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Short-Term Forecasting of the Portuguese Economy

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Abstract

This Dissertation focuses on exploring Dynamic Factor Models methodologies allowing for an efficcient and reliable forecast of Quarterly real GDP growth rates on a timely maner. Alternative forecasting models will be described, together with the most recent litterature focusing on the experience of the European Monetary Union (EMU), Spain and Portugal. The accuracy of the created Dynamic Factor Model will be compared with the Portuguese Statistical Office preliminary announcement, 45 days after the end of the reference quarter. The nature of the economic variables to be used, their timeliness and the weight given by the model to their information content are analyzed, in the search for undoing the "black box" character of factor models. A wide range of future developments are identified while acquiring the understanding that a Forecaster will always have to deal with open questions.

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Preface

Writing a dissertation on the subject "Short-Term Forecasting of the Portuguese Economy" was a challenging experience, full of enriching and learning opportunities, enhanced by the methodological novelty and the dedication and perseverance that helped me mark the beginning of a new stage in the course of my personal and professional life.

All the setbacks and milestones strengthened my conviction that it is possible to achieve goals when we give ourselves completely to them. I thank my family and Lisa, for their unconditional support, given to me in this journey, even during the times I could not be available to them due to the demands of my professional activity.

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With all the support I have listed, this project turned out to be an important foundation for my development as a person and as a professional.

1 Introduction

"Tell us what the future holds, so we may know that you are gods." (Isaiah 41:23)

Our time is one of great uncertainty. Economic agents expectations and behaviour are difficult to model – an even more challenging task in the Portuguese case. The adjustment process that followed the MoU was not circunscript to Public Finances. The deleveraging of the Banking System and the decline in disposable income led to a contraction of Economic Activity only smoothed by the robustness of external trade. In this context, institutional forecasts, published on MoU revisions and agreed with Troika representatives, have been under intense scrutiny and subject to significant revisions. As stressed in Iacoviello (2001) for short-term forecasting of the Italian Economy, foretelling the economy is not often a risk-free task, since a variety of difficulties arise in creating models which deliver reliable predictions both in a successful and consistent fashion. The demand for short-term forecasts of economic activity and a real time assessment for and from policy makers sparkles a renewed interest on the topic. In their paper, Camacho and Perez-Quiros (2009) describe the explosive interest from the press and the academia for early assessments on the evolution of economic activity, present in the constant references to short term GDP growth rate forecasts and their successive revisions. The task of testing and selecting a wide range of indicators trying to extract some explanatory power over such complex realities is mesmerizing. How expectations affect and are affected by forecasts is also a challenging study of behavioural economics and microeconomics.

This Dissertation starts by exploring the available literature on short-term forecasts and studying the available alternatives. The methodology is particularly inspired by the work developed by Camacho and García-Serrador (2011) on behalf of BBVA Research, an extension of the Euro-Sting single-index dynamic factor model. The goal is to adapt their methodology for the particular case of the Portuguese Economy, in order to obtain short-term real GDP growth forecasts and to evaluate the results.

It should be warranted that all models and methodologies have their drawbacks. Specifically, by constructing a dynamic factor model that is simultaneously easy to interpret, to replicate, and to update[1], professional judgement is diminished to variable selection. Although making it a less subjective exercise, the importance of judgement should not be neglected. In fact, it helps to adapt the forecasts to information not statistically captured by any variable while relying on the extensive experience of the Forecaster. The Forecaster itself should be conscientious that when there are no historical benchmarks there is an increased propensity for error. Plausibility can be enhanced by complementing and cross-checking projections. The exercise hereby proposed is enriched by using data covering a number of recessions, enabling the model to learn from those experiences. Given the complexity of this subject, and as part of a longer term view, it was chosen to start by developing and studying short-term forecasting methods yielding the most comprehensive results, while preparing the way for longer-term projections, which can be explored at a later stage.

This paper is structured as follows: the next section presents the literature review. The Dynamic Factor Model methodology is introduced in Section 3. Section 4 details the data selection procedure, nature and treatment. Section 5 presents the results of the Model and its real-time evaluation. Section 7 presents the concluding remarks and possible future developments.

[1] Camacho and Perez-Quiros (2008)

2 Literature Review

2.1 Forecasting Models

In a policy context, a useful survey of short-term forecasting methods is given in Bundesbank (2009) and ECB (2008). The application of forecasting exercises to Monetary Policy communication and effectiveness from the perspective of policy-makers explains the role of forecasts in anchoring longer-term expectations of households and firms. The forecasters key tasks can be coherently outlined as: selection and weighting of economic indicators; raise awareness for the uncertainty and limitations of point forecasts; move towards the incorporation of risk analysis in macroeconomic forecasts. In order to do so, a number of tools are at his disposal and which can be pooled into two approaches: structural approaches[2] (better linked with the economic theory and comprising medium and longer horizons) and more statistical approaches (covering horizons up to two quarters, e.g. nowcasting when making estimates for GDP of the current quarter and nearcasting). Focusing on short-term forecasting, forecasters usually resort to two methods: forecast averaging, based on a number of Bridge Equations, and Dynamic Factor Models.

Generally, Dynamic Factor Models are created to extract and synthesise the common movements from a large set of data into a number of artificial latent factors, which typify the most relevant sources of variation. It commonly assumes the existence of an economic structure, through behavioural relationships linking key macroeconomic variables. However, one idea present in the literature is that econometric short-term forecasting models don't have a clear link with economic theories. As we are told in Bundesbank (2009), models intend to synthesize observed dynamic relationships of the past by means of purely statistical criteria.

The literature covers a number of factors extraction methods, namely simple principal components[3] and a two-step approach relying on principal components and Kalman filtering. Using the Kalman filter, factors are able to synthesize present and past patterns weighting them according to their persistence and heterogeneity. Factors resulting from principal components are linear combinations of recent observations since persistence is not regarded and the information content of all monthly indicators are equally weighted. Also, the number of static and dynamic factors and the number of lags need to be specified, which Barhoumi et al. (2008) have solved through a recursive minimum RMSE criterion. As in Nunes (2005), factor models provide both estimates of the common component, underlying a set of key indicators, of the unobserved monthly series, underlying the quarterly indicator, and of any missing values, while a coincident indicator on the quarterly variable is obtained.

Starting from the single-index coincident indicator model produced by Stock and Watson (1989, 1991) where a coincident index is built as the estimate of the common component, the model is frequently extended in order to allow variables with mixed frequencies and missing observations to be included. Its flexibility is reinforced by its ability to include series with different starting dates and with sampling frequencies changing over time. Although having the same starting point, the modifications included in the State-Space Representation by Nunes (2005), similar to the approach described in Harvey (1989) differs from the one applied by Camacho and Doménech (2010) or Camacho and Perez-Quiros (2008) which follow Mariano and Murasawa (2003) for handling missing observations.

Camacho and Perez-Quiros (2009) explores alternative approaches where "automatic" forecasting methods are concerned computing short term forecasts of the Spanish GDP growth rate in real time. The most familiar methods are the standard time series processes made known by Box and Jenkins together with its following improvements as multivariate time series processes and error correction models,

[2]Structural models can be divided in two classes: Econometric multi-equation models estimated based on Quarterly National Accounts data and DSGE models with stronger microeconomic foundations.

[3]These do not take into account the dynamic properties of the common factors and, as such, do not allow for factors to be forecasted.

usually conditional on quarterly series. It's disadvantages regard the difficulty of capturing abrupt economic changes and the strong revisions of the reference series[4]. Another possible alternative could be based on transfer functions as proposed in Nogales and Conejo (2006). This option becomes increasingly problematic as the number of indicators increases.

Alternatives to the Kalman filter have to handle missing observations resorting to other methods, such as univariate forecasts. For addressing the ragged edges issues, Camacho and García-Serrador (2011) fill the gaps according to Giannone et al. (2006), substituting missing observations with means, medians or zeroes. As we are told, this practice is analogous to Banbura and Rüstler (2007), Angelini et al. (2008) and Barhoumi et al. (2008), who use the approximate dynamic factor model proposed by Giannone et al. (2008). This deviates from the univariate bridge equations employed by Rustler and Sedillot (2003) and Diron (2006) or those trying to estimate high-frequency objects on a "daily or hourly" fashion as Aruoba, Diebold and Scotti (2009).

It should be noted that the often changing composition of synthetic models generates some doubt on their "post-sample" performance. To analyse these models conformity, Altissimo et al. (2001) proposes three standard criteria to be fulfilled: cross-sectional smoothing (local or sectoral shocks should have a limited impact on the aggregate, which should be cleaned from the idiosyncratic component); intertemporal smoothing (besides the idiosyncratic noises, seasonal and short-term movements from high-frequency indicators may impact GDP and should be cleared to obtain the underlying tendency of the economy); updating (taking advantage of cross-sectional information and leading variables to reduce forecasting errors).

A distinction is usually made between small-scale and large-scale factor models, according to the number of variables which are considered. This topic is closely linked with the selection process endorsed. The advantages of using small-scale models can be summarized in three points: with their small dimension, it is simpler to evaluate the empirical consequences of the violation of theoretical groundings[5]; it enables a more comprehensive evaluation of out-of-sample forecasts against basic benchmarks as well as professional forecasters; makes it a more straightforward practice to build a real-time data sample accounting for data vintages available at the time of each forecasting period. Camacho and Perez-Quiros (2008) conclude that in the context of Euro area GDP growth there is evidence in favour of small-scale approaches, which do not seem to imply a cost in terms of information and accuracy.[6] The "controversy" between large and small scale factor models is also discussed by Alvarez et al. (2009) where they conclude that more is not always synonymous of better when forecasts are considered. More recently this topic is addressed in Working Papers of these same authors[7]. Camacho and Perez-Quiros (2009) outline two alternatives: factors supported on an extensive amount of indicators estimated as in Angelini et al. (2008) by the use of approximate factor models; the existence of a "pre-screening" of the series estimated by applying strict factor models. Also for Bai and Ng (2008) the forecasting performance can be improved when the variables are correctly selected and have zero loads, reducing the scale of the model, even if the weak cross-correlation holds.[8]

As above mentioned, a prominent role is given to the Kalman filter in Dynamic Factor Models, since it

[4] Without the most timely information standard autoregressive models frequently exhibit strong mean reverting patterns, with forecasts biased towards the mean.

[5] Camacho and Perez-Quiros (2008) propose as an evaluation method a modified version of Engle's (2007) McGyver method allowing to estimate the covariance matrix of the idiosyncratic shocks by blocks. The authors find that some cross-covariance is present in the estimated idiosyncratic components, although non-significant in the estimation of factors.

[6] The authors argue that although much attention as been given to big data, Boinvin and NG (2006) and Bai and NG (2008) find evidence that forecast accuracy does not necessarily increase with the number of series included in the factor model and that Banbura and Rustler (2007) concluded that most of the predictive content of their large-scale model was contained in a small set of variables.

[7] Alvarez et al. (2012)

[8] "(...) adding more variables to the core of representatives of different categories may add mainly noise and cross-correlation of the idiosyncratic shocks, generating idiosyncratic correlations that might be larger than those warranted by theory".

allows efficient forecasts in case that both past or future observations contain missing data. Giannonne et al. (2005) and Banbura and Rüstler (2007) have shown that the application of the Kalman filter enables the creation of well fitted models for handling with unbalanced samples derived from desynchronized data releases. However, authors such as Altissimo et al. (2001) make use of cross-sectional information in forecasting lagged variables, with monthly GDP estimates being obtained by interpolating quarterly data, using it as a proxy of the non-observable GDP and ensuring a reliable estimate when the error is not correlated with the dynamic factors. This has been oftenly classified as an ad-hoc procedure. To estimate the cyclical indicator, Baxter and King (1999) filter or the approximation techniques of Christiano and Fitzgerald (2001) are suggested although not exploiting in depth the cross-sectional dimension of the model. As such, a multivariate version of the latest is explored to obtain a reasonable temporal smoothing, avoiding end-of-sample bias of two-side filtered data. Stressing the role of real time measurements of the Economy[9], Azevedo et al. (2003) defend the importance of real GDP for business cycle assessment, distinguishing their method for the inclusion of a Quarterly variable from the one of Altissimo et al. (2001). Quarterly figures are treated as monthly figures with missing observations, allowing the construction of the indicator without previous data transformation, similarly to the method proposed by Mariano and Murasawa (2003). Again, by making it possible to decompose time series into trend, cycle and irregular component, this proceeding originates two products: a business cycle indicator (interpreted by the authors as a "monthly proxy for the output gap") and a growth rate indicator, compared with the EuroCOIN.

By supporting the use of quarterly real GDP, the Kalman filter creates a set of advantages: a coherent computation of the common component; an improved estimate of the coincident index for the current month when quarterly GDP data is not available; the simultaneous estimation of a monthly coincident index and quarterly GDP and a more clear distinction between the two[10]. As reported by Camacho and Perez-Quiros (2008), using real GDP as a coincident business cycle indicator not only grants a higher adherence of models to real economic activity but also supports interpreting the common factor as the first difference of the log of latent monthly real GDP.

A number of authors, such as Rua (2004) and Azevedo et al. (2003), argue that the general structure of the State-Space framework of Dynamic Factor Models (e.g. Equation (1)), is not sufficiently suited to capture the business cycle since lead and lagged links between variables are not accounted for nor the dominant role played by low frequencies in macroeconomic time series is considered. This caveat is extended by not allowing a model to incorporate phase shifts and different reference cycles to be explored. Although the cycle is assumed to be common to all series, it can be calibrated differently compared to a reference series used for cycle identification. Altissimo et al. (2001) make use of the estimated Euro area coincident indicator as a reference cycle to assess *ex post* the pro-cyclicality, acyclicality and the phase shift of their variables sample at business cycle frequencies. This will also enable their classification as leading, coincident and lagging. For procyclical variables, a time shift of the maximal positive correlation smaller than -2 classifies the indicator as leading and lagging when higher than 2, otherwise it will be named as coincident. In a sectorial environment, the authors evaluate business cycle co-movements by means of an average spectral shape[11] - arithmetic average of spectral density functions - to calculate how average volatility is spread among periods and its low frequency dynamics. In general, it iss found that monthly indicators have a distinct cyclical behaviour responsible for a considerable part of their variation. In a cross-sectional dimension, the commonality of cyclical movements is evaluated in a principal components analysis to measure the dynamic relationships between the series in the panel as explored by Brillinger

[9]"Given the importance of this knowledge (real state of the economy) for the policy-maker, a clear economic picture needs to be present at any time"

[10]"avoiding the problems involved when trying to scale the coincident index to match the mean and variance of the reference series"Altissimo et al. (2001)

[11]"according to the phase angle with respect to the reference series evaluated at zero frequency (...) (the average correlation with the reference cycle across all lags)

(1981). These adaptations allow for an easier creation of composite leading indicators, by categorizing and selecting a large number of variables according to the intended foresight. Seen as an informative tool about future movements in the variable of interest, models based on these indicators have to some extent been labelled as a reaction to “perceived failures by macro-econometric systems” (Emerson and Hendry, 1996).

