting around 30 out of the 132 indicators provides the lowest average forecast errors for most of the pooling approaches. While it needs this critical number to include the relevant information for forecasting Euro Area GDP, adding further indicators leads to overrepresentation of financial and survey indicators - and apparently to lower forecast precision. Interestingly, the forecasting performance of targeted predictors is significantly better in comparison to the whole indicator set if we leave out the period of the Great Recession.

The rest of the paper is structured as follows. Section 2 introduces the threshold algorithms used for the pre-selection of indicators. Section 3 introduces the system of bridge models and the different pooling techniques and it explains the measurement of forecasting performance. Section 4 reports the empirical results before section 5 concludes.

2 Selection of targeted predictors

Ideally, a set of predictors is chosen to include all relevant information for forceasting the target variable. If, however, one predictor is highly correlated with another, this bears the risk that instead of adding predictive power to the set, it only adds noise, making forecasts less efficient. Further, if a certain group of predictors is overrepresented in the set of indicators, this may bias forecasts toward the part of the target variable this group explains. Then a more parsimonious but balanced set of predictors may provide more accurate forecasts.

Looking to the literature, the finding of Bai and Ng (2008) that identifying a subset of suitable predictors is effective in improving forecast performance of factor models was recently confirmed in several studies. Caggiano et al. (2011) showed that using smaller subsets of the available large data set improves the forecast performance of factor models for the six largest Euro Area economies, the Euro Area aggregate and UK. Using Monte Carlo analyses, Alvarez et al. (2012) show that small scale factor models outperform larger ones in terms of forecast precision. To reduce the size of the data, they group indicator series into different categories and choose one representative indicator from each group.

Focusing on forecasting models of Euro Area GDP, Girardi et al. (2014) analyzed dimension reduction methods. They used factor models that bridge factors extracted from a large panel to quarterly national accounts and conclude that using targeting predictors is an effective way to improve forecast performance. In the field of BM, the related literature is scarce. To the best of our knowledge there is only one paper, Bulligan et al. (2012), which investigates the effect of screening targeted predictors on forecast precision. Focusing on Italian GDP, the authors use different data reduction rules, namely hard- and soft-thresholding methods, to reduce the dimension of the data and find that the forecasting performance improves by screening targeted predictors. However, other than we do, Bulligan et al. (2012) use the set of targeted predictors and extract the most informative among them to set up a *single* forecast equation.

In the present paper, we adhere to the literature in using hard- and soft-thresholding algorithms to select targeted predictors. The selection processes start from a large set of 132 potentially relevant indicators, chosen in line with the forecasting literature. It consists of real-economy indicators, survey indicators, financial-market indicators, prices, as well as global economic indicators (see Section A.2). All indicators enter the thresholding algorithms as stationary variables. Below we describe how the algorithms work.

2.1 Hard-thresholding

Hard-thresholding algorithms aim to select those indicators which are most highly correlated with the target according to some predetermined threshold. In order to find those indicators, we adhere to Bair et al. (2006) and Bai and Ng (2008). Precisely, for each of the 132 potentially relevant indicators we run a regression of the quarterly growth rate of Euro Area GDP (y_t) on an indicator-specific function $f_i\left(x_{i,t-p_i}, (L)y_t\right)$, where $x_{i,t-p_i}$ is the potentially lagged indicator with $p_i \in \{0, ..., 6\}$ and $(L)y_t$ is a lag polynomial of degree $q_i \in \{0, ..., 4\}$. In each regression, p_i and q_i are determined by the SIC to equal the optimal number of lags. The estimation period consists of 24 quarters between 1999Q1 and 2004Q4.

In what follows, an indicator is selected as targeted predictor if and only if the significance level (*p-value*) of the associated regression coefficient exceeds some threshold α. In our forecast exercise we choose the common significance levels, $\alpha = 0.9$, $\alpha = 0.95$ and $\alpha = 0.99$.

While hard-thresholding is a very simple procedure, one obvious shortcoming is that the selection process ignores the cross-correlations between indicators. If the targeted predictors are highly correlated with each other, this bears the risk that important information for forecasting is ignored. Methods of soft-thresholding can remedy this deficiency.

2.2 Soft-thresholding

As soft-thresholding rule, we apply a forward selection algorithm, which will be explained in the next paragraph. This algorithm explicitly accounts for the correlations between indicators. Originally, soft-thresholding methods were applied in biostatistics to find out if groups of genes in a DNA microarray can be applied to predict the appearance of a certain disease (Donoho and Johnstone (1994)). Bai and Ng (2008) used the soft-thresholding approach for the first time to determine a smaller group of indicators from a large data set in the forecasting literature.

The forward selection algorithm proceeds stepwise. Within the estimation period ($1999Q1 - 2004Q4$) it tries to find at each step the indicator which best explains the part of the target not explained by the predictors selected so far.

Among our candidate set of 132 indicators, the algorithm starts from the indicator (afterwards called x_1) most highly correlated with y. Then, it searches for a second indicator ($x_2 \neq x_1$), which is most highly correlated with the residual (u_1) from the regression of y on x_1, where x_1 enters the regression with its optimal lag $p \in \{0, ..., 6\}$ according to the SIC. Regressing u_1 on x_2 again leaves some unexplained part (u_2) and again the algorithm searches among the remaining indicators the one - then called x_3 - that shows the highest correlation with u_2.

The algorithm proceeds like this until there is no indicator left, where in each regression of u_i on x_{i+1}, x_{i+1} enters with its optimal lag, restricted to a maximum of six. As a result, we are provided with a ranking of indicators. To select the targeted predictors, we simply select the k highest ranked indicators. In our forecast exercise, we set k equal to the two extreme values 1 and 132 as well as the multiples of 10 in between.

All in all, we end up with 17 different sets of targeted predictors, which are related to 3 different thresholds with the hard-thresholding approach and 14 different thresholds with the soft-thresholding approach. Based on this variety, we are given the opportunity to investigate the sensitivity of forecasting performance with regards to the size and the contribution of the predictor set.

3 Forecast evaluation framework

Having selected different sets of targeted predictors, we compare them with regard to their forecasting performance. The forecasts are derived from linear estimations of Euro Area GDP on the predictors. To cope with the different frequencies of GDP and indicators, we calculate quarterly aggregates of the monthly indicators. In doing so, we only account for data which were available at the time of each forecast and predict the respective missings with the help of univariate autoregressive models.[7] Since the ragged edge of the data frequently changes over a month, we have to be precise in determining the date of each forecast.

For the present paper, we updated the data on July 10, 2014 and applied the corresponding shape of the ragged edge to the whole forecast period.[8] Figure 1 gives an illustration of this pattern for three successive months, in which one and the same GDP growth rate is forecasted. As an example, it is considered the monthly cycle of forecasting GDP in Q2. Since second-quarter GDP is released around August 15, the three forecasting rounds take place on June 10, July 10 and August 10.

3.1 Bridge equations

For any set of targeted predictors and any forecasting round, we have 36 quarterly GDP growth rates ($y_1 \dots y_{36}$) between 2005q1 and 2013q4 to be forecast one step

[7]For each indicator and each forecasting round, the number of lags of the autoregressive model is determined by the SIC and restricted to a maximum of 12 months.

