Predicting Belgium's GDP using targeted bridge models

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by Christophe Piette

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Abstract

This paper investigates the usefulness, within the frameworks of the standard bridge model and the 'bridging with factors' approach, of a predictor selection procedure that builds on the elastic net algorithm. A pseudo-real time forecasting exercise is performed, in which estimates for Belgium's quarterly GDP are generated using a monthly dataset of 93 potential predictors. While the simulation results indicate that specifying forecasting models using this procedure can lead to a slight improvement in terms of predictive accuracy over shorter horizons, the forecasting errors made by these 'targeted' models are not found to be significantly different from those based on the principal components extracted from the entire set of available indicators. In other words, the only advantage of following such an approach lies in the fact that it enables the forecaster to streamline the information set.

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1. Introduction

Among all the statistical information economists have at their disposal for monitoring real economic developments, quarterly GDP is definitely one of the most relevant. This aggregate can be viewed as the most representative of the state of the economy at a given point in time in the sense that it covers all the industries and incorporates all the demand components. However, GDP figures, like other quarterly national accounts statistics, have the disadvantage of being released with some delay after the end of the period they relate to. Consequently, the lack of any timely data for GDP is often overcome by relying on other indicators such as those obtained from sentiment surveys, financial markets or administrative sources. In addition to being released earlier than the quarterly national accounts data, these indicators are often available at higher frequencies, typically monthly or daily, and can thus give at least a partial view on the economic developments in a given quarter, even before its end.

There are different techniques – often referred to as *nowcasting* methods – that can be used to extract the information conveyed by these advanced indicators and to convert it into early estimates of GDP or other macroeconomic aggregates. Among practitioners, the most popular ones are typically the factor models and the bridge models, as well as a combination of these two approaches, referred to as 'bridging with factors'. A recent survey of the literature on nowcasting can be found in Bańbura *et al.* (2013).

Models based on factors, in particular that developed by Giannone *et al.* (2008) who formalise the process of nowcasting by introducing the release calendar as an essential element, have received much attention in the literature over the past twenty years. The idea that underpins these models is quite simple: it consists in estimating one or several unobserved variables, called 'factors', that capture the main co-movements driving a large set of macroeconomic indicators assumed to reflect developments in the business cycle. The main asset of these models lies in their predictive performance. They have indeed proved to be relatively more accurate than other short-term forecasting methods. An implementation of a related approach based on Belgian data can be found in de Antonio Liedo (2014).

Standard bridge models, on the other hand, have an advantage in terms of readability. The fact that they take the form of a simple linear equation makes it easier to grasp the link between the indicators included on its right-hand side and the forecast inferred from their movement. From the point of view of an economic analyst, this feature facilitates considerably the communication about his/her assessment of the current economic situation by referring to a limited number of advanced indicators. However, the fact that they can include only a small number of explanatory variables is also one of their main drawbacks, as it entails the risk of neglecting some indicators that could otherwise improve the accuracy of the forecast. It is therefore essential, when specifying such a forecasting model, to correctly identify the most informative variables among a larger set of indicators.

This paper explores the potential benefits from predictor selection to forecast Belgium's quarterly GDP, using both standard bridge models and the bridging with factors approach. The selection algorithm used takes two aspects into account, which are particularly relevant in the context of a real-time forecasting exercise. The first is, obviously, the individual indicators' predictive power over GDP. The second relates to the data release calendar, in particular to the fact that the availability of monthly data differs depending on the point in time at which the forecast is made.

In that perspective, I have opted for one of the variable selection procedures suggested by Bai and Ng (2008), namely the elastic net algorithm originally proposed by Zou and Hastie (2005). Bai and Ng (2008) implement this algorithm in order to select a sub-set of 'targeted' predictors they include in a monthly factor model for inflation in the US. Using this method has two advantages. Firstly, it makes it possible to perform a selection among a very wide panel of potential predictors, which allows for some agnosticism in the variable selection process. Secondly, as underlined by Bai and Ng (2008), it avoids selecting variables that are too similar. I also take into account the fact that monthly indicators are not all released at the same time and that short-term forecasts of GDP are consequently usually based on 'ragged-edge' datasets. For that purpose, I resort to a refinement suggested by Bessec (2013) that, in substance, involves running the elastic net on a dataset transformed in order to reflect the situation of data availability as it stands at the time the forecasting exercise is carried out.

The relevance of this strategy for predicting Belgium's quarterly GDP growth is evaluated on the basis of a dataset consisting of 93 monthly indicators deemed relevant for the analysis of the Belgian business cycle, and whose release calendar is also documented in this paper. Applying this selection procedure to these indicators, and using the outcome to specify *targeted* bridge model yields, within the framework of a pseudo real-time forecasting exercise, results that are in line with those obtained by Bai and Ng (2008) and Bessec (2013), in that the inclusion of only a sub-set of the indicators selected using this procedure gives rise to a slight reduction in the models' forecast errors. However, this finding holds mainly for shorter forecast horizons and, in any case, the differences in terms of predictive accuracy with respect to a more standard diffusion index forecast based on the full dataset of monthly indicators are not significant, neither when the predictor selection is based on the entire sample period nor – and even less so – when it is carried out recursively based on past observations. In other words, the advantage of using this approach would lie exclusively in the streamlining of the dataset used to produce the GDP forecasts, with neither gains nor detrimental effects on the model's predictive performance.

Furthermore, as already shown by Bessec (2013), the composition of the set of selected indicators differs strongly at various points in the data release calendar. Typically, the selection algorithm tends to favour soft data – such as indicators obtained from business and consumer sentiment surveys – for the earliest estimates, when some observations are available solely for these indicators, which are therefore the only ones that provide some information on the developments in the quarter considered. Then, when hard data – in particular the turnover of Belgian firms – become available, some of them appear among the most relevant predictors owing to their higher correlation with GDP.

Incidentally, the program platform used to carry out the different stages of the forecasting process described in this paper was named **BREL**, as it combines **BR**idge models with the **EL**astic net algorithm to select their right-hand-side variables. This platform has now become one of the main tools used by the National Bank of Belgium, along with the dynamic factor model of de Antonio Liedo (2014), to produce short-term forecasts of various quarterly macroeconomic aggregates and to monitor the business cycle in Belgium.

The remainder of this paper proceeds as follows. The second and the third section briefly describe the two forecasting techniques used, namely the standard bridge model and the bridging with factors approach, and the predictor selection procedure, respectively. The forecasting performances of the targeted models specified on the basis of the predictor selection procedure are then assessed by means of a pseudo real-time exercise in the fourth section. The outcome of the predictor selection, in particular its sensitivity to the availability of monthly data, is also examined in that part. Conclusions are drawn in the fifth and last section.

2. Bridge models

2.1. Standard bridge models

As its name indicates, a bridge model relates a quarterly aggregate Y_t to a set of monthly predictors converted to the quarterly frequency, denoted $X_{i,t}^{Q}$. In its most general form, the model's main equation – the bridge equation – is specified as an autoregressive-distributed lag model (ADL):

$$Y_{t+h} = \mu + \sum_{j=1}^{p} \rho_j Y_{t-j} + \sum_{i=1}^{n} \sum_{j=0}^{q} \beta_{i,j} X_{i,t-j}^{Q} + \varepsilon_t \tag{1}$$

where *p* is the number of autoregressive terms, *n* is the number of predictors, and *q* the number of lags for the explanatory variables. The parameters, i.e. the constant μ, the autoregressive parameters ρ_j and the coefficients $\beta_{i,j}$ are estimated via an ordinary least squares (OLS) regression.

If $h = 0$, Equation (1) generates an out-of-sample prediction for Y_t in the quarter that follows the last observation available, which will be henceforth referred to as the *current* quarter. For that purpose, the observation for the monthly predictors should in principle cover that quarter entirely. However, in a real-time forecasting exercise, these observations are often missing or available only for the first month or the first two months, depending on the indicators. These gaps are usually filled in by extending the predictor series over the remainder of the quarter using univariate 'satellite' models, such as autoregressive (AR) or autoregressive moving-average (ARMA) processes. The former of these two options is by far the most popular because it is much less computationally intensive than the latter[1]. The satellite AR model for a given monthly predictor ($X_{i,m}$) can be written as

$$X_{i,m} = \phi_0 + \sum_{j=1}^{l} \phi_j X_{i,m-j} + \eta_m \tag{2}$$

[1] The estimation of the parameters of an ARMA process requires an iterative procedure, such as the Kalman filter or the non-linear least squares estimator. Consequently, it takes much more time to identify and estimate models with moving averages than models that include only autoregressive terms using the standard Box-Jenkins procedure. Yet, experiments carried out based on the monthly indicators used in this paper did not show any significant differences between most of the forecasts obtained from these two approaches. These computational considerations also motivate the use of AR processes in the selection procedure described in Section 3.

where l stands for the number of autoregressive parameters. As a rule, the number of lags is selected so as to minimise Schwarz's Bayesian information criterion (BIC), with a maximum of six lags.

In addition to predicting the value of Y_t in the current quarter, for which some monthly data are assumed to have already been released, forecasts for the next few quarters can also be generated using models with leads, i.e. with $h \geq 1$. In principle, the satellite AR models could be used to extend the monthly predictor series beyond the current quarter, and the quarterly aggregation of their forecasts could then be plugged into the bridge equation, along with the estimate of Y_t, to generate predictions for quarters *t+1*, *t+2*, and the subsequent ones. However, this strategy runs the risk of compounding forecast errors for the monthly predictors over the forecast horizon, which might then have detrimental effects on the accuracy of the prediction of the quarterly aggregate. This issue can arise if the AR models are somehow misspecified, which is likely to be the case in the sense that they can only be considered as an approximation of the true data generation processes[1]. In order to limit the ensuing uncertainty, I follow an approach similar to that of Andreou *et al.* (2013) within the mixed data sampling (MIDAS) framework. In that approach, the *h*-quarters ahead forecast is not obtained iteratively, but on the sole basis of the monthly data related to the current quarter (if necessary complemented with autoregressive forecasts so as to make conversion to the quarterly frequency possible).

The main downside of the bridge model is that it can incorporate only a limited number of predictors. Indeed, like in any other linear model estimated by OLS, including too many explanatory variables for a given number of observations increases parameter uncertainty, leading thereby to higher forecast errors. On the other hand, by restricting the number of predictors, one also runs the risk of ignoring some that could possibly provide relevant indications on the developments in the quarterly aggregate.

2.2. Bridging with factors

Unlike standard bridge models, the so-called 'bridging with factors' approach is not constrained by a limited number of predictors since these are replaced by some sort of weighted averages, called factors, which capture their main 'co-movements'. This approach has been implemented in multiple ways, which mainly differ in the way factors are extracted. For ex-

[1] See also Marcellino *et al.* (2006) for an in-depth discussion on this topic.

ample, Giannone *et al.* (2008) exploit the Kalman filter to extract the main common factors from a large unbalanced dataset of predictor series, improving on the approach of Stock and Watson (2002), who aim to capture the information content of the data by estimating principal components. Both of these two approaches exhibit generally good forecasting performances. Cross-country empirical analyses, such as those conducted by Barhoumi *et al.* (2008) and Jansen *et al.* (2013), show that they are generally more accurate in predicting quarterly GDP growth than several alternative methods, in particular those that consist in averaging predictions obtained from individual bridge equations, vector autoregressive (VAR) models or MIDAS models.