The results of Factor Models are usually difficult to interpret giving frequently rise to criticism that they constitute a “black box”. Undoing the “black box” character of factor models is a primary goal when forecasts communication is concerned. Rather recently Banbura and Rüstler (2007) obtained forecast weights and uncertainty measures in order to evaluate the importance of individual series. They determined that surveys and financial data exhibit relevant information content beyond the traditional monthly real activity measures. Besides, a valuable finding was that differences in publication lags play a central role and should be considered when performing forecast evaluations. Publication lags affect differently the contributions of hard and soft indicators: when no control is introduced in publication lags, real activity data are the most critical source of information, specially in the case of industrial production. However, if timeliness is considered, the implicit usefulness of real activity data is diminished, being replaced by business surveys. As such, widespread attention is given to a so-called weakness of these models: their lack of diagnostic measures on the individual role of the series. It undermines the much warranted need for forecasters have an insight on the forecast differences among models and the sources of revisions with new data releases. Whereas the computation of these weights would be clear in static models, it is a more difficult exercise when dealing with a dynamic factor model with unbalanced samples. To surpass such difficulty two steps are proposed in a forecast: derive the weights of the individual monthly indicators to conduct contribution analysis; evaluate the gains in forecast accuracy by inspecting the increase in forecast uncertainty once an indicator is removed from the sample. The first is made possible by the extraction of the estimates of the state vector from an algorithm developed by Harvey and Koopman (2003). The latest will be subsequently explored.

To perform these exercises the authors start by building a factor model based on Doz et al. (2005) and Giannone et al. (2005), implementing common factors as unobserved components in the state space representation with a forecast equation for quarterly GDP, in the context of the Kalman Filter. A pseudo real-time forecast in then performed, in the spirit of Altissimo et al. (2007). When dealing with unbalanced samples, the authors found that 25 indicators account for at least 75% of the overall sum of weights and that the majority represent forward-looking items of business surveys. Nevertheless, , theses same weights are not static in time: the weights quantitative variables relative to qualitative ones are significantly lower at longer horizons but gain considerable importance for shorter ones. The robustness of these findings is reinforced by the filter uncertainty measure for an unbalanced data set: moderate marginal gains from financial data for the precedent quarter forecasts and, if survey data were to be excluded, noticeable increases in uncertainty over the entire horizon. In turn, when balanced data sets are considered this finding “is turned on its head”.

In traditional bridge equations, the results from different regressors are averaged, and quarterly vector autoregressive models (VAR) are applied solely making use of quarterly data. This is done by: computing the quarterly value of a set of monthly indicators; calculating a quarterly bivariate VAR with GDP growth and determining the lag of each VAR by the Schwartz information criterion. Ragged Edges issues do not need to be addressed. On the other, one can consider forecasting the monthly indicators over a pre-defined horizon (applying univariate autoregressive models) and obtaining its quarterly aggregates to estimate GDP growth on a more timely maner. On the averaging from bridge equations, it is advisable to cross-check forecasts, as in Diron (2006), where 8 equations are used to forecast Euro area GDP directly. An alternative to this method would be to forecast both demand and supply side components of GDP, reconciling both approaches. A more thorough description on Bridge Equations can be found in the

Appendix.[12]

Both Bridge Models and Dynamic Factor approaches aim at extracting the common trend underlying a set of indicators, while isolating the idiosyncratic irregular movements of individual series. In practice, both econometric tools are closely related since they serve the purpose of monitoring economic activity, deliver quantitative estimates and forecast GDP. They should be seen as complementary instruments, with specific advantages and disadvantages, used to cross-check projections.

A comparison of GDP forecasts[13] between bridge models forecast average, dynamic factor model forecast and a naïve approach is provided in ECB (2008). It suggests that Dynamic Factor Models forecasts have a tendency to be relatively more precise when compared with forecast averages obtained from bridge equations at longer horizons. However, for forecasts produced one month ahead of the GDP release, the performance of Bridge Equations is approximately equal to that of a Dynamic Factor Model. Also Barhoumi et al. (2008) evaluates the performance of different models on short-term GDP forecasting used in Central Banks for ten European countries and the Euro area. Models exploring monthly information have a better performance than those relying solely on quarterly data, highlighting factor models in the former. The authors corroborate their findings by concluding that for GDP, factor models forecasts "beat" the performance of alternative methods of quarterly models and bridge equations. The same could not be found for private and public consumption.

All these applications lead to interesting findings: models relying on monthly real-time data are more accurate than those using quarterly data; factor models forecasts outperform those from simple bridge equations; bridging with factors is more reliable than averaging a number of bridge equations based on individual indicators; forecasts based on factors extracted with the Kalman filter are the most accurate, ranking in the first place for most of the countries examined; estimates for the aggregate Euro area are more reliable than those for individual member states. For Portugal, Barhoumi et al. (2008) rank the three versions of factor models as the ones better minimizing the RMSE for backcasting, nowcasting and forecasting estimates. According to Angelini et al. (2008), the reliability of factor models forecasting in the context of the EMU is also reported by Banerjee et al. (2005) and Banbura and Rüstler (2007).

2.2 Challenge of data selection

Data selection improvements are a never ending quest. Besides the problems created by indicators timeliness (incomplete data availability at the end of the samples), frequency issues (the simultaneous use of daily, monthly and quarterly indicators), the exploitation of economic reasoning and the use of data vintages, all interfere in modelling and forecasting procedures. Not only the indicators and their time coverage is often limited, they are usually compromised by measurement errors which tend to increase with the release frequency and imply renewed revisions as covered by Iacoviello (2001). The economic structure is not static in time and evolves through internal and external shocks. With the contribution to growth shifting between economic sectors, it is difficult to synthesize behavioural relationships. Also, missing observations may occur in a number of situations as detailed by Nunes (2005): data from monthly indicators may be available for all months in the last quarter but unavailable for the quarterly variable due to the delay of Quarterly National Accounts publication; because of different release dates, data for the last month of the quarter may not be completely available for every indicator; the available series may start in different dates or their frequency change over time.

Given the heterogeneity of data availability in terms of calendar, the reliability of any tool depends on its ability to effectively explore the information content of all observations available at a given point in time, while enabling forecasts to be updated as new data is released. The challenge of data selection is well

[12]From Angelini et al. (2008) examples of Euro Area application of Bridge Models are: Rustler and Sédillot (2003), Baffigi et al. (2004), Diron (2006).

[13]Picturing a compared evolution of percentage GDP forecast precision by means of RMSE.

structured by Rua (2004) on a five-step approach, constraining potential choices according to: variables available on a high frequency basis; promptly released variables with a minimum time span for business cycle analysis; a preliminary analysis to assess the informative content about the business cycle resorting to a band-pass filter[14] (evaluating the co-movement with GDP cycle through a cross-correlogram); making use of economic reasoning and obtaining broadly based measures of economic activity[15].

Camacho and Perez-Quiros (2009) distinguish two phases in data selection procedures: firstly, the selection is based as suggested by Stock and Watson (1991) following an National Accounting logic by computing GDP from the income side, the supply side and the demand side; secondly, following Camacho and Perez-Quiros (2008), the Stock and Watson initial group of indicators is extended in two dimensions: including: soft indicators series, as prompt indicators of activity; enlarging the selection whenever the variance of GDP explained by the factor increases with the inclusion of additional variables. From a total of 3000 variables, Altissimo et al. (2001) only selected the ones satisfying two major requirements: series length (the longest common time span possible within the sample, ultimately being a trade-off between data quality and cross-sectional dimension); homogeneity over space and time, avoiding overweighting and overspecification. Furthermore the authors also consider the share of cyclical variation explained by four common shocks in a dynamic factor model scenario, only keeping variables whose 60-70% of the variance was explained by the dynamic factors.

In principle, model flexibility is enhanced by using series which are both of quantitative and qualitative nature, diversifying and not overemphasising any of the groups. According to Iacoviello (2001) indicators arising from surveys are gaining an increasing amount of attention, mainly in the context of near-term outlook changes in response. Nevertheless, attention should be given to the significant level of correlation between business cycle surveys, avoiding multicollinearity issues. Altissimo et al. (2001) refers to survey data as mostly leading but containing noisy signals which have to be interpreted with caution after being updated.

In the context of the EMU [16], high frequency usually comprises data on unemployment, industrial production and retail sales (available on a monthly basis with different lags), as well as data reflecting market sentiment and expectations about future economic activity (e.g. business and consumer surveys, financial market data, monetary and trade and international environment). By scale, financial statistics and surveys are usually the most timely, with daily[17] and end of the month releases, respectively. They are followed by labour market data and monetary aggregates (around one month delay) and Industrial Production (six weeks after the reference month). Camacho and García-Serrador (2011) uses financial variables as leading indicators of GDP growth in a dynamic factor model that accounts for asynchronous co-movements between financial and real activity indicators.

For a forecaster, besides a selection criteria, the interpretation of trends and the extense of its consequences is the cornerstone of any analysis. Dealing with contradicting signals arising from the wide variety of available indicators nowadays at our disposal should be a constant concern. Angelini et al. (2008) point to the challenge of efficiently exploring information from an increasing number of indicators with different publication delays while avoiding their intrinsic noise. When dealing with large samples with unclear signals, model-based procedures[18] can be particularly valuable, mostly when the contribu-

[14]For more information on the Eviews application of this analysis see EViews 7 User's Guide I, 2009, "Frequency (Band-Pass) Filter", page 371-377

[15]In the end, 8 series were selected: real GDP, retail sales volume (retail trade survey), sales of heavy commercial vehicles, cement sales, manufacturing production index, household's financial situation (consumer survey), new job vacancies and an external environment proxy. Some of these variables were also included in the current model.

[16]"The monitoring of current economic conditions is an important input for monetary policy, (...) affect the assessment of the economic outlook and associated risks in the context of a monetary policy strategy aimed at preserving price stability over the medium term".ECB (2008)

[17]Daily data can then transformed into monthly data by means of an arithmetic average.

[18]Forecasting models differ by the number of variables they include, the econometric process and the theoretical backbone on which they are supported. It must be kept in mind that "even sophisticated models are an oversimplification of the complex reality".

tions of economic indicators can be measured and accounted for. ECB (2008) stresses the limitations of relying on purely judgemental approaches when assessing a large number of economic indicators with mixed signals. For consistency purposes, both expert knowledge and model estimates should be seen as an iterative process of complementing tools. Expert judgement is particularly important to consider recent developments not yet captured or weighted for. Judgement-based forecasts imply obvious shortcomings as highlighted by Robertson and Tallman (1999)[19], who are nevertheless quoted as saying "Successful model specifications also depend heavily on the skill and ingenuity of particular individuals" as "no model can be left on automatic pilot for long". Nevertheless, forecasts based on past patterns of experience and evidence can only be obtained through a degree of uncertainty as mentioned by Bundesbank (2009). Uncertainty management and measurement is part of the roles of any professional forecaster, and its evaluation is only attainable *ex post*.

Following the same line of thought, Camacho and Perez-Quiros (2008), call into question the forecasting exercises of the Euro-Area most relevant institutions[20] since they are permeable to judgement bias which does not allow for an easy replication and a correct interpretation of failures. In fact, relying on expert judgement makes the forecasting process a black box solely clear in the mind of the forecaster and a subjective exercise not objectively quantifiable[21].

The consideration of data vintages (real time data) is equivalent to the use of the exact information available at the time of each forecast, without allowing for data changes. Its importance is stressed by the need to correctly evaluate forecast errors when making comparisons between models and benchmarks besides out-of-sample simulations. As we are told by Camacho and Perez-Quiros (2008), real-time forecasting specialists usually stress that the evaluation of forecast errors from latest-available data is questionable, as comparisons between recent models, competitors and benchmark forecasts should be based on real-time data besides out-of-sample simulation.

2.3 Empirical Findings

The empirical findings under the application of Dynamic Factor Models can be grouped between applications to country-specific scenarios (e.g. Portuguese and Spanish Economy) and the Euro area Economy.

The context of the Portuguese Economy is explored both by Nunes (2005) and Rua (2004, 2005). The first presents a coincident indicator model for the Portuguese economy as a by-product of a forecasting process developed under the Single-Index model proposed by Stock and Watson and following a similar approach to Harvey (1989). The latest follows the methodology proposed by Azevedo et al. (2003) while merging a number of recent innovations for dealing with unobserved components time series models and building both a Coincident Indicator for the Portuguese Economy and Private Consumption. Comparing their results with previous indicators developed at Banco de Portugal[22] it provides a thorough overview of the challenges and particularities of the forecasting exercise and the data synthesization process. An interesting finding is that the Portuguese business cycle has a duration of almost 122 months (around 10 years). The trend-cycle modelling adopted by Rua (2005) follows Harvey and Trimbur (2003) and allows for a smooth cycle to be computed as when using a band-pass filter[23].

[19]These shortcomings include: "(i) their accuracy can be evaluated only after a track record is established; (ii) given the element of subjectivity (...) changes in the forecasting staff will affect the accuracy of these forecasts; (iii) they are impossible to replicate or validate by independent forecasters; (iv) they normally do not come with a probabilistic assessment of a range of alternative outcomes; (v) they are deemed unable to predict recessions or strong booms".

[20]The authors label as the most significant: the European Commission's macroeconomic forecasts of DG ECFIN, the IFO-INSEE-INSAE economic forecast and the OECD Economic Outlook.

[21]Together with Camacho and Perez-Quiros (2009), a judgement-free algorithm is proposed by enabling for an automatic computation of forecasts as new information becomes available by means of a uncomplicated factor model algorithm which the authors claim is able to forecasts as accurately as professional forecasters by means of a clear and replicable methodology.

[22]Gomes (1995) and Dias (1993) for Private Consumption and Economic Activity respectively

[23]Harvey, A. and Trimbur, T. (2003), "General model-based filters for extracting cycles and trends in economic time series", Journal of Applied Econometrics, 85, 244-255.

Focusing on small-scale models, Camacho and Perez-Quiros (2009) draw an interesting perspective in their "Ñ-Sting: España Short Term Indicator of Growth", by testing a variety of forecasting models and opting for a dynamic factor model whose indicators are readily available. The reliability of this model[24] is tested by in-sample and real-time data. The econometric methodology that is followed is similar to the one proposed in the Euro-Sting Model. For deeper examination, forecasts from a standard autoregressive (order 2) model and actual GDP growth are pictured together. The advantages of real time forecasting are illustrated as higher reliability and sensitivity to new information (which is reflected in forecast updating), reflected on the ability to anticipate unexpected cycle changes.

