A dynamic factor model for forecasting house prices in Belgium

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by Marina Emiris

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Abstract

The paper forecasts the residential property price index in Belgium with a dynamic factor model (DFM) estimated with a dataset of macro-economic variables describing the Belgian and euro area economy. The model is validated with out-of-sample forecasts which are obtained recursively over an expanding window over the period 2000q1-2012q4. We illustrate how the model reads information from mortgage loans, interest rates, GDP and inflation to revise the residential property price forecast as a result of a change in assumptions for the future paths of these variables.

JEL classification: E32, G21, C53

Keywords: dynamic factor model, conditional forecast, house prices

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1 Introduction

The aim of this paper is to compute real house price forecasts that are compatible with the evolution of macroeconomic variables in Belgium and the euro area. This type of forecast is widely used in several contexts in central banks as the outlook for residential property prices helps assess the state of the macroeconomy and financial stability. For example, national central banks in the euro area are required to send in forecasts to the ECB on the likely path of a national index of residential property prices over a horizon of 12 quarters as part of the macroeconomic projection exercises in June and in December each year. The outlook for house prices is also used as an input for bank stress-testing.

House prices, along with other financial indicators, move jointly with future economic activity and inflation. The recent financial crisis, as well as its links with the housing market boom and bust in several countries around the world, has provided additional evidence that housing variables comove strongly with the business cycle (Heathcote and Davis (2005), Leamer (2007), Case and Wachter (2005), Girouard *et.al* (2006)). House price busts accompanied by credit contractions have been shown to precede longer and deeper recessions (Claessens, Cose and Terrones (2008)). Recent research also has focused on the feedback mechanisms between housing markets and the economy, investigating for example the role of monetary policy in fuelling or preventing a house price bubble (Luciani (2013), Jarocinski and Smets (2008)), and studying the "housing cycle" and spillovers from housing to consumption before and after the financial crisis.

This paper acknowledges these complex interactions between the housing market and the rest of the economy by proposing a joint model for residential property prices and a large number of indicators that are relevant to characterise the Belgian economy, including its external environment. The paper has a twofold objective. First, to jointly forecast residential property prices and the economy in Belgium. Second, to use this framework to impose alternative scenarios on the path of some variables, such as interest rates, and to deduce the conditional forecasts or the paths for the residential property price index that are consistent with these scenarios. The modelling approach followed in this paper borrows from the literature on dynamic factor models. The aim is to extract the key driving factors from a large information set of macroeconomic variables in Belgium and the euro area in a parsimonious manner in order to ensure their usefulness for out-of-sample forecasting.

The dynamic factor model exploits the fact that the residential property price index, interest rates and other macroeconomic and financial variables comove strongly. In its simplest form, any series is modelled as a sum of two components: a "common component", which is driven by an unobserved common factor (for example "the business cycle") and produces the observed correlation of the residential property price index with the other series; an "idiosyncratic component", which is uncorrelated with the common component and is specific to each of the series and uncorrelated from the other idiosyncratic components. The factors are dynamic, in the sense they are driven by a few common shocks that propagate across variables and in time through the factors themselves.

By making the assumption that there is only a small number of unobserved common sources producing the observed comovement of the different time series, the dynamic factor model offers a parsimonious representation of each variable in the dataset. It maps the information from all the variables into a few factors and implies that the number of parameters to estimate remains small as we add variables to the dataset (see Stock and Watson (2011)).

This assumption is too restrictive in large datasets. For example, in large datasets of macroeconomic variables, the idiosyncratic component for series that are similar in nature ("prices", grouping such variables as a consumer price index, GDP deflator, etc. or "real variables" grouping GDP and its components, consumption, investment etc.) or variables concerning the same geographical area, are bound to be correlated even after we control for a few common economy-wide factors. We deal with this problem by incorporating several factors in each block of variables in such a way that the residual cross-correlation patterns can be considered idiosyncratic or at least weakly correlated across variables[1].

Although there is a large literature on modelling and explaining house prices, few papers focus specifically on forecasting. The most widely used empirical approach is based on an inverted demand equation. The supply of housing services is assumed to be relatively inelastic in the short run and it is mainly changes in demand that explain variation in house prices. In this context, housing is treated as a consumption good and its demand is a function of such variables as household income, interest rates, the mortgage rate, financial wealth, demographic and labour market factors. This approach links the level of house prices to its short-run and long-run determinants in an error correction model (ECM) or a vector error correction model (VECM). Changes in house prices are a function of changes in the explanatory variables and an error-correction term which reflects the adjustment of house prices to a disequilibrium. An example of this approach is given by Gattini and Hiebert (2010) for the euro area.

These models are mainly used to determine any over/undervaluation of house prices as a deviation from the values implied by a long-run equilibrium. Although VECMs have been used for forecasting, other types of models that allow for more flexibility in their parameters should outperform the VECM forecasts. For example, Bayesian vector autoregressions (BVARs) should perform better. Examples in the literature of BVARs with house prices, residential investment along with other macroeconomic variables are Jarocinski and Smets (2008), Iacoviello and Neri (2010). These papers model the level of house prices along with other macroeconomic and financial determinants. BVARs have been used in combination with structural theoretical models to impose restrictions on the BVAR parameters stemming from a theoretical dynamic stochastic general equilibrium model (DSGE). However, in these papers, the focus is not so much on

[1] The literature on so-called "approximate" dynamic factor models has shown that even if the data-generating process has locally, or mildly correlated idiosyncratic components, it is still possible to estimate the parameters of the above dynamic factor model in a consistent way (see Forni, Hallin Lippi, and Reichlin (2000); Stock and Watson (2002), Bai and Ng (2002); Bai (2003); Forni, Hallin, Lippi and Reichlin (2004); Doz, Giannone and Reichlin (2012)).

forecasting as it is on explaining the interactions of house prices / the housing sector and the economy and finding empirical support for the proposed DSGE model.

Similarly, models that make it possible to increase the number of variables included in the dataset such as factor-augmented vector auto-regressions (FAVARs), as in Eickmeirer and Hofmann (2013), or structural dynamic factor models, as in Luciani (2013), have modelled house prices and their interactions with the economy in a structural context, seeking to understand the role of monetary policy and credit in fuelling the house price bubble in the US during the period 2000-2006.

The focus of our paper is on forecasting house prices. Therefore, the dynamic factor model will be estimated in reduced form, without imposing any identifying restrictions on the parameters, so as to give it as much flexibility as possible to maximise its forecast performance. The link with a structural model can be achieved in a subsequent step by identifying the shocks as in the structural models, even though this task will not be undertaken in this paper.

The model will be written in state space form and estimated by (quasi-) maximum likelihood following Doz, Giannone and Reichlin (2012). The estimation procedure is based on the expectation-maximisation (EM) algorithm and a Kalman filter/smoother which jointly estimates the factors, the factor dynamics and the loadings of the variables on the factors. The advantage of the state-space approach is the possibility to recursively obtain forecasts conditional on assumptions on the evolution of a block of variables of interest.

First, the parameters and the factors are estimated over a given sample. Then, residential property prices are forecast over different horizons in two ways. In the first part of the empirical section, we use the final data *realisations,* as available in 2013q3, thereby ignoring data revisions. We start with an out-of-sample experiment where unconditional forecasts for house prices are recursively calculated using a balanced panel. Then, we assess the extent to which those house price forecasts for a given period would have improved had we made them conditional on data, up to that period, for a block of variables such as mortgage loans, interest rates, the GDP and inflation rate. Thus, in this first exercise, the conditioning information refers to actual data. This experiment is designed to answer the question: "Had the actual data on the macroeconomic environment been ´revealed ´ to us at the time of the forecast (and before it was actually published) and had it been exploited by the model, would the forecast have improved relative to the forecast obtained without this information?". This particular out-of-sample forecasting exercise is important to understand the second part of our empirical application, in which the conditioning information is taken from *expectations*, published in the NBB Economic Review, regarding those series over the forecasting horizon.

In the second part of the empirical section of the paper, we apply this forecasting methodology to account for the revisions in real house price forecasts in terms of changes in the conditioning assumptions. We produce forecasts for the residential property price index at two points in time. The first time is in September 2007 given the assumptions for the December 2007 macroeconomic projection exercise and then, one year later, given the new assumptions for the December 2008 macroeconomic projection exercise. When a new scenario becomes available, the conditional forecast is updated and a new conditional forecast can be derived. The update is broken down into several components, each tracing back to the variable whose path changed under the new scenario.

The next section focuses on the modelling approach. In the third section, we describe the data, estimate and validate the model and forecast the residential property price index. The final section concludes.

2 Modelling Approach

2.1 Model

All variables $y_{it}(i = 1...n)$ in the dataset are jointly represented by a dynamic factor model. The idea is that all the variables, both those that describe the macroeconomic environment in Belgium, and those that describe the housing market and the external environment have common dynamics which are generated by a few common shocks w_t, such as monetary policy, that propagate to the common factors f_t (a common underlying "business cycle" for example) and to the observable variables.

The dynamic factor model decomposes any stationary observable variable in the dataset, $\{y_{it}\}$, $t = 1...T$, measured in quarters, into a component $\Lambda_i^{'} f_t$ driven by r shocks u_t common to all variables and a component e_{it} that is specific to that particular variable i and uncorrelated from all other e_{jt}, $j \neq i$ and its past $e_{it-1}, ..., e_{it-p}$.

The vector $y_t = [y_{1t}, y_{2t}, ..., y_{nt}]^{'}$, $t = 1, ...T$ that groups the variables is a stationary $n-$dimensional vector process. Each variable is standardised with mean 0 and unit variance[2] and y_t has the following dynamic factor model representation:

$$
\begin{aligned}
y_t &= \Lambda f_t + e_t, \quad e_t \sim N(0, R) && (1) \\
f_t &= A_1 f_{t-1} + ... + A_p f_{t-p} + u_t && (2) \\
u_t &= B w_t \quad w_t \sim N(0, I_r) \\
E[e_t w_t^{'}] &= 0
\end{aligned}
$$

where f_t is a $r \times 1$ vector of unobserved stationary common factors and $e_t = (e_{1t}, ..., e_{nt})'$ is the idiosyncratic component. R is assumed to be diagonal. This implies that the factor model is exact; all the dynamic interactions between the observable variables can be attributed to the r factors.

The r factors are modelled as a stationary vector autoregressive process of order p, where $A_1, ..., A_p$ are $r \times r$ matrices of autoregressive coefficients; the common shocks u_{jt} , $j = 1..r$ and the idiosyncratic components e_{it} are normally

[2] Stationarity is obtained by taking log-differences of the non-stationary variables in levels. The variables are standardised before estimation by substracting their sample mean and dividing by their sample standard deviation. The variables are re-scaled at the end of the estimation process. More details on the data treatment of the variables in the dataset in Table 1.

distributed and cross-sectionally and serially uncorrelated variables. The $n \times r$ matrix Λ denotes factor loadings for the variables in y_t. The shocks u_t are common shocks that affect all factors f_t by A_j. They also affect the series if the loading in Λ on a particular factor is non-zero. The matrix $Q = BB^{'}$ is the variance-covariance matrix of the common shocks and a full matrix.

In large datasets, the assumption of uncorrelated idiosyncratic components can be too restrictive. Macroeconomic variables that are similar in nature such as interest rates, or prices and real variables for the euro area and Belgium are bound to be correlated even after we control for a few economy-wide factors. We deal with this problem by incorporating several factors, some which are common to all the variables and some specific for a block of variables. As a result, the residual cross-correlation patterns can be considered as idiosyncratic or at least as weakly correlated across variables.

Thus, some loadings in Λ are restricted to zero, as shown in equation (5), so that the loadings matrix becomes block-triangular. In the application, we consider a housing-specific factor. Variables like residential investment or residential property prices will load not only on the general "business cycle" factor but also on this "housing-specific" factor (on which the other variables will not load). Note that the number of factors for each block r and r_h , as well as the lags p and p_h can be different across blocks to allow for common "cycles" with different dynamics.

