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FORECASTING ECONOMIC ACTIVITY WITH HIGHER FREQUENCY TARGETED PREDICTORS

by Guido Bulligan*, Massimiliano Marcellino(1) e Fabrizio Venditti*

Abstract

In this paper we explore the performance of bridge and factor models in forecasting quarterly aggregates in the very short-term subject to a pre-selection of monthly indicators. Starting from a large information set, we select a subset of targeted predictors using data reduction techniques as in Bai and Ng [5]. We then compare a Diffusion Index forecasting model as in Stock and Watson [20], with a bridge model specified with an automated General-To-Specific routine. We apply these techniques to forecasting Italian GDP growth and its main components from the demand side and find that bridge models outperform naive forecasts and compare favorably against factor models. Results for France, Germany, Spain and the euro area confirm these findings.

JEL Classification: C52, C53, E37
Keywords: short-term GDP forecast, factor models, bridge models, General To Specific.

Contents

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1 Introduction

Although a large number of indicators covering all aspects of the economy is usually available at very high frequency, quarterly national accounts still play a central role in guiding economic decisions and policy analysis. The delay with which they are released, however, greatly complicates decision making. In the past decade a number of econometric tools have been developed to solve this problem. In particular bridge models are a relatively simple but popular method for forecasting quarterly variables on the ba monthly indicators (see for example Baffigi et al. [4], Diron [13], Barhoumi et al. [8] and Hahn and Skudelny [15]). They are widely used within policy institutions and by private forecasters for a number of reasons. Firstly, they strike a good compromise between simplicity and accuracy: a small set of indicators appropriately chosen usually guarantees a good forecasting performance. Secondly, forecasts based on linear single equations are very easy to explain and to communicate to decision makers. Thirdly, in a linear context also dissecting forecast errors is very easy: discrepancies between actual and predicted values in the target variables can be straightforwardly related to those between actual and predicted values in the underlying indicators. However, compared to factor models, which have recently become the workhorse model in short-term forecasting, bridge models use much less information, potentially leaving out informative predictors. Angelini et al. [2], for example, suggest that models that exploit large information sets score better than bridge models in forecasting euro area GDP. Furthermore the specification of the forecasting equation often relies on the experience of the econometrician and it is therefore quite difficult to replicate. Indeed, bridge forecasting is often perceived as an “art". On the contrary, forecasting with a factor model is relatively straightforward: once the number of factors has been determined on the basis of some information criteria, the common factors can be estimated via principal components analysis (PCA) and a forecasting equation which combines autoregressive terms and the estimated factors (Diffusion index model) is easily specified and estimated.

The issue of variable selection, crucial in the context of bridge models, is usually swept under the carpet in the factor model literature where it seems that all is needed is just a large number of variables that can be used to average out the influence of idiosyncratic components and to estimate the common factors. A recent branch of the literature has questioned the usefulness of “too much information" for factor forecasts. Boivin and Ng [9], for example, argue that increasing the N-dimension of large panels can be detrimental, especially if errors are strongly cross-correlated and if the forecasting power is provided by a factor that is dominant in a small panel but dominated in a larger panel. This problem arises because factors are extracted 'blindly', without taking into consideration the properties of the variable the researcher is really interested in forecasting. To put it roughly, since principal components maximize the signal to noise ratio of the whole panel, they are well suited for forecasting the variables which load the common factors more strongly, but they can perform poorly for other variables. Tailoring the predictors to a specific target variable can then bring substantial gains. Bai and Ng [5] show that factor forecasts can be improved by identifying, on the basis of various hard and soft thresholding methods, targeted predictors. Their analysis proceeds in two steps. First, a number of informative regressors are selected from a large information set, then Diffusion Indexes (DI) are computed via principal components analysis as in Stock and Watson [20] and used to forecast.

Yet, if a small number of carefully selected variables delivers good forecasts the question arises whether this second step is the best way to proceed. Once a set of targeted predictors has been identified it could also be used to specify a linear equation rather than using principal components. These equations would give the advantages of the bridge models described above, while exploiting at the same time an information set comparable to that of factor models.

This constitutes the research question of our paper. We address the issue by intersecting the targeted predictors argument with the General To Specific (GETS) modeling philosophy (Perez and Hoover [16] and Hendry and Krolzig [17]) to construct bridge models that can be used to forecast quarterly variables using monthly indicators. Our analysis also proceeds in two steps. In the first step we follow Bai and Ng [5], and use a range of hard- and soft-thresholding methods to reduce the dimension of a large dataset to a limited number of potential regressors. In the second step, information extraction is accomplished through an automatic selection algorithm to pick the most informative variables and specify parsimonious bridge equations.[1] We compare the forecasting performance of this approach with that of Diffusion Index models estimated on targeted predictors as in Bai and Ng [5], of benchmark AR models and of general Diffusion Index models based on all the information available in a pseudo out of sample forecast exercise. We can therefore assess: i) the accuracy gain associated with exogenous information, ii) the "harmfulness" of "too much information" and iii) the relative gains of two alternative ways of extracting information from targeted predictors.

Our empirical analysis focusses on Italian GDP and on the main demand. The motivation for looking not only at GDP but also at the demand breakdown is twofold. First, factor models have typically been employed for forecasting GDP, but seldom, if ever, for forecasting demand components. The business cycle behavior of aggregate GDP is, however, very different from that of its components. Investment and trade variables, for example, are much more volatile than aggregate GDP, while Private Consumption is typically smoother than total activity (Artis et al. [3]). Checking how models compare in forecasting variables that behave so differently over the business cycle is an interesting exercise per se. Second, forecasting demand aggregates is extremely important at the turn of the cycle and in turbulent phases. Investment, for example, tends to trough before GDP. Consumption, on the other hand, only takes momentum when an expansion is well under way and peaks after the cycle. Having models that complement GDP forecasts with a view on the main drivers of economic activity enables business cycle analysts to provide a much more accurate reading of the cyclical phase. Our application is to one step ahead forecasts of Italian GDP and of the main demand breakdown, that is Private Consumption, Investment in Construction, Other Investment, Exports and Imports. By *one step ahead* we mean *the next quarterly release*. Given the delay with which quarterly series are published this actually amounts to performing a nowcast/backast exercise. We deliberately limit our forecast horizon to the next quarterly release because we are interested in gauging the relative merits of linear projections of the targets on *different spaces* (one spanned by the factors estimated on the targeted predictors, one by the few indicators included in bridge models, one by the factors estimated on the whole information set) when some information on the quarter of interest is

[1]The GETS methodology is implemented using the freeware software GROCER (see `http://dubois.ensae.net/grocer.htm`)

already available. Once the forecast horizon moves further ahead, the balance of merits in forecasting accuracy is bound to shift from the projection method to how monthly indicators are forecast into the future. How to forecast monthly business cycle indicators is itself a very interesting topic, which, however, goes beyond the scope of the present work.

The paper is structured as follows. In section 2 we discuss some preliminary issues. In section 3 we describe the strategies employed to select the targeted predictors and how we implement the General to specific (GETS) procedure. In section 4 we briefly present the main features of our dataset. In section 5 we discuss the results of our empirical analysis. Section 6 concludes.

2 Preliminaries: temporal aggregation and ragged-edged data

As we are interested in forecasting a quarterly target variable by means of monthly indicators we need to clarify how we address two important issues: temporal aggregation and ragged-edge data. In the factor model literature different approaches have been considered. In recent papers quarterly and monthly variables are cast in a factor model with latent variables and the missing observations are filled with the Kalman filter (Banbura and Modugno [6]). Other authors fit a factor model to the monthly indicators and then use an auxiliary equation to forecast GDP, either taking quarterly averages of the factors (Angelini et al. [2]) or with a MIDAS regression (Marcellino and Shumacher [18]). In the context of bridge models the problem of mixed frequencies is usually bypassed by taking quarterly averages of monthly indicators. For example, in a bridge model in which quarterly GDP growth is forecast on the basis of industrial production, the predictor is the quarter on quarter percentage change of the industrial production index.

In our case the choice of how to deal with mixed frequencies is constrained by the fact that the selection algorithms we rely on are not designed to deal with data at different frequencies. Having to homogenize the data frequency we therefore chose to work with the lowest one (quarterly) by taking quarterly average of the monthly regressors. The alternative route (monthly interpolation of quarterly GDP) would require the use an arbitrary interpolation method and was therefore discarded.

The second issue is how to deal with the asynchronous release of the indicators. In absence of a real-time dataset for the large number of indicators that we consider in this study we proceed via a pseudo real-time exercise in which we replicate the monthly release pattern of the indicators.[2] In particular we suppose to be in the middle of the month, after an industrial production data has been released by Istat but not surveys on the current month are yet available. Forecasts of the next GDP release are produced until a flash estimate becomes available, roughly 45 days after the end of the quarter. In figure 1 we provide a

[2]We approximate the overall availability of indicators that a forecaster would have faced at that time. In other words, the panel dimension of the dataset N, increases through time: for instance, until 1993 the dataset available to the researcher consists of 68 variables, while after 1993 it consists of 225 variables. According to our reconstruction, the largest increases in the number of available variables occurs among surveys and interest rates: the number of survey variables increases from 8 in January 1995 to 69 in December 2006, that of interest rate variables from 4 to 24.

stylized description of the timing of the information flow and forecasting cycle relative to GDP in Q2 (see also table 19 for a detailed list of indicators and their publication lag). We start nowcasting Q2 in May, when a flash estimate for Q1 is made available. In figure 1 we report the publication lag of four representative groups of variables: industrial production, surveys, interest rates, stock market indices and trade variables. As it can be seen, at the time of the release of the Q1 flash estimate, the industrial production index and trade data for March are also released. Survey data, on the other hand, are published at the end of the reference month, so that by the middle of May, the April release of the surveys is known. Stock market indices and interest rate data are available at daily frequency, so they are virtually available in the current month. Since the predictive content of hard data is known to be much higher than that of soft data (Banbura and Runstler [7]) the first forecast for Q2 is also the least accurate. The next nowcast for Q2 is produced in June, when one month of hard data and two months of soft data for the quarter of interest are available. Our forecasting cycle terminates with a backast in July when the information on the monthly indicators is almost complete. In August the flash estimate for Q2 is released and we start forecasting Q3.

At each monthly iteration, the ragged edge nature of the data requires some observations to be forecast in order to have a corresponding quarterly figure. In this respect, we simply forecast each indicator with a univariate autoregressive model. [3]

Formally our forecasting exercise works as follows. For each year y and for each quarter $t = q1, q2..., q4$, we produce three forecasts $i = 1, 2, 3$. We estimate the parameters of a linear equation (either a bridge or a factor model) with available data up to the previous quarter and then compute a forecast. For example in the second quarter ($t = 2$) of a given year ($y = \bar{y}$) the first forecast ($i = 1$) is computed by setting up the linear model:

$$target_{\bar{y},q1} = \alpha + \beta x_{\bar{y},q1} + \epsilon_{\bar{y},q1} \tag{1}$$

where $target_{\bar{y},q1}$ is our quarterly target (either GDP or other quarterly aggregates), $x_{\bar{y},q1}$ is a vector of dimension k which collects the predictors, $\epsilon_{\bar{y},q1}$ is a forecast error. In the case of bridge equations the vector x is a set of appropriately chosen indicators, in the case of factor models the vector x collects an autoregressive term and quarterly averages of the monthly factors. The forecast is then obtained as:

$$target_{\bar{y},q2} = \hat{\alpha}^{OLS} + \hat{\beta}^{OLS} x^{1}_{\bar{y},q2} \tag{2}$$

where $\hat{\alpha}^{OLS}$ and $\hat{\beta}^{OLS}$ are consistent OLS estimates of the parameters α and β in equation 1. Notice that in the forecast equation a subscript $i = 1$ arises, which indicates that the quarterly regressors x are averages of monthly indicators that are themselves partly forecast on the basis of the information set available in the first month of the reference forecast cycle (in this specific example April).

[3]The number of lags of the autoregressive model is chosen with the Akaike Information Criterion each month.

3 Identifying targeted predictors

Our dataset is characterized by a large degree of collinearity within block of variables and non-negligible idiosyncratic errors across variables belonging to different blocks. Picking the right regressors to form parsimonious linear bridge equations and/or selecting the appropriate amount of information to estimate factor models can therefore be quite challenging. Before proceeding it is useful to fix at the outset some terminology that will be used in the rest of the paper. We use the term *target* to indicate a quarterly variable which we want to forecast on the basis of monthly information, the term *indicators* for the monthly variables that are available in our dataset, the term *targeted predictors* for the *indicators* that have passed our selection tests. As anticipated in the Introduction we proceed by ordering and selecting indicators according to the rules suggested by Bai and Ng [5] to end up with a dataset of lower dimension. These data reduction methods can be classified in HARD- and SOFT-thresholding rules. Under HARD-thresholding an indicator is selected according to the significance of its correlation coefficient with the target. Typically only indicators whose correlation with the target is above a given threshold are selected as targeted predictors. The obvious shortcoming of this selection criterion is that it only takes into account the bivariate relationship between the target and each indicator, without accounting for the information contained in other indicators. As a result HARD-thresholding tends to select highly collinear targeted predictors. SOFT-thresholding rules, on the contrary, order and select indicators on the basis of a minimization problem of the following form:

$$\underbrace{min}_{\beta} \Phi\left(RSS\right) + \lambda\Psi\left(\beta_1, \ldots, \beta_j, \ldots, \beta_N\right) \tag{3}$$

where RSS is the Residual Sum of Squares of a regression of the target on the N indicators, and the Lagrange multiplier λ governs the shrinkage (the higher λ the higher is the penalty for having extra regressors in the model), while Φ and Ψ are functions of RSS and the N regression coefficients (β_j). Clearly, the cross-correlations among indicators are taken into consideration explicitly when minimizing this loss function. Depending on the functional form of Φ and Ψ, different SOFT-thresholding rules can be obtained. In the empirical application we will focus on the following SOFT-thresholding rules:

- Least angle regressions (LARS);
- Least absolute shrinkage selection operator (LASSO);
- Elastic net estimator (NET);
- Forward selection regressions (FWD).

