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In 2009 all ECB publications feature a motif taken from the €200 banknote.

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Abstract

The yield spread between nominal and inflation-linked bonds (or break-even inflation rates, BEIR) is a fundamental indicator of inflation expectations (and associated premia). This paper investigates which macroeconomic and financial variables explain BEIRs. We evaluate a large number of potential explanatory variables through Bayesian model selection techniques and document their explanatory power at different horizons. At short horizons, actual inflation dynamics is the main determinant of BEIRs. At long horizons, financial variables (i.e. term spread, bond market volatility) become increasingly relevant, but confidence and cyclical indicators remain important.

Keywords: break-even inflation rates, inflation risk premia, business cycle indicators, Bayesian model selection

JEL Classification: C11, C52, E31

Non-technical summary

The break-even inflation rate (BEIR) – the spread between nominal and inflation-linked bonds – has become one of the most important indicators of inflation expectations, as it provides timely information about inflation expectations over a large number of horizons.

Measures of BEIR reflect the overall inflation compensation requested to hold nominal bonds, comprising both the expected level of inflation and a premium to compensate for inflation risks. Therefore, establishing a link between BEIRs and macroeconomic and financial variables can provide a framework to analyse a large number of issues regarding inflation expectations.

The paper investigates the role that macroeconomic and financial variables have played in explaining the euro area monthly BEIRs developments at different horizons since the start of the euro area single monetary policy in 1999.

In principle, there are many potential variables that can help market participants form inflation expectations (and associated premia). To determine whether, when and by how much BEIRs (and their components) are linked to oil, real, monetary or financial developments, or a combination of these and perhaps other variables and shocks, the paper evaluates the explanatory power of a large number of potential BEIR determinants, searching for a parsimonious (and yet robust to possible omitted variables) model. The variable selection problem is solved by means of Bayesian model selection techniques, which are particularly suited to select relevant regressors among a wide pool of candidate explanatory variables.

The paper uses the BEIRs at different horizon obtained from García and Werner (2008), who model euro area BEIRs between 1995-2006 within a term structure model that employs inflation-linked bond yields to pin down real yields, computes BEIRs as the spread with nominal yields, and decomposes the latter into inflation expectations and inflation risk premia with the help of survey inflation expectations. BEIRS are regressed on all possible combinations of 27 macroeconomic and financial variables over the sample 1999-2006.

A relatively large number of these variables contribute to explain BEIRs, with remarkable differences between short and long-term horizons. Short-term BEIRs are mainly explained by inflation dynamics, but indicators of price pressures (wage growth) and of cyclical conditions (consumer confidence, the unemployment rate, and the US business cycle conditions) also play a role. In contrast, financial variables (i.e. the yield curve spread, implied volatility in the bond market) become increasingly relevant with the horizon, reflecting the increasing role of inflation risk premia in long-term BEIR dynamics. Moreover, results highlight the dynamic nature of those relationships, since the impact of most of those variables extends over time well beyond their impact effect.

To our knowledge, this is the first attempt to explicitly link BEIR developments and macroeconomic and financial conditions.

1 Introduction

The yield spread between nominal and inflation-linked bonds, commonly referred to as the break-even inflation rate (BEIR henceforth), is nowadays the most important indicator of inflation expectations. Since most major economies have issued inflation-linked debt in recent years, measures of the BEIR are now widely available and provide timely information about inflation expectations over a large number of horizons. Central banks, market participants and media regularly discuss changes in BEIRs, but their interpretation in the context of the macroeconomic and financial situation is often far from straightforward. BEIRs reflect the overall inflation compensation requested to hold nominal bonds, comprising both the expected level of inflation and a premium to compensate for inflation risks. Establishing a link between BEIRs and macroeconomic and financial variables can therefore provide a framework to analyse a large number of issues regarding inflation expectations.

This paper investigates the role that macroeconomic and financial variables have played in explaining the euro area monthly BEIRs developments at different horizons since the start of the euro area single monetary policy in 1999. The first bond linked to euro area inflation was issued in late 2001, but the observed BEIRs calculated from market prices were not sufficiently reliable for research purposes before 2004. To overcome this problem, our data come from García and Werner (2009), who model euro area BEIRs between 1995-2006 within a term structure model similar to Ang, Bekaert and Wei (2007) and D'Amico, Kim and Wei (2007) for the US economy. The model uses inflation-linked bond yields to pin down real yields, computes BEIRs as the spread with nominal yields, and decomposes the latter into inflation expectations and inflation risk premia with the help of survey inflation expectations. Using model-based BEIRs allows us to analyse their developments over the whole period of the single monetary policy in the euro area, as well as to investigate the determinants of BEIRs at short and long horizons without being constrained to the issuance of inflation-linked bonds with different maturities.

In principle, there are many potential variables that can help market participants form inflation expectations (and associated premia). To determine whether, when and by how much BEIRs (and their components) are linked to oil, real, monetary or financial developments, or a combination of these and perhaps other variables and shocks, we evaluate the explanatory power of a large number of potential BEIR determinants, searching for a parsimonious (and yet robust to possible omitted variables) model. We solve the variable selection problem by means of Bayesian model selection techniques, which are particularly suited to select relevant regressors among a wide pool of candidate explanatory variables (for other applications see, e.g., Fernandez, Ley and Steel, 2001, and Ciccarelli and Mojon, 2005).

Market practitioners often consider a very limited number of variables to model BEIRs (see, for instance, Barclays Capital, 2007, Goldman Sachs 2006a,b). By selecting a single model the researcher however risks ignoring statistical evidence from other plausible models. To tackle similar problems, the academic literature instead favours considering a large number of potential predictors and reducing dimensionality by extracting a few factors using sequential testing procedures or information criteria. Evaluating an information criterion for every possible model, however, is often not feasible: if K is the number of potential explanatory variables, then 2^K possible models exist, and evaluating an information criterion for every model becomes computationally prohibitive. An increasingly-used alternative is to extract a small number of factors out of K potential regressors of interest on the basis of a statistical criterion typically based on the size of their eigenvalues (see, e.g., Stock and Watson, 1999). Factor analysis, however, summarises the information content of the potential explanatory variables and not their explanatory power for the dependent variable: it is possible that some factors associated with large eigenvalues have no explanatory power while some with small eigenvalues do have explanatory power for the dependent variable (Koop and Potter, 2004). The researcher therefore risks including irrelevant factors or omitting important ones associated with small eigenvalues.

To overcome those shortcomings, we apply Bayesian model selection techniques to search over a high-dimensional model space and find the variables with the highest information content (the highest marginal likelihood) in model space instead of parameter space. Specifically, we employ a search algorithm to detect the variables with high explanatory power without the need to evaluate the marginal likelihood (or an information criteria) for every model. We then quantify the explanatory power of the determinants of euro area BEIRs at short and longer-term horizons by means of their contributions in our dynamic framework and impulse responses.

Our approach is therefore similar to the analysis of movements in BEIRs based on event studies (see for instance Gürkaynak, Levin and Swanson, 2006), but there are also at least three important differences. First, while event-studies focus on BEIR changes during very short time windows, we search for macroeconomic and financial variables that help explain the trends in BEIRs historical movements. To our knowledge, this is the first attempt to explicitly link BEIR developments and macroeconomic and financial conditions. Second, in contrast to the static approach of the overwhelming majority of event-studies, our framework allows to assess the dynamic impact of the macro and financial variables on BEIRs. Finally, by modelling BEIRs in a multivariate setting, we can control for the effects of other variables when assessing the explanatory power of the macro and financial series. The multivariate modelling also improves the interpretation of the results by taking into account the effects of a given variable not only on the BEIRs but also on the other variables.

We analyse the determinants of euro area BEIRs over the sample 1999M1-2006M12, and show that they are indeed influenced by a relative large number of macroeconomic and financial variables. The complexity of the link between BEIRs and macroeconomic and financial conditions increases with maturity, and we reveal interesting differences between the BEIR determinants at short and long horizons.

At shorter horizons, current inflation dynamics appears to be the main determinant of BEIRs, as one would expect. One-year ahead BEIRs, are mainly explained by inflation dynamics and other indicators of price pressures (such as wage growth), with other cyclical indicators (consumer confidence, the unemployment rate, and the US business cycle conditions) playing a minor role. The relative importance of actual inflation dynamics decreases with horizon, but broadly the same factors explain the two-year ahead BEIRs.

The determinants of long-term BEIRs, instead, are qualitative and quantitatively different. First, observed inflation is no longer an important determinant of long-term (five-year ahead) BEIRs. Second, financial variables (such as the yield curve term spread and the implied volatility in the bond market) become increasingly relevant, and this, in turn, reflects the increasing role of inflation risk premia in long-term BEIR dynamics. A limited number of cyclical and confidence indicators (notably the Purchaser Manager's index) remain important determinants of BEIRs even at longer horizons. Impulse response analysis also suggests that it is crucial to take into account the dynamic nature of the relationship between BEIRs and the most relevant factors identified with the selection technique, as the effects of these determinants on the BEIRs may last for several months.

The remainder of the paper is organised as follows. Section 2 describes the main trends of BEIRs and its two components, inflation expectations and inflation risk premia between 1999-2006. Section 3 illustrates the macroeconomic and financial explanatory variables, and the selection methodology. Section 4 discusses the results. Finally, Section 5 concludes.

2 The euro area break-even inflation rates

Inflation expectations play a fundamental role in modern economic analysis, and are important determinants for investment decisions and monetary policy making. To gauge inflation expectations, researchers, investors and policymakers have over recent years benefited from the issuance of inflation-linked bonds in major bond markets. Bonds whose coupon payments and principal are protected against inflation are by now a standard investment instrument in modern financial markets. The spread between the yields of a conventional nominal bond and an inflation-linked bond of the same maturity is often referred to as the "break-even" inflation rate (BEIR), because, risk premia aside, it would be the hypothetical rate of inflation at which the expected return from the two bonds would be the same.

