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Forecasting euro area inflation using targeted predictors: is money coming back?

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ABSTRACT

This paper sheds new light on the information content of monetary and credit aggregates for future price developments in the euro area. Overall, we find strong variation in the information content of these variables over time. We show that monetary and credit aggregates are very often selected among the top predictors of inflation, with their predictive power relative to other predictors generally improving in the post-2012 period. An out-of-sample forecasting exercise indicates that, when monetary and credit aggregates are loaded directly in the forecasting equation, the additional gains over the benchmark model are generally high and significant across horizons and HICP components only in the most recent period. When the forecasts are computed using factor-augmented regressions based on the best predictors, we confirm the importance of monetary and credit variables in forecasting inflation, even if their information content is diluted in a much broader pool of variables.

JEL Classification: C53, E37, E41, E51, E58

Keywords: Money, Inflation, Forecasting, Diffusion index, Targeted predictors

Non-technical summary

The close long-run association between the price level and money is a well-established economic relationship and is confirmed by several studies. The channels through which money transmits to inflation may be both direct and indirect. The direct channel is described by the quantity theory of money and emphasises the role of money as a medium of exchange and temporary store of purchasing power. The indirect channel highlights the effects of liquidity on financing constraint and asset prices, which eventually influence wealth, confidence and prices. In light of the money-inflation connection, the analysis of monetary developments may provide policy-makers with valuable information regarding future price developments. In recognition of the leading indicator properties of money, at the European Central Bank (ECB) the monetary analysis complements the economic analysis in the assessment of the risks to price stability.

Notwithstanding the long-run money-inflation link, the empirical evidence on the information content of money for future price developments seems to vary depending on the country and the historical period considered (Benati, 2009; ECB, 2010; Mandler and Scharnagl, 2014; Gertler and Hofmann, 2016). As for the euro area, empirical studies show that in the period preceding 2001 monetary indicators contain some information regarding future inflation (Gottschalk et al., 2000; Nicoletti-Altimari, 2001; Trecoci and Vega, 2002; Gerlach and Svensson, 2003). Many studies find a decline in the forecastability of euro area inflation as well as a diminished predictive power of monetary variables during the period of low inflation volatility between 2001 and the Great Recession (Alves et al., 2007; Lenza, 2008; Rua, 2012). There is also empirical research showing that the information content of monetary indicators in the euro area is better exploited when they are combined with other predictors of inflation (Scharnagl and Schumacher, 2007; Lenza, 2008; Fischer et al., 2009).

In this paper we attempt to shed new light on the information content of monetary and credit aggregates for future price developments in the euro area, looking at different forecast horizons and HICP components. There are basically two reasons that motivate us to pursue this research. First of all, it should be noticed that the latest evidence is quite outdated. The aim of this work is primarily to remove some dust on a topic that has been recently overlooked, but is of high relevance for euro area policy-makers. Second, there are signs pointing to an increased importance of monetary aggregates (and their main counterparts) in predicting euro area inflation, restoring the positive money-inflation link that appears to have broken down during the turbulent crisis period. Since 2012 the euro area has been experiencing a prolonged period of disinflationary pressures, which increased the risk of entering a deflationary spiral. Since then, macroeconomic projections from different institutions have systematically over-predicted both headline and core inflation at all horizons. On the one hand, this sequence of systematic forecasting errors suggests that forecasting inflation can be even more challenging in a low inflation environment. On the other hand, the increased volatility in inflation

observed since 2008 suggests that it may be easier in the post-crisis period to outperform naïve benchmark forecasting models, which are particularly hard to beat during periods of low volatility. Moreover, the role of money as a predictor of inflation is likely to have recently increased as a result of the introduction of ECB's non-standard measures. For example, the increase in money (M3) associated with the Asset Purchase Programme (APP) results mainly from an exogenous shift in the supply of money and therefore is potentially more informative for future spending and inflation.

From an operational point of view, we follow a two-step empirical approach. First of all, by means of techniques designed to identify targeted predictors, we investigate how the predictive content of monetary and credit aggregates compares to that of other potential leading indicators of inflation. Second, we assess the forecasting properties of monetary and credit aggregates by running an out-of-sample forecasting exercise, in which the benchmark model is augmented with different sets of predictors or diffusion indices.

We find strong variation in the information content of monetary and credit aggregates over time, but overall our results confirm the need to continue to complement the economic analysis with the monetary analysis in the assessment of the risks to price stability in the euro area. More in detail, our results can be summarised as follows. In the first step of our empirical analysis, we report evidence that monetary and credit aggregates are very often selected among the top predictors, and their predictive power relative to other predictors generally improved in the post-2007 period. These results seem to become gradually less clear-cut when looking at HICP excluding energy and HICP excluding food and energy. The out-of-sample forecasting exercise shows that when monetary and credit aggregates are included directly in the forecasting equation the additional gains over the benchmark model are generally high and significant across all horizons and HICP components only in the most recent period. When the forecasts are computed using factor-augmented equations, we highlight the importance of monetary and credit variables in forecasting inflation, even if their information content is diluted in a much broader pool of best predictors. The marginal contribution of monetary and credit aggregates seems to be particularly relevant to the forecast of HICP inflation in the most recent period. Both empirical exercises point to a better relative forecasting ability of monetary and credit aggregates for headline inflation than for measures of core inflation. This seems to reflect the better ability of other predictors to forecast measures of core inflation compared to the case of headline HICP. According to our findings, monetary analysis should continue to play an important role in ECB's monetary policy-making, as a means to cross-check the assessment of risks to price stability obtained from economic analysis.