In Appendix A we review in more detail how they arise from the general penalized regression (3).

The next step is to design a selection algorithm that combines the 5 screening rules above to extract the targeted predictors from our large dataset. We start by slicing our dataset in 138 rolling windows of 13 years of data. The size of each sample is 157 months, with the first one spanning from 1982m1 to 1995m1, and the last one from 1993m6 to 2006m6.[4] For each sample period we use the five methods above to rank the indicators. We then

[4]The results are robust to different sizes of the rolling window.

associate to each indicator and for each selection method a binary variable which takes value 1 if that indicator was ranked by that given algorithm among the top 15, 0 otherwise. We run this exercise on all the 138 rolling windows. At the end of the exercise we obtain for each indicator five binary variables (one for each selection method) with 138 observations. The sample mean of these binary variables, which is included between 0 (if the indicator was *never* selected by the specific selection method) and 1 (if the indicator was *always* selected by the specific selection method), can be interpreted as the probability of being selected conditional on a given thresholding method. We include the indicator in the pool of targeted predictors if the probability of being included exceeds 0.6 conditional on at least one of the thresholding rules. A specific example can make the algorithm clearer. Take for example industrial production (IP). For each rolling window we check whether IP was ranked among the top 15 predictors by HARD, LARS, LASSO, NET and FWD. We then obtain five binary variables, let us call them IP^{HARD}, IP^{LARS}, IP^{LASSO}, IP^{NET}, IP^{FWD} with 138 zero/one realizations. If the mean of at least one of these variables is above 0.6, IP is included in the set of targeted predictors. Since an indicator can be selected on the basis of more than one thresholding method we take the *union* of the indicators selected by each thresholding method as our final set of targeted predictors. Two issues need further clarification: (1) the choice of working with a rolling window instead of running the exercise once and for all on the full sample and (2) the choice of the 0.6 probability threshold. We choose to work with a rolling window to have some control over possible structural breaks. Suppose we run the selection exercise on the full sample and an indicator which was very informative at the beginning of the sample is poorly correlated with the target in the last part of the sample. Depending on some conditions (for example whether the measurement error of the target variable has also varied over time) it can happen that the indicator is selected by some thresholding rule despite the fact that its predictive content at the end of the sample is low. The same would happen if the correlation between an indicator and the target depended on an outlier located somewhere in the sample. We therefore require that an indicator is picked as consistently as possible over 138 rolling windows to be included in the pool of targeted predictors. The 0.6 probability threshold is worked out backwards as the cut-off that ensures that we do not end up with more than 30 targeted predictors, which is roughly the maximum number of variables that the GETS routine that can handle given the number of available observations for the targets. In a way this threshold can therefore be seen as an additional shrinkage parameter that we calibrate to make our selection algorithm operational.

3.1 Forecasting with targeted predictors

Having identified a subset of targeted predictors, two alternative strategies are available to extract their predictive content for the target variable. The one analyzed by Bai and Ng consists in setting up diffusion index models (or factor augmented models) where the estimated factors (principal components) condense efficiently the information dispersed in the dataset. The alternative approach is to specify linear (bridge) models relating the target variable to few indicators and their lags. This is accomplished with an application of the so called General-to-specific (GETS) model selection procedure, advocated by Krolzig and Hendry [17] and Hoover and Perez [16] and often associated with the LSE methodology, which starting from a general statistical model (here defined by the set of targeted predictors), suggests standard testing procedures to reduce its complexity by eliminating statistically insignificant variables and checking that the resulting model satisfies some predetermined test. In our application, following Krolzig and Hendry recommendations, we include in the battery of diagnostic tests the following:

- Chow predictive failure test with a break at 50% of the sample for parameter constancy;
- Chow predictive failure test with a break at 90% of the sample for parameter constancy;
- Doornik and Hansen's test for normality of the residuals;
- LM autocorrelation test up to fourth order autocorrelation in the residuals;
- Heterosckedasticity test for the residuals

The significance level for the selection t-tests is set to 0.05, while the significance level for the five diagnostic test is set to 0.01.

4 Data description

We assemble a dataset for the Italian economy whose panel dimension N is comparable to that of most factor models in the empirical literature. Our final dataset is composed of 247 time series covering several aspects of the Italian economy and taking into account its main characteristics. The information set includes:

- Hard indicators from the supply side.
- Hard indicators from the demand side.
- Manufacturing, construction, retail and consumer surveys.
- Trade variables.
- Interest rates and stock market indexes.
- Monetary and credit aggregates.
- Exchange rates (nominal, effective, real exchange rates).
- Labour market variables.
- Price variables.

Here we comment briefly on the main characteristics of our dataset, referring to Appendix B for the full list of indicators and metadata (Table B7). Among supply-side hard indicators, the most important group of variables is that of industrial production indexes. Such variables are among the key indicators of the Italian business cycle (see for instance Altissimo et al. [1]). The group includes both the general index and some of its sectoral components, as their performance can differ substantially from the aggregate in different phases of the business cycle. Among demand indicators, the dataset includes retail sales, car registration and electricity consumption in eight Italian district as well as in the railway grid. While such indexes reflect both energy demand for production as well as domestic uses, their usefulness for nowcasting industrial production is well documented in Marchetti and Parigi [19] as well as Bulligan et al. [10]. Among survey variables, a central role is played by business surveys. In this respect we include the balances between positive and negative answers for all questions in the Isae survey both at the aggregate level (total economy) as well as at the main industrial grouping level. We also include in the dataset the aggregate information available in the Reuters-Markit PMI survey. The latter has become one of the most watched indicators of the business cycle in Europe and in Italy and here we include both the manufacturing index as well as the composite index (which includes also information from the service sector). We also include the PMI manufacturing indexes for France, Germany, Spain and the Euro area which proxy for the international real linkages between Italy and its main euro area trading partners. Among interest rate variables we include most reference rates in the term structure and spreads between different maturity as well as banking rates charged to firms for short and long term borrowing and to households for house purchases. Considering the central role played by banks in the financial intermediation process, the latter as well as some credit aggregate related series (selected according to duration and recipients) might convey additional valuable information on the availability and on the cost of credit and therefore on the interaction between monetary and real aggregates. A further set of variables covers the international linkages of the Italian economy with the rest of the world. Considering the high sensitivity of the Italian economy to external conditions, we include value and volume indexes of exports and imports as well as nominal and real effective exchange rates based on the consumer price index. Among labour market indicators we include the number of extra time hours as well as the number of hours subsidized trough the wage supplementation fund (CIG), a highly countercyclical indicator. Finally we include only few aggregate price indexes while most disaggregate indexes are used indirectly to deflate nominal variables.

5 Results

The first output of our empirical exercise is given by the sets of targeted predictors identified by our selection algorithm for each target variable. While the detailed results can be found in the additional Tables provided in Appendix B (see Tables B.1 to B.6) some interesting patterns emerge from this screening exercise, which are worth commenting on. First, Forward selection on the one hand and HARD- thresholding on the other hand are, respectively, the most and the least parsimonious selection methods. This was largely expected as Forward selection tends to kick-out indicators that are correlated to those that have been already identified as targeted predictors, while HARD-thresholding ignores any information about the rest of the information set when screening each indicator. According to our algorithm Forward selection never picks more than four indicators, HARD-thresholding never less than twelve. The number of targeted predictors chosen by methods based on LARS (LARS, LASSO and NET) is somewhere in between. Second, the targeted predictors identified by LARS, LASSO and NET are broadly the same for each quarterly target. Third, HARD-thresholding tends to give a lot of weight to the industrial production block, to the Purchasing Manager Indexes (PMI) and to Business and Consumer surveys which are typically also the most correlated with the first principal component in large panels.

5.1 Bridge equations and DI forecasts

Feeding the sets of targeted predictors to the GETS routine, allows us to specify a bridge equation for each target. The results of this specification search are reported in Tables 1 to 6 where for each bridge model we report the regressors, the estimated coefficients and some regression statistics. It is worth noting at the outset that the GETS procedure delivers very parsimonious specifications, as the number of regressors (excluding the constant) is in most cases 4 and in only one case 7 (consumption).[5] Still, the in-sample fit is very satisfactory as it ranges between 0.6 and 0.8. It is interesting to notice that in no specification the lag of the dependent variable is selected. Since the lack of residual autocorrelation is one of the prerequisites for an acceptable specification of the GETS procedure this means that the contemporaneous and lagged values of the indicators are generally sufficient to catch the dynamics of the dependent variables. As a result all equations pass the test of autocorrelated residuals at the usual confidence levels. The only exception is given by the Investment in Construction equation, where residual autocorrelation, however, shows up only when estimating the equation after 2006, and therefore it could not be caught by the GETS selection.[6] Finally for each equation, it is possible to single out a few regressors that are usually considered as monthly proxies for the quarterly variable of interest and that receive specific scrutiny by most economic analysts and commentators. This is a comforting outcome as it indicates that the procedure delivers interpretable results and interpretability is one of the strengths of bridge models.[7] Starting with GDP, the GETS procedure selects three industrial production indexes: the index for the intermediate good sector, that for the investment goods sector and the first lag of the index of repair and installation of machinery. Although the total index, a standard regressor in most bridge equations, is not picked up by the algorithm, the industrial production subcomponents which are included are known to have a leading role in driving cyclical fluctuations in economic activity. Among the regressors of the consumption equation the number of car registration, the index of retail sales volume and the assessment of future business situation from the Isae survey among retailers are selected. The main driver in the equation for construction investment is the index of production in construction.[8] Turning to investment in machinery equipment, transport and patents (other investment), the regressors are the number of registered commercial vehicles and the Ip index. In the import and export equations the drivers are the volume of imported goods and that of exported goods, respectively.

The corresponding DI forecasting equations are relatively straightforward as they are simply obtained by regression of GDP on the first f principal components and their first p lags, where f and p chosen by the Akaike Information Criterion.[9]

[5] In some equations intervention dummies capturing specific episodes were added to the specification after the GETS selection. In no case adding the dummy variables led to a loss of significance of the remaining coefficients.

[6] An ex post check shows that the inclusion of the second lag of the endogenous variable proves sufficient to eliminate any residual autocorrelation in this equation.

[7] Notice that we use very intuitive transformations of the indicators. In some studies goodness of fit is achieved through complicated non linear transformations of the indicators, at the cost of reducing the interpretability of the equation.

[8] As Istat releases only a quarterly version of its underlying monthly index, our index is obtained by aggregating the real turnover of industries providing inputs for the construction industry.

[9] In the Tables we report the results obtained by estimating the equations on the *last estimation sample* used in our out of sample forecasting exercise, that is up to the first quarter of 2010. We stress, however, the quasi-real time nature of our exercise as the bridge model specification *via* GETS is performed on a sample spanning from 1994 to June 2006.

5.2 Forecasting performance comparison

To gauge the forecasting ability of our models we run a pseudo out of sample forecasting exercise. We start from January 2007 up until January 2010. As explained in section 3 we produce two forecasts and one backcast for each quarter. For each macro aggregate, the two main models to be compared are the bridge (BRIDGE) equation selected on the basis of available information up to 2006 and the diffusion index forecasting model selected on the same information set (TP-F), while the benchmark models are in turn a simple AR process (AR) and a diffusion index forecasting model, where the factors are extracted from the full dataset (ALL-F). While comparison with the AR model is a standard exercise in most forecasting applications as it allows to quantify the accuracy gains associated with models that incorporate additional external information, comparison with the ALL-F model allows to quantify the importance of pre-selecting indicators and therefore to reduce in a meaningful way the information set. For completeness, in the following out-of-sample forecasting exercise, we also report the results obtained selecting a specific diffusion index forecasting model for each of the five selection methods (LARS-F, LASSO-F, NET-F, FWD-F and HARD-F). When interpreting the results obtained with these model it must be kept in mind that in a real time context a researcher could not exploit this information as she would not know a-priori which selection procedure would deliver the most accurate results. Nonetheless it is important to check whether one of these criteria emerges as uniformly superior in an ex-post forecast evaluation. Before turning to the results, it is important to keep in mind that throughout the forecasting exercise while the information set (the number and the type of indicators) is kept fixed to that selected in December 2006, the parameters of the models (both the regression coefficients and the parameters that determine the number of static factors as well as the number of their lags) are re-estimated at each monthly iteration.

To have a first idea of how our models forecast we present in Figure 2 the ratio of the Root Mean Square Forecast Error (RMSFE) of the bridge model and that of the TP-F model to the RMSFE obtained with the benchmark autoregressive model (AR).[10] Two results are worth highlighting. First, in the case of GDP, both approaches perform better than the AR model at each forecasting step, as the RMSFE ratios are always below 1 and decline progressively as more monthly information accrues. In the first two forecasting steps the bridge model and the TP-F model give broadly the same results, yet when backasting (that is when two months of hard data have already been released) the TP-F model gives more accurate forecasts. Second, when turning to demand components bridge models always outperform both the AR benchmark and the TP-F models. They also generally show uniformly declining RMSFE over the forecasting exercise, indicating that they make good use of the new monthly releases. TP-F models on the other hand, are outperformed by AR models in a couple of cases (Consumption and Investment in Construction). Furthermore, they do not always make an efficient use of incoming information as their RMSFE increase rather than decaying over the forecast cycle in the case of Investment in Construction and, to a lesser extent, of Other Investment.