[8]Using the data from mid-2014 rather than real-time data for each forecaast, it should be noted that our forecast exercise is *pseudo*-real time.

ahead. In the run-up of forecasting y_t in round j, we determine a rolling window of 24 in-sample quarters between $t-24$ and $t-1$ to estimate the relationship between the targeted predictors and GDP growth.[9]

The in-sample estimations are based on a large variety of bridge equations (*system of bridge equations*), which consists of three different *subsystems*. The first *subsystem* includes K single indicator equations of the type

$$y_\tau = c_k + \sum_{m=0}^{p} \beta_{m,k} \cdot x_{k,\tau-m} + \epsilon_{k,\tau} \quad \tau = t-24, \ldots, t-1 \ , \tag{1}$$

where $x_{k,\cdot}$ is the quarterly average of a representative predictor in the total set of K targeted predictors. The second *subsystem* includes the $K \times \frac{K-1}{2}$ possible combinations of pairwise indicator equations of the type

$$y_\tau = c_{k,o} + \sum_{m=0}^{p} \gamma_{m,k} \cdot x_{k,\tau-m} + \sum_{n=0}^{q} \gamma_{p+1+n,o} \cdot x_{o,\tau-n} + \epsilon_{k,o,\tau} \quad \tau = t-24, \ldots, t-1 \ ; o \neq k \ . \tag{2}$$

The third *subsystem* includes K equations each using one of the targeted predictors as well as lagged dependent variables as regressors. A representative type of such equation is given by

$$y_\tau = d_k + \sum_{m=0}^{p} \delta_{m,k} \cdot x_{k,\tau-m} + \sum_{n=1}^{q} \delta_{p+n,k} \cdot y_{t-n} + \mu_{k,\tau} \quad \tau = t-24, \ldots, t-1 \ . \tag{3}$$

In equations (1)-(3), parameters c and d denote the regression intercepts, the β's, γ's and δ's give the regression coefficients estimated by OLS, while ϵ and μ denote usual zero-mean error terms. p and q give the number of lags of the respective regressor, restricted to a maximum of 6 and optimized by the SIC. We denote the optimal values of p and q by p^{opt} and q^{opt}, respectively.

[9] Note that we need at least one forecast error if we want to pool forecasts based on their past performances. Hence, our investigation starts with the forecasts of GDP in 2005q2.

3.2 Forecasts

Based on estimates of $\widehat{\beta}$, $\widehat{\gamma}$, $\widehat{\delta}$, $\widehat{c}$ and $\widehat{d}$ from equations (1)-(3), $2K + K \times \frac{K-1}{2}$ single forecasts of y_t are calculated in each forecasting round. Recall that in contrast to the in-sample period, monthly indicator values are not entirely observable over the forecast period. Hence, the quarterly aggregates x partly rely on forecasts of monthly indicators, which in turn depend on the information available and thus on the time it was computed. This is why the forecasting round j enters the forecast equations below.

$$\widehat{y^j_{k,t}} = \widehat{c_k} + \sum_{m=0}^{p^{opt}} \widehat{\beta_{m,k}} \cdot x^j_{k,t-m} \quad \forall\, k = 1, \ldots, K \tag{4}$$

$$\widehat{y^j_{k,o,t}} = \widehat{c_{k,o}} + \sum_{m=0}^{p^{opt}} \widehat{\gamma_{m,k}} \cdot x^j_{k,t-m} + \sum_{n=0}^{q^{opt}} \widehat{\gamma_{p+1+n,o}} \cdot x^j_{o,t-n} \quad \forall\, k = 1, \ldots, K \tag{5}$$

$$\widehat{y^j_{k,y,t}} = \widehat{d_k} + \sum_{m=0}^{p^{opt}} \widehat{\delta_{m,k}} \cdot x^j_{k,t-m} + \sum_{n=1}^{q^{opt}} \widehat{\delta_{p+n,k}} \cdot y_{t-n} \quad \forall\, k = 1, \ldots, K\,, \tag{6}$$

3.3 Pooling of forecasts

To end up with a single forecast in each forecasting round, we apply various linear pooling approaches widely used in the literature: the mean, median, several approaches that consider the in-sample fit (R^2 and the AIC) as well as approaches which weight models' past forecasting performance (Trimming approaches).[10] These approaches have in common that the pooled forecast is constructed as a weighted average of all or a subsample of underlying forecasts, where individual weights sum to one.

We start with very simple approaches commonly used as benchmarks. The most simple one is the mean forecast, which gives equal weight to all forecasts.

[10] In the literature it has been shown that forecast combination is able to reduce forecast errors on average compared to single forecasts, see e.g. Stock and Watson (2003a), Stock and Watson (2004), Timmermann (2006) and Drechsel and Scheufele (2012a,b).

Another approach simply selects the median of all forecasts.

In a second group are pooling approaches that take into consideration the in-sample fit of bridge equations. We use two approaches that assign weights according to the variance of models' in-sample estimation errors. We consider the R^2 and the AIC as information criteria, where the weights given to the forecasts of the single model $i = 1, \ldots, 2K + K \cdot \frac{K-1}{2}$ are constructed in the following way:

$$\omega_{i,t}^{IC} = e^{-0.5\cdot(|IC_{i,t} - IC_{opt,t}|)} / \sum_{h=1}^{2K+K\cdot\frac{K-1}{2}} e^{-0.5\cdot\left(|IC_{h,t} - IC_{opt,t}|\right)} . \quad (7)$$

IC denotes the respective information criterium, R^2 or AIC. Depending on the criterium, $IC_{opt,t}$ either equals the largest R^2 value ($R^2_{max,t}$) or the smallest AIC value ($AIC_{min,t}$) among the in-sample estimations.[11]

Using in-sample information for the assignment of weights is reasonable if the estimated relationships remain stable over the forecast horizon. In the presence of structural instabilities, however, models which perform good in-sample may generate poor forecasts, see e.g. Stock and Watson (2003b). Taking this critique into consideration, we introduce a third group of pooling approaches, which accounts for models' past forecast errors. Since the forecast environment systematically changes over the forecasting rounds, we only account for past forecast errors made in the same forecasting round to assign the weights.

A first approach, called trimming approach, takes the mean forecast from only the best $1 - x\%$ of models in terms of past forecast performance (Timmermann, 2006).[12] In line with the literature we set different thresholds of x, 0.25, 0.5 and 0.75. A second approach calculates weights according to the discounted

[11] Among the in-sample pooling approaches, note that we abstain from employing a "restricted least squares estimator". With the weights constructed from the estimated coefficients of regressing GDP on its single forecasts, the in-sample RMSFE would be minimized (Granger and Ramanathan, 1984; Drechsel and Scheufele, 2012b). However, given our relatively small sample size and 405 forecasts on each y_t, the restricted least squares estimator is likely to suffer from overparameterization, as argued e.g. in Drechsel and Scheufele (2012b).

[12] Past forecast performance is measured in terms of the mean squared forecast error from the complete history of forecasts.

means of models' past squared forecast errors. The weights assigned are inversely proportional to the sum of discounted means of past squared forecast errors of all models:[13]

$$\omega_{i,t}^{j} = \frac{\left(\sum_{l=1}^{t-1} \delta^{t-l} \cdot \left(\hat{\epsilon}_{i,l}^{j}\right)^2\right)^{-1}}{\sum_{h=1}^{2K+K\cdot\frac{K-1}{2}} \left(\sum_{l=1}^{t-1} \delta^{t-l} \cdot \left(\hat{\epsilon}_{h,l}^{j}\right)^2\right)^{-1}} \ . \tag{8}$$

3.4 Measuring Forecasting performance

With 8 different pooling approaches and three different forecasting rounds, there are 3·8 levels to systematically compare the 17 different sets of targeted predictors (3 sets for the hard- and 14 for the soft-threshold approach) with regard to their forecast performance. To measure the forecast performance of the 3·8·17 forecast procedures, we relate their RMSFE to the RMSFE conducted by a benchmark autoregressive model of GDP growth

$$\hat{y}_t = \hat{a} + \sum_{m=1}^{p^{opt}} \hat{\lambda}_m \cdot y_{t-m} \ , \tag{9}$$

where each forecast $\hat{y}_t$ is based on estimating $\hat{a}$ and the $\hat{\lambda}_m$ between $t-24$ and $t-1$.[14] With the forecasts of the benchmark AR model, the relative RMSFE then reads as follows:

$$relative\ RMSFE = \frac{\sqrt{\sum_{t=1}^{36}\left(y_t - \hat{y}_{w,t}^{j,s}\right)^2}}{\sqrt{\sum_{t=1}^{36}\left(y_t - \hat{y}_t\right)^2}} \ . \tag{10}$$

In equation (10), $\hat{y}_{w,t}^{j,s}$ describes the forecast of y_t conducted in forecasting round j which was pooled from the set of targeted predictors s using the pooling approach w.