BEIRs present two main advantages as a source of information on private sector inflation expectations. First, they are the most timely source of information on inflation expectations since they are available in real time every trading day. Second, as conventional and inflation-linked bonds are issued over a variety of maturities, they in principle allow for obtaining inflation expectations at several horizons, which is of considerable interest for researchers, central banks and private investors.

Developments in BEIRs are nowadays extensively reviewed in the regular publications of major central banks and specialised media. Comments are usually restricted to the description of their changes, and evidence on the factors behind those movements is often missing. Changes in BEIRs over time could reflect changes in the level of expected inflation, changes in the perceived risks about future inflation or a combination of both. Understanding what drives the level of BEIRs can therefore shed light not only on the most important factors affecting inflation expectations and their formation, but also on the pricing of the risks associated to future inflation.

Explaining the determinants of euro area BEIRs poses two important challenges. First, BEIRs are still only available over relatively short samples. Despite a significant growth in recent years, issuance and liquidity considerations limit significantly the period of time over which BEIRs over different horizons can be reliably calculated from inflation linked-bonds: the first bond linked to euro area inflation was issued in November 2001, but the market did not reach a significant level of depth in terms of number of bonds and trading volumes until 2004.[1]

A second challenge concerns the number of potential determinants behind the movements in BEIRs. In principle, any factor affecting inflation expectations and the risks surrounding them can be an important determinant of BEIRs. For example, recent research on the effects of data releases on bond markets considers a large number of macroeconomic variables ranging from official statistics to a wide range of confidence indicators (Gürkaynak, Levin and Swanson, 2006; Beechey, Johannsen and Levin, 2007; and Ehrmann *et al.*, 2007 among others). Such a large number of potential explanatory factors forces the researcher to a rigorous selection process to avoid omitting relevant variables while at the same time keeping the exercise tractable.

Our purpose is to explain developments in BEIRs over the ECB years. To solve the short-sample problem, we use monthly BEIR data from García and Werner (2009) for

[1] García and van Rixtel (2007) and references therein describe the euro area inflation market in detail.

the period 1995-2006. To cope with the high dimension of the model selection problem, we evaluate a large number of potential explanatory variables through Bayesian model selection techniques and document their explanatory power at different horizons. We explain our approach in detail in the next section.

García and Werner (2009) BEIRs are based on a euro area term structure model built along the lines of Ang, Bekaert and Wei (2007) and D'Amico, Kim and Wei (2007) models for the US term structure. Specifically, the model has three factors: two latent factors and inflation as observable factor. To improve the decomposition of the nominal term structure the estimation incorporates two key pieces of additional information, namely inflation-linked bond yields and survey data on inflation expectations, and identify the nominal, real, inflation and risk premia term structures, thereby providing reliable estimates of BEIRs and its main components.[2] Specifically, the model uses inflation-linked bond yields to pin down real yields, computes BEIRs as the spread with nominal yields, and decomposes the latter into inflation expectations and inflation risk premia with the help of survey inflation expectations.

Figures 1 to 3 depict the BEIR data used in our analysis. Figures 1 and 2 show two short-term BEIRs, one year ahead and two year ahead respectively. Figure 3 shows the one-year forward BEIR four years ahead, which reflects inflation expectations (and associated premia) over the longer horizon of five years ahead. For completeness, the charts also plot the decomposition of BEIRs into their two components, inflation expectations and inflation risk premia.

Some key patterns exhibited by BEIRs over the years 1999-2006 are worth discussing. First, BEIRs are more volatile at short than at longer horizons: the standard deviation of the one-year ahead BEIR (BEIR10 henceforth) is twice as high as that of the one-year forward BEIR four years ahead (BEIR14 henceforth). Moreover, in terms of their two components, all the variation in the short-term BEIRs basically reflects the movements in (short-term) inflation expectations, with the inflation risk premia playing a limited role. In contrast, reflecting the fairly strong anchoring of euro area long-term inflation expectations, the volatility of longer-term BEIR appears to be mainly explained by time-varying inflation risk premia. Formally, a variance decomposition shows that about 2/3 of the variation in short-term BEIRs is due to inflation expectations, while about 90% of the variation in longer term BEIRs reflects changes in the inflation risk premia.

In terms of overall developments in BEIRs over those seven years, there are also some

[2] We use seasonally-adjusted inflation-linked bond yields from Ejsing *et al.* (2007), which is particularly important at the short-to-medium horizon BEIRs we consider here. The model includes inflation expectations one, two and five years ahead calculated from the ECB´s Survey of Professional Forecasters following Garcia and Manzanares (2007).

striking differences between short and longer-term BEIRs. Despite the volatility discussed above, short-term BEIRs have fluctuated around the 2% mark over the whole period. In contrast, longer-term BEIRs have fluctuated around a lower average between 2004 and 2006 (about 2%) than in the first four years of the single monetary policy (about 2.2%).

3 Modelling break-even inflation rates

To determine whether, when and by how much BEIRs (and therefore inflation expectations and the associated risk premia) may be linked to price, costs, real, monetary or financial developments or a combination of these and perhaps other information and shocks, we evaluate the explanatory power of a large set of potential inflation determinants. To make the exercise tractable but nonetheless robust, we proceed with a Bayesian model selection analysis that is particularly suited to select relevant regressors among a wide pool of candidate explanatory variables. We present in this section the set of potential explanatory variables and the methodology used to select the best predictors for BEIRs. Results are discussed in the next section.

3.1 Potential explanatory variables

Given the complexity of the BEIRs, which potentially reflect time-varying inflation expectations, the perceived risks surrounding them, as well as the pricing of those risks in the light of the prevailing market conditions, the list of potential explanatory variables is extensive.

Our pool of candidate explanatory variables comprises real, nominal, monetary and survey indicators whose usefulness to predict euro area inflation and economic activity has already been demonstrated (see, e.g., Giannone *et al.,* 2008). To capture the effects of financial market conditions on BEIRs (i.e. flight-to-safety flows; risk perceptions and risk aversion; potential relocation across financial assets), we also include some additional financial variables.

The potential explanatory variables we consider are grouped as follows:

1. **Monetary factors**: M1 and M3;

2. **Commodity prices and exchange rates:** Index of world market prices of raw materials (excluding energy); crude oil prices (in USD); and the trade-weighted euro exchange rate (NEER);

3. **Price and costs indicators**: Headline HICP and core HICP (excluding unprocessed food and energy), as well as the volatility of their year-on-year rates over the previous 24-months; PPI; the ECB's wage growth indicator (the last two capture price

pressures at early stages in the production chain and should therefore help revise inflation expectations and related risks);

4. **Economic activity indicators**: Industrial production and the unemployment rate (to gauge business cycle conditions;);

5. **Confidence indicators**: European Commission industrial and consumer confidence indexes; the PMI composite;

6. **Financial variables**: The yield curve slope in the US and euro area; the differential between the long-term (ten-year) bond yields in both economic areas; implied volatility extracted from options on the ten-year German bund; 12-month return in the S&P500 and the EuroSTOXX 50 indices, as well as the VIX and VSTOXX volatilities.

Finally, additional variables whose releases often trigger some changes in financial market indicators, are also considered. In particular, we take the US CPI, the US industrial production, and the US non-farm payroll data, as they represent not only indicators of global economic conditions but also good candidates for signalling potential revisions in US macroeconomic expectations that may trigger trading opportunities.

A detailed list of all 27 variables is reported in Table 1 together with the data transformations undertaken.

3.2 Methodology

The key problem to build a multivariate linear regression model is the selection of explanatory variables. The basic model considered here is of the form

$$BEIR_t(h) = a\,(L)\,BEIR_{t-1}(h) + b\,(L)\,X_t + \varepsilon_t \tag{1}$$

where, $BEIR_t(h)$ denotes our (forward) break-even inflation rate at the short and long-term horizons of $h = 1$, 2, and 4 years ahead, and X_t represents the set of K possible explanatory variables listed above. The problem is to identify the variables with the highest explanatory power at each horizon, while, at the same time, considering all possible models resulting from the combinations of the K potential explanatory variables. Even within the simple model outlined in (1) above, the selection procedure must therefore consider 2^K models, which, when K is a relatively high number, imposes unbearable computational requirements for standard model selection criteria (e.g. AIC or BIC). In our case $K = 27$ leads to more than 130 million potential models to evaluate.

To identify the most promising explanatory variables we rely on Bayesian model selection techniques that focus on the posterior probability distribution of the potential models.

In our setting, models differ by the set of explanatory variables they include (i.e. models are defined by the inclusion or exclusion of each explanatory variable). Accordingly, we denote with M_r, $(r = 1, ..., R)$, the potential R different models constructed by combining our $K = 27$ explanatory variables. Each model therefore depends upon a vector of parameters θ_r, and is characterized by a prior for that parameter vector $p(\theta_r \mid M_r)$, a likelihood $p(y \mid \theta_r, M_r)$ and a posterior $p(\theta_r \mid y, M_r)$, where y denotes the data.[3] Using Bayes' theorem, we can obtain the posterior model probabilities, $p(M_k \mid y)$ as follows

$$p(M_r \mid y) = \frac{p(y \mid M_r)\ p(M_r)}{p(y)} \tag{2}$$

where $p(M_k)$ is the prior model probability, i.e. our prior "subjective" support for the model, and $p(y \mid M_k)$ is the marginal likelihood, i.e. what the data should look like under model M_k before seeing the data itself.

We will evaluate the posterior probability of the potential models and use the probability with which the explanatory variable appears in them as quantitative indicator of the variable's explanatory power. Our approach, to be outlined below, follows closely Koop (2003) and Fernandez *et al.* (2001a, b), so we refer to those contributions for specific details and a discussion of different possibilities.