I have opted here for the diffusion index framework because of its computational simplicity. In its general form, this model can be compiled by replacing the *n* monthly predictors in Equation (1) by their common factors:

$$Y_{t+h} = \mu + \sum_{j=1}^{p} \rho_j Y_{t-j} + \sum_{i=1}^{r} \sum_{j=0}^{q} \varphi_{i,j} F_{i,t-j}^{Q} + \varepsilon_t \tag{3}$$

where $F_{i,t}$ is one of the *r* factors included in the model, with $r << n$, estimated using the principal components method. Let X_t be a vector of size *n*, which contains the (standardised) monthly series, and F_t the vector of size *r* that includes the common factors. It is assumed that the former and the latter are related according to the following equation:

$$X_t = \Lambda F_t + \nu_t \tag{4}$$

where the loadings in Λ are normalised so that $(1/n)\Lambda'\Lambda = I_r$. The principal component estimator for Λ and F_t is obtained from minimising the sum of squared residuals of Equation (4). Finding the solution to this minimisation problem amounts to calculating the (normed) eigenvectors, denoted *V*, of the sample variance matrix of X_t, i.e. $\hat{\Sigma}_X = (1/T)\sum_{t=1}^{T} X_t X_t^{'}$, associated with the *r* first eigenvalues. The estimates for the common factors can then be calculated as

$$\hat{F}_t = X_t V \tag{5}$$

In a way, Equation (5) can be viewed as a weighted average of the monthly predictors. Finally, $\hat{\Lambda}$ can be obtained from a simple OLS regression of X_t on $\hat{F}_t$:

$$\hat{\Lambda} = \left(\hat{F}'\hat{F}\right)^{-1}\hat{F}'X \tag{6}$$

To identify the optimal number of factors (*r*) in model depicted in Equations (3) and (4), I rely on the method of Bai and Ng (2002), who proposed a series of estimates based on various information criteria. Basically, the identification of the number of factors amounts to solving an optimisation problem, which, if based on their IC_{p2} criterion, can be formulated as

$$\hat{r} = \underset{0\le k\le r^{\max}}{\operatorname{argmin}} \ln\left(V\left(k,\hat{F}^k\right)\right) + k\left(\frac{n+T}{nT}\right)\ln\left(\min\left\{n,T\right\}\right) \tag{7}$$

where $V\left(k,\hat{F}^k\right) = \left(1/nT\right)\sum_{t=1}^{T}\left(X_t - \hat{\Lambda}\hat{F}^k\right)'\left(X_t - \hat{\Lambda}\hat{F}^k\right)$ is the sum of the squared residuals from Equation (4). $\hat{F}^k$ and $\hat{\Lambda}^k$ are the estimates from Equations (5) and (6), respectively, allowing for *k* factors in the model. The simulations performed by Bai and Ng (2002) show that this information criterion provides a consistent estimate of *r*. It is furthermore better at identifying the true number of factors than more conventional information criteria, such as the Akaike and the Bayesian information criteria.

As for the selection of the number of lagged factors (*q*) and lagged dependents (*p*) to be included in the model, I simply follow Stock and Watson (2002) by using the combination of these two parameters that minimises the BIC of Equation (3), allowing in each case for a maximum of two lags.

Since $\hat{F}^k$ can only be calculated using a balanced dataset, forecasts for one or several periods ahead based on the diffusion index framework of Stock and Watson (2002) are usually made using models with leads. In order to exploit the monthly data released in the course of the current quarter, I extend the factors series until the last month of that quarter in the same way as Barhoumi *et al.* (2008). This is done by generating forecasts of the monthly series contained in X_t by means of individual satellite AR models – analogous to those used in the bridge model – and multiplying them by the weights from the matrix *V*, as in Equation (5).

The way the non-synchronous monthly data releases are treated in the bridging with factors approach followed throughout this paper is thus different from that proposed by

Gianonne *et al*. (2008). It is also different from the multivariate method used by de Antonio Liedo (2014) on Belgian data, where all the variabes are jointly specified in terms of factors. As highlighted in the survey paper by Bańbura *et al*. (2013), the advantage of that latter approach is the possibility to derive the impact of news on the forecast for GDP. However, this issue is not dealt whith in this paper, which focuses on the identification of the variables that are most helpful at forecasting quarterly GDP growth, and not the analysis of forecasting revisions. In this regard, the diffusion index framework, like the standard bridge model, is a suitable and transparent methodology.

3. Predictor selection

The predictive performance of a forecasting model can be optimised by avoiding including indicators that do not convey any adequate information on changes in the dependent variable. To this end, one can rely on a variable selection procedure that helps in identifying the most relevant variables and leaving out the most 'noisy' ones. Such a procedure is best automated so that the selection and the resulting model can be reviewed periodically, as the correlation of some potential predictors with the dependent variable, and hence their relevance, might change over time.

Different selection methods were proposed in the literature. One selection algorithm often used within the framework of bridge models[1] is the general-to-specific modelling strategy (*PCGets*) of Krolzig and Hendry (2001). This algorithm starts from a general unrestricted model, typically specified based on the econometrician's assumptions on the data generating process, and estimated using an OLS regression. Non-significant variables are then removed sequentially and a battery of tests is run to check the validity of the reduction. In the final stage, the models obtained from different search paths are compared in order to select the final model. The main disadvantage of this variable selection procedure is that it requires a pre-selection of a limited number of variables so as to ensure a sufficient number of degrees of freedom in the OLS estimation. Sédillot and Pain (2005) avoid such a pre-selection, which may to some extent be arbitrary, by first generating a ranking of a large set of predictors based on the adjusted R^2 from bivariate regressions with GDP growth as the dependent variable. Then they estimate ARDL models with all possible combinations of the four top-ranked

[1] See for example Barhoumi *et al.* (2011).

variables. The final bridge equation is the one that exhibits the smallest BIC. This type of method is known as *hard thresholding*.

I have opted here for a *soft thresholding* method, namely the elastic net algorithm proposed by Zou and Hastie (2005). In a nutshell, the elastic net, like the lasso which is a particular case of it, is based on a standard linear model augmented with a penalty, and the numerical method used to estimate the coefficients makes it possible to set to zero those for the less relevant explanatory variables. The number of the variables excluded from the model in that way is determined by a specific parameter, which can therefore be used to generate an ordering of a large number of potential predictors according to their explanatory power over the dependent variable. Another important advantage of this algorithm is that the initial model can include considerably more variables than available observations. Consequently, the selection can be carried out in a fairly agnostic way since a pre-selection of a limited number of potential variables is not necessary.

The elastic net was first used in the context of economic forecasting by Bai and Ng (2008) within the diffusion index forecasting framework for predicting inflation in the US, along with alternative methods. They show that using only the most informative predictors – which they refer to as 'targeted' predictors – and leaving out the less relevant ones can improve forecast accuracy. They also show that the gain is greater when predictors are selected using soft-thresholding methods like the lasso or the elastic net. One explanation for this finding is that, in contrast to variable rankings based on hard-thresholding rules like the Student statistics from individual bivariate regressions[1], the elastic net makes it possible to avoid selecting variables which are too similar. Obviously, this feature is also of prime interest in the standard multivariate linear regression framework which forms the basis of the bridge model described in the previous section, as it should help avoid potential multicollinearity issues to which this type of model is prone. To my knowledge, the soft-thresholding selection methods advocated by Bai and Ng (2008) had thus far only been applied to bridge models by Bulligan *et al.* (2012), who used them in combination with the general-to-specific routine. Their findings are consistent with those of Bai and Ng (2008), in that the forecasts from the models inferred from the variable selection outperform in most cases those from a diffusion index model estimated on the basis of the entire dataset. Another study worth mentioning is that of De Mol *et al.* (2008), who propose a soft-thresholding selection technique similar to the lasso in a much different framework, namely the Bayesian regression with a prior intended to

[1] This rule tested by Bai and Ng (2008) along with the lasso and the elastic net is very similar to that of Sédillot and Pain (2005).

shrink all the coefficients towards zero. Using a large panel of time series characterised by a strong collinearity between them, they find that the forecasts obtained from that *variable selection* approach are highly correlated with those obtained from *variable aggregation* based on principal components. These findings are compatible with the results that will be discussed in section 4.

The elastic net algorithm used in this study involves more specifically minimising the sum of square errors from a linear model, like in the simple OLS regression, adding two penalties for the number of parameters to the objective function which, if based on Equation (1), can be formulated as

$$\min_{\rho,\beta} \frac{1}{2T}\sum_{t=1}^{T}\left(\tilde{Y}_t-\tilde{Y}_t^e\right)^2+\frac{\lambda(1-\alpha)}{2}\left[\sum_{j=1}^{p}\rho_j^2+\sum_{i=1}^{n}\sum_{j=0}^{q}\beta_{i,j}^2\right]+\lambda\alpha\left[\sum_{j=1}^{p}\left|\rho_j\right|+\sum_{i=1}^{n}\sum_{j=0}^{q}\left|\beta_{i,j}\right|\right] \tag{8}$$

where $\tilde{Y}_t^e=\sum_{j=1}^{p}\rho_j\tilde{Y}_{t-j}+\sum_{i=1}^{n}\sum_{j=0}^{q}\beta_{i,j}\tilde{X}_{i,t-j}^{Q}$. The variables marked with tildes represent demeaned series (e.g. $\tilde{Y}_t=Y_t-\bar{Y}$). The value of α is comprised between 0 and 1, and λ is a real number greater than 0.

The second and the third terms of Equation (8) make up the elastic net penalty, which actually combines two pre-existing variable selection methods, namely the ridge regression (Hoerl and Kennard, 1988) and the lasso (Tibshirani, 1996). Setting the value of α to 0 gives the objective function used in the former, which minimises the sum of squared errors subject to a penalty defined as the sum of the squared of the coefficients, while setting it to 1 yields one equivalent to that of the lasso, in which the penalty is defined as the sum of the absolute value of the coefficients. The downside of the ridge regression is that it does not actually result in a restricted model, as all of the estimated coefficients remain different from zero, although those pertaining to the less relevant variables are smaller. The lasso, on the other hand, sets to zero the coefficients pertaining to the most irrelevant predictors, the proportion of which is determined by the value of λ. This feature is particularly convenient as it enables λ to be used to generate a ranking of the potential predictors included in the model according to their explanatory power over the variable of interest. This can be done simply by running the algorithm several times with different values for that parameter. However, Zou and Hastie (2005) point out that the lasso tends to select only one predictor within groups of strongly correlated variables, and might thus overlook other potentially relevant predictors. In such a case, which is typically encountered with monthly indicators used for short-term forecasting, the predictive performance of the ridge regression dominates that of the lasso. The elastic net is basically a compromise between these two selection methods, as it enables irrelevant variables to be excluded from a large dataset and, furthermore, it performs well with highly correlated variables.

In contrast to the standard OLS regression, the elastic net is based on an estimation algorithm that makes it possible to include many more explanatory variables than that of the available observations (i.e. with $n >> T$). The algorithm used by Zou and Hastie (2005) builds on the LARS (least angle regression) algorithm of Efron *et al.* (2004). I use an alternative algorithm developed by Friedman *et al.* (2010), which relies on a numerical optimisation technique known as the 'coordinate descent'[1], to estimate the coefficients pertaining to the potential predictors (ρ_j and $\beta_{i,j}$) for given values of α and λ. Finding an optimal value for λ is not necessary, as this parameter is actually used to establish a ranking of the 'best' predictors that will be subsequently included in the forecasting model. As for α, which is bounded between 0 and 1, its optimal value can be easily determined by means of a grid search. Concretely, in every variable selection process, the elastic net is first run on the basis of different values for α, within an interval ranging from 0.1 to 1 and with increments of 0.1, and, for each of them, the average root mean square error of the fitted dependent variable ($\tilde{Y}_t^e$) is calculated over the spectrum of the possible values of λ. The value of α which is eventually picked is the one that minimises this criterion. In practice, however, it can be noticed that the outcome of the selection is little sensitive to the value chosen for α.