[13] In line with the literature, the discount factor δ is set equal to 0.95.

[14] The number of lags $p^{opt} \in \{1, 2\}$ is optimized in-sample by the SIC before each forecast.

While a relative RMSFE smaller than one means that the considered forecast procedure outperforms the prediction accuracy of the benchmark AR model, we need to consider the standard deviation of forecast errors to judge whether the difference is statistically significant. In the literature, different tests on equal predictive ability exist. One popular test goes back to Diebold and Mariano (1995) which employs unconditional probability limits of coefficients' estimates. This is appropriate to compare the *general* predictive ability of two models.

However, to test which model performs better conditional on the date of the forecast t, Giacomini and White (2006) have developed a conditional test of predictive ability, which uses parameter estimates $\hat{\beta}_t$ instead. The null hypothesis is tested using a Wald-type test statistic T. It states that the expected loss functions L of the two compared forecast procedures are equal, where L increases with the squared forecast error of the considered procedure.[15] Following the literature, the Giacomini-White test should be given priority unless the uncertainty concerning β does not bias forecast errors. In our analysis, the conditions of such *asymptotic irrelevance* (West, 2006) are not fulfilled since coefficients as well as estimation specifications may vary over time due to an updated rolling window of in-sample quarters.[16] Hence, we apply the Giacomini-White test to compare our forecast procedures with the benchmark AR model.

4 Results

4.1 The sets of targeted predictors

In this section we briefly discuss the results of the indicator selection exercise. The sets identified with the hard- and soft-thresholding algorithms can be found in Tables 1−5. By construction, the soft-thresholding algorithm selects predictor sets, which are very much balanced over the different groups. However, as the

[15] For a detailed description of the test and the test statistic see Giacomini and White (2006).

[16] Moreover, using the Giacomini-White test, it allows us to compare the forecast accuracy of nested and non-nested models.

whole indicator set is itself overrepresented by financial and survey indicators for reasons of data availability, this unbalanced pattern emerges for some of the thresholds. In fact, with $k = 50$ for the soft-thresholding approach, the vast majority of real- and global-economic indicators are already included, while large parts of financial and survey data is not.

Considering the hard-threshold approach, the results change. Since this approach ignores the correlation between indicators, the selected predictor sets are less balanced: Relatively large weight is given to survey indicators while price data are not covered at all. However, besides the sets of targeted predictors are broadly balanced over the groups.

4.2 Forecasting performance

To compare the forecast ability of the 17 different sets of indicators, we conduct the same forecast exercise for each set, as explained in section 3. The results of these exercises are summarized by means of relative RMSFEs in tables 6−8, where the three tables refer to forecasts conducted in the respective three different forecasting rounds. Each Table is structured in the same way: The rows refer to the pooling approaches, introduced in section 3.3. The columns refer to the different sets of targeted predictors that enter the *system of bridge equations*. Figures 2−7 provide a graphical analogue of Tables 6−8. Several interesting patterns turn out.

First, the influence of the pooling approaches on forecast accuracy is much less pronounced in the first compared to the second and third forecasting round. This applies to both threshold approaches and is most conspicuous if we compare the naive pooling approaches to out-of-sample schemes based on past forecasting performance. Apparently, the more indicator data has to be predicted in first place, the more biased becomes the assessment of bridge equations' true forecasting performance. Compared to Figures 2 to 6, the superiority of out-of-sample schemes is much more pronounced than in Figures 3 to 7.

Second, the targeted predictors chosen by the hard-thresholding algorithm generate smaller forecast errors if we compare sets with a similar number of indicators. No matter the forecasting round and the pooling approach, choosing 20 targeted predictors by the soft-thresholding approach, this set performs worse forecasts than the corresponding set of 20 targeted predictors chosen with the hard-thresholding method ($\alpha = 0.05$). This conclusion also stands if we compare the best performing sets of both algorithms in each forecasting round and with each pooling approach. We will turn to analyzing the backgrounds of this result in more detail in the following paragraphs.

Third, the impact of the size of the indicator set shows an interesting pattern, which emerges very similarly in all forecasting rounds, with all pooling approaches and for both thresholding algorithms: While forecast accuracy increases with the number of included predictors up to a certain quantity of around 20 indicators, adding more indicators beyond this number does not improve the forecast accuracy. It even reduces it once the number of indicators becomes too large. This is most apparent with the trimmed mean (75%) in the third forecasting round for the soft-thresholding approach.

Forecast accuracy dramatically increases once we move from $k = 10$ to $k = 20$ and goes on increasing if we add another 10 indicators. However, taking more than 30 indicators, the forecast performance gradually worsens. The set of $k = 30$ indicators includes the vast majority of real economic, global economic and price indicators. Moving towards $k = 132$, the representation of financial market and survey indicators becomes larger and so do forecast errors. As we will show in the next paragraphs, this kind of overrepresentation leads to increased forecast errors foremost during and after the Great Recession, $2008q2 - 2009q2$.[17] In fact, our results are significant if we leave out the period of the Great Recession.[18]

[17] To define the period of the Great Recession we adhere to the Center for Economic and Policy Research.

[18] The results of the Giacomini-White test reveal that there is no significant difference between the relative RSMFEs of the pooled forecasts and the benchmark model. However, if we leave out the Great Recession, our results become significant. This is mainly due to the high forecast errors during this period.

In what follows, we want to go in more detail what is behind the impact of the size (and composition) of the set of targeted predictors on forecast accuracy. To simplify notation we denote by S^k and H^α the respective sets produced with soft- and hard-thresholding, where the subscripts refer to the chosen thresholds. As a first step, we identify the best-performing combination of pooling approach and set of targeted predictors from each forecasting round and for both thresholding algorithms separately. Throughout, the best pooling approach is given by the trimmed mean (75%). Moreover, with soft-thresholding, S^{60}, generates the lowest relative RMSFE in the first forecasting round, while forecast errors are lowest with S^{30} in the second and third round. Presumably, it needs less indicators to cover the information for forecasting GDP as data availability improves over the forecasting rounds. With hard-thresholding, it is always the same set ($H^{0.05}$) which generates the lowest errors in all forecasting rounds.[19]

Overall, it seems that a critical quantity of indicators is needed to cover the relevant information for explaining GDP. Meanwhile, there is not much benefit from adding further indicators. We conjecture that adding "too" many variables comes at the risk of increased error variance, and it comes at the risk of biased forecasts if certain groups of indicators become overrepresented.

Based on the best-performing sets identified above, we want to go in further detail and identify the quarters of the forecast periods, in which these sets show their superiority. Again we proceed this analysis separately for each forecasting round and for both thresholding algorithms, see Figures 8−13. In all six figures, it is shown the time series of GDP growth as a solid line. Besides, it is shown three series of forecast errors as bars. One refers to the errors conducted by the respective best-performing set (blue bars). As benchmarks, the second one refers to a set which comprises a very small number of indicators (S^{10} and $H^{0.01}$

[19]While we focus on the typical significance levels, $\alpha = 0.9$, $\alpha = 0.95$ and $\alpha = 0.99$ as a robustness check, we also calculated the forecasting errors in steps of 0.01 from $\alpha = 0.99$ to $\alpha = 0.9$ and it turned out that the results are very similar to those of the soft-thresholding approach. If a certain level of indicators is achieved, the forecasting performance does not improve anymore.

respectively (black bars)) and the third one refers to the errors conducted with the full set of indicators (red bars). For comparability reasons, all sets are combined with the pooling approach trimmed mean (75%).[20]

Comparing the three sets with regard to their forecast performances in each figure, a clear pattern emerges. While the differences are not much pronounced in "calm times" of stable growth, they became apparent during the Great Recession and the European Debt Crises. Precisely, we can identify the quarters between $2008Q4 - 2009Q2$ and between $2011Q3 - 2012Q3$ as periods, where the best-performing sets stand out.

