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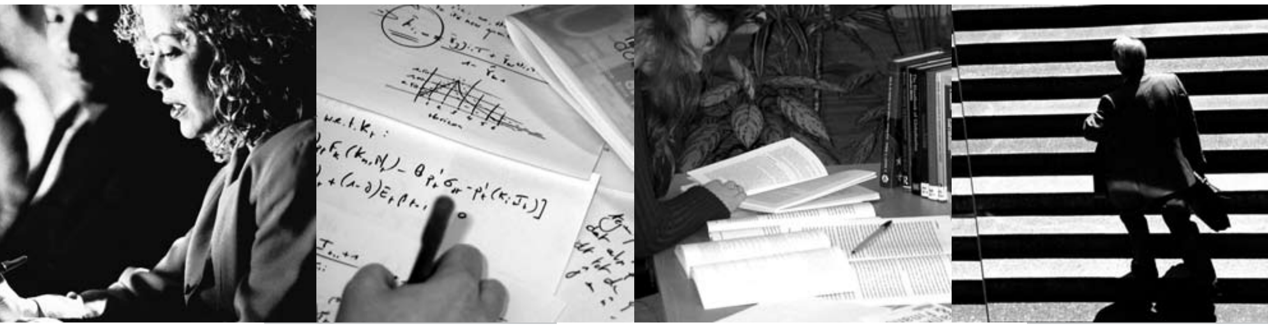

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A GENERALISED DYNAMIC FACTOR MODEL FOR THE BELGIAN ECONOMY

Useful business cycle indicators and GDP growth forecasts

Christophe Van Nieuwenhuyze[(*)]

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Abstract

This paper aims to extract the common variation in a data set of 509 conjunctural series as an indication of the Belgian business cycle. The data set contains information on business and consumer surveys of Belgium and its neighbouring countries, macroeconomic variables and some worldwide watched indicators such as the ISM and the OECD confidence indicators. The statistical framework used is the One-sided Generalised Dynamic Factor Model developed by Forni, Hallin, Lippi and Reichlin (2005). The model splits the series in a common component, driven by the business cycle, and an idiosyncratic component. Well-known indicators such as the EC economic sentiment indicator for Belgium and the NBB overall synthetic curve contain a high amount of business cycle information.

Furthermore, the richness of the model allows to determine the cyclical properties of the series and to forecast GDP growth all within the same unified setting. We classify the common component of the variables into leading, lagging and coincident with respect to the common component of quarter-on-quarter GDP growth. 22% of the variables are found to be leading. Amongst the most leading variables we find asset prices and international confidence indicators such as the ISM and some OECD indicators. In general, national business confidence surveys are found to coincide with Belgian GDP, while they lead euro area GDP and its confidence indicators. Consumer confidence seems to lag. Although the model captures the dynamic common variation contained in the data set, forecasts based on that information are insufficient to deliver a good proxy for GDP growth as a result of a non-negligible idiosyncratic part in GDP's variance.

Lastly, we explore the dependence of the model's results on the data set and show through a data reduction process that the idiosyncratic part of GDP's quarter-on-quarter growth can be dramatically reduced. However, this does not improve the forecasts.

JEL Classification: C33, C43, E32, E37.

Key Words: Dynamic factor model, business cycle, leading indicators, forecasting, data reduction.

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1 Introduction

According to the well-known definition of Burns and Mitchell (1946), that describes the business cycle as a type of fluctuation found in many economic activities, business cycle research should be characterised by a huge amount of data. The business cycle is in the first place an empirical phenomenon, whereby preferably information belonging to different economic spheres such as national accounts data, financial and monetary variables, retail sales, etc. should be analysed. The common fluctuation in these data series could be described as the business cycle. In the past, econometric theory, as opposed to the availability of macroeconomic information, has not been very helpful in identifying the business cycle since most econometric models are small-scaled and contain only a handful of variables to describe the economy (e.g. VARs). When a lot of series are used, models become hard to identify since the number of parameters that needs to be estimated increases accordingly. To solve this problem, business cycle researchers mostly rely on a broad measure of economic activity, such as GDP. However, since GDP itself needs to be estimated, it may contain measurement errors and the amount of data it is based upon, while extensive, may not be broad enough to capture all macroeconomic realities.

Burns and Mitchell proposed to analyse the business cycle through an index model, which, by taking contemporaneous averages of the series, summarised their data into a single index. This is what is called the NBER-method and it has been widely used to identify the business cycle (e.g. Zarnowitz, 1992). However, the method is informal and relies to a large extent on arbitrariness both in method and variable selection. The method does e.g. not allow to distinguish data series according to their "usefulness", since all series are equally weighted in the aggregate.

A formal representation of index models can be found in factor models, which, by assuming the data is driven by a few factors, dramatically reduce the dimension and make identification feasible. The factors take on the role of the index in the model of Burns and Mitchell. Under the factor model approach each time series is represented as the sum of two orthogonal components: the common or business cycle component, which is strongly correlated with the rest of the panel and is a linear combination of the factors, and the idiosyncratic component. In the classic or exact factor model, idiosyncratic components are mutually uncorrelated, which limited its economic applications and maintained the use of informal methods.

Recently serious progress has been made in the theory of factor models through the Generalised Dynamic Factor Model (GDFM) of Forni, Hallin, Lippi and Reichlin, henceforth FHLR (2000b, 2001, 2004, 2005). The model differs from the classic factor model in that it allows the idiosyncratic errors to be weakly serial and cross-sectional correlated to some extent. It thereby combines the so-called "approximate static factor model" of Chamberlain and Rothschild (1983), widely applied in financial econometrics (e.g. Arbitrage Pricing Theory, APT) and the Dynamic Factor Model of Geweke (1977), Sargent and Sims (1977) for which respectively cross-sectional and serial correlation was allowed. The model is dynamic since the common shocks can hit the series at different times as opposed to the static model. The common shocks and components, which are a linear combination of them, are inherently unobservable and are estimated by means of dynamic principal components. While the familiar static principal components are based on an eigenvalue decomposition of the contemporaneous covariance matrix, dynamic principal components are based on the spectral density matrix (i.e. dynamic covariations) of the data and consequently are averages of the data weighted and shifted through time.

In this paper, we explore the richness of the GDFM by applying it to a large data set containing information on the Belgian economy and its indicators. Since the GDFM is based on the spectral density of the data (i.e. dynamic covariations), the model is two-sided in the sense that the common components are a projection onto the leads and lags of the common factors. Consequently, problems arise at the end of the sample since future observations are needed to estimate the common components. Therefore we have used the one-sided version of the GDFM as proposed by FHLR (2005). In this one-sided model, the common components are a linear combination of contemporaneous and lagged observations only. For each variable, we measure the amount of business cycle information they contain, as the ratio between the variance of their common component and their total variance. Furthermore, we define a reference cycle as the common variation contained in GDP's variance and classify each series into leading, lagging and coincident and measure their time delay with respect to this cycle. Results are reported for individual series and different variable groups, which is highly desirable since it can be used as a guide for assessing the importance of individual macroeconomic indicators as "warning signals" for the Belgian economy.

Moreover, we forecast quarter-on-quarter real GDP growth using the dynamic common information in the data set. Through the model's features, this takes place within the same unified setting, which makes the model very useful for business cycle analysis. However, we show that the results rely for a great part on the composition of the data set. In general, this is a feature of many econometric models, but for factor analysis a more profound understanding of the relation between the models' outcome and the composition of the data set would be desirable.

The current application is an extension of previous research conducted at the NBB by De Mulder and Dresse (2002). Compared to their model, a larger data base was constructed and the estimation and forecasting is now performed within the same setting, whereas previously it were disjoint operations. Moreover, attention has been paid to the business cycle properties of individual variables and groups of variables.

Because the GDFM is quite novel, applications are few. The best known application is the construction of a coincident indicator for the euro area business cycle (EuroCOIN, Altissimo et al. 2001). Using a selection of 951 indicators,[1] the authors found 4 common factors to explain the aggregate dynamics at business cycle frequency. Furthermore, they report time delays for different variable groups with respect to a reference business cycle, defined as the common component of GDP. Examples of the construction of leading, lagging and coincident indicators and forecasting include FHLR (2000a) and FHLR (2003). A larger literature exists on the dynamic factor model estimated through static principal components as proposed by Stock and Watson (1998b, 2002). Since static principal components are solely based on contemporaneous covariations, the method does not allow to directly measure the time lag between the variables and to classify them as coincident, leading or lagging with respect to a particular reference cycle.[2] These papers therefore

[1] This data set was further reduced in Altissimo et al. to 246 variables according to specific criteria concerning delays in publication and estimation/forecasting purposes. We rejected on forehand the variables with long publication delays so that the longest delay with respect to the reference period amongst our 509 indicators is no longer than 3 months. Concerning the second criteria, we perform a similar reduction as in Altissimo et al. albeit at some looser criteria delivering 382 series (see 6.2.2). Apart from that, we perform a more discriminating reduction exercise with the view on forecasting, resulting in a whole range of subsamples of varying size and composition (see 6.2.3).

[2] Apart from the greater analytic purposes (study of the business cycle properties next to forecasting), FHLR(2003b) show that the dynamic method performs better than the static method of Stock and Watson

mainly focus on forecasting and its performance, examples include Artis et al. (2002), Boivin and Ng (2003), Hansson et al. (2003), Dreger and Schumacher (2002), Stock and Watson (2002) and Watson (2003). Unlike what is done in most of the existing empirical literature, we want to cover the main aspects of business cycle analysis within one single model. This will also allow us to empirically explore the relationship between "estimation performance" and "forecast performance" of the GDFM.

The paper proceeds as follows. Section 2 describes the one-sided GDFM and how it is estimated. In Section 3 the data set is described. Section 4 reveals how much business cycle information the variables contain and defines a reference cycle as the common component of quarter-on-quarter GDP growth. Section 5 examines whether the series are pro- or countercyclical with respect to this cycle and orders them into leading, lagging and coincident variables by measuring their time lag. Section 6 forecasts quarter-on-quarter real GDP growth using the dynamic common variation and explores the relationship between estimation and forecast performance of the GDFM. Finally, Section 7 concludes and raises some questions for further research.

2 The One-sided Generalised Dynamic Factor Model

2.1 Description

The model used in this paper is the GDFM of FHLR (2000b, 2001, 2004, 2005). The representation theory can be found in Forni and Lippi (2001). The model has been developed in order to deal with large data panels, both in time and cross-sectional dimension. Similar to other factor models, a vector of N time series is represented as the sum of two mutually orthogonal components: a common component driven by a small number $q < N$ of common shocks or factors and an idiosyncratic component related to N variable specific shocks.

The model is called general, since (i) it does not restrict the order of the dynamic loadings of the common factors and (ii) the idiosyncratic component is allowed to be mildly cross-correlated at all leads and lags. Giving up the factor analysis orthogonality conditions between the idiosyncratic components requires assumptions on the eigenvalues of the spectral density matrix of the data to separate the idiosyncratic sources of variation from the common ones and to identify the model. When the series follow a GDFM with q common factors it is required that the first q eigenvalues of the spectral density matrix diverge, while the other eigenvalues remain bounded. After all, the rate of divergence of the eigenvalues indicates "how common" the shocks are. The more they diverge, the more likely the shocks are present in infinitely many cross-sectional units since they keep on contributing in a non-decreasing manner to the variance of a progressively larger panel. This divergence assumption also ensures a minimum amount of cross-correlation between the common components. On the other hand, the boundedness assumption ensures that the idiosyncratic causes of variation, although possibly shared by many units, have their effects concentrated on a finite number of series, and tend to zero as N tends to infinity. FHLR show that the model is asymptotically identified when $(N, T) \to \infty$.

when there is a substantial heterogeneity in the fraction of variance explained by the common component between the variables (which seems to be the case here, see Section 4).

2.2 Estimation[3]

We assume that the N time series included in our panel are, after suitable transformations, a realisation of a real-valued stationary N-dimensional vector process with zero mean $\{x_{it} = (x_{1t}, \ldots, x_{nt})'; n \in \mathbb{N}, t \in \mathbb{Z}\}$. Under the GDFM, satisfying the necessary conditions and assumptions, it is shown that each time series can be decomposed into two components:

$$x_{it} = \chi_{it} + \xi_{it} = \textstyle\sum_{j=1}^{q} b_{ij}(L)u_{jt} + \xi_{it} \tag{1}$$

where χ_{it} is the common component and ξ_{it} the idiosyncratic component. $b_{ij}(L) = B_n(L) = B_0^n + B_1^n L + \ldots + B_s^n L^s$ represents the (dynamic) loadings of order s, which are allowed to differ in coefficient and lags across the series. The q common shocks $(u_{jt}; j = 1, \ldots, q; t \in \mathbb{Z})$ are assumed to be mutually orthogonal white noise processes (at all leads and lags) with unit variance.[4] The idiosyncratic component is driven by variable-specific shocks, for which the GDFM allows a certain amount of correlation. The dynamic factor structure implies that the idiosyncratic component of any series is orthogonal to all common shocks at any lead or lag.

The common shocks u_{jt} are latent and need to be estimated. This is done through the estimation of dynamic principal components. These are obtained by the dynamic eigenvalues and eigenvectors decomposition of the spectral density matrix of x_{nt}, which is a generalisation of the orthogonalisation process of the variance-covariance matrix of x_{nt} in case of static principal components. Contrary to static principal components, the data are shifted through time before averaging along the cross-section, taking into account the whole set of dynamic covariances, whereas static principal components are only based on the contemporaneous covariances.[5] With $N \to \infty$, the dynamic principal components become increasingly collinear with the common shocks. The idea behind this method is that by averaging along the cross-section and by shifting the series through time the idiosyncratic components which are poorly correlated cancel out, whereas the common sources of variation do not. Hence, the factor space spanned by the common shocks and the factor space spanned by the dynamic principal components (which approximate the common shocks) coincide when $N \to \infty$.

The spectral density matrix $\sum_n(\theta) = (\sigma_{ij}(\theta))$ of x_{nt} is estimated using the frequency representation of the time series.[6] For each frequency $-\pi < \theta < \pi$, we obtain dynamic principal components through the dynamic eigenvector and eigenvalue decomposition of the spectral density matrix, as outlined in Appendix A.1. The common components are the orthogonal projections of the data on the present, past and future of the first q dynamic principal components. Since the dynamic principal components themselves are a

[3] The model has been estimated using MATLAB. MATLAB procedures were taken from http://www.dynfactors.org and further extended. To perform the data reduction exercise as described in part 6.2.3 an additional algorithm was written in MATLAB.

[4] This vector process has a non-singular spectral density matrix, equal to the first q dynamic eigenvalues of the data.

[5] More information on dynamic principal components can be found in Brillinger (1975), who shows that the first q dynamic principal components are the best approximation of x_{nt} by means of q linear combinations of the data.