Below, we summarise the state space representation of the dynamic factor model with block-specific factors which is estimated in the empirical section. Grouping the factors in a vector F_t and re-writing, we obtain the "measurement equation" (3) and the "transition equation" (4) of the state space representation of the model:

$$y_t = \Lambda^* F_t + e_t, \quad e_t \sim N(0, R) \tag{3}$$

$$F_t = A^* F_{t-1} + u_t^* \quad , \quad u_t^* \sim N(0, Q^*), \tag{4}$$

Or, in expanded form, for $y_{it}, i = 1...n$ observable variables:

$$
\begin{pmatrix} y_{1t} \\ : \\ y_{nt} \end{pmatrix} = \begin{bmatrix} \Lambda_{1f} & 0 & 0 & 0 \\ & & & \\ \Lambda_{nf} & 0 & \Lambda_{nh} & 0 \end{bmatrix} \begin{pmatrix} f_t \\ f_{t-1} \\ : \\ f_{t-p+1} \\ h_t \\ h_{t-1} \\ : \\ h_{t-p_h+1} \end{pmatrix} + \begin{pmatrix} e_{1t} \\ : \\ e_{nt} \end{pmatrix}, \tag{5}
$$

$$
e_t \sim N(0, \begin{bmatrix} R_{11} & 0 \\ 0 & R_{nn} \end{bmatrix}) \tag{6}
$$

$$
\begin{pmatrix} f_t \\ f_{t-1} \\ : \\ f_{t-p+1} \\ h_t \\ h_{t-1} \\ : \\ h_{t-p_h+1} \end{pmatrix} = \begin{bmatrix} A_{ff} & ... & & A_{fh} & ... \\ I & 0 & ... & 0 & 0 \\ & ... & & 0 & 0 \\ 0 & I & 0 & 0 & 0 \\ A_{hf} & & ... & A_{hh} & ... \\ 0 & 0 & & I & 0 \\ & ... & & 0 & 0 \\ 0 & 0 & & I & 0 \end{bmatrix} \begin{pmatrix} f_{t-1} \\ f_{t-2} \\ : \\ f_{t-p} \\ h_{t-1} \\ h_{t-2} \\ : \\ h_{t-p_h} \end{pmatrix} + \begin{pmatrix} u_{ft} \\ 0 \\ : \\ 0 \\ u_{ht} \\ 0 \\ : \\ 0 \end{pmatrix} \tag{7}
$$

$$
u_t^* \sim N(0, \begin{bmatrix} Q & 0 \\ 0 & 0 \end{bmatrix}) \tag{8}
$$

2.2 Estimation

The dynamic factor model set in state space form is estimated with maximum likelihood using an expectation-maximisation (EM) algorithm. The estimation procedure follows Doz, Giannone and Reichlin (2012). As the factors F_t in the system (3) and (4) are unobserved, there is no analytical solution for the maximum likelihood estimators of the parameters of the model[3]. Doz *et.al.*

[3]On the other hand, a direct numerical maximisation of the likelihood is possible but can be computationally demanding especially in models with a large number of factors and

(2012) show that an alternative and feasible approach in large datasets is to use the EM algorithm. They also show that the maximum likelihood estimators of the model's parameters are consistent estimators of the true parameters even if the idiosyncratic components are mildly correlated and therefore violate the normality and diagonal covariance matrix assumption in equation 6. In a large cross-section, the misspecification error will go to zero and this result will hold without any constraint on the relative size of the cross-section n and sample size T.

The EM algorithm is an iterative estimation procedure. More specifically, let $\widehat{F}^{\ (k)}$ and

$$\widehat{\theta}^{(k)} = \left\{ \ \widehat{\Lambda^*}^{(k)}, \quad \widehat{A}^{(k)}, \quad \widehat{Q^*}^{(k)}, \quad \widehat{R}^{(k)} \ \right\}$$

be the estimate of the factors and the parameters obtained in the k^{th} iteration. Then, at the $(k+1)^{th}$ iteration, (1) in the E-step ("expectation-step") the algorithm uses the Kalman smoother to estimate the common factors $\widehat{F}^{\ (k+1)}$ given $\widehat{\theta}^{(k)}$; (2) in the M-step (maximisation-step") an estimate of $\widehat{\theta}^{(k+1)}$ given $\widehat{F}^{\ (k+1)}$ is obtained by maximising the expected likelihood. This is achieved through substitution of the sufficient statistics with their expectations, through a set of multivariate regressions where the unobserved factors are replaced with their expected values, $\widehat{F_t}^{(k+1)} = E_{\widehat{\theta}^{(k)}} \left(F_t | \ y_1 ... y_T \right)$ and corrected for estimation uncertainty in the common factors. (3) This procedure is repeated until convergence to a local maximum of the expected likelihood.

As shown in the appendix, an advantage of this state-space approach is the possibility of recursively obtaining forecasts conditional on assumptions regarding the future evolution of endogenous variables and also of dealing with missing observations at the beginning of the sample. The state-space approach can also be applied in the context of BVARs, as done for example in Banbura, Giannone

complex block structure. As an example of an application in nowcasting GDP in Belgium, see de Antonio Liedo (2015), where the empirical application is executed using the EM algorithm. Numerical optimisation, the EM algorithm or a combination of the two are used to estimate dynamic factor models in the nowcasting plugin distributed as part of the software JDemetra+ developed by the National Bank of Belgium (see www.nnb.be/jdemetra).

and Lenza (2015).

The unbalanced end-of-sample structure is a natural outcome of our conditional forecasting exercise and the fact that missing values occur at the beginning of the sample for some of the series that do not have a long history. Technically, the missing observations are replaced by efficient estimates conditional on the model parameters and the *realisation* of all the series over the whole estimation sample. The idea is used during the estimation process, and is also part of the procedure that generates the conditional forecasts. All details regarding the use of the Kalman filter/smoother in the presence of missing observations can be found in Durbin and Koopman (2001)[4].

3 Empirical Results

The empirical exercise is focused on the estimation of a forecasting model for the "Dwellings" residential property price index, which is a weighted average of re-sale prices for different types of residential property and geographically covers all three Regions in Belgium (Brussels, Wallonia and Flanders). All property price indices are used in real terms: nominal indices are deflated by the private consumption deflator (PCD) for Belgium[5]. The dataset and transformations, the model specification and evaluation of the out-of-sample forecasting ability of the model are described in detail in the following sub-sections.

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[4] Durbin and Koopman (2001) apply the Kalman filter to a modified state-space representation, with y_t, Λ^* and R , replaced by $\overline{y}_t, \overline{\Lambda}^*$ and $\overline{R}$ respectively. The latter are derived from the former by removing the rows (and, for R the columns too) that correspond to the missing observations in y_t^{obs}.

[5] The results are robust to whether the property price indices are taken in nominal or in real terms. On the other hand, a model in real terms requires us to select a deflating variable, which can be arbitrary. We follow the literature and use the PCD (private consumption deflator) here. This deflator is preferred in the literature because it is in general less volatile than the HICP for example and will therefore dominate the dynamics of the real variables to a lesser extent.

3.1 Data

The quarterly dataset is composed of seven residential property price indices, and 28 variables describing the Belgian and the euro area economy, including demand variables (GDP, consumption, investment, exports, imports, residential investment), price variables (HICP, NCPI and national account deflators), unemployment rates, interest rates (a policy rate, a long yield and a mortgage interest rate for Belgium as well as the two-, five- and ten-year German zero-coupon bond yields) and mortgage loans. The data span the period 1970q1 to 2012q4, except for all the residential property price series which start in 1973q3 and mortgage loans which start in 1980q1. The full list of the variables and their transformations is given in *Table 1*.

The property price indices included in the dataset are indices constructed by the National Bank of Belgium based on the latest releases of data on the average price and number of transactions published by the FPS Economy. The data are published with a time lag of two quarters relative to the current quarter. The average price is computed as the average over all re-sale residential property transactions for which registration fees were paid, as reported to the Land Registry ("Cadastre, SPF Finances").

The NBB indices are weighted average prices per area and type of housing, where the weights are the number of transactions. The growth rate of the index is influenced by a change in the average prices of the components rather than a relative change in the number of transactions. The indices included in the dataset are the aggregate "Dwellings Country" Index, and the disaggregated indices, ("Houses Country", "Flats Country ", "Villas Country", "Houses Brussels", "Houses Flanders" and "Houses Wallonia") reflecting the price trends for different types of housing across the Regions. Note that these re-sale property price indices are not constructed using a repeat sales methodology so they do not keep track of any improvement in the quality of the house, as is the case with the S&P/Case-Shiller U.S. National Home Price Index for example. This means that an increase in the price over time could always reflect an improvement in house quality rather than an overvaluation.

The longest available property price series starts in 1973q3. A long history is essential to model accurately the co-movement between residential property price growth, interest rates and the business cycle, especially in Belgium where residential property prices (in real terms) exhibited negative growth rates only in the late 1970s. Since then, the residential property price index has been growing steadily, rising faster over the period $1986-2007$ and decelerating since 2008. During the same period, the Belgian economy went through several recessions and expansions.

Mortgage loan data are available back to 1980q1. They are computed as the total mortgage amount divided by the number of loans requested. The data are published by the Union Professionelle du Crédit (Professional Bankers Association) and are available on a monthly basis, also during the current forecast quarter.

The interest rates include a policy rate and a range of interest rates capturing the yield curve in Belgium and the euro area, and a mortgage interest rate capturing the interest margin on adjustable-rate mortgages. The policy rate is the Euribor for the years after the introduction of the euro in 1999 and is constructed as a weighted average of country rates for the years before.

The official MIR mortgage interest rate for Belgium is available back to 2003q1. It is a synthetic rate computed as the weighted average of mortgage interest rates (MIR) rates up to one year, between one and five years and above ten years initial rate fixation, where the weights are the amounts originated with the corresponding rate ("new business"). To construct a longer mortgage interest rate series, the RIR ("retail interest rate") was used for the period covering 1992q1-2002q4 and an in-house mortgage interest rate was used for the period 1970q1-1991q4. The long-term bond yield for Belgium is constructed as the average yield on the secondary (foreign and domestic) market for the period 1970q1-1991q4. After 1992q1, the long-term bond yield for Belgium is the 10-year "OLO" rate. For the euro area, the data includes the euro area synthetic long interest rate, and the two-, five- and ten-year zero-coupon German government bond yield.

3.2 Model specification

The dynamic factor model is estimated for the dataset. Five factors ($r = 4, r_h = 1$, see equations 3-4) are included in the factor model. Four of the factors span all the variables for Belgium and the euro area, as well as the residential property prices. One factor is "housing-specific" and spans only residential property prices, residential investment and mortgage loans. Three lags ($p = 3, p_h = 3$) are included in the VAR of the factors. The choice of the number of factors and the number of lags is based on a comparison of the out-of-sample forecasting performance of the alternative specifications[6].

A dynamic factor with one single factor would imply that all the variables, real macroeconomic, inflation, house prices in Belgium and the euro area co-move perfectly, their dynamics being perfectly synchronised with that of "the business cycle factor". Intuitively, this is not a realistic representation of the dataset, given its heterogeneity. Including more factors helps to capture the common dynamics of interest rates and inflation apart from the macroeconomic real variables, while the housing-specific factor helps with capturing the fact that house prices in Belgium have only slowed down once after the beginning of the 1980s, exhibiting a different pattern in the dynamics compared to that of other real variables. Finally, including more factors in the specification may help improve the in-sample fit of such variables as unemployment, but the improvement in terms of out-of-sample forecasting for the residential property price is minimal.

[6] These are not shown here but are available upon request.

3.3 Forecasting

3.3.1 Model Validation - Recursive Out-of-Sample Unconditional and Conditional Forecasts

Given the specification described in the previous section, we estimate the dynamic factor model and evaluate its forecasting ability in terms of out-of-sample unconditional and conditional forecasts over an evaluation period. We use an iterative procedure to obtain the h-step ($h = 1, 4, 8$ quarters) ahead out-of-sample forecasts.

The intuition behind the forecasting approach is the following. Since the dynamics of all the variables in the model, macroeconomic and house prices, are driven by the same common factors, information over the forecasting horizon for the paths of some of the variables in the dataset can be exploited to deduce the path of the factors over the forecasting horizon. Thus, the methodology works out the most likely evolution of the factors given the available information over the forecasting horizon for the conditioning variables. Once the forecast of the factors has been computed, the forecast of all the variables, the residential property price index included, can be computed using the previously estimated parameters. The procedure is illustrated in Figure 1 and is described next.