Hence, we pick two characteristic quarters, $2009Q1$ and $2012Q3$, to illustrate which bridge equations and thus predictors help to create the superiority of the best-performing sets. Again we compare them to S^{10} and $H^{0.01}$ as well as to the full set $S^{132} = H^1$. For simplicity, we only focus on the third forecasting round (Figure 12 and Figure 13), in which forecasts are least affected by missing indicator data and we apply the trimmed mean (75%) as the pooling approach.

Starting with $2009Q1$, where GDP collapsed by -2.9% qoq, all sets produced too positive pooled forecasts. While the deviation is relatively small with the respective best sets (0.31 percenatage points (pp) with $H^{0.05}$ and 0.55 pp with S^{30}), the small sets S^{10} and $H^{0.01}$ produce errors of 0.95 pp and 1.45 pp. Taking a look inside the indicator sets, the small sets lack most of the financial variables, which proved to be very important predictors during the Great Recession. Above that, $H^{0.01}$ also discards all real economic data, which well explained GDP at that time, particularly in combination with financial indicators. In addition, the small set includes only one survey indicator, while the optimal sets takes five survey indicators into account.

Turning to the full set, the error amounted to 0.96 pp in $2009Q1$. While this is very much the same as the one conducted by $H^{0.01}$, the background is completely

[20] In all forecasting rounds and in combination with both thresholding approaches, the trimmed mean (75%) showed the lowest relative RMSFE. However, we cannot determine any significant difference between the trimmed mean (75%) and the other applied threshold approaches.

different. Rather than a lack of variables, it suffers from too many indicators. Since half of the indicators of the full set are related to survey data, the forecasts became biased. There is no clear pattern which of the survey indicators works poorly, but if the share of survey indicators becomes too large, this worsens the forecasting performance.

Turning to the forecasts for 2012$Q3$, the explanation is different. The general deviation is smaller since the decline of GDP was not quite as pronounced as in 2009$q1$. Nevertheless, the best performing sets (S^{30} and $H^{0.05}$) outperformed S^{10} and $H^{0.01}$ as well as the full set $S^{132} = H^1$. This is mainly due to the different number of survey indicators included in the indicator sets. At least a certain number of them perform well during the European Debt Crises. This result is not surprising since the weak economic activity originated from uncertainty in the Euro area.[21]

The small sets S^{10} and $H^{0.01}$ lack most of the survey indicators. Hence, their deviation (S^{10} with -0.53 pp and $H^{0.01}$ with -0.62 pp) is higher than for the best performing models (0.06 pp with $H^{0.05}$ and 0.12 pp with S^{30}). The reason for the weak forecasting performance of the full sets is mainly the same as for 2009$q1$. However, this time too many of the real economic indicators (among others) are included which perform poorly.

5 Conclusions

Short-term forecasting relies on timely available indicators with a higher frequency than the target variable. In recent times, the availability of indicators has grown and the question arises if a selection of indicators provides a better forecasting performance than including all available information. In this paper we apply two threshold algorithms in combination with various pooling approaches to analyze if different sizes of indicator sets have an impact on the forecasting

[21]For example, the Policy Uncertainty Index for the Euro Area shows several peaks in 2012 and indicates high uncertainty (Baker et al., 2013).

performance of bridge models to forecast Euro Area GDP. Furthermore, we focus on the performance of the different sizes of indicator sets during periods of weak economic activity.

It turns out that a selection of indicators improves the forecasting performance in comparison to a benchmark model, especially in times of weak economic activity. This is true if forecasts for Euro Area GDP are conducted with predicted values for the respective missings of the indicators. However, the more official data is published the more important becomes a selection of indicators. More precisely, the combination of the hard-thresholding algorithm and the trimmed mean (75%) shows always the lowest relative RMSFE in relation to the benchmark model. Nevertheless, these results are only statistically significant if the Great Recession is not included. By highlighting the important role of carefully selecting predictors especially in turbulent times of large turning points, we believe to substantially contribute to the existing literature on short-term forecasting.

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A Appendix

A.1 Tables and Graphs

A.2 Selection of targeted predictors

Table 1: Selection of Real Economic indicators

	Hard threshold α			Soft threshold k													
	0.01	0.05	0.1	1	10	20	30	40	50	60	70	80	90	100	110	120	132
Prod.; Total industry excl. constr.[1]		x	x				x	x	x	x	x	x	x	x	x	x	x
Prod.; Mining & quarrying[1]						x	x	x	x	x	x	x	x	x	x	x	x
Prod.; Durable consumer goods[1]		x	x			x	x	x	x	x	x	x	x	x	x	x	x
Prod.; Non-durable consumer goods[1]			x	x			x	x	x	x	x	x	x	x	x	x	x
Prod.; Energy[1]									x	x	x	x	x	x	x	x	x
Prod.; Capital goods[1]						x	x	x	x	x	x	x	x	x	x	x	x
Prod.; Intermediate goods[1]													x	x	x	x	x
Prod.; Manufacturing[1]		x	x							x	x	x	x	x	x	x	x
Prod.; Electricity, gas, steam etc.[1]					x	x	x	x	x	x	x	x	x	x	x	x	x
Prod.; Construction[1]					x	x	x	x	x	x	x	x	x	x	x	x	x
Retail sales; Volume[1]		x	x				x	x	x	x	x	x	x	x	x	x	x
Registrations; New passenger cars;[2]									x	x	x	x	x	x	x	x	x
Earnings, per hour[1]							x	x	x	x	x	x	x	x	x	x	x

[1] = EMU; 2005=100, sa;

[2] = EMU; 1000;

