NBP Narodowy Bank Polski

NBP Working Paper No. 191

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Economic Institute
Warsaw, 2014

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This research project was conducted under the NBP Economic Research Committee's open competition for research projects to be carried out by the NBP staff and economists from outside the NBP and was financed by the NBP.

Print:
NBP

Published by:
Narodowy Bank Polski
Education & Publishing Department
ul. Świętokrzyska 11/21
00-919 Warszawa, Poland
phone +48 22 653 23 35
www.nbp.pl

ISSN 2084-624X

Contents

Abstract

In this article we present four diversified approaches to forecasting main macroeconomic variables without a priori assumptions concerning causality. We include tendency survey data in both the Bayesian averaging of classical estimates (BACE) and the dynamic factor models (DFM) frameworks. With respect to the forecasting models based on BACE we propose two methods of regressors' selection: frequentist (FMA) and averaging (BMA). Our approaches are a priori atheoretical and we refrain from the theory-based selection of exogenous variables. For comparison between forecasts we apply ARIMA method as well.

Our approach is comprehensive with respect to the datasets used. We apply data from the tendency surveys conducted at the Research Institute for Economic Development (RIED) at the Warsaw School of Economics (WSE), Poland, on sentiment in the manufacturing industry, trade and construction as well as among households. We additionally include data from foreign and domestic institutes that construct their own leading indicators. We also use the Purchasing Managers' Index (PMI) for Polish industry.

In order to assess the quality of results we check in-sample and out-of-sample performance. The results show that, although the results does not significantly differ, the best results are observed in Bayesian models with frequentist approach.

Keywords: Bayesian Averaging of Classical Estimates, Dynamic Factor Models, business survey data, forecasting

JEL Classification: C10, C38, C83, E32, E37

1. Introduction

In the history of macroeconomic forecasting two major and complementary trends can be observed. They have led to two diversified approaches to modelling and forecasting economic processes. One group of models is based on inclusion of stylized facts from macroeconomic theory and thus causal effects are incorporated in modelling, while the other group of methods is atheoretical and based only on the observed properties of time series from an economy.

The first of these trends was historically initialized by construction of the structural multi-equation econometric models. However, models from this group are currently very scarce (Welfe, 2013). The subsequent step in the development of this form of modelling and forecasting was based on inclusion of structural relations between variables in the general equilibrium framework. This approach combines many pieces of macroeconomic theory and, based on a consistent methodology, leads to a system of interrelated equations which as a result produce an equilibrium. One of the representatives of the group are computable general equilibrium models (CGE). They are usually built as static models and assume no uncertainty. These strong simplifying assumptions do not help in a realistic forecasting, despite the efforts made by researchers to introduce dynamics in this framework (Gradzewicz, Griffin, & Żółkiewski, 2006).[1]

Inclusion of a stochastic factor in economic processes and dynamic expectations of households and enterprises in the general equilibrium framework led to a new class of models known as dynamic stochastic general equilibrium models (DSGE). For several years this type of models had dominated the approach to macroeconomic modelling (Grabek, Kłos, & Koloch, 2011). These models were initially based on real business cycle assumptions and were developed within the real business cycle framework with the fundamental work of Kydland & Prescott (1982). Subsequently, the new Keynesian methodology started to take over (see Rotemberg & Woodford, 1997 for examples) From the theoretical perspective, model structure in DSGE framework is satisfactory and the disadvantages of the previous approaches are essentially removed. There have been even efforts to eliminate the representative agent paradigm and introduce heterogeneity of households and producers present on the market (Brzoza-Brzezina, Kolasa, Koloch, Makarski, & Rubaszek, 2013; Heathcote, Storesletten, & Violante, 2009).

1 Nevertheless, developments in the area of numerical modelling and computational capabilities of computers resulted in a significant improvement of the CGE approach.

A criticism of DSGE models is still present in many dimensions. From the perspective of this paper the most important is the accuracy of predictions derived from DSGE models compared with the forecasts received from other classes of models - even in comparison to expert forecasts. There are studies showing that the accuracy of predictions of DSGE models as well as expert forecasts is low (Kolasa, Rubaszek, & Skrzypczyński, 2012; Rubaszek & Skrzypczyński, 2008). There are also examples of studies leading to negative results in an assessment of dynamic stochastic general equilibrium models with respect to their coherence with macroeconomic data from the economy (Wróbel-Rotter, 2014). Due to this, we decided to pursue the second path, namely atheoretical modelling. An approach to construction of econometric models designed for forecasting changes in the GDP growth, the unemployment rate and the consumer price index was developed in several previous publications (Białowolski, Kuszewski, & Witkowski, 2010, 2011, 2012, 2014).

The origins of our approach can be traced back to a brief comparison between seven structural models of the US economy and simple ARIMA forecasts (Cooper, 1972). The fundamental finding of the analyses conducted then was that the forecasts obtained from the time series models were more accurate than those produced by large scale structural models. Although, in the ARIMA model only one endogenous variable was used and both testing and interpretability of the results were much more limited than in the case of a structural model, the effort associated with construction and testing of such a model was substantially lower than in the case of a structural one. Similar analyses were also conducted by Stockton and Glassman (1987). To this end, vector autoregressive models (VAR) were also accessible as an alternative proposed by Sims (1980). One of the arguments raised by Sims was that parameters in the autoregressive system are not interpretable. This conclusion was essential for later developments of the atheoretical macroeconomic modelling, in which the stylized facts were left aside. In this trend were also the works of Geweke (1977) and Stock and Watson (1998) with introduction of the dynamic factor models. Stock and Watson (1998) were dealing with the problem of dealing with the number of time series which was exceeding the number of observations in the estimation time frame. Application of traditional econometric methods in such a case naturally results in a problem of identification. The natural solution seems to be application of the well-known in statistics factor analysis, which allows for dimension reduction, and in this case, it means that the common factors driving the changes in many series simultaneously are extracted. Baranowski, Leszczyńska, & Szafrański (2010) note that "These factors, although from an economic point of view possess atheoretical structure, might be an expression of unobservable causal forces present in the economy". This statement confirms that in-depth exploration of causal relations between economic variables is almost impossible. The data from tendency surveys seems to be very naturally filled with common factors, which has been used in many studies oriented on analysis of macro level variables (Costantini, 2013; Gayer & Genet, 2006), but also with respect to micro level relations (Białowolski, 2011a, 2013).

The goals of this paper are as follows. First, we want to develop an effective system for forecasting macroeconomic variables in Poland with atheoretical framework. Second, we want to evaluate competing models with respect to their in-sample and out-of sample forecasting performance. Although arguments for the use of forecasting models with tendency survey data and application of Bayesian averaging of classical estimates were already stated (Białowolski et al., 2012, 2014) we introduce an important novelty by conducting a twofold analysis with the use of both the approach known as „frequentist" (applied in the previous papers), which is based on the use of Bayesian averaging for the purpose of *selection* of the variables for the model and the approach known as "averaging", which is based on an idea not to select the independent variables but to average over the results obtained in different model structures with all the possible regressors. Additionally, for the first time we use such a large set of Poland's tendency survey data in the dynamic factor framework for forecasting of the main macroeconomic variables. We confront the results with results obtained with ARIMA models. Thus we end up with four forecasting scenarios, which are subsequently evaluated.

Our approach to forecasting main macroeconomic indicators is a multi-model one. It constantly gains more attention from modellers dealing with quantitative analyses (Gatnar, 2008), especially because of its advantages associated with aggregation of results coming from diversified model classes. Our hypothesis is that aggregating forecasts from different forecasting models – those regression based and those based on dynamic factor approach – should lead to better forecasts then in the best of individual models.

It should be also underlined that in Poland the interest in tendency survey data is constantly increasing. It is supported by growing number of publications summarizing current impact of tendency survey data on forecasting (Adamowicz, 2013; Drozdowicz-Bieć, 2012), but also those which show current applications of tendency survey data for analysing business cycle behaviour (Adamowicz & Walczyk, 2013; Bialowolski & Dudek, 2008; Białowolski et al., 2007, among others) and the micro level behaviour of the tendency survey data (Białowolski, 2011b, 2013). At the same time, methodological issues in tendency survey data are developed with special focus on sample design and aggregation of results (Białowolski, Dudek, & Kowalczyk, 2006; Kowalczyk, 2013).

Following its objectives the paper is arranged as follows. The following section (Sec. 2) focuses on the data used for estimating the econometric models and on the statistical properties of the time series used. In section 3 we provide a brief overview of the methodology. Section 4 describes the modelling results and in section 5 we provide the fit of obtained forecasting models and compare out-of-sample forecasts with actual realizations from quarters in year 2013 and 2014. This part comprises also a proposal for aggregation of forecasts. Additionally, we compare our results with forecasts published in the National Bank of Poland Survey of Professional Forecasters. Part 6 concludes.

2. Data – sources and preparation

In order to build forecasting models, quarterly data covering the years from 1996 to 2013 were collected. The data on the gross domestic product (GDP), the consumer price index (CPI) and the unemployment rate (UNE) come from a publication by Poland's Central Statistical Office (CSO). The unemployment rate has been set on the basis of a Labour Force Survey. GDP, CPI and UNE serve in our models as endogenous variables. With respect to the previous research, the set of indicators was extended with time series on individual consumption, investment outlays, export and import but also value added in 16 sectors of the economy. Those additional variables were used as potential regressors.

In addition to the lagged endogenous variables and data from national accounts, tendency survey data are assumed to play the role of regressors in the designed econometric models either in their original form or as the variables explained by the presence of common factors. The tendency survey data is usually published in the form of monthly statistics. In line with the standard practice, business survey data for the first month of each quarter, i.e. January, April, July and October, are considered as a quarterly data. The database applied in the procedure comprises a time series from the Research Institute for Economic Development (RIED) at the Warsaw School of Economics (WSE), on sentiment in the manufacturing industry, trade and construction and among households. Data published by the Centre for European Economic Research (ZEW), the Leibniz Institute for Economic Research at the University of Munich (Ifo Institute), Bureau for Investments and Economic Cycles (BIEC), and the Purchasing Managers' Index (PMI) for Polish industry, were also collected and subsequently applied in the analysis. In addition to this, data on consumer confidence from the Central Statistical Office and IPSOS group were included in the analysis. The symbols adopted for the variables in the estimated models are presented in Appendix 1.

Similarly to the most of empirical illustrations of economic processes, also in the conducted research, data generating processes were verified with respect to their stationarity. Most of the research provide verification of stationarity with respect to the mean, rarely stationarity with respect to variance is subject to verification. Lack of stationarity with respect to variance is usually accounted for by taking logarithm of the time series. However, such procedure appeared to be not necessary in the case of our series. The problem of stationarity with respect to the mean is usually accounted for by differencing the time series (difference order is usually described by letter d and stands for the order of integration). In our case, stationarity was checked with ADF and KPSS tests (Kwiatkowski, Phillips, Schmidt, & Schin, 1992) used in order to study an order of integration. No time series with an order of integration higher than 1 were identified in the database. Nevertheless, the analysis showed that it can be assumed that the time series for responses to business survey questions targeted at the industrial sector are stationary I(0) time series, while the time series for responses to business survey questions targeted at households are integrated I(1) time series. The remaining regressors time series appeared to be stationary ones. This explains why we decided against differentiating the values of the series I(1); instead we decided to study the statistical properties of the residual series of the estimated models. Stationarity of the time series of regressands has been investigated with KPSS test. Time series of GDP is stationary, but CPI and UNE are integrated of degree 1 (d=1).[2]

Discussion regarding the seasonality of time series is constantly present in the literature (see, e.g.,Clements & Hendry, 2011). The voices of those in favour of deseasoning in economic modelling are more less equal to those having the opposite opinion. However, the seasonality treatment of the time series was omitted in our analysis because the results presented in Białowolski et al. (2014) show its marginal influence in both deterministic and stochastic specification of seasonal factor. It follows a common econometric finding that with either version of the seasonality (deterministic or stochastic), due to the fact that different patterns of seasonality are present among regressors, it is hard to predict the influence of seasonality on parameter estimates and, more importantly, on the forecasts. Similar views are supported by Mycielski (2010).

In the literature one can find also arguments that deseasonised time-series are in fact obtained via estimation and due to this some of the information content of time series subject to deseasoning is lost (see e.g. Bloem, Dippelsman, & Maehle, 2001). It has been also pointed out that seasonality correction should be rather performed when the same months, quarters are compared to each other for different years in an analysis of a single times-series, while the seasonal correction is less justified when the time-series data serve for modelling of the economic processes (Manski, 2014). As an example, in the case of macroeconometric model for the Polish economy WK2009 (Welfe, 2013) based on quarterly data only not seasonally adjusted data were used.

The influence of deseasoning of a time-series on quality of estimates and testing of autoregressive models was assessed by Hecq (1998). He obtained a strong support for lack of seasonal treatment of time-series data. However, if time-series are to be used in different applications than econometric modelling, seasonal treatment might be more justified (Baranowski et al., 2010). Consequently, in all our models we decided to use raw time series.

2 The level of integration is important for specification of the ARIMA models. Their estimation is presented in the subsequent sections of the paper.

3. Prognostic models

Throughout the study it has been assumed that the main research interest is focused on explaining the GDP growth (GDP), the rate of inflation (CPI) and the rate of unemployment (UNE). Because forecasts of each of these variables should be generated, the natural solution is a three equation model. It is quite natural to assume that all three time series GDP_t, UNE_t and CPI_t are related with one another, as well as each of these variables is strongly autocorrelated. Thus one possible approach would be to construct a three equation model which symbolically could be denoted as

$$\begin{aligned} &GDP_t = f_1(GDP_{t-1}, UNE_t, CPI_t, \boldsymbol{V}_1, \varepsilon_{1t}) \\ &UNE_t = f_2(UNE_{t-1}, GDP_t, CPI_t, \boldsymbol{V}_2, \varepsilon_{2t}) \\ &CPI_t = f_3(CPI_{t-1}, GDP_t, UNE_t, \boldsymbol{V}_3, \varepsilon_{3t}), \quad t = 1, \dots, T. \end{aligned} \tag{1}$$

where the $\boldsymbol{V}_1, \boldsymbol{V}_2$ and $\boldsymbol{V}_3$ stand for "any other specified explanatory variables". These might mean: the first or any further lags of GDP, UNE and CPI respectively, as well as any exogenous variables, such as economics situation indicators. Such a model can be viewed as a VAR and estimated as such. However, we adopt two different approaches in this paper (dynamic factor and Bayesian averaging) due to the following reasons. First, our main target is to provide a model which would be capable of providing short term forecasts of GDP, UNE and CPI. Thus the $\boldsymbol{V}_1, \boldsymbol{V}_2$ and $\boldsymbol{V}_3$ might only contain the lags of endogenous variables and such variables whose values are known for the near future. We believe that they are economic situation indicators among the series in our dataset which might serve as reasonable determinants of GDP, UNE and CPI and whose values are indeed known slightly in advance: they are available at the beginning of the quarter, which makes it possible to use them for forecasting purposes for the period of almost three months ahead. Furthermore, in the process of construction of leading indicators at the RIED, entrepreneurs and households are asked about their expectations regarding the economic situation in the near future. This makes it reasonable to use k-th lags of the business tendency indicators rather than their current values, which makes it possible to extend the horizon of forecast further by additional k periods (quarters). That unfortunately comes at a cost. The series of business tendency and consumer sentiment indicators described in the previous section begin in 1996, thus only 68 quarterly observations are available till the end of 2012. Such a short series make it doubtful whether it would make much sense to adopt a VAR approach. Yet another problem is the issue of selection of "adequate" economic situation indicators for the model. Firstly, the number of available indicators is high, even if we just limit our attention to those provided by RIED. Not only would that mean very low (or even negative if additional lags of endogenous variables were also considered) number of degrees of freedom of the specified model, but also multicollinearity of them would be an issue. Naturally one could preselect just a few indicators for the $\boldsymbol{V}_1, \boldsymbol{V}_2$ and $\boldsymbol{V}_3$ sets, however it would certainly be difficult to give prior rationale for choosing a given subset of all the available economic situation indicators.

3.1. Bayesian Models – modelling strategy

In Bayesian approach in order to overcome these problems we propose the following approach. Firstly, we replace the model (1) with the following structure:

$$GDP_t = f_1(GDP_{t-1}, \boldsymbol{X}_{1,t-k}, \varepsilon_{1t}) \tag{2a}$$

$$UNE_t = f_2(\widehat{GDP}_t, UNE_{t-1}, \boldsymbol{X}_{2,t-k}, \varepsilon_{2t}) \tag{2b}$$

$$CPI_t = f_3(\widehat{GDP}_t, \widehat{UNE}_t, CPI_{t-1}, \boldsymbol{X}_{3,t-k}, \varepsilon_{3t}), t = 1, \dots, T; k \in \{0,1,2,3,4\}, \tag{2c}$$

where $\boldsymbol{X}_{i,t-k}, i = 1,2,3,$ stands for the set of economic situation indicators from period *t-k* influencing the GDP growth, the rate of unemployment and the rate of inflation respectively; $\varepsilon_{it}, i = 1,2,3,$ represents the error terms for subsequent equations, $f_i, i = 1,2,3,$ is a certain linear function, $\widehat{GDP}_t$ is the theoretical rate of GDP growth obtained from the equation (2a) and $\widehat{UNE}_t$ is the theoretical rate of unemployment obtained from the equation (2b). Estimating (1) on the equation-by-equation basis would not be adequate due to endogeneity of particular variables. In order to overcome the problem of endogeneity we use the 2SLS-type logic by replacing given variables with their theoretical values making the (2) feasible for recursive estimation with the use of a simple least squares estimator. The order of equations in (2) is based on our previous research: naturally one could order the dependent variables in (2a)-(2c) in six different ways, yielding six different sets of recursive equations. However, as shown in Białowolski et al. (2010), this way of ordering provided the set of equations that allowed for obtaining the most accurate forecasts in the past. We also adopt all the classical assumptions that make it possible to estimate the subsequent equations with the use of OLS: in particular we treat the error term as spherical.

The next issue is the problem of selecting the "best" $\boldsymbol{X}_{i,t-k}, i = 1,2,3$ for a given k. Firstly, it is not clear which lags of the economic situation indicators should be used so as to maximize the quality of the forecast, except that it seems obvious that those should not be lagged by too far. For that reason we estimate separately the set of (2a)-(2c) for different k between 0 (current values of economic situation indicators) up to their 4^{th} lags, without mixing different lags in one equation. It would be tempting to use more lags of the same indicator in the same equations (say, 1^{st} and 2^{nd} lags of them in one model), this is however problematic due to very strong autocorrelation in the series of most indicators and high multicollinearity as its result. Next issue is: which of the indicators select for particular $\boldsymbol{X}_{i,t-k}, i = 1,2,3$ – clearly the set of indicators that would serve as best determinants of unemployment need not be the same as those used for the CPI or rate of GDP growth, thus each of the $\boldsymbol{X}$'s should be selected separately. Since the economic rationale is highly unclear and subjective in this case, we adopt the Bayesian model averaging (BMA) approach for this purpose, which in the case where OLS is used for estimation purposes, degenerates to so called Bayesian averaging of classical estimates. The core of the approach is to avoid subjectivity of the selection of independent variables for the model. Step one usually consists of preselecting a set of "possible" relevant independent variables. This set usually is numerous. In the step two researchers who use a traditional approach pick some of the possible independent variables for their final model, usually on the basis of their earlier knowledge, experience, subjective views, etc. Sometimes the model obtained in this process is not satisfactory, so they retake step two and select a different set of independent variables for the final model, which clearly reflects the subjectivity of the process. Furthermore, if we really treat all the potential independent variables as (from the prior point of view) equally "likely to be good", it would be fairly difficult to find the optimally forecasting model by retaking step two as long as we are "satisfied with the model", which is what most researchers would actually do.

Instead of that, in BMA in step two we construct all the possible to be constructed subsets of the set of potential independent variables and then estimate all the possible models (which differ by the set of explanatory variables) $M_j, j = 1, \dots, J$, however, if the number of variables in the set of considered potential regressors is big (i.ee, exceeds about 20 variables), a random sample of possible models is drawn and estimated. Next, for every j-th estimated model $M_j, j = 1, \dots, J$ a posterior probability P_j (such that $\sum_{j=1}^{J} P_j = 1$) of its relevance is computed: this value shows to what extent should we believe that the $M_j$is the true model. The technical details of BMA can be found in numerous papers, such as the milestone article of Sala-i-Martin, Doppelhoffer and Miller (2004) or Próchniak and Witkowski (2013) and shall not be discussed here.

Further steps depend on the adopted approach. There are two types of Bayesian-averaging, which can be found in the literature: the "frequentist" and the "averaging" procedure (Moral-Benito, 2013). In the frequentist approach, for every considered regressor one would compute its posterior probability of relevance as the sum of the posterior probabilities P_j for the models in which the given regressor was included and find it relevant if such a posterior probability of relevance of the regressor was greater than its prior probability of relevance, usually computed as the ratio of the preassumed number of the variables in the true model and the number of variables in the considered set of "possible" regressors (some would use the pseudo *t* statistic based on the weighted result of the significance *t* test from all M_j where the given regressor was included instead of the posterior probabilities analysis). Thus a set of "relevant" independent variables is selected and subsequently the final model can be estimated with the set of regressors limited to the selected variables. An advantage of this approach is that the set of regressors is "objectively" selected from the presumed set of "possible" ones, rather than "subjectively chosen". In the case of the averaging approach, no variables are dropped or selected. For each of the possible regressors an average regression parameter is computed as a mean of all its estimates from all the M_j's where the considered variable was included. This approach is actually not about "selecting" the "good" and "bad" variables, but about attaining the influence of any considered regressor on the independent variable, which is made feasible even if the number of considered regressors is greater than the number of observations in the sample: it is just about drawing for the analyses such regressions in which there would never be excessively many independent variables.