First, the parameters and the factors are estimated over a given estimation sample with information on all variables in the dataset. For example, in the first iteration ($iter = 1$ and $t = 1999q4$), an initial sample with data on all the variables spanning the period $1970q1$-$1999q4$ (blue bars in Figure 1) is used to obtain estimates of Λ and A and F_t. Then, unconditional and conditional h-quarter-ahead out-of-sample forecasts are computed. These forecasts are depicted with an "x" and a cross "+" on the left- and right-hand panel of Figure 1.

To obtain the unconditional forecast, the same information set as for estimation is used, including all the variables in the dataset up to $1999q4$ for the first iteration. No information over the forecasting horizon is used. We call this information set Ω_t. The unconditional forecast is thus computed with information set $\Omega^U \equiv \{\Omega_t\}$.

To obtain the conditional forecast, information on the paths of five conditioning variables (EA policy interest rate, BE OLO 10-year bond yield, BE PCD, BE GDP and BE mortgage loans deflated by BE PCD inflation) over the forecasting horizon are added to Ω_t. We call this information set Ω_{t+h} and depict it with grey bars in the left-hand panel of Figure 1. The conditional forecast is thus computed with information set $\Omega^C = \{\Omega_t + \Omega_{t+h}\}$.

The forecast errors are computed as the difference between the actual data and the forecasts. Then, the sample is increased by one quarter and the process is repeated over the next iteration ($iter = 2$ and $t = 2000q1$). The model is re-estimated, and h-step-ahead forecasts and the associated forecast errors are produced. These steps are repeated until all h-step-ahead forecast errors are computed over the period $2000q1$-$2012q4$.

To summarise, given information Ω^U or Ω^C and the estimated parameters $\widehat{\Lambda}$ and $\widehat{A}$, iterative h-step ahead unconditional or conditional forecasts of the factors $\widehat{f}^U_{t+h/t}$, $\widehat{f}^C_{t+h/t}$and the variables $\widehat{y}^U_{t+h/t}$, $\widehat{y}^C_{t+h/t}$ are obtained with the Kalman filter[7]. The root mean squared forecast error (root MSFE) is computed as the average squared error in the evaluation period [8]:

$$MSFE^{U,C}(h, M) = \frac{1}{t_1 - t_0 + 1} \sum_{t=t_0}^{t_1} \frac{1}{h} \left(y^{obs}_{t+h} - \widehat{y}^{U,C}_{t+h/t}(M) \right)^2 \tag{9}$$

where t_1 and t_0 denote the start and end of the evaluation period ($2000q1 - 2012q4$), y^{obs}_{t+h} denotes the observation for $t + h$ for the variable, $\widehat{y}^{U,C}_{t+h/t}(M)$ denotes the h-step-ahead forecast using model M and the information sets Ω^U or Ω^C .

The unconditional forecast of the dynamic factor model is evaluated against the forecasts obtained from two benchmark models. The first is a naive benchmark, that is a random walk with drift for the (log -) level of each variable i

[7] More details on the Kalman filter equations can be found in the Technical Appendix.

[8] The evaluation criterion is univariate as opposed to a multivariate criterion like the log determinant of the covariance of the forecast errors. This is because the aim here is to evaluate the specific performance of each type of model for property prices and not the overall forecast performance of the model.

in the dataset. The second benchmark model is a vector autoregression (VAR) which includes six variables: EA policy interest rate, BE OLO 10-year bond yield, BE PCD, BE GDP, BE residential investment and real residential property price index (Dwellings). The variables are transformed in the same way as for the DFM, so they are taken in log differences. This type of VAR is often used to obtain empirical estimates of the reaction of house prices to monetary policy, credit or technology shocks and of the reaction of GDP to shocks to the supply or demand of housing services (in the framework of dynamic stochastic general equilibrium models, see for example Iacoviello and Neri (2010), Jarosinksi and Smets (2008)). Empirical unrestricted VARs allow for more flexibility than traditional vector error-correction models (VECMs)[9], which link the log level of house prices to a set of short- and long-run determinants making use of economic theory to determine a long-run equilibrium between demand and supply. If these restrictions do not hold in practice, the forecast obtained from the VAR will be more accurate.

The DFM forecasts are compared to those obtained with the random walk and the VAR which uses data available *at the time of the forecast*. In other words the same iterative procedure and the information set used for the unconditional DFM forecast is used for the alternative benchmark model forecasts as well.

To test for the significance of the difference between the accuracy of alternative forecasts, we use a Diebold-Mariano test. This test compares the values of a loss function[10] of the errors $e_t(.)$ from the two alternative forecasts M_1, M_2 and also corrects for the autocorrelation of these forecast errors which typically occurs for a forecast of a horizon longer than one quarter. The test statistic is defined below:

$$S = \frac{\frac{1}{t_1-t_0+1}\sum_{t=1}^{t_1-t_0+1}\left(\left[e_t(M_1)\right]^2 - \left[e_t(M_2)\right]^2\right)}{\widehat{\sigma}\left(\left[e_t(M_1)\right]^2 - \left[e_t(M_2)\right]^2\right)} \tag{10}$$

where $\widehat{\sigma}(.)$ is a consistent estimate of the standard deviation of the difference,

[9] VECMs are widely used across central banks in the euro area as a valuation model for the level of house prices, see for example Gattini and Hiebert (2010).

[10] Here we use the square function.

based on the autocovariance generating function with a truncation lag given by $h-1$. Under the null hypothesis of equal forecast accuracy of the two models the test statistic follows a standard normal distribution.

Table 2 and *Table 3* present the results for the unconditional and conditional forecasts over horizons $h = 1, 4, 8$ quarters. *Table 2* reports the RMSFE ratio of the DFM and the VAR with respect to a random walk with drift, while *Table 3* reports the RMSE ratio of the conditional against the unconditional forecast for the DFM. In both exercises, the evaluation sample is 2000q1-2012q4. The out-of-sample 1-quarter and 4-quarters-ahead forecasts and the data are depicted in *Figures 3* to *10*.

(Insert Table 2 and Table 3 here)

Table 2 shows that, for $h = 1$, the DFM forecast for the residential property price (Dwellings index) outperforms the random walk and the VAR forecast. However, for $h = 4$, the unconditional forecast of the VAR outperforms that of the DFM.

Most of the remaining property price indices are better forecast with the DFM and the VAR than the random walk over short and longer horizons[11]. At longer horizons, the difference between the two models' performance is not significant.

In the case of real variables and inflation, the 1-quarter-ahead unconditional forecasts of the DFM perform better than the random walk in Belgium and the euro area. The difference in performance with the random walk disappears for the 4- and 8-quarter horizon unconditional forecasts. The DFM and the VAR perform in a similar way. One exception is residential investment, where the VAR performs slightly better than the DFM.

The results in *Table 3* show that conditioning on available information improves the out-of-sample DFM forecast for the residential property price (Dwellings) index , especially in the 4-quarter and 8-quarter horizon. The reduction in the RMSE of the conditional forecast compared to the unconditional

[11] The only exception is the Villas index. This is probably due to the idiosyncratic behaviour of the series.

forecast is statistically significant and amounts to 16% ($h = 4$) and 19% ($h = 8$).

As expected, most conditional forecasts for the other variables largely improve over the unconditional forecasts. The five conditioning variables broadly capture the evolution of the macroeconomic environment and the reduction in the RMSE, both at short and long horizons, is large and statistically significant (see *Table 3*).

3.4 Accounting for Revisions in the Residential Property Price Forecast in Terms of Changes in the Conditioning Assumptions

Next, we illustrate how conditional forecasting can be used to produce forecasts for house prices which are consistent with given assumptions on the paths of variables describing the macroeconomic environment in Belgium and the euro area over a specific forecasting horizon. To make the exercise consistent with the conditioning approach presented in the previous section, the conditioning variables are those used previously, i.e. EA policy interest rate, BE OLO 10-year bond yield, BE PCD, BE GDP and BE mortgage loans deflated by BE PCD inflation.

In our example, we focus on the period 2007-2009. In particular, we compute two conditional forecasts for the "Dwellings" residential property price index (in real terms) over the period 2007q1-2009q4. For the first forecast, which we assume is performed in September 2007, we show how the model reads the data and the conditioning information available at that time (left-hand panel of *Figure* 2). For the second forecast, which we assume takes place one year later in September 2008, we show how the house price forecast is revised given the new data and assumptions available (right-hand panel of *Figure* 2). We use expectations on future paths of the conditioning variables as published in the December 2007 and December 2008 NBB Economic Reviews for each forecast respectively[12].

[12] The timing of the two forecasts closely resembles that of the Autumn "projection exercise".

For the September 2007 forecast, the available residential property price data only goes up to 2006$q4$, since the official residential property price data are published with a two-quarter time lag. Thus, the house price forecast will start in 2007$q1$ and will use the available data (blue and gray bars in the left-hand panel of *Figure* 2) and expectations on the future paths of the conditioning variables (light grey bars in the left-hand panel of *Figure* 2).

The second forecast is assumed to be performed in September 2008. Now, the conditioning information will change as four more quarters of residential property price data, covering 2007q1-2007q4 (depicted by a green bar in right-hand panel of *Figure* 2) and four more quarters of mortgage loans, GDP, interest rates and inflation data, covering the period 2007q4-2008q3 will have been published. Note that interest rates and mortgage loan data over 2007q1-2007q3 are final (in grey in the right-hand panel of *Figure* 2) while BE GDP and inflation over the same period have been revised (in darker green in right-hand panel of *Figure* 2). Finally, a new *Autumn 2008* scenario over the period 2008q4-2009q4[13] is available (in lighter green in right-hand panel of *Figure* 2).

3.4.1 House prices up to 2007 and a summary of the 2007 and 2008 scenarios

Next we briefly describe the trends inhouse prices up to 2007 and the December 2007 and December 2008 NBB Economic Review paths for the conditioning variables.

The year 2006 marked the end of a five-year period of upward-trending residential property price year-on-year growth rates which started in 2000, both in nominal and real terms. In quarterly growth rate terms, this translated into an average of 1.7% per quarter growth rate between 2001 and 2006. Growth rates had already started slowing down during the course of 2006: the average

Therefore expectations for the paths of the conditioning variables, which are published in December, are already available to the forecaster in September.

[13] Even though the scenarios span over 3 years, only the years relevant to the present forecasting exercise are shown.

quarterly growth rate in 2006 was equal to 1.85%, lower than the quarterly growth rate average of 2.38% for 2005. Mortgage loans followed the same trend (0.15% average growth rate in 2006 against 2.55% in 2005).

The macroeconomic context at the end of 2007, as described in the December 2007 NBB Economic Review, was coloured by the beginning of the financial crisis, with the economy holding up well for the first half of 2007 and expected to remain stable for the remaining part of 2007 and in 2008 (0.5% GDP growth rate in 2008q4), even though the uncertainty surrounding these projections was high. GDP growth was expected to be sustained by internal consumption growth and investment. Exports were not expected to be affected much by the financial developments abroad, as it was thought that the crisis, mainly in the US at that time, would be contained in the financial sector and would not spill over to the real economy. On the price front, rising oil prices and the appreciation of the euro were driving an acceleration of both euro area and Belgian inflation. The policy rate and Belgian 10-year bond yields were expected to decline very slightly.

The picture had changed by the end of 2008. Even though the situation had been stable up to mid-2008, soon after that it became clear that the financial crisis had spilled over to the real economy, drastically curtailing international demand and inducing a decrease in oil prices. As a result, GDP growth for Belgium was revised downwards in the December 2008 NBB Economic Review, when it was forecast to slow down significantly for 2008 and drop in 2009, while inflation, having reached a peak in mid-2008, was projected to drop in 2009. In this context, policy interest rates were cut in 2008 and were forecast to be even lower in 2009, while long-term rates rose slightly as a result of pressure from deteriorating public finances.

3.4.2 The residential property price forecast and the impact of the change in the macroeconomic environment

How were the paths of the conditioning variables (December 2007 NBB Economic Review) taken into account by the model to produce the *Autumn 2007* house price forecast? And then, one year later, what was the impact of the negative evolution of the macroeconomic environment (December 2008 NBB Economic Review) on the residential property price forecast when the *Autumn 2008* forecast was produced? *Table 4* and *Figure 11* show the results.