[6] The frequency representation of a time series allows to represent a stationary time series by means of its autocovariance function -which summarises its dynamic correlation properties- in the frequency domain. Through the Fourier transform it is decomposed into sized and delayed (co)sine waves of different frequencies (see Harris, 1967).

linear combination of the data, the same holds for the common components. The idiosyncratic components are found after subtraction of the common components from the data or equivalently as the projections of the data on the remaining $N-q$ dynamic principal components. The eigenvalue-eigenvector decomposition also allows to split up the spectral density matrix into a spectral density matrix of the common component $\sum_{n}^{\chi}(\theta)$ (first q dynamic eigenvalues and eigenvectors) and of the idiosyncratic component $\sum_{n}^{\xi}(\theta)$ (remaining dynamic eigenvalues and eigenvectors).

The projection coefficients of the common components, $b_{ij}(L)$, are the result of an inverse Fourier transform[7] of the first q dynamic eigenvectors. Since they are dynamic, they are two-sided, both lagged and future values of the common shocks can be loaded. This causes a problem at the end of the sample to estimate and forecast the common component since no future observations are available. To solve this problem FHLR (2005) suggested a refinement of their procedure that retains the advantages of the dynamic approach, while the common component is based on a one-sided filter of the observations. Following this procedure, the factor space is approximated by r static aggregates instead of q dynamic principal components. These r contemporaneous averages are however based on the information of the dynamic approach. The procedure consists of two steps. In the first step, it relies on the dynamic approach, which delivers estimates of the covariance matrices of the common and idiosyncratic component (at all leads and lags) through an inverse Fourier transform of the spectral density matrices. In the second step, this information is used to construct the factor space by r contemporaneous averages, wherein the variables are weighted according to their common/idiosyncratic variance ratio obtained from the contemporaneous covariance matrices estimated in the first step. These r aggregates are the solutions from a generalised principal component problem and have the efficient property of reducing the idiosyncratic disturbance[8] in the common factor space to a minimum, by selecting the variables with the highest common/idiosyncratic variance ratio. The number of aggregates is equal to $r = q(s+1)$, which is the static rank of the spectral density matrix of the common factors, s indicates the order of the lag operator in [1]. It is worth noting that this one-sided refinement is only used to estimate and forecast the common component. The business cycle characteristics such as cyclical behaviour and timing are deduced in the spectral domain, without the need to actually estimate the common component and thus the use of the one-sided approach.

2.3 Parameter values

Prior to the actual estimation, the lead/lag of the cross-covariance matrices and the number of frequencies at which the spectral density is evaluated has to be determined. Details on this issue are provided in Appendix A.1. The number of leads/lags of the covariances is set at 3, and the number of frequencies at 7. Apart from these parameters, the number of common shocks, q, has to be determined. If the data share q sources of variation, then according to the assumptions of the GDFM, the first q dynamic eigenvalues of the spectral density matrix diverge, while the other remain bounded. This rate of divergence is examined by letting $N \rightarrow \infty$ and is thus of asymptotic nature. In finite samples it

[7] This transform translates the results found in the spectral domain (dynamic eigenvectors) into a filter in the time domain ($b_{ij}(L)$).

[8] When an idiosyncratic component is large it could possibly survive aggregation and be part of the first principal components. However letting $N \rightarrow \infty$ and attributing lower weights to the highly idiosyncratic variables reduces this risk and makes the principal components increasingly collinear with the common factors.

is not clear how a slowly diverging sequence can be distinguished from an eventually bounded one. Therefore we need to rely on a heuristic inspection of the eigenvalues against the number of series as suggested by Forni and Lippi (2001). Having N series and T observations, spectral density matrices $\sum_g^T(\theta), g \leq N$, for $g \rightarrow N$ can be estimated and the corresponding dynamic eigenvalues can be computed for different frequencies. To determine the number of common factors, Forni and Lippi (2001) suggest to take the following rules into account:

1. The average over frequencies θ of the first q eigenvalues diverges when $g \rightarrow N$, whereas the average over θ of the $(q+1)$-th eigenvalue remains relatively stable.

2. At $g = N$, there should be a substantial gap between the variance explained by the q-th principal component and the variance explained by the $(q+1)$-th one.

This last rule suggests to add dynamic principal components until the increase in explained variance is larger than some pre-specified value. Setting this at 10%, the number of common factors driving our data set of 509 indicators is equal to 2.

Figure 1a shows the first 20 dynamic eigenvalues averaged over the different frequencies, plotted against the number of series g. From this it can be seen that the first 2 eigenvalues diverge most probably. In Figure 1b, the contribution of the first 20 dynamic principal components to the total variance of the data set is shown. The second dynamic principal component accounts for 10%. Together with the first one, about 38% of the total variance is explained.[9]

While 2 factors driving 509 indicators may seem low, it is not uncommon for macroeconomic data to be well-approximated by low-dimensional factor structures. Forni and Reichlin (1998) and FHLR (2001) for example also found 2 factors to be helpful in understanding the aggregate dynamics of 450 and 123 series respectively. Moreover, the factors are dynamic and thereby have a more extreme "reducing capacity" compared to static factors. For the actual estimation of the common component we will treat the past values of the common factors as separate static factors, which delivers 8 static factors $(= r)$ out of 2 dynamic ones $(= q)$, which is already considerably higher. In order to avoid a too large number of static factors, we set a relatively strict criterion for the explanatory power of the dynamic factors at 10%. The low number of factors is not only convenient but also ensures the idea of a commonly present business cycle (i.e. the comovement of the series). Furthermore, as shown later, the results are quite robust to the number of factors.[10] Although, logically, commonality increases with the number of factors, the results regarding the cyclical features of the series remain largely the same.

[9] Altissimo et al. (2001) found the first two factors to explain a comparable 34% of the variance for the euro area economy. Contrary to our case, however, they study monthly data -for which commonality is likely to be lower- and also found the next two factors to exceed the 10% condition. As a result, they end up with four common factors, which on aggregate explain 55% of the variance of their data set. Ignoring the discriminative power of our factors, the first four factors would explain 51% of the total variance in our data set. The relatively low share of explained variance in our sample is possibly a consequence of (i) the diversity of the data set and (ii) the more volatile character of the Belgian economy compared to the euro area.

[10] Results of the model estimated with 3 till 5 dynamic factors can be obtained from the author upon request.

3 Data Set

3.1 Description

Constructing a rich data base is a crucial step to extract the business cycle information through the GDFM. The factors are always defined with respect to a data set and therefore the business cycle information depends on the data set. Furthermore, the data set should be constructed in view of the exercise on hand. Next to extracting the business cycle information in each variable, we want (i) to evaluate the variables with respect to a reference variable (GDP) (ii) to make reliable forecasts for quarter-on-quarter GDP growth using the common variation.

To that end, we tried to include a large number of variables which are likely to comove with each other and more specifically with Belgian GDP. The large number of variables should allow to "kill" the idiosyncratic variance over the cross-section. At first sight, selecting only national economic indicators would be appropriate in order to identify the Belgian cycle. On the other hand, it is known that the Belgian business cycle, due to the openness of its economy, strongly comoves with that of the euro area and more specifically with those of the neighbouring countries, suggesting international indicators could convey important information for the Belgian business cycle as well. Therefore we also included economic indicators for the euro area as a whole, Germany, France and the Netherlands. Possible differences in synchronisation are not a problem given the dynamics of the model. Moreover, including these variables enables us to fully benefit from the dynamic structure of the model. Furthermore, since some international indicators are widely used to assess the state of the business cycle beyond the scope of their national economy (e.g. US Institute of Supply Management (ISM) indicators), we also included some economic indicators from the US, UK and Japan. The results of the model will allow us to check whether these indicators are driven by the common factors of the data set and consequently whether they contain valuable information about the Belgian economy.

In contrast to these benefits, including international variables might disturb the extracted business cycle as those international shocks which are unrelated to the Belgian economy might be picked up in the common movement. However, since the esimation procedure implies that the common shocks are present in a majority of variables (preferably all), these disturbances tend to be rather limited if the number of international variables is not too high. To limit the number of international variables, non-survey variables only include national variables, with the exception of GDP[11] and financial variables. Survey variables include both national and international variables. Additional requirements concerning homogeneity, both across time and cross-section dimension were taken into account.[12] All in all, this provided 509 time series available on a quarterly or monthly basis between 1990Q1 – 2003Q3. The starting date was the result of a trade-off between obtaining a richer data set and maintaining a relatively large time dimension.[13]

[11] Apart from the countries mentioned, we also included GDP series for other euro area countries, as the main indicator of their business cycle, in order to shed some light on their behaviour with respect to the Belgian cycle.

[12] Apart from the harmonised surveys of the EC and OECD, survey results from the national sources of the countries were used (obtained through Thomson Financial Datastream). Regarding consistency, we only included those indicators which correspond to the published indicators of the NBB business survey (see http://www.nbb.be/doc/dq/E/dq3/PEC.pdf). If the overall indicator of the national source consists of various overall sub indicators (e.g. IFO overall indicator, which is split into an IFO overall current climate and an IFO overall forecasts indicator), all of these components are applied.

[13] This trade-off is well illustrated by the service sector surveys. Due to the large weight of the service

For the purpose of reporting, we regrouped our series in homogeneous groups and subgroups according to their economic classification, source and geographical relevancy. The composition of the data set is shown in Table 1 and in detail in Table 3. A first major distinction was made between survey and non-survey data:

Non-survey data represent 36% and were further regrouped into:

- Activity variables (55 variables): National accounts data, industrial production, retail sales, international trade and car sales.
- Labour market variables (32 variables): Employment and unemployment.
- Price variables (47 variables): Consumer prices, producer prices, commodity prices and wages.
- Financial variables (51 variables): Interest rates and asset prices (stock prices, real estate prices, exchange rates and precious metals).

Survey data represent 64% of the data set and were split into two main groups:

- Consumer confidence indicators (77 variables)
- Business confidence indicators (247 variables)

The survey data were additionally split up according to their source: Bank of Japan (BOJ), Statistics Netherlands (CBS), European Commission (EC), Ifo Institute for Economic Research (IFO), National Institute for Statistics and Economic Studies (INSEE), Institute of Supply Management (ISM), Organisation for Economic Co-operation and Development (OECD) and National Bank of Belgium (NBB). For business confidence, further distinctions were made according to the geographical relevant domain of the indicator (Belgium, non-Belgium) and, wherever possible, according to the indicator category:

- Overall indicators
- Manufacturing industry
- Trade sector
- Building
- Capacity utilisation

Together, these distinctions and the variety of data should allow to get a deeper insight into the appropriateness of various indicators as assessing instruments for the Belgian business cycle. Other classifications are possible, but the implemented structure fitted the purposes of the paper the best. Moreover, individual results are reported in Table 3.

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sector in the economy, these surveys are likely to contain valuable information on the business cycle and should therefore be included. Nevertheless, it was preferred to leave them out given the short time period they cover (since 1995 in case of Belgium), which would have violated the model's identification criteria. However, note that the data set contains several "hard data" on this sector (value added, employment).

3.2 Data treatment

Before the data can be used, the series need to be transformed. Both the question of interest and the features of the model determine the undertaken procedures. Since the paper aims to extract the business cycle information and to forecast real GDP quarter-on-quarter growth, the paper focuses on the growth cycle concept of the business cycle (unlike for instance the NBER method, which measures cycles in the level of the series, see Burns and Mitchell, 1946), defined as the quarter-on-quarter variation of the underlying variables. Being measured at a quarterly frequency, the series available on a monthly basis were transformed to a quarterly basis by taking averages, leaving 55 observations between 1990Q1 and 2003Q3. To obtain a meaningful concept of the quarter-on-quarter variations, seasonality was removed where necessary. This was done using the deseasonality procedure Tramo/Seats (see Gomez and Maravall, 1996). Furthermore, all activity variables are expressed in real terms. These are obtained by deflating nominal variables by the CPI index, with the exception of the national accounts concepts which are deflated by their own deflator. For all other variables (e.g. interest rates and exchange rates) both nominal and real concepts were included in the data set.

The estimation of the spectral density and the GDFM requires stationary time series. We opted to apply the same stationary procedure to all series. We first-differenced the series' levels by taking percentage changes compared to the previous quarter and by a simple difference when the level possibly exhibits negative values.[14] We also applied this procedure to the variables which were stationary from the outset. The reason for this is twofold i) having all variables defined in quarter-on-quarter variations enables to capture the growth cycle concept of the business cycle and ii) taking on variables in their level, even when stationary, would seriously disturb the mutual relations in the frequency domain causing phase shifts and thus invalid deduced time lags.[15] Interest rate spreads, which were taken on in levels, are the only exception to this rule. These levels are however stationary and are the result of a cross-sectional difference instead of a difference in time. Given their widely illustrated covariation with the growth cycle concept of the business cycle (e.g. Estrella and Mishkin, 1997), this is common practice.

In a last step, the series were normalised in order to have a zero sample mean and unit variance by subtracting their mean and dividing by their standard deviation. This standardisation is necessary to avoid overweighting of the series with large variance when estimating the spectral density matrix. Afterwards, the common component is denormalised, so as to correspond to the actual series.

4 Degree of Commonality and Reference Business Cycle

As stated in the introduction, the business cycle is an empirical phenomenon characterised by comovement of economic time series. According to Stock and Watson (1989), the business cycle can be interpreted as one common factor affecting all time series at the

[14] For price variables (consumer prices, stock prices, ...) percentage changes with respect to the previous quarter of the index were taken. The suitable transformations were sufficient to render all 509 variables into stationary variables.

[15] In general, taking growth rates generates a time series that leads the underlying series (for instance, both the peaks and troughs come earlier) and consequently induces a phase shift with respect to the series in level (Cohen, 2001). Deducing and comparing time lags from both concepts would be improper to do.

same moment. In our case, such a factor is non-existent, since we allow different common factors to affect the time series at different moments in time.

How can we then identify a reference business cycle? Through the GDFM, each time series is split into a common component which is a linear combination of the common factors and thereby represents the business cycle information present in the variable, next to an idiosyncratic component which captures variable specific variation unrelated to the business cycle. Having more than one common factor and different loadings to these factors, we can identify a reference business cycle as the common component of a particular variable. A priori, being a broad measure of economic activity, it is convenient to choose GDP as reference. Since it is also the key-variable in our forecasting exercise, we will follow this approach throughout the paper. Of course, other variables could have been used as reference variable.[16] Ideally, a good reference variable should have a common component, which represents a large part of the variable since in practice the common component is not observable and practitioners have to rely on the variable itself in order to assess the state of the business cycle.

Figure 2 illustrates the growth cycle of GDP and its common component. From this figure it can be seen that the common component of GDP generally comoves with the variation in GDP, although its variation is milder and flattens out the sharp growth peaks and troughs of GDP. Later on, we will evaluate each variable with respect to this reference cycle by analysing the mutual relation between the common component of the series and the common component of GDP, representing the "essential business cycle relation".