1. Introduction

The close long-run association between the price level and money is a well-established economic relationship and is confirmed by several studies.[1] The channels through which money transmits to inflation may be both direct and indirect (ECB, 2010). The direct channel is described by the quantity theory of money and emphasises the role of money as a medium of exchange and temporary store of purchasing power. The indirect channel highlights the effects of liquidity on financing constraint and asset prices, which eventually influence wealth, confidence and prices. In light of the money-inflation connection, the analysis of monetary developments may provide policy-makers with valuable information regarding future price developments. In recognition of the leading indicator properties of money, at the European Central Bank (ECB) the monetary analysis complements the economic analysis in the assessment of the risks to price stability.[2]

Notwithstanding the long-run money-inflation link, the empirical evidence on the information content of money for future price developments seems to vary depending on the country and the historical period considered (Benati, 2009; ECB, 2010; Mandler and Scharnagl, 2014; Gertler and Hofmann, 2016). As for the euro area, empirical studies show that in the period preceding 2001 monetary indicators contain some information regarding future inflation (Gottschalk et al., 2000; Trecoci and Vega, 2002; Gerlach and Svensson, 2003). In a seminal work, Nicoletti-Altimari (2001) shows that monetary and credit aggregates provide useful additional and independent information on inflation prospects for the euro area, especially at medium term horizons. Moreover, he finds that for longer horizons broad monetary aggregates are better indicators for future inflation than narrow aggregates.

Many studies find a decline in the forecastability of euro area inflation as well as a diminished predictive power of monetary variables during the period of low inflation volatility between 2001 and the Great Recession (Alves et al., 2007; Lenza, 2008; Rua, 2012). Extending the end of the forecasting period to 2010, Dreger and Wolters (2014) find that the out-of-sample forecasting performance of a model with M3 growth is worse than the benchmark of an autoregressive process for inflation and models with excess liquidity, excess inflation and the spread.

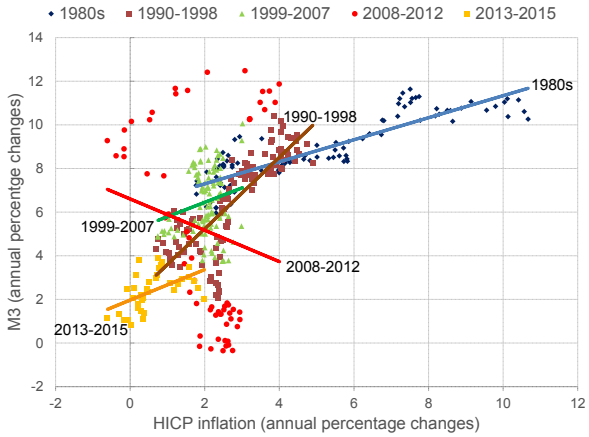
There is also empirical research showing that the information content of monetary indicators in the euro area is better exploited when they are combined with other predictors of inflation. For example, Lenza (2008) evaluates the predictive power of money and credit aggregates for HICP inflation in the euro area using a bivariate model containing M3 and bivariate models containing factors capturing information from several real and nominal variables. He finds that monetary variables provide information about inflation at long horizons even after many alternative predictors have been

[1] For an extensive review of these studies, see ECB (2010, Chapter 1).
[2] For more details on ECB's monetary analysis, see Issing (2005), Fischer et al. (2009) and ECB (2010).

considered. However, forecasts based exclusively on M3 growth do not show improvements compared to benchmark models, suggesting that the information in monetary variables is best retrieved when these variables are combined with non-monetary variables. Similar conclusions are drawn by Scharnagl and Schumacher (2007) and Fischer et al. (2009).

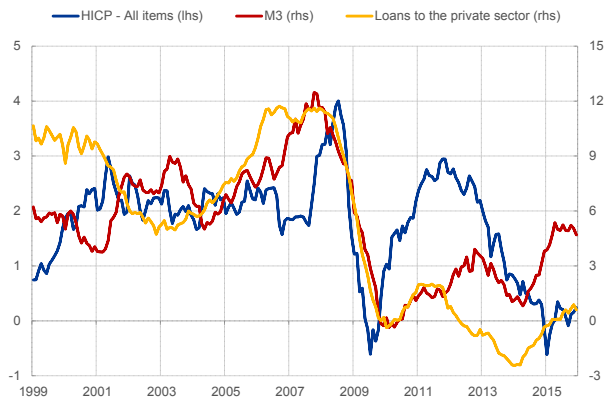
In this paper we attempt to shed new light on the information content of monetary and credit aggregates for future price developments in the euro area, looking at different forecast horizons and HICP components. There are basically two reasons that motivate us to pursue this research. First of all, it should be noticed that the latest evidence is quite outdated. The aim of this work is primarily to remove some dust on a topic that has been recently overlooked, but is of high relevance for euro area policy-makers. Second, there are signs pointing to an increased importance of monetary aggregates (and their main counterparts) in predicting euro area inflation, restoring the positive money-inflation link that appears to have broken down during the turbulent crisis period (Figure 1). Since 2012 the euro area has been experiencing a prolonged period of disinflationary pressures, which increased the risk of entering a deflationary spiral (Figure 2). Since then, macroeconomic projections from different institutions have systematically over-predicted both headline and core inflation at all horizons.[3] On the one hand, this sequence of systematic forecasting errors suggests that forecasting inflation can be even more challenging in a low inflation environment. On the other hand, the increased volatility in inflation observed since 2008 suggests that it may be easier in the post-crisis period to outperform naïve benchmark forecasting models, which are particularly hard to beat during periods of low volatility (Atkeson and Ohanian, 2001; D'Agostino et al., 2006; Stock and Watson, 2007; Lenza, 2008; D'Agostino and Surico, 2012).

Figure 1. The relationship between M3 and future HICP inflation
(annual percentage changes)



Source: ECB.
Notes: The figure shows the relationship between the annual growth rate of M3 and future (12 months ahead) HICP inflation.

Figure 2. HICP, M3 and loans to the private sector
(annual percentage changes)



Source: ECB.