The full set of results of this exercise are shown in Tables 7 to 12. Before commenting on the numbers, an explanation of how these tables are organized is in order. Each table is divided into three panels. The upper panel shows the RMSFE, while the remaining two

[10] The number of lags to be included in the autoregressive model is re-optimized at each forecasting step.

reports the relative RMSFE with respect to the benchmarks (autoregressive model (AR) in the central panel, DI forecasting model without pre-selection (ALL-F) in the bottom panel). In the central and bottom panels, entries higher (lower) than 1 mean that the corresponding models under(out)-perform the benchmark. In each panel the three rows refer to the three monthly forecasts with increasing amount of information. The first four columns refer to the AR model, the bridge model, the ALL-F model and the TP-F model, respectively. The next five columns report for completeness, the DI forecasting models based on each of the five selection criteria. The last column finally reports for each month the best performing model.

Some interesting results emerge from a bird-eye look at the tables. Firstly, one can notice that for most quarterly targets exploiting additional information embedded in monthly indicators generally leads to more accurate forecasts than with simple AR models (entries lower than 1 are highlighted in bold in the central panels). The only exception is Investment in Construction and to a lesser extent Consumption. Secondly, focusing on the relative benefits of pre-selecting information (benchmark ALL-F model in Panel c), the accuracy gains in forecasting using targeted predictors (highlighted in bold) are more scattered across targets, so that one cannot state that filtering information always lead to better forecasts. In this respect, however, using targeted predictors in combination with the GETS procedure generally gives better results than using TP-F model. Bridge models, in fact, are outperformed by the ALL-F model in only three out of eighteen cases (1st fore Import, 2nd fore and backast Consumption). Thirdly, the selection method that delivers the best results is not constant across tables nor within a single table across monthly forecasts, suggesting that a-priori it would be difficult to choose for a specific selection method and "averaging across methods" (TP-F or bridge) is therefore a good idea. Focusing on GDP (Table 7), in the first forecast the accuracy gain with respect to the AR model ranges from 15% (bridge) to 24% (TP-F), in the second forecast the gain ranges from 26% (FWD-F) to 50% (TP-F) and in the third forecast (backcast) from 24% (FWD-F) to 69% (LARS-F). In this rich landscape of forecast models picking bridge models seems to be a good idea, as they are selected as best the performing model in 7 out of 18 cases closely tracking the performance of the best models in the other cases. Indeed, selecting the bridge model as forecasting tool would lead to an accuracy gain with respect to the AR model between 50% and 70% (from forecast to backcast) for Export, between 40% and 60% for Import, between 22% and 2% for Investment in construction, between 37% and 30% for Other Investment and between 15% and 28% for Consumption.

5.3 Forecasting during the Great Recession

As the forecasting period is not particularly long and furthermore includes the so called Great Recession, the question arises whether the previous results are driven by few observations. In particular the accuracy gains of models based on targeted predictors with respect to the benchmark AR model could be the reflection of the poor performance of the latter during a rather unique event with no historical precedent. Indeed several authors (see for instance D'Agostino and Giannone [12]) have highlighted how during the late 1990s early 2000s, a period often referred to as the Great Moderation, even sophisticated models failed to outperform simple AR models. Dissecting the performance of TP-F and bridge models over appropriate subsample is also an interesting exercise in evaluating the reliability of models regularly used by policy makers during the Great Recession. In the following, we distinguish therefore the performance of models for GDP during the period 2008Q3-2009Q2 usually referred to as the Great Recession (crisis) from the rest of sample (no crisis).[11] Considering the rather small number of observations available, formal statistical inference cannot be performed so that the exercise should be taken as an event study providing qualitative results. Figure 4 reports the RMSFE of TP-F and bridge models relative to that of the benchmark AR model during normal times (2006Q4-2008Q2 and 2009Q3-2009Q4) and the Great Recession. The accuracy gains during the no-crisis subsample tend to be smaller than those over the whole sample, ranging from 20% (first forecast) to 40% (backcast). However they are still substantial and confirm that even during normal times models based on targeted predictors outperform benchmark AR models.[12] Looking more deeply into such finding allows to characterize the models performance during the Great Recession, a rather serious test for any forecasting model. Figure 5 reports for each of the four models mainly considered in the previous analysis and for each of the three forecasting rounds within the quarter, the ratio of the RMSFE during the Great Recession (crisis) relative to that during normal times (no-crisis). We can clearly see that during the Great Recession, the forecast accuracy in the first round deteriorates tremendously across models (values bigger than 1 and around 2), reflecting the lack of hard data on the current quarter and the inadequacy of AR models to provide accurate forecasts for the missing monthly observations within the quarter. However, already in the second forecast round the RMSFE goes back to values not dissimilar from those recorded in normal times (values close to 1). Finally, some models in the last forecast round turn out to perform slightly better (value lower than 1) during the Great Recession than in normal times. Overall the sub-sample analysis, although of qualitative nature, suggests that the gains associated with models based on targeted predictors are not driven by few exceptional observations.

5.4 Results for the euro area, Germany, France and Spain

Our main empirical exercise focuses on Italian GDP and on its main demand components. However, the methodology that we use first to shrink the information set and then to specify the bridge equations is general and can be applied to any large dataset. In order to check the robustness of our results and validate our methodology we extend the analysis to short-term GDP forecasts of four other countries (the euro area, Germany, France and Spain).

The analysis follows the exact same steps as those described above. First, for each country we gather a monthly dataset comprising the most commonly watched indicators on economic activity. Despite being unable to replicate the wide coverage of the Italian dataset, the dimension of these information sets is quite large and varies from 60 indicators for Spain to 140 for Germany. More importantly they all include indicators that according both to

[11] In the four quarters considered, the quarterly rate of growth of Italian GDP was on average -1.6 percent, reaching a historical minimum of -2.7 percent in 2009Q1. Such values are to be compared to an average quarterly rate of growth of 0.3 percent and a standard deviation of 0.7 since 1980. Despite woes still hinder the financial sector after 2009Q2, GDP resumed to expand at positive and “normal” rates since then.

[12] The same exercise also confirms that models based on targeted predictors outperform factor models based on all available information (ALL-F). Results are available upon request from the authors.

the available empirical country-specific literature and to indications from the results for the Italian GDP are considered reliable indicators of the business cycle. After removing seasonal factors and outliers, all data are transformed in order to guarantee stationarity.[13] Second, we apply hard and soft thresholding techniques to reduce the country specific datasets to around 20 indicators.[14] Third, we turn to the GETS procedure and starting from the reduced information set we specify four parsimonious country specific bridge equations for forecasting GDP. The set of indicators selected by the GETS procedure is fairly standard. In particular, the variables included in the bridge equations are:

1. for the euro area Industrial production (basic metals and electrical equipment), retail sales and short term interest rates
2. for Germany Industrial production (manufacturing and construction), the IFO Index (Assessment of business situation in trade), and Industrial orders of consumer non-durables
3. for France Industrial production (manufacturing), expected demand in services (survey), the export order book position in Industry (survey) and the OECD composite leading indicator
4. for Spain Industrial production (non mineral products), the Economic Sentiment indicator and the stock market Index.

We run a pseudo-out of sample forecast exercise akin to the one performed for Italy and compare the forecast accuracy of the bridge, TP-F and ALL-F models. The main findings from this exercise are reported in Figure 6, where the RMSEs of the different models are compared to that of a benchmark AR model. By looking at the histograms one can easily notice the superior performance of bridge models compared to both the benchmark AR model as well as to the two factor models (TP-F and All-F). Relative to the AR, RMSEs from bridge models are always below 1 (with the exception of the first forecast for Spain) and decrease monotonically, as conjunctural information accumulates. Turning to factor models, selecting indicators (TP-F models) leads to an improvement over the ALL-F model for the euro area, but to a slight deterioration of accuracy in the other cases (more markedly for France). Also notice that in the case of Spain factor forecasts perform worse than the AR model. Taken together these results confirm those obtained in the case of Italy: bridge models specified by combining targeted predictors with the GETS specification procedure tend to outperform factor models either based on all the available information or subject to a pre-screening of the variables.

6 Conclusions

Forecasting quarterly variables relies on the availability of timely monthly indicators. In this paper we have compared two approaches to information extraction from large panels. Both approaches rely on a pre-selection of the available indicators but differ in the way the information is extracted. While TP-F models exploit the covariance structure of the

[13]The large datasets used for this robustness check are drawn from Cristadoro et al. [11]. Details on the variables included for each country can be found therein.

[14]We kept the value of the probability threshold at 0.6 as for the Italian dataset

data to estimate the driving common factors to be used in the forecasting equation, bridge models rely on a general to specific approach to find the most accurate approximation to the true unknown data generating process within a set of admissible models. The resulting models generally show a good forecasting performance, clearly outperforming a benchmark AR model and comparing well with factor models that use all the available information. The lesson we learn from the exercise is that the forecasting gains obtained by exploiting the timely information provided by monthly indicators can be further increased by carefully screening available information. While in our application no single selection rule stands out as best performing, we find that their use in conjunction with more traditional approaches (GETS) leads to the specification of simple linear models (bridge equations) that (i) are easily interpretable, (ii) increase their forecasting ability as monthly information accrues, (iii) outperform forecasts which are based either exclusively on quarterly information (AR models) or that blindly use all the available monthly indicators.

A Selection algorithms in detail

A.1 Hard thresholding

The hard thresholding algorithm consists of running a regression of the target variable y_t on each indicator at a time in the dataset x_t. Under this rule only the variables that show a regression coefficient significant at the 5% level are kept as targeted predictors. Upon deciding whether to include or not a variable in the set of predictors this method ignores the information contained in all the other variables. It can therefore end up selecting variables that are too strongly correlated with each other.

A.2 Soft thresholding

Soft thresholding methods are based on different variants of the more general LARS (Least Angle Regression) algorithm devised by Efron et al. [14]. To have an intuition of what LARS consists of it is instructive to briefly discuss a popular, selection method, Forward Selection, which we include among selection criteria.

A.2.1 Forward Selection

Suppose a researcher wants to study the forecasting relationship between a target variable y and a large set of covariates X. A good starting point is to identify the regressor which shows the highest correlation with the target, say x_1. At this point Forward Selection consists of regressing y on x_1, storing the residuals (u_1) and then looking for the covariate in the X information set with the highest correlation with this residual, say x_2. The residual u_1 is projected onto x_2, a new residual u_2 is stored and the covariate mostly correlated with u_2 is next identified. The procedure can go on up until all the variables in the information set have been ranked. The philosophy underpinning Forward selection is exactly the opposite of that behind hard thresholding. While hard thresholding can select a large number of regressors very correlated with each other Forward selection tends to keep fewer variables, as orthogonal as possible to each other.

A.2.2 LARS

LARS starts as Forward selection, by identifying the covariate that has the highest correlation with the target. Like in Forward selection the largest step in the direction of this covariate x_1 is taken until a new predictor x_2 has as much correlation with the current residual. After this step, however, LARS proceeds equiangularly between x_1 and x_2 rather than orthogonally as in Forward Selection. After k steps, there are k variables in the active set. If the algorithm is stopped here the coefficients of the remaining N - k regressors are all set to zero. The desired shrinkage can therefore be seen as a stopping rule for k. Efron et al. [14], show that the LARS algorithm encompasses other popular shrinkage methods, including Forward selection itself, LASSO and the Elastic Net to which we now turn.

A.2.3 LASSO and the Elastic Net

LASSO can be obtained in the LARS algorithm by imposing at each step of the algorithm a restriction on the sign of the correlation between the new candidate regressor and the projection along the equiangular direction in the previous step. To get an intuition let us start again from step 1, when the variable which is most correlated with the target enters the active set. Suppose that this correlation is positive. In selecting the second variable for the active set, LARS is agnostic on the sign of the correlation between the target and the new variable. If one imposes that the sign of this correlation must not switch the LASSO regression is obtained.

LASSO can also be related to the RIDGE estimator, a constrained OLS estimator that penalizes overfitting. Given M regressors RIDGE coefficients are obtained by solving the following minimization problem.

$$\underbrace{min}_{\beta} RSS + \lambda \sum_{j=1}^{M} \beta_j^2 \tag{4}$$

where RSS is the Residual Sum of Squares. The Lagrange multiplier λ governs the shrinkage: the higher λ the higher is the penalty for having extra regressors in the model. LASSO is a slight modification of the penalty function of the RIDGE regressor, which, rather than being a quadratic function shows a kink at zero:

$$\underbrace{min}_{\beta} RSS + \lambda \sum_{j=1}^{M} |\beta_j| \tag{5}$$

This modification implies that, unlike in the RIDGE setup, in the LASSO some regression coefficients are set exactly at zero.

The Elastic Net is a refinement of LASSO, and it is the solution to the following minimization problem:

$$\underbrace{min}_{\beta} RSS + \lambda_1 \sum_{j=1}^{M} |\beta_j| + \lambda_2 \sum_{j=1}^{M} \beta_j^2 \tag{6}$$

Shrinkage under EN depends on two tuning parameters, λ_1 and λ_2. Bai and Ng [5] show that it suffices to apply a variable transformation to reformulate the EN as a LASSO problem, which can be therefore obtained through the LARS algorithm.