The selection algorithm described above can only be used on a balanced panel dataset, i.e. a dataset in which all of the explanatory and the dependent variables cover exactly the same period. However, the situations of data availability generally faced by professional forecasters in the context of real-time exercises are considerably different. Regardless of the model used to generate them, early estimates of GDP or other macroeconomic aggregates are usually based on a set of various monthly indicators released before the official quarterly statistics, although at staggered dates. Some of these indicators are already available at the middle or the end of the month they relate to. This is typically the case with survey-based sentiment indicators. Others might be released only one or two months after. Hard indicators, such as

[1] The coordinate descent is an iterative procedure in which the objective function is optimised with respect to one single parameter in each iteration, considering the value of the other parameters as given. This operation is repeated for every parameter based on the value obtained for the other parameters in the previous iteration. The complete sequence of iterations is repeated until the vector of parameters has converged to one single value. Friedman *et al*. (2010) implemented their method by means of a program written in *R*. In the simulations presented further this paper, I used the version provided in MATLAB's Statistics Toolbox.

industrial production indices, data on firms' turnover and foreign trade data, belong to that category. As a result, monthly datasets used by forecasters do not cover the entire forecasting horizon and are usually characterised by a 'ragged edge', in which monthly observations are more often missing for those indicators that are released with some delay. Within the two forecasting frameworks discussed in the previous section, these missing observations need to be filled in by means of autoregressive forecasts in order to generate an estimate for the quarterly variable.

Running the selection algorithm in-sample, without accounting for possible ragged edges, would obviously lead to selecting those indicators that are the most strongly correlated with GDP, in particular the hard indicators which are typically used to compile the quarterly statistic. However, these indicators are also those released with the longest delays, making it necessary, in a real-time forecasting exercise, to extend their series with autoregressive forecasts up to the end of the current quarter, thereby increasing the magnitude of forecast errors. On the other hand, since they are made available more rapidly, survey and financial indicators do not have that drawback, or at least to a lesser extent, even though their in-sample correlation with GDP is weaker. This means that earlier estimates using these indicators can be based more on real observations than on autoregressive forecasts, which reduces uncertainty linked to the prediction from the AR satellite models. Consequently, they might even have a higher predictive power over GDP in the absence of monthly data for hard indicators within the current quarter.

It is therefore important to adapt the selection procedure in order to take into account both the publication lags and the staggered releases of the monthly data. For that purpose, I follow the approach proposed by Bessec (2013), who refined the selection procedure advocated by Bai and Ng (2008). It involves running the elastic net on a transformed dataset in such a way that it reflects the availability of monthly data at the time the forecast is made. Concretely, if some monthly observations for a given indicator are lacking within the current quarter, which is more likely to be the case if it is subject to longer publication lags, the observations for the corresponding months within the other quarters in the whole sample period over which the elastic net is run are replaced by autoregressive forecasts. The idea is to assess the predictive ability of that indicator based only on the information conveyed by the partial intra-quarterly data available rather than on its in-sample explanatory power. Clearly, this substitution penalises the indicator concerned by reducing its correlation with GDP.

Bessec (2013) applied this refined selection procedure to the model of Giannone *et al.* (2008) and she used standard autoregressive forecasts to extrapolate the monthly series because of the analogy with the AR process followed by the factors in that class of models. In my view, this argument makes even more sense for the bridge model and the bridging with factors approach discussed in the previous section, in which AR models are explicitly part of the forecasting process.

The construction on the transformed dataset is illustrated in Figures 1 and 2 by means of a simplified example. Figure 1 represents a set of monthly series with the observation available at the time a prediction for the quarterly variable of interest (Y_t) must be made. The latest observation for Y_t relates to quarter *T* and a forecast must be generated for the current quarter, i.e. quarter *T+1*, and possibly the subsequent quarter(s). In that example, monthly data are available over the entire current quarter for two indicators (indicators 1 and 3) but some observations are lacking for others. This is the case for indicators 2 and 4, for which monthly data are missing for the third and the two last months, respectively, whereas no observation at all is yet available for indicator 5. Therefore, in order to perform a forecast for Y_{T+1} using one of the two models described in Section 2, these series must be extended with autoregressive forecasts up to the last month of the current quarter. The transformed dataset, shown in Figure 2, aims at reflecting this situation of data availability. In the case of indicator 4, for instance, the observations for the last two months in every quarter covered by the sample are replaced by predictions from AR models estimated using the preceding observations. Thus, each quarterly data point related to that indicator used for running the elastic net consists of the aggregation of one observation and two autoregressive forecasts. On the other hand, the series for which monthly data are available over the entire current quarter (such as those of indicators 1 and 3) remain unchanged.

Figure 1 – Simplified example of a set of monthly series with staggered data releases

Quarter	Month	Indicator 1	Indicator 2	Indicator 3	Indicator 4	Indicator 5
1	1	$X_{1,1}$	$X_{2,1}$	$X_{3,1}$	$X_{4,1}$	$X_{5,1}$
⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮
T-2	3*T*-8	$X_{1,3T-8}$	$X_{2,3T-8}$	$X_{3,3T-8}$	$X_{4,3T-8}$	$X_{5,3T-8}$
T-2	3*T*-7	$X_{1,3T-7}$	$X_{2,3T-7}$	$X_{3,3T-7}$	$X_{4,3T-7}$	$X_{5,3T-7}$
T-2	3*T*-6	$X_{1,3T-6}$	$X_{2,3T-6}$	$X_{3,3T-6}$	$X_{4,3T-6}$	$X_{5,3T-6}$
T-1	3*T*-5	$X_{1,3T-5}$	$X_{2,3T-5}$	$X_{3,3T-5}$	$X_{4,3T-5}$	$X_{5,3T-5}$
T-1	3*T*-4	$X_{1,3T-4}$	$X_{2,3T-4}$	$X_{3,3T-4}$	$X_{4,3T-4}$	$X_{5,3T-4}$
T-1	3*T*-3	$X_{1,3T-3}$	$X_{2,3T-3}$	$X_{3,3T-3}$	$X_{4,3T-3}$	$X_{5,3T-3}$
T	3*T*-2	$X_{1,3T-2}$	$X_{2,3T-2}$	$X_{3,3T-2}$	$X_{4,3T-2}$	$X_{5,3T-2}$
T	3*T*-1	$X_{1,3T-1}$	$X_{2,3T-1}$	$X_{3,3T-1}$	$X_{4,3T-1}$	$X_{5,3T-1}$
T	3*T*	$X_{1,3T}$	$X_{2,3T}$	$X_{3,3T}$	$X_{4,3T}$	$X_{5,3T}$
T+1	3*T*+1	$X_{1,3T+1}$	$X_{2,3T+1}$	$X_{3,3T+1}$	$X_{4,3T+1}$	$X^f_{5,3T+1}$
T+1	3*T*+2	$X_{1,3T+2}$	$X_{2,3T+2}$	$X_{3,3T+2}$	$X^f_{4,3T+2}$	$X^f_{5,3T+2}$
T+1	3*T*+3	$X_{1,3T+3}$	$X^f_{2,3T+3}$	$X_{3,3T+3}$	$X^f_{4,3T+3}$	$X^f_{5,3T+3}$

$X_{i,m}$ = observation for indicator *i* on month *m*; $X^f_{i,m}$ = forecast from an autoregressive model.

Figure 2 – Construction of the pseudo dataset

Quarter	Month	Indicator 1	Indicator 2	Indicator 3	Indicator 4	Indicator 5
8	22	$X_{1,22}$	$X_{2,22}$	$X_{3,22}$	$X_{4,22}$	$X^f_{5,22}$
⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮
T-2	3*T*-8	$X_{1,3T-8}$	$X_{2,3T-8}$	$X_{3,3T-8}$	$X_{4,3T-8}$	$X^f_{5,3T-8}$
T-2	3*T*-7	$X_{1,3T-7}$	$X_{2,3T-7}$	$X_{3,3T-7}$	$X^f_{4,3T-7}$	$X^f_{5,3T-7}$
T-2	3*T*-6	$X_{1,3T-6}$	$X^f_{2,3T-6}$	$X_{3,3T-6}$	$X^f_{4,3T-6}$	$X^f_{5,3T-6}$
T-1	3*T*-5	$X_{1,3T-5}$	$X_{2,3T-5}$	$X_{3,3T-5}$	$X_{4,3T-5}$	$X^f_{5,3T-5}$
T-1	3*T*-4	$X_{1,3T-4}$	$X_{2,3T-4}$	$X_{3,3T-4}$	$X^f_{4,3T-4}$	$X^f_{5,3T-4}$
T-1	3*T*-3	$X_{1,3T-3}$	$X^f_{2,3T-3}$	$X_{3,3T-3}$	$X^f_{4,3T-3}$	$X^f_{5,3T-3}$
T	3*T*-2	$X_{1,3T-2}$	$X_{2,3T-2}$	$X_{3,3T-2}$	$X_{4,3T-2}$	$X^f_{5,3T-2}$
T	3*T*-1	$X_{1,3T-1}$	$X_{2,3T-1}$	$X_{3,3T-1}$	$X^f_{4,3T-1}$	$X^f_{5,3T-1}$
T	3*T*	$X_{1,3T}$	$X^f_{2,3T}$	$X_{3,3T}$	$X^f_{4,3T}$	$X^f_{5,3T}$

$X_{i,m}$ = observation for indicator *i* on month m; $X^f_{i,m}$ = forecast from an autoregressive model.

Formally, the formula used to calculate the transformed quarterly series from a monthly series $X_{i,t}$, for which the last data available refers to month M_i is

$$X^{Qf}_{i,t} = \sum_{l=0}^{2}\left\{ X_{i,3t-l} 1\left(3T + 3h^* - M_i \le l\right) + X^f_{i,3t-l} 1\left(3T + 3h^* - M_i > l\right)\right\} \tag{9}$$

h^* denotes the number of quarters following quarter T for which some monthly information is already available (in the example illustrated in Figure 1, $h^* = 1$) and $X^f_{i,m}$ stands for the forecast of $X_{i,m}$ generated by an AR model. The forecast is made over a horizon of $3T + 3h^* - M_i$ months, i.e. the same number of forecasts that needs to be generated in order to obtain a prediction for Y_{T+h^*}, on the basis of the past observed values:

$$X^f_{i,m} = \hat{E}\left(X_{i,m} \mid X_{i,m-3T-3h^*+M_i}, X_{i,m-3T-3h^*+M_i-1}, X_{i,m-3T-3h^*+M_i-2}, ..., X_{i,1}\right) \tag{10}$$

Since the generation of these forecasts requires some back data, the time coverage of the transformed dataset is necessarily shorter than that of the original dataset. In my computations, I have set to 22 the minimum number of observations used to estimate the AR models. As a result, the period covered by the transformed dataset runs from the eighth quarter of the original sample period.

Once they are calculated, the transformed series (X_i^{Qf}) are plugged into Equation (8), where they substitute to the original quarterly variables (X_i^{Q}), and the elastic net is then run based on that specification.

The outcome of this procedure is a ranking, in which indicators are ordered according to their predictive power over Y_t. The number of top-ranked indicators to take into account in the model should be determined in the next step of the forecasting process. One option is relying on standard information criteria, such as the BIC, which entails little computational cost. A more rational approach in the context of real-time forecasting, albeit more computationally intensive, is using a measure of predictive accuracy for each n^* first top-ranked variables (with $n^* < n$) and pick the number of variables that yields the best performance over a recent period. In practice, the measure I use for that purpose is the root mean square forecast error (RMSFE[1]).