In this study, with regards to Bayesian averaging, three types of approaches were analysed: the averaging approach, the frequentist approach and the frequentist approach with the control of collinearity. In the last one, after selecting the set of variables on the basis of their posterior probabilities, the variance inflation factors were checked and the regressors with highest VIFs were eliminated recursively until all VIFs were acceptable (the usual VIF<10 rule was adopted for this purpose). The problem of collinearity is indeed an issue. In the classical BMA approach with binomial priors (as they are used here) the assumption is made that the probability of relevance is the same for each of the variables considered as potential regressors irrespectively of the existence of collinearity in the data set. Such an attitude is not the only possibility: Ghosh and Ghattas (2014) for example suggest testing sets of strongly correlated potential independent variables rather than individual variables and only after selecting particular ones of them. They, however, refer to rather stronger correlated variables than it can be found in the considered data set. The problem with proposing a sensible procedure, which would be economically sound is the following: suppose that there are some 2 or more candidate variables in the data set and these are strongly correlated. The prior probabilities of relevance for such variables should be modified as compared to the classical formulas if one believes that such a correlation in the data modifies the probability of relevance of such variables. The question is: does it? If so, is it rather increasing the probability of relevance of them or rather lowering them? Suppose that one of the strongly correlated variables indeed is relevant and further suppose we know which one it is. Should we then increase the prior probability of relevance of the variables correlated with it (assuming that they might be generated by a similar or related process) or rather decrease it (in order to technically lower the chance of having multicollinear variables in the final model)? We have not found the answer to these questions neither in literature, nor do we suppose that these questions can be answered properly. That is why we decided to use the above mentioned approach based on eliminating ex post from the model the variables with excessive VIFs.

Considering the fact, that 5 different sets of lags of $\boldsymbol{X}_{i,t-k}, i = 1,2,3$ were considered ($k = 0,1,2,3,4$) and three above described approaches (averaging, frequentist, frequentist with collinearity correction) were tested, a total of 15 model structures were found. For every k and approach, firstly the equation (2a) was BMA-estimated and the theoretical values of GDP_t were found. In the case of frequentist approach, those were the theoretical values of GDP from a single equation with "BMA-selected" economic situation indicators and the lagged GDP (having additionally eliminated the statistically collinear indicators in the collinearity corrected frequentist approach). In the case of the averaging approach, averaged parameter estimates for each regressor were found from all the estimated M_j's and those were used as is a single equation had been estimated with all the considered regressors to attain the theoretical GDP. Then the process was repeated for the equation (2b), except that the theoretical GDP from (2a) was used as one of the regressors (for each of the three considered approaches, theoretical GDP obtained with the same approach applied to equation 2a was used). Finally, the same process was applied to equation (2c), while theoretical GDP from (2a) and theoretical unemployment rate from (2b) were additionally used as independent variables.

In all the Bayesian averaging models we decided to use only the prognostic variables from the tendency survey time series. Due to computational complexity of those methods but also research question oriented on forecasting, we decided to omit the indicators which were describing the current state of economic affairs or merely assessing the current climate.

With such an approach we were able to significantly reduce the amount of computations required to obtain the results.

3.2. Dynamic factor models – modelling strategy

Application of dynamic factor models to forecasting of macroeconomic time series has been already extensively developed in the literature (Baranowski et al., 2010; Boivin & Ng, 2006; Reijer, 2012; Stock & Watson, 2002, among others). Nevertheless, with minor exceptions it has been rarely focused on defining the dynamic factors with tendency survey data (Frale, Marcellino, Mazzi, & Proietti, 2010; Hansson, Jansson, & Löf, 2005; Kaufmann & Scheufele, 2013). However, it should be underlined that dynamic factor models have significant advantages over other approaches to modelling. Breitung & Eickmeier (2006) enumerate advantages of dynamic factor approach which can be summarized in following points: (1) Factor models can cope with many variables without running into low number of degrees of freedom, which can be often the case when we want to employ a lot of variables in a regression based modelling[3]; (2) In factor models idiosyncratic movements of specific variables, which possibly include measurement error and local shocks, can be eliminated; (3) with application of dynamic factor models it is possible for modellers to remain agnostic about the structure of the economy and do not rely on different assumptions, which is often the case in structural models.

With regards to forecasting, an especially important advantage of using dynamic factor models is elimination of noise from the data. Hansson et al. (2005) claim that idiosyncratic processes that are present in different sectors are probably rather not relevant to general economic processes in the economy. Eliminating them with factor approach might be of crucial importance, when the focus of analysis is on macroeconomic aggregates, which is the case in our analyses. We find dynamic factor models especially useful, as (see point 3 above) their structure and implied modelling strategy matches our initial assumptions regarding modelling with very limited influence of modellers on the forecasting process.

It needs to be taken into account that the dynamic factor models have also certain drawbacks. A disadvantage of common factor models is that factors are hardly (or even completely not) interpretable. Due to that, Stock & Watson (2002) suggest that they should be interpreted as diffusion indexes oriented on assessment of average economic activity.

[3] Time series models usually contain no more than 10 time series (Boivin & Ng, 2006; Stock & Watson, 2002). Even our approach based on Bayesian Averaging was constructed in such a way that the optimal number of time series in an equation should be around 6.

Naturally, there are also caveats associated with the number of indicators. Larger number of indicators is not always the most desirable case even in the dynamic factor specification. Boivin & Ng (2006) show that adding a series that is highly correlated with other series might reduce rather than improve efficiency of the factor estimates. On the other hand, adding a 'noisy' time series, that share little common variance with other series also reduces the efficiency of factor estimates, because the average common component becomes smaller. So, our goal in establishing the common factor was to pick diversified data from tendency surveys in our data set but at the same time eliminate series providing noise in the final factor solutions.

Regardless of the character of time series data used, the structure of dynamic factor model is similar. Starting point for the analysis is approximate factor model with K factors, which takes the form:

$$\mathrm{X}_t = \Lambda F_t + \varepsilon_t \text{ , where}$$

X_t represents (Nx1) vector of consumer and business tendency survey indicators (also composite indicators used in the analysis) measured at a given time point t, Λ is a matrix of factor loadings of dimension N x K, F_t is the K x 1 vector of period specific factor loadings, ε_t is a N x 1 vector of measurement errors in a given period.

Following the Stock & Watson (2002) approach we assume propose that the number of factors is determined based on the simple principal component approach.[4] Additionally, we assume that the number of factors is determined based on the standard Cattell criterion (Rószkiewicz, 2011). In order to eliminate from certain factors those variables which have very low factor loadings, assumption from other factor models was adopted that the loadings need to be salient, which was assumed to be over 0.5. Brown (2006) suggests range between 0.4 and 0.6 for factor models based on individual data, however we assume the mid of the interval as an appropriate for dynamic factors. A drawback of dealing with static factors only, is that the dynamic structure, which is likely to exist between the factors, might not be accounted for. In order to account for this possible dynamics, based on the obtained static factors, dynamic component was introduced. The dynamic factor model is an extended form of the static, where the factors are assumed to follow dynamic, autoregressive process:

4 Naturally, for extraction of the common factors, a different factor analytical approach can be used, like exploratory factor analysis. Nevertheless, differences in the results (factor loadings) between various factor analytical approaches are usually very small and thus this issue was not subject to profound analysis.

$$F_t = \Phi(L) F_{t-1} + \mu_t \text{, where}$$

$\Phi(L)$ is a lag polynomial describing the autoregressive structure of the data generating process of factors and μ_t describes the error. In our empirical approach, we assessed models with lag polynomial of the form: 1, L, L^2, L^3 and $1+L^3$, so we were interested in lags equal to 1,2,3,4 and 1 and 4 simultaneously. Selection of the appropriate lag is based on the Schwarz Information Criterion.

Final step of the analysis oriented on forecasting with dynamic factor models, is inclusion of dynamic factors into the forecasting process of economic variables of interest. Standard specification of a model with dynamic factors used as forecasting tools can be presented by the following system of equations (see Baranowski et al., 2010; Stock & Watson, 2002, among others)

$$y_t = \alpha + \sum_{m=1}^{L} \beta_m \cdot y_{t-m} + \sum_{n=0}^{L} \gamma_n \cdot F_{t-n} + \varepsilon_t \text{ , where}$$

y_t represents vector of macroeconomic variables of interest, α stands for a vector of constants, L is the number of lags included in the analysis, β_m is a vector of autoregressive coefficients standing by variables of interest lagged by m periods and γ_n is a vector of coefficients standing by dynamic factors lagged by n periods.

In our case due to the fact that we wanted to include interrelations between the current level of indicators, we followed a slightly modified approach. In our previous studies the established order in which macroeconomic variables should be related to each other is defined by equations (2a-2c). Inclusion of these interrelations between the macroeconomic variables results in a slightly modified framework with dynamic factors used for the forecasting purposes. Having $y_{t=}\,[GDP_t, UNE_t, CPI_t]^T$ but also additional assumptions that only one lag of the variable of interest is included in the equation for this variable and that dynamic factor estimates are taken only for a single quarter depending on the chosen lag (five possibilities of lags were checked k=0,1,2,3,4), our final model can be presented by the following system:

$$GDP_t = \alpha_{GDP} + \beta_{GDP} \cdot GDP_{t-1} + \gamma_{GDP,k} \cdot F_{t-k} + \varepsilon_{t,GDP,k}$$

$$UNE_t = \alpha_{UNE} + \kappa_{UNE} \cdot \hat{GDP}_t + \beta_{UNE} \cdot UNE_{t-1} + \gamma_{UNE,k} \cdot F_{t-k} + \varepsilon_{t,UNE,k}$$

$$CPI_t = \alpha_{CPI} + \kappa_{CPI,1} \cdot \hat{GDP}_t + \kappa_{CPI,2} \cdot \hat{UNE}_t + \beta_{CPI} \cdot CPI_{t-1} + \gamma_{CPI,k} \cdot F_{t-k} + \varepsilon_{t,CPI,k}$$

In the final specification, in the second equation (for UNE) estimated value of GDP for period t is included as exogenous variable, while in the third equation (for CPI) both estimates of GDP and UNE are included as exogenous variables. In addition to this, all dynamic factors are present in all equations.

Thus, although the variable selection procedure is significantly different, the modelling strategy implemented in the dynamic factor framework shares with Bayesian approaches the final structure of forecasting models, which serve as a tool for generating the final forecasts. However.

3.3. ARIMA models

A common procedure when constructing forecasting models and comparing forecasts provided by multiple approaches is to refer to basic models, i.e. time series models ARIMA (p, d, q). These models are a combination of autoregressive and moving average models. The idea of its design comes down to the statement that the timing of the past processes and shocks affect the results of the future. There is an extensive literature dealing with identification of ARIMA models and verification of their statistical properties (Box & Jenkins, 1976; DeLurgio, 1998; Enders, 1995; Kirchgässner, Wolters, & Hassler, 2013, among others). Although, with such an approach a good fit is usually obtained, they fail to identify and predict correctly turning points in time-series.

It is not our objective to critically assess the ARIMA type models. Nevertheless, it should be underlined that proper specification of a the model for a time series observations on a particular variable requires 3 parameters: the order of the autoregression process - p, the order of the moving average process – q, and the order of integration – d, which defines the number of times the time series is being differentiated. The degree of integration of the variable is the consequence of the search for stationarity of the time series. The quality of a ARIMA model is assessed on the basis of information criteria that allow, given the number of observations, the number of estimated parameters and the fit of the model, to select the model carrying the most information on the assessed process with reasonable number of estimated parameters.

The choice of p and q values is traditionally based on evaluation of the autocorrelation function and the partial autocorrelation function. Another method is to treat these functions as additional diagnostic tools and base the selection process on the general to specific approach for a given time-series. Practitioners claim that it is worth the search over (p, q) pairs for p, q = 0,1,2. A more complicated situation emerges in the case of seasonal treatment of the data because then the number of parameters of the process is increased twofold. The seasonal component is also assumed to follow AR and MA processes and might be also integrated of degree higher than 0. In the seasonal ARIMA model six parameters are estimated and the model is described with two sets of parameters (p, d, q) (P, D, Q) [4]. The first three parameters characterize the trend, while the other three parameters the seasonal fluctuations (the number - [4] - indicates only that we are dealing with a series of quarterly data and thus seasonality of such a frequency is expected).[5]

[5] Specialized computer packages offer automatic matching values at the criterion of maximizing the fit of the model to the data based on the information criteria. For example, the package R task can be performed using auto.arima (). In the following part of the paper we show that the automated matching of model parameters does not necessarily lead to obtain the model with the best predictive properties.

4. Estimation results

Following the adopted modelling strategy and based on the methodology presented in section 3, parameters of forecasting models have been estimated. The adopted procedure is consistent between Bayesian and dynamic factor models with respect to the treatment of endogeneous variables. Let us recall that the assumed recursive process of estimation is executed by estimating the first equation describing the growth rate of gross domestic product (GDP), in second place - the unemployment rate according to the Labour Force Survey (UNE) with predicted current GDP growth rate from the first equation and at the end the equation for the consumer price index growth (CPI) is estimated given the predicted values of GDP and UNE.

The parameters of the models both in the Bayesian and the dynamic factor approach were estimated in five specifications with tendency survey indicators (or dynamic factors obtained on the base of these survey indicators) lagged between zero and four quarters (k=0,1,2,3,4). The specificity of the tendency survey data collection implies that for a given quarter they are already present in the first month of the quarter, i.e. in January, April, July or October. The models with k = 0 implies the ability to forecast variables of interest for one quarter without taking any additional assumptions about the time series properties of regressors. The delay k = 1 implies that we are able to make forecasts of GDP, UNE and CPI for 2 quarters ahead. Then, for k = 2 the forecast for 3 quarters ahead, for k = 3 - 4 quarters ahead, and for k = 4 - 5 quarters ahead. Longer forecasting horizons were not subject to the analysis.

Modelling strategy implied presentation of the results, which is shown in the next section of the paper. Equations describing the variables GDP, UNE and CPI comprise a three equation system. Only in the case of ARIMA based forecasts the situation is different. In this case, the model for each endogenous variable is estimated separately. The parameters of all models were estimated for time series data from the first quarter of 1996. to the fourth quarter of 2012. Then the length of the time series was extended for another observation, and consequently generated forecast horizon also shifted by one quarter. This procedure was repeated for subsequent quarters.

4.1. Bayesian models

Due to considerable amount of estimates generated during the Bayesian averaging procedure, we decided to present only the set of regressors from the sets X in equations (2a)-(2c). In the BMA method, following the philosophy of this method, in each the three equations and for each lag k, the set of regressors from the tendency surveys was the same and comprised the following indicators (Appendix 2):

Ifo_be	gus2	gus4	gus7	gus11	ips_wo	biec_wwk	biec_wpi
biec_wrp	biec_wd	ind_q1f	ind_q2f	ind_q3f	ind_q4f	ind_q5f	ind_q6f
ind_q8f	hhs_q1	hhs_q2	hhs_q4	hhs_q6	hhs_q7	hhs_q9	hhs_q11

In the frequentist approach the set of regressors differed in models with collinearity correction (Appendix 4) and without it (Appendix 3).

Table 1 Variables in the GDP equations – frequentist approach

Regressor X_K	Time lag of regressors				
	k = 0	k = 1	k = 2	k = 3	k = 4
ifo_be			M C	M C	M C
gus2		M		M	
gus4		M C		M	
gus7				M	
gus11		M C	M C	M C	M C
ips_wo				M C	M C
biec_wwk		M C	M C	M C	M C
biec_wpi		M C	M C	M C	M C
biec_wrp		M C			
ind_q2f				M C	M C
ind_q3f	M C			M	M C
ind_q4f					M C
ind_q5f				M C	M C
ind_q6f				M	M C
ind_q8f	M C	M C	M C		
hhs_q1					
hhs_q2	M C	M C			
hhs_q4		M			
hhs_q6				M C	M
hhs_q7					M C
hhs_q9	M C		M C		

Own estimates. “M” – variable in model without collinearity correction; “C” – variable in model with collinearity correction.

Table 2 Variables in the UNE equations – frequentist approach

Regressor X_K	Time lag of regressors				
	k = 0	k = 1	k = 2	k = 3	k = 4
ifo_be				M C	
gus2			M		
gus4			M C		
gus7			M	M	
gus11	M C	M C	M C	M C	M C
ips_wo				M C	M C
biec_wwk			M	M	
biec_wpi	M C			M C	M C
biec_wrp	M C	M C		M	M
biec_wd			M C		
ind_q1f		M C	M C	M C	
ind_q2f	M C		M	M	M C
ind_q3f			M	M C	M
ind_q4f	M C			M C	M C
ind_q5f	M		M C		M C
ind_q6f			M C		M C
ind_q7f	M	M C			M
ind_q8f				M C	M C
hhs_q1				M C	
hhs_q2	M C		M		M
hhs_q4			M	M	M C
hhs_q6					
hhs_q7		M C		M C	
hhs_q9			M C		M C
hhs_q11			M C		M C

Own estimates. “M” – variable in model without collinearity correction; “C” – variable in model with collinearity correction.

Analysis of patterns of explanatory variables in the equations for macroeconomic variables enables to formulate the following conclusions:

- The cases with exactly the same the set of indicators for models with and without collinearity correction imply that the collinearity was not observed.
- The set of regressors depends on the lag (k). In the equations for GDP and CPI similarities are observed with in the sets: {k=0}, {k=1, k=2}, {k=3, k=4}, in the equations for UNE the sets are: {k=0, k=1}, {k=2, k=3, k=4}.
- A significant role is played by the regressors from consumer tendency surveys.
- The most frequently occurring indicators (except for the equation on GDP) are those of the Bureau of Investment and Economic Cycles - biec_xxx.

Table 3 Variables in the CPI equations – frequentist approach

Regressor X_K	Time lag of regressors				
	k = 0	k = 1	k = 2	k = 3	k = 4
ifo_be	M C				M C
gus2	M		M		
gus4	M C	M C			
gus7			M		M
gus11		M C	M C		
ips_wo					M C
biec_wwk				M	M
biec_wpi	M	M C	M		M C
biec_wrp	M	M C			M
biec_wd					
ind_q1f			M C		
ind_q2f		M C		M C	M C
ind_q3f		M C	M		M
ind_q4f					
ind_q5f		M C	M C		
ind_q6f		M C	M C	M C	M C
ind_q7f					
ind_q8f	M C		M C		M C
hhs_q1	M C				M
hhs_q2		M C			M
hhs_q4		M C		M C	
hhs_q6		M C	M C		
hhs_q7		M C	M C		M
hhs_q9		M C		M C	M C
hhs_q11					M C

Own estimates. “M” – variable in model without collinearity correction; “C” – variable in model with collinearity correction.

4.2. Dynamic factor models

In the dynamic factor framework all of the variables from tendency surveys were used with addition of composite indicators from tendency surveys in Poland and indicators of business climate in Germany. Following the most frequent approach we standardise our time-series (see e.g. Baranowski et al., 2010). Nevertheless, we do not use seasonally adjusted data. Following the procedure presented in 3.2. the first step of the analysis was oriented on extracting static factors from the indicators from tendency surveys. In order to do it, principal components analysis was executed on the set of 54 time series. The final solution, as we are not interested in orthogonal factors, was rotated with non-orthogonal algorithm Oblimin. Based on the Cattell criterion we chose to include three factors.

Following the adopted procedure, in the final set of indicators for each factor we chose only those indicators that were associated with factor loadings higher than 0.5. Indicators included in all three factors are given in the table below.

Table 4 Indicators of factors in the model

Factor 1	gus1 gus2 gus3 gus4 gus8 gus7 gus11 gus_wb gus_ww ips_wok ips_kg ips_sz ips_wb ips_wo biec_wrp biec_wd ind_q5f hhs_q1 hhs_q2 hhs_q3 hhs_q4 hhs_q7 hhs_q8 hhs_q9 hhs_q10 hhs_q11
Factor 2	pmi ifo_bc ifo_be ind_q1s ind_q1f ind_q2s ind_q2f ind_q3s ind_q3f ind_q6s ind_q6f ind_q7s ind_q7f ind_q8s ind_q8f constr
Factor 3	zew_ies ifo_bs gus1 gus2 biec_wwk biec_wpi biec_wrp ind_q1f ind_q2f ind_q3f ind_q4s ind_q4f ind_q5f hhs_q9 hhs_q12

The division of indicators clearly depicts that in the first static factor (Factor 1) mostly the indicators regarding the consumer confidence are present. Although they are gathered by different institutions (Central Statistical Office, Research Institute for Economic Development, IPSOS) they cover opinions of households regarding their financial situation, general economy, but also savings and intentions to make durable goods purchases. In addition there are two composite indicators of the Bureau of Investment and Economic Cycles (BIEC), which cover the predicted situation on the labour market but also wealth of households. Those indicators, although not purely based on tendency surveys, also describe areas important for the functioning of households. In Factor 2 industrial indicators are present. Almost all indicators from the survey of manufacturing industry conducted by the Research Institute for Economic Development are present in this factor, but also indicators of the climate in Germany measured by the Ifo institute. The indicators reflected by factor 2 are those that cover production, orders, employment, general situation among manufacturing firms, but also situation in the construction industry and also importantly, the PMI index for the Polish economy. Indicators in factor 3 are mostly selected from the set of general economic situation indicators (ifo_bs, biec_wwk, zew_ies), sector specific indicators concerning the most important area in the sector (households – financial situation gus1 gus2; companies – production: ind_q1f ind_q2f), but also an important role is played by indicators of prices (biec_wpi, ind_q5f) and stocks (ind_q4s, ind_q4f).

The second step of the procedure was to evaluate the dynamic structure of factors. In order to do so “dfactor” procedure in Stata was applied with different orders of autoregressive process in the error component of the factor. For all of the factors, the model was selected from the set of AR(1), AR(2), AR(3), AR(4) and AR(1,4). The models were assessed based on the BIC criterion and the results are presented in table below.

Table 5 BIC values for different orders of autoregressive process in models for factors

	AR(1)	AR(2)	AR(3)	AR(4)	AR(1,4)
Factor 1	**2788.776**	2835.302	2855.008	2867.897	2792.78
Factor 2	2250.814	2293.23	2312.831	2322.311	**2250.672**
Factor 3	2672.938				**2672.528**

Note: with resepect to Factor 3, estimation of models AR(2), AR(3), AR(4) was not successful.

With respect to Factor 1, the best specification proved to be autoregressive of order 1, but with respect to Factor 2 and 3 also information lagged by 4 quarters seemed to be of crucial importance. The results of estimation of the dynamic part of the factor model are presented below, while the exact data on the factor structure of each factor are given in Appendix 5.

$$Factor1_t = \underset{(0.050)}{0.917} \cdot Factor1_{t-1} + \mu_{1,t}$$
$$Factor2_t = \underset{(0.073)}{0.962} \cdot Factor2_{t-1} - \underset{(0.072)}{0.161} \cdot Factor2_{t-4} + \mu_{2,t}$$
$$Factor3_t = \underset{(0.065)}{1.132} \cdot Factor3_{t-1} - \underset{(0.070)}{0.176} \cdot Factor3_{t-4} + \mu_{3,t}$$

The results indicate that the autocorrelation of all the dynamic factors is very strong, which indicates that the changes in the factor are propagated slowly. In Factors 2 and 3, where factor lagged by 4 quarters is present, it has always a corrective character.