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Table 1: GDP - Bridge equation

Regressors	$\hat{\beta}$	P-val.
Constant	-1.00	0.07
IP: Other Manuf. Repair (lag)	0.01	0.26
PMI Manufacturing Euro Area	0.02	0.03
Electricity Consumption - Florence	0.11	0.00
IP: Intermediate goods	0.10	0.00
IP: Investment goods	0.06	0.00
D9601	0.55	0.08
Regression statistics		
Adjusted R-squared	0.80	
S.E. of regression	0.30	
S.D. dependent var	0.68	
No. observations	73	
Serial Correlation LM Test (P-val.)	0.45	
Heteroscedasticity Test (P-val.)	0.34	

Note to Tables 1 to 6: The Auto correlation test refers to the Breusch-Godfrey serial correlation LM test with four lags. The heteroskedasticity test refers to the Breusch-Pagan-Godfrey test. The estimation sample goes from 1992Q1 to 2010Q1.

Table 2: Export - Bridge equation

Regressors	$\hat{\beta}$	P-val.
Constant	0.17	0.32
Electricity Consumption - Milan (lag)	0.25	0.00
Export Volume	0.60	0.00
Hourly Wage Rate (Deflated)	-0.89	0.02
Real effective exchange rate - cpi based	-0.27	0.00
Regression statistics		
Adjusted R-squared	0.76	
S.E. of regression	1.36	
S.D. dependent var	2.75	
No. observations	73	
Serial Correlation LM Test (P-val.)	0.52	
Heteroscedasticity Test (P-val.)	0.84	

Figure 1: Timing of forecasting exercise and availability of GDP data

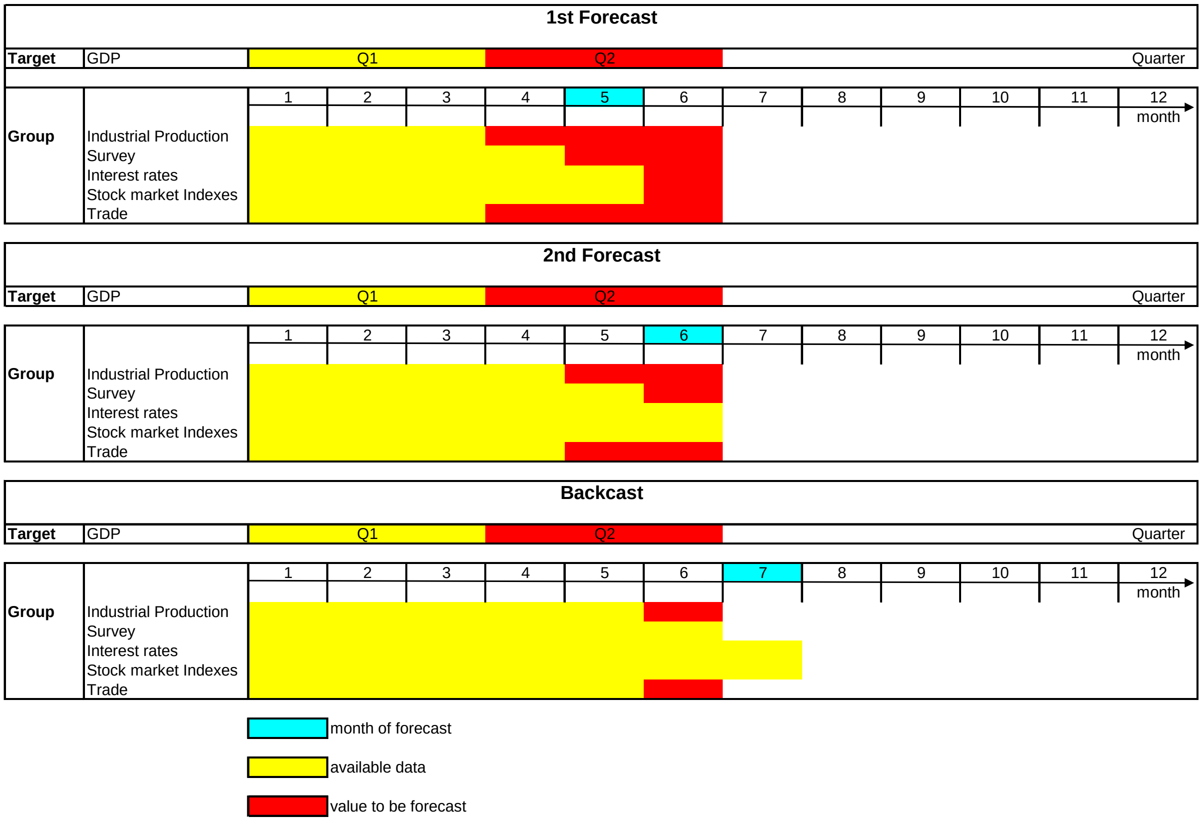


Table 3: Import - Bridge equation

Regressors	$\hat{\beta}$	P-val.
Constant	0.47	0.01
IP: Means of Transport (lag)	0.12	0.00
Import Volume	0.52	0.00
IP: Rubber and Materials	0.29	0.00
Regression statistics		
Adjusted R-squared	0.75	
S.E. of regression	1.38	
S.D. dependent var	2.77	
No. observations	73	
Serial Correlation LM Test (P-val.)	0.37	
Heteroscedasticity Test (P-val.)	0.62	

Table 4: Investment in construction - Bridge equation

Regressors	$\hat{\beta}$	P-val.
Constant	0.11	0.44
Stock Price Index - Electricity	-0.03	0.03
Ip: construction	0.38	0.00
Ip: investment goods-new orders(motor vehicles)	0.07	0.01
D974	6.63	0.00
D981	-5.41	0.00
Regression statistics		
Adjusted R-squared	0.71	
S.E. of regression	1.20	
S.D. dependent var	2.22	
No. observations	73	
Serial Correlation LM Test (P-val.)	0.04	
Heteroscedasticity Test (P-val.)	0.68	

Table 5: Other Investment - Bridge equation

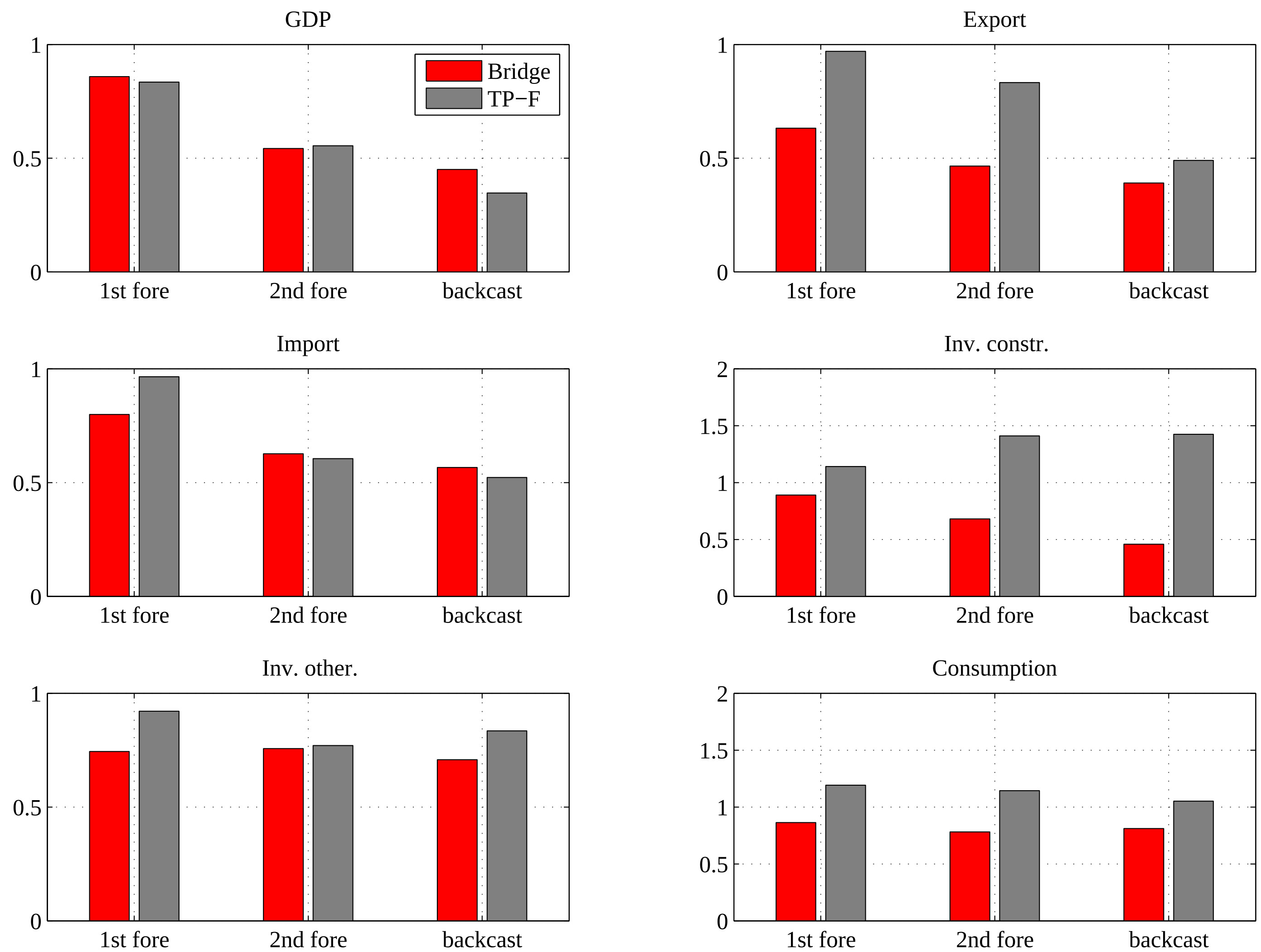
Regressors	$\hat{\beta}$	P-val.
Constant	0.52	0.03
Commercial vehicle registration	0.07	0.04
IP: Investment Goods	0.54	0.00
D031	-5.13	0.01
Regression statistics		
Adjusted R-squared	0.67	
S.E. of regression	1.7	
S.D. dependent var	3.0	
No. observations	73	
Serial Correlation LM Test (P-val.)	0.6	
Heteroscedasticity Test (P-val.)	0.23	

Table 6: Private Consumption - Bridge equation

Regressors	$\hat{\beta}$	P-val.
Constant	-1.60	0.01
PMI Manufacturing France	0.03	0.01
IP: Metal and Metal products	0.04	0.07
New passenger car registration	0.04	0.00
Electricity consumption Palermo (lag)	-0.05	0.12
Retail survey: future business situation	0.01	0.02
Retail sales volume index	0.27	0.02
D9601	1.84	0.00
Regression statistics		
Adjusted R-squared	0.56	
S.E. of regression	0.47	
S.D. dependent var	0.71	
No. observations	73	
Serial Correlation LM Test (P-val.)	0.90	
Heteroscedasticity Test (P-val.)	0.34	

Note to Table 6: the retail sales volume index was included in the specification *ad-hoc*, as the available series is too short to be included in the targeted selection algorithm.

Figure 2: RMSFE - BRIDGE model and TP-F model relative to AR



Note to Figure 2: the figure reports the ratio of the Root Mean Squared Forecast Errors (RMSFE) of the Bridge models and of the TP-F model to that of an AR model. The number of lags of the AR model is selected optimally based on the Akaike Criterion at each step. The three bars refer to the three different forecast horizons, which are the second and third month of the current quarter (1st fore and 2nd fore) and the first month of the next quarter (backast).