(Insert Table 4 and Figure 11 here)

Table 4 reports the conditional forecast for the residential property price index (Dwellings) between 2007q1 and 2009q4.

Accuracy of the Autumn 2007 forecast for 2007q1-2007q4 The average of *Autumn 2007* forecast of the quarterly growth rates of the Dwellings index in 2007q1-2007q4 equals 0.5%. This average is substantially lower than the actual average growth rate computed a year later with the final data for the Dwellings index for 2007q1-2007q4 and the *Autumn 2008* PCD inflation data (line 3 in the table). This average equals 1.8% [14]. The *Autumn 2007* forecast is computed conditionally on data from mortgage loans and the macroeconomic environment. The forecast error shows that these "fundamental" factors were not sufficient to capture house prices during 2007. However, the forecast error for the period is not higher than the RMSE computed for the forecast evaluation exercise in the previous section.

Accuracy of the Autumn 2007 forecast for 2008q1-2008q4 and 2009q1-2009q4 The average of *Autumn 2007* forecasts for the quarterly growth rates of the Dwellings index in 2008q1-2008q4 and 2009q1-2009q4 equals 0.3% and 0.4% respectively. These lie below the unconditional forecast for house prices mainly because, as we saw earlier, the outlook for GDP growth in the *Autumn*

[14] When the final data for PCD is released the average quarterly growth rate for the Dwellings index will be lower, at 1.1%.

2007 projection exercise had already deteriorated at the onset of the financial crisis. The role of interest rates and inflation is only minor at this point in time.

Accuracy of the Autumn 2008 forecast for 2008q1-2008q4 and 2009q1-2009q4 In 2008q3, when the *Autumn 2008* forecast is made, the latest available data for house prices ends in 2007q4. Thus, the *Autumn 2008* forecast starts in 2008q1. The *Autumn 2008* forecast for the Dwellings index in 2008 and 2009 equals 0.2% and -0.4% respectively[15], while the data deflated by the final data on BE PCD inflation in 2008 and 2009 equals 0.3% and 0.5% [16]. On average, the forecast error in 2008 is very small while, in 2009, it is close to the RMSFE computed for the forecast evaluation exercise in the previous section.

Explaining the Autumn 2008 forecast for 2008q1-2008q4 and 2009q1-2009q4 What is the reason behind the downward revision of the quarterly growth rate of house prices in 2008 and 2009? The second part of *Table 4* shows us how current and past forecast errors in the conditioning variables contribute to the forecast update of the residential property price[17].

In 2008q1 for example, the new forecast is 0.27% higher than the previous one. This is mainly due to negative growth in lending in 2008q1 and past positive innovations in house prices still having informative content even if there are no current house price data available[18].

The slightly positive component for BE GDP (0.14%) comes from the current and past quarters' positive components. The same profile holds for 2008q2 and

[15] As previously, forecasts and data in the text are computed as averages of quarterly growth rates within the year, as shown in Table 4.

[16] The same averages for house prices deflated by the Autumn 2008 PCD scenario are slightly higher, 0.8% and 0.7% in 2008 and 2009 respectively.

[17] See the Technical Appendix for the details on how this decomposition is obtained as a by-product of the Kalman filter iterations.

[18] The relative importance of past house prices in the current forecast can be seen more clearly in Figure 13 were the impact coefficients ψ_{ij} are displayed : i is the BE residential property price index (Dwellings) and j are the five macroeconomic conditioning variables. More details on impact coefficients can be found in the Technical Appendix.

2008q3, except that now the information derived from mortgage loans is close to 0% for 2008q2 and negative for 2008q3 (-0.48%). The information on past house price data is discounted more heavily as it becomes older and therefore plays a decreasing role.

Starting from 2008q4, the same forces are at play but to a smaller extent as now there is no new information from mortgage loans.

In 2008q4, GDP plays as big a role as past mortgage loans and past house prices in explaining the -0.46% downward revision in the *Autumn 2007* house price forecast. Added to this is information from short- and long-term interest rates in 2009q1 and 2009q2 which plays a more important role[19].

Finally, in 2009q4, a higher spread caused by higher long-term interest rates and lower short-term interest rates implies an overall decline in the residential property price index of -0.13%[20]. Additionally, the lower-than-expected GDP growth rate and higher-than-expected inflation rate imply a further drop in the residential property price index by -0.27% and -0.02% respectively. Overall, the impact of the revised paths of the macroeconomic conditioning variables on the residential property price forecast is equal to -0.63% for $2009q4$.

4 Conclusion

The paper has forecast the residential property price index in Belgium with a dynamic factor model estimated with maximum likelihood and the EM algorithm.

The dynamic factor model has been estimated with a dataset of macroeconomic variables describing the Belgian and euro area economy. The model has

[19] Figure 13 depicts the impact coefficients for the forecast in 2009q1. Note that in the absence of current information from mortgage loans, the current impact coefficient ($\tau = 0$) is zero. The importance of GDP is higher with respect to the situation in 2008q1 when mortgage loan data together with very recent house price data were available. The impact coefficients of the short and long interest rates are unchanged and inflation plays virtually no role.

[20] -0.13% is obtained as the sum of -0.26% update related to the BE Long IR and 0.13% update related to the Short IR.

been validated with recursive unconditional out-of-sample forecasts against a random walk with drift and a vector autoregressive benchmark. Conditional out-of-sample forecasts have been obtained recursively over the period 2000q1-20012q4 and have been shown to improve over unconditional forecasts. A forecasting exercise has illustrated how information from mortgage loans, interest rates, GDP and inflation is combined in forecasting residential property prices in Belgium.

The forecast for property prices over 2008q1-2009q4 was relatively accurate during 2008 while it clearly underestimated quarterly growth rates in 2009. Given the model's impact coefficients, lower quarterly growth rates were expected as a result of the spillover of the financial crisis to the real economy. This deceleration materialised only in part, during 2008. By the end of 2009, house prices were accelerating again.

There are two limitations to the approach used for this paper. The first is that, at this stage, it is a reduced-form exercise. Future work may focus on identification of the shocks and their impact on the residential property price index forecast. The second limitation is that this approach does not deliver an equilibrium *level* for the real residential property price index. As a result, this type of model is not suited for identifying periods of price misalignments and bubbles in the property market.

However, the forecasting approach, based on the Kalman filter modified for ragged-edge data structures, is flexible, easily adaptable to a larger dataset or to data with different frequencies and can be used to produce real-time forecasts as well as other types of scenario analysis, such as risk analysis and stress-testing.

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Appendix

Technical Appendix

We provide a short description of the Kalman filter iterations used for forecasting conditional on information from a subset of the variables $\widehat{y}_t^{obs}$ in the dataset. The filter gain and innovations are used to compute the forecast update and its decomposition.

Formally, we are interested in obtaining the forecast of the residential property price index for Belgium, $y_{it,}$ at time $t > t_0$, conditional on the available time series for a subset of the data. The conditional forecast uses information from data or future scenarios for a subset of variables in $y_{t,}$, for $t > t_0$, whenever this information or scenario is available[21].

As for the unconditional forecast, QMLE estimation over $t = 1, .., t_0$ yields estimates of the factors, and the model parameters $\widehat{\Lambda}_{/t_0}, \left(\widehat{A}\right)_{/t_0}, \widehat{R}_{/t_0}$ and $\widehat{Q_{/t_0}}$. Once these estimates are obtained, the Kalman filter is applied on the state space representation of the model in eq. 3 and 4. The filter is nevertheless modified to take into account the fact that there is no information for $t > t_0$ for the variables that are forecast (residential property prices). These variables can be assimilated to series with "missing observations" and the approach of Durbin and Koopman (2001) can be used to obtain the forecasts. The filter is modified by removing the rows in Y_t and the rows and columns in R that correspond to the series with the missing values. Then, the Kalman filter iterations are run as usual to obtain the path of the estimated factors conditional on the variables in y_t^{obs}. These variables are observed either because they are available earlier than the residential property price or because there is a scenario that we would like to impose.

The conditional mean of the factor F_t based on information available at time $t-1$ is defined as $F_{t/t-1} = E(F_t| \; y_1^{obs}...y_{t-1}^{obs})$ and the conditional variance as $P_{t/t-1} = var(F_t|y_1^{obs}...y_{t-1}^{obs})$. The Kalman filter equations compute $F_{t/t} = E(F_t|$

[21] The conditional forecast used here is in "reduced-form" in the sense that the scenario is imposed on the future paths of the variables and not on the future paths of the structural ("identified") shocks.

$y_1^{obs}...y_t^{obs})$ and $P_{t/t} = var(F_t|y_1^{obs}...y_t^{obs})$:

$$F_{t/t} = F_{t/t-1} + K_t v_t \tag{11}$$

$$P_{t/t} = P_{t/t-1} - K_t P_{t/t-1}\widehat{\Lambda}^{'} \tag{12}$$

where

$$v_t = y_t^{obs} - \widehat{\Lambda} F_{t/t-1} \tag{13}$$

$$K_t = P_{t/t-1}\widehat{\Lambda}^{'}\left(\widehat{\Lambda} P_{t/t-1}\widehat{\Lambda}^{'} + \widehat{R}\right)^{-1} \tag{14}$$

The variable v_t is the measurement equation innovation or "prediction error" and the term $\left(\widehat{\Lambda} P_{t/t-1}\widehat{\Lambda}^{'} + \widehat{R}\right)$ is defined as the variance of the prediction error $var(v_t)$. K_t is the Kalman gain matrix.
The prediction equations of the Kalman filter compute $F_{t+1/t} = E(F_{t+1}|\ y_1^{obs}...y_t^{obs})$ and $P_{t+1/t} = var(F_{t+1}|y_1^{obs}...y_t^{obs})$ using:

$$F_{t+1/t} = \widehat{A} F_{t/t} \tag{15}$$

$$P_{t+1/t} = A P_{t/t} A^{'} + B B^{'} \tag{16}$$

Once the path of the factors is known, the conditional forecast $\widehat{y}_t$ for any variable in y_t (whether the variables is observed or not) is given by:

$$\widehat{y}_t = \widehat{\Lambda} F_{t/t}$$

By replacing recursively, we find:

$$\begin{aligned}\widehat{y}_t &= \Lambda A^t f_{0/0} + \Lambda A^{t-1} K_1 v_1 + \Lambda A^{t-2} K_2 v_2 + ... \\ & ... + \Lambda A K_{t-1} v_{t-1} + \Lambda K_t v_t \end{aligned} \tag{17}$$

The N elements in $\lambda_i^{'}$, the row that corresponds to the i^{th} variable in the loadings matrix Λ , inform us which factors are important for forecasting y_i (eq.17). The (r, N) elements of the Kalman gain K_t tell us which part of the innovation v_t in each of the N series is used to update the factors F_t, or, in other words which part of the innovation corresponds to the common shock u_t as opposed to the measurement error/idiosyncratic component e_t (eq. 3). The last equation (eq. 17) tells us that at each point in time t, we can decompose the conditional forecast for each variable into a weighted sum of all current and past forecast errors:

$$\widehat{y}_{it} = \sum_{j=1}^{N}\sum_{\tau=0}^{t}\psi_{ij}(\tau)v_{j,t-\tau} \tag{18}$$

$$= \sum_{j=1}^{N} c_{ij,t} \tag{19}$$

The weights $\psi_{ij}(\tau)$ depend on the estimated loadings matrix and the Kalman gain. In this model, the loadings and the Kalman gain are time-invariant. The Kalman gain nevertheless depends on the pattern of the missing values in the observed variables (see Banbura and Runstler (2011)). As this pattern changes at each point in time, so will the weights $\psi_{ij}(\tau)$.