The likelihood function for each of the models is based on our (normal) linear regression model (1). Formally, for each model r, X_{rt} is a $N \times K_r$ matrix containing some (or all) candidate variables K. The N vector of errors, ε_r, is assumed to be distributed as a $N(0_N,\ h_r^{-1} I_T)$. Our prior for h_r is a standard non-informative prior, $p(h) \propto 1/h$. For θ_r, we use a Normal-Gamma natural conjugate prior, $\theta_r \mid h_r \sim N(\overline{\theta_r},\ h_r^{-1}\overline{V_r})$, which allows for analytical results for posterior model probabilities and does not require detailed input from the researcher.[4] As it is common practice in the related literature, we set $\overline{\theta_r} = 0_{k_r}$ and a *g-prior* for $\overline{V_r} = [g_r X_r' X_r]^{-1}$, where our specification of g_r follows Fernandez *et al.* (2001a).[5]

We allocate equal prior probability to all models ($p(M_r) = 1/R$), and, up to a constant, calculate the posterior model probabilities using equation (2).[6]

[3] The parameter vector θ_r is common to all possible models, in case some variable is not included in a given model, its corresponding coefficient is simply zero.

[4] A prior is needed to compute the posterior odds we will use to compare the models. To this end, it is acceptable to use noninformative priors over parameters that are common to all the models (Koop, 2003). Moreover, we also standarise all the explanatory variables as recommended by Fernandez *et al.* (2001a).

[5] The g-prior, first introduced by Zellner (1986), depends upon the data X_r, but, since we are conditioning on X_r in the likelihood function and the posterior distribution, we can also do so in the prior without violating the rules of conditional probability. On the basis of their numerical simulations, Fernandez *et al.*(2001a) recommend choosing $g_r = \begin{Bmatrix} 1/K^2 & \text{if N} \leq K^2 \\ 1/N & \text{if N} > K^2 \end{Bmatrix}$.

[6] Note that by focusing model selection the posterior odds our approach implicitly rewards parsimony

To gauge the explanatory power of the candidate variables, we calculate the posterior probability of the variable defined as the proportion of R models that contain that variable. Evaluating the posterior probability of all the possible 2^{27} models however remains infeasible, so we simulate the posterior distribution of the model space by means of the Markov Chain Monte Carlo Model Composition methodology (MC^3) of Madigan and York (1995).[7] We use the posterior probability of the variable as a diagnostic statistic to determine whether a given variable plays an important role in explaining BEIR developments. In practice, such a statistic is similar to a Granger causality test in a multivariate setting, where variables are simultaneously included and optimally chosen.

4 What drives euro area break-even inflation rates?

This section reports the results of the Bayesian model selection approach, the dynamic contribution of the explanatory variables, and the dynamic impact as gauged by impulse responses and variance decomposition from a small-scale VAR model.

4.1 Variable selection results

Table 2 presents the results over the sample 1999M1-2006M12. The entries in the table reflect the proportion of models that contain the corresponding explanatory variable, and can be interpreted as the posterior probability that the corresponding explanatory variable should be included. As argued above, this is a useful statistics to decide whether an individual variable has an important role to explain movements in BEIRs: the higher the frequency a given variable appears in the models the more important it is to explain BEIRs in any model. The average number of regressors in the selected models suggested by our search algorithm is also reported.

At short horizons, for the BEIR one year ahead (BEIR10 henceforth), our search algorithm suggests that there are, on average, 6/7 regressors included in the models. The posterior probabilities reported in the third column identify HICP inflation as the strongest determinant, which underscores that short term BEIRs variability mainly reflects inflation expectations. Beside inflation, there are some variables related to price pressures – notably wages– and business cycle conditions – consumer confidence, unemployment rate– as well

as a desirable model property (see Koop, 2003).

[7] The MC^3 is a Metropolis algorithm that generates draws through a Markov Chain. Specifically, at a given model M_0, a new model Mj is proposed randomly through a uniform distribution on the model space that contains model M_0 and all models with either one regressor more or one regressor less than M_0. The chain moves to Mj with probability $p = min(1, L_y(Mj)pj \ / \ L_y(M_0)p_0\}$ where $L_y(Mj)$ denotes the marginal likelihood of model Mj, and remains at M_0, with probability $1 - p$.

as cyclical variables from the U.S. economy –non-farm payroll data– that also appear to have some strong explanatory power, though with lower posterior probabilities.

Longer horizon BEIRs (two years ahead, BEIR11 henceforth) are influenced by a larger number of variables. Actual inflation is still a strong determinant of BEIR11, but cyclical indicators play a more significant role. The variables discussed above (wages, consumer confidence, US non-farm payroll data) remain the most relevant ones to explain BEIRs up to two years ahead, and show higher posterior probabilities than at shorter horizons. In addition, other indicators (NEER, industrial confidence and core inflation) that appear to be not important for shorter term BEIRs become now relevant, underlying the higher complexity of two year ahead BEIRs. The presence of core inflation for instance is particularly interesting: to the extent that core inflation can be considered as better indicator of inflation trends, it suggests that markets considered some of the shocks affecting energy and unprocessed food prices in the euro area over the last few years (food price spikes due to animal diseases —BSE, foot-and-mouth—or the sharp increase in oil prices following hurricane Katrina to name a few) as mainly temporary.

At long horizons, the link between BEIRs and macroeconomic and financial variables becomes more complex. For the one year forward BEIR four years ahead (BEIR14 henceforth), the average number of regressors in the models is substantially higher, about 11, which suggests that longer-term BEIRs are more difficult to explain than shorter horizon ones. Indeed, a rather heterogeneous subset of eight variables comprising "real" factors (the unemployment rate, US non-farm payroll data), confidence indicators (PMI, consumer confidence) and early indicators of price pressures (PPI) but also some financial variables (the NEER, the yield curve slope and bond market volatility) concentrate most of the explanatory power (see column 4).

Most of the factors affecting the BEIR14 also explain the dynamics of the inflation risk premia embodied in long-term BEIRs (see column 5). The posterior probabilities however display some key differences. For instance, the explanatory power of the spread in the US yield curve is a more important determinant for the inflation risk premia, possibly related to its effects on the overall pricing of risks in global markets. Also the euro area industrial production plays a more important role for the premia component. In contrast, price pressures at early stages in the production chain as measured by the PPI do not help explain the premia.

Another important result of our analysis is that some of the variables often deemed as important to explain BEIRs – notably commodity prices (oil and raw materials), monetary aggregates, inflation and core inflation volatility – do not seem to play a considerable role in our framework. We believe that this somewhat counterintuitive finding is the consequence of our modelling choices. By construction, our approach identifies the macroeconomic variables whose effects are significant at monthly frequency, independently of whether those variables do or do not move markets short after their release. Some variables may have a punctual impact soon after their release, but such effect may vanish over time, while others may not move markets upon release and trigger revisions in inflation expectations at a later stage. We nonetheless believe that our results underscore the importance of considering the explanatory power of the variables in a multivariate framework. Ex ante, it is hard to question the potential relevance of those variables –or of any of our initial 27 variables– for the analysis of BEIRs. In a multivariate framework, however, all variables are likely to be simultaneously affected by all other pieces of available information. In particular, the statistical significance of soft indicators such as PMI or industrial confidence allegedly more sensitive to all news prior to their compilation is likely to be capturing a good deal of the information content embedded in the "excluded" variables.

The above results are quite robust. To avoid the influence of the initial condition in the calculation of the posterior probabilities, we run six million iterations and disregard the first 500.000. As discussed in the previous section, our assumptions allow to compute the model posterior probabilities analytically. The high correlation of the posterior probabilities based on the empirical frequency of visits in the chain and the analytical marginal likelihood suggests that the simulation effectively replicated the posterior distribution of models. Indeed, doubling the number of replications does not lead to any noticeable change. Similar (qualitative and quantitative) results were also obtained by enlarging the time span to include also the run-up to EMU, and using data from 1995M1.

4.2 Dynamic analysis

4.2.1 Contribution of explanatory variables

To quantify the impact of the factors discussed above, we now report their explanatory power by means of an accounting exercise based on our dynamic linear regression (1). With the BMA selection procedure, in the previous section we have ranked the regressors in terms of their statistical significance in a multivariate setting. The model estimation allows us to calculate the contributions of the each of these explanatory variables, i.e. the standard decomposition of the values of the endogenous variable as the sum of the various components defined by the explanatory variables and the residual term.

As in the BMA exercise all variables are defined in difference from the sample mean, we interpret the historical values of the endogenous variable as departure from a baseline or reference path. In the contribution analysis, this departure is explained by the departure of each of the explanatory variables from their respective reference path (i.e. the unconditional mean). The sum of all contributions returns the historical values of the endogenous variable in deviation for the baseline. Finally note that, to compute the dynamic contributions, we use the posterior mean of the regression coefficients averaged across all models.

The main insights are as follows.

Figure 4 displays the contributions of the different variables to the BEIR10. Reflecting the fact that inflation expectations are the main components of BEIRs over short horizons, the short end of the term structure of BEIRs is almost fully explained by the dynamics of inflation. Indeed, the rather low levels of BEIRs at the beginning of our sample and the spikes observed later on (mid-2001 or Autumn 2005) do correspond to movements in overall HICP inflation. Other indicators of price pressures (wages), and cyclical and confidence conditions (unemployment rate, consumer confidence, US non-farm payroll data) contribute to a much less extent in quantitative terms.

Moving along the term structure of BEIRs suggests that the longer the horizon the lower the role of inflation dynamics and the higher the role of other macroeconomic and financial factors. Recall that two years ahead inflation expectations are still the main component of BEIRs, with the inflation risk premia playing an increasing but still limited role (see Section 2). Figure 5 shows that the dynamics of BEIRs two years ahead also reflects the dynamics of the inflation rate: for instance, the inflation spikes in mid-2001 or Autumn 2005 do have a visible impact. The dynamics of BEIRs however becomes more complex with maturity.

As identified in the previous section, to explain BEIRs, the importance of price pressures (wages, core inflation), cyclical (unemployment rate, US non-farm payroll data) and confidence (consumer and industrial confidence) conditions increases with horizon. Specifically, industrial and consumer confidence contributed positively until about mid-2001, but exerted a negative pressure afterwards until 2006, in line with the momentum of economic activity in the euro area. Interestingly, inflation and core inflation dynamics have exerted an opposite influence on BEIRs for most of the sample. Such opposing contributions are not easy to rationalise with their relative levels *vis-a-vis* each other in our sample, but are most likely related to the strong fluctuations in the energy and unprocessed food components of HICP along those years. The contribution of wage growth is relatively modest, but it is interesting that, after being positive between 2001-mid-2003, in the last part of the sample it becomes systematically negative. Finally, the influence of US job creation is also clearly visible in the figure, turning from negative in the early part of the sample to positive between mid-2001 and end-2003, and negative again afterwards.