Figure 3: BRIDGE model and TP-F model forecast errors:GDP

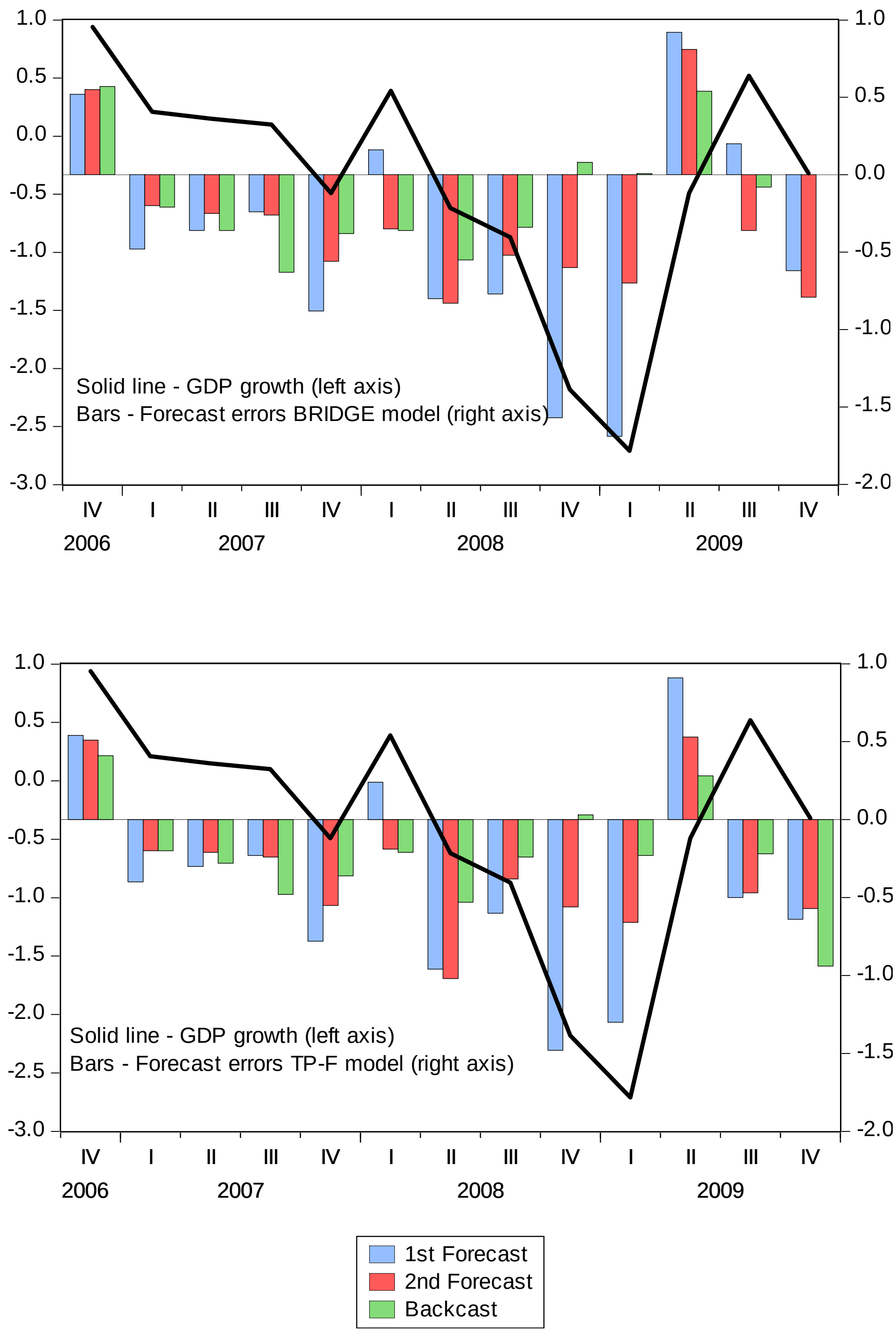


Table 7: RMSFE GDP

	AR	BRIDGE	ALL-F	TP-F	LARS-F	LASSO-F	NET-F	FORW-F	HARD-F	BEST
					Panel a: RMSFE					
1st fore	0.93	0.80	0.80	0.77	0.82	0.88	0.84	0.84	0.86	**TP-F**
2nd fore	0.93	0.50	0.71	0.51	0.58	0.57	0.53	0.77	0.59	**Bridge**
backcast	0.90	0.41	0.48	0.31	0.31	0.40	0.41	0.75	0.36	**Lars-F**
					Panel b: relative RMSFE (benchmark AR)					
1st fore	1.00	**0.86**	**0.87**	**0.83**	**0.88**	**0.94**	**0.91**	**0.91**	**0.93**	
2nd fore	1.00	**0.54**	**0.77**	**0.55**	**0.62**	**0.61**	**0.57**	**0.83**	**0.64**	
backcast	1.00	**0.45**	**0.53**	**0.35**	**0.34**	**0.45**	**0.46**	**0.83**	**0.40**	
					Panel c: relative RMSFE (benchmark ALL-F)					
1st fore	1.16	**0.99**	1.00	**0.96**	1.02	1.09	1.05	1.05	1.07	
2nd fore	1.30	**0.70**	1.00	**0.72**	**0.81**	**0.80**	**0.74**	1.07	**0.83**	
backcast	1.89	**0.85**	1.00	**0.66**	**0.64**	**0.84**	**0.86**	1.58	**0.75**	

Note to Tables 7 to 12: Entries report the Root Mean Squared Forecast Error (Panel a), and the relative RMSFE with respect to a AR model (Panel b) and the DI model with no pre-selection of indicators (ALL-F). In panels b and c a value below 1 indicates that the model in column outperforms the benchmark. For ease of visualization entries below 1 are highlighted in bold. The rows refer to the month of the forecasts (1st forecast is performed in the second month of the quarter, 2nd forecast is performed in the third month of the quarter and backcast is performed in the first month of the following quarter). The last column (BEST) reports for each forecast period the model with the smallest RMSFE. Each model is evaluated in a rolling (estimation sample is 13 years) pseudo out-of-sample real time forecasting exercise over the period 2006Q4-2009Q4.

Table 8: RMSFE Export

	AR	BRIDGE	ALL-F	TP-F	LARS-F	LASSO-F	NET-F	FORW-F	HARD-F	BEST
					Panel a: RMSFE					
1st fore	3.66	2.31	3.25	3.55	2.81	3.07	2.86	3.16	3.15	**Bridge**
2nd fore	3.50	1.63	2.41	2.91	2.71	2.53	2.60	3.16	1.90	**Bridge**
backcast	3.50	1.37	1.93	1.71	1.48	1.07	1.38	2.52	1.18	**Lasso-F**
					Panel b: relative RMSFE (benchmark AR)					
1st fore	1.00	**0.63**	**0.89**	**0.97**	**0.77**	**0.84**	**0.78**	**0.86**	**0.86**	
2nd fore	1.00	**0.47**	**0.69**	**0.83**	**0.77**	**0.72**	**0.74**	**0.90**	**0.54**	
backcast	1.00	**0.39**	**0.55**	**0.49**	**0.42**	**0.30**	**0.39**	**0.72**	**0.34**	
					Panel c: relative RMSFE (benchmark ALL-F)					
1st fore	1.13	**0.71**	1.00	1.09	**0.87**	**0.94**	**0.88**	**0.97**	**0.97**	
2nd fore	1.45	**0.67**	1.00	1.21	1.12	1.05	1.08	1.31	**0.79**	
backcast	1.81	**0.71**	1.00	**0.89**	**0.76**	**0.55**	**0.71**	1.30	**0.61**	

Table 9: RMSFE Import

	AR	BRIDGE	ALL-F	TP-F	LARS-F	LASSO-F	NET-F	FORW-F	HARD-F	BEST
Panel a: RMSFE										
1st fore	3.12	2.50	2.43	3.01	2.97	3.69	3.41	2.39	3.10	**Forw-F**
2nd fore	3.00	1.88	2.10	1.81	2.08	2.32	2.37	2.59	1.99	**TP-F**
backcast	3.00	1.70	1.75	1.57	1.56	1.97	2.00	2.36	1.80	**Lars-F**
Panel b: relative RMSFE (benchmark AR)										
1st fore	1.00	**0.80**	**0.78**	**0.96**	**0.95**	1.18	1.09	**0.76**	**0.99**	
2nd fore	1.00	**0.63**	**0.70**	**0.61**	**0.69**	**0.77**	**0.79**	**0.86**	**0.66**	
backcast	1.00	**0.57**	**0.58**	**0.52**	**0.52**	**0.66**	**0.67**	**0.79**	**0.60**	
Panel c: relative RMSFE (benchmark ALL-F)										
1st fore	1.29	1.03	1.00	1.24	1.23	1.52	1.41	**0.98**	1.28	
2nd fore	1.43	**0.89**	1.00	**0.86**	**0.99**	1.10	1.13	1.23	**0.95**	
backcast	1.72	**0.97**	1.00	**0.90**	**0.89**	1.12	1.14	1.35	1.03	

Table 10: RMSFE Investment in construction

	AR	BRIDGE	ALL-F	TP-F	LARS-F	LASSO-F	NET-F	FORW-F	HARD-F	BEST
Panel a: RMSFE										
1st fore	2.03	1.81	2.33	2.31	2.42	1.98	2.17	1.74	2.47	**Forw-F**
2nd fore	1.99	1.35	2.37	2.81	2.31	2.18	2.18	2.08	2.69	**Bridge**
backcast	1.99	0.91	2.70	2.83	3.00	2.12	2.71	1.97	2.46	**Bridge**
Panel b: relative RMSFE (benchmark AR)										
1st fore	1.00	**0.89**	1.15	1.14	1.19	**0.98**	1.07	**0.86**	1.22	
2nd fore	1.00	**0.68**	1.19	1.41	1.16	1.09	1.10	1.05	1.35	
backcast	1.00	**0.46**	1.36	1.42	1.51	1.07	1.36	**0.99**	1.24	
Panel c: relative RMSFE (benchmark ALL-F)										
1st fore	**0.87**	**0.78**	1.00	**0.99**	1.04	**0.85**	**0.93**	**0.75**	1.06	
2nd fore	**0.84**	**0.57**	1.00	1.18	**0.97**	**0.92**	**0.92**	**0.88**	1.13	
backcast	**0.74**	**0.34**	1.00	1.05	1.11	**0.79**	1.00	**0.73**	**0.91**	

Table 11: RMSFE Other investment

	AR	**BRIDGE**	**ALL-F**	**TP-F**	**LARS-F**	**LASSO-F**	**NET-F**	**FORW-F**	**HARD-F**	**BEST**
Panel a: RMSFE										
1st fore	3.76	2.80	3.50	3.46	3.63	3.28	3.53	3.22	3.65	**Bridge**
2nd fore	3.65	2.76	3.08	2.81	3.33	3.23	2.84	2.59	3.05	**Forw-F**
backcast	3.65	2.59	2.99	3.05	3.39	2.70	3.06	3.06	2.94	**Bridge**
Panel b: relative RMSFE (benchmark AR)										
1st fore	1.00	**0.74**	**0.93**	**0.92**	**0.96**	**0.87**	**0.94**	**0.86**	**0.97**	
2nd fore	1.00	**0.76**	**0.84**	**0.77**	**0.91**	**0.89**	**0.78**	**0.71**	**0.83**	
backcast	1.00	**0.71**	**0.82**	**0.83**	**0.93**	**0.74**	**0.84**	**0.84**	**0.80**	
Panel c: relative RMSFE (benchmark ALL-F)										
1st fore	1.07	**0.80**	1.00	**0.99**	1.04	**0.94**	1.01	**0.92**	1.04	
2nd fore	1.19	**0.90**	1.00	**0.91**	1.08	1.05	**0.92**	**0.84**	**0.99**	
backcast	1.22	**0.86**	1.00	1.02	1.13	**0.90**	1.02	1.02	**0.98**	

Table 12: RMSFE Consumption

	AR	**BRIDGE**	**ALL-F**	**TP-F**	**LARS-F**	**LASSO-F**	**NET-F**	**FORW-F**	**HARD-F**	**BEST**
Panel a: RMSFE										
1st fore	0.72	0.62	0.64	0.86	0.91	0.82	0.74	0.80	0.44	**Hard-F**
2nd fore	0.67	0.52	0.49	0.77	0.61	0.62	0.72	0.61	0.55	**All-F**
backcast	0.67	0.54	0.47	0.71	0.49	0.74	0.73	0.64	0.47	**All-F**
Panel b: relative RMSFE (benchmark AR)										
1st fore	1.00	**0.86**	**0.89**	1.19	1.27	1.14	1.04	1.12	**0.61**	
2nd fore	1.00	**0.78**	**0.73**	1.14	**0.91**	**0.92**	1.08	**0.91**	**0.81**	
backcast	1.00	**0.81**	**0.70**	1.05	**0.73**	1.10	1.08	**0.96**	**0.71**	
Panel c: relative RMSFE (benchmark ALL-F)										
1st fore	1.12	**0.97**	1.00	1.34	1.42	1.28	1.16	1.25	**0.69**	
2nd fore	1.36	1.07	1.00	1.56	1.23	1.25	1.47	1.24	1.11	
backcast	1.42	1.15	1.00	1.50	1.04	1.56	1.54	1.36	1.01	

Figure 4: RMSFE BRIDGE model and TP-F model relative to AR - GDP Subsample decomposition