For the Euro Area economy, Azevedo et al. (2003) propose to build a multivariate unobserved components model that includes a stationary higher order cycle. As aforementioned, cycle shifts for individual series and the remaining parameters are embodied and estimated simultaneously[25], enabling the computation of a business cycle coincident indicator while valuing the information content of lagging, coincident and leading variables without previous analysis. Another contribution is the inclusion of a cycle component whose properties are approximated to those of band-pass filter. Their analysis diverges from previous multivariate approaches, being more "parsimonious" and achieving a similar growth indicator to that of EuroCOIN, which uses hundreds of variables from specific Euro area countries. It also contrasts with the previous proposal of Altissimo et al. (2001) in a Bank of Italy-CEPR project. By means of a generalized dynamic factor model, they estimate an index on the basis of an Euro area harmonized data sample of 951 indicators, with a coverage comparable to that of the US, taking into account cross-country and country specific correlation structures, told to be free of idiosyncratic national dynamics and filtered from seasonal and short-term noises.

Even when measuring the business cycles of particular countries, the importance of international indicators linked to trade flows, exchange rates, monetary aggregates or interest rates is grounded by the evidence of an increasing degree of integration and synchronization among EMU economies. An an example, the authors find that Belgium and the Netherlands lead on average Euro area cycles whereas Spain and Italy lag it.

Also for the Euro Area economy, Angelini et al. (2008) investigate a common procedure for both GDP and its demand and value added components interpolation and forecasting.[26] The prediction of both Quarterly GDP and its components simplifies and improves results communication to policy-makers, easing the interpretation of the links between quarterly forecasts for intra-quarter dynamics. This approach detaches itself from common bottom-up approaches based on estimates of monthly components.[27] The authors caution for the robustness risks issuing from weak interpolation of components may hinder the aggregate interpolate. It is accomplished by building a dynamic factor model[28] that obtains forecasts in the state-space representation through the Kalman smoother.

Enriched by its extensions, such as Camacho and Doménech (2010) and Camacho and García-Serrador (2011), Camacho and Perez-Quiros (2008) Euro-STING[29] proposal is to build real-time short-term forecasts of Euro area GDP growth rate by using data vintages[30]. Although modifying Stock and Watson (1991) similarly to other approaches, the Kalman filter is computed as proposed by Mariano and Murasawa (2003) when dealing with different frequencies. The contribution of their model formulation is

[24]"the model is a simple algorithm, (...) automatically updated (...), because, if the predictive power of any variable diminishes during the course of some periods, the variable will reduce its weight and its loading factor."

[25]The multivariate cycle model allows individual cycles to be shifted with respect to a base cycle.

[26]GDP demand components comprise private and public consumption, gross fixed capital formation (GFCF), export and imports and the statistical discrepancy. On the value added side, the authors consider the total value added (VAD) plus its breakdown into VAD industry and VAD services.

[27]Mitchell et al. (2005a, 2005b), Proietti and Frale (2007).

[28]Doz et. al. (2005), which are told to differ from Stock and Watson (2002) and Forni et al. (2000).

[29]Short-Term INdicators of Growth (STING)

[30]It should be noted that further on in their paper the authors specify that "(...) not explicitly consider all the vintages for all revisions for all the variables included in our model but only for GDP growth since these are the most relevant in our real-time forecasting exercise".

extended by explicitly modelling the data revision procedure of Eurostat GDP data releases and by introducing preliminary announcements as noisy signals of revised data[31] [32]. Further innovations include the proposal of a statistical method for data selection focused on the object of interest: the forecast of Euro area growth rates.

[31] In particular, they find that "revisions are much more correlated with preliminary announcements than with final estimates, that the noise-to-signal ratio for revisions is sizeable, that the forecast efficiency test fails to reject the noise hypothesis and that the revisions from flash to second are less volatile than the revisions from first to second"."

[32] For the US see Evans (2005) and a theoretical application to Euro area Coenen, Levin, Wieland (2005)

3 Methodology

In the spirit of Camacho and Doménech (2010), the following exercise is a judgment-free algorithm automatically computing forecasts when new information becomes available. An econometric routine is programmed whose methodology can be easily adapted to forecast other macroeconomic variables such as Private Consumption, Gross Fixed Capital Formation and Employment. The linkage between short-term forecasting and Coincident Indicators will also enrich its output.

A variety of methodological characteristics of the Model will be addressed throughout this chapter: Mixing variables with different frequencies (monthly and quarterly); Dealing with missing observations; the dynamic properties and the state space representation.

An assumption is made that at the moment of the projection all the chosen economic indicators are readily available. By making use of this assumption one avoids end-of-sample missing observations (i.e. ragged edges). Nevertheless, it should be kept in mind that similarly to real GDP, the Kalman filter can be used to estimate the remaining model's parameters. In fact, as mentioned by Angelini et al. (2008) this system of equations remains valid with missing data after performing slight adaptations. The application of the Kalman Filter enables the model to deal with misaligned data availability caused by unbalanced real-time samples.[33] As such, given the importance of GDP for Economic Activity forecasts, if observations are missing, the updating equations are disregarded and the filter will obtain forecasts for all the series of the model.

The model is estimated recursively starting in the first quarter of 1996 (when the first annual change rate of GDP is available) and the forecasting period is encompassed between de first quarter of 2005 and the first quarter of 2013. The chosen measure of uncertainty (namely when selecting variables) is the RMSE. As a starting point, it is expected that, as the information content increases, uncertainty decreases. A comparison between the Flash Estimates of INE (used as benchmark)[34] and the nowcast of the model is made.

As aforementioned, the contribution of individual indicators is not straightforwardly available in factor models. The same is applicable to its economic interpretation, since the extracted common factors summarise the relationships between a number of economic variables while representing an artificial aggregate. Here arises one relevant problem for a forecaster: communication. When exposing a projection, contextualizing it with the moving forces behind the economic forecast increases its reliability and assessment. By breaking-down the contributions of different variables, *ex post* evaluation of the results will be clearer, potentially improving future outcomes. Nevertheless, macroeconomic uncertainty[35] is a common ground for all methodologies.

One possible source of deviation between the forecasts and the observed value is that not all the variables included in the model are adjusted for calendar effects (i.e. Passenger Vehicles sales, Electricity Consumption) although a number of methodologies and programs are publicly provided by National Statistics Institutes[36]. Also, discretionary policy decisions will not be captured by the model unless their effects on economic activity are readily measurable by the sampled economic indicators. The selection of a variable linked with fiscal policy decisions was not attempted. Also, vintage data are not considered but might be a natural development for future work.

[33]Quoted as Giannone et al. (2008)

[34]Available since the 1st Quarter of 2005 and 45 days after the reference quarter.

[35]The uncertainty is characterized by a mixed international environment, still dominated by market-driven stress indicators as well as the sovereign debt crisis in the Euro Area. This scenario is complemented by the Economic and Financial Adjustment Program and Public Finances adjustments.

[36]Recently, the CROS (Collaboration in Research and Methodology for Official Statistics) has published the documents supporting their 2012 Workshop - http://www.cros-portal.eu/content/2012-workshop-methodological-issues-seasonal-adjustment

3.1 Single-Index Model

This summary of the Single-Index Model presented by Stock and Watson is based on the methodological explanations of Nunes (2005). The standard assumption is that all z^i $(i = 1, ..., n)$ monthly time series have been transformed so that they are stationary. Accordingly, Stock and Watson take the first difference of the logarithm of each coincident series and standardize them to have zero mean and unit variance[37]. A single-index model is considered such that each variable can be written as the sum of two stochastic components: a common component given by the unobserved (latent) scalar variable C_t (cycle) and an idiosyncratic component $u_{i,t}$:

$$z_{i,t} = \alpha_i + \beta_i C_t + u_t^i \tag{1}$$

with all the stochastic components following a finite order AR procedure:

$$\phi(L)C_t = \delta + \eta_t \tag{2}$$

$$d_i(L)u_{i,t} = \varepsilon_{i,t} \tag{3}$$

with the lag polynomials $\phi(L)$ and $d_i(L)$ $(i = 1, ..., n)$ given by

$$\phi(L) = 1 - \phi_1 L - ... - \phi_p L^p \tag{4}$$

$$d_i(L) = 1 - d_{i,1} L - ... - d_{i,k} L^k \tag{5}$$

As we are told in Rua (2004), aggregate output fluctuations picture business cycle movements and thus the real GDP cyclical component can be used as a proxy for monitoring the overall business cycle in a comprehensive way. The cornerstone of this rational is in holding as true that the cycle is made of expansions and recessions occurring in a synchronized fashion among several economic activities.

3.2 Mixing Frequencies

Since GDP is only published on a quarterly or yearly basis and monthly variables are used to forecast it, we must find a method on how to mix these different frequencies. As mentioned by Banbura and Rüstler (2007), the scope of available indicators and their heterogeneous release dates make a challenging task the efficient use of the information embedded in the various indicators. Some modifications are introduced to the above mentioned methodology. Commonly, the non-observed monthly values of GDP are considered to follow a relation in which the quarterly growth rate consists of a quarterly average of non-observable monthly values (Nunes (2005);Leite (2009)), and can be written as:

$$y_{i,t}^* = \frac{1}{3}\left(y_{i,t} + y_{i,t-1} + y_{i,t-2}\right), \quad t = 3, 6, 9, 12, ... \tag{6}$$

Assuming the hypothesis that the level of GDP for a given quarter is equal to the sum of the three unobservable monthly values of GDP:

$$Y_{II}^* = Y_{04} + Y_{05} + Y_{06} \tag{7}$$

or

[37] Also, "their index in levels is obtained by cumulating the estimated common component after adding a mean growth rate obtained as a weighted average of the growth rates of the coincident series".

$$Y_{II}^{*} = 3\left(\frac{Y_{04}+Y_{05}+Y_{06}}{3}\right) \tag{8}$$

where the quarterly value is considered to be three times the arithmetic mean. For Camacho and Perez-Quiros (2008), handling this definition without further specification would imply using non-linear state space models. As we are told, Mariano and Murasawa (2003) have demonstrated that if the sample mean of equation (8) can be well approximated by the geometric mean, then the growth rate of a given quarter can be decomposed as a weighted average of monthly growth rates[38]. Before that, Rua (2004) states that Stock and Watson (1989) disregarded GDP because it was only available on a quarterly basis. As such, in the static one-factor model for monthly and quarterly series, we approximate the quarterly variable observable every third month of the quarter as monthly series with missing observations.

$$Y_t^{*} = 3Y_t^{1/3}Y_{t-1}^{1/3}Y_{t-2}^{1/3} \tag{9}$$

Taking logs of equation (9):

$$lnY_t^{*} = ln3 + \frac{1}{3}\left(lnY_t + lnY_{t-1} + lnY_{t-2}\right) \tag{10}$$

Where $Y_t^{*}$is the level of quarterly GDP and Y_t is the unobservable monthly value. Taking the second quarter of a year as an example and calculating its three period differences:

$$lnY_{II}^{*} - lnY_{I}^{*} = \frac{1}{3}\left(lnY_{04}+lnY_{05}+lnY_{06}\right) - \frac{1}{3}\left(lnY_{01}+lnY_{02}+lnY_{03}\right) =$$

$$= \frac{1}{3}\left[\left(lnY_{06}-lnY_{03}\right)+\left(lnY_{05}-lnY_{02}\right)+\left(lnY_{04}-lnY_{01}\right)\right] \tag{11}$$

Defining $y_{II}^{*} = lnY_{II}^{*} - lnY_{I}^{*}$ and $y_j = lnY_j - lnY_{j-1}$ one can simplify the formula so that:

$$y_{II}^{*} = \frac{1}{3}y_{06} + \frac{2}{3}y_{05} + y_{04} + \frac{2}{3}y_{03} + \frac{1}{3}y_{02} \tag{12}$$

Different from a variable where its monthly values are observable, in the case of a quarterly variable, its quarterly growth rate is depicted as the weighted sum of five months growth rates in a geometric approximation.[39]

3.3 Dynamic Properties

The proposed dynamic factor model fundamentals are thoroughly explained in Camacho and Perez-Quiros (2008). It is itself an extension of the dynamic factor model proposed by Stock and Watson (2011). Not only are we able to estimate a common non-observable component, c_t, to a range of relevant variables and working as a proxy the business cycle, but we can also forecast the missing values from the lowest frequency (quarterly) variable. As the authors explain, considering the notion of co-movements among the GDP series and the economic indicators, time series are modelled as the sum of two orthogonal components: the common component, C_t, common to all variables and weighted differently between

[38]Alternatively, some authors propose dynamic factor models that allow for exact filtering, but which are not exempt from problems. "Proietti and Moauro (2006) and Aruoba, Diebold and Scotti (2009) develop an exact filter in a non-linear framework which also involves approximations", whereas Camacho and Perez-Quiros (2008) propose a filter that is developed in a dynamic factor model, assuming the trends trends of all the indicators used in the filter to be polynomial trends. Following the same reasoning, Camacho and Perez-Quiros (2009) state that Aruoba, Diebold and Scotti (2009), who started by avoiding the approximation assuming series evolve as deterministic trends without unit roots recently disregard their exact filter and use the approximate filter by taking growth rates of the time series.