[3] For details on the factors driving these errors for the ECB macroeconomic projections, see ECB (2014).

Moreover, the role of money as a predictor of inflation is likely to have recently increased as a result of the introduction of ECB's non-standard measures. For example, the increase in money (M3) associated with the Asset Purchase Programme (APP) results mainly from an exogenous shift in the supply of money and therefore is potentially more informative for future spending and inflation. Movements in broad money that can be traced back to a higher demand for monetary assets have lesser implications for future inflation, as the higher money holdings in fact reflect portfolio decisions and will not therefore trigger portfolio rebalancing or increased spending. In the case of the APP, most of the associated increase in M3 reflects an exogenous augmentation of bank deposits engineered by the central bank (ECB, 2015).

From an operational point of view, we follow a two-step empirical approach. First of all, by means of techniques designed to identify targeted predictors, we investigate how the predictive content of monetary and credit aggregates compares to that of other potential leading indicators of inflation. To the best of our knowledge, a systematic analysis of the role of monetary and credit aggregates via the approach of targeted predictors has never been conducted. Second, we assess the forecasting properties of monetary and credit aggregates by running an out-of-sample forecasting exercise, in which the benchmark model is augmented with different sets of predictors or diffusion indices.

We find strong variation in the information content of monetary and credit aggregates over time, but overall our results confirm the need to continue to complement the economic analysis with the monetary analysis in the assessment of the risks to price stability in the euro area. More in detail, our results can be summarised as follows. In the first step of our empirical analysis, we report evidence that monetary and credit aggregates are very often selected among the top predictors, and their predictive power relative to other predictors generally improved in the post-2007 period. These results seem to become gradually less clear-cut when looking at HICP excluding energy and HICP excluding food and energy. The out-of-sample forecasting exercise shows that when monetary and credit aggregates are included directly in the forecasting equation the additional gains over the benchmark model are generally high and significant across all horizons and HICP components only in the most recent period. When the forecasts are computed using factor-augmented equations, we highlight the importance of monetary and credit variables in forecasting inflation, even if their information content is diluted in a much broader pool of best predictors. The marginal contribution of monetary and credit aggregates seems to be particularly relevant to the forecast of HICP inflation in the most recent period. Both empirical exercises point to a better relative forecasting ability of monetary and credit aggregates for headline inflation than for measures of core inflation. This seems to reflect the better ability of other predictors to forecast measures of core inflation compared to the case of headline HICP. According to our findings, monetary analysis should continue to play an important role in ECB's monetary policy-making, as a means to cross-check the assessment of risks to price stability obtained from economic analysis.

This paper is structured as follows. In Section 2 we discuss the nature of the forecasting exercise as well as the main features of the dataset. Section 3 presents the methodology used for identifying the targeted predictors and reports the main results. In Section 4 we discuss the results of the out-of-sample forecasting exercise. Section 5 concludes.

2. The data and the timing of the forecasting exercise

Let y_t be the variable to be forecasted and let X_t be the $n \times 1$ vector of predictors. We are interested in forecasting euro area HICP inflation, HICP inflation excluding energy (HICPXE) and HICP inflation excluding food and energy (HICPXEF).[4] Our forecast exercise is based on the following equation:

$$y_{t+h}^{h} = \alpha_0 + \sum_{j=1}^{p} \gamma_j' \, y_{t-j+1} + \sum_{j=1}^{m} \beta_j' \, X_{t-j+1} + \varepsilon_{t+h} \tag{1}$$

where y_{t+h}^{h} is the h-step ahead value of the variable to be forecasted, α_0 is a constant, p are lags of the dependent variable, m are lags of the predictors and ε_{t+h} is the error term. The h-step ahead forecast given information at time t is given by:

$$\hat{y}_{t+h|t}^{h} = \hat{\alpha}_0 + \sum_{j=1}^{p} \hat{\gamma}_j' \, \hat{y}_{t-j+1} + \sum_{j=1}^{m} \hat{\beta}_j' \, \hat{X}_{t-j+1} \tag{2}$$

To ensure stationarity the data are transformed by taking logarithms and first or second differencing if necessary. To check the presence of unit roots, three tests are conducted: the augmented Dickey–Fuller (ADF) test, the Phillips–Perron (PP) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. In particular, since the HICP indices are found to be integrated of order one, we define

$$y_{t+h}^{h} = \frac{1200}{h} \ln\left(\frac{HICP_{t+h}}{HICP_t}\right) \tag{3}$$

and

$$y_t = 1200 \ln\left(\frac{HICP_t}{HICP_{t-1}}\right) \tag{4}$$

In order to carry out the empirical analysis described in Sections 3 and 4, we set up a large pseudo real-time dataset containing 438 potential predictors of inflation. The dataset is organised in monthly

[4] For a review of the state of the art in inflation forecasting, see Faust and Wright (2013).

time series available from January 1980 to December 2015 for a total of $T = 432$ observations. The data collected fall into the following categories:

- Supply-side hard indicators (industrial production indices, new orders, etc.)
- Demand-side hard indicators (car registration, retail sales, etc.)
- Labour market variables
- Price variables (producer prices, construction prices, commodity prices, import prices)
- Trade variables (exports, imports, etc.)
- External variables (US industrial production, US CPI, US monetary aggregates, etc.)
- Coincident and leading indicators
- Survey data on manufacturing, construction, retails, consumers, labour market
- Monetary and credit aggregates (M1, M2, M3, loans to the private sector, loans to non-financial corporations (NFCs) and loans to households)
- Interest rates, stock market indices, bond yields and other financial variables
- Exchange rates

Details on the data are reported in the Appendix. The number of predictors increases over time, as we have 19 predictors available at the beginning of our sample period in January 1980 and 438 predictors in December 2015.[5]