The amount of business cycle information present in each variable x_i can be measured by the degree of commonality C_i:

$$C_i = \frac{var(\chi_i)}{var(x_i)} \tag{2}$$

Table 1 shows the degree of commonality for our different regroupings. Individual results, which received a ranking number according to the importance of the common component, are reported in Table 3.

Averaging over all series, the common component represents 30% of the series' total variance. This may seem low, but one has to remember that we focus on quarter-on-quarter variations. The degree of commonality would possibly have been higher when year-on-year variations were used, since macroeconomic variables rather tend to comove in the long run than in the short run.[17] On average, the commonality of survey data is higher than that of non-survey data, meaning that the former convey more business cycle information. Within the non-survey data, variables related to the labour market show the highest commonality. Price variables show the lowest degree of commonality.

Looking at individual variables, GDP has a relatively high commonality ratio, 47% of the variation of GDP is related to the business cycle, justifying the choice of GDP as reference variable. However, there still remains a non-negligible idiosyncratic component and 109 variables have a larger commonality ratio than GDP, suggesting that these indicators better represent the business cycle and consequently might haven been better options to

[16] Since all mutual relations between the common components of all variables are known, variables can be easily assessed with respect to another variable than GDP or with respect to each other.

[17] Estimations of the model with year-on-year variations show that the average commonality of the series increases to 47%, using the same model parameters. Although quarter-on-quarter results are less appealing in terms of commonality, they are preferred above year-on-year variations given that they provide more insight in the momentum of the economy and they allow cleaner forecasts (no base effect), see also IMF, 2001.

act as reference variable. In Section 6.2.3 we will shed further light on the appropriateness of GDP as reference variable. From Table 3, it can be seen that the commonality ratio of the variables ranges between 81.6% and 1.1%. The highest commonality ratio is found for the economic sentiment indicator of Belgium from the EC. Among all indicators, this indicator should consequently give the most adequate view of the state of the business cycle. This is a nice result given the fact that it is a broadly composed indicator, which is widely used by practitioners for assessing the business cycle. In fact, the construction of this indicator (i.e. weighted average across the cross-section dimension) is closely linked to the technique of the GDFM (i.e. weighted average across the cross-section dimension of time-shifted series). Within the top-5 of the indicators containing the most business cycle information, also the NBB overall synthetic curve is found, for which the same remarks hold as for the EC economic sentiment indicator. More surprising is the fact that the EC industrial confidence indicator for the euro area and the OECD leading indicator for the Netherlands are found to have a high fraction of business cycle information. This possibly hints at a strong relationship between the Belgian business cycle and the business cycle of the euro area and the Netherlands. Looking at the indicators with the lowest share of common variation, we find among others Japanese GDP and Belgian government consumption. The high idiosyncratic component of Belgian government consumption is interesting given the fact that it is a part of GDP.[18] Nonetheless, its common component is small, suggesting variation of government consumption is unrelated to the business cycle and more likely evolves according to (idiosyncratic) government actions.

Some robustness analysis shows that the relative suitability of an indicator to represent the business cycle is not very sensitive to the number of factors. Raising the number of dynamic factors to as much as 5 does not affect the results to a great extent. Although, quite naturally, commonality increases and ranges between 87.3% and 7.0%, the ranking of the variables according to their commonality only slightly changes. The top-10 of indicators is largely similar and variables such as Japanese GDP and Belgian government consumption are still ranked among those with the lowest commonality.[19]

5 Cyclical Behaviour of the Variables

Having identified the business cycle information in each variable as the common component, we can now evaluate each variable's cyclical behaviour with respect to the reference cycle. To do so, out of the spectral density matrix of the common components $\sum_n^\chi(\theta)$, the cross-spectral density of each common component is calculated with respect to the common component of the reference variable GDP: $\sigma_{i,GDP}(\theta)$. From this density,[20] we can estimate the phase angle shift $\phi_{i,GDP}(\theta)$ or time lag $\psi_{i,GDP} = \phi_{i,GDP}(\theta)/\theta$ of the common

[18] In general, there is a large dispersion in the commonality ratio of the national accounts variables. While the value-added concepts, apart from the non-market services, have a relatively high degree of commonality, the expenditure components are characterised by a high idiosyncratic component. This is striking, since once they are aggregated (i.e. GDP), they adequately represent the business cycle, while this is not the case when they are taken separately.

[19] Within the top-10 series with the highest commonality, some indicators change from position. The EC economic sentiment indicator for Belgium has the second highest commonality ratio, while the first place is occupied by the OECD composite leading indicator for Belgium. However, apart from these minor ranking changes, the overall conclusions regarding the relative appropriateness of a variable and/or type of series to represent the business cycle are still valid. Detailed results of the estimation of the GDFM with more than 2 dynamic factors are available from the author upon request.

[20] The cross spectral density $\sigma_{ij}(\theta)$ out of $\sum_n^\chi(\theta)$ represents the mutual relation between two common components which can be written in the frequency domain as the sum of waves of different frequency,

component with respect to the common component of GDP, allowing us to classify the series as pro- or countercyclical and as coincident, leading or lagging.

5.1 Pro- and countercyclical variables

Following FHLR (2000a) we classify the series as pro- and countercyclical by computing the phase angle shifts at the zero frequency with the reference cycle: $\phi_{i,GDP}(0)$. At this frequency, the long-run correlation between the two common components is measured. Depending on whether this long-run correlation is positive or negative, the phase angle shift will be either 0 or π. A positive long-run correlation ($\phi_{i,GDP}(0) = 0$) is interpreted as a procyclical variable, a negative ($\phi_{i,GDP}(0) = \pi$) as a countercyclical one (see also Granger and Hatanaka, 1964).

Overall we find 409 variables to be procyclical and a minority of 100 to be countercyclical (see Tables 1 and 3). The procyclical variables include, among others, all expenditure and value-added components of GDP, which is consistent with common knowledge. The only exception to this are the inventory changes which seem to behave countercyclical. Also the assessment of their level in business surveys is classified as countercyclical.[21] Furthermore, all series related to unemployment are countercyclical. Amongst the financial variables, the exchange rate and gold price behave in an opposite way to the reference cycle. More surprising is the countercyclical behaviour of consumer prices.[22]

The classification of variables as pro- or countercyclical is robust to the number of factors. When the number of factors is raised to 3, no single variable is classified differently. Only when the number of factors is further raised to 4 or 5, a marginal fraction of the variables (respectively 1% and 1.8%) change from sign.[23]

5.2 Coincident, leading and lagging variables

5.2.1 Classification

A classification of the variables into coincident, leading or lagging can be obtained by evaluating the phase angle shift at a typical business cycle frequency θ^*. There is no such thing as a standard frequency or length of a growth cycle. However, looking at the estimated common component of GDP and defining the length of a cycle as the sum of the length of a boom (defined as an above-average common component) and the length of the

amplitude and phase. The phase angle shift $\phi_{ij}(\theta)$ measures how much a wave i (and thus common component) is shifted with respect to a reference wave j, measured at a particular frequency θ. The phase angle shift can be translated to a time lag ψ_{ij} in the time domain by dividing it by its frequency θ.

[21] This underpins the methodology for the construction of the NBB overall synthetic curve, according to which the sign of the individual indicators related to the inventories is reverted (National Bank of Belgium, 1990).

[22] The countercyclical behaviour of consumer price inflation is robust, both to the consumer price aggregate and to the number of factors, and henceforth is supportive for an economy dominated by supply shocks instead of demand shocks, linked to the discussion between the RBC school and the more common Keynesian view. While looking at the reasons for the illustrated countercyclical behaviour of inflation is beyond the scope of the present work, we can argue that as suggested in the literature (Backus and Kehoe, 1992 and Chadha and Prasad, 1994), results depend on the period studied, the method employed and the measure of inflation used. The illustrated countercyclical behaviour might thus be specific to the sample and/or due to the difficulties the method has to capture a great deal of inflation's variation, even when the number of factors is raised.

[23] In particular the countercyclical behaviour of employment in the trade and public sector seems to depend on the number of factors. This might point to the absence of a clear connection between the business cycle and employment in these sectors, which certainly is defendable for the latter.

subsequent recession[24] (defined as a below-average common component), 4 cycles occurred since 1990 with an average length of 13 quarters or about 3 years. Taking 3 years as the length of a typical business cycle, we calculated the phase shift at a frequency $\theta^* = \frac{\pi}{6}$. Dividing the obtained phase angle shifts by this frequency delivers the time lags $\psi_{i,GDP}$. Variables were classified as leading when the time lag exceeded 1 (quarter), lagging when it was lower than -1 and coincident otherwise. The time lags are reported in Tables 1 and 3.

From the 509 variables, we find 22% to be leading, 27% to be lagging and 51% to be coincident. In general non-survey data contain a higher proportion of leading and lagging indicators compared to survey data. Categories with a high proportion of leading indicators include financial variables, for which asset prices contain an overwhelming amount of leading indicators, and international confidence indicators, such as the indicators of the ISM-institute and the international OECD confidence indicators. On the other hand, a high proportion of lagging indicators is found within the variables related to the labour market, consumer prices and consumer confidence. Whereas consumer confidence generally tends to lag the business cycle, business survey indicators generally coincide.[25]

Generally, the most important expenditure components are classified as coincident, which is compatible with the idea that the business cycle is a phenomenon that roughly occurs at the same time for most expenditure components.[26] Private investment and imports seem to lag the business cycle. For investment, these results are in line with reported business cycle facts for the US and the euro area (see Stock and Watson, 1998a and Bergman et al., 1998).

Similar to the pro- and countercyclical behaviour, the classification of variables into coincident, leading or lagging is robust to the number of dynamic factors. The amount of leading variables raises somewhat from 22% to 24% when 5 instead of 2 dynamic factors are used, while the percentage of lagging variables diminishes slightly from 27% to 24%. Also, all variable groups keep their classification. The only exception to this are wages, which are classified as leading instead of lagging. Furthermore, also the extent of the lead/lag, reported in 5.2.2, seems not very sensitive to the number of factors.

5.2.2 Time lag

Looking at the estimated time lags in Tables 1 and 3, we find the highest leads in the category of asset prices.[27] Both the exchange rate and stock prices as well as real estate prices are found to lead GDP by 2 to 3 quarters. Within the non-survey data, the only other category of variables that leads GDP are car sales, which are found to lead by

[24] Taking into account a minimal duration of 2 quarters for the booms and recessions.

[25] The coincident behaviour of the national business survey indicators might somewhat be puzzling compared to their documented leading behaviour (Vanhaelen et al., 2000). Note however that these conclusions are still valid as shown in footnote 28. National business survey indicators are only found to be coincident with respect to Belgian GDP. As stated in footnote 28, national business survey indicators lead euro area GDP and most of its survey indicators.

[26] The comovement between GDP and government outlays is less evident. Here they are found to lead GDP. As documented in Stock and Watson (1998a) and Bergman et al. (1998), the cyclical properties of government outlays are diverse and do not show a clear pattern across time or countries.

[27] In a limited number of cases (18 variables), the calculation of the time lags delivered leads and lags exceeding 4 quarters. Since it is difficult to say whether these variables lag the previous cycle or lead the next one and since they are disturbing for the reported results, we excluded them from the calculation of the average time lag of the different regroupings in Table 1 and 3. The concerning variables are grey-shaded in Table 3.

almost 3 quarters. Looking at the survey data, the ISM indicators are found to lead GDP on average by almost 2 quarters. Furthermore, the IFO confidence indicators concerning the German building sector have a lead that hovers around 1.5 quarters. The NBB survey indicators related to the Belgian building sector also lead, albeit by 1 quarter. Finally, the international OECD confidence indicators are found to lead GDP, on average, by about 4 months.

Highly lagging variables include the labour market variables, which are estimated to lag GDP on average by about 2 quarters. Furthermore, industrial production seems to lag by 1 quarter, which is somewhat surprising given it is widely used as alternative for GDP when measuring the business cycle. Another surprising result is the lagging behaviour of short-term interest rates, which lag the reference cycle by about 2 quarters. Lastly, consumer confidence is found to lag GDP by about one quarter.[28]

6 Forecasting

6.1 Forecasting GDP by means of its common component

In this part we try to forecast quarter-on-quarter real GDP growth using the GDFM. Within the GDFM, forecasts of the x_i's can be obtained by separately forecasting the common component and the idiosyncratic component given the components' orthogonality to each other at all leads and lags. Since the idiosyncratic components are mutually orthogonal or weakly correlated, their forecast can be obtained using traditional univariate methods or low dimension models, such as ARMA or VAR models. The common component, being based on the common factorspace, can be forecasted by projecting the variables on carefully constructed aggregates approximating this (theoretical) common factorspace. In Appendix A.2 it is shown that the common component can be best estimated and forecasted by constructing aggregates in which variables with a higher commonality ratio receive larger weights. The commonality ratio is important in two perspectives for the forecast of a particular variable (i) the higher the common component of the variables, the more accurate the common factor space will be approximated and thus the more accurate the forecast of the common component will be (ii) the higher the commonality ratio of the variable of interest, the less one has to rely on popular, but in general unsatisfying models to forecast the idiosyncratic component. If for example the commonality ratio of x_i were a hypothetical 100%, the forecast of x_i would coincide with the forecast of the common component and one could totally rely on the GDFM to forecast the variable of interest.

Since this paper focuses on the features of the GDFM and not on those of ARMA or VAR models, we limit ourselves to the forecast of the common component of GDP and

[28] It is worth noting that each variable can be easily evaluated with respect to another. If, for instance we were interested in the cyclical behaviour of the variables with respect to the euro area economic activity, we could have evaluated them with respect to the common component of euro area GDP. Since the time lags are mutually consistent, the time lags with respect to this new reference cycle can be simply calculated out of Table 3. From this table we see that euro area GDP lags Belgian GDP by almost one quarter. Taking into account this time delay, the EC industrial confidence indicator for Belgium would lead euro area GDP by 1.3 quarters (=0.9+0.4), showing its leading behaviour for euro area GDP, similar to the results found on a more classical basis by analysing timing differences in turning points in Vanhaelen et al. (2000). These results show that the leading behaviour of national survey indicators for the euro area is largely attributable to the lead Belgian GDP has with respect to that of the euro area. A similar conclusion holds for overseas indicators such as the US ISM indicators, which partly lead the Belgian economy since US GDP leads Belgian GDP by almost one quarter. However, contrary to most euro area confidence indicators, the US ISM indicators also seem to lead their national GDP by one quarter.

examine how well this serves as a proxy for realised GDP growth in an out-of-sample exercise. It is thought that the quality of this proxy depends both on the commonality of the included variables and on the commonality of GDP itself. By changing the size and composition of our data setwe will look in a first section at the influence of the commonality of the included variables, in a second section we will pay attention to the importance of GDP's commonality.[29] We first report the forecast results for the full data set.