4. Empirical analysis

In this section, the gain in terms of predictive performance that can potentially arise from the selection procedure, both within the standard bridge framework (SB) and the bridging with factors approach based on the diffusion index (DI), is evaluated through a pseudo real-time forecasting exercise. This exercise involves performing a series of recursive forecasts of the Belgian GDP using 'targeted' models with different numbers of indicators taken from the highest positions in the ranking (i.e. different n^*) obtained from the selection procedure, and according to six different scenarios of data availability. The predictors included in the models are selected among a pre-selection of 93 monthly indicators deemed relevant for monitoring the business cycle in Belgium and covering a sufficiently long time period.

[1] The RMSFE is defined as $\sqrt{\left(1/T\right)\sum_{t=1}^{T}\left(\hat{Y}_t - Y_t\right)^2}$, for a series of recursive forecasts ($\hat{Y}_t$) carried out over a period spanning over T periods.

4.1. Data

The dataset used in the simulation exercise includes both hard and soft indicators, as well as some financial series, which are listed in Annex 1.

Some of the hard indicators taken into consideration are those used by the Belgian National Accounts Institute (NAI) to compile quarterly GDP, namely the turnover of Belgian companies such as reported in their returns to the VAT administration and the industrial production index. Since the turnover data can be broken down by industry, I also considered the turnover in some of the most important ones separately (namely manufacturing, construction, retail trade, hotels and restaurants, business services, and the service branches taken as a whole). Industrial production indices are also available for several industries but, in order to avoid excessively volatile variables due to a too refined breakdown, I limited the pre-selection to the two main industries covered by these data, i.e. manufacturing and construction, and to the grouping by product category (energy, capital goods, intermediate goods, as well as durable and non-durable consumer goods). The dataset also comprises industry-specific hard indicators, such as the number of building permits granted for new constructions and the number of new cars registered, as well as others related to the developments in the labour market in Belgium, namely the unemployment rate, the number of job-seekers and the work volume of temporary workers (which includes both blue- and white-collar workers).

Most of the soft indicators are derived from the replies to the business survey conducted by the National Bank of Belgium in four major industries, namely manufacturing, construction, trade and business-related services. The pre-selection was restricted to the main survey indicators, i.e. the replies to the individual survey questions reported on a monthly basis in the Bank's publications. I did not consider the synthetic indicators since they do not provide any additional information. They are actually calculated as the averages of some indicators pertaining to specific questions. I also included the four main indicators from the consumer survey.

As for the financial series, their number is more limited. They include a Belgian and a European stock market index (the Brussels All Shares Index and the Euro Stoxx Broad Index), the ten-year Belgian government bond yield as well as the spread of this yield compared to that of the German Bund, oil prices, a broader price index for energy raw materials and a price index for other commodities.

Finally, the dataset also comprises some hard and soft indicators related to external developments, notably production and foreign trade indices in the euro area, the advanced economies and in the emerging economies, as well as industrial and consumer confidence indicators for Belgium's neighbours.

All the series, with the exception of the financial indicators, are seasonally adjusted and, if relevant, corrected for calendar effects. They are all log-transformed, unless they can take zero or negative values (which is the case of survey indicators) and expressed in first difference if a unit root is detected either by the ADF or the Philips-Perron test.

The quarterly GDP series used in the simulations run from the first quarter of 1995 to the last quarter of 2013. Most of the 93 indicators cover the same period but two of them do not start until April 1996, namely the price index for energy raw materials and that for other commodities. Consequently, taking the differentiation of these two non-stationary series into account, the predictor selection procedure is performed over a period starting from the third quarter of 1996. Furthermore, the simulation results presented below are based on a series of recursive forecasts carried out from the first quarter of 2005 onwards, so as to ensure that both the predictor selections and the model estimations are made using a sufficiently large number of observations.

It should be noted that the simulations are based on the most recent data vintage, both for the monthly indicators and quarterly GDP, since I did have the information that would have enabled me to construct different series corresponding to the different vintages. Nonetheless, as far as the monthly indicators are concerned, this limitation does not affect the survey-based indicators and the financial series, which are not subject to revisions[1]. In addition, an inspection of the last releases did not reveal any major changes between the successive vintages for most of the hard indicators. But this is the case for certain indicators related to real economic activity, such as the monthly data on foreign trade in goods and on construction of new buildings started, for which revisions might sometimes be important. These monthly series were excluded from the pre-selection for that reason. Quarterly GDP, on the other hand, may be subject to revisions up to two years after the initial release, and the revisions may sometimes be substantial. The series used in this paper correspond to the latest official estimates of GDP available at the time the simulations were performed, i.e. the final estimates up until the last quarter of 2012 and the 'one-year' estimates for the four quarters of 2013. Therefore, the predictive accuracy of the various models are largely assessed by their ability to predict the latest data released by the NAI.

[1] With the exception of revisions due to methodological changes. For instance, the NBB changed the way it calculated its synthetic survey indicators – which are not included in the dataset – in 2009 (De Greef and Van Nieuwenhuyze, 2009).

4.2. Design of the simulation exercise

The predictive performance of the various models is evaluated according to the six different data scenarios described in Table 1. Each of them corresponds to a situation of data availability that could be encountered by a forecaster who needs an estimate for Belgian GDP in quarter *Q* at a certain point in time. The idea is to replicate, in a simplified manner, the release calendar of the various monthly indicators included in the dataset.

Table 1 – Data availability scenarios for forecasting GDP in quarter *Q*

Scenario	Survey and financial data	'Early' hard data†	Hard data	Lagged dependent
1. Three months before the end of *Q*	3rd month of *Q*-1	2nd month of *Q*-1	1st month of *Q*-1	*Q*-2
2. Two months before the end of *Q*	1st month of *Q*	3rd month of *Q*-1	2nd month of *Q*-1	*Q*-2
3. One month before the end of *Q*	2nd month of *Q*	1st month of *Q*	3rd month of *Q*-1	*Q*-2
4. End of *Q*	3rd month of *Q*	2nd month of *Q*	1st month of *Q*	*Q*-1
5. One month after the end of *Q*	1st month of *Q*+1	3rd month of *Q*	2nd month of *Q*	*Q*-1
6. Two months after the end of *Q*	2nd month of *Q*+1	1st month of *Q*+1	3rd month of *Q*	*Q*-1

† Including, in particular, data related to the labour market and new car registrations.

Survey indicators, whether they relate to Belgium or other countries, are typically available at the end of the month they pertain to. For instance, Eurostat publishes the results from the monthly consumer and business surveys conducted in the EU countries by the end of each month, while the National Bank of Belgium publishes those for Belgium earlier, around the 18^{th} day of the month for the consumer survey and around the 24^{th} for the business survey. Since stock market data, interest rates and commodity prices (i.e. the 'financial' data) are available on a daily basis, their monthly averages are known at the end of the month. On the other hand, hard indicators such as industrial production or turnover data are generally released much later, most of the time seven or eight weeks after the end of the month considered. Nonetheless, others types of hard data, like those for unemployment, temporary work and the number of cars registered, are released earlier. These indicators are classified as a separate category, named 'early hard' data.

Furthermore, the fact that quarterly GDP is published 70 days[1] after the end of the quarter it pertains to has also been accounted for. It is therefore considered as known at the end of third month that follows that quarter. Consequently, an observation for the model's lagged dependent variable – i.e. GDP growth in the previous quarter – is only available starting from the end of quarter Q, that is as from the fourth data scenario.

Two simulations are performed. In the first, predictors are selected on the basis of data from the entire sample period. So, the specification of the forecasting model, for a given data scenario, remains the same for all the recursive forecasts. The models' parameters, including those of the satellite AR models, are nevertheless re-estimated in each recursion. In the second simulation, the selection is made recursively. That is, a different 'targeted' model is used for each quarter in the simulation period and includes predictors selected on the basis of observations available for the previous quarters. Of course, the exact number of intra-quarterly observations taken into account in the selection procedure differs across monthly indicators and is determined by the data availability scenario.

These two types of simulation serve different purposes. Those based on the selection that exploits the entire sample are the ones a forecaster would use in order to assess the error margin of different models if he/she were to make a prediction for GDP in the quarter after the last one covered by the available data. It is also the most suitable option for assessing the predictive ability of the indicators that emerge from the selection procedure. On the other hand, repeating the selection procedure at each recursion is clearly more appropriate to measure the performance of the forecasting strategy as a whole. In particular, it gives a better view of the accuracy of the forecasts that would have been produced if that method had been used over a relatively long time period.

In the results reported below, the predictive performances of the various targeted models specified based on the rankings obtained via the selection procedure are compared to two benchmark models. The first, which is often used in the literature on short-term forecasting, is the simple AR model. This benchmark can be interpreted as a 'naive' prediction in the sense that it involves forecasting GDP growth using only its past observations (the exact number of which is determined on the basis of the BIC), without taking into account the information conveyed by the monthly indicators. While this benchmark is helpful in assessing

[1] This was the time limit set by Eurostat in the period over which the simulations are performed. According to the new publication rules that came into force in the second half of 2014, quarterly national accounts are to be published 60 days after the end of the quarter. A first estimate of GDP, known as the 'flash' estimate, is also released by the National Accounts Institute 30 days after the end of the quarter. It is nevertheless based on partial information, as only the hard data for the two first months are available at that moment. That first estimate is consequently often revised in the subsequent publications.

the informative content of the predictors included on the right-hand side of the targeted models, it remains quite weak in terms of predictive capability. So I rely on the forecasts from a more conventional diffusion index model as the main benchmark, i.e. the model described in Section 2.2 based on all of the 93 indicators included in the dataset, without running the predictor selection procedure beforehand. The motivation for this choice is twofold. Firstly, as discussed in Section 2, this forecasting approach appears as one of the most accurate. Secondly, using all the indicators from the dataset also makes it possible to gauge whether it is worth relying on the selection procedure. Indeed, if the principal component(s) extracted from all the indicators exhibit better predictive performances than a model using only a subset of selected predictors, this could naturally cast some doubt on the reliability and the usefulness of the selection procedure.

In the results presented in the next section, the accuracies of the forecasts from the targeted SB and DI models are compared to that of the benchmark factor model by means of the test proposed by Diebold and Mariano (1995). Basically, the Diebold-Mariano (DM) test statistic determines whether the magnitudes of the forecast errors from two distinct models are statistically equal based on the difference between their respective loss functions (the loss differential). Assuming these loss functions are both quadratic, the DM test statistic is defined as

$$DM = \frac{\bar{d}}{\left(1/T\right)\sum_{t=1}^{T}\left(d_t - \bar{d}\right)^2} \tag{11}$$

$\bar{d}$ stands for the average of the loss differential $d_t = e_{1,t}^2 - e_{2,t}^2$ (where $e_{1,t}$ and $e_{2,t}$ are the forecast errors from models 1 and 2, respectively)[1]. In large samples, and under the null hypothesis that the magnitudes of the errors from the two models are similar, the DM test statistic follows a normal distribution with a zero mean and a unit variance.

[1] Equation (11) is actually a particular form of the DM test statistics that does not take into account the possible autocorrelation in d_t that might arise when performing multiple-step-ahead forecasts. Since the forecasts made within the framework of the simulation exercise are carried out over a horizon of only one quarter, this refinement is not relevant in this case.