Table 1: Data and Transformations

Variable (Source)	(1)	(2)
BE Residential property prices, existing dwellings, whole country, chained index 2005=100 (NBB)	dln	1
BE Residential property prices, existing houses, whole country, chained index 2005=100 (NBB)	dln	1
BE Residential property prices - existing mansions and villas, whole country, index 2005=100 (NBB)	dln	1
BE Residential property prices - flats, whole country, chained index 2005=100 (NBB)	dln	1
BE Residential property prices, existing houses,,Brussels, chained index 2005=100 (NBB)	dln	1
BE Residential property prices, existing houses, Flanders, chained index 2005=100 (NBB)	dln	1
BE Residential property prices, existing houses, Wallonia, chained index 2005=100 (NBB)	dln	1
BE Gross Domestic Product, Millions of euros, chained , reference year 2009 : NAT. ACC.(Belgostat)	dln	0
BE Private Consumption , Volumes, Millions of euros, chained , reference year 2009 : NAT. ACC.(Belgostat)	dln	0
BE Business Investment, Volumes, Millions of euros, chained , reference year 2009 : NAT. ACC. (Belgostat)	dln	0
BE Exports, Volumes, Millions of euros, chained , reference year 2009 : NAT. ACC. (Belgostat)	dln	0
BE Imports, Volumes, Millions of euros, chained , reference year 2009 : NAT. ACC. (Belgostat)	dln	0
BE Residential Investment , Volumes, Millions of euros, chained , reference year 2009 : NAT. ACC. (Belgostat)	dln	1
BE Consumer Price Index - GENERAL INDEX (NCPI) (Belgostat)	dln	0
BE Deflator, Gross Domestic Product, index 2009 = 100, NAT. ACC. (Belgostat)	dln	0
BE Deflator, Private Consumption, index 2009 = 100, NAT. ACC. (Belgostat)	dln	0
BE Mortgage loans (total amount/total number of loans deflated by BE PCD) (Union Professionnelle du Crédit)	dln	1
EA GDP (Real) (ECB / AWM)	dln	0
EA Private Consumption (Real) (ECB / AWM)	dln	0
EA Government Consumption (Real) (ECB / AWM)	dln	0
EA Gross Investment (ECB / AWM)	dln	0
EA Exports of Goods and Services (Real) (ECB / AWM)	dln	0
EA Imports of Goods and Services (Real) (ECB / AWM)	dln	0
EA GDP Deflator (ECB / AWM)	dln	0
EA Consumption Deflator (ECB / AWM)	dln	0
EA Unemployment rate (as a pct of labour force) (ECB / AWM)	dlevel	0
EA HICP (ECB / AWM)	dln	0
EA Short-Term Interest Rate (Nominal) (ECB / AWM)	dlevel	0
BE Long Bond Yield (OLO 10-year)	dlevel	0
EA Long-Term Interest Rate (ECB)	dlevel	0
BE Mortgage Rate (NBB, constructed series based on MIR rates)	dlevel	0
GER 10-year Zero-Coupon Bond Yield (Bundesbank)	dlevel	0
GER 2-year Zero-Coupon Bond Yield (Bundesbank)	dlevel	0
GER 5-year Zero-Coupon Bond Yield (Bundesbank)	dlevel	0

Note: The table shows the list of variables, their source, the transformations used in column (1): "dln": change in logs, "level", "change in level" . "EA": Euro Area, "BE": Belgium, "GER": Germany. Column (2) indicates whether a variable is included in the "housing block".

Table 2: Ratio of RMSFE for DFM and VAR relative to a random walk with drift benchmark: Unconditional forecasts

	DFM			VAR		
	h=1	h=4	h=8	h=1	h=4	h=8
BE Property Price (Dwellings), real	0.78***	0.86	0.94	0.83*	0.88*	1.02
BE Prop.P. houses, real	0.78***	0.88	0.93			
BE Prop.P. villas, real	1.02	1.05	1.12			
BE Prop.P, flats, real	0.92*	0.98	1.00			
BE Prop. P. houses, Brussels, real	0.96	0.95	0.96			
BE Prop. P, houses, Flanders, real	0.84**	0.88	0.95			
BE Prop.P, houses, Wallonia, real	0.86**	0.98	0.99			
BE Real GDP	0.82*	1.01	1.02	0.89	1.00	1.19
BE Private consumption	1.01	1.10	1.09			
BE Gross fixed capital formation	0.93*	0.98	0.97			
BE Exports	0.92	1.01	0.98			
BE Imports	0.90	1.02	0.98			
BE Residential Investment	0.98**	1.03	1.08	0.75*	1.33	2.21
BE NICP	1.08	1.23	1.12			
BE Private consumption deflator	1.23	1.17	1.06	1.34	1.32	1.42
BE GDP deflator	1.09	1.20	1.16			
BE Mortgage loans, real	6.36	6.84	6.70			
EA Real GDP	0.82*	1.07	1.06			
EA Private Consumption	0.96	1.15	1.19			
EA Gov. Consumption	0.98	0.99	1.07			
EA Gross Investment	0.87*	1.07	1.04			
EA Exports	0.85*	1.03	0.97			
EA Imports	0.81**	1.05	1.03			
EA GDP Deflator	0.60***	0.79***	0.93			
EA Consumption Deflator	0.66***	1.00	1.02			
EA Unemployment rate	0.62***	0.62**	0.60			
EA HICP	0.81**	1.05	1.10			
EA Short-Term IR	0.73*	0.96	0.93	0.84	1.10	1.05
BE Long-Term IR	1.00	0.97	0.96	1.02	1.15	1.15
EA Long-Term IR	1.05	0.98	0.99			
BE Mortgage IR	0.86*	0.92	0.92			
GER 10-year ZC Bond Yield	1.00	1.02	0.98			
GER 5-year ZC Bond Yield	0.98	1.01	0.96			
GER 2-year ZC Bond Yield	0.92	0.98	0.95			

Note: The table reports the ratio of the root mean squared forecast errors (RMSFE) of the DFM and the VAR over the RMSFE of a random walk with drift for each variable. The ratio is reported for unconditional forecasts h=1, 4 and 8 quarters ahead over the period 2000q1-2012q4. A value smaller than one indicates that the RMSFE of that model is lower than the RMSFE of the random walk for that variable. An asterisk (*,**,***) denotes that the null of equal forecast accuracy between the model and the random walk is rejected at the 90, 95, 99 percent level correspondingly (Diebold-Mariano test). The transformations of the variables can be found in Table 1.

Table 3: Ratio of RMSFE for conditional relative to unconditional forecast.

	h=1	h=4	h=8
BE Property Price (Dwellings), real	0.99	0.84^{**}	0.81^{*}
BE Prop.P. existing houses, country, real	1.01	0.84^{**}	0.84^{*}
BE Prop.P. villas, country, real	1.02	0.91^{*}	0.87^{**}
BE Prop.P, flats, country, real	0.98	0.96	0.89
BE Prop. P. houses, Brussels, real	0.99	0.99	0.98
BE Prop. P, houses, Flanders, real	1.00	0.90^{*}	0.87^{*}
BE Prop.P, houses, Wallonia, real	1.01	0.89^{**}	0.89^{*}
BE Real GDP	0.69^{***}	0.56^{***}	0.51^{***}
BE Private consumption	0.87^{***}	0.79^{***}	0.76^{***}
BE Gross fixed capital formation	0.94^{***}	0.88^{***}	0.84^{***}
BE Exports	0.87^{**}	0.79^{**}	0.77^{**}
BE Imports	0.84^{**}	0.75^{**}	0.72^{**}
BE Residential Investment	0.99	0.83^{***}	0.74^{***}
BE NICP	0.90	0.83^{***}	0.87^{**}
BE Private consumption deflator	0.84^{***}	0.82^{***}	0.89^{***}
BE GDP deflator	0.91	0.85^{***}	0.85^{**}
BE Mortgage loans, real	0.90^{***}	0.83^{***}	0.81^{***}
EA Real GDP	0.78^{***}	0.65^{***}	0.62^{***}
EA Private Consumption	0.91^{***}	0.80^{***}	0.76^{***}
EA Gov. Consumption	1.01	1.01	0.97
EA Gross Investment	0.90^{**}	0.79^{**}	0.76^{**}
EA Exports	0.85^{**}	0.76^{**}	0.74^{***}
EA Imports	0.87^{**}	0.72^{***}	0.67^{***}
EA GDP Deflator	1.01	0.93	0.88
EA Consumption Deflator	0.92	0.79^{**}	0.79^{*}
EA Unemployment rate	0.95^{**}	0.96^{**}	0.94^{**}
EA HICP	0.88	0.79^{**}	0.74^{*}
EA Short-Term IR	0.91^{*}	0.65^{*}	0.64^{*}
BE Long-Term IR	0.62^{***}	0.58^{***}	0.56^{***}
EA Long-Term IR	0.62^{***}	0.59^{***}	0.55^{***}
BE Mortgage IR	1.26	1.25	1.20
GER 10-year ZC Bond Yield	0.76^{***}	0.74^{***}	0.71^{***}
GER 5-year ZC Bond Yield	0.75^{***}	0.71^{***}	0.69^{***}
GER 2-year ZC Bond Yield	0.76^{**}	0.70^{**}	0.68^{**}

Note: The table reports the ratio of the root mean squared forecast errors (RMSFE) of the DFM for a forecast conditional on EA Short interest rate, BE long yield, BE GDP, BE PCD inflation and BE mortgage loans deflated by PCD and an unconditional forecast. The ratio is reported for forecasts h=1, 4 and 8 quarters ahead over the period 2000q1-2012q4. A value smaller than one indicates that the RMSFE of the conditional forecast is lower than the RMSFE of the unconditional forecast for that variable. Asterisks (***, **,*) denote that the null of equal forecast accuracy is rejected at the 99, 95, and 90 percent level (Diebold-Mariano test). The transformations of the variables can be found in Table 1.

Table 4: Forecasting exercise for BE Residential property price (Dwellings Index)

	2007q1	2007q2	2007q3	2007q4	2008q1	2008q2	2008q3	2008q4	2009q1	2009q2	2009q3	2009q4
(1) Forecast 2007	0.34	0.89	0.35	0.24	0.43	0.19	0.20	0.38	0.29	0.42	0.45	0.46
(2) Forecast 2008					0.69	0.64	-0.35	-0.08	-0.64	-0.41	-0.18	-0.17
(3) Data deflated by Autumn 2008 scenario for BE_PCD inflation	3.37	1.90	2.30	-0.53								
(3') Data deflated by BE_PCD inflation (data)	2.50	1.27	1.60	-0.83	0.58	0.87	-0.36	0.06	-0.15	-0.41	0.91	1.46
Decomposition of Total Update (10):												
(4) EA Short-term IR					-0.09	0.06	0.05	-0.09	-0.26	-0.12	0.00	0.13
(5) BE Long-term IR					-0.05	-0.07	-0.11	-0.08	-0.12	-0.10	-0.15	-0.26
(6) BE GDP					0.14	0.02	0.03	-0.28	-0.31	-0.25	-0.26	-0.27
(7) BE PCD					-0.03	-0.03	0.12	-0.01	-0.05	-0.02	-0.13	-0.02
(8) BE Mortgage loans, real					-0.31	0.09	-0.48	-0.22	-0.19	-0.29	-0.16	-0.17
(9) BE Prop. Price (Dwellings), real					0.61	0.37	-0.15	0.22	0.00	-0.05	0.06	-0.05
(10) Total update =sum (4) to (9)					0.27	0.44	-0.55	-0.46	-0.94	-0.84	-0.63	-0.63

Note: The table reports the results from the forecasting exercise in section 3.4 of the paper. "(1) Forecast 2007" is the forecast of the BE residential property price index in real terms obtained by conditioning on the 2007 Autumn scenario for the EA short-term IR, BE long-term IR, BE GDP, BE PCD and data up to 2007q3 for BE mortgage loans, real. "(2) Forecast 2008" is the forecast of the BE residential property price index in real terms obtained by conditioning on the 2008 Autumn scenario for the EA short-term IR, BE long-term IR, BE GDP, BE PCD, data up to 2008q3 for BE mortgage loans, real and data up to 2007q4 for the BE residential property price index deflated by the Autumn 2008 scenario for BE PCD inflation. (3) "Data deflated (...) inflation"). (3') Data deflated by BE_PCD inflation (data) " is the final real Property price index deflated by the final data on BE PCD inflation. The second part of the table reports the components of the total forecast update (10) which equals to the sum of (4) to (9). Note also that Forecast 2008=Forecast 2007+Total update. For details on the decomposition, see Technical Appendix.