We follow a pseudo real-time exercise by aligning the variables in the dataset taking into account the respective publication-lag. For example, at the end of February of a given year only financial variables and very few survey data pertaining to the same month are assumed to be available to the researcher for forecasting. Monetary data are available with a month lag, i.e. in February the researcher only has monetary data of January (ECB press release *"Monetary developments in the euro area"*) on which to base her forecasts. In addition to monetary data, she already knows the January outturn of some variables (e.g. financial variables, most of the survey data), while for others the latest observation available to her is the one of December (e.g. most of the industrial production indices, producer price indices and labour market indicators), November (e.g. most of the turnover indices and trade variables) and even October (e.g. building permits). On the basis of the information available at the end of February, she can nowcast the inflation of February (1-month forecast horizon), forecast the inflation of March (2-month horizon), May (4-month horizon), September (8-month horizon), January of next year (12-month horizon), etc.[6]

[5] The last variables entering our dataset are those available since January 2005.
[6] The detailed publication-lag structure of the 438 potential predictors is available from the authors upon request.

3. Ranking monetary aggregates using targeted predictor methods

3.1 The methodology

In this section we use methods to identify targeted predictors of inflation in order to construct a combined rank of the hundreds of predictors considered. Through this exercise we are able to check the relative importance of monetary and credit aggregates as predictors of inflation over time and across forecast horizons. Moreover, the identification of a set of targeted predictors for each period and each forecasting horizon provides us with an input for the out-of-sample forecasting exercise carried out in Section 4.

The identification of targeted predictors has emerged as a refinement of the standard Diffusion Index (DI) forecasts introduced by Stock and Watson (2002a, 2002b), in which factors are extracted from a large number of predictors by the method of principal components. Factors are then augmented to a linear forecasting equation. The idea of the DI methodology is to incorporate the information contained in a large number of predictors in a handful of estimated factors in order to avoid the undesirable consequences of having too many parameters, i.e. over-fitting and poor forecast performance. The resulting more parsimonious information set usually leads to good forecasting performances.[7]

Recent studies have stressed that the use of too many predictors to compute the factors may be harmful for the forecasting accuracy of a model, as the DI methodology does not take into account the properties of the target variable. In other words, some of the predictors used to construct the factors may not have any predictive power over the series to be forecasted. Boivin and Ng (2006) and Bai and Ng (2008) show that when the factors are estimated using a subset of predictors that are proven to have good predictive power for the variable of interest, there are substantial gains in the forecasting performance over the standard DI forecasts. This refinement of the DI methodology is referred to as "targeted DI forecasts" and the chosen subset of predictors as "targeted predictors" (Bai and Ng, 2008).

This way of reducing the size of the information set has been recently employed by Bulligan et al. (2015) to forecast GDP growth and its main demand components in the euro area, Italy, Germany, France and Spain. Their forecasts are able to improve upon naïve benchmark models and compare favourably with factor models based on all available information. Another application of Bai and Ng (2008) methodology is given by Schumacher (2010), who investigates the role of international data for forecasting German GDP growth with a large factor model. He finds that without preselection of

[7] Another popular way to extract information from a large dataset of predictors consists in using all the predictors but imposing some kind of shrinkage, such as Bayesian shrinkage (De Mol et al, 2008; Belmonte et al., 2013; Korobilis, 2013; Giannone et al., 2014), forecast combinations (Wright, 2009) and dimension reduction techniques (Carrasco and Rossi, 2016).

data, international indicators do not contain additional information for forecasting. However, if variables are preselected prior to factor estimation to take into account their predictive power for GDP, international data generally improves forecasts. Lastly, Dias et al. (2010) propose to assign a weight to each factor that reflects both the fraction of the overall covariation of the series represented by that factors and its ability to forecast the variable of interest. They show that this "targeted diffusion index" approach outperforms considerably standard approaches in forecasting major US macroeconomic series.

Different techniques can be used to identify a subset of targeted predictors. Following Bai and Ng (2008) and Bulligan et al. (2015), we select targeted predictors for euro area inflation by testing both hard and soft thresholding rules.

Hard thresholding considers the bivariate relationship between each predictor and the target variable after controlling for lags of the target variable, regardless of other predictors. In the presence of a statistical significant relationship, a predictor is included in the pool of targeted predictors. More specifically, we proceed as in Bai and Ng (2008). First of all, for each $i = 1, \dots, N$, we estimate equation (1) using OLS with $p = 4$ and $m = 1$. Let ρ_i denote the *t*-statistic associated with X_{it}. We then sort $|\rho_1|, |\rho_2|, \dots, |\rho_n|$ in descending order and select the predictors whose *t*-statistic exceeds a threshold significance level α. Given the bivariate nature of this exercise, hard thresholding tends to choose predictors that are highly correlated.

Soft thresholding methods overcome this drawback by performing simultaneously subset selection and shrinkage on the full set of predictors. They are usually based on the following minimisation problem:

$$\min_{\beta,\alpha} RSS + \lambda\Psi(\beta_1, \beta_2, \dots \beta_N) \tag{5}$$

where $RSS(\alpha, \beta)$ is the sum of squared residuals of equation (1), in which the vector X_t contains all *N* predictors at time *t*. The shrinkage of the coefficients depends on the Lagrange multiplier λ. A higher λ implies a higher penalty for having additional regressors. The functional form of the penalty function Ψ characterises the type of the soft thresholding rule considered. From an operational point of view, all methods start with a model with only a constant and proceed in an iterative manner, adding or dropping variables at each step.[8] The parameter shrinkage and subset selection entailed in

[8] Soft thresholding methods require that the dependent variable be centred, while the predictors are centred and normalised.