4.3. Predictive performance

Table 2 reports the RMSFEs from the recursive out-of-sample forecasts made using SB and DI models that include the top-ranked variables from the ordering obtained by running the selection procedure over the entire sample period, i.e. from the third quarter of 1996 to the fourth quarter of 2013. The forecasts were produced with different numbers n^* of predictors and for each of the six data scenarios described above. In each scenario, the elastic net was run on a dataset transformed so that it reflects the corresponding situation of data availability, following the method discussed in Section 3. The RMSFEs of the two benchmark models, namely the AR model and the DI model that includes all the indicators from the dataset, are also mentioned. In line with the assumptions regarding the data release calendar, the recursive forecasts based on the autoregressive model – like the other models considered – do not take into account GDP growth in the quarter before the current quarter as that observation should be available only at the end of the latter. Therefore, the RMSFEs reported for that model are based on two-quarter-ahead forecasts from data scenarios 1 to 3, and on one-quarter-ahead forecasts starting from scenario 4.

Two patterns emerge from the simulation results presented in Table 2. Firstly, they show a clear relationship between the availability of monthly data within the current quarter and the accuracy of the forecasts generated by the various models. Predictive performance is generally poor in data scenarios 1 and 2, i.e. when no monthly data related to the current quarter, or only one month of survey and financial data, are taken into account. It improves considerably starting from the third scenario, when soft data for the second month and the first hard data (the 'early' hard data) are used. The average errors further decrease in scenario 4 and 5, and the best level of predictive performance appears to already have been reached in the latter. The RMSFEs are indeed quite similar in the two last data scenarios, suggesting that the last observations for the hard indicators taken into account in scenario 6 do not bring about any significant improvement in terms of forecast accuracy. Secondly, the relationship between the forecast errors and the number of top-ranked indicators included in the models is nonlinear. In most of the six data scenarios, the SB model using only the indicator that appears in the first position of the ranking established via the selection procedure exhibits on average the highest forecast errors. The RMSFEs reach considerably lower levels between the fourth and the eight positions, depending on the data scenario, and do not evolve significantly over the subsequent positions. The detrimental effects on forecast accuracy arising from the addition of low-ranked indicators – presumably the most 'noisy' ones – are more noticeable for the targeted DI models. For these models, the ‘optimal’ number of predictors ranges between 5 and 20. Like the SB models, this number differs somewhat across the data scenarios.

Table 2 – RMSFEs of the predictions for quarterly GDP growth, using indicators selected based on the entire data sample
(percentage points; recursive forecasts performed over the period 2005Q1-2013Q4)

	Data scenario					
	1	2	3	4	5	6
Targeted SB model including the n^* top-ranked indicators						
$n^* = 1$	0.638	0.807	0.516	0.475	0.497	0.396
$n^* = 2$	0.616	0.600	0.522	0.407	0.432	0.375
$n^* = 3$	0.575	0.577	0.460	0.422	0.407	0.389
$n^* = 4$	0.560	0.578	0.449	0.417	0.347	0.429
$n^* = 5$	0.575	0.594	0.437	0.398	0.349	0.397
$n^* = 6$	0.579	0.603	0.435	0.444	0.339	0.397
$n^* = 7$	0.574	0.585	0.422	0.422	0.342	0.371
$n^* = 8$	0.568	0.587	0.404	0.423	0.346	0.378
$n^* = 9$	0.566	0.540	0.406	0.417	0.346	0.381
$n^* = 10$	0.547	0.602	0.408	0.424	0.331	0.373
$n^* = 11$	0.526	0.592	0.378	0.434	0.344	0.368
$n^* = 12$	0.505	0.591	0.389	0.447	0.369	0.362
$n^* = 13$	0.488	0.600	0.379	0.400	0.372	0.365
$n^* = 14$	0.489	0.517	0.383	0.410	0.396	0.370
$n^* = 15$	0.489	0.467	0.385	0.432	0.397	0.372
Targeted DI model including the n^* top-ranked indicators						
$n^* = 5$	0.528 *	0.550	0.411	0.338 *	0.354	0.379
$n^* = 10$	0.519 **	0.500	0.369	0.353	0.301 **	0.360
$n^* = 15$	0.542 *	0.500	0.366	0.351 *	0.354	0.339
$n^* = 20$	0.535 **	0.572	0.444	0.393	0.332	0.283 **
$n^* = 25$	0.616	0.593	0.445	0.393	0.336	0.299 ***
$n^* = 30$	0.608	0.680	0.452	0.420	0.389	0.316 **
$n^* = 35$	0.658	0.575	0.450	0.445	0.426	0.324 **
$n^* = 40$	0.562	0.560	0.512	0.444	0.444	0.322 **
$n^* = 45$	0.564	0.654	0.520	0.465	0.454	0.409
$n^* = 50$	0.563	0.567	0.517	0.448	0.462	0.429
DI model including all the indicators	0.586	0.545	0.461	0.404	0.389	0.386
p.m. Autoregressive forecast	*0.767*	*0.767*	*0.767*	*0.553*	*0.553*	*0.553*

The highlights indicate the smallest RMSFEs for a given data scenario. The signs “*”, “**” and “***” indicate the rejection of the null hypothesis of equal forecast accuracy with respect to the benchmark DI model that includes all the indicators, at the 10%, 5% and 1% levels, respectively, based on the DM test statistic.

In practically all cases (with the only exception of the SB model with one single variable in scenario 1), the targeted SB and DI models display significantly lower forecast errors than the simple AR model. This means that the selected indicators do effectively provide some advance information on GDP growth in the current quarter. More strikingly, provided they include a reasonable number of the top-ranked indicators, many of the targeted models perform better than the DI model that includes all the predictors from the dataset. In other words, the selection procedure seems at first sight successful in finding a sub-set of indicators that provides early estimates of GDP growth which are at least as accurate as those obtained from the full information set, if not more. This finding confirms those from existing studies, in particular that of Bai and Ng (2008), that it can indeed pay off to limit the number of variables to the most informative ones and to leave out the 'noisy' indicators. However, the gains in terms of forecast accuracy is rarely significant according to the DM test statistics.

It is also important to stress that the predictors used for this simulation exercise were selected by running the selection procedure over the entire data sample, which means that, in each recursion, data related to time periods after the forecast horizon were used to specify the model. This is obviously a luxury an economic analyst does not have in the context of a real-time exercise since he/she has to specify a forecasting model based only on the quantitative relationships between GDP and the various monthly indicators that were observed in the past. In this regard, one crucial question is whether the forecasting strategy discussed here could also work in a real-time environment, if only past data can be used in the predictor selection process. This question is addressed in the second simulation exercise, in which the selection procedure is repeated at each recursion. The results of this additional exercise are reported in Table 3.

Table 3 – RMSFEs of the predictions for quarterly GDP growth, using indicators selected recursively based on past observations
(percentage points; recursive selections and forecasts performed over the period 2005Q1-2013Q4)

	Data scenario					
	1	**2**	**3**	**4**	**5**	**6**
Targeted SB model including the *n top-ranked indicators**						
$n^* = 1$	1.092	0.848	0.526	0.487 *	0.503 **	0.496 **
$n^* = 2$	0.999	0.689	0.481	0.539 **	0.450	0.405
$n^* = 3$	0.972	0.697 *	0.487	0.497 *	0.423	0.381
$n^* = 4$	0.956	0.631	0.497	0.471	0.398	0.392
$n^* = 5$	0.965	0.624	0.521	0.458	0.372	0.402
$n^* = 6$	0.955	0.660	0.490	0.443	0.357	0.388
$n^* = 7$	0.972	0.679	0.531	0.463	0.388	0.378
$n^* = 8$	1.001	0.664	0.520	0.490 *	0.384	0.375
$n^* = 9$	0.983	0.638	0.513	0.491 *	0.404	0.400
$n^* = 10$	0.979	0.630	0.501	0.476 *	0.387	0.394
$n^* = 11$	0.987	0.670	0.477	0.492	0.397	0.401
$n^* = 12$	0.975	0.611	0.486	0.472	0.396	0.431
$n^* = 13$	0.886	0.650	0.473	0.469	0.380	0.444
$n^* = 14$	0.909	0.648	0.502	0.434	0.403	0.427
$n^* = 15$	0.930 *	0.601	0.485	0.454	0.391	0.430
Targeted DI model including the *n top-ranked indicators**						
$n^* = 5$	0.730 **	0.565	0.542 **	0.409	0.385	0.407
$n^* = 10$	0.812	0.593	0.480	0.415	0.405	0.429
$n^* = 15$	0.772	0.607	0.560	0.411	0.377	0.376
$n^* = 20$	0.787 *	0.594 *	0.477	0.365	0.359	0.362
$n^* = 25$	0.770 *	0.594 *	0.539 *	0.388	0.391	0.379
$n^* = 30$	0.759	0.578	0.535 **	0.412	0.395	0.378
$n^* = 35$	0.757	0.520	0.530 **	0.399	0.395	0.389
$n^* = 40$	0.738	0.531	0.524 *	0.421	0.414	0.403
$n^* = 45$	0.729	0.535	0.503 *	0.412	0.381	0.408
$n^* = 50$	0.720	0.535	0.508 **	0.418	0.517	0.423
DI model including all the indicators	0.586	0.545	0.461	0.404	0.389	0.386
p.m. Autoregressive forecast	*0.767*	*0.767*	*0.767*	*0.553*	*0.553*	*0.553*

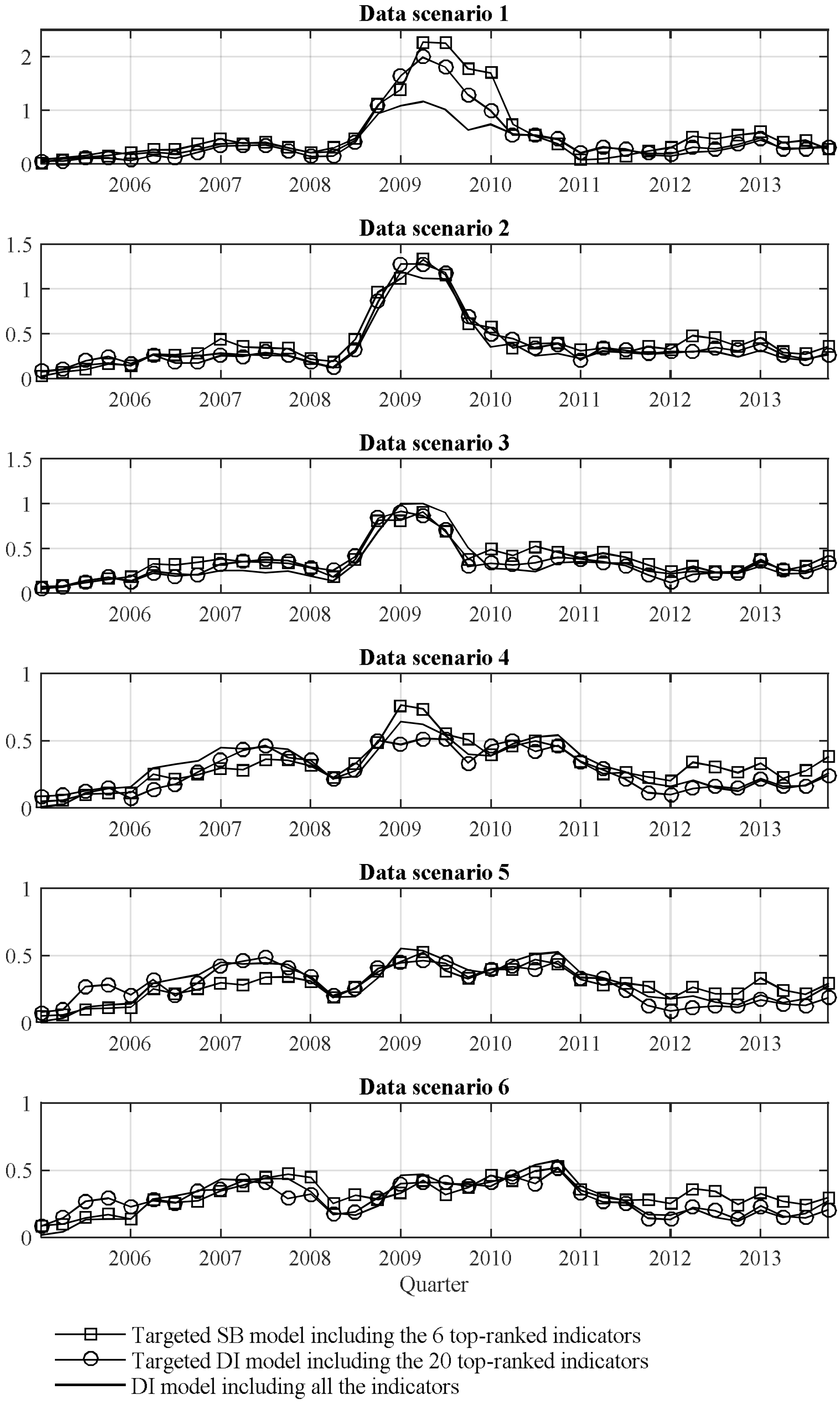
The highlights indicate the smallest RMSFEs for a given data scenario. The signs "*", "**" and "***" indicate the rejection of the null hypothesis of equal forecast accuracy with respect to the benchmark DI model that includes all the indicators, at the 10%, 5% and 1% levels, respectively, based on the DM test statistic.