[39]From Azevedo et al. (2003), "although GDP is recorded on a quarterly basis, the estimated components are monthly. These components can be seen as the outcome of the underlying monthly GDP decomposition which can be recovered resorting to the information contained in the remaining dataset".

them, capturing the co-movements between the series and reflecting the notion that the series dynamics are driven in part by common shocks; and an idiosyncratic component, ${u^y}_t$, that captures movements that are intrinsic to the variable and its dynamics:

$$c_t = p_1 c_{t-1} + (...) + p_{k1} c_{t-k1} + \epsilon_t \tag{13}$$

Where the business cycle proxy is assumed to evolve with an autoregressive process (AR) of order k_1. We can then distinguish between the forecast of the 3 months growth rate of real GDP and the remaining monthly indicators:

$$y_t = \beta_y C_t + u_t^y \tag{14}$$

$$u_t^y = d_1^y u_{t-1}^y + (...) + d_{k2}^y u_{t-k2}^y + \varepsilon_t^y \tag{15}$$

Where the idiosyncratic component, u_t^y , evolves by an autoregressive process (AR) of order $k2$. Also, the set of monthly indicators, z^i, will follow AR processes of k_3 orders:

$$z_t^i = \beta_i c_t + u_t^i \tag{16}$$

$$u_t^i = d_1^i u_{t-1}^i + (...) + d_{k3}^i u_{t-k3}^i + \varepsilon_t^i \tag{17}$$

it follows that $e_t \sim iN(0,\sigma_e^2)$, $\varepsilon_t^y \sim iN(0,\sigma_e^2)$, $\varepsilon_t^i \sim iN(0,\sigma_e^2)$, being mutually uncorrelated in cross-section and time series dimensions. The factor loadings β_i will weight the sensitivity of the series to the movements of the common component, measuring its contribution for each series. As referenced by Rua (2004), currently this formulation only allows for the simultaneous modelling of coincident variables. It is therefore possible to differentiate between leading and lagging variables, by shifting the common cycle for each series according to their lead/lag:

$$z_t^i = \beta_i c_{t+\zeta_i} + u_t^i \tag{18}$$

where ζ_i represents the shift (scaled as time periods) for series i. Since "one series cycle can only be shifted with respect to another cycle (...) one of the series has to be subject to parameter constraints" such as $\beta_j = 1$ and $\zeta_j = 0$, resulting in

$$z_t^j = c_j + u_t^j \tag{19}$$

By doing so, all the other series leading/lag properties would be all studied relatively to the cycle of series j. In Rua (2004), real GDP is used for the reference cycle.

3.4 State-Space Representation

Similarly to Azevedo et al. (2003), the model will be cast in state space for estimation and signal extraction, and variables with different observation frequencies will be straightforwardly treated using the Kalman Filter, having two consecutive monthly observations as missing and a third month with the quarterly observation. Maximum likelihood estimates are computed by maximising the log likelihood function that is evaluated through the Kalman filter.

It is in the State-Space representation that the endorsed method for dealing with mixed frequencies will be mostly useful, being combined with the common component, C_t, and the GDP idiosyncratic component, u_t^y. Using the previous equations we can build a linear relationship as such:

$$y_t^* = \beta_y\left(\frac{1}{3}y_t + \frac{2}{3}y_{t-1} + y_{t-2} + \frac{2}{3}y_{t-3} + \frac{1}{3}y_{t-4}\right)$$

$$+\left(\frac{1}{3}u_t^y + \frac{2}{3}u_{t-1}^y + u_{t-2}^y + \frac{2}{3}u_{t-2}^y + \frac{1}{3}u_{t-4}^y\right) \tag{20}$$

For the remaining indicators, the relationship between the common and the idiosyncratic components can be expressed as follows:

$$z_{i,t}^* = \beta_i \sum_{j=0}^{4} c_{t-j} + u_t^i \tag{21}$$

with i=1,2, (...), 11 and $Z_{i,t}^*$ representing the annual growth rate of hard indicators or the level of soft indicators. For example, the State-Space representation proposed by Camacho and Perez-Quiros (2008) suggested that the relation between the level of soft indicators to the year-on-year common growth rate, could be written as the sum of current values of the common factor and its last eleven lagged values, such that $\sum_{j=0}^{11} c_{t-j}$. Similarly, Camacho and Doménech (2010) apply this approach to financial variables. According to them, Wheelock and Wohar (2009) conclude that financial variables are often leading rather than coincident indicators of economic activity because high slopes of the yield curve are an indication of higher growth rates in future quarters. As such, the authors establish a link between the level or annual growth rate of the financial indicator and the h-period future values of the common factor ($\sum_{j=0}^{11} x_{t+h-j}$).

For the proposed Model, a 4 period lag of the common factor was the one that minimised both the sum of absolute errors (SAE) and the sum of square errors (SSE). This finding goes in line with Altissimo et al. (2001) which show that four common shocks possibly loaded with different lag structures is an adequate representation of the common component of the series included in their data panel. Having the model in State-Space form it will be estimated by maximum likelihood, with c_t as the business cycle indicator.

$$\begin{pmatrix} y_t^* \\ z_{i,t}^* \end{pmatrix} = \begin{pmatrix} 0 & \frac{2\beta_y}{3} & \frac{\beta_i}{3} & \beta_y & \frac{\beta_y}{3} & \frac{2\beta_y}{3} & \frac{2}{3} & \frac{1}{3} & 1 & \frac{1}{3} & \frac{2}{3} & 0 \\ 0 & \beta_i & \beta_i & \beta_i & \beta_i & \beta_i & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} c_t \\ c_{t-1} \\ c_{t-2} \\ \cdots \\ c_{t-4} \\ u_t^y \\ \cdots \\ u_{t-4}^y \\ u_t^i \end{pmatrix}$$

or

$$\begin{pmatrix} y_t^* \\ z_{i,t}^* \end{pmatrix} = \begin{pmatrix} \beta_1(\frac{1}{3}c_t + \frac{2}{3}c_{t-1} + c_{t-2} + \frac{2}{3}c_{t-3} + \frac{1}{3}c_{t-4}) \\ \beta i(c_t + c_{t-1} + c_{t-2} + c_{t-3} + c_{t-4}) \end{pmatrix} + \begin{pmatrix} \frac{1}{3}u_t^y + \frac{2}{3}u_{t-1}^y + u_{t-2}^y + \frac{2}{3}u_{t-2}^y + \frac{1}{3}u_{t-4}^y \\ u_t^i \end{pmatrix} + \begin{pmatrix} 0 \\ e_i \end{pmatrix}$$

As referred by Camacho and Doménech (2010), it is important to remind that the model assumes contemporaneous correlation between non-financial indicators and the state of the economy.

The nature of the indicators will influence their relationship with the common factor. Furthermore, fromCamacho and Perez-Quiros (2008) we are told that the different relationship between soft indicators and the common factor can also be explained by the fact that according to the European Commission (2006), the guiding principle question selection in surveys is to achieve as high as possible coincident correlation of the confidence indicator with the year-on-year growth of the reference series. In order to avoid over differentiation, the level of soft indicators will be related with the year-on-year common growth rate. From this background follows that hard indicators such as Number of Car Sales, Monthly Electricity Consumption and the Industrial Production Index will be used on their year-on-year growth rates.

Following Mariano and Murasawa (2003), missing observations can be replaced with random draws θ from $N(0, \sigma_\theta^2)$, independent from the model parameters. It would also be valid to replace missing observations with means, medians or zeroes.

4 Data and data selection procedure

When looking at possible indicators that would effectively track the Portuguese economic activity in real time, the goal was to create a balanced sample of hard and soft indicators that would yield the most accurate result in a relatively short period of time.

Although in Camacho and Doménech (2010), series have been seasonally adjusted using the TRAMO-SEATS software, the X12-ARIMA package embedded in Eviews Statistical Software could enable the construction of an automated routine where inputs (raw data) would be processed with a minimum of user intervention, since all the programming of the state space representation is performed using the same software. However, to minimize data changes, it was chosen to use year-on-year rates of change, which already absorb most of the seasonal patterns although no working days effects. This approach would not be feasible if quarter-on-quarter change rates were computed. Also, in order to avoid conflicting seasonal treatments, whenever possible, variables included were extracted from the sources without being subject to seasonal treatments *a priori*.

A range of variables, different in nature, have been included[40]. The selection process comprised the following steps: as an initial selection procedure, the indicators to be considered had to be of high frequency, published on a daily or monthly basis; the time lag between the forecasting period and data publication was also deemed relevant since it influences the real-time assessments of the model, and as a consequence, indicators had to be available before the release of national accounts data[41] and the Flash Estimate of GDP; the variables should cover different economic sectors, including real and monetary time series, qualitative and quantitative in nature. This first attempt led to the study of a total of 56 variables, together with the evaluation of their performance in levels or in year-on-year rates of change. Nevertheless, as the purpose of this exercise is to build a small scale factor model, it was understood that there had to be further selection efforts. It should be reminded that one of the hypothesis to be tested is that not all the the indicators available have relevant information content for real activity monitoring, and as such, would fail to improve or would even diminish the forecasting accuracy of the model, in an out-of-sample context.

Due to a considerable number of basis changes, some of the indexes had to be growth chained in order to increase the sample period. For example, the Industrial Production Index, the Industrial Business Volume Index (Total and Domestic Market) and the Retail Trade Business Volume Index (deflated) have a 2005, 2000 and 1995 basis. The Services Business Volume Index and the Construction and Public Works Production Index were available with their 2005 and 2000 basis. All series have been normalized to have 0 mean and unit variance. Resulting from the methodology employed, the Kalman filter will anchor monthly estimates to actual GDP whenever it is observed.

The exercise hereby proposed adapts the data selection method, based on the idea that our object of interest is the real GDP growth forecast. In this case, the method of model enlargement presupposes that an additional indicator is only included when the RMSE of the out-of-sample forecast errors diminishe and its estimate is statistically significant, excluding indicators that do not allow a better fit with the

[40] Just as Camacho and Perez-Quiros (2009) and other authors refer "despite the particularities exhibited in their evolution, all of them seem to share a common pattern with two significant slowdowns at the beginning and at the end of the sample"

[41] The only National Accounts data to be used are the historical values of Real GDP (seasonally and calendar adjusted).

reference series[42]. This is again in line with Banbura and Rüstler (2007)[43] that base their choice on the average RMSE of forecasts from the unbalanced data set[44], making this error mesure a determinant tool to assess potential indicators. The RMSE of a predicted value $\hat{y}$ for times t, when the regression dependent variable is y, can be computed for n different predictions as the square root of the mean square of the deviations:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}}$$

Each of the variables was tested in the state-space routine together with real GDP growth rate to evaluate the RMSE improvement vis-à-vis a model where GDP past observations were the only determinants of the forecast. Also, the hypothesis that both lagged and contemporaneous data patterns might improve accuracy was tested by changing the specification of the common component.

In order to do so, the forecasting accuracy was simulated by modelling the optimal common component lag to each variable. This was performed by selecting the *jth* lag, $\sum_{j=0}^{5} c_{t-j}$, that maximized the model accuracy. The results of this attempt are shown on **Table 1**. To avoid the bias arising from a forecasting exercise covering all the sample period, variable selection only considered the RMSE resulting from out-of-sample forecasts recursively performed from 2005Q1 up to 2013Q1. As such, a group of 28 variables was selected. As previously warranted, the simultaneous use of a number of indicators from different sources and covering different economic areas might create some noise and over parametrization of the model. To move on building a consistent and coherent group of variables, each of the variables, in their optimal lags, was successively included in a forecasting model in the same out-of-sample timespan previously considered. The results shown in **Table 2** determine that some of the variables information content failed to improve the model accuracy when grouped together. This might be due to their information on real economic activity developments being already captured by the synthesis of the common component of the remaining indicators.

Table 8 summarizes the potential forecasting improvement (%), named as the gains in the RMSE resulting from the first step of the selection procedure. As an output of the second step, **Table 9** measures the indicators weight on the overall forecasting accuracy attained. These contributions are not expected to be static in time but they are a move towards undoing the "black box" that characterize such models. As Angelini et al. (2008) mentions, the weights of individual series and estimates of monthly GDP growth in quarterly GDP forecasts can change significantly with the forecast horizon [45]. It may similarly change according to the time at which the forecasting exercise is performed and if there are missing observations which would reinforce the role of qualitative data. This hypothesis is not evaluated for simplification purposes. As such, the Industrial Production Index is the variable which has more explanatory power over the business cycle (33.1%), followed by the Retail Market Business Volume Index (20.7%) and Electricity Consumption (19.5%). Together, these 3 variables represent 73.3% of the model improvement. This goes in line with Banbura and Rüstler (2007) findings, where forecast weights are concentrated among a relatively small set of indicators. Quoting Camacho and Perez-Quiros (2008)[46],

[42]"The root-mean-square deviation (RMSD) or root-mean-square error (RMSE) is a frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed. These individual differences are called residuals when the calculations are performed over the data sample that was used for estimation, and are called prediction errors when computed out-of-sample. The RMSD serves to aggregate the magnitudes of the errors in predictions for various times into a single measure of predictive power. RMSD is a good measure of accuracy, but only to compare forecasting errors of different models for a particular variable and not between variables, as it is scale-dependent." *Wikipedia*

[43]"We assess the gains in forecast precision from certain series by inspecting the increase in forecast uncertainty once the series are removed from the data set".

[44]From Iacoviello (2001) we are told that the difference between the mean forecast error (MFE) and the mean square error (RMSE) is that the first is a measure of unbiasedness, whereas the RMSE is a measure of efficiency - "unbiasedness is a necessary condition for efficiency".

[45]Angelini et al. (2008) quoting Banbura and Runstler (2007).

[46]Citing Stark and Croushore (2002)

the use of out-of-sample forecasts for evaluating forecast performance may not be enough to address the accuracy of a model since error measurements can be artificially lower when making use of the latest available data instead of real-time data.

The non use of data vintages is a clear setback since data revisions tend to be more pronounced in high frequency statistics. Also the contribution to forecast accuracy may be misleading with Banbura and Rüstler (2007) stating that studies generally back the idea that in forecasts under a balanced data sample, weights of survey data clearly drop compared with an unbalanced data set, while the weights of financial data are less affected. The valuable contribution from qualitative information is reinforced by Esteves and Rua (2012), where special reference is made to the importance of confidence indicators due to their ability to track economic fluctuations, with some leading properties vis-à-vis demand side components.

As in Camacho and Perez-Quiros (2009), in order to smooth the noise of hard indicators in monthly growth rates without filtering data with an HP or band pass filter, these series are included in the model in annual growth rates.[47] **Table 5** provides a description of the variables used in the Dynamic Factor Model, together with their sample dimension, source, the data availability delay and the transformation that the indicators were subject to. Their descriptive statistics, namely average, median, standard deviation, maximum, minimum and number of observations are computed in **Table** 7. As previously mentioned, Surveys provide the most timely source of information. Nevertheless, it is increasingly possible to have access to quantitative data with high frequency such as Vehicle Sales, Electricity Consumption or Cement sales. As an example, ATM Statistics from SIBS on money withdrawals and purchases through the ATM system were also tested and included, being available around 12 days after the end of the reference month. Available 7 days after the end of the reference month, Cement Sales, which is usually used in Bridge Models for bridging with Gross Fixed Capital (Construction Component) with excellent results (see Esteves and Rua (2012)) were also included due to the improvement on the forecasting results.

The Cross Correlation between the variables was assessed in **Figure 2**. Unit Root and Stationarity tests were also performed as shown in **Table 6**. As reported in textbooks addressing Unit Root tests, series usually exhibit a trending behaviour, as happens with levels of macroeconomic aggregates or asset prices. If so, a trend removal will be regarded as necessary. There is also evidence of long-run equilibrium relationships among nonstationary time series[48]. Shocks to stationary time series are inherently temporary. The augmented Dickey-Fuller test (ADF), the Phillips-Perron (PP) and Ng-Perron tests will be used to assess the existence of Unit Roots, whereas Kwiatkowski–Phillips–Schmidt–Shin (KPSS) will be used as a stationarity test. Nevertheless, this type of tests are deemed as more relevant for long-term forecasts where stationary time series converge to its unconditional mean.