The final step in the process of generating forecasts, was associated with inclusion of dynamic factors into the forecasting framework of GDP, UNE and CPI. We estimated all the models in five different specifications (for lags of dynamic factors ranging from 0 to 4) and the results are provided in Appendix 5. Regarding the equation for GDP, only the dynamic factor 3 seems to be significant at the 0.1 level in the assumed direction[6] in the equation with dynamic factors lagged from 0 to 2 quarters. In specifications with higher lags all the

6 Assessing the factor loadings it can be noticed that Factors 1 and 2 are positively oriented – the better the business condition indicators, the higher the value of the factor - and Factor 3 is negatively oriented.

factors are not significant. It shows that in the GDP data, much more significant role of autoregressive processes is observed and factors resulting from the common variation of tendency survey data are not so important. With regards to unemployment forecasts the role of dynamic factors is significantly larger. Naturally, in all specifications it is visible that the higher the GDP growth the lower the expected rate of unemployment. Nevertheless, in specification with dynamic factors contemporaneous, lagged by 1 and lagged by 2 quarters, factors 1 and 3 appeared to be significant and of expected sign. In specification with dynamic factors lagged by 3 quarters factor 2 is significant and of expected sign and in specification with dynamic factors lagged by 4 quarters only factor 3 is significant. Finally, in the equation for CPI higher GDP growth rate is likely to correlate with higher inflation and lower unemployment is likely to result in higher inflation. However, the latter relation which can be associated with the Phillips curve (Phillips, 1958) is likely to be present only in the specification with contemporaneous dynamic factors. In this specification it is also visible that better business climate reported by higher values of factors 1 and 2 and lower value of factor 3 is likely to reduce inflation. Although it seems counterintuitive, it is supported by the results of Białowolski (2014) showing that inflation expectations are strongly and consistently influenced by the economic sentiment. Factors 2 and 3 remain significant in the same direction also in the specification with dynamic factors lagged by 1 quarter. In specifications with dynamic factors lagged by 2,3 and 4 quarters, only factor 2 is significant at the 0.1 level.

4.3. ARIMA models

Models for GDP, UNE and CPI in ARIMA specification were estimated. With application of model selection procedure based on the Schwarz information criterion (BIC) the following specifications were obtained as the best ones:[7]

GDP: ARIMA(2, 0, 0) and ARIMA(2, 0, 0)(0, 0, 1)[4];

UNE: ARIMA(1, 1, 3)

CPI: ARIMA(2, 1, 3)(0, 1, 0)[4].

One of the models for GDP (ARIMA(2, 0, 0)(0, 0, 1)[4]) was identified by the procedure auto.arima() in R package as the one best fitting the data. Nevertheless, later we will show that basic approach from general to specific is likely to generate autoregressive models with more exact forecasts than those of the model generated automatically.

[7] Detailed results of are presented in Appendix 6.

5. Forecasting

5.1. Assessment of the in-sample performance

It seems that there is an analogy between the kind of technical analysis used on assessment of the financial market performance and views reflected in business surveys. One argument in favour of using technical analysis to predict future trends on the stock market and changes in the prices of shares is the hypothesis that the market tends to act ahead of actual events and that massive stock exchange trends precede real macroeconomic developments. It is consequently possible to venture a statement that opinions reflected in respondents participating in a business survey create a platform for an exchange of views about the future course of economic processes, and that these views may precede economic trends allowing those surveyed to act ahead of what is expected to happen in the future.

In order to assess the performance of the model for GDP, UNE and CPI, we compare the results in terms of how well they fit the data. We determine the root mean square errors (RMSE) for individual quarters of 1997-2012 treating the theoretical values of the endogenous variables as ex post forecasts (Table 6). In the case of analysis of RMSE for the period 1997q1 – 2012q4 it is possible to assess the fit of the model by comparing empirical and theoretical values of the endogenous variables.

The RMSE values are expressed in the same units of measurement as each endogenous variable. In our case, these units are percentage points. The way in which the model results reproduce past data seems to be satisfactory. The values given in Table 4 show that:

- Ex post forecast accuracy for quarters 1997-2012 is higher in the averaging approach than in the adopted frequentist approach,
- For k>2 it is visible that the collinearity correction seems to positively affect accuracy of forecasts in the frequentist approach,
- Higher lags of tendency survey data do not result in increased volatility of forecasts,
- The forecasts with the dynamic factor framework seem to be placed in the middle – they are better than those generated with the averaging approach but worse than those produced with the frequestist one.

The in-sample forecast accuracy of ARIMA models measured with RMSE is better than with the averaging approach but was worse than that of models estimated with the frequentist one. The forecasts of GDP and UNE generated by ARIMA approach are better than those obtained with the dynamic factor models but with respect to CPI they are inferior.

Table 6 Root mean square errors for quarters 1997-2012

Regressand	k = 0	k = 1	k = 2	k = 3	k = 4
	Time lag of regressors				
	Bayesian averaging approach				
GDP	1.6	1.2	1.1	1.2	1.0
UNE	1.5	1.6	1.4	1.6	0.8
CPI	2.6	1.0	0.8	1.4	1.1
	Bayesian frequentist approach without collinearity correction				
GDP	0.8	0.7	0.8	0.7	0.8
UNE	0.6	0.6	0.6	0.6	0.5
CPI	0.6	0.6	0.6	0.6	0.5
	Bayesian frequentist approach with collinearity correction				
GDP	0.8	0.7	0.8	0.8	0.8
UNE	0.7	0.6	0.6	0.6	0.6
CPI	0.7	0.6	0.7	0.7	0.6
	Dynamic factor models				
GDP	0.9	0.9	0.9	0.9	0.9
UNE	0.8	0.8	0.8	0.8	0.9
CPI	0.7	0.7	0.7	0.7	0.7
	ARIMA models				
GDP	0.886 [0.872]				
UNE	0.5				
CPI	0.9				

Own estimates.

The same comparison is also performed for the quarters of 2013 and 2014 (Table 7 and Appendices 7-10), with the only difference that the values of endogenous variables were generated as forecasts from the estimated models for different lags of tendency survey data. There were however differences with respect to the forecasting ability between frequentiest, averaging approach and the forecasts generated from the dynamic factor models. In the first and third approach, stepwise forecasts were obtained without model reestimation, while in the second the models have been reestimated in both variants – with and without collinearity corrections, yet the set of independent variables selected for the model in this frequentist approach was all the way the same, selected on the basis of the firstly performed procedure of selection with the use of the data that ended in the fourth quarter of 2012. It might be noted that the quality of in-sample forecasts in the equation for GDP estimated in the ARIMA specification with the procedure auto.arima() from the R package is worse (RMSE=0.9) than the forecast obtained in the ARIMA specification but with general to specific approach (RMSE=0.5). Although ARIMA models have similar forecasting errors as other approaches, it needs to be remembered that with application of these model it is possible to predict only 1 or 2 quarters ahead.

5.2. Assessment of the out-of-sample performance

Comparison of the forecasted values for time span ranging from the 1st quarter 2013 to the 1st quarter 2014 should be preceded by in-depth explanation. It has been already stated that the prognostic models were estimated based on data ranging from the 1st quarter 1996 to the 4th quarter 2012. With such an approach, depending on the assumed lag of dependent variables, it was possible to obtain forecasts for GDP, UNE and CPI for the 1st quarter 2013 (k=0) up to 1st quarter 2014 (k=4). The quality of forecasts was assessed with RMSE for the models obtained in the Bayesian approach. It appeared that the forecast error in the averaging approach for the CPI amounted to 4.39, while in the frequentist approach without collinearity correction – 0.93 and with collinearity correction – 0.73. The forecast error in the averaging approach is not acceptable and thus all the forecasts obtained in this approach were excluded from further analyses.

Consequently, forecast errors in frequentist approach and those obtained with dynamic factor models were compared (table 7). Assuming that the last quarter of data used for the estimation purposes was 4th quarter 2012, the values of RMSE obtained for 15 forecasted values, depending on the assumed lag k. For the forecasts generated with that the last quarter of observations was in the 1st quarter of 2013, 15 forecasts were obtained, when the last observed data were from the 2nd quarter 2013 – 12 forecasts were obtained, when the last observed data were from the 3rd quarter 2013 – 9 forecasts were obtained; when the last observed data were from the 4th quarter 2013 – 6 forecasts were obtained; when the last observed data were from the 1st quarter 2014 – 3 forecasts were obtained.

Table 7 Root mean square errors for quarters 2013 and 2014

Regressand	Last period of data				
	2012q4	2013q1	2013q2	2013q3	2013q4
	Bayesian frequentist approach without collinearity correction				
GDP	0.71	0.95	1.01	0.68	0.39
UNE	1.27	1.97	1.03	0.35	0.57
CPI	0.93	1.01	1.60	0.69	0.27
	Bayesian frequentist approach with collinearity correction				
GDP	0.65	0.79	1.01	0.68	0.42
UNE	1.06	1.89	1.19	0.51	0.56
CPI	0.73	0.55	0.97	0.35	0.18
	Dynamic factor models				
GDP	0.59	0.68	1.01	0.68	0.42
UNE	1.64	2.62	1.19	0.51	0.56
CPI	0.64	0.46	0.97	0.35	0.18

Own estimates.

Among the three groups models assessed with respect to their out-of-sample forecasting performance it seems that Bayesian models based on the frequentist appraoch with collinearity correction generated the most accurate forecasts. Only a slightly lower accuracy of forecasts measured with RMSE was obtained with application of the dynamic factor models. It might be noted that the forecasts of all models converge (difference in the forecast accuracy measured with RMSE between different models decreases) when we go further away from the last quarter used in the estimation sample (4th quarter 2012).[8]

A slightly different perspective can be gained from comparing the number of overestimated (positive forecast error) and underestimated forecasts (negative forecast error). Comparison of signs of forecasting errors for all possible forecasts generated at a given time point is only possible for the forecasts with the final period of observed data in the 4th quarter 2012.[9] There has been 15 forecasts made (see table 9) for each value of lag

[8] It is extremely interesting that forecasts obtained from the models using frequentist approach with collinearity correction and those obtained with dynamic factor models are identical for the calculations conducted under assumption that the last period of data is 2nd quarter 2013, 3rd quarter 2013 and 4th quarter 2013.

9 For the forecasts based on data exceeding this time point, the number of forecasts exceeds the number of accessible realizations. The last observed values of GDP, CPI and UNE relate to the 1st quarter 2014.

associated with exogenous variables used (k = 0,1,2,3,4). The forecasts have been made for quarters 2013q1 – 2014q1. The results of are summarised in table 8.

Table 8 Signs of errors in forecasts for the quarters 2013q1-2014q1

	Last period of data 2012q4 positive errors / negative errors			
Regressand	Bayesian averaging approach	Bayesian frequentist approach without collinearity correction	Bayesian frequentist approach with collinearity correction	Dynamic factor models
GDP	3/12	5/10	6/9	9/6
UNE	2/13	11/4	11/4	10/5
CPI	6/9	11/4	13/2	13/2

Own estimates.

The forecast errors appear to be systematic. Although the situation was not standard (forecasts are generated for five dfferent lags of regressors and the number of generated forecasts is small) and did not allow for the use of standard randomness tests based on the number of series, but even without formal testing, it is clearly visible that almost in all cases a majority of either overestimated or underestimated forecasts is obtained.

5.3. Raw forecasts and combined forecasts of GDP, UNE and CPI

Forecast errors presented in Table 7 indicate that their accuracy is far from being perfect. In the Bayesian approach the scale of the errors of forecasts for all regressands is similar. In this case, it is difficult to justify the superiority of the approach with the collinearity correction.

Based on the estimates of ARIMA models dynamic forecasts have been made. This procedure does not require adoption of any additional assumptions regarding the lagged values of regresands. It is assumed that their values necessary to obtain forecasts are predicted based solely on their previous values. This approach to forecasting results sometimes in accumulation of forecast errors especially in the vicinity of turning points, as the previous values and trends determine predictions. In the case of our forecasting exercise with ARIMA models, they predictions do not clearly outweigh the accuracy of forecasts from other types of models. However, forecasts of the CPI variable obtained from the ARIMA model are unacceptable.

In this paper we present only the point forecasts. We do not report confidence intervals for our predictions because we believe that their usefulness is limited due to complicated form of presentation and limited audience able to understand their outcomes.[10] When a considerable number of point forecasts is obtained problem of aggregation arises. In the proposed methodological approach, in each of the model families with a given lag k, we obtain 15 different forecasts. As an example (in Table 9) we present forecasts of given endogenous variable (CPI) based on a model estimated on data with the last quarter of observation being the 4th quarter 2012. There are five different forecasts obtained for the 1st quarter 2013, which are based on different models. Hence, in a further step an average of them could have been calculated for a given quarter of forecasts. Subsequently, If the forecasting exercise would have been conducted repeatedly, the optimal lag k could have been established with respect to their validity.

Table 9 CPI forecasts from DFM model

	Last period of data 2012q4. Forecast for:				
Regressand	2013q1	2013q2	2013q3	2013q4	2014q1
k = 0	1.97				
k = 1	2.07	1.50			
k = 2	1.92	1.40	1.10		
k = 3	1.95	1.19	0.92	0.80	
k = 4	2.07	1.54	1.15	1.03	1.,01

Own estimates

Even a brief look at the model results presented in Appendices 8 and 9 leads to a conclusion that forecasts generated by different models are not consistent. Given the lag k=4 which enables forecasts for five quarters ahead we were able to compare predicted and actual values of GDP, UNE and CPI for the time span from the 1st quarter 2013 to the 1st quarter 2014.[11]

10 Further research might benefit from constructing confidence intervals for multi-period forecasts (Kamiński & Koloch, 2011).

11 The values are presented in Table 10, in which we conduct comparisons between forecasts of different academic forecasters.

After a series of forecasts has been made with time series extended each time by one observation, forecasted value for a given time point is obtained many times given a model with predetermined lag k=k*. Due to this, there is a possibility of taking into account many forecasts for a given time point, obtained at different moments. In order to combine the information of all accessible forecasts to a single value, an aggregation procedure needs to be developed.

The structure of accessible forecasts is presented in tables in appendices 8-10. Regarding GDP forecast for the 1st quarter 2014 we were able to assess its accuracy due to the fact that the real values have been already published. For the first time it has been forecasted in the model with last observation of data in the 4th quarter 2014, when the lag order was assumed to be k=4. In the following step, when information regarding the 1st quarter 2013 was already at hand, two forecasts were accessible (for k=3 and k=4). Finally, when the data up to the 4th quarter 2013 were gathered, forecast for the 1st quarter 2014 was executed with k=0,1,2,3,4. Consequently, having the information gathered up to the 4th quarter 2013, we were able to obtain 15 forecasts obtained in five different quarters.

In the process of aggregation of the forecasts obtained in different periods weights are applied. They should be non-negative real numbers with sum equal to one. It is also assumed that the forecast made in period t for a given quarter is more important than forecast made at period t-1. Finally, it is assumed that the second derivative of a weight with respect to t is nonnegative. The last condition is driven by the assumption that the difference in importance between the information from time point t and information from point t-1 is at least as high as the difference in importance between the information present at t-1 and that present at t-2. A family of weight functions fulfilling this condition can be shown (Czerwiński & Guzik, 1980). The most popular are harmonic, linear and exponential weights. The weights are usually described by a sequence of m observations ordered with respect to t (t=1,2,…,m) given the following formulas:

- harmonic weights $\boldsymbol{w_t^m = w_{t-1}^m + \frac{1}{m(m-t+1)}}\ , \mathbf{t = 1, 2, \ldots, \boldsymbol{m};\ \boldsymbol{w_0^m} = 0}$;

- linear weights $w_t^m = \frac{2t}{m(m+1)}\ , \mathrm{t} = 1,2, \ldots, m;$

- exponential weights $w_t^m = \frac{(1-q)q^{m-1}}{1-q^m}\ , \mathrm{t} = 1,2, \ldots, m;\ 0 < \mathrm{q} < 1.$

Growth of harmonic weight are proportional to the difference between m and t. Differences in the linear specification of weights are constant. Differences of exponential weights grow with the growth of t. Exponential weights have an additional important feature. By taking an adequate value of q, the decline of importance of observations from older periods can be managed.

Table 10 comprises the information regarding the process of aggregation of forecasts regarding GDP, UNE and CPI values for the 1st quarter 2014 under three different assumptions regarding weights. The aggregation procedure was two step. During the first step, all the values of forecasts obtained at a given time point were averaged. In the following step forecasts from different quarters were aggregated with specially designed weights. The averaging procedure for all forecasts obtained in a given quarter was based on arithmetic average with weight equal from 1, 1/2, 1/3, 1/4 to 1/5. Due to the fact that the oldest forecast is a single one and was calculated five quarters earlier and taking into account that with the most recent data there are five forecasts for the nearest quarter, five weights are required. For exponential weights the value q=0.2 was selected, which implies much lower importance of older forecasts.

The aggregated forecasts are close to the real statistical estimates of the proposed macroeconomic variables. In the 1st quarter 2014 the value of GDP amounted to 3.4, the unemployment rate was equal to 10.6 and the inflation was at the level 0.6. Forecasts regarding the 2nd quarter were done before even preliminary information regarding GDP, UNE and CPI was released. It needs to be underlined that aggregated forecasts derived from different types of models do no differ significantly.

Finally, we want to compare our forecasts with forecasts obtained in similar forecasting conditions by other institutions providing forecasts.

Table 10 Forecasts for quarters 2014q1 and 2014q2

Regressand	Weights: Harmonic		linear		Exponential	
	2014q1	2014q2	2014q1	2014q2	2014q1	2014q2
	Bayesian frequentist approach without collinearity correction					
GDP	2.91	3.74	2.76	3.71	3.29	3.78
UNE	10.69	10.43	10.89	10.51	10.23	10.29
CPI	0.22	0.55	0.16	0.54	0.44	0.59
	Bayesian frequentist approach with collinearity correction					
GDP	2.91	3.68	2.75	3.65	3.28	3.70
UNE	10.66	10.34	10.83	10.41	10.25	10.22
CPI	0.52	0.74	0.46	0.76	0.67	0.65
	Dynamic factor models					
GDP	2.92	3.72	2.77	3.65	3.28	3.81
UNE	10.86	10.60	11.14	10.66	10.26	10.56
CPI	0.51	0.75	0.45	0.75	0.67	0.72
	Weights					
Harmonic		0.04	0.09	0.16	0.26	0.45
Linear		0.07	0.13	0.20	0.27	0.33
Exponential		0.00	0.01	0.03	0.16	0.80

Own estimates

5.4. Comparative evaluation of forecasts

To evaluate forecasts obtained in our study, we decided to confront them with forecasts of two important institutes. Gdańsk Institute for Market Economics (IBnGR) regularly publishes its forecasts in reports on the „State and Forecast of the business climate in Poland". The second source of data were the data from the National Bank of Poland Survey of Professional Forecasters but also forecasts in cyclical projections of inflation and growth based on the NECMOD model, which have been carried out in the Economic Institute of the National Bank of Poland. The only drawback of the data used for comparisons is that the Gdańsk Institute for Market Economics does not provide forecasts with respect to the Labour Force Survey methodology (only registered unemployment), in the NBP Survey of Professional Forecasters we were able to compare only the pace of GDP growth, while the third source enabled full comparability of results. In the projections from the NECMOD model quarterly forecasts of all variables of interest are reported and they are released at the same period as the forecasts from our study (Bayesian and dynamic factor based) could have been reported.

In order to conduct comparisons, forecasts published on 11th March 2013 by the Economic Institute of the National Bank of Poland were chosen. The number of quarters in the forecast is equal to five and covers the period from the 1st quarter 2013 to the 1st quarter 2014. Forecasts published by the Gdańsk Institute for Market Economics were published on 5th February 2013 and thus they were based probably on earlier data which might affect their accuracy. The values of basic macroeconomic indicators and forecast errors are presented in Table 11.

Based on the obtained results it might be noticed that accuracy of forecasts obtained with Bayesian approach and dynamic factor models is not lower than the forecasts from the NECMOD model. It is however an advantage of our approach that the forecasts are automated, while the procedure in NECMOD is based on subjective assumptions concerning economy made by forecasters during the process.

Table 11 Forecasts for quarters 2013 and 2014

Regressand	2013q1	2013q2	2013q3	2013q4	2014q1	RMSE
			Quarter			
	Bayesian frequentist approach without collinearity correction					
GDP	0.07	0.66	1.58	1.88	2.26	0.67
UNE	10.94	11.66	11.40	12.01	11.68	1.44
CPI	1.33	0.99	0.86	0.95	0.89	0.30
	Bayesian frequentist approach with collinearity correction					
GDP	-0.05	0.64	1.31	1.66	1.94	0.89
UNE	10.51	11.06	10.98	11.23	11.52	1.03
CPI	1.70	1.29	0.98	0.92	0.87	0.43
	Dynamic factor models					
GDP	1.01	1.34	1.64	2.01	2.33	0.70
UNE	10.78	11.52	12.57	12.55	12.84	1.98
CPI	2.07	1.54	1.15	1.03	1.01	0.63
	ARIMA models					
GDP	0.96	1.65	2.42	3.09	3.59	0.53
UNE	11.00	10.40	10.70	10.50	10.60	0.52
CPI	2.00	0.90	-0.20	-0.40	-1.10	1.15
	Economic Institute NBP					
GDP	0.9	1.2	1.3	1.7	2.2	0.82
UNE	10.7	-	11.0	-	11.8	1.04
CPI	1.9	1.4	1.7	1.6	1.7	0.84
	IBnGR					
GDP	0.5	0.5	1.9	2.3	-	0.26
CPI	2.3	2.3	2.5	2.6	-	1.57
	Real					
GDP	0.4	0.8	2.0	2.7	3.4	
UNE	11.3	10.4	9.8	9.8	10.6	
CPI	1.3	0.5	1.1	0.7	0.6	

Own estimates and Economic Institute NBP

6. Concluding remarks

This paper is a follow-up to our previous research conducted in 2010 - 2013. In this study, we construct a prognostic model for three key macroeconomic indicators: GDP growth, the unemployment rate and the consumer price index. We use four approaches. Two of them comprise a variation of Bayesian averaging methods ("averaging" and "frequentiest" approach) and the third one is the result of dynamic factor approach. The last from the list is ARIMA approach. In all models we use the set of indicators from tendency surveys. The way in which the business and consumer sentiment indicators are collected but also approach in which lagged values of tendency survey data are used as regressors enables to generate forecasts without any additional assumptions regarding their values. Such an approach eliminates from the estimation process all subjective assumptions made by forecasters regarding economic processes in the economy. It might be stated that forecaster's intuition is replaced by aggregated intuition present in the business and consumer tendency survey data.