Table 2: Selection of Survey indicators

	Hard threshold α			Soft threshold k													
	0.01	0.05	0.1	1	10	20	30	40	50	60	70	80	90	100	110	120	132
EMU Business confidence; Manufacturing; %, sa																x	x
EMU Business climate; Manufacturing; 2000=100, sa															x	x	x
EMU Order book level assessment; Manufacturing; %, sa																	x
EMU Stocks assessment (finished products); Manufacturing; %, sa													x	x	x	x	x
EMU Employment expectations for the months ahead; Manufacturing; %, sa											x	x	x	x	x	x	x
EMU Production trend observed in recent months; Manufacturing; %, sa													x	x	x	x	x
EMU Export order book level assessment; Manufacturing; %, sa;															x	x	x
EMU Production expectations for the months ahead; Manufacturing; %, sa									x	x	x	x	x	x	x	x	x
EMU Selling price expectations for the months ahead; Manufacturing; %, sa										x	x	x	x	x	x	x	x
EMU Ass. of export order book; Manufacture of machinery and equipment; %, sa																x	x
EMU Ass. of export order book; Manufacture of motor vehicles etc.,%, sa											x	x	x	x	x	x	x
EMU Ass. of order book; Manufacture of machinery and equipment; %, sa															x	x	x
EMU Ass. of order book; Manufacture of motor vehicles etc, %, sa											x	x	x	x	x	x	x
EMU Ass. of order book; Other manufacturing; %, sa														x	x	x	x
EMU Ass. of stocks (fin. prod.); Manufacture of electrical equipment; %, sa													x	x	x	x	x
EMU Ass. of stocks (fin. prod.); Manufacture of machinery and equipment; %, sa							x	x	x	x	x	x	x	x	x	x	x
EMU Ass. of stocks (fin. prod.); Manufacture of motor vehicles etc., %, sa						x	x	x	x	x	x	x	x	x	x	x	x
EMU Ass. of order book; Manufacture of electrical equipment; %, sa											x	x	x	x	x	x	x
EMU Asse.of export order book; Manufacture of electrical equipment; %, sa											x	x	x	x	x	x	x
EMU Ind. Confidence Indicator; Manufacture of electrical equipment; %, sa															x	x	x
EMU Ind. Confidence Indicator; Manufacture of machinery and equipment; %, sa													x	x	x	x	x
EMU Ind. Confidence Indicator; Manufacture of motor vehicles etc., %, sa							x	x	x	x	x	x	x	x	x	x	x
EMU Stocks assessment (finished products); Manufacturing; %, sa													x	x	x	x	x
EMU Business confidence; Construction industry; %, sa													x	x	x	x	x
EMU Activity trend observed; Civil engineering; %, sa									x	x	x	x	x	x	x	x	x
EMU Price expectations; Construction industry; %, sa												x	x	x	x	x	x
EMU Employment expectations; Construction industry; %, sa		x	x											x	x	x	x
EMU Order book level assessment; Construction industry; %, sa										x	x	x	x	x	x	x	x
EMU Activity trend; Construction industry; %, sa														x	x	x	x
EMU Business confidence; Retail trade; %, sa				x									x	x	x	x	x
EMU Business expectations over next 3 months; Retail trade; %, sa								x	x	x	x	x	x	x	x	x	x
EMU Business activity (sales) over past 3 months; Retail trade; %, sa			x							x	x	x	x	x	x	x	x
EMU Employment expectations over next 3 months; Retail trade; %, sa							x	x	x	x	x	x	x	x	x	x	x
EMU Ordering intentions over next 3 months; Retail trade; %, sa									x	x	x	x	x	x	x	x	x
EMU Demand development over past 3 months; Services; %, sa		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
EMU Demand expectations over next 3 months; Services; %									x	x	x	x	x	x	x	x	x
EMU Employment expectations over next 3 months; Services; %, sa												x	x	x	x	x	x
EMU Employment development over past 3 months; Services; %, sa		x	x								x	x	x	x	x	x	x
EMU Business confidence; Services; %, sa			x	x									x	x	x	x	x
EMU Business situation development over past 3 months; Services; %, sa								x	x	x	x	x	x	x	x	x	x
EMU Economic sentiment; Business sector & consumers; sa	x	x	x													x	x
EMU Leading indicator (OECD); Amplitude adjusted, long term average = 100			x							x	x	x	x	x	x	x	x
EMU Consumer confidence; %, sa																	x
EMU Consumer climate (OECD); Normal = 100, sa																	x
EMU Consumer climate; 2000=100, sa																	x
EMU Major purchases planned, next 12 months; Consumers; %, sa								x	x	x	x	x	x	x	x	x	x
EMU Major purchases intended, currently; Consumers; %, sa													x	x	x	x	x
EMU Savings planned, next 12 months; Consumers; %, sa																x	x
EMU Savings intended, currently; Consumers; %, sa															x	x	x
EMU Unemployment expectations, next 12 months; Consumers; %, sa												x	x	x	x	x	x
EMU Financial situation, last 12 months; Consumers; %, sa														x	x	x	x
EMU Financial situation, next 12 months; Consumers; %, sa												x	x	x	x	x	x
EMU General economic situation, last 12 months; Consumers; %, sa																	x
EMU General economic situation, next 12 months; Consumers; %, sa								x	x	x	x	x	x	x	x	x	x
EMU Price trend assessment, last 12 months; Consumers; %, sa										x	x	x	x	x	x	x	x
EMU Price trend expectations, next 12 months; Consumers; %, sa										x	x	x	x	x	x	x	x
EMU Statement on financial situation of household; Consumers; %, sa												x	x	x	x	x	x
EMU Unemployment rate; Based on survey data; % of labor force, sa		x	x										x	x	x	x	x

Table 3: Selection of Price indicators

	Hard threshold α			Soft threshold k													
	0.01	0.05	0.1	1	10	20	30	40	50	60	70	80	90	100	110	120	132
EMU Producer price; Excl. energy; 2005=100					x	x	x	x	x	x	x	x	x	x	x	x	x
EMU Producer price; 2005=100							x	x	x	x	x	x	x	x	x	x	x
EMU Consumer price; Harmonized to EU guidelines; 2005=100, sa					x	x	x	x	x	x	x	x	x	x	x	x	x
EMU Consumer price; Energy, harmonized to EU guidelines; 2005=100															x	x	x
EMU Consumer price; Industrial goods, harmonized to EU guidelines; 2005=100							x	x	x	x	x	x	x	x	x	x	x
EMU Export price; 2005=100								x	x	x	x	x	x	x	x	x	x
EMU Import price; 2005=100															x	x	x

Table 4: Selection of Financial market indicators

	Hard threshold α			Soft threshold k													
	0.01	0.05	0.1	1	10	20	30	40	50	60	70	80	90	100	110	120	132
EMU MSCI share price index; Euro based, 1996.12.31=100						x	x	x	x	x	x	x	x	x	x	x	x
EMU Assets of MFIs; Loans to Euro area pr. sector; Outstanding amount, bn Euro		x	x					x	x	x	x	x	x	x	x	x	x
EMU Assets of MFIs; Loans to Euro area Non-MFIs; Outstanding amount, bn Euro		x	x							x	x	x	x	x	x	x	x
EMU Money supply M1; Level, bn Euro, sa		x	x						x	x	x	x	x	x	x	x	x
EMU Money supply M2; Level, bn Euro, sa	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x
EMU Money supply M3; Level, bn Euro, sa					x	x	x	x	x	x	x	x	x	x	x	x	x
EMU Credit; Loans to Euro area private sector; Level, bn Euro		x	x						x	x	x	x	x	x	x	x	x
EMU Loans; To priv. households; Cons. loans, fixed 5+ yrs, outst., bn Euro						x	x	x	x	x	x	x	x	x	x	x	x
EMU Loans; To priv. households; Cons. loans, fixed < 1 yr, outst., bn Euro									x	x	x	x	x	x	x	x	x
EMU Yield; Government bonds, maturity 10 years; monthly ave.					x	x	x	x	x	x	x	x	x	x	x	x	x
EMU Yield; Government bonds, maturity 2 years; monthly ave.																	x
EMU Yield; Government bonds, maturity 5 years; monthly ave.													x	x	x	x	x
EMU Spread; Swaps vs. German govt. bonds, mat. 2-3 y.; Basis pts; monthly ave.										x	x	x	x	x	x	x	x
EMU Spread; Swaps vs. German govt. bonds, mat. 4-5 y.; Basis pts; monthly ave.															x	x	x
EMU Spread; Swaps vs. German govt. bonds, mat. 9-10 y.; Basis pts; monthly ave.																	x
EMU Spread; Swaps vs. German govt. bonds, mat. 1-2 y.; Basis pts; monthly ave.																x	x
EMU Exchange rate; Euro/US$; Monthly average														x	x	x	x
EMU Exchange rate; Euro/£; Monthly average													x	x	x	x	x
EMU Exchange rate; Euro/100 ¥; Monthly average											x	x	x	x	x	x	x
EMU Exchange rate; Trade-weighted, nominal, partner currencies/Euro; 2010=100														x	x	x	x
EMU Interbank rate, uncollateralized (EURIBOR); 3 month, offered																	x
EMU Interbank rate, uncollateralized (EURIBOR); 1 month, offered; monthly ave.														x	x	x	x
EMU Interbank rate, uncollateralized (EURIBOR); 12 month, offered; monthly ave.																x	x
EMU Swap rate; Euro, 1 year vs. 6-month Libor; monthly ave.																x	x
EMU Swap rate; Euro, 2 years vs. 6-month Libor; monthly ave.												x	x	x	x	x	x
EMU Swap rate; Euro, 8 years vs. 6-month Libor; monthly ave.																	x
EMU Swap rate; Euro, 9 years vs. 6-month Libor; monthly ave.																	x
EMU Swap rate; Euro, 10 years vs. 6-month Libor; monthly ave.																	x
EMU Call money rate, uncollateralized (EONIA); monthly ave.;														x	x	x	x
EMU Citigroup bond performance index; US$ based, 1998.12.31=100;								x	x	x	x	x	x	x	x	x	x
EMU DJ Euro Stoxx share price index; Euro based, 1991.12.31=100							x	x	x	x	x	x	x	x	x	x	x
EMU DJ Euro Stoxx TMI share performance index; Euro based, 1991.12.31=100;										x	x	x	x	x	x	x	x
EMU DJ Euro Stoxx 50 (blue chip) share prices ind.; Euro bs., 1991.12.31=1000											x	x	x	x	x	x	x
EMU DJ Euro Stoxx price index; Total; Euro based, 1991.12.31=100											x	x	x	x	x	x	x
EMU DJ Euro Stoxx performance index; Total; Euro based, 1991.12.31=100										x	x	x	x	x	x	x	x
EMU iBoxx bond performance index; Corporates, AAA, all maturites																x	x
EMU iBoxx bond performance index; Corporates, BBB, all maturites														x	x	x	x
EMU iBoxx bond performance index; Corporates, overall, all maturites																x	x
EMU iBoxx bond performance index; Overall, all maturites																x	x
EMU Citigroup money market performance index; Euro based, 1997.12.31=100																	x
EMU Stock volume currently hold; Retail trade; Balance, %	x	x	x					x	x	x	x	x	x	x	x	x	x
EMU Central bank deposit rate; Month end														x	x	x	x
EMU 3-month Euribor future; Nearest expiration; Monthly average																x	x
EMU Marginal lending facility; Volume borrowed; Bn Euro			x			x	x	x	x	x	x	x	x	x	x	x	x
EMU Money market funds; Flows, bn Euro													x	x	x	x	x
EMU Money market funds; 12-month growth, %															x	x	x