Compared to short-term BEIRs, the macroeconomic determinants of longer-term BEIRs are qualitative and quantitatively different.[8] Despite their heterogeneity, in terms of their

[8] Note also that the high probability of the autorregressive coefficient (see Table 2) reflects some notable

contributions over time the factors affecting long-term BEIRs can be grouped in three main blocks (see Figure 6). First, a rather diverse set comprising "real" (unemployment rate), confidence (PMI, consumer and industrial confidence) and the exchange rate indicators contributed positively until about mid-2001, exerted a negative pressure between mid-2001 and late 2005, and their contributions turned positive again in 2006 in line with the momentum of economic activity in the euro area. Second, over most of the sample such contributions were to a large extent counterbalanced by those of the US non-farm payroll data. Finally, the third block of contributions is given by financial variables (yield curve spread and bond market volatility), which, apart from the period mid-2000 to end-2001, contributed positively until mid-2005, when their contributions turned again negative.

These findings seem to suggest that the decline observed in the long-term BEIR in the second half of the sample, since 2003, was largely due to the negative contributions of euro area real and confidence indicators as well as to the effective exchange rate, whereas US and financial variables let alone would have given rise to more positive deviation of the endogenous variable form the reference path.

Reflecting the strong role of inflation risk premia in the dynamics of longer term BEIRs, the pattern of the contributions discussed above also holds for the decomposition of the long-term inflation risk premia (see Figure 7). The additional contribution of the US yield curve slope to the dynamics of the long-term inflation risk premia is similar over time to that of the euro area yield curve slope, which, at least in our sample, highlights the strong comovement across bond markets.

4.2.2 Impulse responses

To gauge the dynamic impact of those variables on long-term BEIRs and related premia, we estimate a small-scale VAR for the long-term BEIR and some selected determinants. The latter have been chosen among those variable with a posterior probability greater or equal than 0.5. Shock identification is achieved by means of a Cholesky decomposition. Following standard praxis in VAR analysis, the ordering of the variables respond to real (unemployment rate, PMI, US non-farm payroll), nominal (PPI), and financial factors (yield spread, bond market volatility, nominal effective exchange rate), with the BEIR placed last as being affected by all other variables. Results anyway appear to be robust to alternative orderings of the variables.

Figure 8 displays the impulse responses of the BEIR14 for each of those variables. With the exception of the unemployment rate, the impact effect of all the selected variables is limited to a few basis points, but is statistically significant. The impulse responses

persistence of the horizon BEIRs, which in turn might be the consequence of a strong anchoring of inflation expectations in the euro area.

highlight that modelling the relationship among the BEIR and the macroeconomy requires a dynamic model. As a matter of fact, the impact of shocks to macroeconomic and financial conditions on BEIRs often remains statistically significant for several months. Consistently with the complexity of long-term BEIRs identified in the previous subsection, the persistence of the shocks may reflect the large amount of past and current information incorporated by financial market participants into the formation of inflation expectations and related premia.

Turning to specific effects, shocks to the slope of the euro area yield curve and to the PMI have the strongest effect on impact. The former also displays the most persistent effect. Economic activity variables (unemployment rate, US non-farm payroll) tend to have a negative effect on long-term BEIRs. An increase in the unemployment rate therefore appears to be perceived by market participants as attenuating inflation pressures. Among the financial variables, BEIR movements following shocks to the euro area yield spread are the most important ones, but those to volatility in the bond market and the exchange rate do exhibit a hump shape, reaching the maximum impact around 3-4 months ahead.

The impact of job creation in the US economy is of particular interest. Available results suggest that its releases cause significant movements not only in US bond yields and inflation compensation measures, but also in other bond markets in the euro area, the U.K. and Sweden (Gürkaynak *et al.*, 2006, Ehrmann *et al*, 2007). Considering the impact of a data release over a single asset at a time may identify only a partial and potentially misleading link between the variables. For instance, Beechey and Wright (2008) have argued that a substantial part of the response to non-farm payroll data releases attributed to the long-term nominal yields reflects changes in real yields more than in the BEIRs.

Our multivariate analysis sheds new light on the channels through which the impact of non-farm payroll data feed onto euro area BEIRs and long-term bond yields. Strong job creation in the US economy raises expectations of higher policy rates by the Fed, and also seems to be positive news for the euro area economic activity (unemployment rate falls). Moreover, it flattens the euro area yield curve, possibly by pointing to higher inflation pressures ahead and thereby raising expectations of policy rate hikes in the euro area. Together with the positive impact often found on long-term nominal yields, the negative impact on long-term BEIRs we identified suggests that the impact on real yields via economic activity and policy rate expectations may be stronger than the one on nominal yields.

Reflecting the fact that movements in long-term BEIRs are strongly influenced by changes in the inflation risk premia, the impulse responses for long-term inflation risk premia do exhibit the same patterns (see Figure 9).

Tables 3 and 4 report the variance decomposition for long-term BEIRs and the associated inflation risk premia. In both cases, although the contribution of the own lag value decreases over time, it remains one of the most important factors explaining the variability in BEIRs and inflation risk premia. Interestingly, the yield spread plays a prominent role at all horizons by explaining about 25% of the variation in long-term BEIRs and about 20% of that of the inflation risk premia. In general, financial factors (the yield spread, bond market volatility, the exchange rate and the lag of the variable of interest) explain about 75% of the variability of BEIR and inflation risk premia up to a year, and without the own lag between 30% to 50%. In contrast, economic activity and price pressures only explain a substantial proportion of the variability at longer horizons.

5 Concluding remarks

To the extent that break-even inflation rates reflecting the yield spread between nominal and inflation-linked bonds are nowadays a key indicator of inflation expectations (and related premia) it is fundamental to understand their link to the macroeconomic and financial conditions. To our knowledge, this paper is the first formal attempt to establish such a link. We evaluate the explanatory power of a large set of potential determinants by applying Bayesian model selection techniques, and document the dynamic impact of macro and financial variables on both short and long-term BEIRs.

A relatively large number of macroeconomic and financial variables contribute to explain BEIRs, but we find notable differences between short and long-term horizons. Short-term BEIRs are mainly explained by inflation dynamics, but indicators of price pressures (wage growth) and of cyclical conditions (consumer confidence, the unemployment rate, and the US business cycle conditions) also play a role. In contrast, financial variables (i.e. the yield curve spread, implied volatility in the bond market) become increasingly relevant with the horizon, reflecting the increasing role of inflation risk premia in long-term BEIR dynamics. Moreover, our results highlight the dynamic nature of those relationships, since the impact of most of those variables extends over time well beyond their impact effect.

Some considerations are important to assess the implications of our approach and the robustness of our results.

First of all, accurate measures of the BEIRs are a prerequisite to establish correct relationships with the macroeconomy. Measuring BEIRs is unfortunately far from straightforward, and ignoring the important caveats associated to the calculation of BEIRs may lead to the wrong conclusions. As described in Section 2, our BEIRs are extracted from a no-arbitrage term structure model, and are therefore subject to estimation error. Alas BEIRs are not directly observable and, consequently, all possible measures of BEIRs are potentially subject to estimation error of some kind. We could instead use BEIRs measures directly calculated from the spread between nominal and traded inflation-linked bond yields. These alternative measures are, however, more prone to financial market distortions than our model-based ones. In fact, before 2004, euro area (and also U.S.) inflation-linked bond yields incorporate an important liquidity premium compared to their nominal counterparts. The time-varying nature of such a premium would significantly cloud the link with macroeconomic variables. In addition, as the residual maturity of the bonds used in the BEIR calculation decreases over time, it would also be difficult to identify differences across horizons. Our constant maturity model-based BEIRs are free from those two problems.

A second concern might have to do with the chosen sample. To help focus on the impact of fundamentals on BEIRs, our analysis focuses on the period 1999-2006. Extending the sample backward is not problematic and provides the same (at least qualitative) results. A forward extension, however, would be more challenging, for BEIR movements (and measurement) since mid-2007 would also require dealing with significant turbulences in financial markets, which could contribute to cloud the stylized facts we aim at uncovering here.

Our findings may have valuable implications for the modelling of the term structure of interest rates. Among other things, the results discussed above suggest that including current inflation in the set of states variables help estimate inflation expectations (and therefore BEIRs) embodied in nominal yields on shorter more than longer horizons (for a discussion see also Kim, 2007).

Moreover, to the extent that our findings establish a link between the term structure of interest rates and the macroeconomy, our results may also be relevant for the recent literature that aims at modelling jointly these two parts (see, for instance, Ang and Piazzesi 2003, and Hördahl *et al.* 2007). This literature uses small-scale macroeconomic models to incorporate information about inflation and the output gap into the estimation of the nominal term structure and its components, including BEIRs. Instead, we have followed an implicit sequential approach, modelling first the nominal term structure and the BEIRs using a latent-factor model, and then exploring the link between those BEIRs and the macroeconomy. Our finding that a relatively large and heterogeneous set of macroeconomic variables indeed help interpret BEIRs may cast doubts on the use of a limited number of macroeconomic variables as state variables. In this respect, our results tend to lend further support to other recent approaches that use composite factors as state variables (see e.g. Mönch, 2008).

Finally, our work provides a solid framework to address further issues concerning the determinants of BEIRs that were beyond the scope of this paper. For instance, the effects of monetary policy on inflation expectations, particularly at longer horizons, has recently received a great deal of attention becoming an important research topic. To the extent that monetary policy is a fundamental determinant of the slope of the yield curve, the prominent role of the yield spread in explaining long-term BEIRs we found in our analysis is a promising starting point. The selection approach developed here to model BEIRs can also be particularly suitable to address the effects of monetary policy actions or central bank communication issues on inflation expectations. These extensions are in our current research agenda.