6.2 Out-of-sample exercise

6.2.1 Full data set

In this exercise, out-of-sample forecasts[30] of the common component of GDP are calculated over the period 1997Q3 till 2003Q3 for different forecast horizons $h = 1, \ldots, 3$ (1 till 3 quarters ahead). The initial estimation window contains 30 observations[31] from 1990Q1 till 1997Q2 and forecasts are made for 1997Q3 till 1998Q1. A second estimation and forecasting round estimates from 1990Q1 till 1997Q3 and produces forecasts for 1997Q4 till 1998Q2. At the end, forecasts are truncated to 2003Q3 so that when the model is estimated in the last step till 2003Q2, only the one-step ahead forecast is retained. This delivers a total of 25, 24 and 23 observations for respectively the one-step, two-steps and three-steps ahead forecasts. For each forecasting horizon we measure how well these forecasts proxy real GDP growth by means of forecast performance statistics such as the mean absolute error (MAE) and root mean squared error (RMSE). Furthermore, the results are compared with the one obtained by an ARMA(4,4) model for GDP by means of the Diebold-Mariano test for equal forecast accuracy. Table 2 presents the results.

For the full model (GDFM, $N = 509$), the MAE and RMSE are quite high given an average GDP growth rate of 0.5% with a standard deviation of 0.7. Both the MAE and RMSE slightly increase over the forecast horizon. Although the RMSE almost equals the standard deviation of GDP and thus points to poor forecasting results, they outperform those obtained by an ARMA model. The gain as indicated by the Diebold-Mariano test is significant for the longest horizon at the 10% level. Furthermore, one has to remember that this is only a partial forecast (i.e. forecast of the common component) and forecast results for GDP growth would improve if an accurate forecast of the idiosyncratic component was added.[32] Moreover, theory suggests that the proxy of the common component would be better if a number of variables with a high idiosyncratic component were excluded. Therefore in the next session we will evaluate the accuracy of the forecasted common component of GDP as a proxy for real GDP growth using a reduced data set excluding variables with a low commonality ratio.

[29] The idea that a subsample, and thus smaller N, might provide better forecast results is not new and is amongst others stated in Boivin and Ng (2003). However, while they focus on the role of N, we investigate the influence of the properties of the included variables on the forecast performance.

[30] It concerns pseudo out-of-sample forecasts since only one vintage of historical data is used to estimate and forecast the model. A more useful measure of the forecast performance would be offered by real-time out-of-sample forecasts which use the actual data vintages published at the time the forecast is constructed. As it would obviously take some data storage capacity to keep track of several different vintages of the 509 series, pseudo out-of-sample forecasts were nevertheless preferred.

[31] A minimum amount of 30 observations was set in order to allow for a reasonable forecasting horizon and to meet the estimation criteria of the GDFM (relatively large T).

[32] In practice, it seems however difficult to forecast the idiosyncratic component given its "white noise character". Estimates show that adding a forecast of the idiosyncratic (generated by an ARMA model) to the forecast of the common component actually leads to even worse forecasts of GDP, although the difference is not significant.

6.2.2 Influence of the commonality of the included variables

The average commonality ratio of the variables in our data set amounts to 30% (see Section 4). There is however a wide dispersion with commonality ratios ranging from 81.6% to 1.1%. Given the high proportion of the idiosyncratic component in some cases, these variables do not deliver valuable information and likely only "disturb" the estimation and the forecast of the common component. To extract a cleaner forecast, we perform a data reduction selecting the variables with a relatively high commonality ratio, defined as the 75% percentile of the ordered commonality ratios. This rule suggests to exclude all variables with a commonality ratio lower than 14.4%. The reduced data set contains 382 variables. For this reduced data set (GDFM, $N = 382$), we extract the common component of GDP and calculate whether its forecasts are a better proxy for real GDP growth as compared to the forecasts obtained from the full model. From Table 2 it can be seen that the resulting forecasting errors do not differ a lot from the full model. The model slightly outperforms the full model at the short horizons but performs worse for the three-steps ahead forecasts. Overall, the differences are not significant. Consequently, "getting rid of the dirt" does not seem to alter the forecasting results to a great extent.[33]

6.2.3 Importance of the commonality of GDP

Throwing away the bad variables (i.e. low commonality), does not alter the forecast performance significantly. This might be not so surprising since in the one-sided model variables with a high idiosyncratic component receive low weights, so that throwing them away might not be that different. On the other hand, it might indicate that the variables thrown away were not that poor in forecasting GDP. A possible explication why this might be the case lies in the fact that while those variables' idiosyncratic component might be high with respect to the whole sample, it might be low with respect to GDP. Let us clarify. While the whole set of variables is explained by two factors, GDP can possibly be determined by for instance one of these factors and some other factors common to GDP and a small subset of variables. However, when the full model is estimated, these factors are likely to remain hidden in favour of the dominant factors, common to a larger subset of variables (preferably all), causing the idiosyncratic component of the subset of variables to be high. While these hidden factors (and thus variables which load upon them) are unimportant to identify the business cycle (measured as the common variation), they are important when one wants to predict a certain variable. Chances that such factors exist are higher when commonality is low. Since 53% of the variation of GDP remains unexplained, there seems to be room for improvement by selecting variables which are determined by the same factors that underlay GDP, driving up its commonality ratio and thus the forecast accuracy of GDP through the dynamic common variation.[34] Higher

[33] Not only the forecasting results alter a little, also the estimated common component is not clearly different from the full model. Nevertheless, the commonality ratio of GDP raised somewhat from 47% to 49%.

[34] Note that alternatively, we could increase the number of factors in order to improve GDP's commonality. However, the more factors are added, the more likely they are common to an increasingly smaller subset of the data, which not necessarily includes our variable of interest (GDP). To avoid a pick-up of such "junk factors" that would deteriorate the forecast of GDP we try to select the "right factors" by a data reduction process aimed at maximising GDP's commonality. Moreover, simulations of the GDFM with more than 2 factors show that the improvement for GDP's commonality (commonality of 59.9% in case of 5 factors) stays limited compared to the data reduction exercise and that they do not lead to significant better forecasts.

forecast accuracy could thus be reached by constructing a subsample in which the factors driving GDP are dominant.

However, since the factors are unidentified in the GDFM, there is no formal method to extract these factors and to retain the variables which load upon them. A sign that a subsample contains the "right" factors is however provided by the commonality ratio of GDP. The higher the commonality, the more likely it is that the factors which drive GDP are driving the sample. We therefore propose a data reduction procedure based on a maximisation of GDP's commonality. This procedure is empirical and proceeds as follows. We construct all possible $N-1$ subsamples of $N-2$ variables out of all variables excluding GDP. To these subsamples we add GDP and estimate for each subsample the GDFM. The subsample delivering the highest commonality ratio for GDP is retained. This subsample will contain all variables except one. This variable drags down the commonality of GDP the most and is therefore excluded. In a second step we repeat the procedure on the retained sample, which this time allows $N-2$ combinations of $N-3$ variables to which we add GDP. Again one variable will be left out. We repeat this procedure until the number of variables of the subsample (including GDP) equals the number of factors. In total this requires the estimation of a GDFM for:

$$\frac{(N-1)N}{2} - \frac{(r-1)r}{2} = 129\ 258 \ \text{ data sets}$$

The retained subsamples contain for a given n ($r < n < N$), the variables which maximise the common component of GDP out of the previous subsample. The amount of progress obtained by this data reduction in terms of the commonality of GDP is shown by the bold line in Figure 3. From this picture, we see that by leaving out the variables which drag down the commonality of GDP the most, the commonality ratio of GDP increases dramatically when $n \to r$. The commonality ratio rises from 46.7% to 94.2%. The dependence of the commonality ratio on the composition of the data set is in itself an interesting feature. In many applications, a high degree of commonality of GDP is taken as evidence that GDP is a good business cycle indicator (FHLR, 2000b). The current practice does however show that a variety of values for this commonality ratio can be obtained by varying the size and composition of the data set. A high commonality for GDP could therefore be the result of "luck" selecting the right data. One should therefore be cautious about drawing conclusions on the appropriateness of a particular indicator as a good business cycle indicator. It should be borne in mind that these conclusions only hold with respect to a particular data set. Much care should therefore go to the construction of the data set in view of the practice at hand.

While the selected subsamples are able to increase the commonality of GDP in a rather impressive way, it remains to be seen if these subsamples also lead to better GDP forecasts based on the common variation compared to the full model. In Figure 3 the RMSE for the different forecast horizons and the different subsamples maximising GDP's common component are plotted. As can be seen, the RMSE is quite volatile and increases extensively for the combinations with the highest commonality ratio for GDP. Looking at the one-step ahead forecast, there is a sound relation between the RMSE and the commonality ratio of GDP (higher commonality/lower RMSE) up to a certain sample size. However, from then onwards the RMSE rises fast. While the subsamples lead to better estimation results (a larger part of GDP can be explained), they do not seem to lead to better forecasts. Given the still large size of most of these subsamples, which consequently satisfies the conditions of the GDFM, it is not clear what causes these forecasts to be bad. Having tried to increase the accuracy of the forecasting results by letting vary the commonality of the included variables and the commonality of GDP, none of these strategies proved to be fruitful to obtain better forecasting results. Better "estimation" results do not deliver better "forecast" results. It is unclear what causes this mismatch and it should therefore be a topic for future research, as is the dependence of the estimation results on the selected data set.

7 Conclusion

In this paper, we investigated the business cycle information content of 509 variables and identified a reference business cycle as the common variation contained in quarter-on-quarter Belgian GDP growth. Furthermore, we explored the cyclical behaviour of the variables with respect to this reference cycle and forecasted quarter-on-quarter GDP growth. All of this took place within one unified setting by applying the Generalised Dynamic Factor Model (GDFM) of FHLR (2000b, 2001, 2004, 2005) to a large data set containing information on the Belgian economy and its indicators. Through its richness, the model provides useful information for both the business cycle analyst and the market parties interested in the Belgian business cycle and its indicators. The model reduces the variables to their core business cycle information, defined as that part of the variables' variation which is common to the data set. The results show that some well-known indicators such as the EC economic sentiment indicator for Belgium and the NBB overall synthetic curve contain a high amount of business cycle information. Given the importance of GDP for forecasting purposes, we defined a reference business cycle as the common variation contained in the quarter-on-quarter GDP growth and classified the whole set of indicators with respect to this reference cycle. 22% of the variables were classified as leading, 27% as lagging. Amongst the most leading variables we find asset prices and international confidence indicators such as the ISM and some OECD indicators, which lead Belgian GDP by 2 to 3 quarters. In general, national business confidence surveys are found to coincide with Belgian GDP, while they lead euro area GDP and its confidence indicators. Consumer confidence seems to lag. For each of the 509 indicators, individual results are reported, which could be used as a guide for assessing the importance of an indicator as "warning signal" for the Belgian economy.

Although the model captures the dynamic common information contained in the data set, forecasts based on that information are insufficient to deliver a good proxy for GDP growth as a result of a non-negligible idiosyncratic part in GDP's variance. It should however be noted that the model focuses on quarter-on-quarter variations, for which, comovement in general is low. Consequently they are highly idiosyncratic and hard to predict. However, through the use of a data reduction process we show that the GDFM is able to reduce the unexplained variation in GDP growth. However, forecasts do not improve, which indicates there is a clear distinction between the forecasting and estimation results of the model. The exercise also sheds some light on the dependence of the model's results on the underlying data set. In particular, the amount of business cycle information present in a certain indicator seems to depend highly on the data set. It should therefore be borne in mind that the conclusions only hold with respect to a certain data set. Although this is a feature of many econometric models, a more profound understanding of the relation between the GDFM's outcome and the composition of the data set would be desirable. Further research could therefore focus on the exploration of this relationship. Apart form this, it could also further highlight the richness of the model by evaluating the variables with respect to each other and not only with respect to a particular reference variable. This would provide additional insights into the relationships between different variables and address several economic issues.

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A Appendix : Technical Details

In this Appendix we provide a brief outline of the technical details underlying the GDFM used in this paper. We show how the spectral density matrix of x_{nt} can be estimated and the way it is decomposed in an idiosyncratic and common part through a dynamic principal component procedure. This procedure allows to calculate the common and idiosyncratic covariances through an inverse Fourier transform and to estimate the common component. For the latter, we present the one-sided estimation technique based on static factors in Appendix A.2 using the estimated covariances from A.1, which solves the estimation problems for the common component caused by the two-sidedness of the filter applied in Appendix A.1.

A.1 Estimating the spectral density, covariances, common and idiosyncratic components

An estimate of the spectral density matrix $\sum_n(\theta)$ can be obtained by applying a discrete Fourier transform to the sample covariance matrices Γ_k^T of x_{nt}. The spectral density allows to decompose the auto and cross-covariance matrices into periodic components, fruitful for the dynamic analysis in this paper. To allow estimation, the number of cross covariance matrices has to be truncated. For a fixed integer $M(T)$, we compute the sample covariance matrices $\Gamma_k^T = x_{nt}x'_{nt-k}$ with $k = -M, \ldots, M$. The estimation of $\sum_n(\theta)$ is then obtained by multiplying the sample covariance matrices by Barlett-lag window estimator weights $w_k = 1 - \frac{|k|}{M+1}$ and applying the discrete Fourier transform:

$$\textstyle\sum_n^T(\theta_h) = \frac{1}{2\pi}\sum_{k=-M}^{M} w_k\ \Gamma_k^T\ e^{-ik\theta_h}$$

The Barlett-weights are needed to avoid biases caused by the truncation. Consistent estimates are ensured, provided that $M(T) \to \infty$ and $M(T)/T \to 0$ as $T \to \infty$. FHLR (2000b) show that a rule of $M = round(\sqrt{T}/4)$ performs well. Here, with $T = 55$ this delivers $M = 2$, we conducted estimates with $M = 2$ and $M = 3$ and decided in favour of $M = 3$ because the rule of $M = 2$ is too restrictive in the sense that only a small part of the dynamic information would be considered. In the Fourier transformation, the spectra are evaluated at $2M + 1 = 7$ equal spaced frequencies (including the zero-frequency) in the interval $[-\pi, \pi]$ as suggested by FHLR (2000b), namely at the frequencies $\theta_h = \frac{2\pi h}{6}, h = -3, \ldots, 3$.