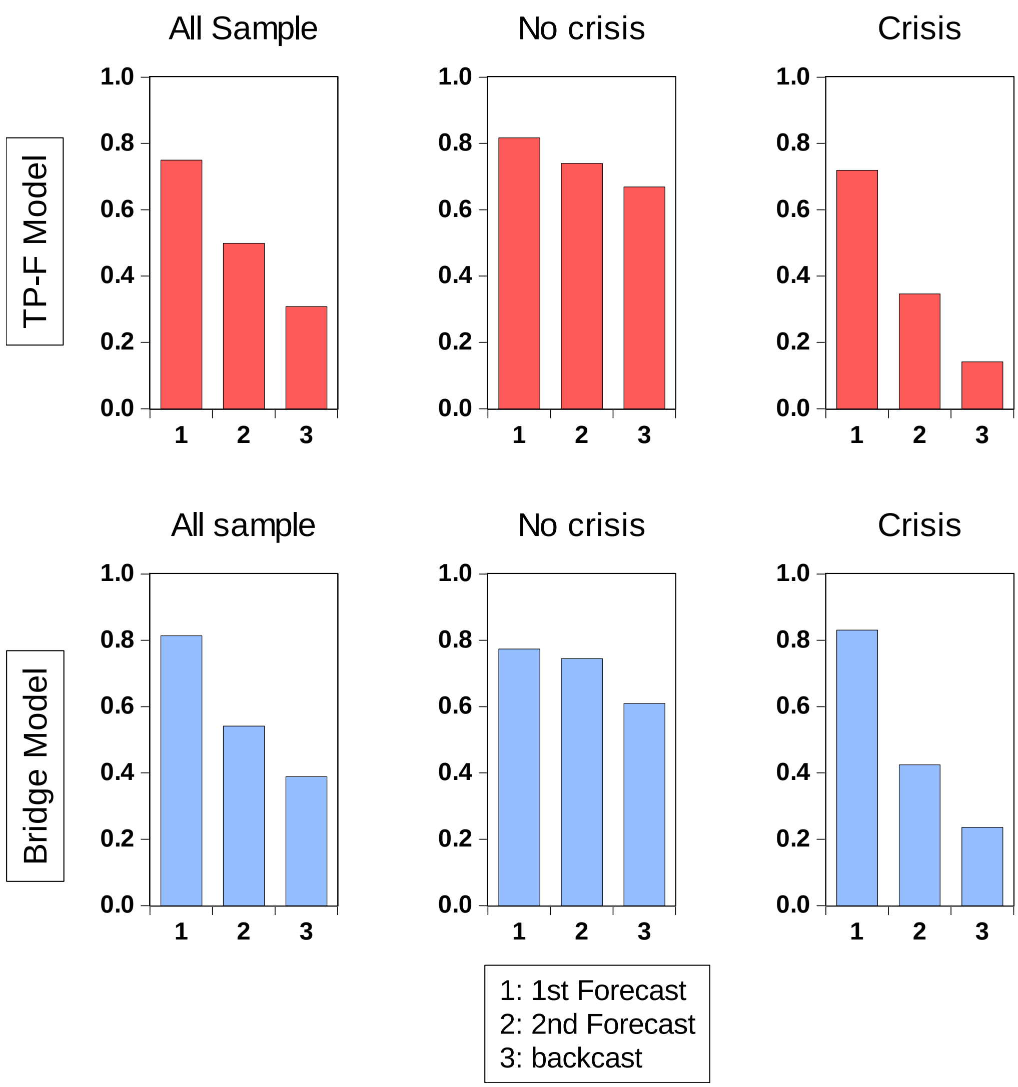
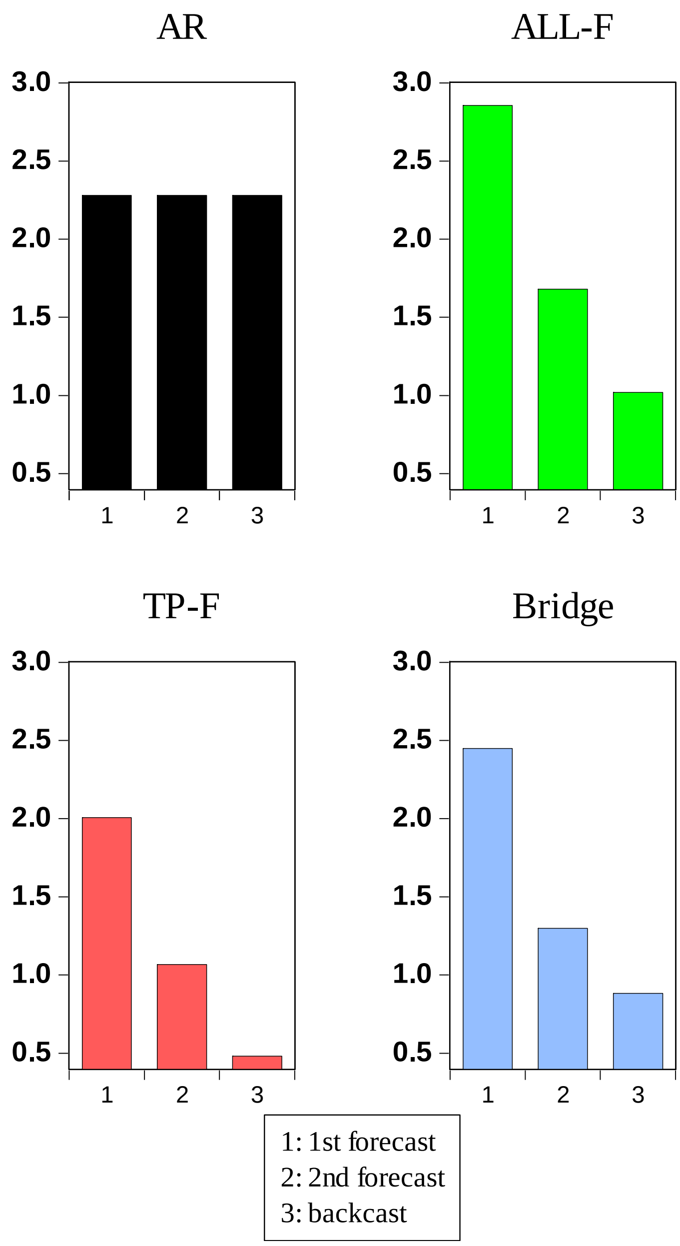
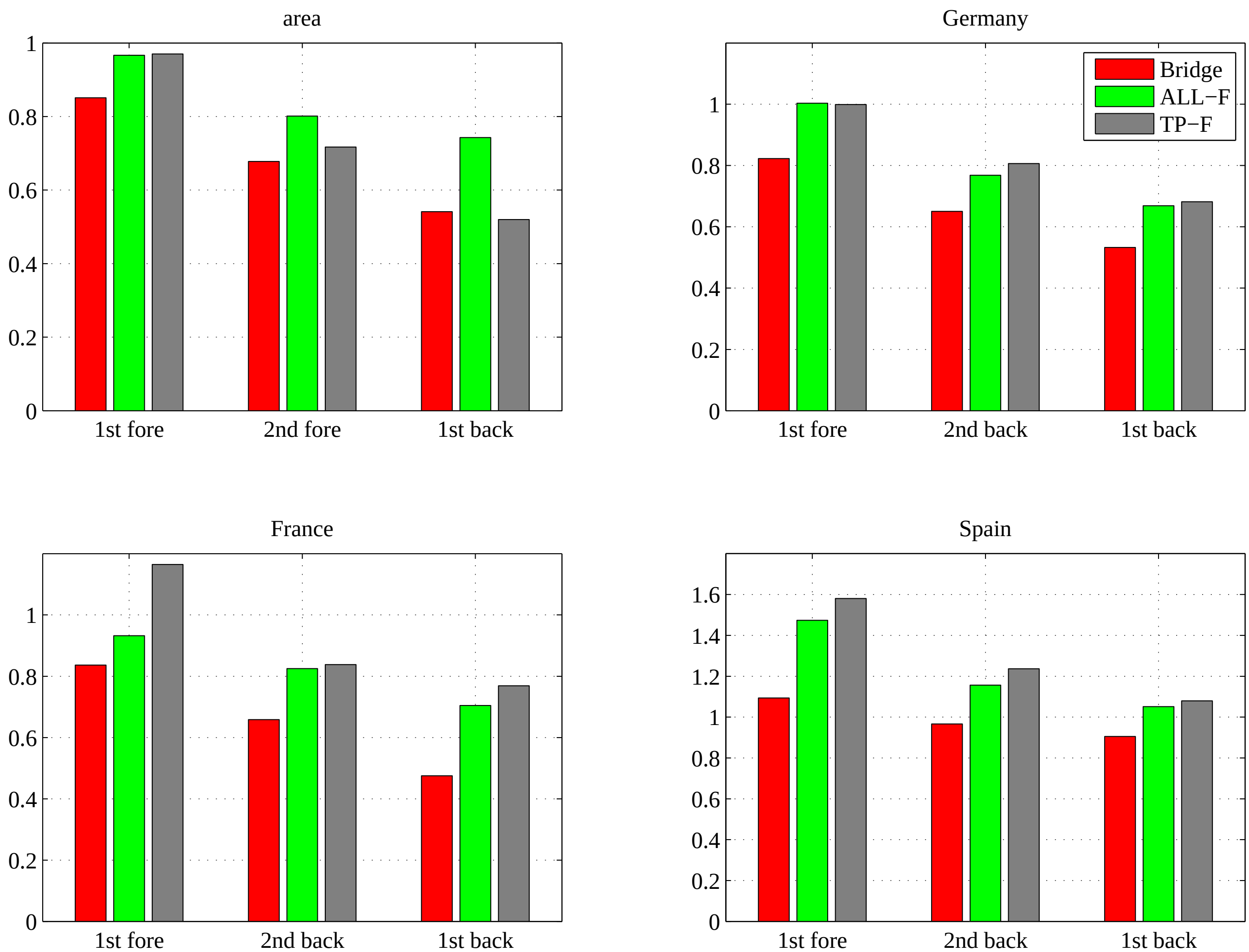


Figure 5: RMSFE: GDP crisis relative to no crisis



Note to Figure 5: the figure reports for each of the four models considered, the ratio of the Root Mean Squared Forecast Errors (RMSFE) computed during the period 2008Q3-2009Q2 relative to the RMSFE computed over the period 2006Q4-2008Q2 and 2009Q3-2009Q4. The three bars refer to the three different forecast horizons, which are the second and third month of the current quarter (First Forecast and Second Forecast) and the first month of the next quarter (Backcast).

Figure 6: RMSFE: BRIDGE TP-F and ALL-F model relative to AR - GDP



B Additional Tables

Table B.1: GDP - Variable selection

	LARS	LASSO	NET	FWD	HARD
ELECTRICITY CONSUMPTION TOTAL					0.7
ELECTRICITY CONSUMPTION MILAN					0.8
ELECTRICITY CONSUMPTION FLORENCE	0.9	1.0	1.0	0.7	0.7
CIG ORDINARY					0.7
IP	0.7		0.6		1.0
IP - MANUFACTURING	0.8	0.7	0.8	0.7	1.0
IP: INVESTMENT	1.0	1.0	1.0		1.0
IP: INTERMEDIATE	1.0		0.4		1.0
IP: METALS					1.0
IP: RUBBER & PLASTIC			0.7		
IP: TEXTILE & CLOTHING	0.8	0.8	0.8		
ISAE BUS.SVY.: INV.GDS.- ORDER BOOKS IN NEXT 3MOS., NET					0.7
ISAE BUS.SVY.: INV.GDS.- PRODUCTION IN NEXT 3MOS., NET	0.8		0.6		1.0
PMI MANUFACTURING Euro Area	0.7				1.0
PMI MANUFACTURING Germany					1.0
PMI MANUFACTURING France					0.8
PMI MANUFACTURING Italy	0.7	0.6	0.6		1.0
PMI COMPOSITE Euro Area	0.6				1.0
MIB PRICE INDEX - ELECTRONIC SECTOR (lag)	0.7	0.7	0.7		
IP: RUBBER & PLASTIC (lag)	1.0	0.8	0.9		0.9
IP: OTHER MANUF, REPAIR (lag)	1.0	1.0	1.0		

Note to Tables B.1 to B.6 presents the indicators that were ranked among the top fifteen predictors by the HARD- and SOFT-thresholding rules in the rolling exercise described in section. The exercise runs over 144 rolling samples. The size of each sample is 154 months, with the first one spanning from 1982m1 to 1995m1, and the last one from 1993m6 to 2006m6. For each indicator we show the probability of being selected by each thresholding rule. When the probability is lower than 0.6 we leave the cell empty.

Table B.2: Export - Variable selection

	LARS	LASSO	NET	FWD	HARD
REAL EFFECTIVE EXCHANGE RATE - CPI BASED	1.0	0.8	0.8		0.9
ITALIAN LIRE TO EURO (ECU)					0.8
SPREAD 12-3					1.0
INDUSTRIAL TURNOVER					1.0
SALES: FOREIGN	1.0	1.0	1.0		1.0
TURNOVER-DEFL					1.0
ISAE BUS.SVY.: INTERMED.GDS.- SELL.PRICE IN NEXT 3MOS					1.0
ISAE BUSINESS SVY.: SELLING PRICE IN NEXT 3MOS					0.6
RETAIL SURVEY: STOCKS - ITALY	0.7	0.6	0.6		
EXPORTS OF GOODS FOB					0.7
IMPORT UNIT VALUE INDEX					0.8
EXPORT VOLUME INDEX					0.9
EXPORTS: INTERMEDIATE GOODS					0.7
EXPORTS: INVESTMENT GOODS					0.6
EXPORT VALUE	0.8		0.7		1.0
IMPORT VALUE					1.0
EXPORT VOLUME	1.0	1.0	1.0	0.6	1.0
IT HOURLY WAGE RATE INDEX-DEFL	1.0	1.0	1.0		
ELECTRICITY CONSUMPTION MILAN (lag)	0.9	0.9	0.9	0.6	
IP: TEXTILE & CLOTHING (lag)	0.8	0.6	0.7		

Table B.3: Import - Variable selection

	LARS	LASSO	NET	FWD	HARD
PPI - LINKED & REBASED	0.7	0.8	0.8		
IP: INTERMEDIATE GOODS					0.9
IP: RUBBER & MATERIALS	1.0	1.0	1.0		1.0
IP: MANUFACTURE OF BASIC PHARMACEUTICAL	0.8	0.9	0.8		
IP: OTHER MANUF, REPAIR	0.9	0.7	0.7		
ISAE BUSINESS SVY.: ORDER BOOKS IN NEXT 3MOS					1.0
ISAE BUS.SVY.: INV.GDS.- ORDER BOOKS IN NEXT 3MOS					1.0
PMI MANUFACTURING Euro Area					1.0
PMI MANUFACTURING Germany	0.6				1.0
PMI MANUFACTURING France					1.0
PMI MANUFACTURING Italy					1.0
PMI MANUFACTURING Spain					1.0
PMI COMPOSITE Euro Area	0.8				1.0
ISAE CONSUMER SURVEY: GENERAL ECONOMIC EXPECTATIONS					0.7
IMPORT VALUE	0.9	0.9	0.9		1.0
IMPORT VOLUME	1.0	1.0	1.0	1.0	1.0
COMMERCIAL VEHICLE REGISTRATION (lag)	0.9	0.9	0.9	0.8	0.8
CIG CONSTRUCTION (lag)		0.6	0.6		
IP: MEANS OF TRANSPORT (lag)	0.9	0.8	0.8		
PMI MANUFACTURING Euro Area (lag)					0.7
PMI MANUFACTURING France (lag)					0.6
PMI COMPOSITE Euro Area (lag)					1.0
IMPORT UNIT VALUE INDEX (lag)	0.7	0.7	0.7	0.6	