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Table 1: Potential explanatory variables

VarNo	Type	Description	Acronym	Country	Transformation
1	monetary factors	Index of notional stocks M1 - seasonally adjusted	M1	Euro Area	yoy
2		Index of notional stocks M3 - seasonally adjusted	M3	Euro Area	yoy
3	FX	ECB Nominal effective exch. rate, ECB EER core group of currencies against Euro	NEER	Euro Area	yoy
4	Commodities	World market prices of raw materials in Euro. Index Total, excluding Energy, HWWA	Rawmat	Euro Area	yoy
5		World market prices, crude oil, in USD, HWWA	OIL	Euro Area	yoy
6	Prices & costs	Overall index - seasonally adjusted	HICP	Euro Area	yoy
7		HICP - All-items excluding energy and unprocessed food, seasonally adjusted	HICPex	Euro Area	yoy
8		HICP Volatility	HICPvol	Euro Area	24m rolling window
9		HICP excluding energy and unprocessed food, volatility	HICPexVol	Euro Area	24m rolling window
10		PPI-Total Industry (excluding construction), seasonally adjusted	PPI	Euro Area	yoy
11		ECB index of Negotiated wages (3mma)	Wages	Euro Area	yoy
12	Real economy	Industrial production, total (excluding construction), working day and seasonally adjusted	IndP	Euro Area	yoy
13		Unemployment rate, Total (all ages), Total (male & female), Seasonally adjusted, not working day adjusted	Urate	Euro Area	12m difference
14	Confidence indicators	Industry Survey: Industrial Confidence Indicator - Balances, seasonally adjusted	IndConf	Euro Area	level
15		Consumer Survey: Consumer Confidence Indicator - Balances, seasonally adjusted	ConConf	Euro Area	level
16		PMI composite	PMI	Euro Area	level
17	Bond market	Yield spread 10y-3m	EAyspread	Euro Area	Spread
18		10-year bond yield US-German differential	10ydif	Euro Area-US	Spread
19		Yield spread 10y-3m	USyspread	US	Spread
20		BUND implied volatility	BUNDvol	Euro Area	level
21	Stock market	EUROSTOXX 50 index	EuroSTOXX50	Euro Area	12m return
22		S&P 500 composite index	S&P500	US	12m return
23		VIX	VIX	US	level
24		VDAX-VSTOXX	VDAX	Euro Area	level
25	US variables	US consumer prices, all items, all urban consumers, seasonally adjusted	USCPI	US	yoy
26		US Industrial production, total excluding construction, seasonally adjusted	USIndP	US	yoy
27		Non-farm payroll data	Nfpayroll	US	12m difference

Note: The table reports all explanatory variables included in the selection analysis of Section 3, grouped by type. All variable are stationary or have been stationarized with appropriate transformation. "yoy" means four-quarter growth rates; "24m rolling window" is a standard deviation using a two-year window; "12m difference" is a change with respect to 12 month before; "12m return" is growth rate of the stock price index over 12 months.

Table 2: Proportion of models visited containing each potential explanatory variable

	Variable	1-year BEIR	2-year BEIR	5-year BEIR	5-year IRP
1	Own lag	0.13	**0.98**	**0.89**	**1.00**
2	M1 - seasonally adjusted	0.16	0.08	0.07	0.08
3	M3 - seasonally adjusted	0.38	0.11	0.10	0.09
4	Nominal effective exchange rate	0.09	**0.66**	**0.99**	**0.99**
5	Raw materials (excluding energy)	0.07	0.12	0.10	0.16
6	Oil prices	0.12	0.08	0.06	0.05
7	Overall HICP inflation	**1.00**	**1.00**	0.14	0.05
8	Core HICP inflation	0.26	**0.83**	0.13	0.23
9	HICP inflation volatility	0.10	0.08	0.11	0.09
10	Core inflation volatility	0.09	0.12	0.17	0.24
11	PPI	0.09	0.18	**0.54**	0.09
12	Negotiated wages	**0.45**	**0.73**	0.07	0.08
13	Industrial production	0.05	0.05	0.07	0.09
14	Unemployment rate	**0.53**	0.40	**0.82**	**0.85**
15	Industrial Confidence	0.29	**0.73**	0.43	**0.66**
16	Consumer Confidence	**0.64**	**0.96**	**0.70**	0.43
17	PMI composite	0.08	0.35	**0.79**	**0.57**
18	Yield spread (10y-3m)	0.31	0.09	**0.84**	**0.48**
19	10-yr US-German differential	0.06	0.10	0.09	0.17
20	US Yield spread 10y-3m	0.11	0.35	0.33	**0.58**
21	BUND implied volatility	0.05	**0.73**	**0.94**	**0.95**
22	EUROSTOXX 50	0.06	0.07	0.17	0.19
23	S&P 500	0.17	0.18	0.32	0.30
24	VIX	0.05	0.07	0.16	0.16
25	VSTOXX	0.05	0.06	0.07	0.07
26	US CPI inflation	0.21	0.49	0.07	0.05
27	US Industrial production	0.37	0.13	0.10	0.09
28	Non-farm payroll data	**0.59**	**0.72**	**0.99**	**0.99**
	Average number of regressors in selected model	7.56	11.48	11.28	10.75

Note: The table reports the posterior probability that the corresponding explanatory variable listed in the first column should be included in the model for each dependent variable. It is computed as the proportion of models drawn by the MC3 algorithm which contain the explanatory variable.Probabilities higher or equal than 0.5 are in bold. Estimation sample: 1999M1-2006-M12. Results are based on 6,000,000 replications, discarding the first 500,000 as burn-in replications.

Table 3. Variance decomposition of long-term BEIRs (60 months ahead)

	Fraction of forecast error variance due to:							
horizon	Urate	PMI	NFPayroll	PPI	EAyspread	BUNDvol	NEER	BEIR14
1	0.01	0.16	0.07	0.01	0.25	0.04	0.02	0.43
2	0.01	0.16	0.08	0.01	0.26	0.06	0.05	0.37
6	0.02	0.11	0.09	0.01	0.28	0.11	0.14	0.24
12	0.08	0.14	0.10	0.03	0.26	0.10	0.12	0.18
18	0.10	0.15	0.09	0.04	0.23	0.09	0.13	0.16
24	0.10	0.15	0.09	0.05	0.22	0.09	0.13	0.17

Note: The values in the table represent the fraction of forecast error variance due to each shock at the horizons in column 1. The results are based on a VAR model estimated with Bayesian methods over the sample 1999M1-2006M12. The endogenous variables of the VAR appear in the first row. Their ordering here corresponds to their ordering in the Choleski decomposition. Endogenous variables are chosen from Table 1 among those with a posterior probability greater or equal than 0.5. Horizons are months ahead. The acronyms of the variables are in Table 1.

Table 4. Variance decomposition of long-term inflation risk premia (60 months ahead)

	Fraction of forecast error variance due to:							
horizon	Urate	PMI	NFPayroll	PPI	EAyspread	BUNDvol	NEER	BEIR14
1	0.01	0.17	0.07	0.01	0.20	0.05	0.03	0.47
2	0.01	0.17	0.07	0.01	0.20	0.07	0.06	0.42
6	0.03	0.13	0.09	0.01	0.21	0.11	0.15	0.27
12	0.09	0.13	0.09	0.03	0.20	0.11	0.14	0.21
24	0.12	0.14	0.10	0.07	0.17	0.09	0.13	0.18

Note: The values in the table represent the fraction of forecast error variance due to each shock at the horizons in column 1. The results are based on a VAR model estimated with Bayesian methods over the sample 1999M1-2006M12. The endogenous variables of the VAR appear in the first row. Their ordering here corresponds to their ordering in the Choleski decomposition. Endogenous variables are chosen from Table 1 among those with a posterior probability greater or equal than 0.5. Horizons are months ahead. The acronyms of the variables are in Table 1.