In the spirit of Stock and Watson (1991), following a National Accounting framework, the selected variables can be divided as:

- Supply Side (Industrial Production Index[49], Construction and Public Works Production Index and the Manufacturing Industry Survey on production assessment);

- Demand Side (Electricity Consumption, Cement Sales, ATM Purchases and Withdrawals, Retail Trade Business Volume Index (deflated), Industrial Business Volume Index (Total and Domestic Market), Services Business Volume Index).

Besides, financial developments are captured by the PSI20, Portuguese stock exchange index. The fact

[47]From the same authors, "the unit root problems associated with the annual growth rates and the levels of the soft indicators are solved by specifying the model with a monthly factor".

[48]http://faculty.washington.edu/ezivot/econ584/notes/unitroot.pdf

[49]The rle of the Industrial Production Index is paramount as is clearly mentioned byIacoviello (2001):"In a horse race with several macroeconomic variables, industrial production is by far the most highly (contemporaneous) correlated variable with GDP growth" being "conceivable to assume that industrial production and GDP share a common trend".

that only the stock index was deemed relevant for out-of-sample forecasting goes in line with some remarks by Altissimo et al. (2001) which report that financial variables are in general leading but poorly correlated with the cycle and that no clear agreement has been reached in the literature about the existence and the direction of a link between money and real activity, although M3 does play a prominent status regarding ECB's monetary policy guidance. Also, interest rates spreads, found to be leading (more than a quarter) and procyclical, have some exceptions such as Belgium and Italy.

It is clear that Demand Side indicators are predominant but that should not be seen as a drawback. In the context of Bridge Equation Modelling, Esteves and Rua (2012) state that the Bundesbank uses a bottom-up approach for both the demand and supply sides despite the fact that the level of disaggregation of the demand side considered is lower than at Banco de Portugal. Being more usual to follow a demand side approach, at Central Banks such as the Bundesbank and Bank of England, the supply side is not disregarded. However, in the case of Portugal the current approach "draws heavily" on bridge models that use extensive economic data to forecast the behaviour of demand side components.

Empirical warnings may show due to the small number of time series, contrary to what theory requires or because they are brought by a limited number of categories. Although this can be considered a small-scale factor model, large-scale models are not exempt from theoretical hypothesis that may be, or not, supported in empirical applications[50] as shown by Camacho and Perez-Quiros (2008). Since macroeconomic data is very collinear, it is foreseeable that considering additional variables may not improve forecasting accuracy and it may pay to focus on some key variables after a solid selection process.

Similarly to Camacho and Perez-Quiros (2009), the model failed to improve its forecast accuracy when disaggregated versions of some variables were included, as was the case of the Industrial Production Index and the Retail Business Volume Index[51]. The only exception goes to the Industrial Business Volume Index where both the Total Index and the Index for the National Markets were considered statistically significant and improved the forecast ability of the model.

[50] "Large-scale models estimate factors that are consistent when the number of variables and observations tend to infinity, under the assumptions that the idiosyncratic components are weakly correlated (in time series and cross-sections) and that the variability of the common component is not too small."

[51] Retail Business Volume Index excluding Fuels; Retail Business Volume Index - food, beverages and tobacco and the Retail Business Volume Index - non-food products (except fuels).

5 The Resulting Model

Having selected the variables, two possibilities remained on the computation of the common component: an individual optimization of the lag of the common component to each of the variables (a) or a common lag applicable to the state state representation of the model (b).

The number of lags in factor dynamics played a decisive role when deciding between a variable optimizing rule or a group optimizing one. There was the hypothesis that the RMSE of a forecasting model where each variable was chosen according to the optimal lag of their common component would perform better than the same group of variables using the same number of lags of the common component. This hypothesis was not verified as the minimum RMSE was achieved by having the selected variables sharing the same phase shifts to the reference cycle.

Consistent with the variable selection method, each of the alternatives was estimated by maximum likelihood between 1995Q1-2013Q1. The selection of this time period and the out-of-sample exercise was paramount for comparability purposes with INE's Flash estimates. All series are plotted in **Figure 1** according to their nature: Hard indicators in log value and Soft indicators in levels. As in Iacoviello (2001), in order to verify the model performance under real time conditions, one-step ahead GDP forecasts are made using a rolling estimation technique, starting in 2005Q1, via rolling regression estimates. It can also be defined as a moving-forward out-of-sample simulation on which the key series to be forecasted is GDP growth rate. As an example, in April 2005, when all the series for the first quarter of that year are made available, a forecast is made for that quarter using all the qualitative and quantitative information available. Again, in October 2005, using the latest data available, the third quarter growth rate is estimated. The developed Eviews program is capable of replicating this forecast procedure where an almost real time setting is simulated for a total of 33 periods.

Table 10 summarizes the findings[52]. According to this exercise, the maximum improvement of the RMSE compared to a scenario in which only GDP is included in the state space representation is achieved by a model in which there is an identical number of lags of the common component to each of the series. However, this is only attained by a lag between 3 and 4 periods. In fact, the RMSE, SAE and SSR observed improvement was of 55%, 52% and 80% respectively in situation a), compared to 47%, 49% and 72% in situation b).

The Eviews Estimation Output of the State Space Representation for the last period of estimation (2013:03) is available on **Figure 9**. It represents the loading factors of the common component for each of the series, as well as their idiosyncratic component coefficient. Significance Tests and Standard Errors for each of the coefficients are also computed. The common factor lagged observations are expressed according to their Final State, Root MSE, z-Statistic and Probability. Other Econometric Tests are automatically performed and made available in the Output. All the variables are statistically significant, as well as the lagged values of the common component.

The maximum likelihood estimates of factor loadings[53] and standard errors of each of the Indicators common component are presented on **Table 12**. Besides real GDP, the Retail Trade Business Volume Index (deflated), the Manufacturing Survey Production assessment (last 3 months), Cement Sales on the Domestic Market (Cimpor+Secil) and the Services Business Volume Index show the larger loading factors. These are also the variables with higher correlation to GDP growth, as reported in **Figure 2**. All the variables present a positive correlation suggesting their pro-cyclical nature.

Similarly with Camacho and Perez-Quiros (2009), GDP is the indicator with the highest impact in the common component. However, it could not be proven that real activity data exhibits the highest loading factors, and therefore that loading factors of soft indicators tend to be lower, as mentioned by Camacho

[52] Together with **Table 4**.

[53] "reflect the degree to which variation in each observed variable can be explained by the latent series" and enable us to "examine the correlation of the indicators and the factor" Camacho and Perez-Quiros (2008)

and Perez-Quiros (2008)[54]. This may be due to the smaller sample on the basis of which estimations are calculated. Nevertheless, the model has the flexibility of attributing greater weight to an indicator when some other has a missing observation (i.e. ragged edges). In practice, in its search for a GDP growth forecast, if the latest release of a quantitative indicator is not yet available, it will explore the information content of the remaining data, weighting it accordingly. Here, it's dynamic response is clearly noted. This analysis might be prompted to further insight in future works.

The Forecasts of real GDP obtained under this model and the observed series as published by INE in their 2nd release are plotted in **Figure 4** and in **Table 11** for a more thorough comparison. Its performance is evaluated vis-à-vis INE's 1st release (Flash) in **Figure 5** where their forecast errors[55] are plotted together. Their relative performance is also assessed in **Table 4,** where the RMSE, SAE, SSR, Mean Error and Mean Absolute Error are compared for the entire sample. Error correlation between the two is also weak, standing at 0.23, compared to a forecast correlation of 0.90. Although INE's Flash shows a better fit with the final release, the difference with the Model Forecast is relatively reduced, considering the information input on which they both rely on, together with the time-span difference of their publication. The quality of an estimate is also a function of the amount of data available in its calculation, especially when the both the forecasting benchmark (INE's Flash Release) and the final figures (INE's second release) are from the same institution. As always, one should stress the reinforced difficulty of making forecasts in turning points of economic activity, creating the expectation of greater revisions.

A distinction should also be made between the qualitative and quantitative nature of the assessment in terms of acceleration/deceleration trend as in Rua (2004), relevating not only the level but also the signal of the estimate.

An Histogram of errors is also made available in **Figure 6** together with a Kernel Density Distribution in **Figure 7**. The Model errors are much more uniformly distributed and appear to be more concentrated around 0.

Available on a monthly frequency, the estimated common cyclical component is plotted in **Figure 3** and can be interpreted as a latent monthly measure of GDP cyclical component within a multivariate framework. One can use the monthly real GDP growth rates, resulting from the Kalman filter, as a Coincident Indicator, having a smooth assessment of the underlying developments of economic activity. This exercise is assessed in **Figure 8**, where the monthly coincident indicator is compared vis-à-vis GDP year-on-year growth rates[56]. The fit of both series is explained by the formulation of the Kalman Filter. Attention should be given to the edges of the figure. Since year-on-year rates of change of real GDP are only available from the first quarter of 1996 onwards, and since most of the qualitative indicators are available since January 1995, the model estimates its monthly evolution during the four quarters of 1995.

In **Figure 10,** the 3 months moving average of Real GDP is compared with the 3 months moving average of INE's Coincident Indicator[57]. This goes in line with Altissimo et al. (2001) that support the interpretation of three month moving average GDP growth rates as deviations of economic activity from its long-term trend. It can be concluded that both follow a close pattern characterized by 3 major slumps in Economic Activity. The new indicator captures three negative growth rate phases: 2002:11-2003:11, 2008:11-2010:02 and more recently 2011:04 with its turning point by 2013:01. INE's Indicator registers three periods as well. although with relatively different dimensions: 2002:11-2003-08; 2008:11-2010:02

[54]The authors add that "this result should not necessarily be interpreted as evidence against survey data" since "estimates may reflect the fact that ignoring the timeliness advantages of soft indicators would diminish their role in factor models when harder indicators are available".

[55]The error is measured as the difference between INE's Flash (first release) and the final figure of real GDP (2nd release).

[56] For comparison purposes, it is assumed that GDP monthly growth rates correspond to the quarterly growth rates.

[57]This transformation was inevitable since INE only publishes its Coincident Indicator as a three months moving average.

and 2011:07 with a business cycle inversion initiated by 2012:06.

As in all temporal analysis, there is the possibility that the forecasting performance of the Model may change through time, as the selected variables may fail to capture a structural break in the economy. To test this hypothesis, forecasting errors are compared between 2005 and 2012 in **Table 13**, being the unit of comparison the RMSE. It is possible to infer that for the years 2005 and 2007 the forecasting accuracy of the Model was better than INE's one, whereas in 2009 they reach a similar accuracy. Although with an higher average RMSE, the deviations from the mean RMSE are significantly lower in the model hereby proposed. It is interesting to see that 2006 was the year where both the Sum of Squared Residuals, the RMSE and the Average Absolute Error reached their highest values between 2005 and 2012 together with the Average Absolute Errors.

6 Conclusion

Economics is a social science on which expectations formation is a cornerstone. Expectations monitoring is made through a complex set of tools, giving the forecaster a prominent role when it comes to communicating his assessments to economic agents of any society. As such, any tool designed today can be immediately seen as an unfinished work in continuous update. For example, as of 2015, the National Accounts transition to ESA 2010 will motivate a thorough revision of any forecasting process, since part of the macroeconomic linkages between aggregates will be changed.

Short-term forecasting role is reinforced as a starting point for longer-term projections, as longer-term regularities of quarterly GDP have been decreasing since the 1990s as proven by Barhoumi et al. (2008). The usefulness of short-term monitoring is reinforced when it comes to signal turning points in economic activity, as was shown by the Model's ability to capture them between the second and third quarters of 2009. Similar to the approach of the previous authors, it would be interesting to better explore the forecast performance of dynamic factor models vis-à-vis bridge models based on quarterly variables, the forecast of monthly variables or bridging with factors. Other reference points could have been obtained by a naive model or a first-order autoregressive model. Their evaluation could be performed by encompassing tests based on a regression of the actual data and the forecasts of two competing models. A parameter would assign the optimal weight of a model relative to another, leading to a combination of forecasts or a complete disregard of one of them if the parameter nears zero or an hypothesis test is performed.

Besides testing for financial variables explanatory power over the business cycle, the greatest value added of this Dissertation was to make a transparent and complete evaluation of a methodological formulation as applicable to the Portuguese economy, clearly stating every step of its design, from variable selection to results comparability. It has proved to yield promising results, making it a useful complement in what economic monitoring is concerned. By allowing for reliable forecasts of real GDP growth rate around one month before the official release and one week before the Statistical Office preliminary announcement, it is an important source of information for any economic agent. The potential of easily changing its reference series to one of GDP main components[58] (e.g. Private Consumption or Gross Fixed Capital Formation) or any other aggregate apart from National Accounts standards, makes it a more complete and reliable *tool-kit*. By building all the exercise into an automate Eviews routine, able to make rolling estimations, the usability and future development of this procedure is furthermore enhanced.

For future development, embedding forward looking common components in the State-Space representation, apart from the lagging phase shifts already tested, may result in more accurate results when comparing to a reference cycle (e.g. real GDP). In the same spirit it would also be interesting to compare the estimates and the weight of each variable on the forecasting accuracy obtained after 15 days, one month or two months after the end of the reference quarter. There is indeed the hypothesis that the explanatory power of more qualitative variables would have been significant for forecasting purposes once missing observations of the quantitative variables occur.

Another possibility would be to increase the sample period from 1995 backwards using the European System of Accounts data growth chained by ESA 1979 quarterly figures. Since most Economic Surveys are available on a monthly basis prior to the 1990's (DG ECFIN Consumer Surveys for Portugal start by June 1986) it would be possible to understand the evolution of this model accuracy through a longer period of time as well as to have a deeper understanding on the Portuguese Business Cycle together with the changing variables contribution. With a larger time frame a valuable insight would be to understand the capacity of different models to adapt to structural shifts in the economy. Also, the inclusion of a measure of Economic Uncertainty, using the disaggregate replies to survey questions following Balta et al. (2013) could provide important information about economic agents perception, enhancing the leading content

[58] $GDP_t = PrivateConsumption_t + PublicConsumption_t + Investment_t + Exports_t - Imports_t$

of coincident or forecasting models. An always lasting topic is the necessity to account for data revisions and vintages, without creating too much complexity when assessing the reliability of any model.