soft thresholding methods allow us to rank the predictors on the basis of their predictive power. As in Bulligan et al. (2015), we focus on the following four soft thresholding methods:[9]

a) Forward selection regression (FWD). Forward selection is the simplest algorithm among the four used in this paper. It consists in adding iteratively to the model the predictor that has the highest absolute correlation with the current residual vector. The residuals are recomputed using the OLS solution using all currently active variables in each step. The algorithm stops when no new predictors can be added. This technique is considered to be overly restrictive, as it may eliminate useful predictors that are correlated with some variables already present in the active set.
b) Least angle regression (LARS). LARS represents a milder version of forward selection regression. Like for FWD, the algorithm starts with an empty model and finds the predictor most correlated with the residual vector. Instead of proceeding by orthogonal projections like FWD, the LARS updating rule uses skewed projections. Therefore, LARS allows predictors that are partially correlated with others already in the active set to be selected.
c) Least absolute shrinkage selection operator (LASSO). The LASSO improves ridge regressions by setting some of the parameters to zero. LASSO performs this shrinkage by imposing a constraint on the absolute values of the coefficients, rather than on the square of the coefficients. The LASSO solution can be derived via a small modification of the LARS algorithm.
d) Elastic net estimator (EN). The EN is a convex combination of ridge regression and LASSO. As shown by Zou and Hastie (2005), the elastic net is particularly useful when the number of predictors is much bigger than the number of observations. In this paper, we implement the elastic net with three different values of the key tuning parameter δ (EN1 with $\delta = 0.01$, EN2 with $\delta = 0.1$, EN3 with $\delta = 1$).

As soft thresholding tends to discard predictors that are highly correlated to others, we run the four methods using one of the six monetary/credit variables at a time together with all the other predictors. Like for hard thresholding, we set $p = 4$ and $m = 1$. For both hard and soft thresholding methods, the estimation is conducted by means of 10-year rolling windows as in Bulligan et al. (2015). The first window covers the period February 1980 – January 1990 and the last one the period December 2005 – November 2015. The number of estimation samples is 309.

For each of the seven selection rules described above (hard-thresholding, FWD, LARS, LASSO, EN1, EN2, EN3) and for each rolling-window, we end up with a rank of predictors ordered on the basis of

[9] The soft thresholding methods are implemented using the Matlab Toolbox for Sparse Statistical Modeling (SpaSM) developed by Sjöstrand et al. (2012). More details on the methods used in our analysis can be found in Tibshirani (1996), Efron et al. (2004), Zou and Hastie (2005), Bai and Ng (2008), Sjöstrand et al. (2012), Bulligan et al. (2015).

their predictive power for euro area inflation. The rank of a variable is determined by the position in which it enters the model. The rank is then divided by the number of predictors available at time *t*, in order to have it as a percentage of the number of available predictors. As regards FWD, LARS and LASSO, we rank the predictors using fractional ranking in order not to penalise excessively predictors that are not selected by the rule only in a few periods. By taking the median of the seven ranks we finally obtain a combined selection rank for each estimation window and for each forecast horizon.

3.2 The results

Tables 1-3 report for each horizon the five predictors that exhibit on average the highest predictive power according to the combined rank computed as describe in the previous sub-section. As regards HICP inflation (Table 1), the results confirm the importance of commodity and producer prices in forecasting inflation especially at short horizons (see, for example, Lenza and Warmedinger (2011)). Moreover, market-based inflation expectations show a good performance as predictors of HICP inflation at the 1- and 2-month horizons. As we move to longer horizons, the relevance of survey data increases, especially for surveys on the construction sector, services and retail trade. Thus, in line with previous studies (Bai and Ng, 2008; Koop and Korobilis, 2012), we find that variables that predict inflation at short horizons are different from those for long horizon forecasts.[10]

Turning to HICP excluding energy and HICP excluding energy and food (Tables 2 and 3), we find that soft data are among the best predictors both at short- and long horizons. Not surprisingly, costs of production inputs are no longer so frequent at short horizons. At such forecast horizons, building permits and turnover indices are found to contain leading information for these consumer price components. All in all, the validity of the targeted selection procedures outlined in the previous sub-section is supported by their ability to deliver sets of best predictors that are plausible and in line with past empirical studies.

Moving to our variables of interest, we find that monetary and credit aggregates are very often selected among the 30 or 50 best predictors.[11] Table 4 shows the frequency of at least one monetary or credit variable among the best predictors in three different periods. A value of 100% means that at least one of these variables is selected among the best predictors in all the estimation windows in a particular period. A value of 0% means that no monetary or credit variable is present among the best predictors in all the estimation windows in that period. The results point to a strong presence of monetary and credit aggregates among the best predictors over time, across forecast horizons and across consumer price components. In particular, at least one monetary or credit aggregate is always

[10] As in Koop and Korobilis (2012), we also find that the set of best predictors changes over time. These results are not reported here, but are available upon request from the authors.
[11] As for monetary and credit aggregates, we disregard the 1-month and 2-month horizons and focus on the predictive power of these variables only at longer horizons.

selected among the 30 and 50 best predictors for most of the horizons in the pre-2009 period, except for HICPXEF. A fall in the frequency of these variables is observed in the second period, though staying at very high levels when considering the 50 best predictors. A reversal of this trend is then visible in the most recent period for many forecast horizons of the 30 best predictors, suggesting an increase in the relative predictive power of these variables.