Quite intuitively, compared to the previous simulations exercise, the RMSFEs are now systematically higher for most of the models considered, which also indicates that the lower forecast errors reported in Table 2 can be attributed to the benefit of hindsight. The DI models that include more than 30 of the top-ranked predictors are a notable exception but, starting from the third data scenario, these are nevertheless still outperformed by many of the more restricted models. Consequently, the magnitude of the forecast errors of most of the targeted models is now larger than that of the benchmark DI model, in particular in the first scenario of data release, albeit the advantage of the former in terms of predictive accuracy is found significant based on the DM test only in a limited number of cases.

The statistics reported in Table 3 should be somewhat nuanced since the forecasting accuracies of various models are not constant over the simulation period. This is illustrated in Figure 3, which displays the evolution of the absolute forecast errors from the targeted SB and DI models that include the 6 and the 20 top-ranked indicators, respectively, i.e. the optimal number of predictors, or nearly, in the last data scenarios. Forecast errors are generally higher in the great recession period, from mid-2008 to mid-2009. In the first data scenario, this is more particularly the case for the targeted SB and DI models, which also means that the higher RMFEs obtained for these models is to a great extent attributable to the errors made for that period. Interestingly, in the last three data scenarios, the SB with 6 predictors performs slightly better than the DI models most of the time during the period that preceded the recession. The DI models (with and without selection) nevertheless provide more accurate predictions from 2011 to 2013. This suggests that more indicators than can be included in an SB model were actually needed to obtain a proper diagnosis of the economic situation in the recent period.

To sum up, these results show that the algorithm seems effective in streamlining the dataset used for performing the forecast. A DI model that takes into account only the 20 first top-ranked indicators that emerge from the selection procedure or a bridge model using only the first 6 or 7 first indicators from that same selection can provide forecasts whose accuracy falls within the same range as a model that encompasses all the available monthly data. This finding is in line with the conclusions of De Mol *et al*. (2008) who argue that, in the presence of strong collinearity in the panel of time series used to generate the prediction, a few appropriately selected variables should capture the bulk of their covariations, thereby delivering a forecast which is highly correlated with that generated from the principal components. The obvious corollary of this finding is that the selection procedure does not lead to any significant improvement in forecasting accuracy compared to that well-proven method.

Figure 3 – Evolution of the absolute forecast errors over the simulation period
(averages over 4-quarter windows expressed in percentage)



Note: the scale of the Y-axes is different for every chart.

4.4. The 'best' indicators

The simulation results examined above suggest that plugging the 6 best indicators picked by the selection procedure into an SB model, or the 20 best into a DI model, produces a relatively sound level of accuracy, regardless of the data release situation. It is nevertheless interesting to note that the set of selected predictors changes significantly depending on the number of available monthly observations, as illustrated by the estimates of the six bridge equations reported in Table 4. These equations are actually those used to generate the forecasts for GDP growth in the last quarter of 2013 based on the 6 first top-ranked variables. A more comprehensive list of indicators, which includes the 20 first positions from these rankings, is enclosed in Annex 2.

The results for the first scenario show that, in the absence of monthly data pertaining directly to the current quarter, the selection procedure tends to favour survey and financial indicators. Survey indicators are still dominant in the subsequent scenarios, i.e. the second to the third scenarios, which simulate their progressive release, while hard data are still either unavailable or scarce. Hard indicators, in particular those related to external developments, represent by contrast a larger proportion of the selection in the two last scenarios, which stand for situations where their observations cover the first two or three months. In the specific case of the 6^{th} data scenario, which assumes that all the monthly data have been released, all of the variables taken into account in the bridge equation are actually hard indicators. Yet, it can be also noted that, when a sufficient amount of hard data can be used, many survey indicators remain highly ranked among the top 20 indicators that emerge from the selection procedure (see Annex 2). This suggests that soft indicators, in particular survey data, still contain some information relevant for estimating GDP growth that is not conveyed by the hard data. These results are broadly in line with those of Bessec (2013), who also emphasised the predominance of indicators characterised by short publication lags when forecasts are to be made over longer horizons and in the absence of a sufficient number of observations for hard indicators.

Even though the rankings, as well as the resulting models, undergo significant changes depending on the data scenario, some indicators keep their relevance in different situations of data availability. This is notably the case of the unemployment expectations taken from the consumer survey, industrial confidence in the Netherlands, the industrial production index for the advanced economies and for the euro area and, in the last two data scenarios, total turnover of Belgian firms based on the VAT returns. The importance among these indicators of those related to the international environment, in particular to industrial confidence in one of Belgium's neighbouring countries, might seem surprising at first sight, as they are by definition not directly related to developments in domestic activity. Their relevance can nevertheless be corroborated by the fact that Belgium is a small open economy and, consequently, heavily reliant on external developments, in particular the economic activity of its main trading partners. By contrast, financial indicators, such as stock market indices, appear only in the top ranking positions in the first data scenario, i.e. in the case of the pure out-of-sample forecast, suggesting they provide some advanced information on developments in real activity in the near future, but not as well as survey indicators. Indeed, they practically disappear from the list of the best 20 ranked indicators when survey data are released in the first month of the current quarter[1].

Besides, the explanatory power of the bridge equation specified for the first scenario is quite weak, with a $\bar{R}^2$ of 42%. This is an indication that its six right-hand-side variables do not provide much information about GDP growth in the subsequent quarter[2], which is already confirmed by the simulation results. The in-sample fits of the equations estimated for the five other data scenarios are better, their $\bar{R}^2$ standing around 70%. The results from the Breusch-Godfrey test, however, point to some autocorrelation in the residuals but the extent of this issue is limited to the equation pertaining to the second scenario. For the other equations represented in Table 4, this test statistic is either significant only at the 10% level or not significant at all.

While the coefficients generally have the expected sign, a large proportion of them are not significant. This stems mainly from the high correlation between the explanatory variables, even though the elastic net should normally avoid selecting too similar indicators. Such correlation is actually quite usual between indicators reflecting trends in economic activity. Of course, DI models, unlike SB models, are not subject to that multicollinearity issue since the factors calculated using the principal components method are orthogonal.

[1] A more thorough analysis, based on the same predictor selection procedure as the one used in this paper, of the most relevant indicators for predicting GDP, as well as other quarterly macroeconomic aggregates is given by Piette and Langenus (2014).

[2] It should be recalled that, for this scenario, the dependent variable has one lead.

Table 4 – Bridge equations used to predict 2013Q4, by data scenario
(dependent variable: log-difference of quarterly GDP[†])

Data scenario 1: three months before the end of the current quarter

Rank	**Variable**	**Coefficient**	
	Intercept	0.0033	***
1	Business-related services survey; general demand expectations	0.0000	
2	Industrial confidence in the euro area	0.0000	
3	Trade survey; trend in prices (lagged)	-0.0004	***
4	Euro Stoxx Broad Index	0.0032	
5	Brussels All Shares Index	0.0152	
6	Commodity import prices in international markets, excluding energy	0.0206	*

$\bar{R}^2$ = 0.415; F = 8.815***; JB = 32.352***; BG = 7.866*; BP = 5.155
Estimation sample: 1996Q4-2013Q2 (67 observations)

Data scenario 2: two months before the end of the current quarter

Rank	**Variable**	**Coefficient**	
	Intercept	0.0037	***
1	Industrial production in the advanced economies	0.1603	***
2	Industrial confidence in the Netherlands	0.0005	
3	Consumer survey; unemployment in Belgium	-0.0001	**
4	Industrial confidence in the euro area	-0.0001	
5	Commodity import prices in international markets, excluding energy	0.0114	
6	Industrial production in the emerging economies	0.0194	

$\bar{R}^2$ = 0.681; F = 24.875***; JB = 4.975*; BG = 13.250**; BP = 7.064
Estimation sample: 1996Q3-2013Q2 (68 observations)

Data scenario 3: one month before the end of the current quarter

Rank	**Variable**	**Coefficient**	
	Intercept	0.0044	***
1	Industrial confidence in the Netherlands	0.0001	
2	Manufacturing industry survey; assessment of total order book	0.0002	*
3	Industrial production in the advanced economies	0.1500	***
4	Construction survey; trend in prices	0.0001	
5	Manufacturing industry survey; demand expectations	0.0001	**
6	Construction survey; price expectations	0.0000	

$\bar{R}^2$ = 0.693; F= 28.098***; JB = 0.711; BG = 3.753; BP = 2.233
Estimation sample: 1995Q2-2013Q2 (73 observations)

[†] In the case of the first data scenario, the dependent variable has one lead.
F = F test statistic for the significance of the model; JB = Jarque-Berra test statistic for normality of residuals; BG = Breusch-Godfrey test statistic for serial correlation in the residuals (using 4 lags); BP = Breusch-Pagan test statistic for heteroskedasticity in the residuals. "*", "**" and "***" stand for significance of a coefficient or a test statistic at the 10%, 5% and 1% levels, respectively.

Table 4 – Bridge equations used to predict 2013Q4, by data scenario (continued)
(dependent variable: log-difference of quarterly GDP)

Data scenario 4: end of the current quarter

Rank	Variable	Coefficient	
	Intercept	0.0044	***
1	Industrial confidence in the Netherlands	0.0004	
2	Manufacturing industry survey; demand expectations	0.0002	**
3	Industrial production in the euro area	-0.0439	
4	Construction survey; trend in prices	0.0001	
5	Consumer survey; unemployment in Belgium	-0.0001	*
6	Industrial production in the advanced economies	0.1718	**

$\bar{R}^2$ = 0.692; F= 28.275***; JB = 1.991; BG = 8.549*; BP = 1.123
Estimation sample: 1995Q2-2013Q3 (74 observations)

Data scenario 5: one month after the end of the current quarter

Rank	Variable	Coefficient	
	Intercept	0.0025	***
1	Industrial production in the advanced economies	0.0430	
2	Industrial confidence in the Netherlands	0.0001	
3	Work volume of temporary workers	0.0385	**
4	Total turnover	0.0857	***
5	Trade in goods in the emerging economies	0.0326	
6	Consumer survey; unemployment in Belgium	-0.0001	

$\bar{R}^2$ = 0.734; F= 34.529***; JB = 0.458; BG =11.007 ; BP = 3.319
Estimation sample: 1995Q2-2013Q3 (74 observations)

Data scenario 6: two months after the end of the current quarter

Rank	Variable	Coefficient	
	Intercept	0.0029	***
1	Industrial production in the euro area	0.0111	
2	Production of intermediate goods	0.0232	
3	Trade in goods in the advanced economies	-0.0068	
4	Trade in goods in the euro area	0.0404	
5	Total turnover	0.0841	***
6	Industrial production in the advanced economies	0.0962	

$\bar{R}^2$ = 0.689; F= 27.972***; JB = 1.810; BG = 8.399*; BP = 3.787
Estimation sample: 1995Q2-2013Q3 (74 observations)

F = F test statistic for the significance of the model; JB = Jarque-Berra test statistic for normality of residuals; BG = Breusch-Godfrey test statistic for serial correlation in the residuals (using 4 lags); BP = Breusch-Pagan test statistic for heteroskedasticity in the residuals. "*", "**" and "***" stand for significance of a coefficient or a test statistic at the 10%, 5% and 1% levels, respectively.