A Forecaster will always have to deal with open questions as is remarkably summarized by Camacho and Perez-Quiros (2008): “How to deal with the lack of information hindering timely publication of macroeconomic variables, how to fill in missing values in time series, how to use (...) aggregates with short time spans, and how many variables should be included in the forecasting model are still open questions”. This Dissertation contributed by opening a few more.

> *“Prediction is very difficult, especially if it’s about the future.” (Nils Bohr, Nobel laureate in Physics)*

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Nomenclature

DSGE Dynamic Stochastic General Equilibrium models

EMU European Monetary Union

MoU Memorandum of Understanding

RMSE Root Mean Squared Errors

7 Appendix

7.1 Model Comparison

A summarized comparison between factor models and bridge equations is made available, following the main conclusions of Bundesbank (2009).

Bridge equations represent the correlation between quarterly variables and monthly economic indicators. A simple autoregressive model is often used for monthly forecasts on high frequency indicators in order to take into account publication lags. The monthly sample is then aggregated (the methods is different between flows or stocks) and included in the quarterly bridge equation. For the case of GDP projections on a quarter-on-quarter basis the relationship can be generalized as:

$$y_{t,q} = \sum \delta_j \left(L\right) x_{j,t}^{mq} + \varepsilon_{t,q}$$

$$t_q = 1, ..., T_q$$

$$j = 1, 2, ..., k$$

where $y_{t,q}$defines seasonally and calendar adjusted GDP and t_q the quarterly periods. The observations of the k monthly indicators, x_j^m, must be transformed into a quarterly frequency x_j^{mq}. The polynomial with the lag operator $\delta_j(L)$ contains the frequencies of the lagged indicators. The forecast horizon h_q and $h_m$for the monthly and quarterly variable will depend of the information available at the current period, so that $x_{j,T_m+h_m|T_m}^{m}$and $y_{T_q+h_q|T_q}^{q}$ are estimated by using the information available until T_m and T_q. It is important to note that bridge equations can be built either for aggregate GDP or its components (e.g. Demand and Supply Side).

Due to methodological constraints, variables with relevant information content have to be in limited number and pre-selected with a variety of statistical tests.Iacoviello (2001) distinguishes Bridge Models as the “Indicator Approach”. Also Angelini et al. (2008) recognise bridge equations as widely used for the short-term forecasting of GDP and its components, since they incorporate intra quarter information from individual indicators. First developed by Klein and Sojo (1989) for the U.S. Economy, it estimates a functional relationship between the variable of interest and others containing useful reference information for its short-term movements. Accordingly, it is build with the purpose of adhering to “prevailing practise” used in the actual construction of Quarterly National Accounts. A warning is commonly made on forecasts from bridge models beyond two quarters horizon, since they tend to build up errors and drift from observed data series in a fast fashion. For an horizon of one to two years, Iacoviello (2001) estimates a Bayesian VAR model which requires the specification of means and standard deviations of the variable’s prior distributions.

On the other hand, factor models are referred to as pure econometric models with no *ex ante* expert input, where a broad number of indicators can be simultaneously tested to infer their similar developments along the business cycle, which is then clustered into factors. *Ex post* econometric procedures can be adapted for data properties and model specification. Also Banbura and Rüstler (2007), state that factor models have emerged as a promising alternative for short-term forecasting of real activity, since they allow large data sets to be handled effectively. By relating individual indicators to a limited number of latent factors, weights are implicitly attached to the former in a reasonable way[59]. Two main approaches are available: estimated factors can be treated as observable indicators and forecasted using individual equations; a closed model with a state space representation where GDP is estimated with monthly factors. Assuming N monthly indicators in a vector I_{tm} is bundled in r factors F_{tm}, where ΛF_{tm} is the common

[59]Stock and Watson, 2002; Forni et al., 2003; Breitung and Shumacher, 2006; Altissimo et al. 2007.

component of I_{tm} , and u_{tm} is the idiosyncratic component, it can be stated that:

$x_{tm} = \Lambda F_{tm} + u_{tm}$

The notion of variable reduction is here firstly introduced. It translates the idea that an undetermined number of monthly indicators N will be explained by $r < N$ factors. Due to this, Factor models are considered more robust to structural breaks and opposing indications from different variables.

A similar comparison between the two models is also available in ECB (2008).

7.2 Additional Notes

One can distinguish between two types of indicators used for assessing the development of economic activity: hard and soft indicators. Focusing on the latest, soft indicators are the result of surveys and usually take the form of Balance of Respondents. Balance of Respondents or Statistics is a method used to aggregate surveys answers when they are scaled according to: positive, neutral and negative. It is defined by the EC as the difference between the percentages of respondents giving positive and negative replies. Their usefulness for economic analysis is thoroughly reported in ECFIN (2007) User Guide.

Being considered a key complement to quantitative statistics, they offer a more timely assessment of short-term economic developments with high frequency (usually monthly). Not only they benefit from a large and comparable sample, but also, in the case of the European Commission, they provide a high degree of comparability between Member-States, since they are harmonized according to a common methodology. These surveys cover most relevant economic sectors[60] and their usefulness can be highlighted in three fronts: a tool for short-term forecasting; a source of information to track and analyse the business cycle; a mechanism to understand agent's behaviour and reaction in times of uncertainty (assessment of the current situation and expectation on future outcomes). It follows that their use as a forecasting tool is not a novelty. As an example, DG ECFIN makes use of surveys as inputs for their Dynamic Factor Model for quarterly GDP growth projections and for the Markov-Switching model used to forecast turning points in industrial production.

7.3 Figures and Tables

[60]Five Economic Sectors in the case of ECFIN: manufacturing industry, services, retail trade, building and consumers.

Figure 1: Series included in the Dynamic Factor Model

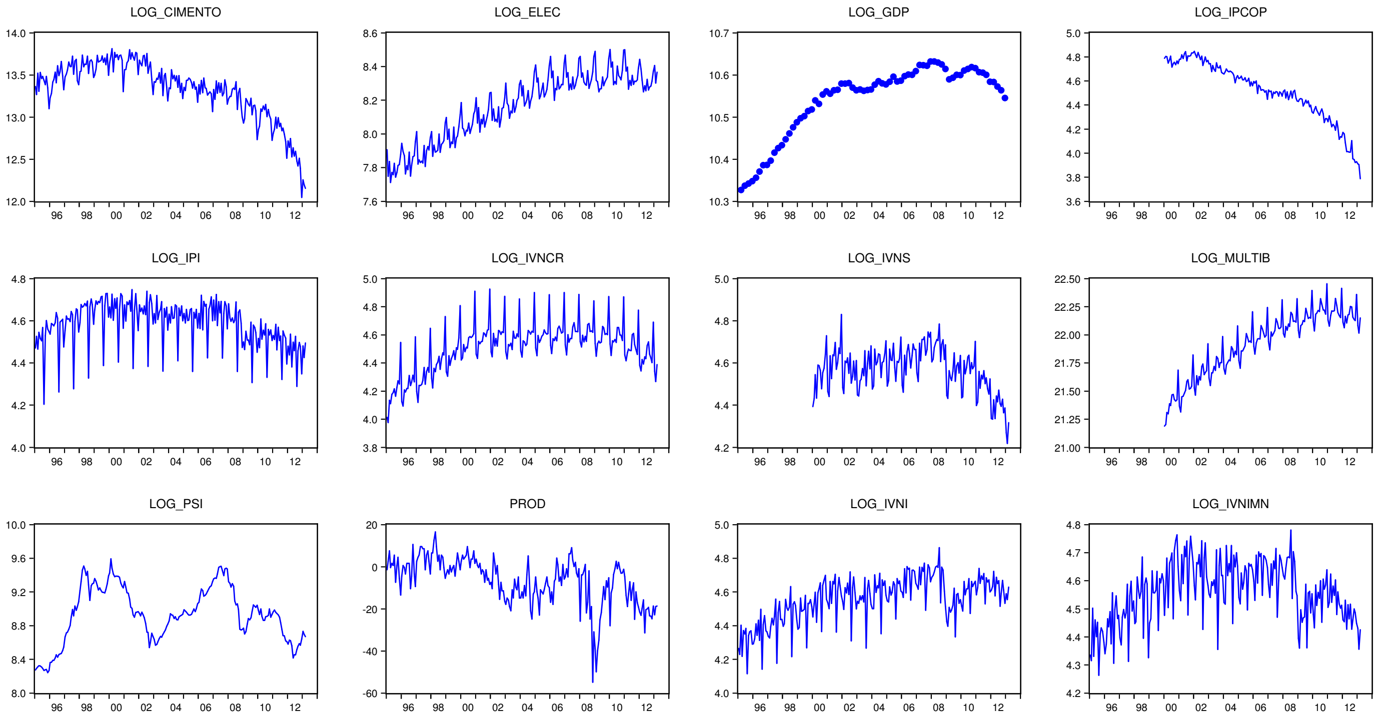


Figure 2: Cross Correlations between the variables in the model

Covariance Analysis: Ordinary
Date: 11/07/13 Time: 20:05
Sample (adjusted): 2001M03 2012M12
Included observations: 48 after adjustments
Balanced sample (listwise missing value deletion)

Correlation	VH_CIMENTO	VH_ELEC	VH_IPCOP	VH_IPI	VH_IVNCR	VH_IVNI	VH_IVNIMN	VH_IVNS	VH_MULTIB	VH_PIB	VH_PSI	PROD
VH_CIMENTO	1.000											
VH_ELEC	0.521	1.000										
VH_IPCOP	0.780	0.547	1.000									
VH_IPI	0.302	0.376	0.164	1.000								
VH_IVNCR	0.540	0.592	0.564	0.260	1.000							
VH_IVNI	0.383	0.517	0.171	0.568	0.366	1.000						
VH_IVNIMN	0.517	0.589	0.346	0.520	0.436	0.937	1.000					
VH_IVNS	0.718	0.809	0.600	0.281	0.659	0.614	0.695	1.000				
VH_MULTIB	0.553	0.593	0.630	0.374	0.811	0.296	0.348	0.563	1.000			
VH_PIB	0.697	0.574	0.538	0.455	0.720	0.630	0.650	0.755	0.707	1.000		
VH_PSI	0.183	0.356	-0.047	0.249	0.353	0.477	0.413	0.406	0.162	0.397	1.000	
PROD	0.273	0.326	0.232	0.274	0.520	0.376	0.312	0.491	0.572	0.725	0.386	1.000

Figure 3: The Common Cyclical Component

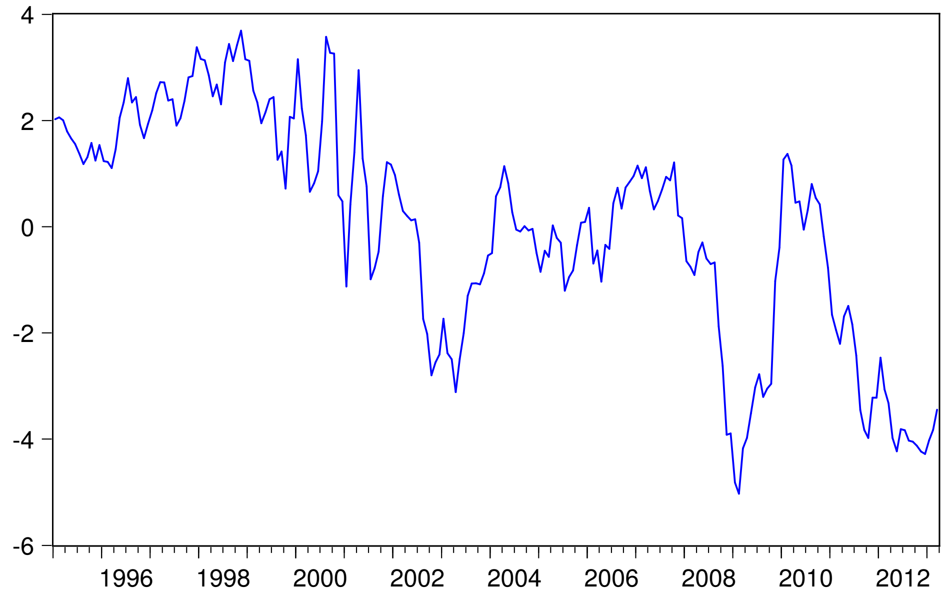


Figure 4: Forecasts and Real GDP

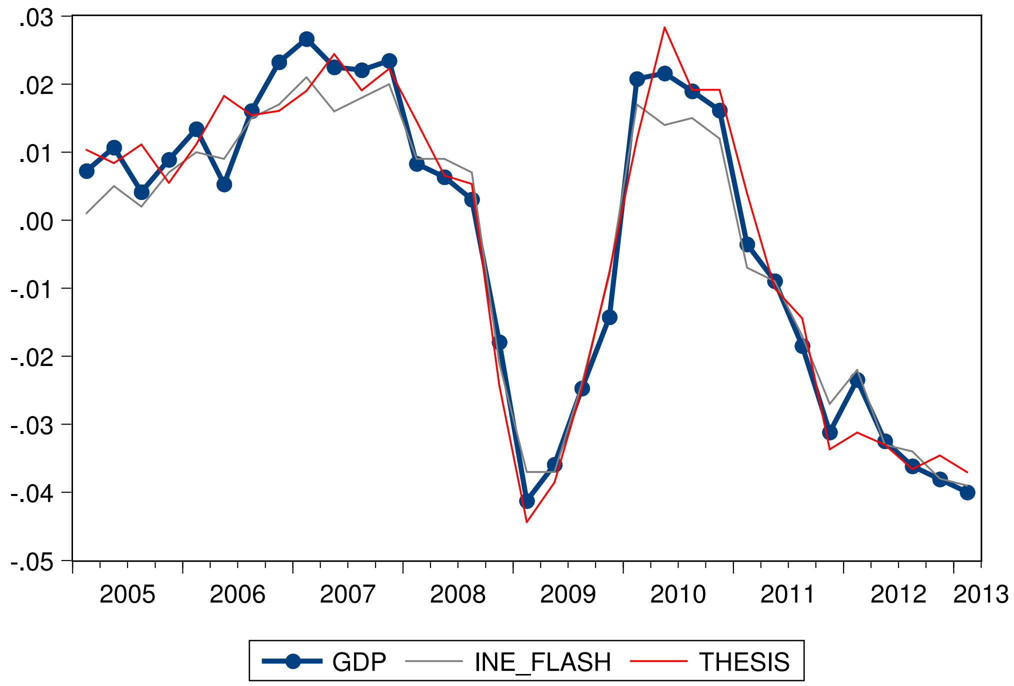
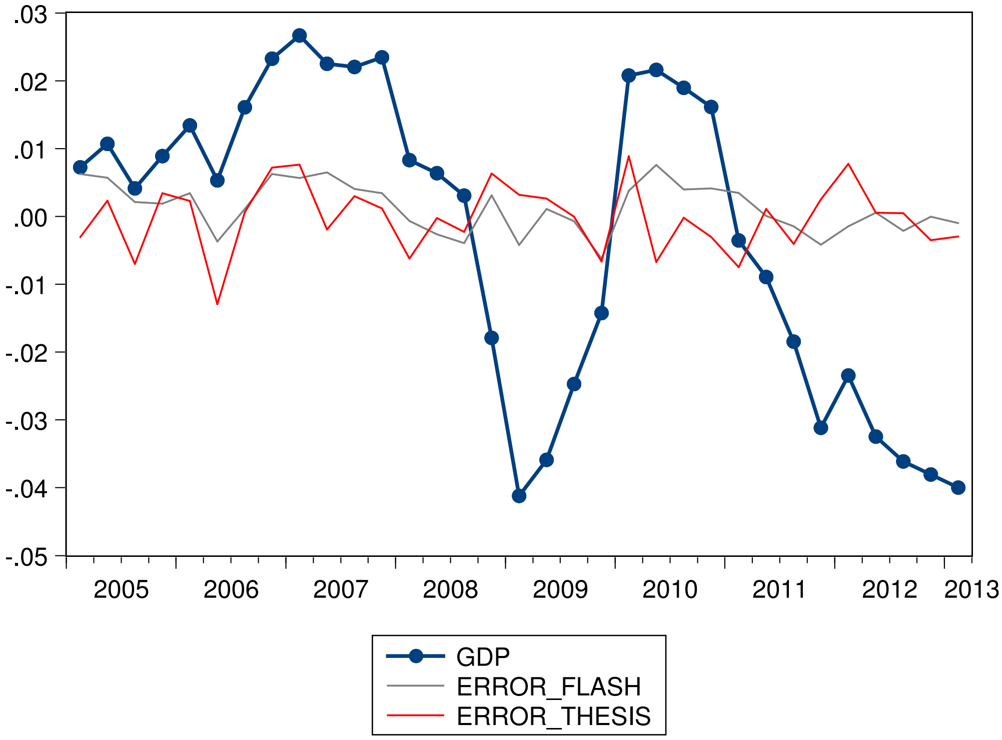