Euro area break-even inflation rates, inflation expectations and risk premia

Figure 1: 12 months ahead

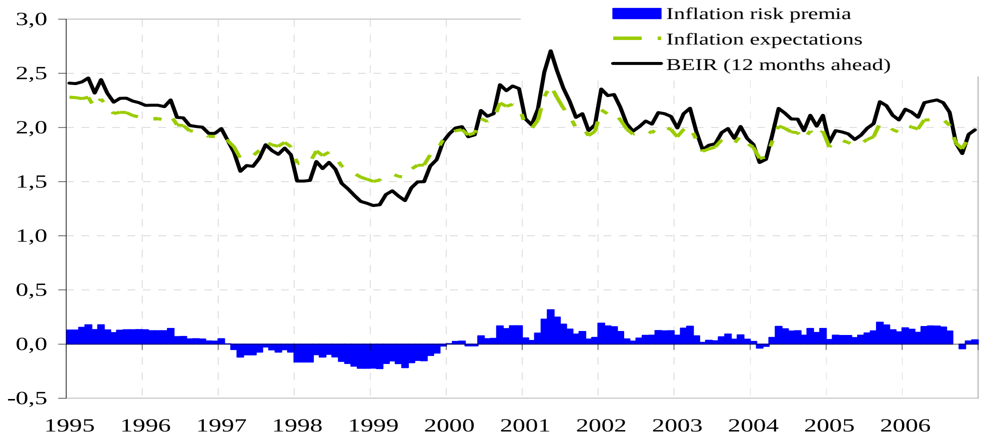


Figure 2: One-year forward in one year

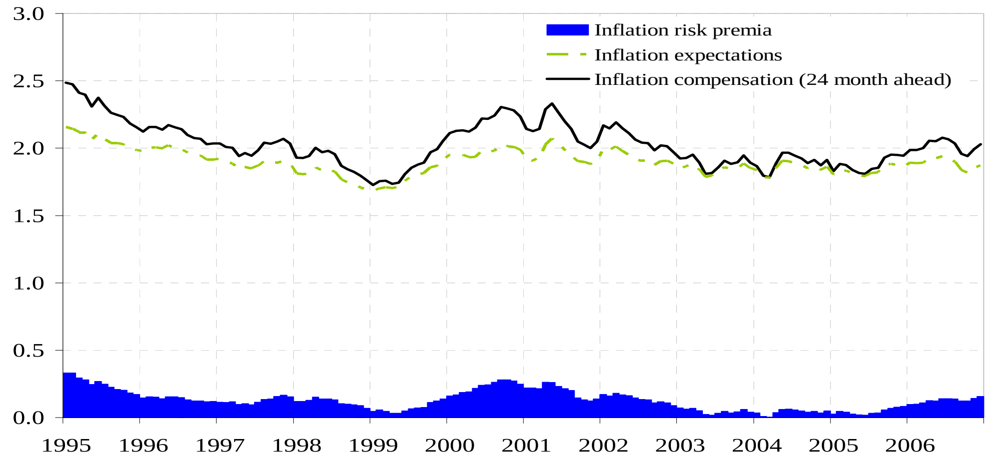
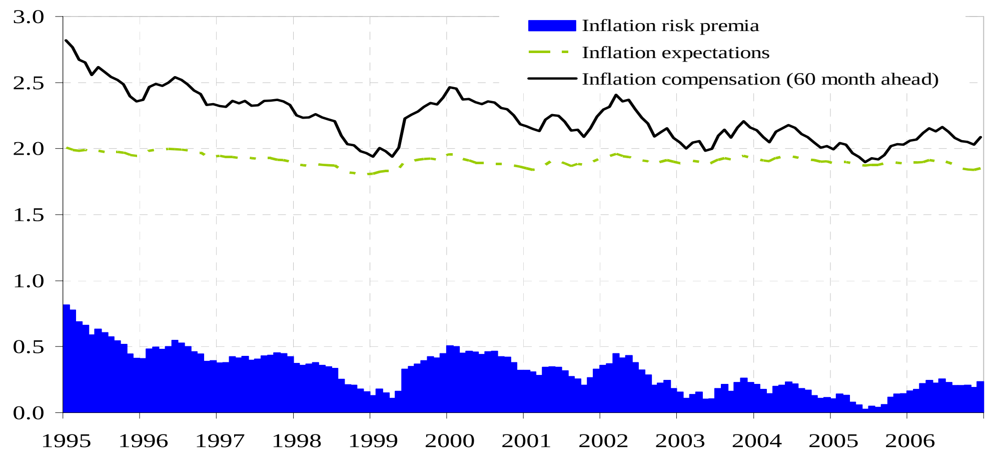
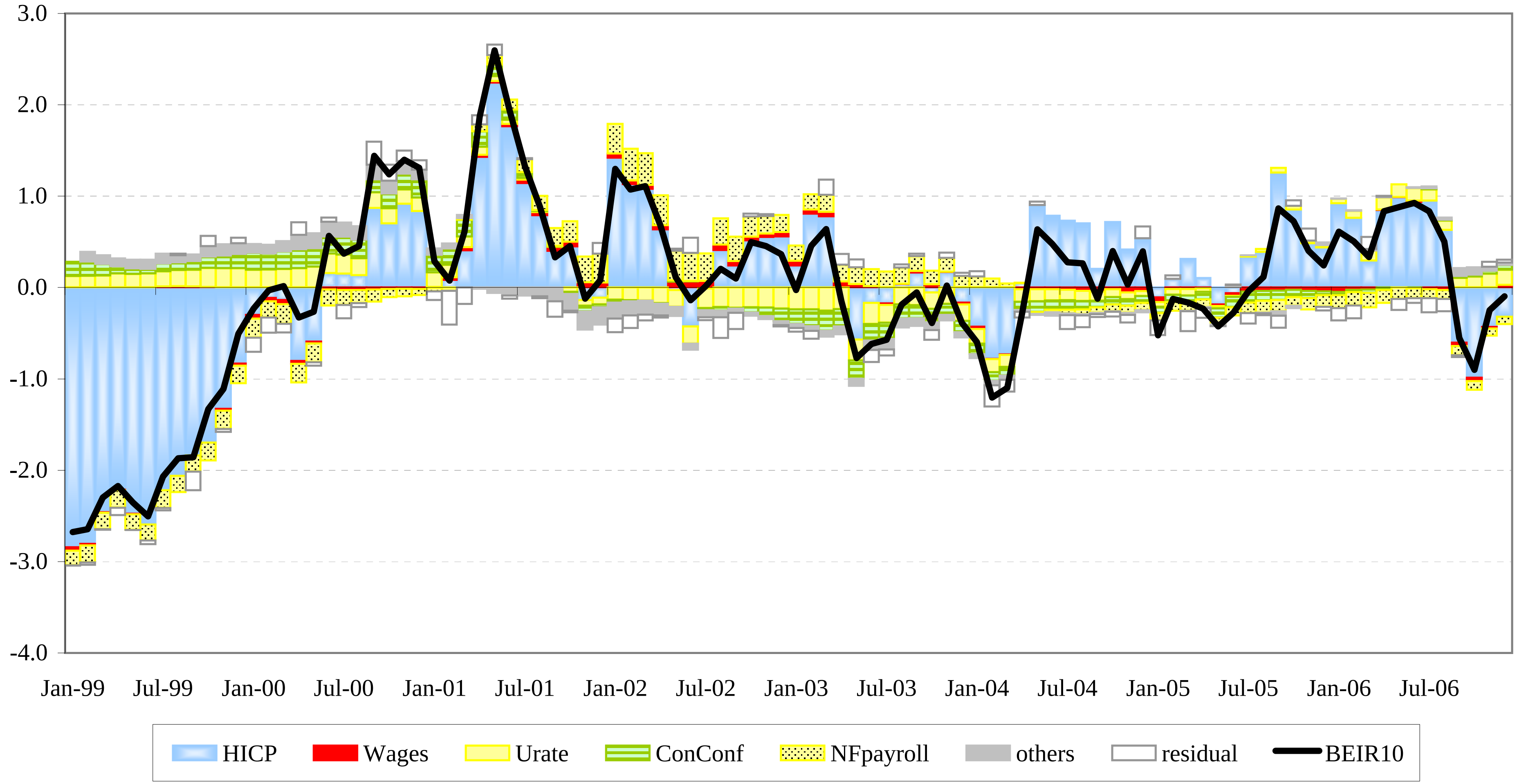


Figure 3: One-year forward in four years



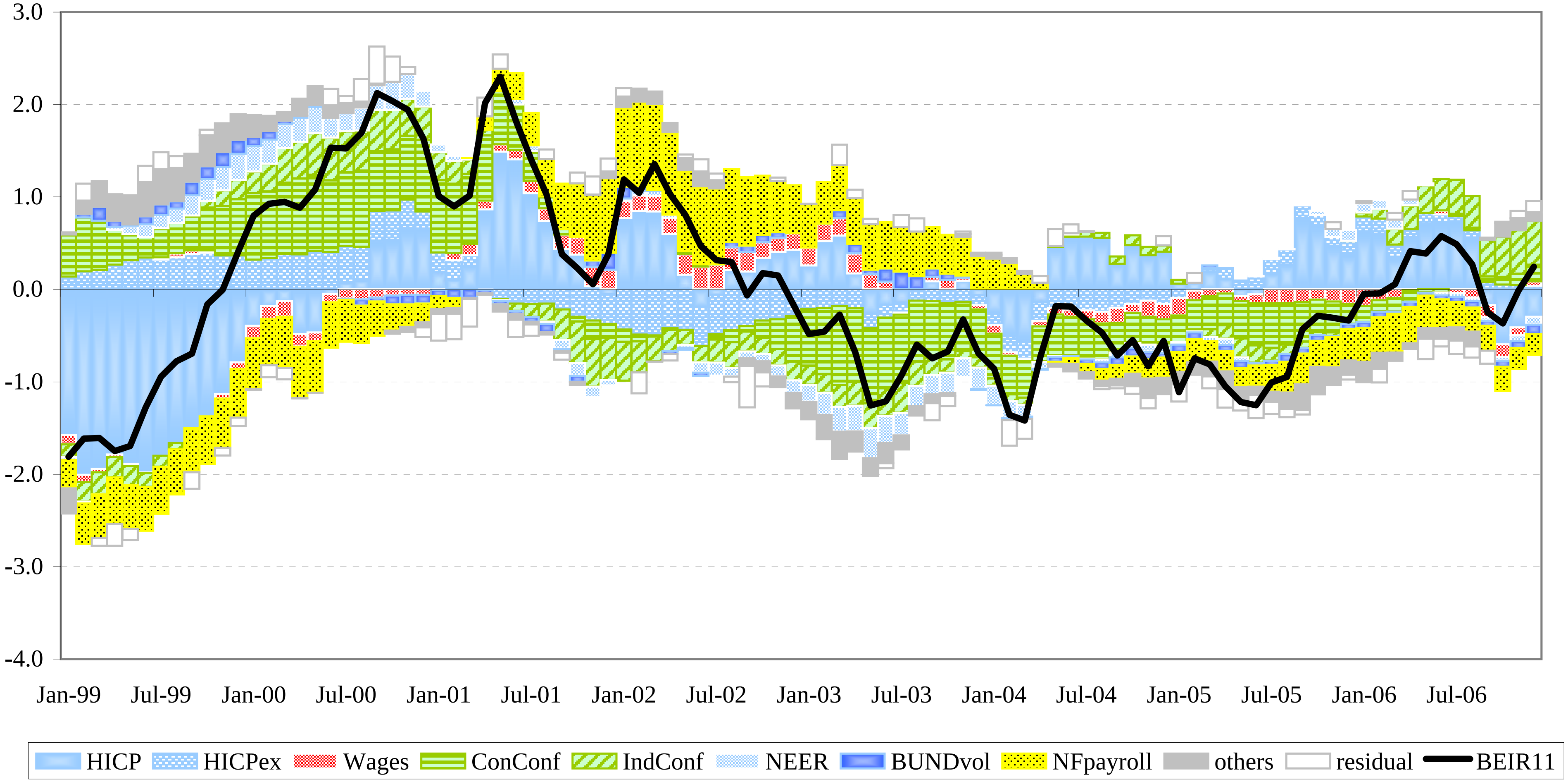
Note: The charts depict the decomposition of BEIRs (or inflation compensation) into its two components, namely the expected level of inflation and the inflation risk premium associated with it, estimated by means of a no-arbitrage term structure model for the euro area (Garcia and Werner, 2008). Data are in percentage points.