It is possible to use stepwise regressions, rather than OLS, to remove the less significant variables from the bridge equations and thus limit the multicollinearity problem. In order to examine whether this refinement could effectively lead to some improvements in terms of predictive performance, I have carried out an additional simulation exercise that involves a series of recursive forecasts based on changing predictor selections (as in Table 3), in which the equations estimated by OLS are replaced by reduced specifications obtained from stepwise regressions, using the BIC as the inclusion criterion. The results from this exercise, reported in Annex 3 are not convincing: the forecast errors generated by these reduced models are, on average, most often higher than those estimated by OLS. This may also be viewed as evidence that the less significant indicators included in the bridge equations do actually provide some relevant information for predicting GDP growth over the short term.

Finally, it might also be worth mentioning that, throughout the simulation period, many indicators keep appearing among the top-ranked ones in similar situations of data availability. For instance, running the selection procedure over a sample period limited to the observations prior to the crisis of 2008 and 2009, in order to identify those indicators that were at the time the most relevant to obtain an estimate for GDP growth in the last quarter of 2007, results in specifications that have many similarities with those obtained from using the entire data sample (see Annex 4). The industrial confidence index for the Netherlands and total turnover, among others, remain in the bridge equation specification for the two last data scenarios. Other variables, by contrast, disappear from the selection if observations for the period corresponding to the crisis and the subsequent periods are taken into consideration, an indication that their quantitative link with contemporaneous GDP growth weakens over time. This is in particular the case of lagged GDP growth which was included in the bridge equations used to predict GDP in the last quarter of 2007 but not in those that generate the forecast for the last quarter of 2013.

5. Concluding remarks

In their study, Bai and Ng (2008) showed that using targeted predictors, that is predictors selected according to the variable of interest and the forecast horizon, could be helpful in improving forecasting accuracy. They also pointed to the effectiveness of the elastic net algorithm for this purpose. Based on Belgian data, the results presented in this paper are in line with their findings in that the elastic net method, along with the refinement proposed by Bessec (2013) in order to take into account the 'ragged edge' of the dataset, can indeed slightly improve predictive performance within the bridge and 'bridging with factors' frameworks. However, these gains do not appear significant compared to a more standard approach that consists in summarising all the information available using the principal component method without any pre-selection. That latter forecasting technique appears actually difficult to surpass.

In addition, the predictive performance of a targeted model specified using that selection procedure is strongly conditioned by the number of indicators placed in the first positions of the resulting ordering that are finally included. In particular, the information provided by the very first top-ranked indicators does not yield a satisfactory level of forecast accuracy, while too many of them entails the risk of also picking the unnecessary and the most noisy indicators. Hence the importance of choosing the cut-off rank carefully on the basis of historical forecasting performances.

In this regard, it is also noteworthy that using only a limited number of selected predictors does not lead to many detrimental effects on the quality of the forecast, compared to using the full set of monthly data. In practice, this can considerably facilitate an analyst's communication, as his/her assessment of the current economic situation can therefore be motivated on the basis of recent developments in a much-reduced set of monthly data. In the absence of significant improvements in terms of predictive accuracy, this is basically the main merit of using a variable selection method in short-term economic forecasting.

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Annex 1 – Indicators included in the dataset

Indicator	Category	Log.	Diff.	Source
Business survey indicators				
Manufacturing industry				
Trend in the production rate	soft	no	0	NBB
Trend in orders from the domestic market	soft	no	0	NBB
Trend in export orders	soft	no	0	NBB
Trend in prices	soft	no	0	NBB
Assessment of total order books	soft	no	1	NBB
Assessment of export order books	soft	no	0	NBB
Assessment of the level of stocks of finished products	soft	no	0	NBB
Employment expectations	soft	no	1	NBB
Demand expectations	soft	no	0	NBB
Price expectations	soft	no	0	NBB
Construction				
Trend in activity	soft	no	0	NBB
Trend in orders	soft	no	0	NBB
Trend in equipment	soft	no	0	NBB
Trend in employment	soft	no	0	NBB
Trend in prices	soft	no	1	NBB
Demand expectations	soft	no	1	NBB
Assessment of order books	soft	no	1	NBB
Employment expectations	soft	no	1	NBB
Price expectations	soft	no	1	NBB
Trade				
Trend in sales	soft	no	0	NBB
Trend in prices	soft	no	0	NBB
Assessment of sales	soft	no	1	NBB
Assessment of the level of stocks	soft	no	0	NBB
Demand expectations	soft	no	0	NBB
Intentions of placing orders	soft	no	1	NBB
Employment expectations	soft	no	0	NBB
Price expectations	soft	no	0	NBB
Business-related services				
Trend in activity	soft	no	1	NBB
Trend in employment	soft	no	1	NBB
Trend in prices	soft	no	0	NBB
Assessment of activity	soft	no	1	NBB
Activity expectations	soft	no	1	NBB
General demand expectations	soft	no	1	NBB
Employment expectations	soft	no	1	NBB
Price expectations	soft	no	0	NBB
Civil engineering and roadworks				
Trend in activity	soft	no	0	NBB
Trend in number of tenders	soft	no	0	NBB
Trend in number of contracts concluded	soft	no	0	NBB
Trend in amount of work to be done	soft	no	0	NBB
Trend in prices	soft	no	1	NBB
Assessment of order books	soft	no	1	NBB
Demand expectations	soft	no	1	NBB
Employment expectations	soft	no	1	NBB
Price expectations	soft	no	1	NBB

EC = European Commission, HWWI = Hamburgisches WeltWirtschaftsInstitut; NAI = National Accounts Institute; NBB = National Bank of Belgium; NEO = National Employment Office; SB = Statistics Belgium; Th. R. = Thomson Reuters.

Annex 1 – Indicators included in the dataset (continued)

Indicator	Category	Log.	Diff.	Source
Consumer survey indicators (forecast for the next 12 months)				
Economic situation in Belgium	soft	no	0	NBB
Unemployment in Belgium	soft	no	1	NBB
Financial situation of households	soft	no	1	NBB
Household savings	soft	no	1	NBB
Indicators on developments in real activity and in the labour market				
Turnover at constant prices (based on the VAT returns)				
Manufacturing	hard	yes	1	NAI†
Construction	hard	yes	1	NAI†
Retail trade	hard	yes	1	NAI†
Hotels and restaurants	hard	yes	1	NAI†
Business services	hard	yes	1	NAI†
Services (total)	hard	yes	1	NAI†
Total turnover	hard	yes	1	NAI†
Industrial production				
Manufacturing	hard	yes	1	SB
Construction	hard	yes	0	SB
Energy	hard	yes	1	SB
Capital goods	hard	yes	1	SB
Intermediate goods	hard	yes	1	SB
Durable consumer goods	hard	yes	0	SB
Non-durable consumer goods	hard	yes	1	SB
Total industrial production, excluding construction	hard	yes	1	SB
Registration of new private cars	early hard	yes	1	SB
Permits for new residential buildings (in m^2)	hard	yes	0	SB
Permits for new non-residential buildings (in m^2)	hard	yes	0	SB
Work volume of temporary workers	early hard	yes	1	Federgon
Unemployed job-seekers	early hard	yes	1	NEO
Harmonised unemployment rate	early hard	no	1	EC
Financial indicators				
Ten-year Belgian government bond yield	financial	no	1	Th. R.
Spread on ten-year Belgian government bonds compared to the German Bund	financial	no	1	Th. R.
Brussels All Shares Index	financial	yes	1	Th. R.
Euro Stoxx Broad Index	financial	yes	1	Th. R.
Crude Oil-Brent Dated Free on Board	financial	yes	1	Th. R.
Import prices of energy raw materials in international markets	financial	yes	1	HWWI
Commodity import prices in international market, excluding energy	financial	yes	1	HWWI
Spot price of gold (Standard & Poors GSCI)	financial	yes	1	Th. R.

† Using data from the FPS Finance, Statistics Belgium and the NBB.

EC = European Commission, HWWI = Hamburgisches WeltWirtschaftsInstitut; NAI = National Accounts Institute; NBB = National Bank of Belgium; NEO = National Employment Office; SB = Statistics Belgium; Th. R. = Thomson Reuters.

Annex 1 – Indicators included in the dataset (continued)

Indicator	Category	Log.	Diff.	Source
Indicators on real external developments				
Trade in goods (average of exports and imports of goods)				
Euro area	hard	yes	1	CPB
Advanced economies	hard	yes	1	CPB
Emerging economies	hard	yes	1	CPB
Industrial production				
Euro area	hard	yes	1	EC
Advanced economies	hard	yes	1	CPB
Emerging economies	hard	yes	1	CPB
Germany	hard	yes	1	EC
France	hard	yes	1	EC
Industrial confidence				
Euro area	soft	no	1	EC
Germany	soft	no	1	EC
France	soft	no	1	EC
Netherlands	soft	no	1	EC
Consumer confidence				
Euro area	soft	no	1	EC
Germany	soft	no	1	EC
France	soft	no	1	EC
Netherlands	soft	no	1	EC

EC = European Commission, HWWI = Hamburgisches WeltWirtschaftsInstitut; NAI = National Accounts Institute; NBB = National Bank of Belgium; NEO = National Employment Office; SB = Statistics Belgium; Th. R. = Thomson Reuters.

Annex 2 – Top 20 indicators for predicting GDP growth, by data scenario
(based on the predictor selection performed over the period 1996Q3-2013Q4)

Data scenario 1: three months before the end of the current quarter

1	Business-related services survey; general demand expectations
2	Industrial confidence in the euro area
3	Trade survey; trend in prices (lagged)
4	Euro Stoxx Broad Index
5	Brussels All Shares Index
6	Commodity import prices in international markets, excluding energy
7	Trade survey; trend in prices
8	Business-related services survey; price expectations (lagged)
9	Civil engineering and roadworks survey; trend in number of contracts concluded
10	Construction survey; trend in orders
11	Construction survey; trend in orders (lagged)
12	Manufacturing industry survey; price expectations (lagged)
13	Consumer confidence in France (lagged)
14	Civil engineering and roadworks survey; trend in number of tenders (lagged)
14[†]	Manufacturing industry survey; assessment of the level of stocks of finished products (lagged)
16	Manufacturing industry survey; trend in prices (lagged)
17	Consumer survey; economic situation in Belgium
18	Turnover in services (lagged)
19	Trade survey; demand expectations
19[†]	Total turnover (lagged)

Data scenario 2: two months before the end of the current quarter

1	Industrial production in the advanced economies
2	Industrial confidence in the Netherlands
3	Consumer survey; unemployment in Belgium
4	Industrial confidence in the euro area
5	Commodity import prices in international markets, excluding energy
6	Industrial production in the emerging economies
7	Manufacturing industry survey; demand expectations
8	Import prices of energy raw materials in international markets
9	Trade survey; trend in prices (lagged)
10	Manufacturing industry survey; assessment of total order books
11	Production in construction (lagged)
12	Business-related services survey; activity expectations
13	Trade survey; intentions of placing orders
14	Manufacturing industry survey; assessment of the level of stocks of finished products (lagged)
15	Civil engineering and roadworks survey; employment expectations (lagged)
16	Civil engineering and roadworks survey; trend in number of tenders
17	Civil engineering and roadworks survey; trend in number of contracts concluded
18	Ten-year Belgian government bond yield
19	Turnover in services (lagged)
20	Total turnover (lagged)

[†] The selection procedure sometimes results in ties. Consequently, the same rank might be attributed to two variables (or more).