We confront the forecasts from the Bayesian approaches with those obtained from dynamic factor model. The results show the best performance of the "frequentist", which is characterized by the lowest in sample and out of sample root mean square errors. The differences in forecasting error between the Bayesian approach and the dynamic factor models is very small, which suggests similar forecasting efficiency of both approaches. It is especially confirmed by very narrow differences in aggregated forecasts for the 1st and the 2nd quarter 2014.

It is worth underlining that parameters of all prognostic models were estimated based on observations of time series up to the 4th quarter 2012. Over the next six quarters the models have not been re-estimated and kept the forecasting ability comparable to other forecasting approaches.

An important feature of our approach is that the forecasting procedure can be mostly automated and the influence of subjective decisions made in the forecasting process can be significantly reduced. It seems that the proposed forecasting methods combine methodology of statistics and econometrics with data mining approach.

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Appendix 1. Description of variables used in the analysis

spingd – households final consumption expenditure index,
nakinw – investment outlays index,
eksptiu – exports of goods and services index,
imptiu – imports of goods and services index,
wdb_xxx – gross value added in xxx sector index (xxx = industry, construction, trade, transport and storage, accommodation and catering, information and communication, financial and insurance activities, real estate activities, professional an scientific activities, administrative and support service activities, public administration and defence, education, human health and social work activities, arts and entertainment, other service activities),
gus_xxx – balance of responses to question 'xxx' from a consumer sentiment survey CSO (Table 2),
gus_wb – current consumer confidence indicator (CSO),
gus_ww – leading consumer confidence indicator (CSO)
ips_wok – consumer sentiment indicator (IPSOS),
ips_kg – economic climate indicator (IPSOS),
ips_sz – advantage to make purchases indicator (IPSOS),
ips_wk – current consumer confidence indicator (IPSOS),
ips_wo – leading consumer confidence indicator (IPSOS),
zew_ies – ZEW indicator of economic sentiment,
ifo_bs – Ifo business situation indicator,
ifo_be – Ifo business expectations indicator,
biec_wwk – BIEC leading index,
biec_wpi – BIEC future inflation index,
biec_wrp – BIEC future unemployment rate index,
biec_wd – BIEC well-being index,
pmi - Purchasing Managers’ index (PMI) for Polish industry,
ind_xxx - balance of responses to question 'xxx' from a business sentiment survey in industry RIED (Table A1),
hhs_xxx - balance of responses to question 'xxx' from a consumer sentiment survey RIED (Table A2),
trade - business sentiment indicator RIED in trade,
agri - business sentiment indicator RIED in agriculture,
cons - business sentiment indicator RIED in construction.

Table A1 Questions from the business sentiment survey in industry

Symbol	Question (ind_xxs – current state, ind_xxf – projection)
ind_q1	Production
ind_q2	total orders
ind_q3	export orders
ind_q4	stock of finished products
ind_q5	prices of goods produced by enterprise
ind_q6	Employment
ind_q7	financial standing
ind_q8	Poland's macroeconomic performance
Business sentiment survey in industry, Research Institute for Economic Development, Warsaw School of Economics	

Table A2 Questions from the consumer sentiment survey CSO & RIED

Symbol	Question
hhs_q1, gus1	Assessment of household financial status, compared with the situation 12 months earlier
hhs_q2, gus2	Projected household financial status in the next 12 months
hhs_q3, gus3	Performance of the Polish economy in the last 12 months
hhs_q4, gus4	Projected performance of the Polish economy in the next 12 months
hhs_q5	Comparison of maintenance costs now and 12 months earlier
hhs_q6	Projection for the inflation rate in the next 12 months
hhs_q7, gus7	Projection for the unemployment rate in the next 12 months
hhs_q8, gus8	An advantage to make major purchases at the present time
hhs_q9	Projected spending on durable consumer goods over the next 12 months in relation to the level reported in the last 12 months
hhs_q10	Assessment of savings and the climate for saving in the context of the country's macroeconomic performance
hhs_q11,gus11	Projected household's saving in the next 12 months
hhs_q12	Financial position of the household
Survey of households, Central Statistical Office, Research Institute for Economic Development, Warsaw School of Economics	

Appendix 2. Parameters of Bayesian models – averaging approach

k oznacza opóźnienie czasowe zmiennych z danymi z testów koniunktury

Zmienne	k=0			k=1			k=2			k=3			k=4		
	gdp	une	cpi	gdp	une	cpi	gdp	une	cpi	gdp	une	cpi	gdp	une	cpi
ifo_be	0,056	0,017	0,009	−0,006	0,043	−0,019	−0,054	−0,026	0,012	−0,039	−0,051	−0,011	−0,039	0,003	0,039
gus2	−0,002	−0,062	−0,082	−0,030	−0,075	0,009	0,055	−0,031	0,055	0,049	−0,014	−0,016	−0,012	0,044	0,009
gus4	−0,040	−0,005	−0,023	−0,053	0,022	−0,009	−0,012	−0,039	−0,043	0,003	0,007	−0,019	0,014	0,015	−0,024
gus7	−0,010	−0,005	−0,017	−0,017	0,005	0,010	0,007	−0,014	0,046	0,014	−0,025	−0,009	0,004	0,001	−0,016
gus11	0,014	−0,044	0,021	0,028	−0,057	0,029	0,027	0,003	0,025	0,025	−0,020	0,013	0,026	−0,039	0,039
ips_wo	−0,014	0,020	−0,019	−0,001	0,012	0,009	−0,018	−0,004	0,042	0,001	0,022	−0,005	−0,005	0,021	0,020
biec_wwk	0,000	−0,012	0,009	−0,044	−0,034	0,012	−0,044	−0,035	0,029	−0,034	−0,029	0,051	−0,029	−0,018	0,012
biec_wpi	−0,024	−0,081	0,124	−0,136	−0,021	0,123	−0,173	0,001	0,172	−0,112	0,023	−0,030	−0,065	−0,035	−0,057
biec_wrp	0,049	0,030	0,034	0,050	0,097	0,030	0,045	0,016	0,059	−0,004	0,026	0,006	−0,046	0,000	−0,059
biec_wd	−0,012	−0,018	−0,046	−0,042	−0,021	−0,041	−0,040	−0,073	−0,007	−0,040	−0,037	0,009	−0,047	0,016	0,022
ind_q1f	0,013	0,013	−0,008	−0,023	−0,080	0,002	−0,028	0,058	−0,001	−0,013	0,031	0,019	−0,003	−0,023	0,041
ind_q2f	0,035	−0,057	−0,015	0,048	0,063	0,018	−0,012	0,008	0,018	−0,037	0,031	−0,008	−0,030	−0,047	−0,002
ind_q3f	0,027	0,019	−0,044	−0,013	−0,026	0,003	−0,020	−0,029	0,003	−0,010	−0,006	0,020	0,005	0,035	−0,011
ind_q4f	−0,020	0,069	−0,044	0,017	−0,033	−0,027	0,016	0,005	−0,019	0,037	0,102	−0,011	0,074	0,079	0,018
ind_q5f	0,015	0,060	0,016	0,028	−0,040	0,018	0,019	−0,042	0,029	−0,038	−0,008	0,026	−0,043	0,052	−0,007
ind_q6f	0,031	−0,024	−0,013	0,025	−0,033	−0,030	0,019	−0,015	−0,038	0,009	−0,004	−0,048	0,034	−0,047	−0,043
ind_q7f	0,059	−0,082	−0,049	−0,036	0,058	−0,002	0,037	−0,007	0,003	0,023	0,003	0,012	−0,015	−0,067	0,021
ind_q8f	0,026	0,024	−0,006	0,023	0,002	−0,006	0,020	−0,005	−0,026	0,014	0,024	−0,006	0,016	0,026	−0,001
hhs_q1	0,029	0,005	0,013	0,024	−0,029	−0,021	−0,008	0,022	−0,007	0,002	−0,014	−0,014	−0,007	0,022	−0,028
hhs_q2	0,036	−0,018	−0,007	0,046	0,032	0,025	0,001	−0,025	−0,038	−0,010	−0,009	−0,022	−0,019	−0,068	0,048
hhs_q4	0,002	0,022	−0,008	0,036	−0,002	−0,020	0,027	0,033	−0,009	0,014	−0,004	−0,004	0,006	0,036	−0,004
hhs_q6	0,013	0,008	0,019	−0,009	−0,011	0,030	−0,015	0,004	0,025	−0,032	−0,009	0,033	−0,032	0,010	0,008
hhs_q7	0,002	0,008	0,009	0,006	−0,007	0,019	−0,009	−0,008	0,045	−0,007	0,023	0,014	−0,012	0,006	0,014
hhs_q9	0,022	0,011	−0,004	0,014	0,014	0,008	0,034	0,022	0,000	0,008	−0,001	0,041	0,000	0,003	0,031
hhs_q11	0,009	−0,035	0,007	−0,011	−0,051	−0,017	−0,016	0,039	−0,019	0,002	−0,013	0,017	0,022	0,006	0,037
gdp_1	0,561			0,836			0,925			0,903			0,832		
une_1		0,885			0,754			0,902			0,835			0,846	
cpi_1			0,787			0,770			0,715			0,847			0,806
gdp_hat		0,043	0,203		−0,023	0,302		−0,203	0,416		−0,126	0,197		−0,087	0,225
cpi_hat			−0,041			−0,034			−0,035			0,085			0,033

Appendix 3. Parameters of Bayesian models – frequentist approach without collinearity correction

k = 0

Source	SS	df MS		Number of obs	67
				F(5, 61)	71,47
Model	249,892471	5 49,9784943		Prob > F	0
Residual	42,6594653	61 ,699335497		R-squared	0,8542
				Adj R-squared	0,8422
Total	292,551937	66 4,4326051		Root MSE	0,83626
pkb	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
pkb					
L1.	0,5412328	,0794026 6,82	0	0,3824574	0,7000082
ind_q3f	0,0334465	,012185 2,74	0,008	0,0090812	0,0578118
ind_q8f	0,0190941	,0091105 2,10	0,04	0,0008765	0,0373118
hhs_q2	0,0155653	,0114064 1,36	0,177	−0,0072433	0,0383738
hhs_q9	0,0159795	,0086194 1,85	0,069	−0,0012561	0,0332151
_cons	2,886448	,4937201 5,85	0	1,899194	3,873703

Source	! df MS			Number of ob	67
				F(10, 56) = 288,21	
Model	1206,18982	10 120,618982		Prob > F = 0,0000	
Residual	23,4367323	56 ,418513077		R-squared = 0,9809	
				Adj R-squared = 0,9775	
Total	1229,62655	66 18,6307053		Root MSE = ,64693	
une	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf, Interval]**	
une					
L1.	0,8637283	,047271 18,27	0	,7690331	,9584235
pkb_teor	0,179374	,1510324 1,19	0,24	−,1231803	,4819283
gus11	−0,0442655	,0130369 −3,40	0,001	−,0703816	−,0181494
biec_wpi	−0,1020245	,0367476 −2,78	0,007	−,1756387	−,0284103
biec_wrp	0,0363974	,0198071 1,84	0,071	−,0032809	,0760758
ind_q2f	−0,0469518	,0205798 −2,28	0,026	−,0881781	−,0057255
ind_q4f	0,0703111	,0297728 2,36	0,022	,0106691	,1299532
ind_q5f	0,053237	,0187694 2,84	0,006	,0156373	,0908367
ind_q7f	−0,0213542	,0280061 −0,76	0,449	−,0774572	,0347489
hhs_q2	−0,0047796	,0117131 −0,41	0,685	−,0282439	,0186846
_cons	−1,839559	,9312418 −1,98	0,053	−3,705061	,025942

Source	SS	df MS		Number of obs	67
				F(10, 56)	325,86
Model	1635,69332	10 163,569332		Prob > F	0
Residual	28,1096929	56 ,501958801		R-squared	0,9831
				Adj R-squared	0,9801
Total	1663,80302	66 25,2091366		Root MSE	0,70849
cpi	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
cpi					
L1.	0,7574684	,0475764 15,92	0	0,6621615	0,8527753
pkb_teor	0,0486998	,187564 0,26	0,796	−0,3270361	0,4244357
une_teor	−0,084082	,0672432 −1,25	0,216	−0,2187862	0,0506222
ifo_be	0,037386	,0272531 1,37	0,176	−0,0172087	0,0919806
gus2	−0,0204715	,0375274 −0,55	0,588	−0,0956479	0,0547048
gus4	−0,0372836	,0215052 −1,73	0,088	−0,0803636	0,0057964
biec_wpi	0,1753729	,0645662 2,72	0,009	0,0460313	0,3047146
biec_wrp	0,0350313	,0306864 1,14	0,258	−0,0264409	0,0965036
ind_q8f	0,0095569	,0106625 0,90	0,374	−0,0118027	0,0309165
hhs_q1	0,0245912	,0137289 1,79	0,079	−0,0029111	0,0520936
_cons	3,561479	1,531254 2,33	0,024	0,4940081	6,62895

k = 1

Source	SS	df MS		Number of obs	67
				F(10, 56)	41,19
Model	257,540707	10 25,7540707		Prob > F	0
Residual	35,0112296	56 ,625200529		R-squared	0,8803
				Adj R-squared	0,859
Total	292,551937	66 4,4326051		Root MSE	0,7907
pkb	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
pkb					
L1.	0,8055313	,0940352 8,57	0	0,6171562	0,9939064
gus2					
L1.	-0,0117593	,0517091 -0,23	0,821	-0,1153451	0,0918264
gus4					
L1.	-0,0484791	,0339378 -1,43	0,159	-0,1164648	0,0195066
gus11					
L1.	0,0256196	,0146023 1,75	0,085	-0,0036324	0,0548716
biec_wwk					
L1.	-0,0379448	,021974 -1,73	0,09	-0,0819639	0,0060743
biec_wpi					
L1.	-0,1720673	,04756 -3,62	0,001	-0,2673414	-0,0767932
biec_wrp					
L1.	0,0028824	,0273049 0,11	0,916	-0,0518158	0,0575806
ind_q8f					
L1.	0,0259277	,0103074 2,52	0,015	0,0052795	0,0465758
hhs_q2					
L1.	0,0408238	,0243296 1,68	0,099	-0,0079142	0,0895619
hhs_q4					
L1.	0,0158119	,0215485 0,73	0,466	-0,0273549	0,0589787
_cons	2,257556	,7882568 2,86	0,006	0,6784874	3,836624

Source	df MS			Number of obs = 67	
				F(7, 59) = 403,01	
Model	1204,43688	7 172,062411		Prob > F = 0,0000	
Residual	25,1896683	59 ,426943531		R-squared = 0,9795	
				Adj R-squared = 0,9771	
Total	1229,62655	66 18,6307053		Root MSE = ,65341	
une	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf, Interval]**	
une					
L1.	0,742496	,0417523 17,78	0	,6589498	,8260422
pkb_teor	−0,0462908	,072557 −0,64	0,526	−,1914771	,0988954
gus11					
L1.	−0,0596381	,0120967 −4,93	0	−,0838435	−,0354327
biec_wrp					
L1.	0,0967255	,0196527 4,92	0	,0574005	,1360505
ind_q1f					
L1.	−0,0813045	,0156927 −5,18	0	−,1127056	−,0499035
ind_q7f					
L1.	0,0586167	,0229704 2,55	0,013	,0126531	,1045803
hhs_q7					
L1.	−0,0069608	,0077494 −0,90	0,373	−,0224673	,0085457
_cons	2,957348	,8345765 3,54	0,001	1,287364	4,627332

Source	SS	df MS		Number of obs	67
				F(16, 50)	198,35
Model	1637,99655	16 102,374785		Prob > F	0
Residual	25,806463	50 ,516129261		R-squared	0,9845
				Adj R-squared	0,9795
Total	1663,80302	66 25,2091366		Root MSE	0,71842
cpi	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
cpi					
L1.	0,7026106	,0633329 11,09	0	0,5754027	0,8298185
pkb_teor	0,2890385	,1064265 2,72	0,009	0,0752746	0,5028023
une_teor	0,1718866	,1001789 1,72	0,092	−0,0293285	0,3731018
gus4					
L1.	0,0076191	,0245813 0,31	0,758	−0,0417539	0,0569921
gus11					
L1.	0,0473954	,0209903 2,26	0,028	0,0052351	0,0895556
biec_wpi					
L1.	0,1268648	,0626127 2,03	0,048	0,0011034	0,2526262
biec_wrp					
L1.	0,0167268	,0400999 0,42	0,678	−0,0638162	0,0972697
ind_q2f					
L1.	0,0608155	,0271628 2,24	0,03	0,0062574	0,1153736
ind_q3f					
L1.	−0,0389551	,0294548 −1,32	0,192	−0,0981168	0,0202066
ind_q5f					
L1.	0,0059482	,0213359 0,28	0,782	−0,0369063	0,0488027
ind_q6f					
L1.	−0,020994	,0248915 −0,84	0,403	−0,07099	0,029002
hhs_q2					
L1.	0,0473305	,0284051 1,67	0,102	−0,0097228	0,1043838
hhs_q4					
L1.	−0,0220873	,0203799 −1,08	0,284	−0,0630215	0,018847
hhs_q6					
L1.	0,0376579	,0153828 2,45	0,018	0,0067607	0,0685551
hhs_q7					
L1.	0,0159035	,0135914 1,17	0,248	−0,0113956	0,0432026
hhs_q9					
L1.	0,0116826	,0126101 0,93	0,359	−0,0136455	0,0370107
_cons	−0,8360416	2,009299 −0,42	0,679	−4,871838	3,199755

k = 2

Source	SS	df MS		Number of obs	66
				F(7, 58)	55,84
Model	252,979944	7 36,139992		Prob > F	0
Residual	37,5353562	58 ,647161315		R-squared	0,8708
				Adj R-squared	0,8552
Total	290,5153	65 4,46946615		Root MSE	0,80446
pkb	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
pkb					
L1.	0,8765432	,0856282 10,24	0	0,7051397	1,047947
ifo_be					
L2.	-0,0513404	,0226609 -2,27	0,027	-0,0967011	-0,0059797
gus11					
L2.	0,0195004	,0106347 1,83	0,072	-0,0017871	0,040788
biec_wwk					
L2.	-0,0382542	,0103803 -3,69	0,001	-0,0590327	-0,0174757
biec_wpi					
L2.	-0,2185128	,038623 -5,66	0	-0,2958252	-0,1412004
ind_q8f					
L2.	0,0215902	,0079928 2,70	0,009	0,0055909	0,0375896
hhs_q9					
L2.	0,0203052	,0107248 1,89	0,063	-0,0011627	0,0417732
_cons	1,148066	,8151038 1,41	0,164	-0,483542	2,779673

Source	SS	df MS		Number of ol	66
				F(17, 48)	151,95
Model	1206,30153	17 70,9589135		Prob > F	0
Residual	22,4160255	48 ,467000531		R-squared	0,9818
				Adj R-square	0,9753
Total	1228,71756	65 18,903347		Root MSE	0,68337
une	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
une					
L1.	0,8641761	,0767338 11,26	0	0,7098924	1,01846
pkb_teor	-0,1767886	,0926412 -1,91	0,062	-0,363056	0,009479
gus2					
L2.	0,0255256	,0553159 0,46	0,647	-0,085695	0,1367457
gus4					
L2.	-0,0537888	,0320673 -1,68	0,1	-0,118264	0,0106868
gus7					
L2.	0,005152	,0172298 0,30	0,766	-0,029491	0,0397949
gus11					
L2.	0,0028178	,019466 0,14	0,886	-0,036321	0,0419568
biec_wwk					
L2.	-0,000643	,0189572 -0,03	0,973	-0,038759	0,037473
biec_wd					
L2.	-0,0408499	,0465596 -0,88	0,385	-0,134464	0,0527644
ind_q1f					
L2.	0,0616686	,0324623 1,90	0,063	-0,003601	0,1269384
ind_q2f					
L2.	0,0137201	,0386507 0,35	0,724	-0,063992	0,0914324
ind_q3f					
L2.	-0,0050208	,0273805 -0,18	0,855	-0,060073	0,0500313
ind_q5f					
L2.	-0,0581516	,0207004 -2,81	0,007	-0,099773	-0,0165306
ind_q6f					
L2.	-0,0345642	,0236452 -1,46	0,15	-0,082106	0,0129777
hhs_q2					
L2.	-0,0745498	,0390214 -1,91	0,062	-0,153008	0,003908
hhs_q4					
L2.	0,0422467	,0230861 1,83	0,073	-0,004171	0,0886645
hhs_q9					
L2.	0,0081271	,0141752 0,57	0,569	-0,020374	0,0366283
hhs_q11					
L2.	0,0507068	,0262054 1,93	0,059	-0,001983	0,1033962
_cons	3,707733	1,387928 2,67	0,01	0,9171163	6,49835

Source	SS	df MS		Number of obs	66
				F(14, 51)	228,67
Model	1434,57222	14 102,469444		Prob > F	0
Residual	22,8540337	51 ,448118307		R-squared	0,9843
				Adj R-squared	0,98
Total	1457,42626	65 22,4219424		Root MSE	0,66942
cpi	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
cpi					
L1.	0,6793681	,062206 10,92	0	0,5544843	0,8042519
pkb_teor	0,5746935	,0782232 7,35	0	0,4176539	0,7317331
une_teor	0,2330987	,071146 3,28	0,002	0,0902671	0,3759302
gus2					
L2.	0,0942546	,0365897 2,58	0,013	0,0207977	0,1677116
gus7					
L2.	0,0375859	,0212594 1,77	0,083	−0,0050942	0,080266
gus11					
L2.	0,026363	,0189791 1,39	0,171	−0,0117392	0,0644651
biec_wpi					
L2.	0,1894259	,0612825 3,09	0,003	0,066396	0,3124557
ind_q1f					
L2.	0,0143427	,0178769 0,80	0,426	−0,0215466	0,0502321
ind_q3f					
L2.	−0,0248027	,0223496 −1,11	0,272	−0,0696714	0,020066
ind_q5f					
L2.	0,0461525	,0218418 2,11	0,04	0,0023032	0,0900018
ind_q6f					
L2.	−0,0119674	,0217355 −0,55	0,584	−0,0556032	0,0316684
ind_q8f					
L2.	−0,0188614	,0110767 −1,70	0,095	−0,0410987	0,0033759
hhs_q6					
L2.	0,0194771	,0110109 1,77	0,083	−0,0026282	0,0415824
hhs_q7					
L2.	0,0598391	,020491 2,92	0,005	0,0187018	0,1009765
_cons	−2,521097	1,519387 −1,66	0,103	−5,571394	0,5292003