Table B.4: Investment in construction - Variable selection

	LARS	LASSO	NET	FWD	HARD
NEW ORDERS: MANUFACTURING - MOTOR VEHICLES	1.0	1.0	1.0		
LOANS TO NON-FIN CORP.:LESS 1Y-DEFL					0.6
IP: INVESTMENT GOODS	0.7	1.0	1.0		
IP: MEANS OF TRANSPORT		0.7			
IP IN CONSTRUCTION	1.0	1.0	1.0	1.0	1.0
MIB PRICE INDEX - ELECTRONIC SECTOR	0.8	0.8	0.8		
ISAE BUSINESS SVY.: ORDER BOOKS - DOMESTIC					1.0
ISAE BUS.SVY.:INVESTMENT GOODS - ORDER BOOKS DOMESTIC					1.0
ISAE BUS.SVY.: CONSUMER GOODS - ORDER BOOKS DOMESTIC					1.0
ISAE BUSINESS SVY.: ORDER BOOKS - DOMESTIC					1.0
ISAE HOUSEHOLD CONFIDENCE INDEX					0.9
ISAE CONSUMER SURVEY: GENERAL ECONOMIC SITUATION					0.8
ISAE CONSUMER SURVEY: GENERAL ECONOMIC EXPECTATIONS					0.7
ISAE CONSUMER SURVEY: UNEMPLOYMENT EXPECTATIONS					1.0
ISAE CONSUMER SURVEY: HOUSEHOLDS EXPECTATIONS	0.8			0.7	1.0
RETAIL SURVEY: EMPLOYMENT - ITALY	1.0	0.9	1.0		1.0
ELECTRICITY CONSUMPTION FS (lag)	0.7	0.7	0.7		
ISAE BUSINESS SVY.: ORDER BOOKS - DOMESTIC (lag)					1.0
ISAE BUSINESS SVY.: PRODUCTION IN NEXT 3MOS. (lag)					1.0
ISAE BUS.SVY.:INVESTMENT GOODS - ORDER BOOKS DOMESTIC (lag)	1.0				1.0
ISAE BUS.SVY.: CONS.GDS.- PRODUCTION IN NEXT 3MOS. (lag)					0.7
ISAE BUSINESS SVY.: PRODUCTION IN NEXT 3MOS. (lag)					1.0
PMI MANUFACTURING Italy (lag)					0.8
CONSTRUCTION SURVEY: LIMITS TO ACTIVITY (lag)		0.6	0.6		

Table B.5: Other Investment - Variable selection

	LARS	LASSO	NET	FWD	HARD
CAR REGISTRATIONS - NEW LIGHT COMMERCIAL VEHICLES		0.6	0.8		
NEW ORDERS: MANUFACTURING - MOTOR VEHICLES	1.0	1.0	1.0		
COMMERCIAL VEHICLE REGISTRATION	1.0	0.8	0.8		0.9
REAL EFFECTIVE EXCHANGE RATE - CPI BASED	0.9	0.9	0.9		
CIG ORDINARY	0.6	0.6	0.7		
DOMESTIC ORDERS-DEFL	0.9	0.7	0.8		
IP	0.7	0.7	0.8		0.8
IP: MANUFACTURING	0.7	0.8	0.8		0.9
IP: INVESTMENT GOODS	1.0	1.0	1.0		1.0
IP: MEANS OF TRANSPORT	1.0	0.8	1.0	0.7	0.9
ISAE BUSINESS SVY.: ORDER BOOKS IN NEXT 3MOS.					1.0
ISAE BUSINESS SVY.: PRODUCTION IN NEXT 3MOS.					1.0
ISAE BUS.SVY.: INV.GDS.- ORDER BOOKS IN NEXT 3MOS.	1.0	0.6			1.0
ISAE BUS.SVY.: INV.GDS.- PRODUCTION IN NEXT 3MOS.					1.0
ISAE BUS.SVY.: CONS.GDS.- ORDER BOOKS IN NEXT 3MOS.	0.7				1.0
ISAE BUS.SVY.: CONS.GDS.- PRODUCTION IN NEXT 3MOS.	0.6				1.0
ISAE BUSINESS SVY.: ORDER BOOKS IN NEXT 3MOS.					1.0
PMI COMPOSITE Euro Area	1.0	0.7	0.7	0.9	1.0
ISAE CONSUMER SURVEY: GENERAL ECONOMIC EXPECTATIONS	0.7				0.8
ISAE CONSUMER SURVEY: UNEMPLOYMENT EXPECTATIONS	0.6				0.7
IMPORT VOLUME INDEX	0.6	0.7	0.7		
ITALIAN LIRE TO US $ (MTH.AVG.) (lag)	0.6	0.6	0.6		
IP IN CONSTRUCTION (lag)		0.8	0.6		
MIB PRICE INDEX - (lag)	0.7	0.7	0.7		

Table B.6: Private Consumption - Variable selection

	LARS	LASSO	NET	FWD	HARD
NEW PASSENGER CAR REGISTRATIONS	0.96	1.00	1.00	0.36	0.96
ELECTRICITY CONSUMPTION VENICE	0.66	0.65	0.67	0.36	0.12
HOURS WORKED - MANUFACTURING	0.73	0.73	0.73	0.36	0.73
OTHER MANUFACTURING, REPAIR	0.64	0.70	0.64	0.36	
PMI MANUFACTURING Euro area					0.83
PMI MANUFACTURING Germany					0.83
PMI MANUFACTURING France					0.76
PMI MANUFACTURING Italy					0.78
PMI MANUFACTURING Spain					0.79
PMI COMPOSITE Euro Area	0.78			0.37	0.93
RETAIL SURVEY: FUTURE BUSINESS SITUATION - ITALY	0.98	0.98	0.98	0.74	0.89
IMPORT VOLUME	0.88	0.77	0.84	0.40	0.86
ELECTRICITY CONSUMPTION PALERMO (lag)	0.71	0.77	0.75	0.60	
PMI COMPOSITE RECONSTRUCTED (lag)					0.86

Table B.7: Data description

Block	Description	start date	lag	treatment
DEM	NEW PASSENGER CAR REGISTRATIONS	Jan-90	1	deltap
DEM	CAR REGISTRATIONS - NEW LIGHT COMMERCIAL VEHICLES UP TO 3.5T	Jan-91	2	deltap
DEM	EXPORTS: MOTOR VEHICLES - TRAILERS / SEMI-TRAILERS	Jan-91	3	deltap
DEM	NEW ORDERS: MANUFACTURING - MOTOR VEHICLES	Jan-90	3	deltap
DEM	NEW ORDERS: MFG. - MOTOR VEHICLES / TRAILER BODIES (COACHWORK)	Jan-90	3	deltap
DEM	NEW ORDERS: MFG.- MOTOR VEHICLES, TRAILERS / SEMI-TRAILERS	Jan-90	3	deltap
DEM	RETAIL SALES VOLUME- FOOD	Jan-96	3	deltap
DEM	RETAIL SALES VOLUME- NON FOOD	Jan-96	3	deltap
DEM	RETAIL SALES VOLUME	Jan-96	3	deltap
DEM	COMMERCIAL VEHICLE REGISTRATION	Jan-80	1	deltap
ENEL	ELECTRICITY CONSUMPTION TOTAL	Jan-80	1	deltap
ENEL	ELECTRICITY CONSUMPTION RAILWAY	Jan-80	1	deltap
ENEL	ELECTRICITY CONSUMPTION TURIN	Jan-80	1	deltap
ENEL	ELECTRICITY CONSUMPTION MILAN	Jan-80	1	deltap
ENEL	ELECTRICITY CONSUMPTION VENICE	Jan-80	1	deltap
ENEL	ELECTRICITY CONSUMPTION FLORENCE	Jan-80	1	deltap
ENEL	ELECTRICITY CONSUMPTION ROME	Jan-80	1	deltap
ENEL	ELECTRICITY CONSUMPTION NEAPLES	Jan-80	1	deltap
ENEL	ELECTRICITY CONSUMPTION PALERMO	Jan-80	1	deltap
ENEL	ELECTRICITY CONSUMPTION CAGLIARI	Jan-80	1	deltap
EXCH	REAL EFFECTIVE EXCHANGE RATE - CPI BASED	Jan-80	1	deltap
EXCH	ITALIAN LIRE TO EURO (ECU)	Jan-80	1	deltap
EXCH	ITALIAN LIRE TO US $ (MTH.AVG.)	Jan-80	1	deltap
INT	INTEREST RATE ON 3 MONTH ITALIAN BOND	Feb-88	0	delta
INT	INTEREST RATE ON 6 MONTH ITALIAN BOND	Feb-88	0	delta
INT	INTEREST RATE ON 12 MONTH ITALIANBOND	Apr-87	0	delta
INT	INTEREST RATE ON 10 YEAR ITALIAN BOND	Apr-91	0	delta
INT	3-MONTH INTERBANK RATE ON DEPOSITS	Jan-80	1	delta
INT	INTEREST RATE ON 3 MONTH GERMAN BOND	Jan-80	0	delta
INT	INTEREST RATE 10 YEAR GERMAN BOND	Jan-80	0	delta
INT	3YEARS GOV BOND YIELD	Oct-92	0	delta
INT	5YEARS GOV BOND YIELD	Nov-88	0	delta
INT	10YEARS GOV BOND YIELD	Mar-91	0	delta
INT	30YEARS GOV BOND YIELD	Nov-93	0	delta
INT	LENDING RATE TO FIRMS-SHORT TERM (LESS THAN 1Y)	Apr-99	2	delta
INT	LENDING RATE TO FIRMS-LONG TERM	Jan-95	2	delta
INT	MORTGAGE RATE	Jan-95	2	delta
INT	SPREAD 12-month 3-month	Feb-88	0	none
INT	SPREAD 3-year 3-month	Oct-92	0	none
INT	SPREAD 10-year 3-month	Mar-91	0	none
INT	SPREAD 30-year 3-month	Nov-93	0	none
INT	SPREAD 10-year 3-year	Oct-92	0	none
INT	SPREAD 30-year 3-year	Nov-93	0	none
INT	SPREAD 10-year 5-year	Mar-91	0	none
INT	SPREAD 30-year 5-year	Nov-93	0	none
INT	SPREAD IT-3-month DE-3-month	Jan-80	1	none
INT	SPREAD IT-10-year DE-10-year	Mar-91	0	none
INT	SPREAD on LENDING RATE short	Apr-89	2	none
INT	SPREAD on LENDING RATE long	Jan-95	2	none
INT	SPREAD on MORTGAGE RATE	Jan-95	2	none
LAV	CIG IN MANUFACTURING	Jan-80	1	deltap
LAV	CIG ORDINARY	Jan-80	1	deltap
LAV	CIG CONSTRUCTION	Jan-84	1	deltap
MON	MONEY SUPPLY: M1 - IT CONTRIBUTION TO THE EURO AREA	Jan-80	2	deltap
MON	MONEY SUPPLY: M2 - IT CONTRIBUTION TO THE EURO AREA	Jan-80	2	deltap
MON	MONEY SUPPLY: M3 - IT CONTRIBUTION TO THE EURO AREA	Jan-80	2	deltap
MON	ITM1-DEFL	Jan-80	2	deltap
MON	ITM2-DEFL	Jan-80	2	deltap
MON	ITM3-DEFL	Jan-80	2	deltap
MON	LOANS TO HOUSEHOLD- CONSUMER CREDIT	Mar-80	2	deltap
MON	LOANS TO HOUSEHOLD- FOR HOUSE PURCHASE	Mar-80	2	deltap
MON	LOANS TO HOUSEHOLD- OTHER CREDIT	Mar-80	2	deltap
MON	LOANS TO NON FINANCIAL CORPORATION- TOTAL	Mar-80	2	deltap
MON	LOANS TO NON FINANCIAL CORPORATION- above 1 YEAR	Mar-80	2	deltap
MON	LOANS TO NON FINANCIAL CORPORATION- below 1 YEAR	Mar-80	2	deltap
MON	CREDIT TO PRIVATE SECTOR- TOTAL	Jan-83	2	deltap
MON	SOFFERENZE IN PERC PRESTITI	Jan-90	2	delta
MON	CONSUMER LOANS-DEFL	Mar-80	2	deltap
MON	MORTGAGE LOANS-DEFL	Mar-80	2	deltap
MON	LOANS TO NON-FIN CORP.:LESS 1Y-DEFL	Mar-80	2	deltap
MON	LOANS TO NON-FIN CORP.:OVER 1Y-DEFL	Mar-80	2	deltap
MON	OTHER LOANS TO HOUSEHLD-DEFL	Mar-80	2	deltap
MON	CREDIT TO PRIVATE SECTOR-DEFL	Jan-83	2	deltap
MON	TOTAL LOANS TO NONFIN. CORP-DEFL	Mar-80	2	deltap
ORD-TURN	NEW ORDERS	Jan-90	3	deltap
ORD-TURN	NEW ORDERS: DOMESTIC	Jan-90	3	deltap
ORD-TURN	NEW ORDERS: FOREIGN	Jan-90	3	deltap
ORD-TURN	INDUSTRIAL TURNOVER	Jan-90	3	deltap
ORD-TURN	SALES: DOMESTIC	Jan-90	3	deltap
ORD-TURN	SALES: FOREIGN	Jan-90	3	deltap
ORD-TURN	NEW ORDERS-DEFL	Jan-90	3	deltap
ORD-TURN	DOMESTIC ORDERS-DEFL	Jan-90	3	deltap
ORD-TURN	FOREIGN ORDRES-DEFL	Jan-90	3	deltap