The estimated spectral density matrix is then decomposed in orthogonal components by a dynamic principal component decomposition, in analogy with standard static principal component analysis, albeit at different frequencies. Following Brillinger (1975), we compute the eigenvectors and eigenvalues of $\sum_n^T(\theta_h)$ for each frequency θ_h. Ordering the eigenvalues in descending order for each frequency, the eigenvalue and eigenvector functions $\lambda_{nj}(\theta)$ and $p_{nj}(\theta), j = 1, \ldots, n$ are obtained. The dynamic eigenvectors $p_{nj}(\theta)$ are expanded in Fourier series as:

$$p_{nj}(\theta) = \frac{1}{2\pi}\sum_{k=-M}^{M}\left[\int_{-\pi}^{\pi} p_{nj}(\theta)e^{ik\theta}d\theta\right]e^{-ik\theta}$$

and can be suitably transferred to the time domain by applying an inverse Fourier transform:

$$\underline{p}_{nj}(L) = \frac{1}{2\pi}\sum_{k=-M}^{M}\left[\int_{-\pi}^{\pi} p_{nj}(\theta)e^{ik\theta}d\theta\right]L^k$$

The dynamic eigenvalue function $\lambda_{nj}(\theta)$ is equal to the spectral density matrix of the process $\left\{\underline{p}_{nj}(L)x_{nt,}t \in \mathbb{Z}\right\}$ which is called the j-th dynamic principal component of x_{nt}:

$$p_{nj}(\theta)\textstyle\sum_n(\theta)\tilde{p}_{nj}(\theta) = \lambda_{nj}(\theta)$$

The dynamic principal components are mutually orthogonal at any lead or lag and the ratio

$$c_j = \int_{-\pi}^{\pi}\lambda_{nj}(\theta)d\theta / \sum_{j=1}^{n}\int_{-\pi}^{\pi}\lambda_{nj}(\theta)d\theta$$

represents the contribution of the j-th dynamic principal component to the total variance in the system.

Given the fact that the dynamic eigenvectors $p_{nj}(\theta)$ are an orthonormal system of eigenvectors for I_n and that the common component χ_{nt} is the projection of x_{nt} on the approximate factor space spanned by the first q diverging dynamic principal components, the common component χ_{nt} can be estimated as:

$$\chi_{nt} = \left[\underline{\tilde{p}}^T_{n1}(L)\underline{p}^T_{n1}(L) + \ldots + \underline{\tilde{p}}^T_{nq}(L)\underline{p}^T_{nq}(L)\right] x_{nt}$$

and the residual ξ_{nt} as $\xi_{nt} = x_{nt} - \chi_{nt}$.

The spectral density matrix can correspondingly be decomposed in a spectral density matrix of the common component χ_{nt} and idiosyncratic component ξ_{nt}:

$$\begin{aligned}
\textstyle\sum_n^{\chi T}(\theta) &= \lambda^T_{n1}(\theta)\tilde{p}^T_{n1}(\theta)p^T_{n1}(\theta) + \ldots + \lambda^T_{nq}(\theta)\tilde{p}^T_{nq}(\theta)p^T_{nq}(\theta) \\
\textstyle\sum_n^{\xi T}(\theta) &= \lambda^T_{n,q+1}(\theta)\tilde{p}^T_{n,q+1}(\theta)p^T_{n,q+1}(\theta) + \ldots + \lambda^T_{nn}(\theta)\tilde{p}^T_{nn}(\theta)p^T_{nn}(\theta)
\end{aligned}$$

applying an inverse discrete Fourier transform to these matrices delivers the covariance matrices of χ_{nt} and ξ_{nt} at different leads and lags:

$$\begin{aligned}
\Gamma^{\chi T}_{nk} &= \int_{-\pi}^{\pi} e^{ik\theta} \textstyle\sum_n^{\chi T}(\theta)d\theta \\
\Gamma^{\xi T}_{nk} &= \int_{-\pi}^{\pi} e^{ik\theta} \textstyle\sum_n^{\xi T}(\theta)d\theta
\end{aligned}$$

A.2 Estimating and forecasting the common component through static factors

Being based on the spectral density of the data, the filter applied to x_{nt} in A.1 to estimate the common component χ_{nt} is two-sided. This causes problems at the end of the sample to estimate and forecast the common component since no future values are available. To solve this problem the factor space can alternatively be represented by the use of r static factors u_{jt-k}, $j = 1, \ldots, q$; $k = 1, \ldots, s$, instead of q dynamic factors u_{jt}, $j = 1, \ldots, q$ with $r = q(s + 1)$ and s the order of the lag operator in [1]. Similar to the dynamic factors, these r static factors need to be approximated. Using the estimated covariance matrices $\Gamma^{\chi T}_{n0}$ and $\Gamma^{\xi T}_{n0}$ of A.1 we are able to construct r contemporaneous averages of the $x's$ that minimise the fraction of idiosyncratic variance contained in the aggregates, leading to a better approximation of the common factor space than static principal components. These “efficient” static aggregates are obtained as the solutions of a generalised principal component problem. More precisely, we compute the generalised eigenvalues μ_{nj} of the couple of matrices $(\Gamma^{\chi T}_{n0}, \Gamma^{\xi T}_{n0})$, i.e. the n complex numbers solving $det(\ \Gamma^{\chi T}_{n0} - z\ \Gamma^{\xi T}_{n0}) = 0$, along with the corresponding generalised eigenvectors $V_{nj}, j = 1, \ldots, n$, i.e. the vectors satisfying:

$$V_{nj}\Gamma^{\chi T}_{n0} = \mu_{nj} V_{nj} \Gamma^{\xi T}_{n0}$$

and the normalising condition:

$$V_{nj}\Gamma^{\xi T}_{n0} V'_{ni} = \begin{cases} 0 \text{ for } j \neq i, \\ 1 \text{ for } j = i. \end{cases}$$

Ordering the eigenvalues μ_{nj} in descending order and taking the eigenvectors corresponding to the r largest ones, our estimated static factors are the generalised principal components:

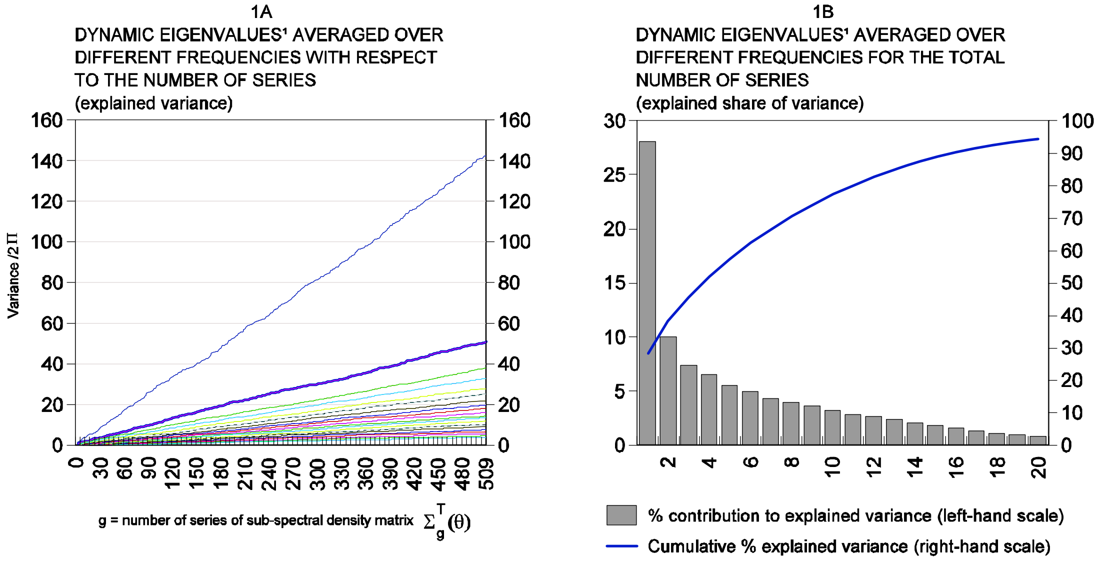
$$W^j_{nt} = V'_{nj} x_{nt}, \ j = 1, \ldots, r.$$

These generalised principal components are the contemporaneous linear combinations of the x_{it}'s, with the smallest idiosyncratic/common variance ratio and allow efficient estimates and forecasts of χ_{nt} without the need of future values. Precisely, setting $\mathbf{V}_n = (V_{n1}, \ldots, V_{nr})$ and $\mathbf{W}_{nt} = (W^1_{nt}, \ldots, W^r_{nt})' = \mathbf{V}'_n x_{nt}$, our estimate of $\chi_{t+h}, h = 0, \ldots, s$, given the information available at time t, is

$$\begin{aligned} \chi^T_{t+h} &= \Gamma^{\chi T}_{nh} V_n (V'_n \Gamma^T_0 V_n)^{-1} W_{nt} \\ &= \Gamma^{\chi T}_{nh} V_n (V'_n \Gamma^T_0 V_n)^{-1} V' x_{nt} \end{aligned}$$

In FHLR(2005) it is shown that, as both n and $T \to \infty$ in a proper way, the estimated χ^T_{nt} and $\chi^T_{n,t+h}$ converges to the theoretical χ_{nt} and theoretical projection of $\chi_{n,t+h}$ on the present and the past of $u_{1t}, \ldots, u_{qt}$.

Figure 1: Heuristic inspection of the eigenvalues



1) Only the first 20 dynamic eigenvalues are shown.

Figure 2: Quarter-on-quarter GDP growth and its common component

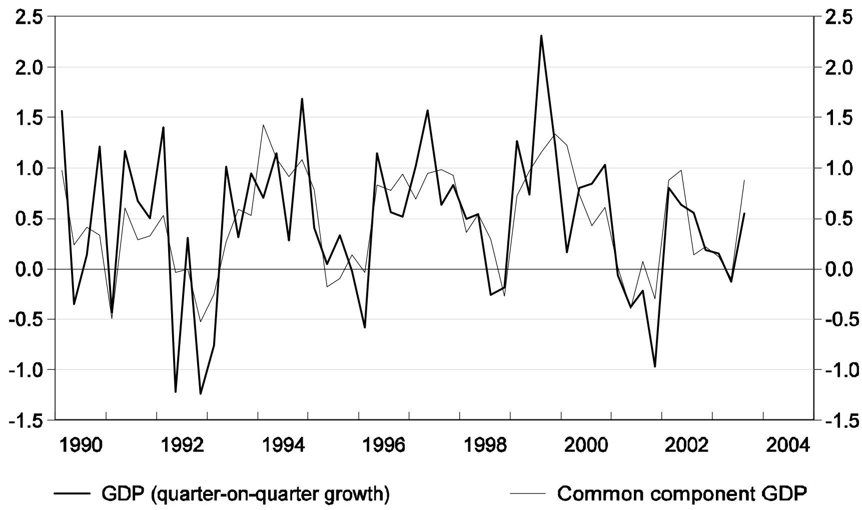


Figure 3: Commonality of GDP and forecast performance

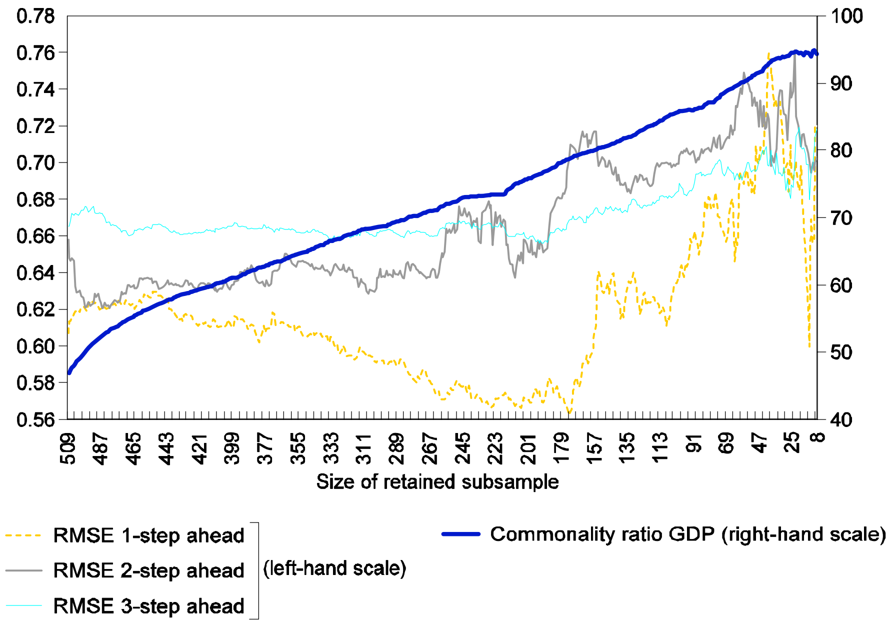


Table 1: Data set and cyclical properties

Series	Nr. of series[1)]	C[2)]	T[3)]	Series	Nr. of series[1)]	C[2)]	T[3)]
TOTAL	509 (100)	30	-0.1				
Non-Survey	185 (55)	23	-0.3				
Activity	55 (1)	20	-0.5	*Labour Market*	32 (24)	35	-1.7
National Accounts	26 (1)	23	-0.6	Unemployment	21 (21)	41	-1.9
Belgium	15 (1)	22	-0.4	Employment	11 (3)	24	-1.1
International	11 (0)	24	-0.8	*Financial*	51 (14)	23	**1.2**
Industrial Production	15 (0)	20	-1.1	Interest Rates	22 (1)	27	-0.8
Retail Sales	8 (0)	11	-0.4	10 Year	7 (0)	30	0.1
International Trade	2 (0)	37	-0.1	3 Month	8 (0)	24	-2.1
Car Sales	4 (0)	12	**2.8**	Yield gap	7 (1)	27	-0.1
Prices	47 (16)	18	-0.7	Asset Prices	29 (13)	21	**2.6**
Commodity Prices	13 (3)	18	-1.0	Stocks	9 (0)	23	**2.3**
Producer Prices	24 (4)	21	-0.5	Real Estate	7 (0)	15	**3.3**
Consumer Prices	8 (7)	9	-0.3	Gold	1 (1)	9	-3.2
Wages	2 (2)	5	-1.9	Exchange Rate	12 (12)	23	**3.0**
Survey	324 (45)	34	0.0				
Business Confidence	247 (26)	37	0.3	IFO	31 (1)	39	0.5
NBB	55 (10)	31	0.3	Overall	3 (0)	67	0.2
Overall	1 (0)	78	0.6	Manufacturing	8 (1)	54	0.3
Manufacturing	11 (1)	57	0.7	Trade	6 (0)	40	0.5
Trade	9 (1)	20	-0.2	Building	10 (0)	13	**1.4**
Building	10 (0)	22	**1.1**	Capacity Utilisation	4 (0)	53	-0.7
Capacity Utilisation	24 (8)	25	0.0	ISM	17 (3)	23	**1.9**
European Commission	109 (10)	38	0.0	INSEE	10 (1)	57	-0.2
Belgium	25 (3)	40	0.4	CBS	2 (1)	52	0.0
Overall	1 (0)	82	0.2	BOJ (Tankan)	5 (0)	21	0.5
Manufacturing	8 (1)	63	0.3	OECD	18 (0)	59	**1.1**
Trade	6 (1)	17	-0.2	Belgium	11 (0)	63	0.9
Building	5 (0)	27	0.9	Overall	1 (0)	77	0.9
Capacity Utilisation	5 (1)	37	0.9	Partial Indicators	10 (0)	62	0.9
Non-Belgium	84 (7)	37	-0.1	International (Overall)	7 (0)	51	**1.4**
Overall	4 (0)	68	-0.3	*Consumer Confidence*	77 (19)	24	-1.1
Manufacturing	30 (4)	57	-0.5	NBB	12 (2)	25	-0.9
Trade	24 (3)	13	-0.1	European Commission	65 (17)	23	-1.2
Building	20 (0)	30	0.1				
Capacity Utilisation	6 (0)	36	0.4				

1) Total number of series in each group, the number of countercyclical variables is indicated between brackets.
2) Commonality ratio of the series, measured as the ratio between the variance of the series' common component and the series' total variance. The reported values are averages.
3) Time lag of the series' common component with respect to the common component of GDP, measured in quarters. Variables are considered to lead GDP when T>1 (bold values), to lag when T<-1 (red values) and to coincide otherwise. The reported values are averages.