Annex 2 – Top 20 indicators for predicting GDP growth, by data scenario (continued)
(based on the predictor selection performed over the period 1996Q3-2013Q4)

Data scenario 3: one month before the end of the current quarter

1 Industrial confidence in the Netherlands
2 Manufacturing industry survey; assessment of total order books
3 Industrial production in the advanced economies
4 Construction survey; trend in prices
5 Manufacturing industry survey; demand expectations
6 Construction survey; price expectations
7 Consumer survey; unemployment in Belgium
8 Import prices of energy raw materials in international markets
9 Industrial production in the euro area
10 Commodity import prices in international markets, excluding energy
11 Trade survey; trend in prices (lagged)
12 Trade survey; trend in prices
13 Production of durable consumer goods (lagged)
14 Construction survey; trend in orders
15 Manufacturing industry survey; assessment of the level of stocks of finished products (lagged)
16 Business-related services survey; trend in activity
17 Consumer confidence in the Netherlands
18 Industrial production in the emerging economies
19 Brussels All Shares Index
20 Construction survey; trend in activity

Data scenario 4: end of the current quarter

1 Industrial confidence in the Netherlands
2 Manufacturing industry survey; demand expectations
3 Industrial production in the euro area
4 Construction survey; trend in prices
5 Consumer survey; unemployment in Belgium
6 Industrial production in the advanced economies
7 Import prices of energy raw materials in international markets
8 Crude Oil-Brent Dated Free on Board
9 Industrial production in the emerging economies
10 Commodity import prices in international markets, excluding energy
11 Manufacturing industry survey; assessment of total order books
12 Trade in goods in the emerging economies
13 Trade survey; trend in prices (lagged)
14 Construction survey; trend in orders
15 GDP at market prices (lagged)
16 Manufacturing industry survey; assessment of the level of stocks of finished products (lagged)
17 Production of durable consumer goods (lagged)
18 Business-related services survey; trend in activity
19 Permits for new non-residential buildings (in m^2)
20 Production in construction (log-transformed)

Annex 2 – Top 20 indicators for predicting GDP growth, by data scenario (continued)
(based on the predictor selection performed over the period 1996Q3-2013Q4)

Data scenario 5: one month after the end of the current quarter

1 Industrial production in the advanced economies
2 Industrial confidence in the Netherlands
3 Work volume of temporary workers
4 Total turnover
5 Trade in goods in the emerging economies
6 Consumer survey; unemployment in Belgium
7 Construction survey; trend in prices
8 Manufacturing industry survey; demand expectations
8[†] Import prices of energy raw materials in international markets
10 Turnover in services
11 Manufacturing industry survey; assessment of total order books
12 Trade in goods in the euro area
13 Crude Oil-Brent Dated Free on Board
14 Trade survey; trend in prices (lagged)
15 Business-related services survey; activity expectations
16 Business-related services survey; trend in activity
17 Construction survey; trend in orders
18 Manufacturing industry survey; assessment of the level of stocks of finished products (lagged)
19 Industrial production in the emerging economies
20 Trade survey; price expectations (lagged)

Data scenario 6: two months after the end of the current quarter

1 Industrial production in the euro area
2 Production of intermediate goods
3 Trade in goods in the advanced economies
4 Trade in goods in the euro area
5 Total turnover
6 Industrial production in the advanced economies
7 Work volume of temporary workers
8 Industrial confidence in the Netherlands
9 Trade in goods in the emerging economies
10 Consumer survey; unemployment in Belgium
11 Manufacturing industry survey; assessment of total order books
12 Manufacturing industry survey; demand expectations
13 Crude Oil-Brent Dated Free on Board
14 Construction survey; trend in prices
15 Turnover in services
16 Business-related services survey; trend in activity
17 Trade survey; trend in prices (lagged)
18 Construction survey; trend in orders
19 Manufacturing industry survey; assessment of the level of stocks of finished products (lagged)
20 Civil engineering and roadworks survey; trend in number of contracts concluded

[†] The selection procedure sometimes results in ties. Consequently, the same rank might be attributed to two variables (or more).

Annex 3 – RMSFEs of the predictions for quarterly GDP growth generated by bridge equations estimated using stepwise regressions

(percentage points; recursive selections and forecasts performed over the period 2005Q1-2013Q4)

	Data scenario					
	1	2	3	4	5	6
Targeted SB model including the *n top-ranked indicators**						
*n** = 1	1.091	0.847	0.525	0.487 *	0.505 **	0.495 **
*n** = 2	1.001	0.711	0.488	0.528 **	0.449	0.401
*n** = 3	0.996	0.745 *	0.491	0.522 *	0.436	0.407
*n** = 4	0.973	0.668	0.495	0.506	0.404	0.432
*n** = 5	0.977	0.653	0.507	0.506	0.383	0.425
*n** = 6	1.010	0.658	0.566	0.504	0.387	0.416
*n** = 7	1.023	0.652	0.562	0.502	0.393	0.428
*n** = 8	0.997	0.654	0.568	0.518 *	0.387	0.427
*n** = 9	0.987	0.657	0.565	0.502 *	0.440	0.423
*n** = 10	0.938	0.654	0.559	0.493 *	0.411	0.417
*n** = 11	0.891	0.653	0.554	0.509	0.429	0.409
*n** = 12	0.883	0.710	0.558	0.503	0.431	0.410
*n** = 13	0.812	0.705	0.552	0.494	0.421	0.408
*n** = 14	0.801	0.704	0.557	0.463	0.421	0.411
*n** = 15	0.801 *	0.703	0.552	0.465	0.413	0.416
DI model including all the indicators	0.586	0.545	0.461	0.404	0.389	0.386
p.m. Autoregressive forecast	*0.767*	*0.767*	*0.767*	*0.553*	*0.553*	*0.553*

The highlights indicate the smallest RMSFEs for a given data scenario. The signs "*", "**" and "***" indicate the rejection of the null hypothesis of equal forecast accuracy with respect to the benchmark DI model that includes all the indicators, at the 10%, 5% and 1% levels, respectively, based on the DM test statistic.

Annex 4 – Bridge equations used to predict 2007Q4, by data scenario

(dependent variable: log-difference of quarterly GDP[†])

Data scenario 1: three months before the end of the current quarter

Rank	Variable	Coefficient	
	Intercept	0.0079	***
1	Trade survey; price expectations (lagged)	0.0000	
2	Manufacturing industry survey; employment expectations	0.0004	**
3	Trade survey; trend in sales	-0.0001	*
4	Manufacturing industry survey; trend in prices (lagged)	0.0000	
5	Civil engineering and roadworks survey; trend in amount of work to be done (lagged)	0.0002	***
6	Manufacturing industry survey; price expectations (lagged)	-0.0002	

$\bar{R}^2$ = 0.430; F = 6.915***; JB = 0.727; BG = 9.859**; BP = 10.897*
Estimation sample: 1995Q3-2007Q2 (48 observations)

Data scenario 2: two months before the end of the current quarter

Rank	Variable	Coefficient	
	Intercept	0.0045	***
1	Business-related services; general demand expectations	0.0000	
2	Trade in goods in the emerging economies	0.0257	
3	Consumer confidence in the Netherlands	0.0003	***
4	Industrial production in the advanced economies	0.1369	
5	Construction survey; trend in prices	0.0002	
6	Manufacturing industry survey; assessment of total order books	0.0001	

$\bar{R}^2$ = 0.494; F = 8.798***; JB = 0.791; BG = 7.815*; BP = 1.999
Estimation sample: 1995Q2-2007Q2 (49 observations)

Data scenario 3: one month before the end of the current quarter

Rank	Variable	Coefficient	
	Intercept	0.0047	***
1	Construction survey; trend in prices	0.0002	
2	Industrial confidence in the Netherlands	0.0003	
3	Consumer confidence in the Netherlands	0.0003	**
4	Industrial production in the advanced economies	0.1196	
5	Trade in goods in the advanced economies	0.0345	
6	Trade survey; trend in sales (lagged)	0.0000	

$\bar{R}^2$ = 0.476; F = 8.265***; JB = 0.901; BG = 12.128**; BP = 8.906
Estimation sample: 1995Q2-2007Q2 (49 observations)

[†] In the case of the first data scenario, the dependent variable has one lead.
F = F test statistic for the significance of the model; JB = Jarque-Berra test statistic for normality of residuals; BG = Breusch-Godfrey test statistic for serial correlation in the residuals (using 4 lags); BP = Breusch-Pagan test statistic for heteroskedasticity in the residuals. "*", "**" and "***" stand for significance of a coefficient or a test statistic at the 10%, 5% and 1% levels, respectively.

Annex 4 – Bridge equations used to predict 2007Q4, by data scenario (continued)
(dependent variable: log-difference of quarterly GDP)

Data scenario 4: end of the current quarter

Rank	Variable	Coefficient	
	Intercept	0.0033	***
1	Industrial confidence in the Netherlands	0.0001	
2	Consumer confidence in the Netherlands	0.0004	***
3	Construction survey; trend in prices	0.0002	
4	GDP at market prices (lagged)	0.2637	**
5	Consumer survey; unemployment in Belgium	0.0000	
6	Trade in goods in the emerging economies	0.0442	

$\bar{R}^2$ = 0.504; F = 9.115***; JB = 1.271; BG = 8.673; BP = 7.623
Estimation sample: 1995Q3-2007Q3 (49 observations)

Data scenario 5: one month after the end of the current quarter

Rank	Variable	Coefficient	
	Intercept	0.0033	***
1	Industrial confidence in the Netherlands	0.0000	
2	Industrial production in the advanced economies	0.1035	
3	Consumer confidence in the Netherlands	0.0004	***
4	Construction survey; trend in prices	0.0001	
5	Trade in goods in the emerging economies	0.0307	
6	GDP at market prices (lagged)	0.2278	*

$\bar{R}^2$ = 0.511; F = 9.356***; JB = 0.342; BG = 7.128; BP = 7.419
Estimation sample: 1995Q3-2007Q3 (49 observations)

Data scenario 6: two months after the end of the current quarter

Rank	Variable	Coefficient	
	Intercept	0.0035	***
1	Industrial confidence in the Netherlands	0.0002	
2	Industrial production in the advanced economies	0.0955	
3	Consumer confidence in the Netherlands	0.0003	**
4	Total turnover	0.0737	***
5	Construction survey; trend in prices	0.0001	
6	GDP at market prices (lagged)	0.1472	

$\bar{R}^2$ = 0.576; F = 11.850***; JB = 1.112; BG = 11.368**; BP = 4.402
Estimation sample: 1995Q3-2007Q3 (49 observations)

F = F test statistic for the significance of the model; JB = Jarque-Berra test statistic for normality of residuals; BG = Breusch-Godfrey test statistic for serial correlation in the residuals (using 4 lags); BP = Breusch-Pagan test statistic for heteroskedasticity in the residuals. "*", "**" and "***" stand for significance of a coefficient or a test statistic at the 10%, 5% and 1% levels, respectively.

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