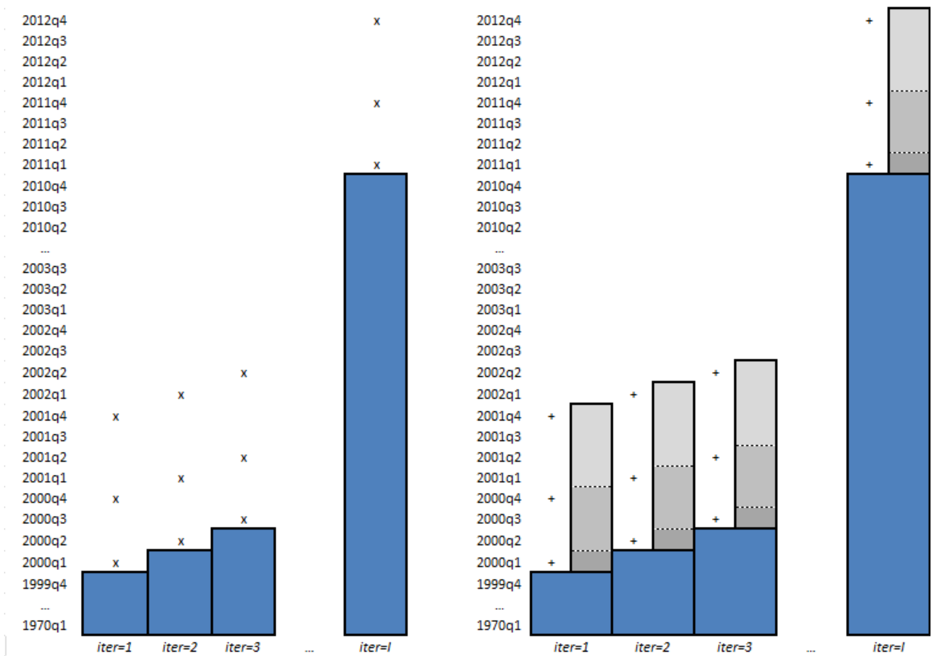

Figure 1: The diagram depicts the structure of the information set used for the recursive (expanding window) unconditional (left-hand side figure) and conditional (right-hand side figure) forecast evaluation exercise. Forecast errors are computed over the period 2000q1-2012q4 recursively. For the first iteration ("iter=1"), an initial sample using data from t=1970q1,..., 1999q4 is used to estimate the model and h-step (1-quarter, 4-quarter and 8-quarter) ahead out of sample forecasts are produced. For the next iteration ("iter=2"), the sample is increased by one quarter, the models are re-estimated, and h-step ahead forecasts are produced starting one quarter later. The bars indicate the information set used for estimation and forecasting at each iteration. Blue indicates the information set used for estimation, which contains ALL the variables listed in Table 1, as published by 2013q3. Grey indicates the information set used for conditional forecasting and contains ONLY the following variables: the EA policy interest rate, the BE OLO 10-year bond yield, the BE Private Consumption inflation (BE PCD), the BE GDP and the BE mortgage loan amount deflated by BE PCD inflation. The diagram also depicts the dates of the forecasts. A cross "x" sign indicates an unconditional forecast (in the sense of absence of information regarding the evolution of any of the variables over the forecasting horizon). A plus "+" sign indicates a conditional forecast (using information over the forecasting horizon for the five conditioning variables ONLY). Note that both unconditional and conditional forecasts for house prices are out-of-sample since house prices are not part of the conditioning information set.

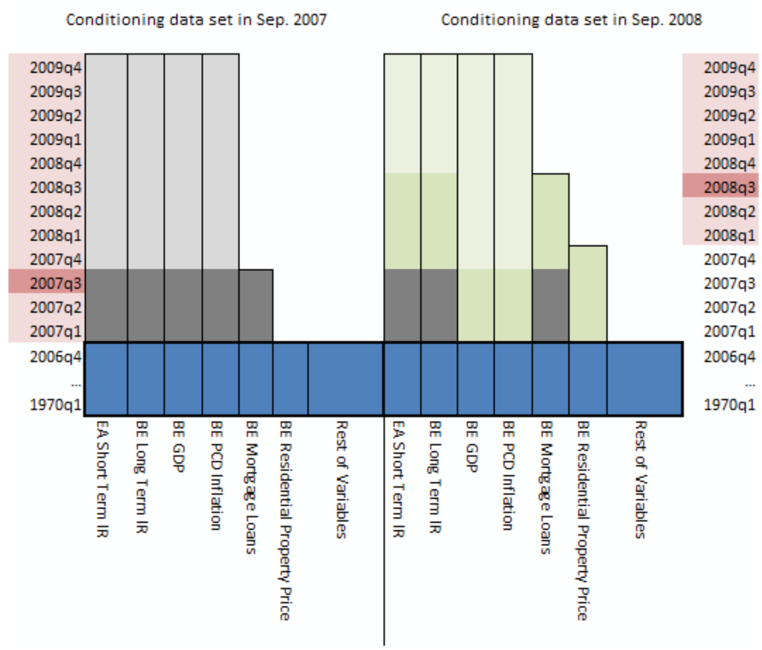

Figure 2: The diagram shows the structure of the conditioning information used to compute the residential property price forecast in September 2007 (left-hand side) and in September 2008 (right-hand side). The vertical axis depicts the reference period of the conditioning variables over the forecast horizon which is shown in light red. The horizontal axis is split in two. The left hand side represents the information for the conditioning variables used in September 2007. The right-hand side represents the information used in September 2008. In both cases, the model is estimated with data over 1970q1-2006q4. Up to 2006q4 the conditioning data set contains final data for ALL variables (see Table 1) (dark blue in the figure). Darker grey (or green) indicates final data as released in 2007q3 (or in 2008q3). Lighter grey or green indicates a scenario : "Autumn 2007" scenario for the forecasting exercise in 2007q3 and "Autumn 2008" scenario for the forecasting exercise in 2008q3. The bright red square highlights when the forecasting exercise for the residential property price is performed. No information over the forecast horizon is available for any of the house prices in 2007q3. In 2008q3 the red square is above the dark green bar for the residential property price index because of a 6-month publication lag.

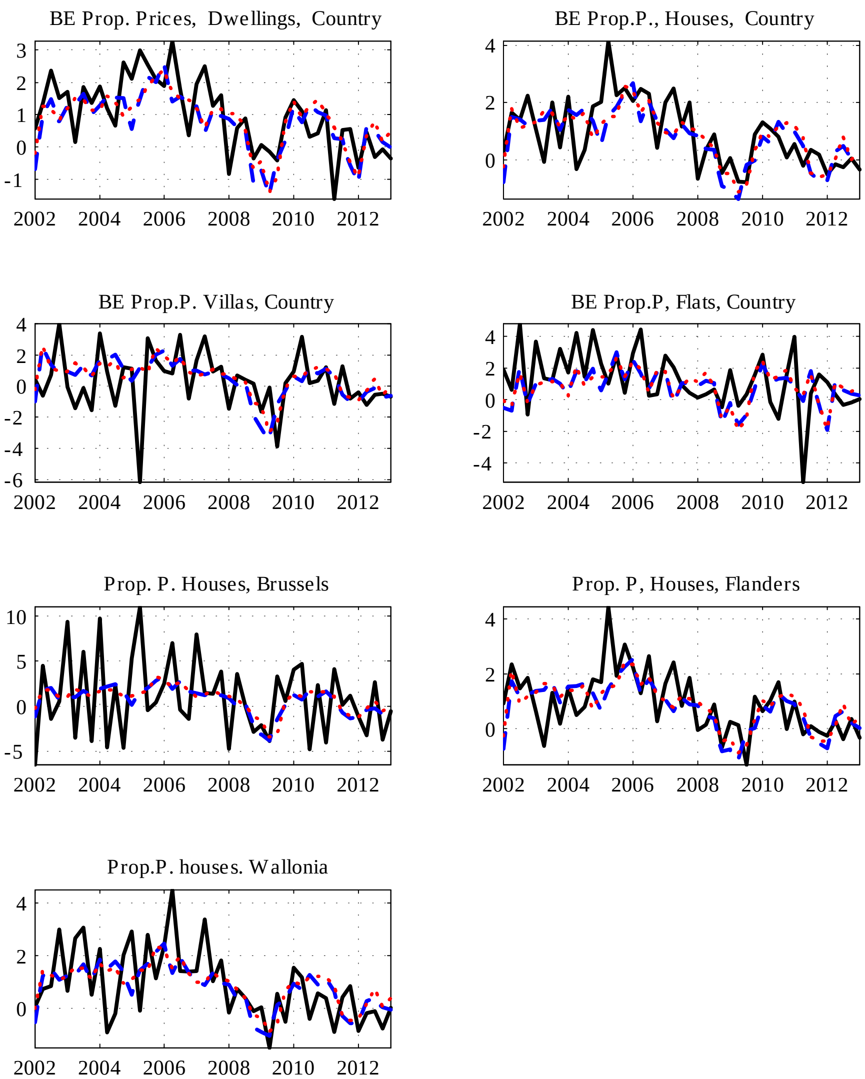

Figure 3: Out-of-sample one-quarter ahead forecasts (1). Data (black dash-dotted line), conditional forecast (blue dashed line), unconditional forecast (red dotted line) Forecasts are out-of sample and obtained by iteration over an evaluation period 2000q1-2012q4. Conditioning variables are BE GDP, EA Short Interest Rate, BE Long Interest Rate, BE P.Consumption Deflator (PCD) and BE Mortgage Loan Amount deflated by PCD. All variables are shown in quarterly growth rates (%) (y-axis) except for interest rates which are shown in differences of levels (y-axis) . For details see Table 1.

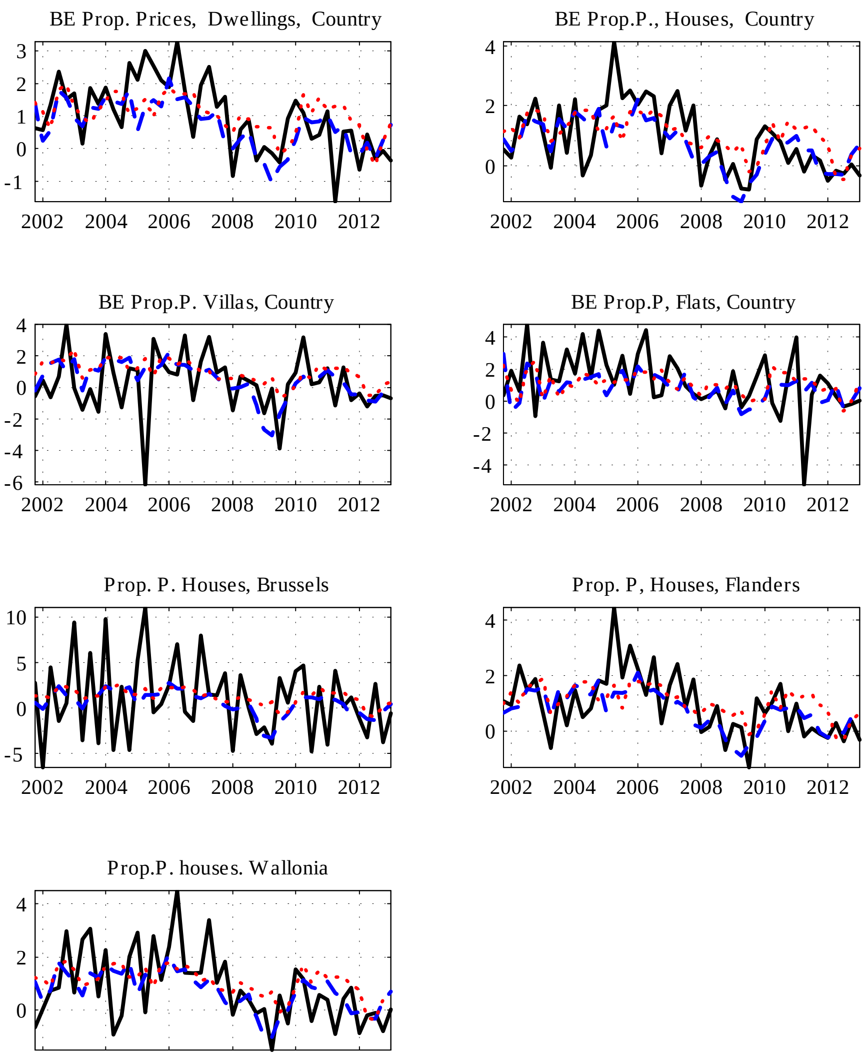

Figure 4: Out-of-sample 4-quarter ahead forecasts (2). Data (black dash-dotted line), conditional forecast (blue dashed line), unconditional forecast (red dotted line) Forecasts are out-of sample and obtained by iteration over an evaluation period 2000q1-2012q4. Conditioning variables are BE GDP, EA Short Interest Rate, BE Long-Term Interest Rate, BE Private Consumption Deflator (PCD) and BE Mortgage Loan Amount deflated by PCD. All variables are shown in quarterly growth rates (%) except for interest rates (y-axis) which are shown in differences of levels (y-axis) . For details see Table 1.