Source	SS	df MS		Number of obs	65
				F(14, 50)	26,85
Model	247,589365	14 17,6849546		Prob > F	0
Residual	32,9281703	50 ,658563406		R-squared	0,8826
				Adj R-squared	0,8497
Total	280,517535	64 4,38308648		Root MSE	0,81152
pkb	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
pkb					
L1.	0,8492499	,0756305 11,23	0	0,6973415	1,001158
ifo_be					
L3.	0,0170794	,0291154 0,59	0,56	−0,0414007	0,0755595
gus2					
L3.	0,0454195	,0544297 0,83	0,408	−0,0639057	0,1547448
gus4					
L3.	−0,0016652	,0378269 −0,04	0,965	−0,0776426	0,0743123
gus7					
L3.	0,0286692	,0162656 1,76	0,084	−0,0040012	0,0613397
gus11					
L3.	0,0133988	,0203645 0,66	0,514	−0,0275045	0,0543021
ips_wo					
L3.	−0,0404233	,0307834 −1,31	0,195	−0,1022536	0,021407
biec_wwk					
L3.	−0,0694908	,0219801 −3,16	0,003	−0,1136391	−0,0253425
biec_wpi					
L3.	−0,105841	,0539011 −1,96	0,055	−0,2141046	0,0024226
ind_q2f					
L3.	−0,0219792	,0275854 −0,80	0,429	−0,0773862	0,0334278
ind_q3f					
L3.	−0,0078547	,0279168 −0,28	0,78	−0,0639273	0,0482179
ind_q5f					
L3.	−0,0103109	,0252394 −0,41	0,685	−0,0610058	0,0403839
ind_q6f					
L3.	0,0020992	,0261615 0,08	0,936	−0,0504477	0,0546462
hhs_q6					
L3.	−0,0200169	,0145026 −1,38	0,174	−0,0491462	0,0091124
_cons	4,800347	1,429924 3,36	0,002	1,928261	7,672434

Source	SS	df MS		Number of ob	65
				F(17, 47)	140,06
Model	1201,84649	17 70,6968525		Prob > F	0
Residual	23,723642	47 ,504758341		R-squared	0,9806
				Adj R-square	0,9736
Total	1225,57013	64 19,1495334		Root MSE	0,71046
une	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
une					
L1.	0,7409685	,0759721 9,75	0	0,5881324	0,8938046
pkb_teor	-0,1548855	,0874075 -1,77	0,083	-0,330727	0,0209556
ifo_be					
L3.	-0,0626671	,0263247 -2,38	0,021	-0,115626	-0,0097086
gus7					
L3.	-0,0377777	,0281432 -1,34	0,186	-0,094394	0,0188391
gus11					
L3.	-0,0250374	,0186335 -1,34	0,186	-0,062523	0,0124483
ips_wo					
L3.	0,0209637	,0258101 0,81	0,421	-0,03096	0,0728868
biec_wwk					
L3.	0,0063557	,0257916 0,25	0,806	-0,04553	0,0582417
biec_wpi					
L3.	0,0113552	,0526753 0,22	0,83	-0,094614	0,1173243
biec_wrp					
L3.	0,0222427	,0434121 0,51	0,611	-0,065091	0,1095765
ind_q1f					
L3.	0,0048477	,0311737 0,16	0,877	-0,057866	0,067561
ind_q2f					
L3.	0,0185182	,0391447 0,47	0,638	-0,060231	0,0972672
ind_q3f					
L3.	0,0024279	,0260277 0,09	0,926	-0,049933	0,0547888
ind_q4f					
L3.	0,0614245	,040413 1,52	0,135	-0,019876	0,142725
ind_q8f					
L3.	0,0204421	,0118268 1,73	0,09	-0,00335	0,0442346
hhs_q1					
L3.	-0,0162211	,0189704 -0,86	0,397	-0,054385	0,0219424
hhs_q4					
L3.	-0,0031284	,0188152 -0,17	0,869	-0,04098	0,0347228
hhs_q7					
L3.	-0,0008406	,022206 -0,04	0,97	-0,045513	0,0438322
_cons	1,886072	1,473662 1,28	0,207	-1,078554	4,850699

Source	SS	df MS		Number of obs	65
				F(8, 56)	304,27
Model	1210,92201	8 151,365251		Prob > F	0
Residual	27,8580208	56 ,497464657		R-squared	0,9775
				Adj R-squared	0,9743
Total	1238,78003	64 19,355938		Root MSE	0,70531
cpi	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
cpi					
L1.	0,8582124	,0403447 21,27	0	0,7773922	0,9390327
pkb_teor	0,2957225	,0633326 4,67	0	0,168852	0,422593
une_teor	0,1332924	,0670562 1,99	0,052	−0,0010373	0,267622
biec_wwk					
L3.	0,0645959	,0206494 3,13	0,003	0,0232302	0,1059616
ind_q2f					
L3.	0,0167106	,0131123 1,27	0,208	−0,0095564	0,0429777
ind_q6f					
L3.	−0,0490325	,0160789 −3,05	0,003	−0,0812425	−0,0168225
hhs_q4					
L3.	−0,0001138	,0088905 −0,01	0,99	−0,0179236	0,017696
hhs_q9					
L3.	0,0418447	,0117464 3,56	0,001	0,0183139	0,0653755
_cons	−4,629644	1,485689 −3,12	0,003	−7,605837	−1,653451

k = 4

Source	SS	df MS		Number of obs	64
				F(13, 50)	24,07
Model	228,639642	13 17,5876648		Prob > F	0
Residual	36,5397264	50 ,730794527		R-squared	0,8622
				Adj R-squared	0,8264
Total	265,179368	63 4,20919633		Root MSE	0,85487
pkb	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
pkb					
L1.	0,7342216	,0765924 9,59	0	0,5803813	0,8880619
ifo_be					
L4.	0,0076629	,0292199 0,26	0,794	-0,051027	0,0663528
gus11					
L4.	0,0145897	,0174017 0,84	0,406	-0,0203626	0,049542
ips_wo					
L4.	-0,0205703	,0228807 -0,90	0,373	-0,0665276	0,025387
biec_wwk					
L4.	-0,0476765	,0182793 -2,61	0,012	-0,0843915	-0,0109614
biec_wpi					
L4.	-0,0526297	,0549318 -0,96	0,343	-0,1629635	0,0577041
ind_q2f					
L4.	-0,0018213	,0269149 -0,07	0,946	-0,0558814	0,0522388
ind_q3f					
L4.	-0,0273869	,0290775 -0,94	0,351	-0,0857907	0,0310169
ind_q4f					
L4.	0,051484	,0437932 1,18	0,245	-0,0364772	0,1394451
ind_q5f					
L4.	-0,0271262	,0251519 -1,08	0,286	-0,0776452	0,0233928
ind_q6f					
L4.	0,0360243	,0295195 1,22	0,228	-0,0232674	0,0953159
hhs_q6					
L4.	-0,021434	,0148671 -1,44	0,156	-0,0512953	0,0084274
hhs_q7					
L4.	-0,0177298	,0145113 -1,22	0,228	-0,0468766	0,011417
_cons	5,056546	1,437636 3,52	0,001	2,168969	7,944124

Source	SS	df MS		Number of ol	64
				F(17, 46)	187,52
Model	1204,56891	17 70,8569949		Prob > F	0
Residual	17,3821613	46 ,377873071		R-squared	0,9858
				Adj R-square	0,9805
Total	1221,95107	63 19,3960488		Root MSE	0,61471
une	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
une					
L1.	0,7785822	,0763262 10,20	0	0,6249456	0,9322188
pkb_teor	-0,0990874	,0861181 -1,15	0,256	-0,272434	0,0742595
gus11					
L4.	-0,0266455	,0175445 -1,52	0,136	-0,061961	0,0086698
ips_wo					
L4.	0,0151664	,0198508 0,76	0,449	-0,024791	0,0551241
biec_wpi					
L4.	-0,0172745	,0432518 -0,40	0,691	-0,104336	0,0697869
biec_wrp					
L4.	-0,0062137	,0288573 -0,22	0,83	-0,064301	0,0518731
ind_q2f					
L4.	-0,0369963	,0263747 -1,40	0,167	-0,090086	0,0160932
ind_q3f					
L4.	0,0508528	,0267187 1,90	0,063	-0,002929	0,1046348
ind_q4f					
L4.	0,0682419	,0364754 1,87	0,068	-0,005179	0,141663
ind_q5f					
L4.	0,0380341	,0203703 1,87	0,068	-0,002969	0,0790373
ind_q6f					
L4.	-0,0501626	,0222108 -2,26	0,029	-0,094871	-0,0054547
ind_q7f					
L4.	-0,065408	,0305715 -2,14	0,038	-0,126945	-0,0038707
ind_q8f					
L4.	0,0245355	,0116815 2,10	0,041	0,0010218	0,0480492
hhs_q2					
L4.	-0,0289149	,0302417 -0,96	0,344	-0,089788	0,0319584
hhs_q4					
L4.	-0,0019317	,0177316 -0,11	0,914	-0,037624	0,0337602
hhs_q9					
L4.	0,0035586	,0109562 0,32	0,747	-0,018495	0,0256123
hhs_q11					
L4.	-0,0006142	,0212925 -0,03	0,977	-0,043474	0,0422453
_cons	0,7120609	1,383378 0,51	0,609	-2,072534	3,496656

Source	SS	df MS		Number of obs	64
				F(18, 45)	134,26
Model	1023,49349	18 56,8607493		Prob > F	0
Residual	19,0576276	45 ,423502835		R-squared	0,9817
				Adj R-squared	0,9744
Total	1042,55112	63 16,5484304		Root MSE	0,65077
cpi	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
cpi					
L1.	0,8367535	,0779026 10,74	0	0,6798495	0,9936575
pkb_teor	0,3583252	,1183741 3,03	0,004	0,1199077	0,5967428
une_teor	0,2199952	,091086 2,42	0,02	0,0365387	0,4034517
ifo_be					
L4.	0,0058994	,0262741 0,22	0,823	-0,0470195	0,0588182
gus7					
L4.	-0,0051315	,0267988 -0,19	0,849	-0,059107	0,0488441
ips_wo					
L4.	0,0289197	,0218849 1,32	0,193	-0,0151588	0,0729981
biec_wwk					
L4.	0,0174597	,0303588 0,58	0,568	-0,043686	0,0786054
biec_wpi					
L4.	-0,0506931	,0768866 -0,66	0,513	-0,2055508	0,1041645
biec_wrp					
L4.	-0,0781828	,0381912 -2,05	0,047	-0,1551038	-0,0012619
ind_q2f					
L4.	0,0276271	,0242952 1,14	0,261	-0,0213061	0,0765602
ind_q3f					
L4.	-0,0158844	,0280333 -0,57	0,574	-0,0723464	0,0405775
ind_q6f					
L4.	-0,0271089	,0278083 -0,97	0,335	-0,0831176	0,0288999
ind_q8f					
L4.	0,0007693	,012497 0,06	0,951	-0,024401	0,0259395
hhs_q1					
L4.	-0,0608726	,0257713 -2,36	0,023	-0,1127786	-0,0089666
hhs_q2					
L4.	0,0257479	,0307807 0,84	0,407	-0,0362477	0,0877435
hhs_q7					
L4.	0,0084815	,0223018 0,38	0,706	-0,0364367	0,0533997
hhs_q9					
L4.	0,0219433	,0152194 1,44	0,156	-0,0087101	0,0525967
hhs_q11					
L4.	0,0774099	,0222796 3,47	0,001	0,0325365	0,1222834
_cons	-2,235593	1,706626 -1,31	0,197	-5,672914	1,201727

Appendix 4. Parameters of Bayesian models – frequentist approach with collinearity correction

k = 0

Source	SS	df MS		Number of obs	67
				F(5, 61)	71,47
Model	249,892471	5 49,9784943		Prob > F	0
Residual	42,6594653	61 ,699335497		R-squared	0,8542
				Adj R-squared	0,8422
Total	292,551937	66 4,4326051		Root MSE	0,83626
pkb	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
pkb					
L1.	0,5412328	,0794026 6,82	0	0,3824574	0,7000082
ind_q3f	0,0334465	,012185 2,74	0,008	0,0090812	0,0578118
ind_q8f	0,0190941	,0091105 2,10	0,04	0,0008765	0,0373118
hhs_q2	0,0155653	,0114064 1,36	0,177	−0,0072433	0,0383738
hhs_q9	0,0159795	,0086194 1,85	0,069	−0,0012561	0,0332151
_cons	2,886448	,4937201 5,85	0	1,899194	3,873703

Source	SS	df MS		Number of obs	67
				F(8, 58)	313,7
Model	1201,84986	8 150,231233		Prob > F	0
Residual	27,7766875	58 ,478908406		R-squared	0,9774
				Adj R-squared	0,9743
Total	1229,62655	66 18,6307053		Root MSE	0,69203
une	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
une					
L1.	0,8067789	,0466639 17,29	0	0,713371	0,9001869
pkb_teor	0,35773	,1253851 2,85	0,006	0,1067445	0,6087154
gus11	−0,0257337	,0123526 −2,08	0,042	−0,05046	−0,001007
biec_wpi	−0,079759	,0384956 −2,07	0,043	−0,1568163	−0,002702
biec_wrp	0,0674275	,0181001 3,73	0	0,0311961	0,1036589
ind_q2f	−0,0487784	,0136708 −3,57	0,001	−0,0761434	−0,021413
ind_q4f	0,07463	,0310303 2,41	0,019	0,0125161	0,1367439
hhs_q2	−0,0256537	,0103574 −2,48	0,016	−0,0463863	−0,004921
_cons	−0,5047541	,7682087 −0,66	0,514	−2,042491	1,032983

Source	SS	df MS		Number of obs	67
				F(7, 59)	400,2
Model	1629,48462	7 232,783517		Prob > F	0
Residual	34,3183975	59 ,581667755		R-squared	0,9794
				Adj R-squared	0,9769
Total	1663,80302	66 25,2091366		Root MSE	0,76267
cpi	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
cpi					
L1.	0,8887886	,0225794 39,36	0	0,8436073	0,9339699
pkb_teor	0,2893781	,1163502 2,49	0,016	0,0565618	0,5221943
une_teor	−0,0384365	,0337119 −1,14	0,259	−0,1058938	0,0290207
ifo_be	0,0053372	,0215194 0,25	0,805	−0,037723	0,0483973
gus4	−0,0606272	,0146639 −4,13	0	−0,0899696	−0,031285
ind_q8f	0,0029791	,0112867 0,26	0,793	−0,0196055	0,0255637
hhs_q1	0,016451	,013429 1,23	0,225	−0,0104203	0,0433223
_cons	−1,205345	,7339641 −1,64	0,106	−2,674004	0,2633138

k = 1

Source	SS	df MS		Number of obs	67
				F(8, 58)	52,41
Model	256,999215	8 32,1249019		Prob > F	0
Residual	35,5527219	58 ,612977963		R-squared	0,8785
				Adj R-squared	0,8617
Total	292,551937	66 4,4326051		Root MSE	0,78293
pkb	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
pkb					
L1.	0,8104698	,0913826 8,87	0	0,6275476	0,993392
gus4					
L1.	−0,044007	,0185655 −2,37	0,021	−0,08117	−0,006844
gus11					
L1.	0,024593	,0128116 1,92	0,06	−0,0010522	0,0502382
biec_wwk					
L1.	−0,0475104	,0190452 −2,49	0,015	−0,0856336	−0,009387
biec_wpi					
L1.	−0,169987	,0457584 −3,71	0	−0,2615823	−0,078392
biec_wrp					
L1.	0,0018868	,026137 0,07	0,943	−0,0504322	0,0542057
ind_q8f					
L1.	0,028872	,0089794 3,22	0,002	0,0108977	0,0468463
hhs_q2					
L1.	0,0505446	,0148967 3,39	0,001	0,0207257	0,0803636
_cons	2,615259	,6684814 3,91	0	1,277148	3,95337

Source	SS	df MS		Number of obs	67
				F(7, 59)	403,16
Model	1204,44616	7 172,063737		Prob > F	0
Residual	25,1803885	59 ,426786246		R-squared	0,9795
				Adj R-squared	0,9771
Total	1229,62655	66 18,6307053		Root MSE	0,65329
une	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
une					
L1.	0,7420742	,0417476 17,78	0	0,6585374	0,825611
pkb_teor	-0,0480337	,0733422 -0,65	0,515	-0,194791	0,0987236
gus11					
L1.	-0,0595971	,0120918 -4,93	0	-0,0837928	-0,035401
biec_wrp					
L1.	0,0969228	,0196923 4,92	0	0,0575187	0,136327
ind_q1f					
L1.	-0,0813681	,0156921 -5,19	0	-0,1127679	-0,049968
ind_q7f					
L1.	0,0590749	,0231632 2,55	0,013	0,0127254	0,1054245
hhs_q7					
L1.	-0,0069221	,0077335 -0,90	0,374	-0,0223968	0,0085526
_cons	2,974814	,8427351 3,53	0,001	1,288505	4,661124

Source	SS	df MS		Number of obs	67
				F(16, 50)	198,22
Model	1637,98009	16 102,373755		Prob > F	0
Residual	25,8229311	50 ,516458623		R-squared	0,9845
				Adj R-squared	0,9795
Total	1663,80302	66 25,2091366		Root MSE	0,71865
cpi	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
cpi					
L1.	0,7007903	,0635449 11,03	0	0,5731565	0,8284241
pkb_teor	0,2853028	,1051637 2,71	0,009	0,0740754	0,4965303
une_teor	0,1691235	,1006203 1,68	0,099	-0,0329783	0,3712253
gus4					
L1.	0,0045685	,0243624 0,19	0,852	-0,0443647	0,0535018
gus11					
L1.	0,0476257	,0210053 2,27	0,028	0,0054354	0,089816
biec_wpi					
L1.	0,1259163	,0625415 2,01	0,049	0,0002981	0,2515345
biec_wrp					
L1.	0,0159975	,0400666 0,40	0,691	-0,0644785	0,0964735
ind_q2f					
L1.	0,0593219	,0272384 2,18	0,034	0,004612	0,1140318
ind_q3f					
L1.	-0,0379132	,0294485 -1,29	0,204	-0,0970622	0,0212358
ind_q5f					
L1.	0,0064633	,0213105 0,30	0,763	-0,0363402	0,0492667
ind_q6f					
L1.	-0,0207285	,0248813 -0,83	0,409	-0,0707041	0,0292471
hhs_q2					
L1.	0,0451029	,0288482 1,56	0,124	-0,0128403	0,1030461
hhs_q4					
L1.	-0,0177469	,0204923 -0,87	0,391	-0,0589068	0,0234131
hhs_q6					
L1.	0,0379227	,015367 2,47	0,017	0,0070572	0,0687882
hhs_q7					
L1.	0,0164102	,0135966 1,21	0,233	-0,0108993	0,0437198
hhs_q9					
L1.	0,0111014	,0126705 0,88	0,385	-0,0143481	0,0365509
_cons	-0,8242085	2,011355 -0,41	0,684	-4,864135	3,215718

Source	SS	df MS		Number of obs	66
				F(7, 58)	55,84
Model	252,979944	7 36,139992		Prob > F	0
Residual	37,5353562	58 ,647161315		R-squared	0,8708
				Adj R-squared	0,8552
Total	290,5153	65 4,46946615		Root MSE	0,80446
pkb	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
pkb					
L1.	0,8765432	,0856282 10,24	0	0,7051397	1,047947
ifo_be					
L2.	-0,0513404	,0226609 -2,27	0,027	-0,0967011	-0,00598
gus11					
L2.	0,0195004	,0106347 1,83	0,072	-0,0017871	0,040788
biec_wwk					
L2.	-0,0382542	,0103803 -3,69	0,001	-0,0590327	-0,017476
biec_wpi					
L2.	-0,2185128	,038623 -5,66	0	-0,2958252	-0,1412
ind_q8f					
L2.	0,0215902	,0079928 2,70	0,009	0,0055909	0,0375896
hhs_q9					
L2.	0,0203052	,0107248 1,89	0,063	-0,0011627	0,0417732
_cons	1,148066	,8151038 1,41	0,164	-0,483542	2,779673

Source	SS	df MS		Number of obs	66
				F(10, 55)	255,02
Model	1202,77689	10 120,277689		Prob > F	0
Residual	25,9406703	55 ,471648551		R-squared	0,9789
				Adj R-squared	0,975
Total	1228,71756	65 18,903347		Root MSE	0,68677
une	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
une					
L1.	0,919417	,0499015 18,42	0	0,8194121	1,019422
pkb_teor	-0,2497071	,0759984 -3,29	0,002	-0,4020113	-0,097403
gus4					
L2.	-0,0232981	,0128049 -1,82	0,074	-0,0489597	0,0023635
gus11					
L2.	0,0050843	,0165464 0,31	0,76	-0,0280754	0,038244
biec_wd					
L2.	-0,0433833	,0317187 -1,37	0,177	-0,106949	0,0201823
ind_q1f					
L2.	0,0632446	,0134568 4,70	0	0,0362766	0,0902126
ind_q5f					
L2.	-0,0386993	,0132797 -2,91	0,005	-0,0653124	-0,012086
ind_q6f					
L2.	-0,014544	,0152877 -0,95	0,346	-0,0451812	0,0160931
hhs_q9					
L2.	0,017485	,0101608 1,72	0,091	-0,0028777	0,0378478
hhs_q11					
L2.	0,0213413	,015182 1,41	0,165	-0,009084	0,0517666
_cons	2,62215	,814675 3,22	0,002	0,9895051	4,254796