Table 2: Forecast performance for quarter-on-quarter growth of real GDP

	1-step ahead	2-steps ahead	3-steps ahead
GDFM, *N=509*			
MAE	0.46	0.51	0.51
RMSE	0.61	0.66	0.67
Diebold-Mariano[1]	-1.41	-1.28	-1.76*
GDFM, *N=382*			
MAE	0.43	0.48	0.53
RMSE	0.60	0.63	0.68
Diebold-Mariano[1]	-1.55	-1.56	-1.64
ARMA			
MAE	0.57	0.61	0.68
RMSE	0.71	0.77	0.93

1) This statistic tests for equal forecast accuracy between two competing models and is based on the difference of the squared forecast errors of the two models. Here it is used as performance statistic of the GDFM with respect to an ARMA (4,4).

*** (**, *) denotes significant negative values at the 1 (5, 10) percent level for which the null of equal forecast accuracy is rejected in favour of a better forecast performance of the GDFM.

Table 3: Data set, commonality and time lag (detail)

Nr.[1]	Series	Source	Number of series	Commonality[2]		Time lag[3]	
				Indiv. score	Group score	Indiv. score	Group score
	NON-SURVEY		**185**		**23.0**		**-0.3**
	ACTIVITY		**55**		**20.2**		**-0.5**
	NATIONAL ACCOUNTS		26		22.9		-0.6
	Belgium		*15*		*22.0*		*-0.4*
110	GDP	NAI		46.7		0.0	
336	Private consumption	NAI		18.6		-0.4	
505	Government consumption	NAI		2.5		1.8	
474	Business investment	NAI		6.8		-2.9	
426	Housing investment	NAI		11.1		-1.4	
446	Government investment	NAI		9.5		2.2	
227	Exports	NAI		27.8		-0.7	
343	Imports	NAI		17.8		-1.2	
502*	Changes in inventories	NAI		3.5		0.0	
263	Value added services	NAI		24.4		-0.9	
281	Value added market services	NAI		22.4		-1.1	
451	Value added non-market services	NAI		9.1		-0.1	
70	Value added manufacturing industry	NAI		56.3		-0.4	
76	Value added industry	NAI		55.0		-0.2	
332	Value added building	NAI		18.7		-0.7	
	International		*11*		*24.1*		*-0.8*
131	GDP Euro area	EC		41.7		-0.9	
115	GDP France	EC		45.8		-1.0	
371	GDP Germany	EC		15.0		-1.6	
175	GDP Netherlands	EC		33.4		-0.7	
265	GDP US	EC		24.3		0.8	
508	GDP Japan	EC		1.7		-3.2	
437	GDP Greece	EC		10.2		-7.0	
252	GDP Spain	EC		25.3		-1.3	
333	GDP Italy	EC		18.7		-0.6	
292	GDP Austria	EC		21.8		0.1	
231	GDP UK	EC		27.3		0.0	
	INDUSTRIAL PRODUCTION		15		20.3		-1.1
257	Total excluding construction (1)	NIS		24.9		-0.6	
156	Total (1)	NIS		37.1		-0.6	
216	Raw materials and intermediate goods	NIS		28.8		-0.4	
367	Non-durable consumer goods	NIS		15.4		-1.9	
430	Durable consumer goods	NIS		11.1		-0.4	
475	Capital goods	NIS		6.7		-2.4	
280	Manufacturing industry (1)	NIS		22.4		-0.5	
274	Building	NIS		23.1		-0.3	
179	Total (2)	EC		33.0		-0.9	
241	Manufacturing industry (2)	EC		26.8		-0.6	
176	Total excluding construction (2)	EC		33.4		-0.8	
501	Food and drink	NIS		3.7		-3.4	
487	Paper	NIS		5.4		-2.6	
423	Textiles	NIS		11.4		-0.6	
288	Crude steel	OECD		22.1		-0.4	
	RETAIL SALES		8		11.0		-0.4
362	Total (1)	NIS		15.8		-0.6	
482	Food	NIS		6.1		0.1	
473	Furniture and household goods	NIS		6.9		1.3	
456	Other goods	NIS		8.8		0.9	
342	Textiles and clothing	NIS		18.1		-2.3	
436	Total (2)	DS		10.3		0.5	
462	Household goods	EC		8.2		-0.4	
385	Textiles	EC		14.1		-2.7	
	INTERNATIONAL TRADE		2		36.8		-0.1
184	Exports (FOB)	NIS		32.6		0.1	
137	Imports (CIF)	NIS		40.9		-0.3	
	CAR SALES		4		11.8		2.8
433	New car registrations (1)	EC		10.5		3.1	
383	New car registrations (2)	NIS		14.3		2.4	
434	New passenger cars sold	NIS		10.5		5.3	
413	New car registrations (3)	OECD		12.0		3.0	
	LABOUR MARKET		**32**		**35.2**		**-1.7**
	UNEMPLOYMENT		21		41.3		-1.9
80*	Unemployed job-seekers (1)	BELGO, NEMO		53.7		-1.7	
92*	Unemployed persons receiving benefit	BELGO, NEMO		50.6		-2.1	
467*	Other unemployed	BELGO, NEMO		7.8		-0.2	
56*	Unemployment - Under 25 years of age	BELGO, NEMO		62.2		-1.5	

105*	Unemployment - Over 25 years of age	BELGO, NEMO		47.0		-1.9	
149*	Unemployment (1)	BELGO, NEMO		38.5		-2.5	
217*	Harmonised unemployment rate: female	EC		28.8		-3.8	
158*	Harmonised unemployment rate: male	EC		36.8		-2.0	
127*	Unemployment (2)	EC		43.2		-2.6	
88*	Unemployed job-seekers (2)	NIS, MEL		52.3		-1.6	
117*	Unemployed job-seekers - Over 25 years of age	NIS, MEL		45.0		-1.7	
275*	Unemployed job-seekers - Female	NIS, MEL		22.9		-0.5	
66*	Unemployed job-seekers - Male	NIS, MEL		57.3		-1.7	
71*	Unemployed job-seekers - Under 25 years of age	NIS, MEL		55.7		-1.4	
500*	Unemployed persons not receiving benefit	NIS, MEL		3.8		-3.4	
90*	Registered unemployment (percent of dependent labour force)	OECD		51.6		-1.5	
101*	Registered unemployment (percent of total labour force)	OECD		48.7		-1.5	
91*	Unemployed job-seekers (3)	OECD		50.6		-1.7	
147*	Harmonised unemployment rate - Over 25 years of age	EC		38.9		-2.8	
202*	Harmonised unemployment rate - Under 25 years of age	EC		30.6		-1.6	
140*	Harmonised unemployment rate - Total	EC		40.5		-2.6	
	EMPLOYMENT		11		23.6		-1.1
232	Vacancies received	BELGO, NEMO		27.3		1.1	
222	Unfilled vacancies	BELGO, NEMO		28.3		-0.2	
393*	Agriculture, hunting, forestry and fishing	NAI		13.0		-0.8	
124	Manufacturing industry	NAI		43.8		-4.1	
441	Building	NAI		9.8		-2.3	
192	Services	NAI		31.3		-3.0	
357*	Trade, transport and communication	NAI		16.2		2.2	
213	Financial, real estate, renting and business services	NAI		29.5		-1.3	
484*	Public administration and education	NAI		5.6		-1.8	
404	Other services	NAI		12.3		-6.0	
129	Total national employment	NAI		42.1		-3.6	
	PRICES		**47**		**17.6**		**-0.7**
	Commodity prices		13		18.2		-1.0
245	All items	BELGO, HWWA		26.2		-1.2	
221	All items excluding energy	BELGO, HWWA		28.4		-1.0	
381	Foodstuffs	BELGO, HWWA		14.5		0.4	
478*	Cereals	BELGO, HWWA		6.6		-2.3	
459*	Oilseeds, oils	BELGO, HWWA		8.7		-3.5	
372	Alcohol, tobacco and sugar	BELGO, HWWA		15.0		0.0	
234	Industrial materials	BELGO, HWWA		27.3		-1.3	
304	Agricultural materials	BELGO, HWWA		20.5		-1.5	
244	Non-ferrous metals	BELGO, HWWA		26.6		-0.9	
461	Iron ore, scrap iron	BELGO, HWWA		8.4		-2.5	
279	Energy	BELGO, HWWA		22.5		-1.1	
443*	Coal	BELGO, HWWA		9.6		3.0	
287	Crude oil	BELGO, HWWA		22.2		-0.9	
	Producer prices		24		21.3		-0.5
347*	Durable consumer goods	EC		17.1		0.2	
259	Energy	EC		24.8		-0.9	
270	Energy (excluding electricity, gas and water supply)	EC		23.6		0.1	
212	Industry excluding construction (1)	EC		29.5		-0.9	
323	Intermediate goods (1)	EC		19.2		-2.1	
209	Manufacturing industry	EC		29.7		-0.8	
398	Non-durable consumer goods	EC		12.8		-0.7	
299	Industry excluding construction and energy	EC		21.0		-1.6	
378	Consumer goods	NIS		14.8		0.0	
305	Energy: electricity, gas, steam and water	NIS		20.5		-0.3	
480*	Extractive industries: mining and quarrying	NIS		6.2		6.6	
382	Food, drink and tobacco products	NIS		14.4		0.6	
182	Industry excluding construction (2)	NIS		32.9		-0.9	
199	Intermediate goods (2)	NIS		30.8		-1.0	
429*	Capital goods	NIS		11.1		1.6	
224	Manufacturing industry	NIS		28.1		-0.8	
186	All items	OECD		32.1		-0.9	
325	Chemicals	OECD		19.1		-2.4	
406	Consumer goods	OECD		12.3		-0.5	
417	Food beverages and tobacco	OECD		11.7		0.2	
197	Intermediate goods	OECD		30.9		-0.9	
396*	Capital goods	OECD		12.8		1.7	
187	Manufacturing goods	OECD		32.1		-0.8	
268	Petroleum products	OECD		23.8		0.1	
	Consumer prices		8		8.6		-0.3
483*	General index	NIS		5.8		1.1	
507*	Foodstuffs	NIS		1.8		2.6	

444	Non-foodstuffs	NIS		9.6		-3.0	
463*	Services	NIS		8.1		-1.4	
345*	All items excluding food and energy	OECD		17.7		-1.2	
361*	Rent	OECD		15.9		-2.3	
468*	Services excluding rent	OECD		7.6		-1.2	
506*	Food excluding restaurants	OECD		2.0		2.8	
	Wages		2		4.9		-1.9
489*	Wage earnings - hourly, males industry	OECD		5.1		-1.8	
495*	Wages in manufacturing industry (per hour)	NIS		4.7		-1.9	
	FINANCIAL		**51**		**23.3**		**1.2**
	INTEREST RATES		22		26.7		-0.8
	10 Year		*7*		*29.7*		*0.1*
174	10YR interest rate: BE	BELGO		33.6		-0.1	
177	10YR interest rate: FR	BELGO		33.1		-0.9	
159	10YR interest rate: NL	BELGO		36.8		-0.3	
203	10YR interest rate: GE	BELGO		30.5		-0.3	
286	10YR interest rate: UK	BELGO		22.2		-0.2	
165	10YR interest rate: US	BELGO		35.5		1.0	
352	10YR interest rate: JA	BELGO		16.5		1.3	
	3 Month		*8*		*24.1*		*-2.1*
460	3M interest rate: BE	BELGO		8.6		-2.3	
442	3M interest rate: FR	BELGO		9.7		-3.3	
226	3M interest rate: NL	BELGO		27.9		-2.4	
267	3M interest rate: GE	BELGO		24.1		-2.7	
154	3M interest rate: UK	BELGO		37.4		-1.6	
112	3M interest rate: US	BELGO		46.4		-0.7	
354	3M interest rate: JA	BELGO		16.5		-1.1	
277	3M interest rate: ECU/EURO	BELGO		22.6		-2.7	
	Yieldgap		*7*		*26.7*		*-0.1*
289	Yieldgap: BE	BELGO		22.0		-1.0	
193	Yieldgap: FR	BELGO		31.3		-0.5	
235	Yieldgap: NL	BELGO		27.2		-0.6	
233	Yieldgap: GE	BELGO		27.3		-0.5	
327	Yieldgap: UK	BELGO		19.0		1.6	
125*	Yieldgap: US	BELGO		43.5		-4.4	
351	Yieldgap: JA	BELGO		16.5		0.3	
	ASSET PRICES		29		20.6		2.6
	Stocks		*9*		*23.3*		*2.3*
450	Brussels stock exchange cash market return index	DS		9.1		3.4	
397	Total market return index: BE	DS		12.8		2.7	
211	Total market return index: GE	DS		29.6		1.3	
255	Total market return index: FR	DS		25.1		1.5	
208	Total market return index: NL	DS		29.7		1.8	
191	Total market return index: EUR12	DS		31.4		1.5	
283	Total market return index: US	DS		22.3		3.2	
314	Total market return index: JA	DS		19.8		2.7	
204	Total market return index: World	DS		30.2		2.7	
	Real estate		*7*		*14.9*		*3.3*
427	Real estate return index: BE	DS		11.1		3.8	
486	Real estate return index: FR	DS		5.4		3.5	
349	Real estate return index: NL	DS		16.9		2.6	
350	Real estate return index: EUR12	DS		16.9		2.7	
366	Real estate return index: US	DS		15.5		3.6	
416	Real estate return index: JA	DS		11.8		3.5	
237	Real estate return index: World	DS		27.1		3.2	
	Gold		*1*		*8.7*		*-3.2*
458*	Gold Bullion $/Ounce	DS		8.7		-3.2	
	Exchange rate		*12*		*22.9*		*3.0*
306*	US $ to Belgian Franc	DS		20.5		3.4	
250*	JP Morgan trade weighted index euro, nominal, broad basis: EUR12	DS		25.4		3.2	
240*	JP Morgan trade weighted index euro, nominal, narrow basis: EUR12	DS		26.9		2.7	
249*	JP Morgan trade weighted index euro, real, broad basis: EUR12	DS		25.7		3.1	
254*	JP Morgan trade weighted index euro, real, narrow basis: EUR12	DS		25.1		3.0	
329*	Nominal effective trade-weighted exchange rate index: BE	DS		18.8		2.8	
228*	Real effective exchange rate index - normalized labour cost based: BE	DS		27.7		2.6	
291*	Real effective exchange rate: BE	DS		21.8		2.8	
447*	Real effective exchange rate - unit labour cost based: BE	IMF		9.4		3.3	
303*	Nominal effective exchange rate: Belgian Franc	BIS		20.7		2.9	
236*	Nominal effective exchange rate EUR, narrow index	ECB, BIS		27.1		2.9	
247*	Real effective exchange rate EUR - CPI-based, narrow index	ECB, BIS		26.0		2.9	