Table 5: Selection of Global-Economic indicators

	Hard threshold α			Soft threshold k													
	0.01	0.05	0.1	1	10	20	30	40	50	60	70	80	90	100	110	120	132
World Commodity price (HWWI); Raw materials, total; US$ based, 2010=100											x	x	x	x	x	x	x
World Commodity price (HWWI); Crude oil; US$ based, 2010=100							x	x	x	x	x	x	x	x	x	x	x
World Commodity price (HWWI); Energy producing raw mat.; US$ based, 2010=100									x	x	x	x	x	x	x	x	x
World Commodity price (HWWI); Raw materials, excl. energy; US$ based, 2010=100					x	x	x	x	x	x	x	x	x	x	x	x	x
USA Production; Total industry excl. construction; 2007=100, sa					x	x	x	x	x	x	x	x	x	x	x	x	x
USA Yield; Treasury bills, maturity 3 months; Monthly average															x	x	x
USA Yield; Treasury bills, maturity 6 months; Monthly average															x	x	x
USA Consumer expectations (Conference Board); 1985=100, sa		x	x				x	x	x	x	x	x	x	x	x	x	x
Germany Business expectations (ifo); Manufacturing; Balance, %, sa	x	x	x					x	x	x	x	x	x	x	x	x	x

Table 6: Relative RMSFE - 1st month

1st month	Hard-threshold α (k)			Soft-threshold k													
Number of indicators	0.01 (4)	0.05 (20)	0.1 (24)	1	10	20	30	40	50	60	70	80	90	100	110	120	132
Mean	0.629	0.528	0.533	0.639	0.662	0.608	0.593	0.597	0.586	0.565	0.556	0.553	0.546	0.544	0.547	0.549	0.553
Median	0.584	0.540	0.542	0.638	0.653	0.641	0.591	0.592	0.585	0.566	0.560	0.556	0.550	0.550	0.552	0.554	0.557
AIC weighted	0.632	0.507	0.517	0.645	0.668	0.588	0.567	0.574	0.564	0.541	0.539	0.539	0.535	0.535	0.538	0.541	0.547
R2 weighted	0.627	0.525	0.530	0.641	0.656	0.601	0.585	0.590	0.578	0.558	0.551	0.549	0.543	0.541	0.544	0.546	0.550
Trimmed mean (75%)	0.604	0.469	0.500	0.731	0.683	0.564	0.542	0.545	0.544	0.521	0.533	0.534	0.535	0.539	0.544	0.550	0.557
Trimmed mean (50%)	0.573	0.535	0.508	0.723	0.697	0.584	0.557	0.559	0.539	0.531	0.537	0.537	0.536	0.541	0.544	0.549	0.558
Trimmed mean (25%)	0.593	0.555	0.517	0.643	0.652	0.595	0.576	0.576	0.558	0.542	0.539	0.537	0.536	0.539	0.542	0.548	0.556
Discounted MSFE weighted	0.620	0.511	0.513	0.645	0.673	0.597	0.577	0.577	0.561	0.540	0.540	0.542	0.537	0.540	0.544	0.548	0.553
All weighting schemes	0.608	0.521	0.520	0.663	0.668	0.597	0.573	0.576	0.564	0.545	0.544	0.543	0.540	0.541	0.545	0.548	0.554
Naive weighting schemes	0.607	0.534	0.537	0.639	0.657	0.624	0.592	0.594	0.586	0.565	0.558	0.555	0.548	0.547	0.550	0.551	0.555
In-sample weighting schemes	0.630	0.516	0.523	0.643	0.662	0.594	0.576	0.582	0.571	0.550	0.545	0.544	0.539	0.538	0.541	0.543	0.549
Out-of-sample weighting schemes	0.597	0.517	0.509	0.686	0.676	0.585	0.563	0.564	0.550	0.533	0.537	0.537	0.536	0.540	0.544	0.549	0.556

Table 7: Relative RMSFE - 2nd month

2nd month	Hard-threshold α (k)			Soft-threshold k													
Number of indicators	0.01 (4)	0.05 (20)	0.1 (24)	1	10	20	30	40	50	60	70	80	90	100	110	120	132
Mean	0.628	0.477	0.486	0.639	0.666	0.569	0.553	0.566	0.560	0.541	0.537	0.536	0.528	0.527	0.532	0.535	0.540
Median	0.578	0.492	0.500	0.638	0.647	0.603	0.560	0.570	0.569	0.555	0.548	0.548	0.538	0.539	0.543	0.544	0.549
AIC weighted	0.633	0.446	0.461	0.645	0.670	0.538	0.513	0.532	0.530	0.509	0.513	0.516	0.511	0.512	0.517	0.522	0.529
R2 weighted	0.627	0.473	0.483	0.641	0.660	0.559	0.542	0.557	0.551	0.532	0.531	0.531	0.524	0.523	0.528	0.531	0.537
Trimmed mean (75%)	0.600	0.351	0.372	0.731	0.687	0.481	0.428	0.455	0.475	0.446	0.463	0.475	0.470	0.480	0.489	0.499	0.513
Trimmed mean (50%)	0.567	0.473	0.434	0.723	0.689	0.531	0.495	0.514	0.506	0.495	0.506	0.510	0.506	0.513	0.519	0.526	0.536
Trimmed mean (25%)	0.596	0.504	0.470	0.643	0.656	0.550	0.521	0.538	0.526	0.513	0.515	0.517	0.514	0.519	0.523	0.530	0.539
Discounted MSFE weighted	0.620	0.424	0.426	0.645	0.672	0.520	0.483	0.499	0.499	0.468	0.478	0.486	0.485	0.491	0.497	0.504	0.514
All weighting schemes	0.606	0.455	0.454	0.663	0.668	0.544	0.512	0.529	0.527	0.507	0.511	0.515	0.509	0.513	0.518	0.524	0.532
Naive weighting schemes	0.603	0.484	0.493	0.639	0.656	0.586	0.557	0.568	0.565	0.548	0.543	0.542	0.533	0.533	0.537	0.540	0.544
In-sample weighting schemes	0.630	0.459	0.472	0.643	0.665	0.549	0.527	0.544	0.540	0.520	0.522	0.524	0.517	0.518	0.523	0.526	0.533
Out-of-sample weighting schemes	0.596	0.438	0.425	0.686	0.676	0.520	0.482	0.502	0.501	0.481	0.491	0.497	0.494	0.501	0.507	0.515	0.526