Figure 4: One-year forward BEIR (inflation compensation)



Notes: 1. The chart depicts the dynamic contribution of all explanatory variables, i.e., the decomposition of the values of the endogenous variable (BEIR) as the sum of the various components defined by the explanatory variables and the residual term. All variables are defined in difference from the sample mean and the historical values of the endogenous variable are interpreted as departure from a baseline or reference path. The bars in the chart reflect therefore the departure of the BEIR from its sample mean explained by the departure of each of the explanatory variables from their respective reference path (i.e. the sample mean). The sum of all contributions returns the historical values of the endogenous variable in deviation for the baseline. The posterior mean of the regression coefficients averaged across all models are used. Only the contributions of explanatory variables with a posterior probability greater or equal than 0.5 are explicitly reported. Estimation sample: 1999M1-2006M12.
2. The acronyms of the variables are described in Table 1.

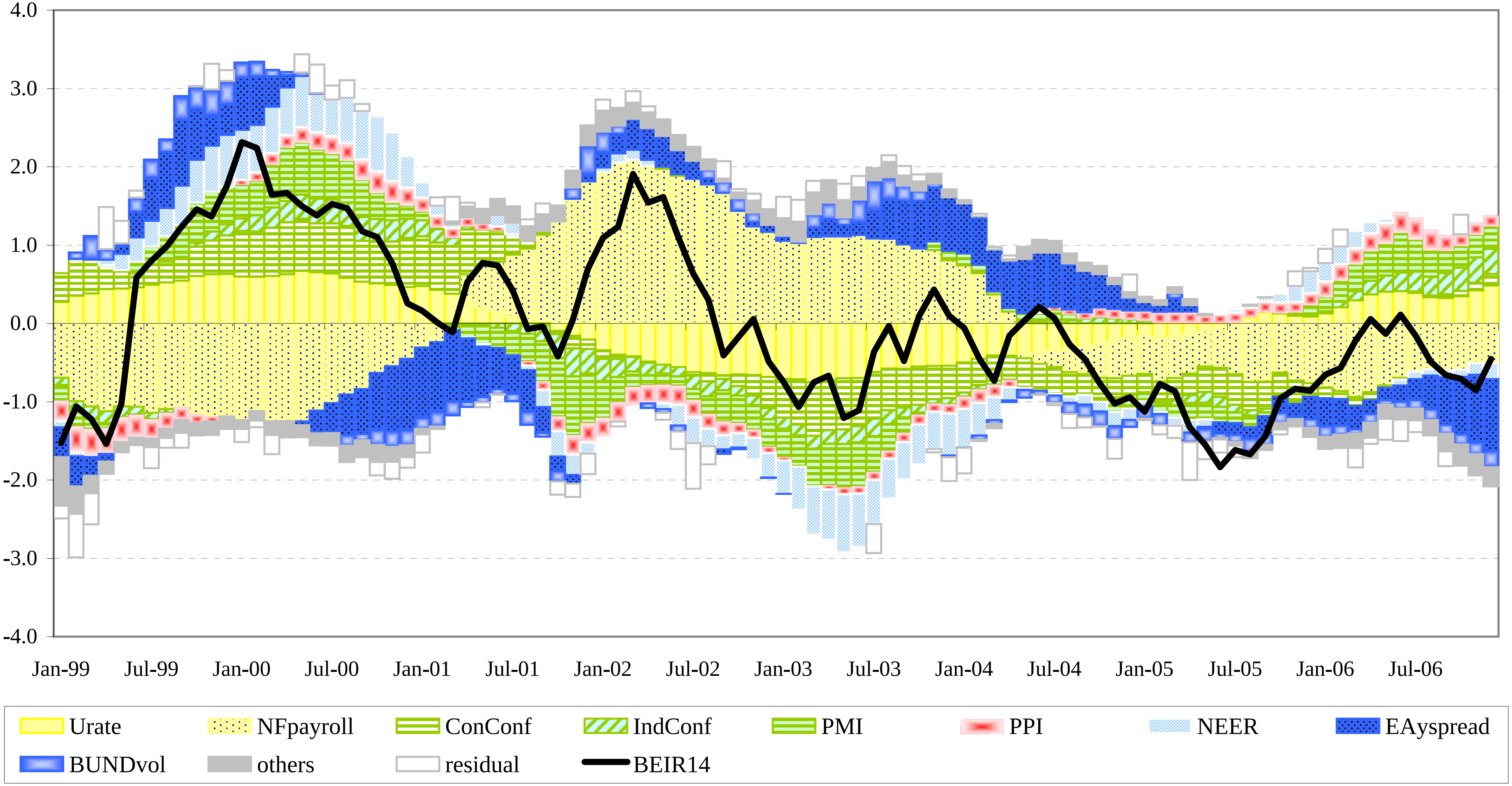
Figure 5: One-year forward BEIR (inflation compensation) in one year



Notes: 1. The chart depicts the dynamic contribution of all explanatory variables, i.e., the decomposition of the values of the endogenous variable (BEIR) as the sum of the various components defined by the explanatory variables and the residual term. All variables are defined in difference from the sample mean and the historical values of the endogenous variable are interpreted as departure from a baseline or reference path. The bars in the chart reflect therefore the departure of the BEIR from its sample mean explained by the departure of each of the explanatory variables from their respective reference path (i.e. the sample mean). The sum of all contributions returns the historical values of the endogenous variable in deviation for the baseline. The posterior mean of the regression coefficients averaged across all models are used. Only the contributions of explanatory variables with a posterior probability greater or equal than 0.5 are explicitly reported. Estimation sample: 1999M1-2006M12.

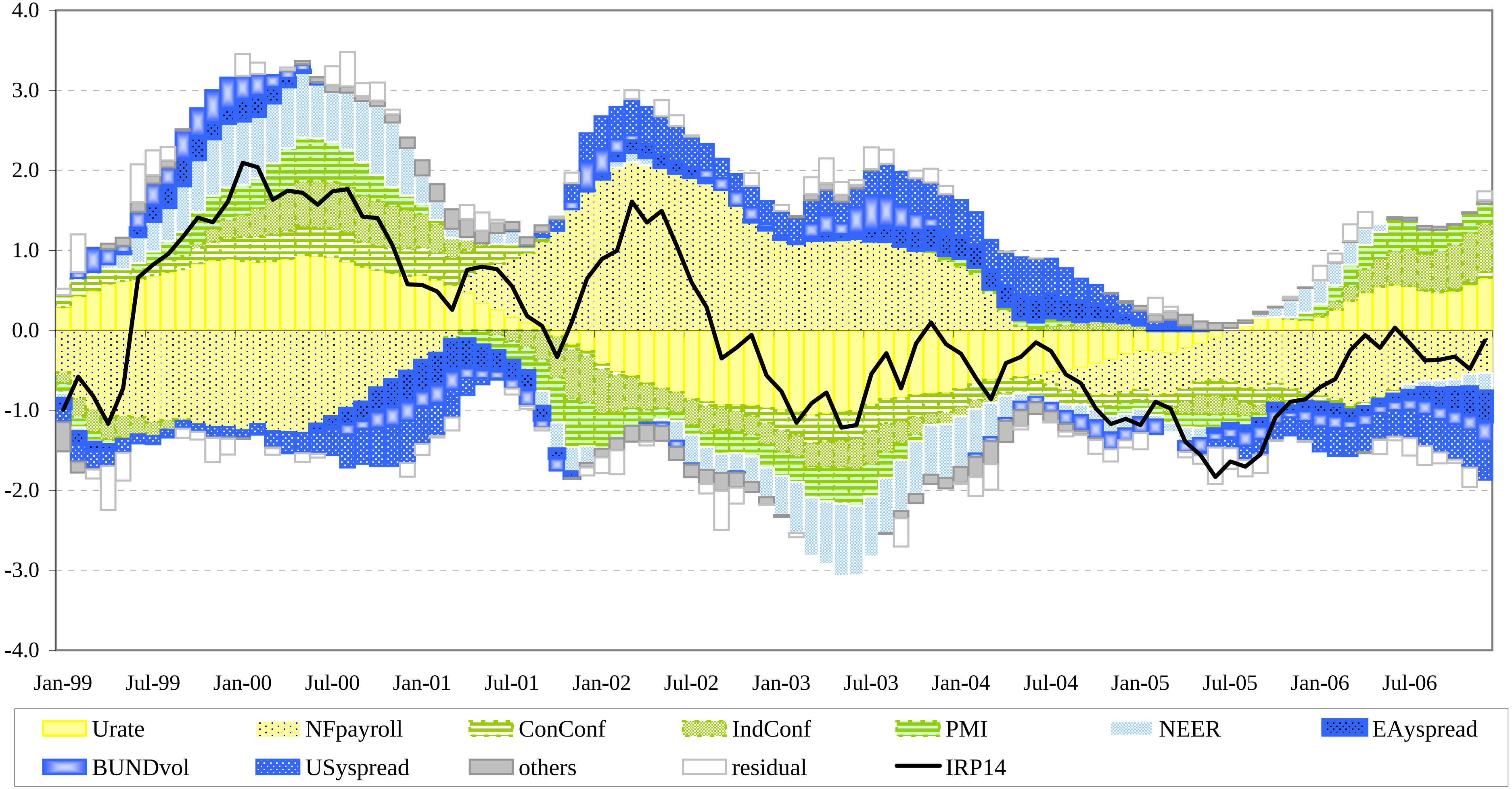
2. The acronyms of the variables are described in Table 1.