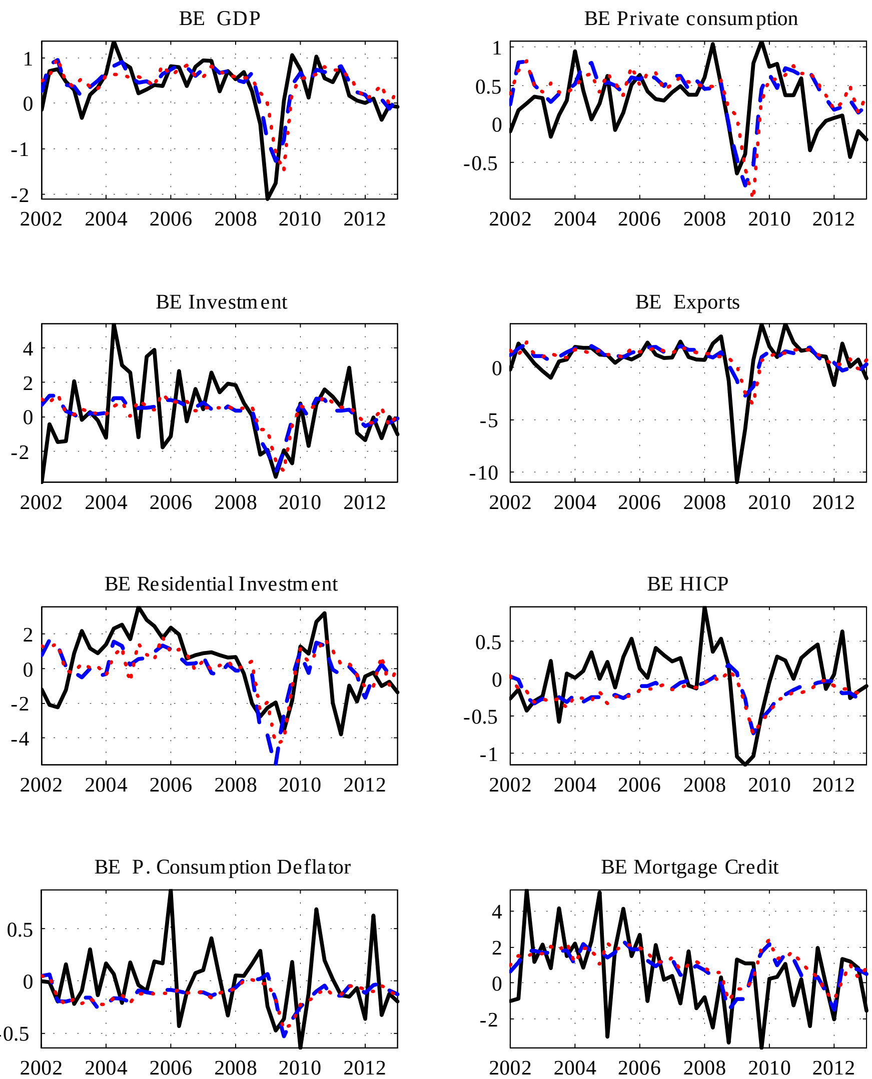

Figure 5: Out-of-sample 1-quarter ahead forecasts (3) . Data (black dash-dotted line), conditional forecast (blue dashed line), unconditional forecast (red dotted line) Forecasts are out-of sample and obtained by iteration over an evaluation period 2000q1-2012q4. Conditioning variables are BE GDP, EA Short Interest Rate, BE Long Interest Rate, BE P.Consumption Deflator (PCD) and BE Mortgage Loan Amount deflated by PCD. All variables are shown in quarterly growth rates (%) (y-axis) except for interest rates which are shown in differences of levels (y-axis) . For details see Table 1.

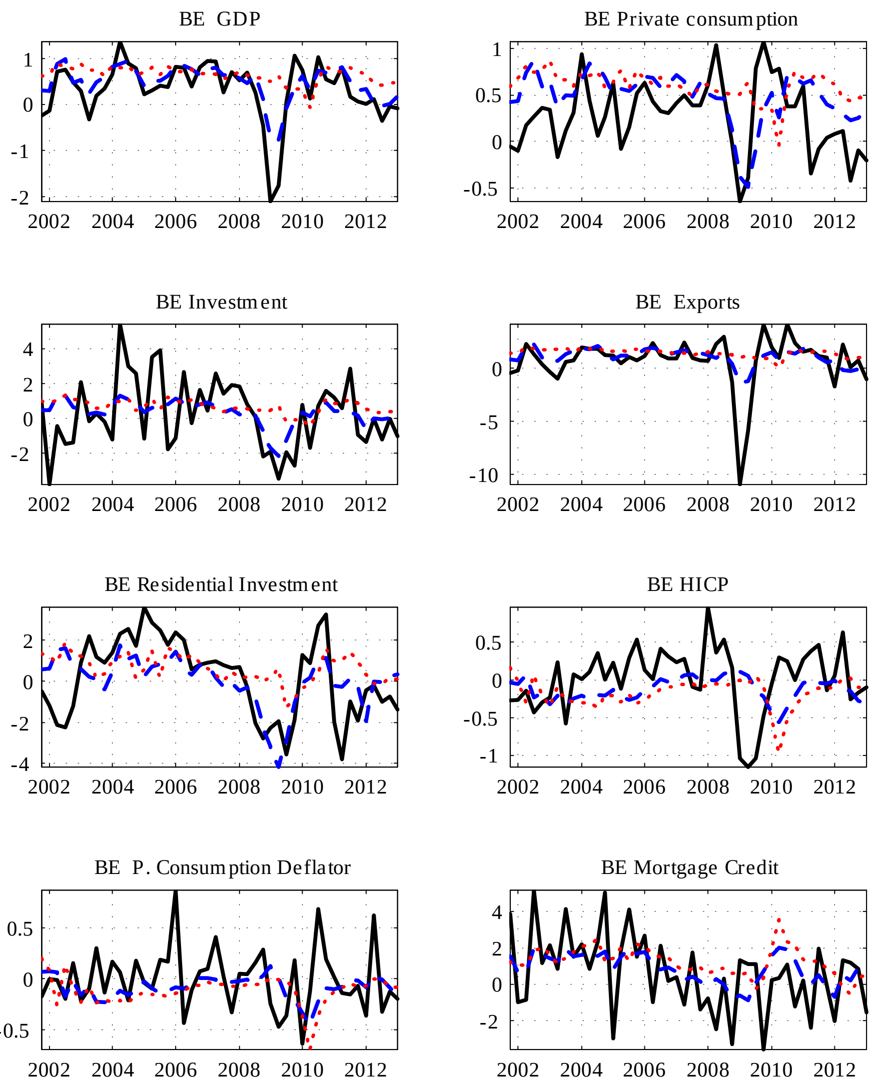

Figure 6: Out-of-sample 4 quarter-ahead forecasts (4). Data (black dash-dotted line), conditional forecast (blue dashed line), unconditional forecast (red dotted line) Forecasts are out-of sample and obtained by iteration over an evaluation period 2000q1-2012q4. Conditioning variables are BE GDP, EA Short Interest Rate, BE Long Interest Rate, BE P.Consumption Deflator (PCD) and BE Mortgage Loan Amount deflated by PCD. All variables are shown in quarterly growth rates (%) (y-axis) except for interest rates which are shown in differences of levels (y-axis) . For details see Table 1.

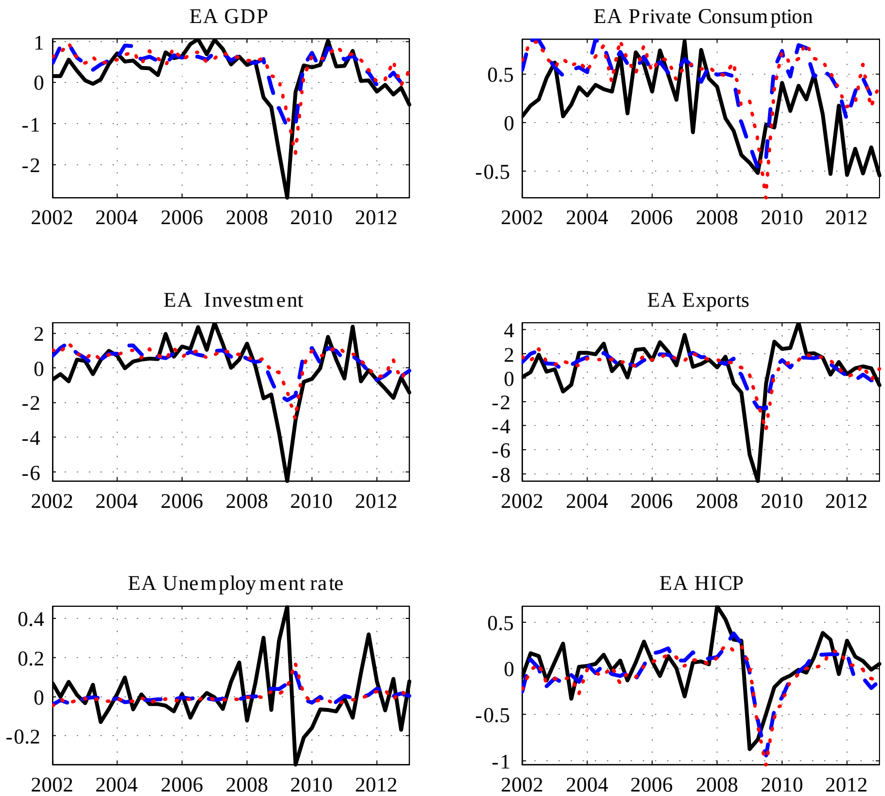

Figure 7: Out-of-sample 1-step ahead forecasts (5). Data (black dash-dotted line), conditional forecast (blue dashed line), unconditional forecast (red dotted line) Forecasts are out-of sample and obtained by iteration over an evaluation period 2000q1-2012q4. Conditioning variables are BE GDP, EA Short Interest Rate, BE Long Interest Rate, BE P.Consumption Deflator (PCD) and BE Mortgage Loans deflated by PCD. All variables are shown in quarterly growth rates (%) (y-axis) except for interest rates which are shown in differences of levels (y-axis) . For details see Table 1.