Figure 5: Thesis and INE's Flash Errors



Because of the monthly nature of the Coincident Indicator, for comparison reasons, the same value is given for within the Quarter GDP year-on-year growth rates.

Figure 6: Thesis and INE's Flash Histogram of Errors

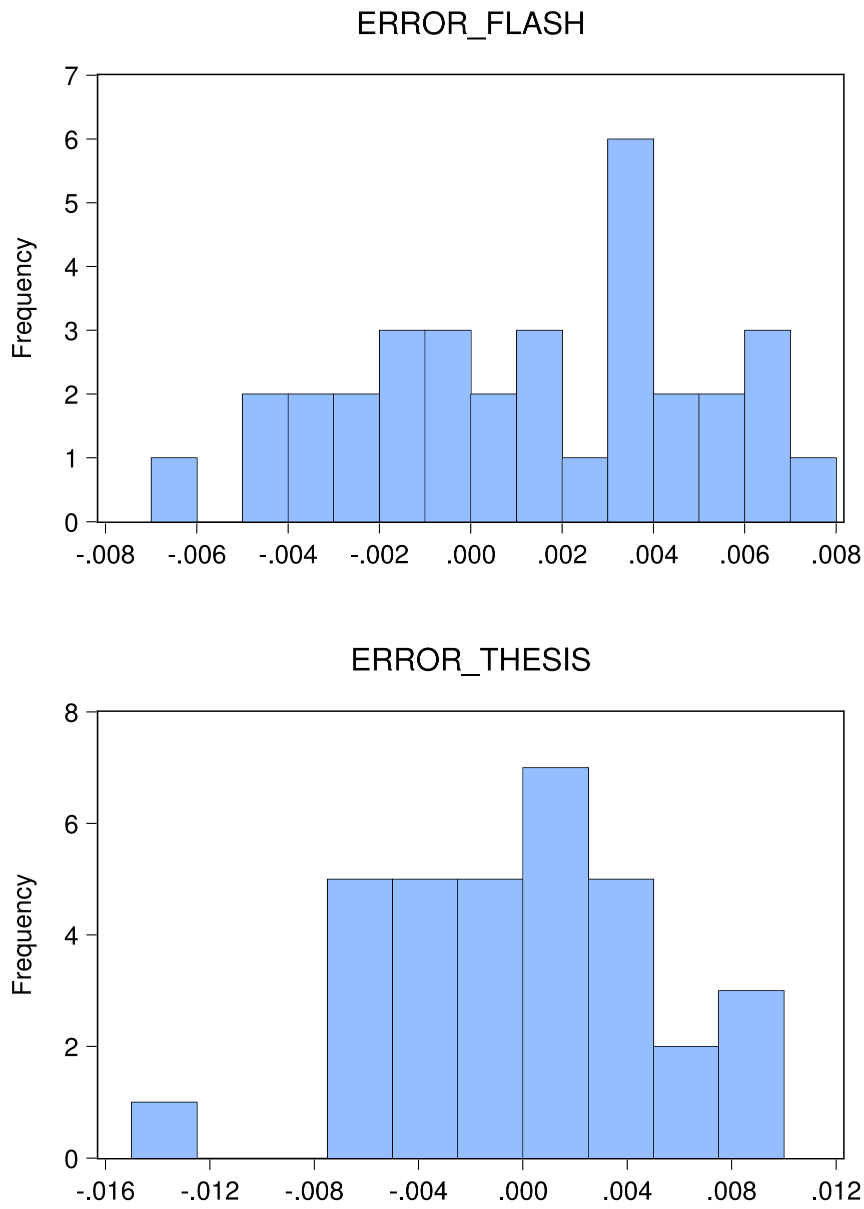


Figure 7: Kernel Density Distribution of Errors

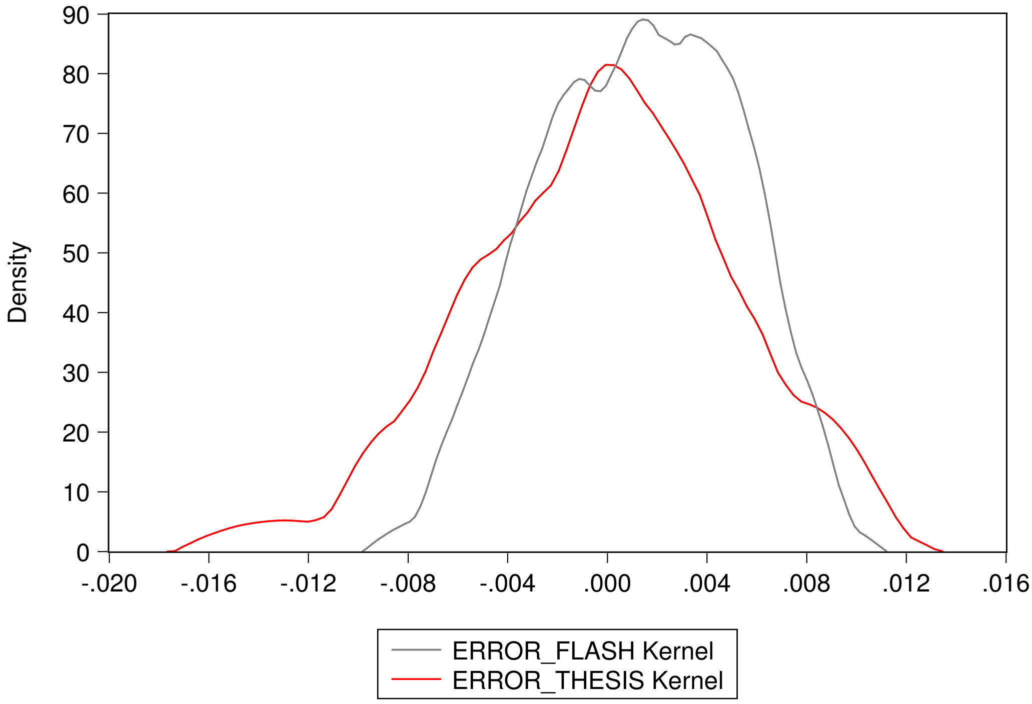
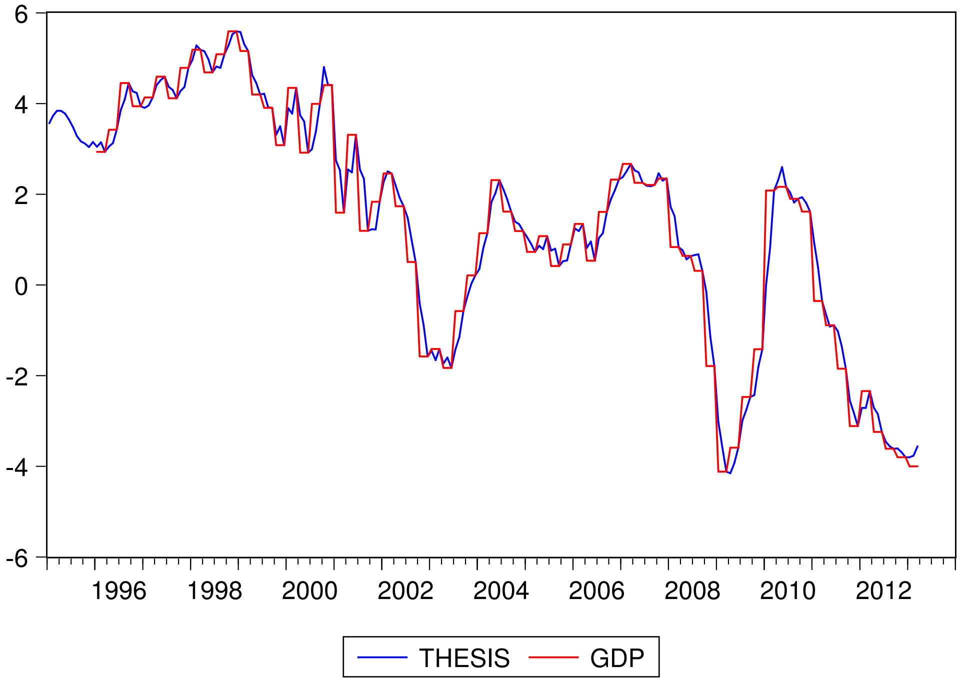


Figure 8: The Coincident Indicator



Because of the monthly nature of the Coincident Indicator, for comparison reasons, the same value is given for within the Quarter GDP year-on-year growth rates.

Figure 9: Eviews Estimation Output

Sspace: SS_THESIS
Method: Maximum likelihood (Marquardt)
Date: 11/07/13 Time: 20:42
Sample: 1995M01 2013M03
Included observations: 219
Partial observations: 171
Convergence achieved after 4 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.16	0.01	13.28	0.00
C(2)	0.06	0.01	7.43	0.00
C(3)	-0.44	0.09	-4.94	0.00
C(4)	0.05	0.01	7.07	0.00
C(5)	-0.36	0.09	-4.06	0.00
C(6)	0.08	0.01	10.60	0.00
C(7)	-1.05	0.10	-11.06	0.00
C(8)	0.07	0.01	6.17	0.00
C(9)	-0.62	0.13	-4.70	0.00
C(10)	0.07	0.01	9.47	0.00
C(11)	-0.87	0.11	-7.88	0.00
C(12)	0.05	0.01	6.58	0.00
C(13)	-0.35	0.11	-3.13	0.00
C(14)	0.08	0.01	10.12	0.00
C(15)	-0.90	0.07	-12.22	0.00
C(16)	0.05	0.01	4.10	0.00
C(17)	-0.33	0.14	-2.28	0.02
C(18)	0.06	0.01	4.84	0.00
C(19)	-0.43	0.13	-3.19	0.00
C(20)	0.06	0.02	3.43	0.00
C(21)	0.05	0.01	4.58	0.00
C(22)	-0.38	0.15	-2.60	0.01
C(23)	0.89	0.04	24.41	0.00

	Final State	Root MSE	z-Statistic	Prob.
SV_T	-3.08	1.46	-2.11	0.03
SV_TM1	-3.44	1.19	-2.90	0.00
SV_TM2	-3.83	0.95	-4.04	0.00
SV_TM3	-4.02	0.81	-4.94	0.00
SV_TM4	-4.28	0.69	-6.16	0.00

Log likelihood	-2449.0	Akaike info criterion	22.576
Parameters	23.0	Schwarz criterion	22.932
Diffuse priors	0.0	Hannan-Quinn criter.	22.719

Figure 10: Real GDP Monthly growth rates and INE's Coincident Indicator

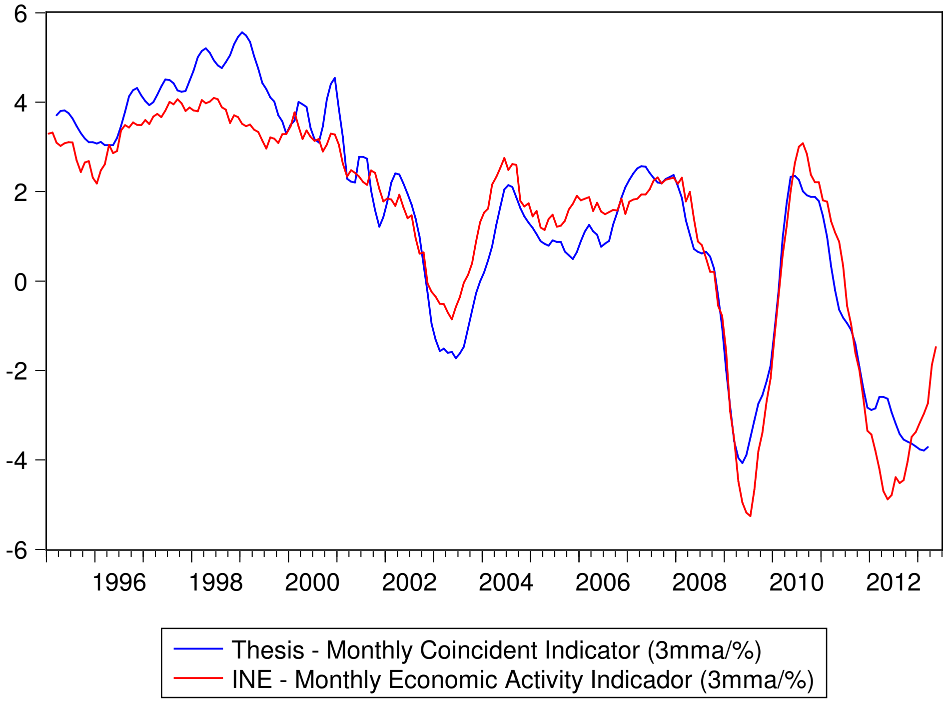


Table 1: First Step of the Selection Procedure (%)