ORD-TURN	TURNOVER-DEFL	Jan-90	3	deltap
PREZZI	PPI - LINKED / REBASED	Jan-81	2	deltap
PREZZI	CPI INCLUDING TOBACCO (NIC)	Jan-80	1	deltap
PREZZI	BALTIC DRY INDEX	May-85	0	deltap
PREZZI	COMPOSITE PRICE INDEX - FOOD COMMODITIES	Jan-80	2	deltap
PREZZI	MARKET PRICE INDEX - PRIMARY COMMODITIES	Jan-83	2	deltap
PREZZI	EXPORT PRICE - NON FUEL PRIMARY COMMODITIES INDEX	Feb-80	2	deltap
PREZZI	PRICE OF OIL BRENT	Feb-82	0	deltap
PROD-IND	IP	Jan-80	2	deltap
PROD-IND	IP: MANUFACTURING	Jan-80	2	deltap
PROD-IND	IP: CONSUMER GOODS	Jan-90	2	deltap
PROD-IND	IP: CONSUMER GOODS - DURABLE	Jan-90	2	deltap
PROD-IND	IP: CONSUMER GOODS - NON-DURABLE	Jan-90	2	deltap
PROD-IND	IP: INVESTMENT GOODS	Jan-90	2	deltap
PROD-IND	IP: INTERMEDIATE GOODS	Jan-90	2	deltap
PROD-IND	IP: ENERGY	Jan-90	2	deltap
PROD-IND	IP: CHEMICAL PRODUCTS / SYNTHETIC FIBRES	Jan-90	2	deltap
PROD-IND	IP: COKE MANUFACTURE / PETROLEUM REFINING	Jan-90	2	deltap
PROD-IND	IP: EXTRACTION OF MINERALS	Jan-90	2	deltap
PROD-IND	IP: FOOD, DRINK / TOBACCO	Jan-90	2	deltap
PROD-IND	IP: MACHINES / MECHANICAL APPARATUS	Jan-90	2	deltap
PROD-IND	IP: MEANS OF TRANSPORT	Jan-90	2	deltap
PROD-IND	IP: METAL / METAL PRODUCTS	Jan-90	2	deltap
PROD-IND	IP: RUBBER ITEMS / PLASTIC MATERIALS	Jan-90	2	deltap
PROD-IND	IP: TEXTILE / CLOTHING	Jan-90	2	deltap
PROD-IND	IP: WOOD / WOOD PRODUCTS	Jan-90	2	deltap
PROD-IND	IP: MANUFACTURE OF COMPUTER, ELECTRONIC AND OPTICAL PRODUCTS	Jan-90	2	deltap
PROD-IND	IP: MANUFACTURE OF ELECTRICAL EQUIPMENT	Jan-90	2	deltap
PROD-IND	IP: MANUFACTURE OF BASIC PHARMACEUTICAL PRODUCTS	Jan-90	2	deltap
PROD-IND	IP: ELECTRICITY, GAS, STEAM AND AIR CONDITIONING	Jan-90	2	deltap
PROD-IND	IP: OTHER MANUFACTURING, AND REPAIR AND INSTALLATION OF MACHINERY AN	Jan-90	2	deltap
PROD-IND	IP IN CONSTRUCTION	Jan-91	3	deltap
SP	MIB PRICE INDEX	Jan-80	0	deltap
SP	MIB PRICE INDEX - BANKING SECTOR	Jan-80	0	deltap
SP	MIB PRICE INDEX - PHARM SECTOR	Feb-86	0	deltap
SP	MIB PRICE INDEX - TELECOM SECTOR	Jan-80	0	deltap
SP	MIB PRICE INDEX - INDUSTRY SECTOR	Jan-80	0	deltap
SP	MIB PRICE INDEX - INSURANCE SECTOR	Jan-80	0	deltap
SP	MIB PRICE INDEX - INFO SECTOR	Feb-86	0	deltap
SP	MIB PRICE INDEX - OIL/GAS SECTOR	Feb-86	0	deltap
SP	MIB PRICE INDEX - ELECTRONIC SECTOR	Feb-86	0	deltap
SP	MIB PRICE INDEX - MEDIA SECTOR	Feb-86	0	deltap
SP	MIB PRICE INDEX - BANKING SECTOR	Dec-88	0	deltap
SP	MIB PRICE INDEX - AUTO SECTOR	Jan-80	0	deltap
SP	ITALY-DS Market -PRICE EARNING RATIO	Feb-86	0	none
SP	ITALY-DS Market - DIVIDEND YIELD	Jan-80	0	none
SUR-BUS	ISAE BUSINESS CONFIDENCE INDICATOR	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: ORDER BOOKS - DOMESTIC, NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: ORDER BOOKS - EXPORT, NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: ORDER BOOKS, NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: STOCKS OF FINISHED GOODS, NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: PRODUCTION LEVEL, NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: ORDER BOOKS IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: PRODUCTION IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: SELLING PRICE IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: ECONOMY IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: INTERMED. GDS.- ORDER BOOKS DOMESTIC, NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: INTERMED. GDS.- ORDER BOOKS EXPORT, NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: INTERMED. GDS.- ORDER BOOKS, NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: INTERMED. GDS.- STOCKS OF FIN.GDS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: INTERMED. GDS.- PRODUCTION LEVEL, NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.:INVESTMENT GOODS - ORDER BOOKS DOMESTIC, NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.:INVESTMENT GOODS - ORDER BOOKS EXPORT, NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.:INVESTMENT GOODS - ORDER BOOKS, NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.:INVESTMENT GOODS - STOCKS OF FIN.GDS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.:INVESTMENT GOODS - PRODUCTION LEVEL, NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: CONSUMER GOODS - ORDER BOOKS DOMESTIC, NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: CONSUMER GOODS - ORDER BOOKS EXPORT, NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: CONSUMER GOODS - ORDER BOOKS, NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: CONSUMER GOODS - STOCKS OF FIN.GDS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: CONSUMER GOODS - PRODUCTION LEVEL, NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: INTERMED.GDS.- ORDER BOOKS IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: INTERMED.GDS.- PRODUCTION IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: INTERMED.GDS.- SELL.PRICE IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: INTERMED.GDS.- ECONOMY IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: INV.GDS.- ORDER BOOKS IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: INV.GDS.- PRODUCTION IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: INV.GDS.- SELLING PRICE IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: INV.GDS.- ECONOMY IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: CONS.GDS.- ORDER BOOKS IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: CONS.GDS.- PRODUCTION IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: CONS.GDS.- SELLING PRICE IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUS.SVY.: CONS.GDS.- ECONOMY IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: ORDER BOOKS, NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: ORDER BOOKS - DOMESTIC, NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: ORDER BOOKS - EXPORT, NET	Jan-91	1	none

SUR-BUS	ISAE BUSINESS SVY.: ORDER BOOKS IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: STOCKS OF FINISHED GOODS, NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: PRODUCTION LEVEL, NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: PRODUCTION IN NEXT 3MOS., NET	Jan-91	1	none
SUR-BUS	ISAE BUSINESS SVY.: SELLING PRICE IN NEXT 3MOS., NET	Jan-91	1	none
PMI	PMI MANUFACTURING RECONSTR EURO AREA	Apr-87	1	none
PMI	PMI MANUFACTURING RECONSTR GERMANY	Apr-87	1	none
PMI	PMI MANUFACTURING RECONSTR FRANCE	Apr-87	1	none
PMI	PMI MANUFACTURING RECONSTR ITALY	Apr-87	1	none
PMI	PMI MANUFACTURING RECONSTR SPAIN	Apr-87	1	none
PMI	PMI COMPOSITE RECONSTRUCTED ITALY	Jan-87	1	none
SUR-CONS	ISAE HOUSEHOLD CONFIDENCE INDEX	Jan-80	1	none
SUR-CONS	ISAE CONSUMER SURVEY: GENERAL ECONOMIC SITUATION (BALANCE)	Jan-82	1	none
SUR-CONS	ISAE CONSUMER SURVEY: GENERAL ECONOMIC EXPECTATIONS (BALANCE)	Jan-82	1	none
SUR-CONS	ISAE CONSUMER SURVEY: UNEMPLOYMENT EXPECTATIONS (BALANCE)	Jan-82	1	none
SUR-CONS	ISAE CONSUMER SURVEY: ECONOMIC SITUATION OF HOUSEHOLDS (BALANCE)	Jan-82	1	none
SUR-CONS	ISAE CONSUMER SURVEY: ECONOMIC EXPECTATIONS OF HOUSEHOLDS (BAL.)	Jan-82	1	none
SUR-CONS	ISAE CONSUMER SURVEY: HOUSEHOLDS BUDGET (BALANCE)	Jan-82	1	none
SUR-CONS	ISAE CONS.SVY.: PRESENT INTENTIONS TO PURCHASE DURABLES (BAL.)	Jan-82	1	none
SUR-CONS	CONSUMER SURVEY: PRICES NEXT 12 MONTHS - ITALY	Jan-85	1	none
SUR-CONS	CONSUMER SURVEY: SAVINGS AT PRESENT - ITALY	Jan-85	1	none
SUR-CONS	CONSUMER SURVEY: SAVINGS OVER NEXT 12 MONTHS - ITALY	Jan-85	1	none
SUR-CONS	CONSUMER SURVEY: PRICES LAST 12 MONTHS - ITALY	Jan-85	1	none
SUR-OTH	RETAIL CONFIDENCE INDICATOR - ITALY	Oct-85	1	none
SUR-OTH	RETAIL SURVEY: CURRENT BUSINESS SITUATION - ITALY	Oct-85	1	none
SUR-OTH	RETAIL SURVEY: STOCKS - ITALY	Oct-85	1	none
SUR-OTH	RETAIL SURVEY: FUTURE BUSINESS SITUATION - ITALY	Oct-85	1	none
SUR-OTH	RETAIL SURVEY: ORDERS PLACED WITH SUPPLIERS - ITALY	Jan-86	1	none
SUR-OTH	RETAIL SURVEY: EMPLOYMENT - ITALY	Nov-03	1	none
SUR-OTH	CONSTRUCTION CONFIDENCE INDICATOR - ITALY	Jan-85	1	none
SUR-OTH	CONSTRUCTION SURVEY: ORDER BOOK POSITION - ITALY	Jan-85	1	none
SUR-OTH	CONSTRUCTION SURVEY: EMPLOYMENT EXPECTATIONS - ITALY	Jan-85	1	none
SUR-OTH	CONSTRUCTION SURVEY: ACT. COMPARED TO LAST MONTH - ITALY	Jan-85	1	none
SUR-OTH	CONSTRUCTION SURVEY: PRICE EXPECTATIONS - ITALY	Jan-85	1	none
SUR-OTH	CONSTRUCTION SURVEY: LIMITS TO ACTIVITY - DEMAND, ITALY	Jan-85	1	none
SUR-OTH	SERVICES SURVEY: EVOLUTION OF DEMAND IN RECENT MONTHS - ITALY	Apr-96	1	none
SUR-OTH	SERVICES SURVEY: EVOLUTION OF DEMAND EXPECTED IN MTH.AHEAD-ITALY	Apr-96	1	none
SUR-OTH	SERVICES SURVEY: EVOLUTION OF EMP EXPECTED IN MTH. AHEAD - ITALY	Apr-96	1	none
SUR-OTH	SERVICES SURVEY: PRICE EXPECTATION IN MONTHS AHEAD - ITALY	Jan-97	1	none
TRADE	EXPORTS OF GOODS FOB	Jan-91	2	deltap
TRADE	IMPORTS OF GOODS CIF	Jan-91	2	deltap
TRADE	EXPORT UNIT VALUE INDEX	Jan-80	2	deltap
TRADE	IMPORT UNIT VALUE INDEX	Jan-88	2	deltap
TRADE	EXPORT VOLUME INDEX	Jan-80	2	deltap
TRADE	IMPORT VOLUME INDEX	Jan-80	2	deltap
TRADE	EXPORTS: CONSUMER GOODS	Jan-91	2	deltap
TRADE	EXPORTS: CONSUMER GOODS - NON-DURABLE	Jan-91	2	deltap
TRADE	EXPORTS: CONSUMER GOODS - DURABLE	Jan-91	2	deltap
TRADE	EXPORTS: INTERMEDIATE GOODS	Jan-91	2	deltap
TRADE	EXPORTS: INVESTMENT GOODS	Jan-91	2	deltap
TRADE	IMPORTS FROM EU27: ENERGY	Jan-93	2	deltap
TRADE	IMPORTS FROM EU27: CONSUMER GOODS	Jan-93	2	deltap
TRADE	IMPORTS FROM EU27: INTERMEDIATE GOODS	Jan-93	2	deltap
TRADE	IMPORTS FROM EU27: INVESTMENT GOODS	Jan-93	2	deltap
TRADE	IMPORTS FROM NON-EU COUNTRIES (EU27): INTERMEDIATE GOODS	Jan-93	2	deltap
TRADE	IMPORTS FROM NON-EU COUNTRIES (EU27): INVESTMENT GOODS	Jan-93	2	deltap
TRADE	IMPORTS FROM NON-EU COUNTRIES (EU27): CONSUMER GOODS - DURABLE	Jan-93	2	deltap
TRADE	IMPORTS FROM NON-EU COUNTRIES (EU27): CONSUMER GOODS - NON-DURAB	Jan-93	2	deltap
TRADE	EXPORT VALUE INDEX	Jan-80	2	deltap
TRADE	IMPORT VALUE INDEX	Jan-80	2	deltap
TRADE	EXPORT UNIT VALUE INDEX	Jan-80	2	deltap
TRADE	IMPORT UNIT VALUE INDEX	Jan-80	2	deltap
TRADE	EXPORT VOLUME INDEX	Jan-80	2	deltap
TRADE	IMPORT VOLUME INDEX	Jan-80	2	deltap
WAGE	HOURLY WAGE RATE INDEX: ALL INDUSTRY - MANUAL / CLERICAL WORKERS	Nov-84	2	deltap
WAGE	WAGE PER EMPLOYEE	Jan-96	2	deltap
WAGE	IT WAGE PER EMPLOYEE-DEFL	Jan-96	2	deltap
WAGE	IT HOURLY WAGE RATE INDEX: ALL IND-MANUAL / CLERICAL WORKERS-DEFL	Nov-84	2	deltap

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