Looking at monetary and credit aggregates separately, we observe that their combined rank (expressed as a percentage of the total number of predictors available at each point in time) varies over time and across HICP components (Table 5). As regards HICP inflation, we find that monetary and credit aggregates are selected among the 30% best predictors before 1999 both at short and long horizons. Notably, M2 and loans to the private sector are ranked among the top 20% for all forecasting horizons. In the second period (with endpoints of rolling windows 1999:1-2007:12), the rank of monetary and credit aggregates worsens, though remaining in most cases in the top 50%. In the most recent period (endpoints of estimation windows 2008:1-2015:12), the combined rank of monetary variables returns in many cases in the top 30%, while the rank of loans ranges from the 12% to the 64% depending on the forecast horizon and the variable considered. The fact that the relative predictive power of monetary aggregates with respect to other predictors declined in the late 1990s and the first half of the 2000s is in line with previous studies showing that money-based models have performed very poorly in the decade prior to the Great Recession, reflecting a low and stable inflation profile (Reichlin and Lenza, 2007; Lenza 2008). By the same token, the improved relative predictive power of monetary variables in the most recent period may be related to the increase in inflation volatility that the crisis and the post-crisis period have brought about.

Regarding the two consumer price components, the pattern described above for HICP becomes feebler. The combined rank of M1, M2 and loans to the private sector continues to remain in the top 30% in the first period for HICPXE, while it hovers around 40-50% in most cases for HICPXEF. In the second period we observe a significant worsening in the predictive power of M1, M2 and loans to the private sector but only for HICPXE. Lastly, M2 and M3 (HICPXE), and M1 and loans to the private sector (HICPXEF) experience a general improvement in their relative predictive power in the post-2007 period.

To sum up, we report evidence that: a) Monetary and credit aggregates are very often selected among the top predictors; b) This finding holds across forecasting horizons; c) Their relative predictive power has generally improved in the post-2007 period with respect to the pre-crisis period; d) The findings in points a), b) and c) seem to become gradually less clear-cut when looking at HICPXE and HICPXEF.

Table 1. Five best predictors according to the combined rank (HICP – all items)

1-month horizon	2-month horizon	4-month horizon	8-month horizon	12-month horizon	18-month horizon	24-month horizon
Brent crude oil 1-month forward	World market prices of raw materials, Index total	World market prices of raw materials, Coal	Farm-gate and wholesale market prices	Farm-gate and wholesale market prices	Markit retail trade survey, prices paid for goods	Markit survey, composite, productivity
Euro 7-year inflation linked interest rate swap	Producer price index, Consumer goods industry	Producer price index, Consumer goods industry	Markit survey, construction, input prices	Markit survey, services, input prices	Markit survey, services, productivity	Markit retail trade survey, prices paid for goods
Euro 8-year inflation linked interest rate swap	Euro 8-year inflation linked interest rate swap	Farm-gate and wholesale market prices	Commodity price index, import weighted, food	Markit retail trade survey, stock of purchased goods	Markit survey, composite, productivity	Markit retail trade survey, value of ordered goods for resale
Producer price index, Consumer goods industry	Euro 9-year inflation linked interest rate swap	US dollar/Euro spot exchange rate	Markit retail trade survey, stock of purchased goods	Producer price index, MIG durable consumer goods industry	Markit survey, services, input prices	Markit retail trade survey, actual sales versus previous month
World market prices of raw materials, Coal	World market prices of raw materials, Iron ore, scrap	CBOE Volatility index, VIX	Building permits, one-dwelling buildings	Markit survey, construction, input prices	ECFIN construction survey, limits to production	Markit survey, construction, new orders

Notes: The predictors reported in the table are the ones with the highest combined rank (average over time). The variables refer to the euro area unless specified otherwise.

Table 2. Five best predictors according to the combined rank (HICP – excluding energy)

1-month horizon	2-month horizon	4-month horizon	8-month horizon	12-month horizon	18-month horizon	24-month horizon
ECFIN retail trade survey, selling price expectations for 3 months ahead	ECFIN retail trade survey, selling price expectations for 3 months ahead	ECFIN retail trade survey, selling price expectations for 3 months ahead	Markit retail trade survey, employment	Import price index, manufacturing	Markit retail trade survey, employment	Markit survey, construction, new orders
Building permits, one-dwelling buildings	Markit retail trade survey, prices paid for goods	Farm-gate and wholesale market prices	ECFIN retail trade survey, selling price expectations for 3 months ahead	Farm-gate and wholesale market prices	Import price index, total industry excl. construction and MIG energy	Markit retail trade survey, value of ordered goods for resale
Total turnover index, wholesale and retail trade; repair of motor vehicles and motorcycles	Euro 10-year inflation linked interest rate swap	Markit retail trade survey, prices paid for goods	Farm-gate and wholesale market prices	ECFIN industry survey, selling price expectations for the months ahead, consumer goods	Farm-gate and wholesale market prices	Markit retail trade survey, prices paid for goods
Euro 3-year inflation linked interest rate swap	ZEW short-term interest rate future (6 months)	Construction costs, labour costs	Markit retail trade survey, actual sales versus previous month	Markit retail trade survey, employment	ECFIN construction survey, trend of activity compared with preceding months, civil engineering	Markit retail trade survey, actual sales versus previous month
Markit retail trade survey, employment	Farm-gate and wholesale market prices	ECFIN industry survey, selling price expectations for the months ahead, consumer goods	ECFIN industry survey, selling price expectations for the months ahead, consumer goods	ECFIN construction survey, trend of activity compared with preceding months, civil engineering	Markit survey, construction, use of subcontractors	ZEW inflation rate future (6 months)

Notes: The predictors reported in the table are the ones with the highest combined rank (average over time). The variables refer to the euro area unless specified otherwise.