Variable	Effective	Transformation	Optimal Lags*	RMSE	SAE	SSR	AAE
GDP	Gross Domestic Product	AG	-	1.10	26.75	0.40	0.81
IPI	Industrial Production Index	AG	0	0.93	25.06	0.28	0.76
ELEC	Electricity Consumption	AG	2	0.91	23.46	0.27	0.71
IVNS	Services Business Volume	SA, AG	2	0.91	23.72	0.27	0.72
IVNCR	Retail Trade Business Volume Index	AG	2	0.85	21.93	0.24	0.66
LIG	Light Passenger Vehicles Sales**	AG	4	1.05	26.78	0.36	0.81
CIMENTO	Cement Sales***	AG	0	0.94	22.75	0.29	0.69
DESEMP	Registered Unemployment (LP)	AG	5	1.06	26.99	0.37	0.82
IVNI	Industry Business Volume Index	AG	5	1.04	27.23	0.36	0.83
IVNIMN	Ind.Bus.Vol.Index Domestic Market	AG	4	1.01	27.59	0.34	0.84
COMLIG	Light Commercial Vehicles	AG	4	1.38	34.28	0.63	1.04
PROD	Manufacturing Industry Survey****	SA, L	1	0.90	23.39	0.27	0.71
CONST	Construction Survey*****	SA, AG	0	0.90	21.76	0.26	0.66
CARTCLI	Manufacturing Industry Survey******	AG	7	1.14	29.13	0.43	0.88
IPCOP	Const. and Public Works Prod. Index	SA, AG	3	1.06	25.54	0.37	0.77
IRS	Services Remuneration Index	AG	3	1.02	24.80	0.34	0.75
PSI	PSI-20 Stock Exchange Index	AG	0	0.92	24.88	0.28	0.75
CAMBIO	Nominal Exchange Rate	AG	5	1.26	32.48	0.52	0.98
MULTIB	ATM Pruchasings and Withdrawals	AG	2	0.94	22.44	0.29	0.68
DORMIDAS	Overnights by Foreigners in Hotels	AG	1	1.20	30.82	0.48	0.93
GASOLINA	Gasoline Consumption	AG	0	1.04	26.46	0.36	0.80
IFO	IFO Exports Climate Germany	L	3	1.02	26.05	0.34	0.79
IFOb	IFO Business Expectations Germany	L	5	1.05	26.58	0.36	0.81
IFOc	IFO Business Situation Germany	L	3	1.34	36.25	0.59	1.10
PRODG	Production Expectations Germany	SA, L	5	1.04	26.63	0.36	0.81
ICC	Consumer Confidence Index	SA, L	0	0.88	21.57	0.26	0.65
BINV	Man.Ind.Survey - Invest. Goods	SA, L	0	0.99	23.60	0.32	0.72
ICCR	Retail Trade Confidence Index	SA, L	0	0.81	21.79	0.22	0.66
-	**Sample**	**-**	**-**	**0.59**	**14.47**	**0.12**	**0.44**

*Optimal number of lags of the idiosyncratic component on the State Space representation; **Passenger Vehicles (light, minivans, all terrain with more than 2300 kg); ***Secil and Cimpor; ****Last 3 months Production assessment (effective change); *****Construction and Public Works Survey, Orderbook assessment (effective change); ******Manufacturing Industry Orderbook level from Client Countries (seasonally corrected change, 3 month moving average)

Table 2: Second Step of the Selection Procedure (%)

Variable	RMSE	SAE	SSR	AAE
GDP	1.10	26.75	0.40	0.81
IPI	0.93	25.06	0.28	0.76
ELEC	0.83	22.48	0.23	0.68
IVNCR	0.72	20.03	0.17	0.61
IVNS	0.68	19.13	0.15	0.58
CIMENTO	0.67	16.76	0.15	0.51
PSI	0.63	15.38	0.13	0.47
PROD	0.61	14.74	0.12	0.45
IPCOP	0.61	14.45	0.12	0.44
MULTIB	0.60	13.96	0.12	0.42
IVNIMN	0.59	13.54	0.11	0.41
Sample	**0.59**	**13.54**	**0.11**	**0.41**

Table 3: Third Step of the Selection Procedure (%)

Common Lags	RMSE	SAE	SSR	AAE
0	0.68	16.39	0.15	0.50
1	0.63	14.82	0.13	0.45
2	0.56	13.23	0.10	0.40
3	0.52	12.59	0.09	0.38
4	**0.49**	**12.88**	**0.08**	**0.39**
5	0.59	13.60	0.11	0.41

Table 4: RMSE and Correlation

Reference Period	INE's Flash Estimate	Model Forecast
Root-mean-square Error	0.383%	0.496%
Sum of Absolute Errors	10.656%	12.935%
Sum of Squared Residuals	0.048%	0.081%
Mean Error	0.126%	-0.022%
Mean Absolute Error	0.323%	0.392%

Table 5: Time Series Included in the Factor Model

Variable	Effective	Sample	Source	Delay	Transformation
VH_PIB	Quarterly Real GDP	1Q95-4Q12	INE	68 days	QGR
VH_PSI	PSI20 Index Level	Jan95-Mar13	CMVM	0 days	AGR
VH_CIMENTO	Cement Sales Domestic Market	Jan95-Mar13	Cimpor+Secil	7 days	AGR
VH_ELEC	Electricity Consumption	Jan95-Mar13	REN	5 days	AGR
VH_IPCOP	Construction&Public Works Prod. Index	Jan00-MAr13	INE	40 days	SA, AGR
VH_IPI	Industrial Production Index	Jan95-Mar13	INE	30 days	AGR
VH_IVNCR	Retail Trade Business Index (deflated)	Jan95-Mar13	INE	30 days	AGR
VH_IVNI	Industrial Business Volume Index	Jan95-Mar13	INE	40 days	AGR
VH_IVNIMN	Ind. Bus. Vol. Index - Domestic Market	Jan95-Mar13	INE	40 days	AGR
VH_IVNS	Services Business Volume Index	Jan00-Mar13	INE	40 days	SA, AGR
VH_MULTIB	ATM Purchases and Widrawals	Jan00-Mar13	SIBS	12 days	AGR
PROD	Manufacturing Industry Survey*	Jan95-Mar13	INE	0 days	SA, L

*Last 3 months Production assessment (effective change).

Table 6: Unit Root and Stationarity Tests

Variable	**ADF**	**Philips-Perron**	**Ng-Perron** (MSB)	**KPSS**
VH_PIB	−1.09	−1.3292	0.2962	0.8233***
VH_PSI	−2.1557	−2.6437*	0.2369*	0.3834*
VH_CIMENTO	−1.6236	−5.2122*	0.2431*	1.1773
VH_ELEC	−2.2066	−8.7363***	0.1900*	1.2200
VH_IPCOP	−0.5849	−2.5147	0.3277	0.8661***
VH_IPI	−3.5361	−10.0675***	0.2950	0.8948***
VH_IVNCR	−2.0368	−4.5179***	0.4987	1.3717***
VH_IVNI	−4.5182***	−6.8271***	0.0119***	0.2510
VH_IVNIMN	−3.1863**	−7.9629***	0.1635***	0.5705**
VH_IVNS	−2.0312	−5.1051	0.3305	0.5242**
VH_MULTIB	−1.2471	−3.3169**	0.6865	1.2150***
PROD	−3.6128***	−5.0854***	0.1530***	1.0409***

*Asterisks denote a rejection of the null hypothesis at a significance level of 10% (*), 5% (**) or 1% (***).

Table 7: Descriptive Statistics of the Series included on the Forecasting Model

Variable	**Average**	**Median**	**Standard Deviation**	**Max**	**Min**	**Observations**
VH_PIB	0.0137	0.0161	0.0255	0.0558	−0.0412	68
VH_PSI	0.0594	0.0658	0.3054	1.1186	−0.5198	207
VH_CIMENTO	−0.0464	−0.0446	0.1326	0.2815	−0.4463	207
VH_ELEC	0.0308	0.0377	0.0426	0.1593	−0.1029	207
VH_IPCOP	−0.0614	−0.0612	0.0653	0.0922	−0.2583	147
VH_IPI	−0.0022	−0.0005	0.0483	0.1430	−0.1647	207
VH_IVNCR	0.01625	0.0143	0.0539	0.1770	−0.1014	207
VH_IVNI	0.0206	0.0270	0.0793	0.1784	−0.2614	207
VH_IVNIMN	0.0065	0.0116	0.0765	0.3149	−0.2185	207
VH_IVNS	−0.0111	−0.0055	0.0739	0.1621	−0.1963	147
PROD	−6.8762	−4.9116	11.1489	16.5498	−54.9116	219
VH_MULTIB	0.0672	0.0734	0.0579	0.2055	−0.0998	147

Table 8: Indicators Potential Forecasting Improvement* (%)

Variable	**RMSE**	**SAE**	**SSR**
GDP	:	:	:
IPI	15.41	6.31	28.45
ELEC	17.24	12.29	31.51
IVNS	17.20	11.34	31.44
IVNCR	22.26	18.04	39.56
LIG	4.71	0.11	9.20
CIMENTO	14.31	17.97	26.56
DESEMP	3.28	-0.89	6.46
IVNI	5.15	-1.81	10.03
IVNIMN	7.64	-3.14	14.69
COMLIG	-25.97	-28.13	-58.69
PROD	18.08	12.58	32.88
CONST	18.30	18.66	33.24
CARTCLI	-4.10	-8.90	-8.36
IPCOP	3.38	4.54	6.64
IRS	7.07	7.30	13.64
PSI	16.16	7.01	29.71
CAMBIO	-14.75	-21.40	-31.66
MULTIB	14.49	16.11	26.89
DORMIDAS	-9.74	-15.22	-20.42
GASOLINA	5.18	1.08	10.08
IFO	7.15	2.62	13.79
IFOb	4.15	0.65	8.12
IFOc	-22.41	-35.49	49.83
PRODG	4.86	0.47	9.48
ICC	19.74	19.38	35.58
BINV	10.05	11.78	19.10
ICCR	26.09	18.56	45.37

*Assuming the First Step of the Selection Procedure

Table 9: Indicators Weight on Forecasting Accuracy* (%)

Variable	**RMSE**	**SAE**	**SSR**
GDP	:	:	:
IPI	33.1	12.8	39.8
ELEC	19.5	19.6	20.3
IVNCR	20.7	18.5	19.1
IVNS	7.8	6.8	6.5
CIMENTO	1.9	18.0	1.6
PSI	9.1	10.4	7.1
PROD	4.0	4.8	2.9
IPCOP	-0.2	2.2	-0.1
MULTIB	1.3	3.7	0.9
IVNIMN	2.7	3.2	1.9
Total Improvement $\sum_{n=1}^{10}$	**100**	**100**	**100**

*Assuming the Second Step of the Selection Procedure

Table 10: Improvement between Methodologies (%)

Model	Common Lags	RMSE	SAE	SSR
a)	Individual Optimization	46.61	49.40	71.50
	1	37.54	38.72	60.99
	2	42.62	44.60	67.07
b)	3	48.95	50.56	73.94
	4	**54.96**	**51.87**	**79.72**
	5	49.46	49.15	71.33

Table 11: Forecast Performance

Reference Period	Real GDP (%)	INE's Flash (%)	Model Forecast (%)
2005 I	0.7	0.1	**1.0**
2005 II	1.1	0.5	**0.8**
2005 III	0.4	0.2	1.1
2005 IV	0.9	0.7	**0.5**
2006 I	1.3	1.0	**1.1**
2006 II	0.5	0.9	**1.8**
2006 III	1.6	1.5	**1.5**
2006 IV	2.3	1.7	**1.6**
2007 I	2.7	2.1	**1.9**
2007 II	2.2	1.6	**2.4**
2007 III	2.2	1.8	**1.9**
2007 IV	2.3	2.0	**2.2**
2008 I	0.8	0.9	**1.5**
2008 II	0.6	0.9	**0.7**
2008 III	0.3	0.7	**0.5**
2008 IV	-1.8	-2.1	**-2.4**
2009 I	-4.1	-3.7	**-4.4**
2009 II	-3.6	-3.7	**-3.9**
2009 III	-2.5	-2.4	**-2.5**
2009 IV	-1.4	-0.8	**-0.8**
2010 I	2.1	1.7	**1.2**
2010 II	2.2	1.4	**2.8**
2010 III	1.9	1.5	**1.9**
2010 IV	1.6	1.2	**1.9**
2011 I	-0.4	-0.7	**0.4**
2011 II	-0.9	-0.9	**-1.0**
2011 III	-1.8	-1.7	**-1.4**
2011 IV	-3.1	-2.7	**-3.4**
2012 I	-2.3	-2.2	**-3.1**
2012 II	-3.2	-3.3	**-3.3**
2012 III	-3.6	-3.4	**-3.7**
2012 IV	-3.8	-3.8	**-3.5**
2013 I	-4.0	-3.9	**-3.7**

Table 12: Factor Loadings and Standard Errors

Coefficient	**Time Series**	**Factor Loading**	**Standard Errors**
$c(1)$	GDP	0.1680	0.0122
$c(2)$	IPI	0.0595	0.0078
$c(4)$	ELEC	0.0552	0.0077
$c(6)$	IVNCR	0.0809	0.0075
$c(8)$	IVNS	0.0730	0.0118
$c(10)$	CIMENTO	0.0764	0.0079
$c(12)$	PSI	0.0545	0.0082
$c(14)$	PROD	0.0778	0.0075
$c(16)$	IPCOP	0.0565	0.0138
$c(18)$	MULTIB	0.0632	0.0130
$c(20)$	IVNIMN	0.0626	0.0114
$c(22)$	IVNI	0.0563	0.0120

Table 13: Forecasting Accuracy by Year (%)

	Thesis Model				**INE's Flash Estimate**	
	RMSE	**Sum Abs. Errors**	**SSR**	**Average Abs. Error**	**RMSE**	**SSR**
2005	0.434	1.581	0.008	0.395	0.447	0.008
2006	0.750	2.304	0.023	0.576	0.404	0.007
2007	0.425	1.372	0.007	0.343	0.506	0.010
2008	0.460	1.510	0.008	0.378	0.285	0.003
2009	0.391	1.250	0.006	0.313	0.382	0.006
2010	0.578	1.886	0.013	0.472	0.512	0.010
2011	0.446	1.513	0.008	0.378	0.281	0.003
2012	0.427	1.224	0.007	0.306	0.132	0.001