Table 8: Relative RMSFE - 3rd month

3rd month	Hard-threshold α (k)			Soft-threshold k													
Number of indicators	0.01 (4)	0.05 (20)	0.1 (24)	1	10	20	30	40	50	60	70	80	90	100	110	120	132
Mean	0.628	0.461	0.475	0.639	0.662	0.556	0.542	0.556	0.551	0.534	0.532	0.532	0.523	0.522	0.527	0.530	0.536
Median	0.577	0.475	0.490	0.638	0.639	0.579	0.543	0.560	0.556	0.545	0.542	0.543	0.532	0.534	0.538	0.540	0.545
AIC weighted	0.632	0.431	0.452	0.645	0.665	0.529	0.504	0.523	0.522	0.503	0.509	0.512	0.506	0.507	0.513	0.518	0.525
R2 weighted	0.626	0.456	0.472	0.641	0.655	0.547	0.531	0.547	0.542	0.526	0.525	0.526	0.518	0.518	0.523	0.526	0.533
Trimmed mean (75%)	0.600	0.378	0.386	0.731	0.693	0.453	0.409	0.443	0.468	0.443	0.461	0.472	0.463	0.473	0.482	0.493	0.506
Trimmed mean (50%)	0.567	0.457	0.430	0.723	0.677	0.525	0.486	0.506	0.502	0.491	0.503	0.507	0.501	0.508	0.514	0.522	0.532
Trimmed mean (25%)	0.595	0.485	0.461	0.643	0.647	0.542	0.513	0.530	0.518	0.507	0.511	0.513	0.510	0.514	0.519	0.527	0.536
Discounted MSFE weighted	0.619	0.420	0.426	0.645	0.670	0.495	0.461	0.479	0.483	0.456	0.469	0.478	0.477	0.483	0.489	0.497	0.507
All weighting schemes	0.606	0.445	0.449	0.663	0.664	0.528	0.499	0.518	0.518	0.501	0.507	0.510	0.504	0.507	0.513	0.519	0.527
Naive weighting schemes	0.602	0.468	0.482	0.639	0.650	0.568	0.543	0.558	0.554	0.540	0.537	0.537	0.527	0.528	0.533	0.535	0.540
In-sample weighting schemes	0.629	0.444	0.462	0.643	0.660	0.538	0.517	0.535	0.532	0.514	0.517	0.519	0.512	0.512	0.518	0.522	0.529
Out-of-sample weighting schemes	0.596	0.435	0.426	0.686	0.672	0.504	0.467	0.489	0.493	0.474	0.486	0.493	0.488	0.495	0.501	0.510	0.520

A.3 Figures

Figure 1: Timing of forecasting exercise and availability of data

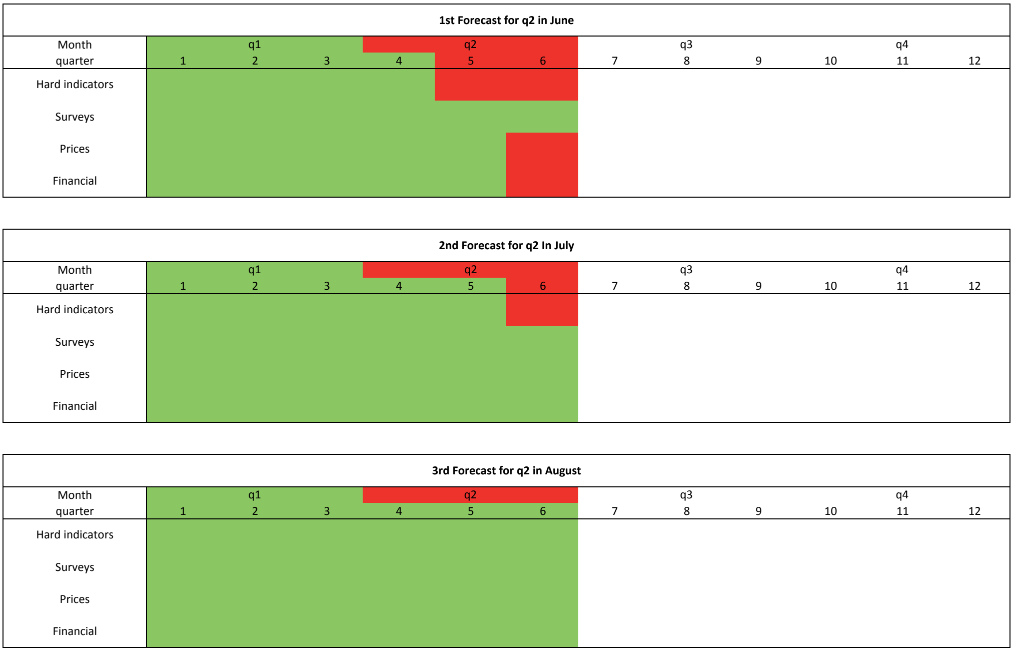

Figure 2: Number of indicators and their forecasting performance: Soft-thresholding: 1st month

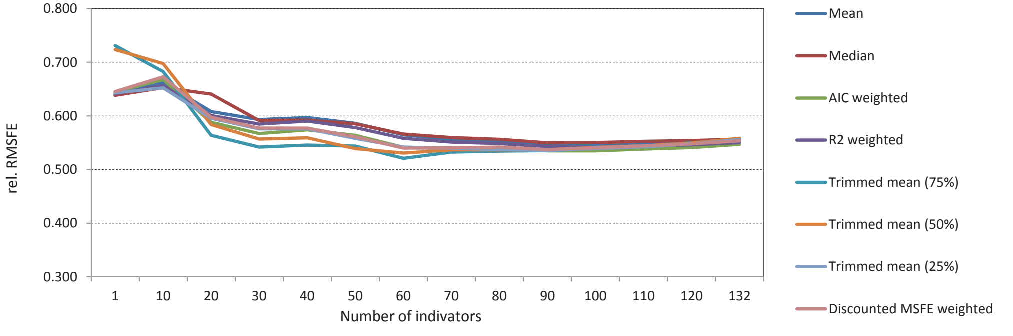

Figure 3: Number of indicators and their forecasting performance: Hard-thresholding: 1st month

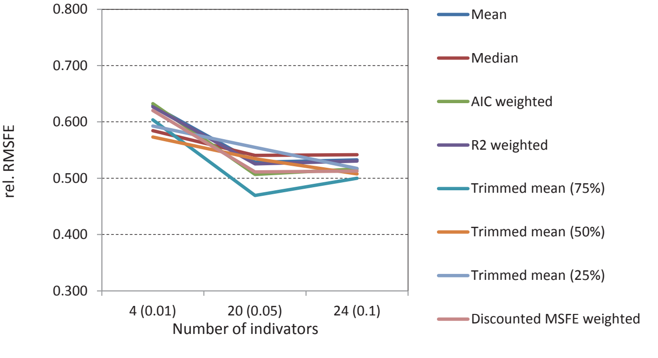

Figure 4: Number of indicators and their forecasting performance: Soft-thresholding: 2nd month

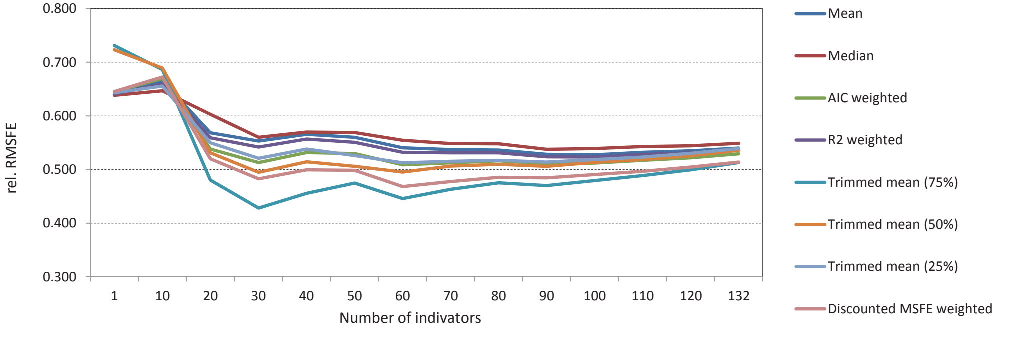

Figure 5: Number of indicators and their forecasting performance: Hard-thresholding: 2nd month