Table 3. Five best predictors according to the combined rank (HICP – excluding food and energy)

1-month horizon	2-month horizon	4-month horizon	8-month horizon	12-month horizon	18-month horizon	24-month horizon
Euro 1-year inflation linked interest rate swap	ECFIN retail trade survey, selling price expectations for 3 months ahead	ECFIN retail trade survey, selling price expectations for 3 months ahead	ECFIN retail trade survey, selling price expectations for 3 months ahead	Markit retail trade survey, value of ordered goods for resale	Markit retail trade survey, value of ordered goods for resale	Markit survey, construction, new orders
OECD business tendency surveys (services), demand evolution, future tendency	Euro 1-year inflation linked interest rate swap	Euro 3-year inflation linked interest rate swap	Markit retail trade survey, value of ordered goods for resale	Import price index, manufacturing	Import price index, total industry excl. construction and MIG energy	Markit retail trade survey, value of ordered goods for resale
Building permits, one-dwelling buildings	Markit retail trade survey, prices paid for goods	Total turnover index, wholesale and retail trade; repair of motor vehicles and motorcycles	Markit retail trade survey, employment	Markit survey, services, productivity	Markit survey, construction, use of subcontractors	Markit survey, construction, use of subcontractors
Total turnover index, wholesale and retail trade; repair of motor vehicles and motorcycles	Total turnover index, wholesale trade, except of motor vehicles and motorcycles	World market prices of raw materials, Coal	Euro 1-year inflation linked interest rate swap	World market prices of raw materials, Coal	Markit retail trade survey, employment	Markit retail trade survey, prices paid for goods
Markit survey, construction, output	Building permits, all residential buildings	Markit survey, construction, supplier delivery times	Merrill Lynch bond index, US financial corporates BBB	Markit retail trade survey, employment	Markit survey, services, productivity	ZEW inflation rate future (6 months)

Notes: The predictors reported in the table are the ones with the highest combined rank (average over time). The variables refer to the euro area unless specified otherwise.

Table 4. Frequency of monetary and credit aggregates among the 30 and 50 best predictors

		HICP - All items					HICP - Excluding energy					HICP - Excluding energy and food				
		4	8	12	18	24	4	8	12	18	24	4	8	12	18	24
30 best predictors	1995:1-1998:12	75%	100%	100%	100%	98%	98%	100%	100%	100%	100%	13%	23%	8%	6%	69%
	1999:1-2007:12	3%	40%	22%	50%	68%	29%	36%	49%	23%	46%	38%	55%	47%	33%	30%
	2008:1-2015:12	47%	56%	51%	56%	25%	54%	85%	76%	58%	12%	55%	42%	48%	35%	22%
50 best predictors	1995:1-1998:12	100%	100%	100%	100%	98%	100%	100%	100%	100%	100%	33%	48%	50%	46%	79%
	1999:1-2007:12	30%	76%	69%	64%	72%	83%	73%	92%	81%	77%	88%	81%	77%	75%	67%
	2008:1-2015:12	81%	71%	75%	94%	68%	80%	100%	96%	70%	44%	88%	63%	66%	70%	37%

Notes: The table reports the frequency of at least one monetary and credit aggregate among the 30 and 50 best predictors according to the combined rank. The combined rank is computed as the median of the ranks from the seven screening rules. The estimation is based on a 10-year rolling window. The second column reports the endpoints of the first and last estimation windows. The first estimation window reported in the table is the one ending in 1995:1, as it is the first window encompassing more than 100 predictors (128).

Table 5. Combined rank of monetary and credit aggregates

		HICP - All items					HICP - Excluding energy					HICP - Excluding energy and food				
		4	8	12	18	24	4	8	12	18	24	4	8	12	18	24
M1	1990:2-1998:12	20%	27%	34%	27%	25%	20%	27%	31%	28%	27%	54%	53%	52%	50%	46%
	1999:1-2007:12	50%	34%	44%	31%	41%	29%	34%	38%	32%	30%	21%	47%	36%	35%	43%
	2008:1-2015:12	51%	28%	26%	16%	29%	35%	35%	40%	43%	46%	24%	36%	29%	20%	41%
M2	1990:2-1998:12	19%	11%	16%	14%	15%	22%	27%	31%	24%	19%	52%	40%	40%	41%	30%
	1999:1-2007:12	42%	30%	36%	30%	26%	48%	43%	40%	39%	27%	44%	45%	44%	40%	42%
	2008:1-2015:12	26%	23%	24%	37%	14%	25%	19%	26%	48%	44%	49%	28%	49%	43%	37%
M3	1990:2-1998:12	24%	14%	21%	16%	16%	37%	40%	40%	25%	20%	47%	42%	38%	37%	31%
	1999:1-2007:12	45%	33%	33%	33%	40%	35%	36%	39%	38%	43%	31%	39%	36%	35%	41%
	2008:1-2015:12	31%	28%	17%	39%	25%	26%	16%	12%	13%	48%	35%	33%	35%	46%	46%
Loans to the private sector	1990:2-1998:12	18%	14%	8%	9%	11%	23%	17%	17%	16%	13%	45%	58%	53%	46%	27%
	1999:1-2007:12	49%	51%	48%	44%	38%	31%	30%	20%	34%	46%	39%	26%	23%	37%	41%
	2008:1-2015:12	18%	56%	52%	27%	36%	47%	40%	41%	45%	33%	30%	25%	29%	39%	44%
Loans to NFCs	2008:1-2015:12	35%	64%	49%	46%	58%	52%	43%	40%	47%	48%	30%	37%	33%	40%	49%
Loans to HHs	2008:1-2015:12	31%	58%	54%	36%	12%	37%	33%	41%	44%	23%	52%	33%	26%	35%	13%

Notes: The table reports the combined rank (as a percentage of the number of available predictors) for monetary and credit aggregates. The combined rank is computed as the median of the ranks from the seven screening rules. Green shades indicate values below 10%, 20% and 30%. The estimation is based on a 10-year rolling window. The second column reports the endpoints of the first and last estimation windows.

4. Forecasting inflation with monetary aggregates and targeted predictors

Having investigated the relative importance of monetary and credit aggregates in predicting inflation, in this section we assess the out-of-sample forecasting properties of these variables.