Figure 6: One-year BEIR (inflation compensation) in four years



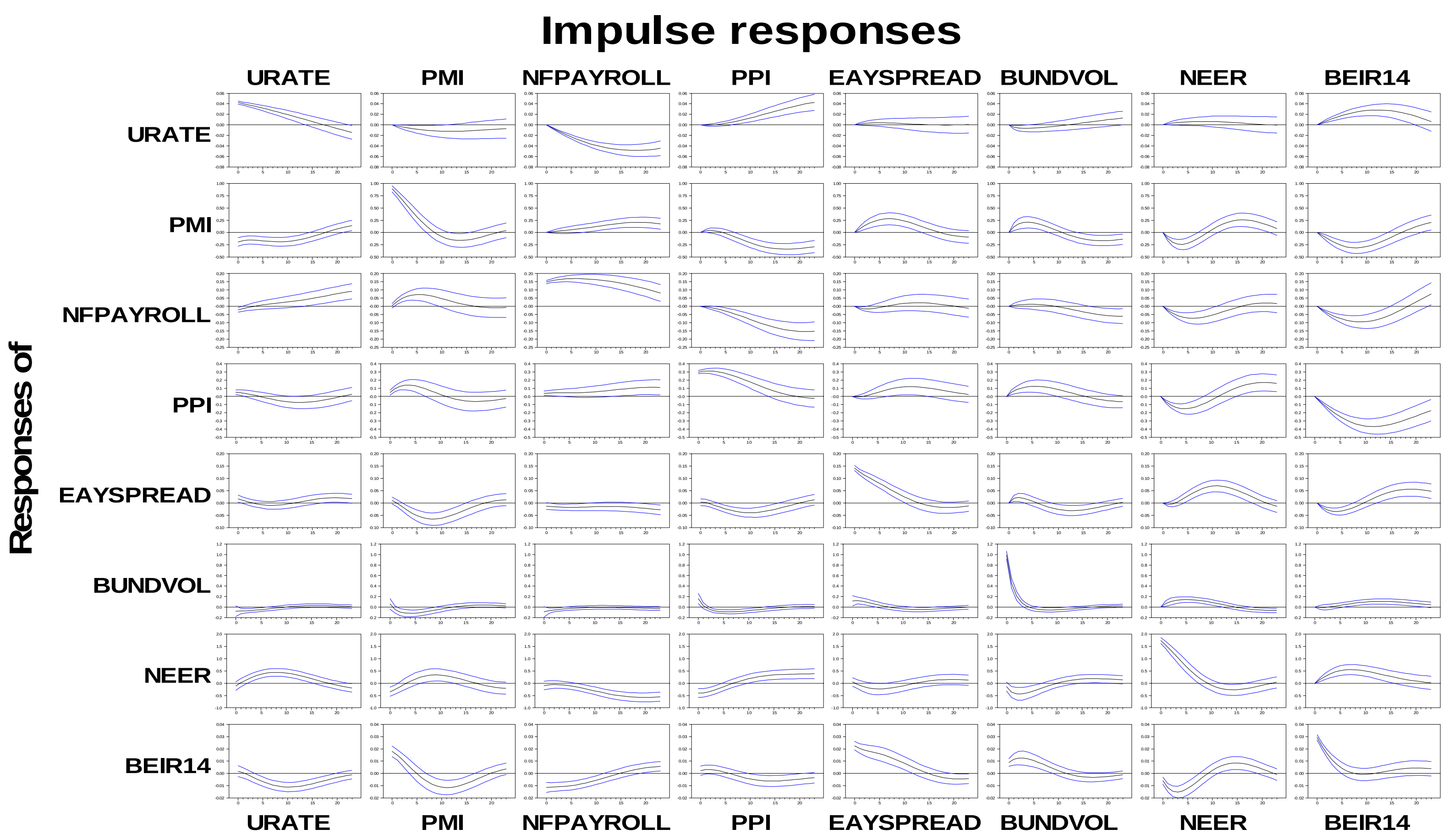
Notes: 1. The chart depicts the dynamic contribution of all explanatory variables, i.e., the decomposition of the values of the endogenous variable (BEIR) as the sum of the various components defined by the explanatory variables and the residual term. All variables are defined in difference from the sample mean and the historical values of the endogenous variable are interpreted as departure from a baseline or reference path. The bars in the chart reflect therefore the departure of the BEIR from its sample mean explained by the departure of each of the explanatory variables from their respective reference path (i.e. the sample mean). The sum of all contributions returns the historical values of the endogenous variable in deviation for the baseline. The posterior mean of the regression coefficients averaged across all models are used. Only the contributions of explanatory variables with a posterior probability greater or equal than 0.5 are explicitly reported. Estimation sample: 1999M1-2006M12.
2. The acronyms of the variables are described in Table 1.

Figure 7: Inflation risk premia one-year forward in four years



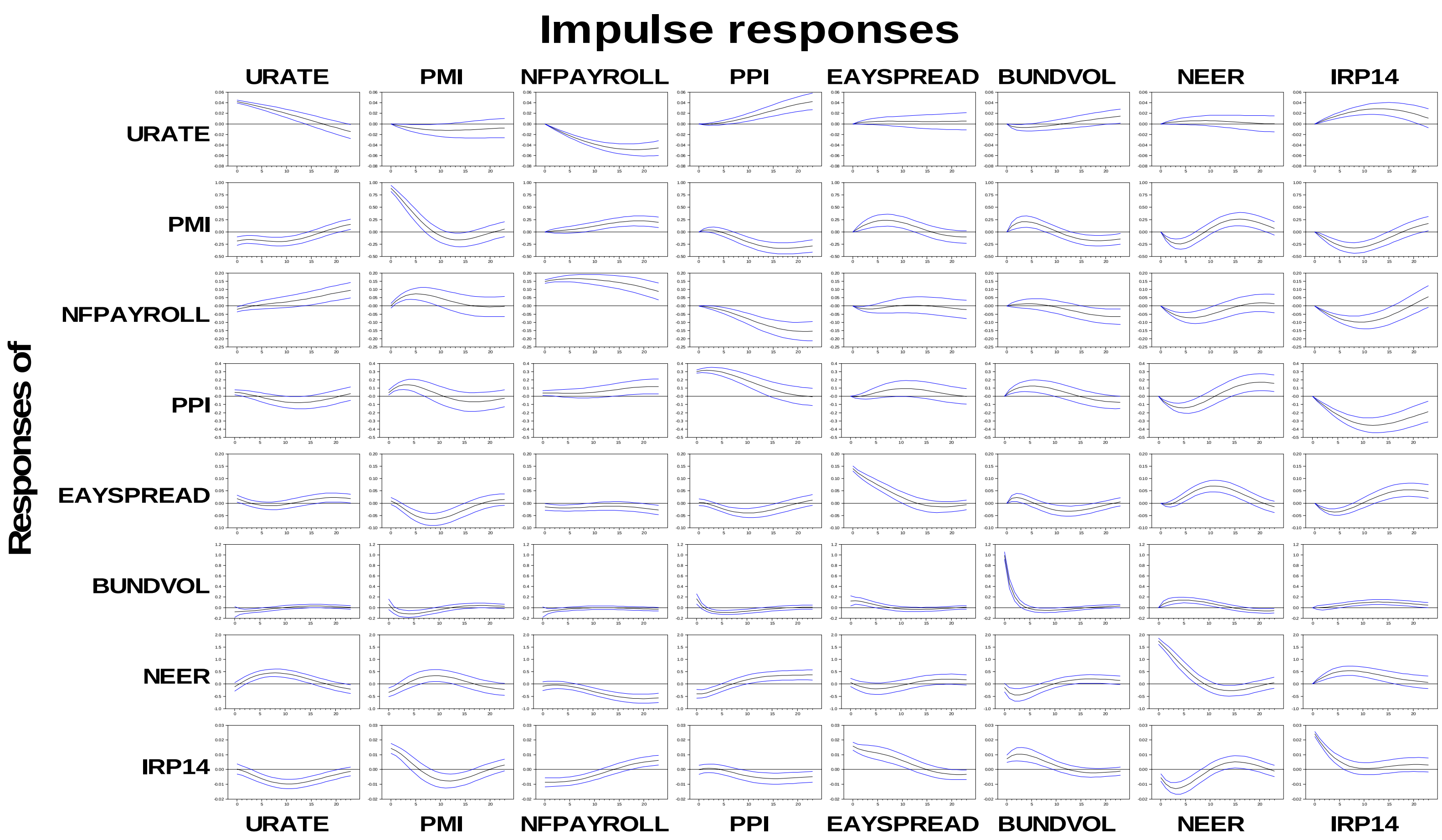
Notes: 1. The chart depicts the dynamic contribution of all explanatory variables, i.e., the decomposition of the values of the endogenous variable (Inflation risk premia) as the sum of the various components defined by the explanatory variables and the residual term. All variables are defined in difference from the sample mean and the historical values of the endogenous variable are interpreted as departure from a baseline or reference path. The bars in the chart reflect therefore the departure of the BEIR from its sample mean explained by the departure of each of the explanatory variables from their respective reference path (i.e. the sample mean). The sum of all contributions returns the historical values of the endogenous variable in deviation for the baseline. The posterior mean of the regression coefficients averaged across all models are used. Only the contributions of explanatory variables with a posterior probability greater or equal than 0.5 are explicitly reported. Estimation sample: 1999M1-2006M12.
2. The acronyms of the variables are described in Table 1.

Figure 8: Impulse responses for BEIR one-year forward in four years



The chart plots the impulse response functions of a VAR model estimated with OLS methods, over the sample 1999M1-2006M12. The endogenous variables of the VAR - ordered as depicted - have been chosen among those variables that in Table 1 show a posterior probability greater or equal than 0.5. Confidence bands are 68% interval. Structural decomposition is given by a Choleski triangularization. The acronyms of the variables are described in Table 1.

Figure 9: Impulse responses for inflation risk premium one-year forward in four years



The chart plots the impulse response functions of a VAR model estimated with OLS methods, over the sample 1999M1-2006M12. The endogenous variables of the VAR - ordered as depicted - have been chosen among those variables that in Table 1 show a posterior probability greater or equal than 0.5. Confidence bands are 68% interval. Structural decomposition is given by a Choleski triangularization. The acronyms of the variables are described in Table 1.

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