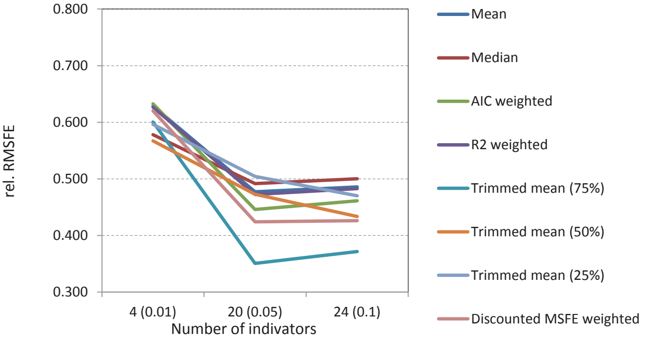

Figure 6: Number of indicators and their forecasting performance: Soft-thresholding: 3rd month

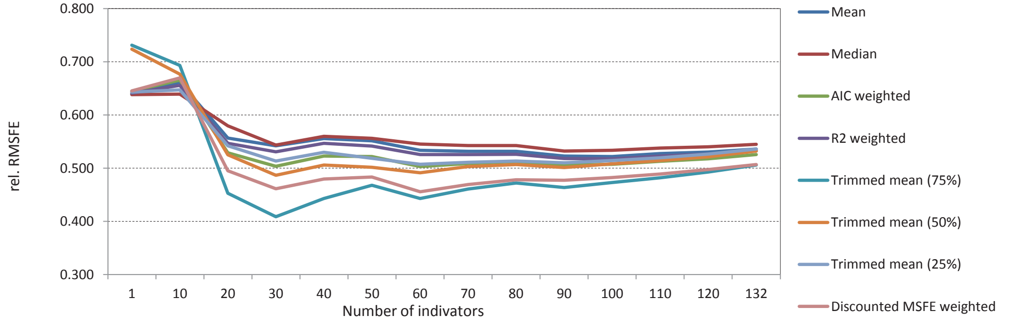

Figure 7: Number of indicators and their forecasting performance: Hard-thresholding: 3rd month

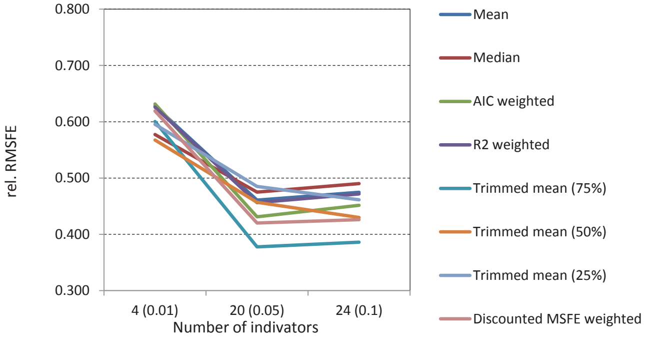

Figure 8: First month (soft-thresholding)

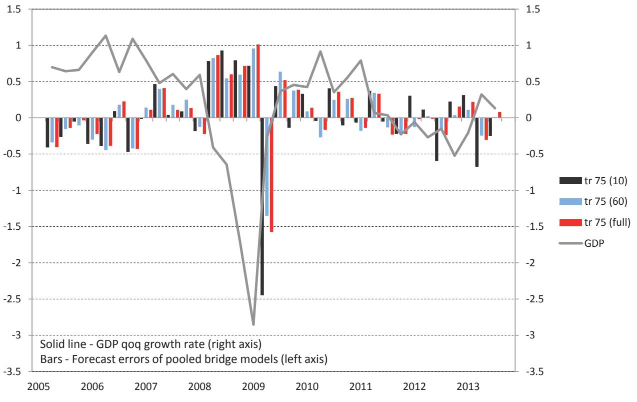

Figure 9: First month (hard-thresholding)

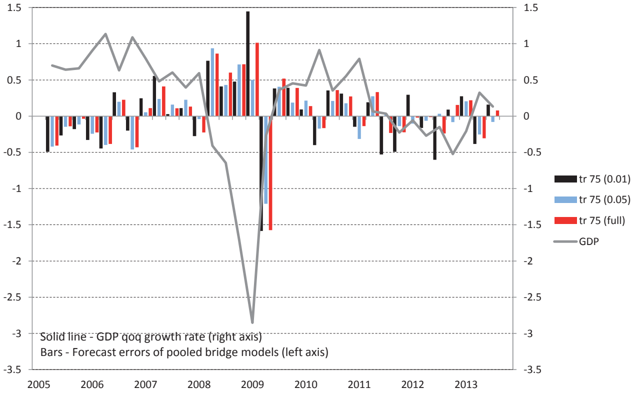

Figure 10: Second month (soft-thresholding)

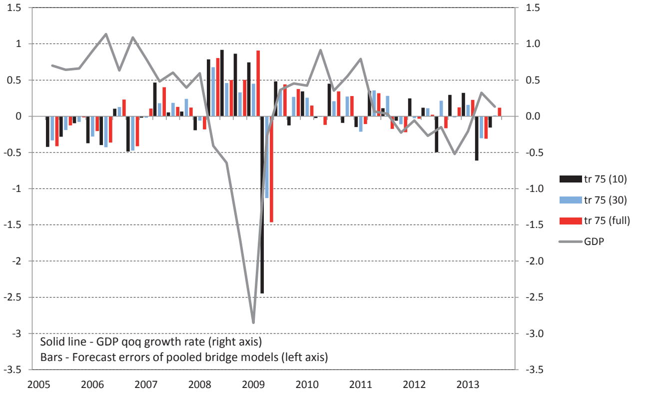

Figure 11: Second month (hard-thresholding)

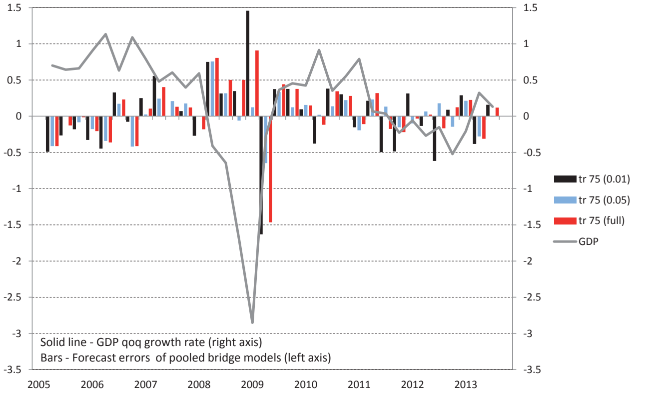

Figure 12: Third month (soft-thresholding)

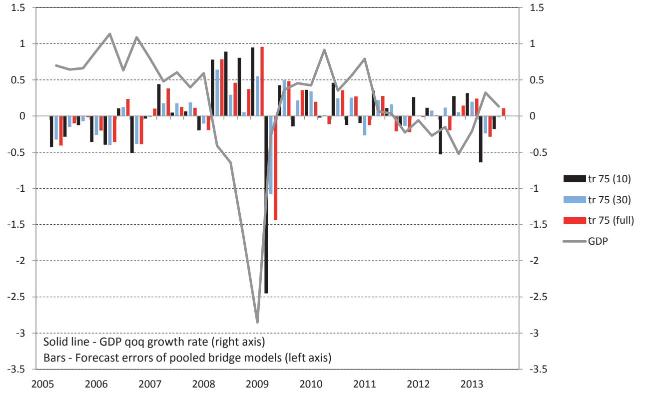

Figure 13: Third month (hard-thresholding)