Source	SS	df MS		Number of obs	66
				F(10, 55)	234,8
Model	1424,06905	10 142,406905		Prob > F	0
Residual	33,3572046	55 ,606494629		R-squared	0,9771
				Adj R-squared	0,973
Total	1457,42626	65 22,4219424		Root MSE	0,77878
cpi	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
cpi					
L1.	0,7880259	,0422106 18,67	0	0,703434	0,8726179
pkb_teor	0,4096775	,080259 5,10	0	0,2488348	0,5705202
une_teor	0,0163536	,0457047 0,36	0,722	-0,0752407	0,107948
gus11					
L2.	0,0267117	,0176799 1,51	0,137	-0,0087195	0,0621429
ind_q1f					
L2.	0,0090565	,0162582 0,56	0,58	-0,0235256	0,0416386
ind_q5f					
L2.	0,0243367	,0194444 1,25	0,216	-0,0146307	0,0633041
ind_q6f					
L2.	-0,0470146	,0204998 -2,29	0,026	-0,0880971	-0,005932
ind_q8f					
L2.	-0,0070984	,0121292 -0,59	0,561	-0,0314059	0,017209
hhs_q6					
L2.	0,0148052	,0118685 1,25	0,218	-0,0089797	0,0385901
hhs_q7					
L2.	-0,0022218	,0090288 -0,25	0,807	-0,020316	0,0158723
_cons	-1,655741	,9353642 -1,77	0,082	-3,530253	0,2187703

k = 3

Source	SS	df MS		Number of obs	65
				F(10, 54)	35,19
Model	243,200487	10 24,3200487		Prob > F	0
Residual	37,3170478	54 ,691056441		R-squared	0,867
				Adj R-squared	0,8423
Total	280,517535	64 4,38308648		Root MSE	0,8313
pkb	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
pkb					
L1.	0,8868679	,0732696 12,10	0	0,7399712	1,033765
ifo_be					
L3.	-0,0195707	,0251391 -0,78	0,44	-0,0699715	0,0308301
gus11					
L3.	0,0122615	,0144226 0,85	0,399	-0,016654	0,0411769
ips_wo					
L3.	0,0151683	,0139684 1,09	0,282	-0,0128366	0,0431731
biec_wwk					
L3.	-0,0333701	,0148427 -2,25	0,029	-0,063128	-0,003612
biec_wpi					
L3.	-0,0681933	,0501453 -1,36	0,18	-0,1687285	0,0323419
ind_q2f					
L3.	-0,0215491	,0196631 -1,10	0,278	-0,0609712	0,0178729
ind_q5f					
L3.	-0,0184616	,0229591 -0,80	0,425	-0,0644918	0,0275687
ind_q6f					
L3.	0,0240216	,0191874 1,25	0,216	-0,0144469	0,06249
hhs_q6					
L3.	-0,0188624	,013684 -1,38	0,174	-0,0462971	0,0085723
_cons	2,971282	1,244365 2,39	0,02	0,4764806	5,466083

Source	SS	df MS		Number of obs	65
				F(12, 52)	199,82
Model	1199,55603	12 99,9630022		Prob > F	0
Residual	26,0141084	52 ,500271315		R-squared	0,9788
				Adj R-squared	0,9739
Total	1225,57013	64 19,1495334		Root MSE	0,7073
une	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
une					
L1.	0,8161855	,0497917 16,39	0	0,7162712	0,9160998
pkb_teor	-0,1052738	,0656447 -1,60	0,115	-0,2369996	0,0264519
ifo_be					
L3.	-0,0551948	,0238854 -2,31	0,025	-0,1031243	-0,007265
gus11					
L3.	-0,0068108	,0120115 -0,57	0,573	-0,0309137	0,0172921
ips_wo					
L3.	0,0168255	,0161706 1,04	0,303	-0,0156233	0,0492742
biec_wpi					
L3.	0,0153344	,0273679 0,56	0,578	-0,0395833	0,0702522
ind_q1f					
L3.	0,02267	,0184503 1,23	0,225	-0,0143533	0,0596932
ind_q3f					
L3.	0,005583	,0189676 0,29	0,77	-0,0324782	0,0436443
ind_q4f					
L3.	0,0540616	,0356937 1,51	0,136	-0,0175631	0,1256863
ind_q8f					
L3.	0,0203627	,0111577 1,83	0,074	-0,0020267	0,0427522
hhs_q1					
L3.	-0,0259125	,0140922 -1,84	0,072	-0,0541904	0,0023655
hhs_q7					
L3.	0,0365077	,0093003 3,93	0	0,0178453	0,0551701
_cons	1,167831	,6591285 1,77	0,082	-0,1548071	2,490469

Source	SS	df MS		Number of obs	65
				F(7, 57)	312,9
Model	1207,35951	7 172,47993		Prob > F	0
Residual	31,4205186	57 ,551237169		R-squared	0,9746
				Adj R-squared	0,9715
Total	1238,78003	64 19,355938		Root MSE	0,74245
cpi	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
cpi					
L1.	0,7797223	,0354457 22,00	0	0,7087435	0,8507011
pkb_teor	0,2937931	,0673909 4,36	0	0,1588451	0,4287411
une_teor	-0,0506615	,0383719 -1,32	0,192	-0,1274999	0,0261769
ind_q2f					
L3.	0,0170961	,0138529 1,23	0,222	-0,010644	0,0448361
ind_q6f					
L3.	-0,0335827	,0158615 -2,12	0,039	-0,0653448	-0,001821
hhs_q4					
L3.	-0,0100446	,0088816 -1,13	0,263	-0,0278296	0,0077404
hhs_q9					
L3.	0,0265604	,0110318 2,41	0,019	0,0044696	0,0486513
_cons	-0,2496095	,4747717 -0,53	0,601	-1,200323	0,7011044

k = 4

Source	SS	df MS		Number of obs	64
				F(12, 51)	25,7
Model	227,551294	12 18,9626079		Prob > F	0
Residual	37,6280742	51 ,737805377		R-squared	0,8581
				Adj R-squared	0,8247
Total	265,179368	63 4,20919633		Root MSE	0,85896
pkb	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
pkb					
L1.	0,7569758	,0746437 10,14	0	0,6071224	0,9068292
ifo_be					
L4.	0,011879	,0291538 0,41	0,685	−0,0466497	0,0704077
gus11					
L4.	0,0244152	,0155009 1,58	0,121	−0,0067041	0,0555345
ips_wo					
L4.	−0,0339317	,0201872 −1,68	0,099	−0,0744592	0,0065958
biec_wwk					
L4.	−0,0383772	,0166947 −2,30	0,026	−0,0718933	−0,004861
biec_wpi					
L4.	−0,0554745	,055145 −1,01	0,319	−0,1661826	0,0552336
ind_q2f					
L4.	0,0019775	,0268622 0,07	0,942	−0,0519506	0,0559055
ind_q3f					
L4.	−0,0141214	,0270982 −0,52	0,605	−0,0685234	0,0402806
ind_q4f					
L4.	0,0603846	,0433882 1,39	0,17	−0,0267209	0,14749
ind_q5f					
L4.	−0,0328813	,024824 −1,32	0,191	−0,0827175	0,016955
hhs_q6					
L4.	−0,0196011	,0148618 −1,32	0,193	−0,0494374	0,0102352
hhs_q7					
L4.	−0,0290018	,0112456 −2,58	0,013	−0,0515782	−0,006425
_cons	4,900277	1,438774 3,41	0,001	2,011817	7,788737

Source	SS	df MS		Number of obs	64
				F(13, 50)	223,44
Model	1201,27267	13 92,4055902		Prob > F	0
Residual	20,6784023	50 ,413568047		R-squared	0,9831
				Adj R-squared	0,9787
Total	1221,95107	63 19,3960488		Root MSE	0,64309
une	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
une					
L1.	0,892004	,0441038 20,23	0	0,8034188	0,9805892
pkb_teor	−0,1415966	,0751613 −1,88	0,065	−0,2925626	0,0093693
gus11					
L4.	−0,0184009	,0139431 −1,32	0,193	−0,0464064	0,0096045
ips_wo					
L4.	0,0015217	,0204107 0,07	0,941	−0,0394744	0,0425179
biec_wpi					
L4.	−0,0558148	,0417654 −1,34	0,187	−0,1397031	0,0280735
ind_q2f					
L4.	−0,0456331	,014087 −3,24	0,002	−0,0739277	−0,017339
ind_q4f					
L4.	0,0884902	,0323098 2,74	0,009	0,0235941	0,1533864
ind_q5f					
L4.	0,0747319	,0150643 4,96	0	0,0444743	0,1049895
ind_q6f					
L4.	−0,0345146	,0165396 −2,09	0,042	−0,0677354	−0,001294
ind_q8f					
L4.	0,0131315	,010881 1,21	0,233	−0,0087237	0,0349867
hhs_q4					
L4.	0,0044756	,0134416 0,33	0,741	−0,0225227	0,0314738
hhs_q9					
L4.	−0,0031313	,0108884 −0,29	0,775	−0,0250013	0,0187387
hhs_q11					
L4.	−0,0153391	,0153467 −1,00	0,322	−0,0461639	0,0154857
_cons	−0,8057101	,8893369 −0,91	0,369	−2,591996	0,9805756

Source	SS	df MS		Number of obs	64
				F(11, 52)	180,58
Model	1015,95548	11 92,3595895		Prob > F	0
Residual	26,5956309	52 ,511454441		R-squared	0,9745
				Adj R-squared	0,9691
Total	1042,55112	63 16,5484304		Root MSE	0,71516
cpi	**Coef,**	**Std, Err, t**	**P>t**	**[95% Conf,**	**Interval]**
cpi					
L1.	0,7638683	,0543539 14,05	0	0,6547992	0,8729374
pkb_teor	0,2338751	,0788926 2,96	0,005	0,0755656	0,3921846
une_teor	0,0306116	,0483362 0,63	0,529	-0,0663821	0,1276052
ifo_be					
L4.	0,010805	,0224797 0,48	0,633	-0,0343037	0,0559138
ips_wo					
L4.	0,0044067	,0145319 0,30	0,763	-0,0247538	0,0335671
biec_wpi					
L4.	-0,0513501	,0559918 -0,92	0,363	-0,1637058	0,0610057
ind_q2f					
L4.	0,0047684	,0145276 0,33	0,744	-0,0243834	0,0339202
ind_q6f					
L4.	-0,0381194	,019002 -2,01	0,05	-0,0762496	0,0000109
ind_q8f					
L4.	0,0103093	,0125475 0,82	0,415	-0,014869	0,0354877
hhs_q9					
L4.	0,0261414	,011692 2,24	0,03	0,0026797	0,0496031
hhs_q11					
L4.	0,0329622	,0147186 2,24	0,029	0,0034272	0,0624973
_cons	1,106572	,8923952 1,24	0,221	-0,6841497	2,897294

Appendix 5. Parameters of DFM models

```
Sample: 1996q1 - 2012q4                                 Number of obs    =         68
                                                        Wald
chi2(27)    =     491.12
Log likelihood = -1282.5713                             Prob > chi2      =
0.0000
-------------------------------------------------------------------------------
             |
OIM
             |      Coef.   Std. Err.       z     P>|z|      [95%
Conf. Interval]
-------------+-----------------------------------------------------------------
f_une        |
       f_une |
         L1. |   .9165311   .0501001    18.29   0.000     .8183368    1.014725
-------------+-----------------------------------------------------------------
gus1_std     |
       f_une |   .3577829   .0453711     7.89   0.000     .2688571    .4467086
-------------+-----------------------------------------------------------------
gus2_std     |
       f_une |   .3512169   .0457982     7.67   0.000      .261454    .4409798
-------------+-----------------------------------------------------------------
gus3_std     |
       f_une |    .425245   .0408448    10.41   0.000     .3451908    .5052993
-------------+-----------------------------------------------------------------
gus4_std     |
       f_une |   .3977298   .0422468     9.41   0.000     .3149277    .4805319
-------------+-----------------------------------------------------------------
gus8_std     |
       f_une |   .3676794   .0443388     8.29   0.000     .2807769     .454582
-------------+-----------------------------------------------------------------
gus7_std     |
       f_une |   .3921641   .0425889     9.21   0.000     .3086913    .4756368
-------------+-----------------------------------------------------------------
gus11_std    |
       f_une |   .2445771   .0493366     4.96   0.000     .1478791    .3412752
-------------+-----------------------------------------------------------------
gus_wb_std   |
       f_une |   .4214824   .0415768    10.14   0.000     .3399932    .5029715
-------------+-----------------------------------------------------------------
gus_ww_std   |
       f_une |    .410031   .0423635     9.68   0.000         .327     .493062
-------------+-----------------------------------------------------------------
ips_wok_std  |
       f_une |   .4296427   .0402615    10.67   0.000     .3507316    .5085538
-------------+-----------------------------------------------------------------
ips_kg_std   |
       f_une |   .4145283   .0412291    10.05   0.000     .3337208    .4953358
-------------+-----------------------------------------------------------------
ips_sz_std   |
       f_une |   .4259702   .0406754    10.47   0.000     .3462479    .5056925
-------------+-----------------------------------------------------------------
ips_wb_std   |
       f_une |   .4367644   .0402927    10.84   0.000     .3577921    .5157367
-------------+-----------------------------------------------------------------
ips_wo_std   |
       f_une |   .4076181   .0415955     9.80   0.000     .3260924    .4891437
-------------+-----------------------------------------------------------------
biec_wrp_std |
       f_une |  -.2835649   .0487202    -5.82   0.000    -.3790548   -.188075
-------------+-----------------------------------------------------------------
biec_wd_std  |
       f_une |   .3743511   .0440579     8.50   0.000     .2879993    .4607029
-------------+-----------------------------------------------------------------
ind_q5f_std  |
       f_une |   .2213912    .049838     4.44   0.000     .1237104     .319072
-------------+-----------------------------------------------------------------
hhs_q1_std   |
```

```
       f_une |   .3799873   .0445415     8.53   0.000     .2926875    .4672871
-------------+----------------------------------------------------------------
hhs_q2_std   |
       f_une |   .3775403   .0445609     8.47   0.000     .2902026     .464878
-------------+----------------------------------------------------------------
hhs_q3_std   |
       f_une |   .4130242   .0415891     9.93   0.000      .331511    .4945374
-------------+----------------------------------------------------------------
hhs_q4_std   |
       f_une |   .3782514    .043746     8.65   0.000     .2925108    .4639921
-------------+----------------------------------------------------------------
hhs_q7_std   |
       f_une |  -.3779876    .044057    -8.58   0.000    -.4643377   -.2916375
-------------+----------------------------------------------------------------
hhs_q8_std   |
       f_une |   .3806266   .0444096     8.57   0.000     .2935854    .4676678
-------------+----------------------------------------------------------------
hhs_q9_std   |
       f_une |   .2681115   .0494416     5.42   0.000     .1712078    .3650153
-------------+----------------------------------------------------------------
hhs_q10_std  |
       f_une |   .2684915   .0491683     5.46   0.000     .1721233    .3648596
-------------+----------------------------------------------------------------
hhs_q11_std  |
       f_une |   .2643224   .0488658     5.41   0.000     .1685471    .3600977
-------------+----------------------------------------------------------------
var(e.gus1_~)|   .3695997   .0649936     5.69   0.000     .2422147    .4969847
var(e.gus2~d)|   .3926941   .0687566     5.71   0.000     .2579337    .5274545
var(e.gus3~d)|   .0701862   .0132296     5.31   0.000     .0442567    .0961157
var(e.gus4~d)|   .1738633   .0307877     5.65   0.000     .1135206     .234206
var(e.gus8~d)|   .3139926   .0553366     5.67   0.000      .205535    .4224503
var(e.gus7~d)|   .2046277   .0362887     5.64   0.000     .1335032    .2757522
var(e.gus1..)|   .6973042   .1201222     5.80   0.000      .461869    .9327394
var(e.gus_..)|   .1050013   .0199839     5.25   0.000     .0658334    .1441691
var(e.gus_..)|    .156593   .0287674     5.44   0.000     .1002098    .2129761
var(e.ips_..)|   .0353458   .0081867     4.32   0.000     .0193001    .0513914
var(e.ips_..)|   .0975414   .0189215     5.16   0.000     .0604559    .1346269
var(e.ips_..)|   .0605502   .0115603     5.24   0.000     .0378925     .083208
var(e.ips_..)|   .0218703   .0052231     4.19   0.000     .0116331    .0321075
var(e.~o_std)|   .1238662   .0230175     5.38   0.000     .0787527    .1689798
var(e.~p_std)|   .6167188   .1065854     5.79   0.000     .4078154    .8256223
var(e.biec..)|   .2926416   .0512626     5.71   0.000     .1921689    .3931144
var(e.ind_..)|   .7434902   .1278078     5.82   0.000     .4929916    .9939889
var(e.hhs_..)|   .2930644   .0512854     5.71   0.000     .1925469    .3935819
var(e.hhs_..)|   .2973979       .052     5.72   0.000     .1954797    .3993161
var(e.hhs_..)|    .119434   .0217717     5.49   0.000     .0767622    .1621057
var(e.hhs_..)|   .2618961   .0461428     5.68   0.000     .1714579    .3523344
var(e.hhs_..)|   .2803506   .0490082     5.72   0.000     .1842963    .3764048
var(e.hhs_..)|   .2834864   .0494129     5.74   0.000     .1866389    .3803339
var(e.~9_std)|   .6613507    .113952     5.80   0.000     .4380088    .8846925
var(e.~0_std)|   .6544283   .1127022     5.81   0.000     .4335361    .8753206
var(e.hhs_..)|   .6532609   .1125769     5.80   0.000     .4326142    .8739077
------------------------------------------------------------------------------
    reference.
```

Dynamic factor model – Factor 2

```
Sample: 1996q1 - 2012q4                          Number of obs   =         68
                                                 Wald
chi2(18)    =      368.07
Log likelihood = -1053.6046                      Prob > chi2     =
0.0000
------------------------------------------------------------------------------
             |
OIM
             |      Coef.   Std. Err.       z    P>|z|      [95%
Conf. Interval]
-------------+----------------------------------------------------------------
f_gdp        |
       f_gdp |
         L1. |    .962153   .0734529    13.10   0.000     .8181879    1.106118
         L4. |  -.1606418   .0721028    -2.23   0.026    -.3019606   -.0193229
-------------+----------------------------------------------------------------
pmi_std      |
       f_gdp |   .3478074   .0555417     6.26   0.000     .2389477    .4566671
-------------+----------------------------------------------------------------
ifo_bc_std   |
       f_gdp |   .2911473    .056876     5.12   0.000     .1796724    .4026221
-------------+----------------------------------------------------------------
ifo_be_std   |
       f_gdp |    .315637   .0568047     5.56   0.000     .2043018    .4269722
-------------+----------------------------------------------------------------
ind_q1s_std  |
       f_gdp |   .2955611   .0583506     5.07   0.000      .181196    .4099262
-------------+----------------------------------------------------------------
ind_q1f_std  |
       f_gdp |   .3374891   .0577731     5.84   0.000      .224256    .4507223
-------------+----------------------------------------------------------------
ind_q2s_std  |
       f_gdp |   .3739783   .0560782     6.67   0.000      .264067    .4838895
-------------+----------------------------------------------------------------
ind_q2f_std  |
       f_gdp |    .393556   .0558524     7.05   0.000     .2840872    .5030247
-------------+----------------------------------------------------------------
ind_q3s_std  |
       f_gdp |   .3853359    .056766     6.79   0.000     .2740766    .4965951
-------------+----------------------------------------------------------------
ind_q3f_std  |
       f_gdp |   .3640401   .0567117     6.42   0.000     .2528872    .4751931
-------------+----------------------------------------------------------------
ind_q6s_std  |
       f_gdp |   .3699047   .0555995     6.65   0.000     .2609316    .4788777
-------------+----------------------------------------------------------------
ind_q6f_std  |
       f_gdp |   .3794848    .054006     7.03   0.000      .273635    .4853346
-------------+----------------------------------------------------------------
ind_q7s_std  |
       f_gdp |   .3829626   .0552913     6.93   0.000     .2745935    .4913316
-------------+----------------------------------------------------------------
ind_q7f_std  |
       f_gdp |   .4368455   .0546402     7.99   0.000     .3297526    .5439383
-------------+----------------------------------------------------------------
ind_q8s_std  |
       f_gdp |   .4477978   .0510791     8.77   0.000     .3476846    .5479109
-------------+----------------------------------------------------------------
ind_q8f_std  |
       f_gdp |   .4369964   .0517843     8.44   0.000      .335501    .5384918
-------------+----------------------------------------------------------------
constr_std   |
       f_gdp |   .3407643   .0551066     6.18   0.000     .2327572    .4487713
-------------+----------------------------------------------------------------
var(e.pmi_~d)|   .4641129   .0831607     5.58   0.000     .3011209    .6271049
var(e.~c_std)|   .6403033     .11219     5.71   0.000     .4204148    .8601917
var(e.ifo_..)|   .5811678   .1023236     5.68   0.000     .3806172    .7817185
var(e.ind_..)|   .6020903   .1060471     5.68   0.000     .3942417    .8099388
var(e.ind_..)|   .4964639   .0912457     5.44   0.000     .3176256    .6753022
```

```
var(e.ind_..)|    .3635526   .0662283     5.49   0.000      .2337475    .4933576
var(e.ind_..)|    .3091161   .0603779     5.12   0.000      .1907776    .4274546
var(e.ind_..)|    .3442004   .0648706     5.31   0.000      .2170563    .4713445
var(e.ind_..)|    .4179923   .0777438     5.38   0.000      .2656172    .5703674
var(e.ind_..)|    .4079706   .0746977     5.46   0.000      .2615658    .5543753
var(e.ind_..)|    .3898749   .0725446     5.37   0.000      .2476902    .5320597
var(e.ind_..)|    .3666806    .067233     5.45   0.000      .2349063    .4984548
var(e.ind_..)|    .1545817   .0342569     4.51   0.000      .0874394     .221724
var(e.ind_..)|    .1070481   .0287382     3.72   0.000      .0507224    .1633739
var(e.ind_..)|    .1478645   .0330863     4.47   0.000      .0830166    .2127125
var(e.cons~d)|    .4412463   .0781659     5.64   0.000      .2880439    .5944487
------------------------------------------------------------------------------
Note: Tests of variances against zero are conservative and are provided only for
    reference.
```