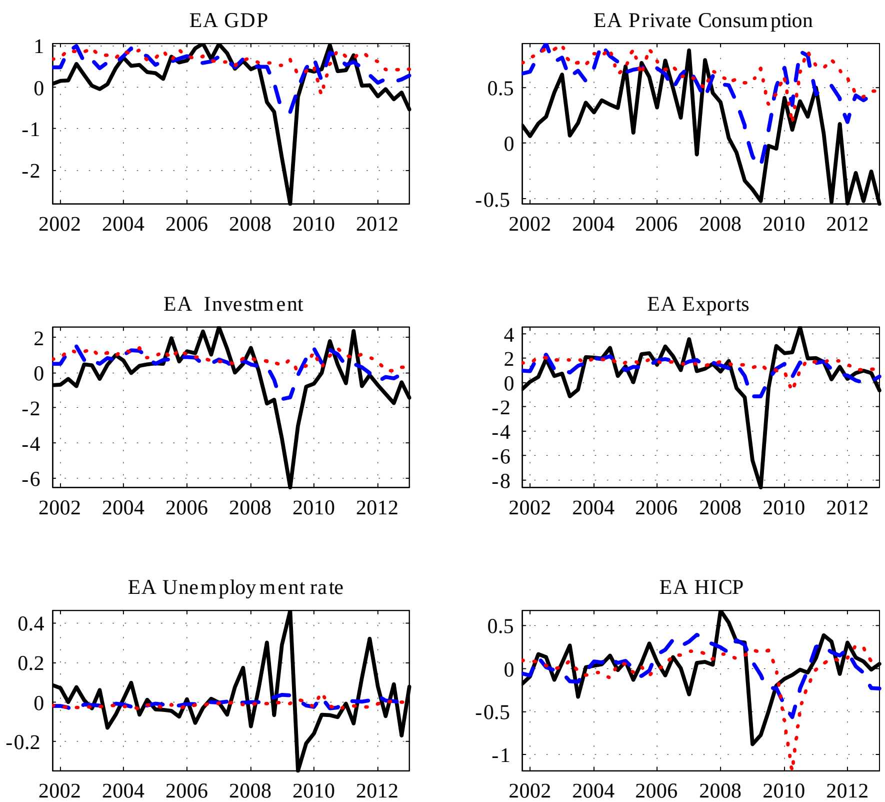

Figure 8: Out-of-sample 4-step ahead forecasts (6). Data (black dash-dotted line), conditional forecast (blue dashed line), unconditional forecast (red dotted line) Forecasts are out-of sample and obtained by iteration over an evaluation period 2002q1-2012q4. Conditioning variables are BE GDP, EA Short Interest Rate, BE Long Interest Rate, BE P.Consumption Deflator (PCD) and BE Mortgage Loans deflated by PCD. All variables are shown in quarterly growth rates (%) (y-axis) except for interest rates which are shown in differences of levels (y-axis) . For details see Table 1.

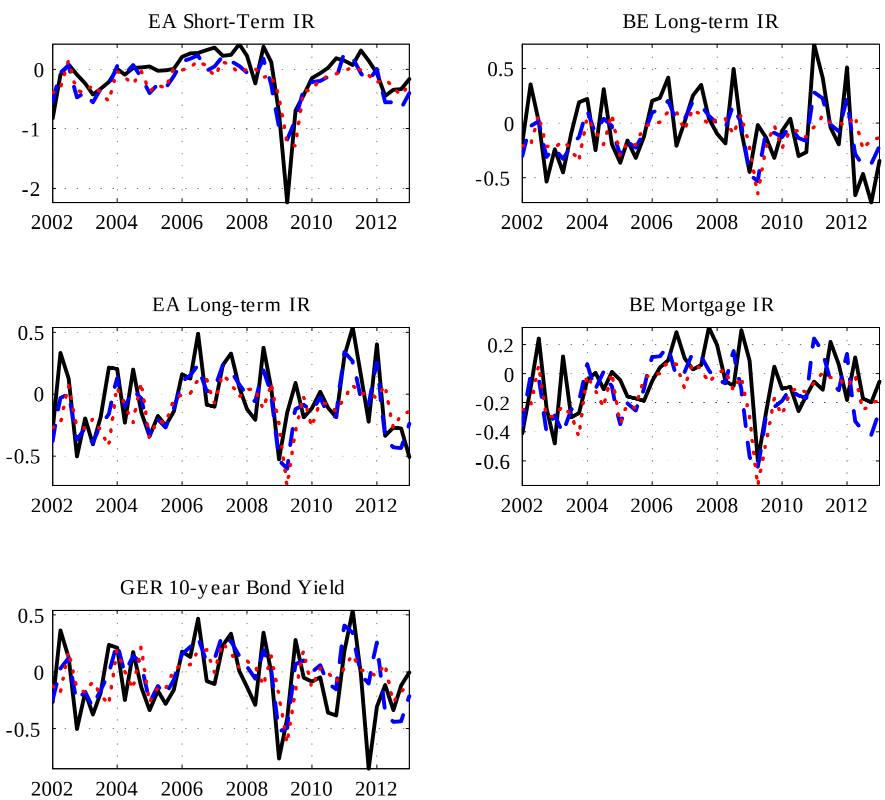

Figure 9: Out-of-sample 1-step ahead forecasts (7). Data (black dash-dotted line), conditional forecast (blue dashed line), unconditional forecast (red dotted line) Forecasts are out-of sample and obtained by iteration over an evaluation period 2000q1-2012q4. Conditioning variables are BE GDP, EA Short Interest Rate, BE Long Interest Rate, BE P.Consumption Deflator (PCD) and BE Mortgage Loans deflated by PCD. All variables are shown in quarterly growth rates (%) (y-axis) except for interest rates which are shown in differences of levels (y-axis) . For details see Table 1.

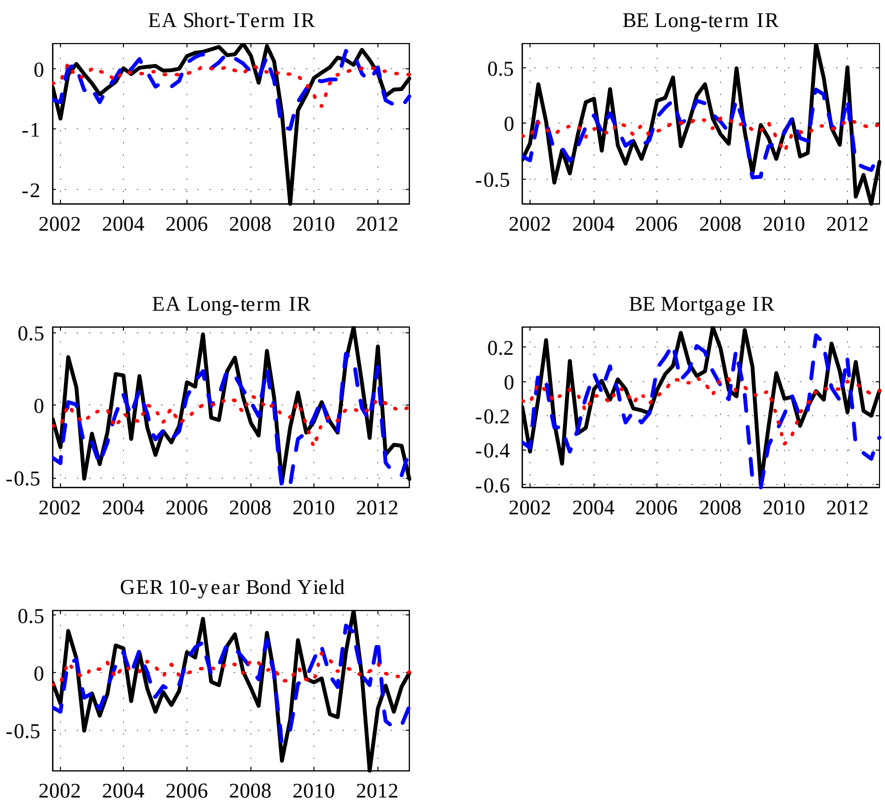

Figure 10: Out-of-sample 4-step ahead forecasts (8). Data (black dash-dotted line), conditional forecast (blue dashed line), unconditional forecast (red dotted line) Forecasts are out-of sample and obtained by iteration over an evaluation period 2000q1-2012q4. Conditioning variables are BE GDP, EA Short Interest Rate, BE Long Interest Rate, BE P.Consumption Deflator (PCD) and BE Mortgage Loan Amount deflated by PCD. All variables are shown in quarterly growth rates (%) (y-axis) except for interest rates which are shown in differences of levels (y-axis) . For details see Table 1.

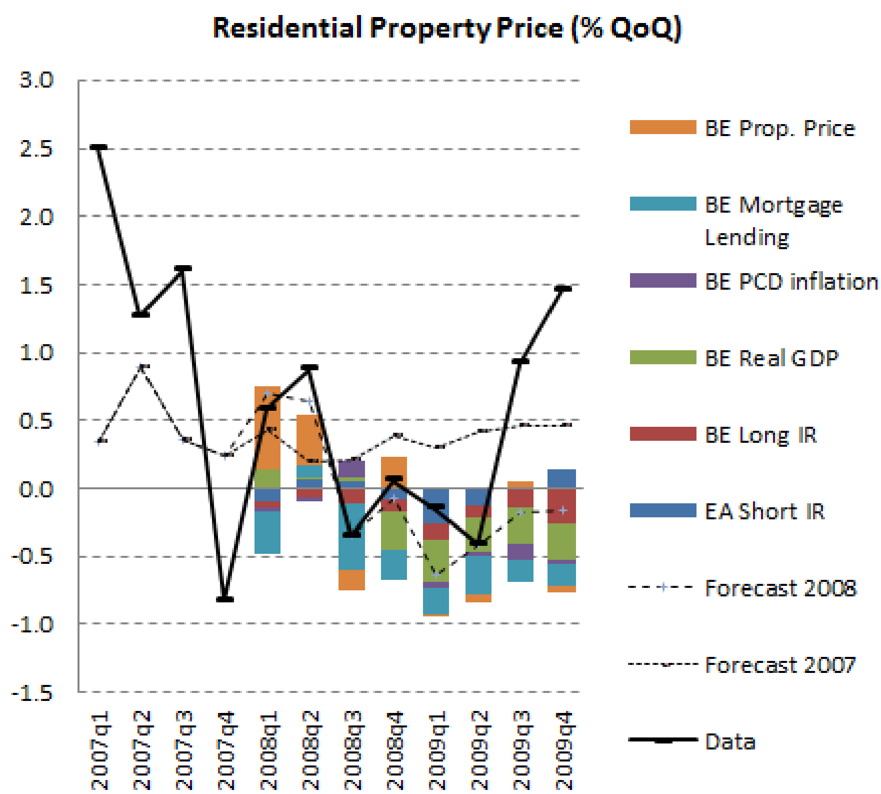

Figure 11: Forecasting exercise (for details see section 3.4): Decomposition of the change in the conditional forecast of the BE Residential Property Price index (Dwellings). For details see Table 4. Data refers to line (3') in Table 4.

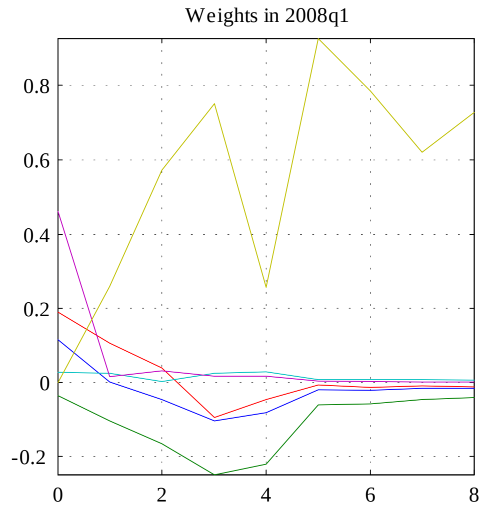

Figure 12: Weights ψ_{ij} for current and past innovations (see equation (20)) for the forecast of BE residential property price index in 2008q1 and 2009q1. Blue line: EA Short-Term IR; dark green line: BE Long-term IR; red line: BE GDP; light blue line: BE PCD; purple line: BE Mortgage Credit; light green line: BE Prop. Prices.

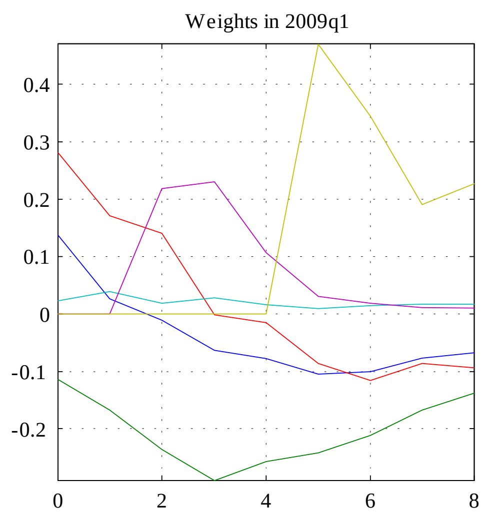

Figure 13: Weights ψ_{ij} for current and past innovations (see equation (20)) for the forecast of BE residential property price index in 2008q1 and 2009q1. Blue line: EA Short-Term IR; dark green line: BE Long-term IR; red line: BE GDP; light blue line: BE PCD; purple line: BE Mortgage Credit; light green line: BE Prop. Prices.

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