	SURVEY		**324**		**34.2**		**0.0**
	BUSINESS CONFIDENCE		**247**		**37.5**		**0.3**
	NBB		55		31.1		0.3
	Overall		*1*		*77.8*		*0.6*
5	Overall synthetic curve	NBB		77.8		0.6	
	Manufacturing industry		*11*		*57.4*		*0.7*
6	Manufacturing industry: Synthetic curve	NBB		77.6		0.7	
98	Manufacturing industry: Trend production rate	NBB		49.5		0.8	
82	Manufacturing industry: Trend domestic orders	NBB		53.3		0.7	
114	Manufacturing industry: Trend export orders	NBB		46.0		1.4	
19	Manufacturing industry: Appraisal total order book	NBB		73.0		0.0	
16	Manufacturing industry: Appraisal export order book	NBB		74.0		0.0	
144*	Manufacturing industry: Appraisal stocks of finished products	NBB		39.5		1.5	
38	Manufacturing industry: Forecast employment	NBB		67.3		0.4	
43	Manufacturing industry: Forecast demand	NBB		65.2		0.9	
181	Manufacturing industry: Trend selling prices	NBB		32.9		0.4	
84	Manufacturing industry: Forecast selling prices	NBB		52.7		0.7	
	Trade		*9*		*20.2*		*-0.2*
239	Trade: Synthetic curve	NBB		27.0		-0.1	
391	Trade: Trend sales	NBB		13.5		-0.4	
348	Trade: Appraisal sales	NBB		17.1		-0.5	
411*	Trade: Appraisal stocks	NBB		12.0		-0.1	
408	Trade: Forecast domestic orders	NBB		12.2		0.7	
223	Trade: Forecast foreign orders	NBB		28.2		0.1	
269	Trade: Forecast demand	NBB		23.6		0.1	
297	Trade: Trend selling prices	NBB		21.1		-1.3	
230	Trade: Forecast selling prices	NBB		27.4		-0.4	
	Building		*10*		*21.7*		*1.1*
253	Building: Synthetic curve	NBB		25.2		1.2	
338	Building: Trend activity	NBB		18.5		0.6	
388	Building: Trend order book	NBB		13.7		1.6	
466	Building: Trend employment	NBB		7.8		0.5	
419	Building: Trend equipment	NBB		11.6		1.6	
334	Building: Assessment of order book	NBB		18.7		1.4	
316	Building: Forecast employment	NBB		19.5		0.4	
266	Building: Forecast demand	NBB		24.1		2.1	
162	Building: Trend selling prices	NBB		36.5		0.6	
136	Building: Forecast selling prices	NBB		41.2		0.9	
	Capacity utilisation		*24*		*25.1*		*0.0*
51	Degree of capacity utilisation: Total industries	NBB		63.1		0.2	
370	Degree of capacity utilisation: Consumer goods	NBB		15.0		-0.3	
418	Degree of capacity utilisation: Capital goods	NBB		11.6		-1.2	
48	Degree of capacity utilisation: Intermediate goods	NBB		64.0		0.5	
94*	Production capacity: Appraisal: Total industries	NBB		50.1		0.7	
386*	Production capacity: Appraisal: Consumer goods	NBB		14.0		0.6	
379*	Production capacity: Appraisal: Capital goods	NBB		14.6		-0.3	
160*	Production capacity: Appraisal: Intermediate goods	NBB		36.7		0.8	
178	Production capacity: No production impediments: Total industries	NBB		33.1		0.1	
392	Production capacity: No production impediments: Consumer goods	NBB		13.3		-1.3	
264	Production capacity: No production impediments: Capital goods	NBB		24.4		0.2	
246	Production capacity: No production impediments: Intermediate goods	NBB		26.2		0.4	
95*	Production capacity: Production impediments : insufficient demand: Total industries	NBB		50.0		0.2	
454*	Production capacity: Production impediments : insufficient demand: Consumer goods	NBB		8.9		0.0	
146*	Production capacity: Production impediments : insufficient demand: Capital goods	NBB		39.0		-0.1	
157*	Production capacity: Production impediments : insufficient demand: Intermediate goods	NBB		36.9		0.3	
324	Production capacity: Production impediments : shortage of skilled labour: Total industries	NBB		19.2		-0.1	
479	Production capacity: Production impediments : shortage of skilled labour: Consumer goods	NBB		6.5		-0.5	
425	Production capacity: Production impediments : shortage of skilled labour: Capital goods	NBB		11.3		-0.4	
310	Production capacity: Production impediments : shortage of skilled labour: Intermediate goods	NBB		20.2		0.2	
356	Production capacity: Production impediments : lack of equipment: Total industries	NBB		16.4		0.0	
499	Production capacity: Production impediments : lack of equipment: Consumer goods	NBB		4.0		-6.0	
464	Production capacity: Production impediments : lack of equipment: Capital goods	NBB		8.1		-0.4	
369	Production capacity: Production impediments : lack of equipment: Intermediate goods	NBB		15.3		0.0	
	EUROPEAN COMMISSION		109		37.8		0.0
	Overall		*5*		*71.0*		*-0.2*
1	Economic sentiment indicator: BE	EC		81.6		0.2	
41	Economic sentiment indicator: GE	EC		66.1		-0.7	
26	Economic sentiment indicator: FR	EC		70.2		-0.4	
10	Economic sentiment indicator: EUR12	EC		76.7		-0.4	
59	Economic sentiment indicator: NL	EC		60.4		0.1	
	Manufacturing industry		*38*		*58.0*		*-0.3*
4	Industrial confidence indicator: BE	EC		78.1		0.4	

22	Industrial confidence indicator: GE	EC		71.0		-0.4	
35	Industrial confidence indicator: FR	EC		67.5		-0.3	
2	Industrial confidence indicator: EUR12	EC		79.8		-0.2	
44	Industrial confidence indicator: NL	EC		65.2		-0.2	
75	Manufacturing industry: Production trend observed in recent months: BE	EC		55.2		0.6	
134	Manufacturing industry: Production trend observed in recent months: GE	EC		41.5		-0.1	
63	Manufacturing industry: Production trend observed in recent months: FR	EC		58.9		-0.8	
25	Manufacturing industry: Production trend observed in recent months: EUR12	EC		70.4		-0.3	
170	Manufacturing industry: Production trend observed in recent months: NL	EC		34.4		0.5	
104	Manufacturing industry: Employment expectations for the months ahead: BE	EC		48.1		-0.1	
60	Manufacturing industry: Employment expectations for the months ahead: GE	EC		60.4		-1.1	
173	Manufacturing industry: Employment expectations for the months ahead: FR	EC		34.0		-1.8	
49	Manufacturing industry: Employment expectations for the months ahead: EUR12	EC		63.9		-1.2	
320	Manufacturing industry: Employment expectations for the months ahead: NL	EC		19.3		-1.8	
18	Manufacturing industry: Assessment of order-book levels: BE	EC		73.1		-0.3	
37	Manufacturing industry: Assessment of order-book levels: GE	EC		67.5		-1.1	
65	Manufacturing industry: Assessment of order-book levels: FR	EC		58.5		-0.8	
11	Manufacturing industry: Assessment of order-book levels: EUR12	EC		76.6		-0.7	
36	Manufacturing industry: Assessment of order-book levels: NL	EC		67.5		-0.6	
12	Manufacturing industry: Assessment of export order-book levels: BE	EC		75.8		-0.2	
40	Manufacturing industry: Assessment of export order-book levels: GE	EC		66.7		-0.9	
62	Manufacturing industry: Assessment of export order-book levels: FR	EC		59.0		-0.6	
17	Manufacturing industry: Assessment of export order-book levels: EUR12	EC		73.8		-0.6	
111*	Manufacturing industry: Assessment of stocks of finished products: BE	EC		46.5		1.3	
79*	Manufacturing industry: Assessment of stocks of finished products: GE	EC		53.8		-0.5	
169*	Manufacturing industry: Assessment of stocks of finished products: FR	EC		34.5		-0.2	
50*	Manufacturing industry: Assessment of stocks of finished products: EUR12	EC		63.8		-0.1	
183*	Manufacturing industry: Assessment of stocks of finished products: NL	EC		32.7		-0.4	
29	Manufacturing industry: Production expectations for the months ahead: BE	EC		68.9		0.6	
52	Manufacturing industry: Production expectations for the months ahead: GE	EC		62.8		0.5	
54	Manufacturing industry: Production expectations for the months ahead: FR	EC		62.6		0.3	
13	Manufacturing industry: Production expectations for the months ahead: EUR12	EC		75.3		0.5	
189	Manufacturing industry: Production expectations for the months ahead: NL	EC		31.6		0.6	
72	Manufacturing industry: Selling price expectations for the months ahead: BE	EC		55.4		0.4	
74	Manufacturing industry: Selling price expectations for the months ahead: GE	EC		55.3		-0.3	
168	Manufacturing industry: Selling price expectations for the months ahead: FR	EC		34.9		-1.5	
64	Manufacturing industry: Selling price expectations for the months ahead: EUR12	EC		58.6		-0.6	
	Trade		*30*		*14.0*		*-0.1*
298	Retail confidence indicator: BE	EC		21.1		-0.2	
402	Retail confidence indicator: GE	EC		12.5		-5.1	
273	Retail confidence indicator: FR	EC		23.1		-0.9	
296	Retail confidence indicator: EUR12	EC		21.5		-1.3	
449	Retail confidence indicator: NL	EC		9.2		2.4	
339	Retail: Present business situation: BE	EC		18.5		-0.5	
422	Retail: Present business situation: GE	EC		11.5		-6.0	
190	Retail: Present business situation: FR	EC		31.5		-0.7	
331	Retail: Present business situation: EUR12	EC		18.7		-1.5	
471	Retail: Present business situation: NL	EC		7.1		3.7	
405*	Retail: Assessment of stocks: BE	EC		12.3		0.0	
431*	Retail: Assessment of stocks: GE	EC		10.6		-4.4	
494	Retail: Assessment of stocks: FR	EC		4.7		-1.1	
491	Retail: Assessment of stocks: EUR12	EC		5.0		2.8	
432*	Retail: Assessment of stocks: NL	EC		10.6		4.6	
293	Retail: Orders placed with suppliers: BE	EC		21.6		0.1	
469*	Retail: Orders placed with suppliers: GE	EC		7.5		-0.3	
389	Retail: Orders placed with suppliers: FR	EC		13.6		0.2	
440	Retail: Orders placed with suppliers: EUR12	EC		9.8		1.3	
377	Retail: Orders placed with suppliers: NL	EC		14.8		1.1	
375	Retail: Expected business situation: BE	EC		14.9		0.1	
428	Retail: Expected business situation: GE	EC		11.1		-0.5	
420	Retail: Expected business situation: FR	EC		11.5		-1.5	
302	Retail: Expected business situation: EUR12	EC		20.7		0.0	
317	Retail: Expected business situation: NL	EC		19.5		1.4	
395	Retail: Employment: BE	EC		12.9		-0.5	
421	Retail: Employment: GE	EC		11.5		-3.3	
476	Retail: Employment: FR	EC		6.6		-2.4	
472	Retail: Employment: EUR12	EC		7.0		-2.1	
341	Retail: Employment: NL	EC		18.3		0.9	
	Building		*25*		*29.6*		*0.3*
260	Building confidence indicator: BE	EC		24.7		1.1	
282	Building confidence indicator: GE	EC		22.3		0.6	
96	Building confidence indicator: FR	EC		49.8		-0.2	

130	Building confidence indicator: EUR12	EC		41.9		-0.6	
335	Building confidence indicator: NL	EC		18.6		0.5	
368	Building: Employment expectations for the months ahead: BE	EC		15.3		1.1	
294	Building: Employment expectations for the months ahead: GE	EC		21.6		-0.2	
118	Building: Employment expectations for the months ahead: FR	EC		44.6		0.1	
171	Building: Employment expectations for the months ahead: EUR12	EC		34.2		-0.5	
409	Building: Employment expectations for the months ahead: NL	EC		12.2		0.2	
242	Building: Trend of activity compared with preceding months: BE	EC		26.7		0.5	
376	Building: Trend of activity compared with preceding months: GE	EC		14.9		2.4	
109	Building: Trend of activity compared with preceding months: FR	EC		46.7		-0.6	
180	Building: Trend of activity compared with preceding months: EUR12	EC		32.9		0.0	
384	Building: Trend of activity compared with preceding months: NL	EC		14.2		1.7	
132	Building: Price expectations for the months ahead: BE	EC		41.6		0.7	
218	Building: Price expectations for the months ahead: GE	EC		28.7		0.6	
141	Building: Price expectations for the months ahead: FR	EC		40.3		-0.9	
106	Building: Price expectations for the months ahead: EUR12	EC		46.9		-0.5	
278	Building: Price expectations for the months ahead: NL	EC		22.5		-1.6	
261	Building: Assessment of order books: BE	EC		24.7		1.1	
374	Building: Assessment of order books: GE	EC		14.9		2.2	
122	Building: Assessment of order books: FR	EC		44.2		-0.6	
153	Building: Assessment of order books: EUR12	EC		37.8		-0.8	
326	Building: Assessment of order books: NL	EC		19.1		1.0	
	Capacity utilisation		*11*		*36.5*		*0.7*
87*	Production capacity: Assessment of current production capacity: BE	EC		52.3		0.4	
322	Production capacity: Duration of production assured by current order-books: BE	EC		19.2		-0.6	
215	Production capacity: New orders in recent months: BE	EC		29.0		2.3	
284	Production capacity: Export expectations for the months ahead: BE	EC		22.3		2.6	
46	Degree of capacity utilisation: BE	EC		64.1		0.0	
220	Production capacity: Export expectations for the months ahead: DE	EC		28.5		1.9	
205	Production capacity: Export expectations for the months ahead: FR	EC		30.1		1.2	
164	Production capacity: Export expectations for the months ahead: EUR12	EC		36.0		1.7	
93	Degree of capacity utilisation: GE	EC		50.1		0.3	
373	Degree of capacity utilisation: FR	EC		14.9		-2.1	
73	Degree of capacity utilisation: EUR12	EC		55.3		-0.5	
	IFO		31		39.0		0.5
	Overall		*3*		*66.6*		*0.2*
14	Overall indicator	IFO		74.7		0.3	
45	Current climate	IFO		64.4		-0.9	
58	Forecasts	IFO		60.8		1.3	
	Manufacturing industry		*8*		*53.7*		*0.3*
15	Manufacturing industry: Synthetic curve	IFO		74.1		-0.3	
116	Manufacturing industry: Trend production rate	IFO		45.0		0.6	
83	Manufacturing industry: Trend domestic orders	IFO		53.3		1.0	
24	Manufacturing industry: Appraisal total order book	IFO		70.6		-0.7	
69*	Manufacturing industry: Appraisal stocks of finished products	IFO		56.4		-0.2	
55	Manufacturing industry: Forecast demand	IFO		62.4		1.3	
148	Manufacturing industry: Trend selling prices	IFO		38.6		0.3	
214	Manufacturing industry: Forecast selling prices	IFO		29.1		0.4	
	Trade		*6*		*39.9*		*0.5*
256	Trade: Synthetic curve	IFO		25.1		-0.3	
113	Trade: Trend sales	IFO		46.2		1.3	
28	Trade: Appraisal stocks	IFO		69.5		-0.7	
188	Trade: Forecast domestic orders	IFO		31.7		0.3	
163	Trade: Forecast demand	IFO		36.4		1.6	
200	Trade: Trend selling prices	IFO		30.7		1.0	
	Building		*10*		*12.7*		*1.4*
251	Building: Synthetic curve	IFO		25.4		1.4	
488	Building: Trend activity	IFO		5.1		4.8	
457	Building: Trend order book	IFO		8.7		5.2	
509	Building: Trend equipment	IFO		1.1		2.4	
503	Building: Trend employment	IFO		3.5		0.6	
424	Building: Assessment of order book	IFO		11.4		3.8	
380	Building: Forecast employment	IFO		14.6		-1.2	
295	Building: Forecast demand	IFO		21.6		1.5	
309	Building: Trend selling prices	IFO		20.2		1.4	
364	Building: Forecast selling prices	IFO		15.7		1.5	
	Capacity utilisation		*4*		*53.2*		*-0.7*
34	Degree of capacity utilisation: Total industries	IFO		67.6		-0.7	
258	Degree of capacity utilisation: Consumer goods	IFO		24.9		-0.7	
100	Degree of capacity utilisation: Capital goods	IFO		48.9		-1.2	
21	Degree of capacity utilisation: Intermediate goods	IFO		71.5		-0.2	