Dynamic factor model – Factor 3

```
Sample: 1996q1 - 2012q4                              Number of obs   =         68
                                                     Wald
chi2(17)    =    1480.66
Log likelihood = -1268.7518                         Prob > chi2 = 0.0
------------------------------------------------------------------------------
             |
OIM
             |      Coef.   Std. Err.       z    P>|z|      [95%
Conf. Interval]
-------------+----------------------------------------------------------------
f_cpi        |
       f_cpi |
         L1. |   1.131776   .0649623    17.42   0.000     1.004452    1.259099
         L4. |  -.1757528   .0698454    -2.52   0.012    -.3126472   -.0388584
-------------+----------------------------------------------------------------
biec_wpi_std |
       f_cpi |   .2081647   .0421243     4.94   0.000     .1256025    .2907268
-------------+----------------------------------------------------------------
zew_ies_std  |
       f_cpi |   .0647955   .0305233     2.12   0.034     .0049708    .1246201
-------------+----------------------------------------------------------------
ifo_bs_std   |
       f_cpi |  -.0006021   .0309591    -0.02   0.984    -.0612807    .0600766
-------------+----------------------------------------------------------------
gus1_std     |
       f_cpi |    .027591   .0318634     0.87   0.387    -.0348602    .0900421
-------------+----------------------------------------------------------------
gus2_std     |
       f_cpi |  -.0115763   .0310277    -0.37   0.709    -.0723895     .049237
-------------+----------------------------------------------------------------
biec_wwk_std |
       f_cpi |  -.1324946    .032339    -4.10   0.000    -.1958779   -.0691114
-------------+----------------------------------------------------------------
biec_wrp_std |
       f_cpi |   .0234926   .0312051     0.75   0.452    -.0376683    .0846534
-------------+----------------------------------------------------------------
ind_q1f_std  |
       f_cpi |    .122523   .0336831     3.64   0.000     .0565053    .1885407
-------------+----------------------------------------------------------------
ind_q2f_std  |
       f_cpi |   .1310303   .0347209     3.77   0.000     .0629786    .1990821
-------------+----------------------------------------------------------------
ind_q3f_std  |
       f_cpi |   .1017093   .0330798     3.07   0.002     .0368741    .1665446
-------------+----------------------------------------------------------------
ind_q4s_std  |
       f_cpi |   .1166494   .0326804     3.57   0.000      .052597    .1807017
-------------+----------------------------------------------------------------
ind_q4f_std  |
       f_cpi |   .0957084   .0306044     3.13   0.002     .0357249    .1556918
-------------+----------------------------------------------------------------
ind_q5f_std  |
       f_cpi |   .1777374   .0398313     4.46   0.000     .0996694    .2558054
-------------+----------------------------------------------------------------
hhs_q9_std   |
       f_cpi |   .1946103    .038563     5.05   0.000     .1190281    .2701925
-------------+----------------------------------------------------------------
hhs_q12_std  |
       f_cpi |   -.069977   .0299136    -2.34   0.019    -.1286066   -.0113475
-------------+----------------------------------------------------------------
var(e.biec..)|    .118603   .0426347     2.78   0.005     .0350406    .2021654
var(e.zew_~d)|   .9607097    .166789     5.76   0.000     .6338093     1.28761
var(e.ifo_..)|   1.022826   .1754135     5.83   0.000     .6790222     1.36663
var(e.gus1_~)|    1.02946   .1770228     5.82   0.000     .6825022    1.376419
var(e.gus2~d)|   1.039697   .1783786     5.83   0.000     .6900815    1.389313
var(e.biec..)|   .6130983   .1185256     5.17   0.000     .3807923    .8454043
var(e.~p_std)|   1.029843   .1769734     5.82   0.000     .6829818    1.376705
var(e.ind_..)|   .7212403   .1288457     5.60   0.000     .4687074    .9737732
```

```
var(e.ind_..)|    .6750704   .1221392     5.53   0.000     .4356819    .9144588
var(e.ind_..)|    .8118476   .1437393     5.65   0.000     .5301238    1.093571
var(e.ind_..)|    .7393189   .1290865     5.73   0.000     .4863141    .9923238
var(e.ind_..)|    .7863679    .137189     5.73   0.000     .5174824    1.055253
var(e.ind_..)|     .414643    .080888     5.13   0.000     .2561055    .5731804
var(e.~9_std)|    .3361956   .0717194     4.69   0.000     .1956282     .476763
var(e.hhs_..)|    .8271886   .1453053     5.69   0.000     .5423955    1.111982
------------------------------------------------------------------------------
Note: Tests of variances against zero are conservative and are provided only
for
    reference.
```

Models for the rate of GDP growth

Model for GDP – dynamic factors with no lag

```
      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  4,    59) =   59.27
       Model |    212.3349     4   53.083725           Prob > F      =  0.0000
    Residual |  52.8444684    59  .895668956           R-squared     =  0.8007
-------------+------------------------------           Adj R-squared =  0.7872
       Total |  265.179368    63  4.20919633           Root MSE      =   .9464

------------------------------------------------------------------------------
         pkb |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         pkb |
         L1. |   .9190194   .1270587     7.23   0.000     .6647755    1.173263
             |
factor1~3_01 |    .018084   .0734466     0.25   0.806    -.1288823    .1650503
factor2~3_01 |   .0620295   .1170105     0.53   0.598     -.172108    .2961669
factor3~3_01 |  -.0905406   .0430569    -2.10   0.040    -.1766972   -.0043839
       _cons |   .2309655   .5510431     0.42   0.677    -.8716692      1.3336
------------------------------------------------------------------------------
```

Model for GDP – dynamic factors lagged 1 quarter

```
      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  4,    59) =   59.08
       Model |  212.198763     4  53.0496908           Prob > F      =  0.0000
    Residual |  52.9806052    59   .89797636           R-squared     =  0.8002
-------------+------------------------------           Adj R-squared =  0.7867
       Total |  265.179368    63  4.20919633           Root MSE      =  .94762

------------------------------------------------------------------------------
         pkb |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         pkb |
         L1. |   .9870708    .093685    10.54   0.000     .7996075    1.174534
             |
factor1~3_01 |
         L1. |   .0177466   .0730927     0.24   0.809    -.1285115    .1640048
             |
factor2~3_01 |
         L1. |  -.0723924   .0996132    -0.73   0.470     -.271718    .1269331
             |
factor3~3_01 |
         L1. |  -.0874251   .0352591    -2.48   0.016    -.1579783   -.0168718
             |
       _cons |  -.0358455   .4096717    -0.09   0.931    -.8555966    .7839056
------------------------------------------------------------------------------
```

Model for GDP – dynamic factors lagged 2 quarters

```
      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  4,    59) =   59.03
       Model |  212.163169     4  53.0407922           Prob > F      =  0.0000
    Residual |  53.0161998    59  .898579658           R-squared     =  0.8001
-------------+------------------------------           Adj R-squared =  0.7865
       Total |  265.179368    63  4.20919633           Root MSE      =  .94793

------------------------------------------------------------------------------
         pkb |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         pkb |
         L1. |   .9714709   .0765641    12.69   0.000     .8182665    1.124675
             |
factor1~3_01 |
         L2. |    .041424   .0729975     0.57   0.573    -.1046437    .1874917
             |
factor2~3_01 |
         L2. |  -.1347366   .0890471    -1.51   0.136    -.3129194    .0434463
             |
factor3~3_01 |
         L2. |  -.0642172   .0327431    -1.96   0.055     -.129736    .0013016
             |
       _cons |   .0434169   .3407257     0.13   0.899    -.6383736    .7252073
------------------------------------------------------------------------------
```

Model for GDP – dynamic factors lagged 3 quarters

```
      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  4,    59) =   54.74
       Model |  208.893518     4  52.2233796           Prob > F      =  0.0000
    Residual |  56.2858502    59   .95399746           R-squared     =  0.7877
-------------+------------------------------           Adj R-squared =  0.7734
       Total |  265.179368    63  4.20919633           Root MSE      =  .97673

------------------------------------------------------------------------------
         pkb |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         pkb |
         L1. |   .9209955   .0694035    13.27   0.000     .7821194    1.059871
             |
factor1~3_01 |
         L3. |   .0079044    .074951     0.11   0.916    -.1420722    .1578809
             |
factor2~3_01 |
         L3. |  -.0786577   .0840179    -0.94   0.353    -.2467772    .0894618
             |
factor3~3_01 |
         L3. |  -.0346581   .0331566    -1.05   0.300    -.1010043    .0316881
             |
       _cons |   .2513884   .3147427     0.80   0.428    -.3784102     .881187
------------------------------------------------------------------------------
```

Model for GDP – dynamic factors lagged 4 quarters

```
      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  4,    59) =   54.15
       Model |  208.412684     4  52.1031711           Prob > F      =  0.0000
    Residual |  56.7666842    59   .96214719           R-squared     =  0.7859
-------------+------------------------------           Adj R-squared =  0.7714
       Total |  265.179368    63  4.20919633           Root MSE      =  .98089

------------------------------------------------------------------------------
         pkb |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         pkb |
         L1. |   .9077449   .0648681    13.99   0.000     .7779441    1.037546
             |
factor1~3_01 |
         L4. |  -.0037691   .0751668    -0.05   0.960    -.1541776    .1466393
             |
factor2~3_01 |
         L4. |   -.088288     .08144    -1.08   0.283     -.251249     .074673
             |
factor3~3_01 |
         L4. |  -.0145921   .0335108    -0.44   0.665    -.0816471    .0524628
             |
       _cons |   .3015188   .3001198     1.00   0.319    -.2990195    .9020571
------------------------------------------------------------------------------
```

Models for the rate of unemployment

Model for UNE – dynamic factors with no lag

```
      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  5,    58) =  318.54
       Model |  1179.0163      5  235.80326            Prob > F      =  0.0000
    Residual | 42.9347729     58  .740254705           R-squared     =  0.9649
-------------+------------------------------           Adj R-squared =  0.9618
       Total | 1221.95107     63  19.3960488           Root MSE      =  .86038

------------------------------------------------------------------------------
         une |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         une |
         L1. |   .9131291   .0369793    24.69   0.000      .839107    .9871511
             |
pkb_k~201301 |  -.2464102   .1269471    -1.94   0.057    -.5005224     .007702
factor1~3_01 |  -.1843162   .0950628    -1.94   0.057    -.3746052    .0059727
factor2~3_01 |   .0762316    .121343     0.63   0.532    -.1666627     .319126
factor3~3_01 |   .0753315   .0340368     2.21   0.031     .0071993    .1434636
       _cons |     2.1609   .7765443     2.78   0.007     .6064773    3.715322
------------------------------------------------------------------------------
```

Model for UNE – dynamic factors lagged 1 quarter

```
      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  5,    58) =  335.33
       Model | 1181.09363      5  236.218726           Prob > F      =  0.0000
    Residual | 40.8574443     58  .704438695           R-squared     =  0.9666
-------------+------------------------------           Adj R-squared =  0.9637
       Total | 1221.95107     63  19.3960488           Root MSE      =  .83931

------------------------------------------------------------------------------
         une |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         une |
         L1. |   .9160509      .0373    24.56   0.000     .8413869     .990715
             |
pkb_k1_201~1 |  -.1675092   .0840662    -1.99   0.051    -.3357859    .0007676
             |
factor1~3_01 |
         L1. |  -.1813311   .0968253    -1.87   0.066    -.3751479    .0124857
             |
factor2~3_01 |
         L1. |  -.0250575   .0881285    -0.28   0.777    -.2014659    .1513509
             |
factor3~3_01 |
         L1. |   .0885911   .0301903     2.93   0.005     .0281586    .1490235
             |
       _cons |   1.789705   .6144343     2.91   0.005     .5597808    3.019628
------------------------------------------------------------------------------
```

Model for UNE – dynamic factors lagged 2 quarters

```
      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  5,    58) =  345.16
       Model |  1182.21912     5  236.443824           Prob > F      =  0.0000
    Residual |  39.7319522    58  .685033659           R-squared     =  0.9675
-------------+------------------------------           Adj R-squared =  0.9647
       Total |  1221.95107    63  19.3960488           Root MSE      =  .82767

------------------------------------------------------------------------------
         une |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         une |
         L1. |   .9001894   .0400357    22.48   0.000     .8200493    .9803294
             |
pkb_k2_201~1 |  -.1270033   .0688544    -1.84   0.070    -.2648303    .0108238
             |
factor1~3_01 |
         L2. |  -.2020449   .1032007    -1.96   0.055    -.4086235    .0045338
             |
factor2~3_01 |
         L2. |  -.0885456   .0757869    -1.17   0.247    -.2402494    .0631583
             |
factor3~3_01 |
         L2. |   .0959772    .029437     3.26   0.002     .0370526    .1549017
             |
       _cons |   1.837695   .6096811     3.01   0.004     .6172858    3.058104
------------------------------------------------------------------------------
```

Model for UNE – dynamic factors lagged 3 quarters

```
      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  5,    58) =  334.30
       Model |  1180.97265     5  236.194529           Prob > F      =  0.0000
    Residual |  40.9784289    58  .706524636           R-squared     =  0.9665
-------------+------------------------------           Adj R-squared =  0.9636
       Total |  1221.95107    63  19.3960488           Root MSE      =  .84055

------------------------------------------------------------------------------
         une |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         une |
         L1. |   .9568926    .044165    21.67   0.000     .8684867    1.045298
             |
pkb_k3_201~1 |  -.1328693   .0651195    -2.04   0.046    -.2632202   -.0025185
             |
factor1~3_01 |
         L3. |   .0206876   .1109285     0.19   0.853    -.2013599    .2427352
             |
factor2~3_01 |
         L3. |  -.2034017   .0713782    -2.85   0.006    -.3462807   -.0605226
             |
factor3~3_01 |
         L3. |   .0671068   .0313287     2.14   0.036     .0043956     .129818
             |
       _cons |   1.099471   .6436657     1.71   0.093    -.1889661    2.387908
------------------------------------------------------------------------------
```

Model for UNE – dynamic factors lagged 4 quarters

```
      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  5,    58) =  288.35
       Model |  1174.69446     5  234.938893           Prob > F      =  0.0000
    Residual |  47.2566103    58  .814769142           R-squared     =  0.9613
-------------+------------------------------           Adj R-squared =  0.9580
       Total |  1221.95107    63  19.3960488           Root MSE      =  .90265

------------------------------------------------------------------------------
         une |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         une |
         L1. |   .9290533   .0470947    19.73   0.000     .8347831    1.023324
             |
pkb_k4_201~1 |  -.1792208   .0657929    -2.72   0.009    -.3109196    -.047522
             |
factor1~3_01 |
         L4. |  -.1032278   .1143168    -0.90   0.370    -.3320577     .125602
             |
factor2~3_01 |
         L4. |  -.0123522   .0737857    -0.17   0.868    -.1600503     .135346
             |
factor3~3_01 |
         L4. |   .0611638   .0348192     1.76   0.084    -.0085344     .130862
             |
       _cons |    1.66126   .6968136     2.38   0.020     .2664364    3.056084
------------------------------------------------------------------------------
```

Models for the rate of inflation

Model for CPI – dynamic factors with no lag

```
      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  6,    57) =  335.07
       Model |  1013.80744     6  168.967906           Prob > F      =  0.0000
    Residual |  28.7436766    57  .504275028           R-squared     =  0.9724
-------------+------------------------------           Adj R-squared =  0.9695
       Total |  1042.55112    63  16.5484304           Root MSE      =  .71012

------------------------------------------------------------------------------
         cpi |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpi |
         L1. |   .7604285   .0460262    16.52   0.000     .6682625    .8525944
             |
pkb_k~201301 |   .5314679   .1063298     5.00   0.000     .3185462    .7443895
une_k~201301 |  -.0504658   .0343064    -1.47   0.147    -.1191632    .0182317
factor1~3_01 |   -.204771   .0857198    -2.39   0.020    -.3764219   -.0331201
factor2~3_01 |  -.2986291   .1033798    -2.89   0.005    -.5056436   -.0916146
factor3~3_01 |    .138413   .0590053     2.35   0.022     .0202569    .2565691
       _cons |  -.5245298   .7681483    -0.68   0.497     -2.06272    1.013661
------------------------------------------------------------------------------
```

Model for CPI – dynamic factors lagged 1 quarter

```
      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  6,    57) =  313.74
       Model |  1011.91053     6  168.651755           Prob > F      =  0.0000
    Residual |  30.6405873    57  .537554162           R-squared     =  0.9706
-------------+------------------------------           Adj R-squared =  0.9675
       Total |  1042.55112    63  16.5484304           Root MSE      =  .73318

------------------------------------------------------------------------------
         cpi |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpi |
         L1. |   .7543201     .05462    13.81   0.000     .6449454    .8636948
             |
pkb_k1_201~1 |   .4522125   .0792334     5.71   0.000     .2935503    .6108746
une_k1_201~1 |  -.0215701   .0372579    -0.58   0.565    -.0961777    .0530375
             |
factor1~3_01 |
         L1. |  -.0561093   .0956465    -0.59   0.560    -.2476381    .1354195
             |
factor2~3_01 |
         L1. |  -.2738256   .0832916    -3.29   0.002    -.4406142   -.1070371
             |
factor3~3_01 |
         L1. |   .1393464   .0659444     2.11   0.039      .007295    .2713978
             |
       _cons |  -.5623517   .6631114    -0.85   0.400    -1.890209    .7655059
------------------------------------------------------------------------------
```

Model for CPI – dynamic factors lagged 2 quarters

```
      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  6,    57) =  279.21
       Model |  1008.24573     6  168.040955           Prob > F      =  0.0000
    Residual |   34.305388    57  .601848912           R-squared     =  0.9671
-------------+------------------------------           Adj R-squared =  0.9636
       Total |  1042.55112    63  16.5484304           Root MSE      =  .77579

------------------------------------------------------------------------------
         cpi |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpi |
         L1. |   .7929357   .0611291    12.97   0.000     .6705269    .9153445
             |
pkb_k2_201~1 |   .3534548   .0761851     4.64   0.000     .2008968    .5060128
une_k2_201~1 |  -.0019089   .0446318    -0.04   0.966    -.0912825    .0874647
             |
factor1~3_01 |
         L2. |   .0255974   .1118109     0.23   0.820       -.1983    .2494948
             |
factor2~3_01 |
         L2. |  -.1565527   .0769371    -2.03   0.047    -.3106165   -.0024888
             |
factor3~3_01 |
         L2. |   .0837043   .0724873     1.15   0.253    -.0614491    .2288576
             |
       _cons |  -.6291251   .7274065    -0.86   0.391    -2.085732    .8274814
------------------------------------------------------------------------------
```

Model for CPI – dynamic factors lagged 3 quarters

```
      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  6,    57) =  274.59
       Model |   1007.6882     6  167.948034           Prob > F      =  0.0000
    Residual |  34.8629134    57   .61163006           R-squared     =  0.9666
-------------+------------------------------           Adj R-squared =  0.9630
       Total |  1042.55112    63  16.5484304           Root MSE      =  .78207

------------------------------------------------------------------------------
         cpi |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpi |
         L1. |   .8199608   .0547179    14.99   0.000     .7103901    .9295316
             |
pkb_k3_201~1 |   .3106863   .0722438     4.30   0.000     .1660206     .455352
une_k3_201~1 |   .0196657   .0449935     0.44   0.664    -.0704323    .1097637
             |
factor1~3_01 |
         L3. |   .1103623   .1058247     1.04   0.301    -.1015481    .3222726
             |
factor2~3_01 |
         L3. |  -.1284608   .0711029    -1.81   0.076     -.270842    .0139204
             |
factor3~3_01 |
         L3. |   .0356366   .0636994     0.56   0.578    -.0919192    .1631924
             |
       _cons |  -.8845774     .69979    -1.26   0.211    -2.285883    .5167278
------------------------------------------------------------------------------
```

```
Model for CPI – dynamic factors lagged 4 quarters

      Source |       SS       df       MS              Number of obs =      64
-------------+------------------------------           F(  6,    57) =  279.10
       Model |  1008.23344     6  168.038907           Prob > F      =  0.0000
    Residual |  34.3176747    57  .602064469           R-squared     =  0.9671
-------------+------------------------------           Adj R-squared =  0.9636
       Total |  1042.55112    63  16.5484304           Root MSE      =  .77593

------------------------------------------------------------------------------
         cpi |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         cpi |
         L1. |   .7985635   .0408884    19.53   0.000     .7166858    .8804412
             |
pkb_k4_201~1 |   .3267522   .0662921     4.93   0.000     .1940045    .4594998
une_k4_201~1 |  -.0207775   .0450736    -0.46   0.647    -.1110359    .0694809
             |
factor1~3_01 |
         L4. |   .0213503   .1035313     0.21   0.837    -.1859676    .2286682
             |
factor2~3_01 |
         L4. |  -.1228076   .0657846    -1.87   0.067    -.2545389    .0089237
             |
factor3~3_01 |
         L4. |   .0757327   .0490566     1.54   0.128    -.0225014    .1739667
             |
       _cons |  -.3043706   .6981035    -0.44   0.664    -1.702299    1.093558
------------------------------------------------------------------------------

.
```

Appendix 6. Parameters of ARIMA models

Model 1: ARMA, using observations 1996:1-2012:4 (T = 68)
Dependent variable: pkb
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
const	4.06473	0.587421	6.9196	<0.00001	***
phi_1	1.30847	0.108539	12.0552	<0.00001	***
phi_2	-0.488547	0.109905	-4.4452	<0.00001	***

Mean dependent var	4.286765	S.D. dependent var	2.090269
Mean of innovations	0.014991	S.D. of innovations	0.886752
Log-likelihood	-89.32828	Akaike criterion	186.6566
Schwarz criterion	195.5346	Hannan-Quinn	190.1743

Model 2: ARMA, using observations 1996:1-2012:4 (T = 68)
Dependent variable: pkb
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
const	4.08302	0.551275	7.4065	<0.00001	***
phi_1	1.30902	0.111095	11.7828	<0.00001	***
phi_2	-0.455561	0.115655	-3.9390	0.00008	***
Theta_1	-0.22613	0.148028	-1.5276	0.12661	

Mean dependent var	4.286765	S.D. dependent var	2.090269
Mean of innovations	0.018257	S.D. of innovations	0.872019
Log-likelihood	-88.28957	Akaike criterion	186.5791
Schwarz criterion	197.6767	Hannan-Quinn	190.9763

Model 3: ARIMA, using observations 1997:2-2012:4 (T = 63)
Estimated using Kalman filter (exact ML)
Dependent variable: (1-L)(1-Ls) cpi
Standard errors based on Hessian

	Coefficient	Std. error	z	p-value	
phi_4	-0.498309	0.110412	-4.513	6.39e-06	***
theta_1	0.872546	0.117963	7.397	1.40e-013	***
theta_2	0.860546	0.157181	5.475	4.38e-08	***
theta_3	0.947339	0.181219	5.228	1.72e-07	***

Mean dependent var	0.026984	.D. dependent var	1.605154
Mean of innovations	0.004609	S.D. of innovations	0.875246
Log-likelihood	-86.16735	Akaike criterion	182.3347
Schwarz criterion	193.0504	Hannan-Quinn	186.5492

Model 4: ARIMA, using observations 1996:2-2012:4 (T = 67)
Estimated using Kalman filter (exact ML)
Dependent variable: (1-L) une
Standard errors based on Hessian

	Coefficient	Std. error	z	p-value	
phi_1	-0.611049	0.129553	-4.717	2.40e-06	***
theta_1	1.21593	0.153796	7.906	2.66e-015	***
theta_2	0.549842	0.205078	2.681	0.0073	***
theta_3	-0.297452	0.131715	-2.258	0.0239	**

Mean dependent var	-0.058209	S.D. dependent var	0.959822
Mean of innovations	-0.037498	S.D. of innovations	0.730035
Log-likelihood	-77.17852	Akaike criterion	164.3570
Schwarz criterion	175.3805	Hannan-Quinn	168.7191

Appendix 7. Forecasts from Bayesian models – averaging approach

PKB FORECASTS							
LAST PERIOD OF DATA FOR PKB UNE CPI							2012q4
	2013q1	2013q2	2013q3	2013q4	2014q1		
k=0	0,67						
k=1	0,40	1,37					
k=2	0,11	-0,72	-1,20				
k=3	0,16	0,84	0,99	0,98			
k=4	-0,36	0,31	1,57	2,23	2,44		

UNE FORECASTS							
LAST PERIOD OF DATA FOR PKB UNE CPI							2012q4
	2013q1	2013q2	2013q3	2013q4	2014q1		
k=0	10,06						
k=1	9,34	8,43					
k=2	11,12	12,13	13,14				
k=3	9,59	8,77	7,59	7,07			
k=4	9,73	9,39	8,76	9,01	8,22		

CPI FORECASTS							
LAST PERIOD OF DATA FOR PKB UNE CPI							2012q4
	2013q1	2013q2	2013q3	2013q4	2014q1		
k=0	1,51						
k=1	6,60	4,17					
k=2	4,08	5,15	3,21				
k=3	0,28	-1,34	-4,41	-2,24			
k=4	-0,27	-2,51	-4,05	-8,25	-6,65		

Appendix 8. Forecasts from Bayesian models – frequentist approach without collinearity correction

GDP FORECASTS										
LAST PERIOD OF DATA FOR GDP UNE CPI							2012q4			
	2013q1	2013q2	2013q3	2013q4	2014q1		RMSE			
k=0	0.96						0.56			
k=1	0.67	1.66					0.64			
k=2	0.51	0.72	1.02				0.57			
k=3	0.66	0.59	1.05	1.22			0.90			
k=4	0.07	0.66	1.58	1.88	2.26		0.67			
RMSE FOR ALL FORECASTS						0.71				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q1			
		2013q2	2013q3	2013q4	2014q1	2014q2				
k=0		1.03								
k=1		1.50	2.12							
k=2		0.71	1.02	1.04						
k=3		0.44	0.89	1.07	1.60					
k=4		1.02	1.87	2.15	2.50	3.86				
RMSE FOR ALL FORECASTS						0.95				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q2			
			2013q3	2013q4	2014q1	2014q2	2014q3			
k=0			1.96							
k=1			1.46	2.37						
k=2			1.10	1.12	1.78					
k=3			1.25	1.43	1.98	2.20				
k=4			1.69	1.99	2.37	3.73	3.80			
RMSE FOR ALL FORECASTS						1.01				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q3			
				2013q4	2014q1	2014q2	2014q3	2014q4		
k=0				2.81						
k=1				2.78	4.16					
k=2				1.89	2.52	3.71				
k=3				2.04	2.56	2.74	3.28			
k=4				2.17	2.52	3.87	3.92	4.59		
RMSE FOR ALL FORECASTS						0.68				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q4			
					2014q1	2014q2	2014q3	2014q4	2015q1	
k=0					3.61					
k=1					4.08	4.93				
k=2					3.28	4.41	4.75			
k=3					3.20	3.34	3.86	3.69		
k=4					2.96	4.22	4.21	4.68	4.72	
RMSE FOR ALL FORECASTS						0.39				
LAST PERIOD OF DATA FOR GDP UNE CPI							2014q1			
						2014q2	2014q3	2014q4	2015q1	2015q2
k=0						3.80				
k=1						4.12	5.13			
k=2						3.83	4.10	4.38		
k=3						3.48	3.42	3.11	2.50	
k=4						3.34	2.87	2.36	2.27	2.08

UNE FORECASTS										
LAST PERIOD OF DATA FOR GDP UNE CPI							2012q4			
	2013q1	2013q2	2013q3	2013q4	2014q1		RMSE			
k=0	10.89						0.41			
k=1	11.33	12.06					1.17			
k=2	10.51	10.70	10.84				0.77			
k=3	10.76	11.45	11.62	11.96			1.53			
k=4	10.94	11.66	11.40	12.01	11.68		1.44			
RMSE FOR ALL FORECASTS						1.27				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q1			
		2013q2	2013q3	2013q4	2014q1	2014q2				
k=0		11.82								
k=1		12.04	12.38							
k=2		11.53	11.74	12.18						
k=4		11.98	11.66	12.26	11.89	11.48				
RMSE FOR ALL FORECASTS						1.97				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q2			
			2013q3	2013q4	2014q1	2014q2	2014q3			
k=0			9.86							
k=1			11.14	11.18						
k=2			10.62	11.08	11.97					
k=3			10.69	11.04	11.47	11.41				
k=4			10.30	11.03	10.79	10.52	9.69			
RMSE FOR ALL FORECASTS						1.03				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q3			
				2013q4	2014q1	2014q2	2014q3	2014q4		
k=0				9.73						
k=1				10.11	10.38					
k=2				10.06	10.86	11.42				
k=3				10.14	10.67	10.64	10.86			
k=4				10.59	10.36	10.03	9.25	8.17		
RMSE FOR ALL FORECASTS						0.35				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q4			
					2014q1	2014q2	2014q3	2014q4	2015q1	
k=0					9.94					
k=1					10.13	10.07				
k=2					10.48	10.96	10.41			
k=3					10.26	10.20	10.40	10.22		
k=4					9.67	9.41	8.62	7.94	7.76	
RMSE FOR ALL FORECASTS						0.57				
LAST PERIOD OF DATA FOR GDP UNE CPI							2014q1			
						2014q2	2014q3	2014q4	2015q1	2015q2
k=0						9.74				
k=1						10.30	9.75			
k=2						10.34	10.12	9.76		
k=3						10.82	10.92	10.50	11.11	
k=4						10.30	9.34	8.33	8.08	6.59

CPI FORECASTS										
LAST PERIOD OF DATA FOR GDP UNE CPI							2012q4			
	2013q1	2013q2	2013q3	2013q4	2014q1		RMSE			
k=0	2.68						1.38			
k=1	1.90	1.45					0.80			
k=2	1.18	0.14	-1.15				1.32			
k=3	2.39	1.96	1.81	1.27			1.02			
k=4	1.33	0.99	0.86	0.95	0.89		0.30			
RMSE FOR ALL FORECASTS						0.93				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q1			
		2013q2	2013q3	2013q4	2014q1	2014q2				
k=0		1.49								
k=1		0.91	0.73							
k=2		0.40	-0.77	-2.06						
k=3		0.89	0.77	0.27	0.00					
k=4		1.12	1.11	1.27	1.26	1.54				
RMSE FOR ALL FORECASTS						1.01				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q2			
			2013q3	2013q4	2014q1	2014q2	2014q3			
k=0			0.71							
k=1			0.01	0.01						
k=2			-0.87	-2.30	-2.86					
k=3			0.33	-0.19	-0.49	0.06				
k=4			0.18	0.13	0.00	0.19	0.40			
RMSE FOR ALL FORECASTS						1.60				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q3			
				2013q4	2014q1	2014q2	2014q3	2014q4		
k=0				1.09						
k=1				0.89	0.69					
k=2				-0.34	-1.05	-1.26				
k=3				0.62	0.35	0.90	1.57			
k=4				1.01	0.86	1.12	1.39	1.81		
RMSE FOR ALL FORECASTS						0.69				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q4			
					2014q1	2014q2	2014q3	2014q4	2015q1	
k=0					0.95					
k=1					0.48	0.49				
k=2					0.14	-0.05	-0.03			
k=3					0.57	1.22	1.96	2.30		
k=4					0.58	0.85	1.10	1.67	2.02	
RMSE FOR ALL FORECASTS						0.27				
LAST PERIOD OF DATA FOR GDP UNE CPI							2014q1			
						2014q2	2014q3	2014q4	2015q1	2015q2
k=0						0.65				
k=1						0.53	1.37			
k=2						0.67	0.59	0.70		
k=3						0.49	0.32	0.01	-0.37	
k=4						0.65	0.58	0.27	-0.79	-0.95

Appendix 9. Forecasts from Bayesian models – frequentist approach with collinearity correction

GDP FORECASTS										
LAST PERIOD OF DATA FOR GDP UNE CPI							2012q4			
	2013q1	2013q2	2013q3	2013q4	2014q1		RMSE			
k=0	0.96						0.56			
k=1	0.60	1.54					0.54			
k=2	0.51	0.72	1.02				0.57			
k=3	0.62	1.26	1.77	2.23			0.36			
k=4	-0.05	0.64	1.31	1.66	1.94		0.89			
RMSE FOR ALL FORECASTS						0.65				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q1			
		2013q2	2013q3	2013q4	2014q1	2014q2				
k=0		1.03								
k=1		1.45	2.11							
k=2		0.71	1.02	1.04						
k=3		0.93	1.42	1.80	2.39					
k=4		1.01	1.71	1.90	2.11	3.25				
RMSE FOR ALL FORECASTS						0.79				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q2			
			2013q3	2013q4	2014q1	2014q2	2014q3			
k=0			1.96							
k=1			1.49	2.41						
k=2			1.10	1.12	1.78					
k=3			1.29	1.66	2.25	2.88				
k=4			1.53	1.75	1.97	3.12	3.19			
RMSE FOR ALL FORECASTS						1.01				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q3			
				2013q4	2014q1	2014q2	2014q3	2014q4		
k=0				2.81						
k=1				2.79	4.14					
k=2				1.89	2.52	3.71				
k=3				2.29	2.89	3.50	4.16			
k=4				2.06	2.25	3.38	3.40	3.75		
RMSE FOR ALL FORECASTS							0.68			
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q4			
					2014q1	2014q2	2014q3	2014q4	2015q1	
k=0					3.61					
k=1					4.06	4.77				
k=2					3.28	4.41	4.75			
k=3					3.29	3.91	4.57	4.68		
k=4					2.79	3.82	3.77	4.06	3.87	
RMSE FOR ALL FORECASTS							0.42			
LAST PERIOD OF DATA FOR GDP UNE CPI							2014q1			
						2014q2	2014q3	2014q4	2015q1	2015q2
k=0						3.80				
k=1						3.77	4.54			
k=2						3.83	4.10	4.38		
k=3						3.49	3.59	3.56	3.22	
k=4						3.12	2.78	2.35	2.23	2.09

UNE FORECASTS										
LAST PERIOD OF DATA FOR GDP UNE CPI							2012q4			
	2013q1	2013q2	2013q3	2013q4	2014q1		RMSE			
k=0	10.61						0.69			
k=1	11.33	12.07					1.18			
k=2	11.04	11.30	11.86				1.31			
k=3	10.82	10.98	10.99	10.87			0.89			
k=4	10.51	11.06	10.98	11.23	11.52		1.03			
RMSE FOR ALL FORECASTS						1.06				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q1			
		2013q2	2013q3	2013q4	2014q1	2014q2				
k=0		11.91								
k=1		12.05	12.39							
k=2		11.58	12.16	13.09						
k=4		11.82	11.74	12.02	12.30	12.05				
RMSE FOR ALL FORECASTS						1.89				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q2			
			2013q3	2013q4	2014q1	2014q2	2014q3			
k=0			10.17							
k=1			11.14	11.18						
k=2			10.93	11.81	13.02					
k=3			10.50	10.48	10.55	10.24				
k=4			10.33	10.61	10.92	10.64	9.41			
RMSE FOR ALL FORECASTS						1.19				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q3			
				2013q4	2014q1	2014q2	2014q3	2014q4		
k=0				10.17						
k=1				10.11	10.38					
k=2				10.49	11.56	12.10				
k=3				9.77	9.87	9.58	9.57			
k=4				10.05	10.35	10.03	8.81	8.25		
RMSE FOR ALL FORECASTS						0.51				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q4			
					2014q1	2014q2	2014q3	2014q4	2015q1	
k=0					9.91					
k=1					10.14	10.07				
k=2					10.68	11.07	10.71			
k=3					9.86	9.53	9.50	9.15		
k=4					10.04	9.70	8.45	7.88	7.58	
RMSE FOR ALL FORECASTS						0.56				
LAST PERIOD OF DATA FOR GDP UNE CPI							2014q1			
						2014q2	2014q3	2014q4	2015q1	2015q2
k=0						9.61				
k=1						10.39	9.99			
k=2						10.76	10.64	10.86		
k=3						10.52	10.08	9.61	9.73	
k=4						9.85	8.78	7.83	7.46	5.83

CPI FORECASTS										
LAST PERIOD OF DATA FOR GDP UNE CPI							2012q4			
	2013q1	2013q2	2013q3	2013q4	2014q1		RMSE			
k=0	2.97						1.67			
k=1	1.88	1.43					0.77			
k=2	1.54	1.03	0.53				0.47			
k=3	2.19	1.63	1.53	1.18			0.79			
k=4	1.70	1.29	0.98	0.92	0.87		0.43			
RMSE FOR ALL FORECASTS						0.73				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q1			
		2013q2	2013q3	2013q4	2014q1	2014q2				
k=0		1.10								
k=1		0.91	0.70							
k=2		0.81	0.32	-0.66						
k=3		0.76	0.65	0.29	0.19					
k=4		0.99	0.75	0.73	0.69	0.81				
RMSE FOR ALL FORECASTS						0.55				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q2			
			2013q3	2013q4	2014q1	2014q2	2014q3			
k=0			0.48							
k=1			0.00	0.00						
k=2			0.06	-0.89	-1.20					
k=3			0.42	0.09	0.00	0.45				
k=4			0.25	0.23	0.20	0.33	0.93			
RMSE FOR ALL FORECASTS						0.97				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q3			
				2013q4	2014q1	2014q2	2014q3	2014q4		
k=0				1.25						
k=1				0.87	0.67					
k=2				0.31	0.09	0.26				
k=3				0.88	0.88	1.39	1.85			
k=4				1.03	0.94	1.04	1.55	2.23		
RMSE FOR ALL FORECASTS						0.35				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q4			
					2014q1	2014q2	2014q3	2014q4	2015q1	
k=0					0.78					
k=1					0.47	0.46				
k=2					0.71	1.02	1.18			
k=3					0.85	1.48	2.04	2.09		
k=4					0.78	0.99	1.58	2.29	2.39	
RMSE FOR ALL FORECASTS						0.18				
LAST PERIOD OF DATA FOR GDP UNE CPI							2014q1			
						2014q2	2014q3	2014q4	2015q1	2015q2
k=0						0.57				
k=1						0.56	1.24			
k=2						0.88	1.24	1.67		
k=3						0.53	0.40	0.19	-0.08	
k=4						0.56	0.37	0.15	-0.18	-0.33

Appendix 10. Forecasts from DFM approach

GDP FORECASTS										
LAST PERIOD OF DATA FOR GDP UNE CPI							2012q4			
	2013q1	2013q2	2013q3	2013q4	2014q1		RMSE			
k=0	1.00						0.60			
k=1	1.02	1.32					0.58			
k=2	0.90	1.33	1.71				0.45			
k=3	1.02	1.32	1.71	2.06			0.54			
k=4	1.01	1.34	1.64	2.01	2.33		0.70			
RMSE FOR ALL FORECASTS						0.59				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q1			
		2013q2	2013q3	2013q4	2014q1	2014q2				
k=0		0.91								
k=1		1.06	1.61							
k=2		0.94	1.60	2.21						
k=3		0.84	1.27	1.82	2.31					
k=4		0.88	1.22	1.63	2.15	2.59				
RMSE FOR ALL FORECASTS						0.68				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q2			
			2013q3	2013q4	2014q1	2014q2	2014q3			
k=0			1.96							
k=1			1.49	2.41						
k=2			1.10	1.12	1.78					
k=3			1.29	1.66	2.25	2.88				
k=4			1.53	1.75	1.97	3.12	3.19			
RMSE FOR ALL FORECASTS						1.01				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q3			
				2013q4	2014q1	2014q2	2014q3	2014q4		
k=0				2.81						
k=1				2.79	4.14					
k=2				1.89	2.52	3.71				
k=3				2.29	2.89	3.50	4.16			
k=4				2.06	2.25	3.38	3.40	3.54		
RMSE FOR ALL FORECASTS						0.68				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q4			
					2014q1	2014q2	2014q3	2014q4	2015q1	
k=0					3.61					
k=1					4.06	4.77				
k=2					3.28	4.41	4.75			
k=3					3.29	3.91	4.57	3.76		
k=4					2.79	3.82	3.77	3.77	3.79	
RMSE FOR ALL FORECASTS						0.42				
LAST PERIOD OF DATA FOR GDP UNE CPI							2014q1			
						2014q2	2014q3	2014q4	2015q1	2015q2
k=0						3.90				
k=1						3.70	3.95			
k=2						3.69	3.80	3.85		
k=3						3.70	3.86	3.90	3.90	
k=4						3.73	3.94	3.99	3.90	3.79

UNE FORECASTS										
LAST PERIOD OF DATA FOR GDP UNE CPI							2012q4			
	2013q1	2013q2	2013q3	2013q4	2014q1		RMSE			
k=0	10.94						0.36			
k=1	10.83	11.43					0.80			
k=2	11.11	11.76	12.26				1.63			
k=3	10.72	11.22	11.82	12.30			1.68			
k=4	10.78	11.52	12.17	12.55	12.84		1.98			
RMSE FOR ALL FORECASTS						1.64				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q1			
		2013q2	2013q3	2013q4	2014q1	2014q2				
k=0		12.06								
k=1		12.05	12.59							
k=2		11.98	12.72	13.24						
k=3		11.84	12.47	13.08	13.54					
k=4		12.08	12.76	13.17	13.51	13.71				
RMSE FOR ALL FORECASTS						2.62				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q2			
			2013q3	2013q4	2014q1	2014q2	2014q3			
k=0			10.17							
k=1			11.14	11.18						
k=2			10.93	11.81	13.02					
k=3			10.50	10.48	10.55	10.24				
k=4			10.33	10.61	10.92	10.64	9.41			
RMSE FOR ALL FORECASTS						1.19				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q3			
				2013q4	2014q1	2014q2	2014q3	2014q4		
k=0				10.17						
k=1				10.11	10.38					
k=2				10.49	11.56	12.10				
k=3				9.77	9.87	9.58	9.57			
k=4				10.05	10.35	10.03	8.81	11.23		
RMSE FOR ALL FORECASTS						0.51				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q4			
					2014q1	2014q2	2014q3	2014q4	2015q1	
k=0					9.91					
k=1					10.14	10.07				
k=2					10.68	11.07	10.71			
k=3					9.86	9.53	9.50	10.05		
k=4					10.04	9.70	8.45	10.53	10.54	
RMSE FOR ALL FORECASTS						0.56				
LAST PERIOD OF DATA FOR GDP UNE CPI							2014q1			
						2014q2	2014q3	2014q4	2015q1	2015q2
k=0						10.70				
k=1						10.48	10.33			
k=2						10.61	10.41	10.21		
k=3						10.75	10.59	10.12	9.61	
k=4						10.69	10.78	10.73	10.65	10.60

CPI FORECASTS										
LAST PERIOD OF DATA FOR GDP UNE CPI							2012q4			
	2013q1	2013q2	2013q3	2013q4	2014q1		RMSE			
k=0	1.97						0.67			
k=1	2.07	1.50					0.90			
k=2	1.92	1.40	1.10				0.63			
k=3	1.95	1.19	0.92	0.80			0.48			
k=4	2.07	1.54	1.15	1.03	1.01		0.63			
RMSE FOR ALL FORECASTS						0.64				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q1			
		2013q2	2013q3	2013q4	2014q1	2014q2				
k=0		0.98								
k=1		1.00	0.90							
k=2		0.78	0.58	0.59						
k=3		0.52	0.25	0.14	0.18					
k=4		0.76	0.38	0.28	0.33	0.47				
RMSE FOR ALL FORECASTS						0.46				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q2			
			2013q3	2013q4	2014q1	2014q2	2014q3			
k=0			0.48							
k=1			0.00	0.00						
k=2			0.06	-0.89	-1.20					
k=3			0.42	0.09	0.00	0.45				
k=4			0.25	0.23	0.20	0.33	0.93			
RMSE FOR ALL FORECASTS						0.97				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q3			
				2013q4	2014q1	2014q2	2014q3	2014q4		
k=0				1.25						
k=1				0.87	0.67					
k=2				0.31	0.09	0.26				
k=3				0.88	0.88	1.39	1.85			
k=4				1.03	0.94	1.04	1.55	1.49		
RMSE FOR ALL FORECASTS						0.35				
LAST PERIOD OF DATA FOR GDP UNE CPI							2013q4			
					2014q1	2014q2	2014q3	2014q4	2015q1	
k=0					0.78					
k=1					0.47	0.46				
k=2					0.71	1.02	1.18			
k=3					0.85	1.48	2.04	1.02		
k=4					0.78	0.99	1.58	1.57	1.56	
RMSE FOR ALL FORECASTS						0.18				
LAST PERIOD OF DATA FOR GDP UNE CPI							2014q1			
						2014q2	2014q3	2014q4	2015q1	2015q2
k=0						0.43				
k=1						0.31	0.15			
k=2						0.74	0.64	0.55		
k=3						0.83	0.98	0.93	0.85	
k=4						1.01	1.37	1.51	1.40	1.25

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