	ISM		17		22.7		1.9
166	Purchasing managers survey (manufactures survey)	ISM		35.0		2.5	
133	Manufactures survey: Prices paid index	ISM		41.6		0.4	
185	Manufactures survey: Supplier delivery index	ISM		32.4		1.3	
143	Manufactures survey: Employment index	ISM		39.7		1.8	
321	Manufactures survey: New export orders index	ISM		19.2		2.3	
355	Manufactures survey: Inventories index	ISM		16.4		1.0	
225	Manufactures survey: New orders index	ISM		28.1		3.1	
206	Manufactures survey: Production index	ISM		30.0		2.8	
414	Manufactures survey results: Employment - Same	ISM		12.0		2.1	
172*	Manufactures survey results: Employment - Lower	ISM		34.2		1.9	
346	Manufactures survey results: Employment - Higher	ISM		17.1		1.7	
318	Manufactures survey results: New exports - Same	ISM		19.3		2.5	
290*	Manufactures survey results: New exports - Worse	ISM		21.9		2.4	
465	Manufactures survey results: New exports - Better	ISM		7.9		2.3	
453	Manufactures survey results: Inventories - Same	ISM		8.9		2.8	
445	Manufactures survey results: Inventories - Higher	ISM		9.5		-0.7	
401*	Manufactures survey results: Inventories - Lower	ISM		12.7		1.8	
	INSEE		10		57.1		-0.2
	Manufacturing industry		*7*		*65.6*		*-0.1*
7	Manufacturing industry: Synthetic curve	INSEE		77.5		-0.1	
57	Manufacturing industry: Trend production rate	INSEE		61.8		-0.4	
23	Manufacturing industry: Trend domestic orders	INSEE		70.8		-0.4	
33	Manufacturing industry: Trend export orders	INSEE		68.5		-0.1	
81*	Manufacturing industry: Appraisal stocks of finished products	INSEE		53.5		0.3	
27	Manufacturing industry: Forecast demand	INSEE		70.2		0.6	
67	Manufacturing industry: Forecast selling prices	INSEE		56.9		-0.7	
	Degree of capacity utilisation		*3*		*37.2*		*-0.5*
120	Degree of capacity utilisation: Total industries	INSEE		44.5		-0.2	
399	Degree of capacity utilisation: Capital goods	INSEE		12.8		-1.2	
77	Degree of capacity utilisation: Intermediate goods	INSEE		54.4		0.0	
	CBS		2		51.7		0.0
42	Manufacturing industry: Synthetic curve	CBS		65.5		0.1	
151*	Manufacturing industry: Appraisal stocks of finished products	CBS		37.9		0.0	
	BOJ		5		21.2		0.5
285	TANKAN: Business conditions - All enterprises, industry	BOJ		22.2		0.6	
276	TANKAN: Business conditions - Large enterprises, industry	BOJ		22.8		0.4	
311	TANKAN: Business conditions - Medium enterprises, industry	BOJ		20.1		0.6	
301	TANKAN: Business conditions - Small enterprises, industry	BOJ		20.9		0.8	
312	TANKAN: Business conditions - Principal enterprises, industry	BOJ		19.9		0.1	
	OECD		18		58.6		1.1
39	Composite leading indicator - trend restored: GE	OECD		67.1		0.7	
61	Composite leading indicator - trend restored: FR	OECD		59.9		0.8	
3	Composite leading indicator - trend restored: NL	OECD		79.6		0.5	
20	Composite leading indicator - trend restored: EUR12	OECD		72.1		1.0	
271	Composite leading indicator - trend restored: UK	OECD		23.4		2.0	
167	Composite leading indicator - trend restored: US	OECD		35.0		2.3	
300	Composite leading indicator - trend restored: JP	OECD		20.9		2.3	
9	Composite leading indicator - trend restored: BE	OECD		77.3		0.9	
30	Business tendency surveys: demand (future tendency): BE	OECD		68.7		1.0	
31	Business tendency surveys: employment (future tendency): BE	OECD		68.7		0.5	
99	Business tendency surveys: export order inflow (tendency): BE	OECD		49.3		1.6	
68	Business tendency surveys: production (tendency): BE	OECD		56.7		0.9	
8	Composite leading indicator (Amplitude adjusted): BE	OECD		77.4		0.9	
32	Composite leading indicator: Demand - Future tendency, manufacturing industry: BE	OECD		68.5		1.0	
53	Composite leading indicator: employment - future tendency, manufacturing industry: BE	OECD		62.7		0.6	
103	Composite leading indicator: export orders inflow - tendency, manufacturing industry: BE	OECD		48.4		1.6	
78	Composite leading indicator: production - tendency, manufacturing industry: BE	OECD		54.3		0.9	
47	Business tendency surveys: capacity utilisation rate: BE	OECD		64.1		0.2	
	CONSUMER CONFIDENCE		**77**		**23.8**		**-1.1**
	NBB		12		25.4		-0.9
107	Consumer confidence indicator	NBB		46.8		-0.3	
139	Consumer confidence: General economic situation in Belgium over the next 12 months	NBB		40.5		0.0	
119*	Consumer confidence: Unemployment in Belgium over the next 12 months	NBB		44.5		-0.5	
194	Consumer confidence: Financial situation households over next 12 months	NBB		31.3		-0.5	
412	Consumer confidence: Saving capacity of households over the next 12 months	NBB		12.0		-0.9	
121	Consumer confidence: Appraisal general economic situation over the last 12 months	NBB		44.3		-1.0	
319	Consumer confidence: Major purchases at present	NBB		19.3		-1.9	
490	Consumer confidence: Major purchases over the next 12 months	NBB		5.0		-2.6	
198	Consumer confidence: Financial situation households over the last 12 months	NBB		30.8		-1.1	
485	Consumer confidence: Financial situation households over the next 12 months	NBB		5.6		-1.1	
448	Consumer confidence: Price developments over the last 12 months	NBB		9.3		-2.8	
359*	Consumer confidence: Price developments over the next 12 months	NBB		16.0		1.9	

	EUROPEAN COMMISSION		65		23.5		-1.2
102	Consumer confidence indicator: BE	EC		48.4		-0.5	
155	Consumer confidence indicator: GE	EC		37.3		-1.4	
201	Consumer confidence indicator: FR	EC		30.7		-0.9	
85	Consumer confidence indicator: EUR12	EC		52.7		-0.8	
142	Consumer confidence indicator: NL	EC		39.7		0.2	
196	Consumer confidence: Financial situation over the last 12 months: BE	EC		31.1		-1.2	
243	Consumer confidence: Financial situation over the last 12 months: GE	EC		26.7		-3.4	
330	Consumer confidence: Financial situation over the last 12 months: FR	EC		18.8		-1.9	
150	Consumer confidence: Financial situation over the last 12 months: EUR12	EC		38.0		-1.6	
390	Consumer confidence: Financial situation over the last 12 months: NL	EC		13.6		-2.9	
210	Consumer confidence: Financial situation over the next 12 months: BE	EC		29.7		-0.7	
238	Consumer confidence: Financial situation over the next 12 months: GE	EC		27.0		-1.8	
272	Consumer confidence: Financial situation over the next 12 months: FR	EC		23.2		-0.5	
138	Consumer confidence: Financial situation over the next 12 months: EUR12	EC		40.7		-0.8	
363	Consumer confidence: Financial situation over the next 12 months: NL	EC		15.8		0.1	
123	Consumer confidence: General economic situation over the last 12 months: BE	EC		43.8		-1.1	
135	Consumer confidence: General economic situation over the last 12 months: GE	EC		41.4		-1.9	
219	Consumer confidence: General economic situation over the last 12 months: FR	EC		28.7		-1.7	
86	Consumer confidence: General economic situation over the last 12 months: EUR12	EC		52.4		-1.3	
161	Consumer confidence: General economic situation over the last 12 months: NL	EC		36.6		-0.4	
128	Consumer confidence: General economic situation over the next 12 months: BE	EC		43.1		-0.1	
145	Consumer confidence: General economic situation over the next 12 months: GE	EC		39.4		-1.1	
262	Consumer confidence: General economic situation over the next 12 months: FR	EC		24.6		-0.4	
97	Consumer confidence: General economic situation over the next 12 months: EUR12	EC		49.6		-0.3	
108	Consumer confidence: General economic situation over the next 12 months: NL	EC		46.7		0.7	
439	Consumer confidence: Price trends over the last 12 months: BE	EC		9.8		-2.9	
313*	Consumer confidence: Price trends over the last 12 months: GE	EC		19.9		7.2	
360	Consumer confidence: Price trends over the last 12 months: FR	EC		15.9		-2.8	
308*	Consumer confidence: Price trends over the last 12 months: EUR12	EC		20.2		5.3	
407	Consumer confidence: Price trends over the last 12 months: NL	EC		12.2		0.0	
365*	Consumer confidence: Price trends over the next 12 months: BE	EC		15.6		1.6	
400*	Consumer confidence: Price trends over the next 12 months: GE	EC		12.8		0.5	
394*	Consumer confidence: Price trends over the next 12 months: FR	EC		12.9		2.4	
344*	Consumer confidence: Price trends over the next 12 months: EUR12	EC		17.8		2.3	
337	Consumer confidence: Price trends over the next 12 months: NL	EC		18.6		-6.7	
126*	Consumer confidence: Unemployment expectations over the next 12 months: BE	EC		43.4		-0.7	
207*	Consumer confidence: Unemployment expectations over the next 12 months: GE	EC		29.9		-1.6	
195*	Consumer confidence: Unemployment expectations over the next 12 months: FR	EC		31.3		-1.3	
89*	Consumer confidence: Unemployment expectations over the next 12 months: EUR12	EC		52.2		-1.1	
152*	Consumer confidence: Unemployment expectations over the next 12 months: NL	EC		37.8		-0.3	
328	Consumer confidence: Major purchases at present: BE	EC		18.8		-1.9	
353	Consumer confidence: Major purchases at present: GE	EC		16.5		-5.2	
358	Consumer confidence: Major purchases at present: FR	EC		16.1		-1.5	
307	Consumer confidence: Major purchases at present: EUR12	EC		20.3		-1.5	
452	Consumer confidence: Major purchases at present: NL	EC		9.0		-3.9	
492	Consumer confidence: Major purchases over the next 12 months: BE	EC		4.8		-2.5	
229	Consumer confidence: Major purchases over the next 12 months: GE	EC		27.6		-2.7	
410	Consumer confidence: Major purchases over the next 12 months: FR	EC		12.1		-2.1	
340	Consumer confidence: Major purchases over the next 12 months: EUR12	EC		18.5		-2.2	
504*	Consumer confidence: Major purchases over the next 12 months: NL	EC		3.2		-3.5	
470	Consumer confidence: Savings at present: BE	EC		7.3		-2.3	
415	Consumer confidence: Savings at present: GE	EC		11.9		-1.6	
496	Consumer confidence: Savings at present: FR	EC		4.3		0.6	
477	Consumer confidence: Savings at present: EUR12	EC		6.6		-1.4	
498*	Consumer confidence: Savings at present: NL	EC		4.1		3.4	
387	Consumer confidence: Savings over the next 12 months: BE	EC		14.0		-0.8	
315	Consumer confidence: Savings over the next 12 months: GE	EC		19.7		-2.2	
435	Consumer confidence: Savings over the next 12 months: FR	EC		10.4		-0.1	
248	Consumer confidence: Savings over the next 12 months: EUR12	EC		25.9		-0.9	
455*	Consumer confidence: Savings over the next 12 months: NL	EC		8.9		-1.1	
493	Consumer confidence: Statement on financial situation of household: BE	EC		4.7		-2.1	
481*	Consumer confidence: Statement on financial situation of household: GE	EC		6.1		-3.3	
403*	Consumer confidence: Statement on financial situation of household: FR	EC		12.3		-4.2	
438*	Consumer confidence: Statement on financial situation of household: EUR12	EC		9.9		-3.9	
497	Consumer confidence: Statement on financial situation of household: NL	EC		4.2		-3.9	
	TOTAL		**509**		**30.1**		**-0.1**

1) Ranking number according to the importance of the commonality ratio. Countercyclical variables are indicated by an asterisk.
2) Commomality ratio of the series, measured as the ratio between the variance of the series' common component and the series' total variance.
3) Time lag of the series' common component with respect to the common component of GDP, measured in quarters. Variables are considered to lead Belgian GDP when the time lag >1, to lag when it is <-1 and to coincide otherwise.

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