4.1 The methodology

We evaluate the out-of-sample forecast performance of a bunch models featuring monetary and credit aggregates as well as the targeted predictors identified in Section 3. The forecasts are computed via recursive OLS estimation of equation (1) with the data available up to time *t*. Two types of models are used. In the first ones (*predictor models*) a number of predictors enter the forecasting equation directly:

$$y_{t+h}^{h} = \alpha_0 + \sum_{j=1}^{p} \gamma_j' \, y_{t-j+1} + \sum_{j=1}^{m} \beta_j' \, P_{t-j+1} + \varepsilon_{t+h} \tag{6}$$

A second set of forecasts is computed using *Diffusion Index (DI) models* (Stock and Watson, 2002b), in which a few estimated synthetic indicators replace the information contained in a large number of predictors. The factor augmented forecast is:

$$y_{t+h}^{h} = \alpha_0 + \sum_{j=1}^{p} \gamma_j' \, y_{t-j+1} + \sum_{j=1}^{m} \beta_j' \, \hat{F}_{t-j+1} + \varepsilon_{t+h} \tag{7}$$

where $\hat{F}_t$ are factors estimated by principal components from a subset of predictors. As in Stock and Watson (2002b) the factors are computed using the EM algorithm that allows us to estimate the principal components in the case of unbalanced panels.[12]

In both types of models, in order to simulate real-time forecasting all the parameters are re-estimated at each monthly iteration and the estimates are used to derive a forecast using the last available observation in the sample. The number of lags of the dependent variable (p) and lags of predictors/factors (m) to be included in the models is re-optimised at each forecasting step using the BIC with the maximum number of lags set to six (Stock and Watson, 2002b). Moreover, in *DI models* also the factors are re-estimated at each monthly iteration using the information available at time *t*, and the number of factors to be included in the models is re-optimised at each forecasting step using the BIC with the maximum number of factors set to three. Stock and Watson (2002b) show that the most accurate forecasts of US inflation are obtained by using a single factor with no lags. Therefore, we complement the forecasts from *DI models* with the automatic selection of the number of factors

[12] The EM algorithm is embedded in the MATLAB routine PPCA (probabilistic principal component analysis).

and lags of factors (DI-ARL models) with forecasts obtained using *DI models* with 1 factor and with no lags ($m = 0$) (DI-AR models).

The first out-of-sample forecast is computed in February 1990 (using data available at the end of February 1990, e.g. January 1990 monetary data) with the estimation conducted over the period 1980:2-1990:1$-h$. The values of the regressors at $t = 1990{:}1$ are then used to forecast $y^h_{1990:1+h}$. The second forecast is computed in March 1990 on the basis of an estimation performed over the period 1980:2-1990:2$-h$. The values of the regressors at $t = 1990{:}2$ are then used to forecast $y^h_{1990:2+h}$. The last out-of-sample forecast is made in December 2015.

The forecast horizons for which the forecasts are computed are 4, 8, 12, 18, 24 months ahead. For the 4-month horizon we compute 308 out-of-sample forecasts, for the 8-month horizon 304 out-of-sample forecasts, for the 12-month horizon 300 out-of-sample forecasts, for the 18-month horizon 294 out-of-sample forecasts, for the 24-month horizon 288 out-of-sample forecasts.

For each *h* we compute the Root Mean Squared Error (MSE) and the Mean Absolute Error (MAE). To evaluate the forecast performance of different models, we refer to the Relative Root Mean Squared Error (RMSE) and the Relative Mean Absolute Error (RMAE), as the ratio of the MSE/MAE for a given model to the MSE/MAE of an AR(BIC) forecast:[13]

$$y^h_{t+h} = \alpha_0 + \sum_{j=1}^{p} \gamma_j' \, y_{t-j+1} + \varepsilon_{t+h} \tag{8}$$

where the number of lags of inflation (*p*) is re-optimised at each forecasting step using the BIC with the maximum number of lags set to six. A value of the RMSE/RMAE lower than one indicates that the specified model outperforms the AR(BIC) benchmark. Moreover, to assess equal forecast accuracy between two models we run the standard Diebold-Mariano test on the forecast errors (Diebold and Mariano, 1995).[14]

4.2 The results

The first exercise consists in forecasting HICP inflation by augmenting the AR(BIC) benchmark model with one monetary/credit aggregate at a time (*predictor model* of equation (6)). Similar money-based forecasting models are used by Nicoletti-Altimari (2001) and Fischer et al. (2009). The results, reported in Table 6, show that when monetary and credit aggregates are included directly in the forecasting equation the additional gains over the benchmark model are generally high and significant

[13] The AR(BIC) model is chosen as the benchmark, as it outperforms both the random walk and the AR(4) model in most cases.
[14] The Diebold-Mariano is calculated by regressing the difference of the loss functions on a constant using Newey-West standard errors. The null hypothesis of the test is equal forecast accuracy between two models.

across all horizons and HICP components only in the most recent period, with the exception of M1 (for HICPXE and HICPXEF). In the pre-crisis period, the differences with the benchmark are rarely significant, except at long horizons for loans to the private sector (HICP) and M2 and M3 (HICPXEF). In these cases, however, we observe a significant worsening versus the benchmark model. This finding is consistent with our analysis in Section 3 and with previous studies, which show that money-based models performed very poorly in the decade prior to the Great Recession, due to the low inflation volatility during that period (Reichlin and Lenza, 2007; Lenza 2008). The RMSE and RMAE are generally above unity during the crisis period (2008-2012), suggesting that models with monetary and credit aggregates underperform significantly the naïve AR(BIC) model.[15] Looking at the size of the relative forecast errors, the specification with loans to the private sector is the one that better outperforms the benchmark model for forecasting HICP inflation in the post-crisis at all horizons, while the model with loans to NFCs provides better forecasts at 4-, 8- and 12-month horizons for HICPXE and at 4- and 8-month horizons for HICPXEF.

We then use synthetic indicators of monetary and credit aggregates estimated by principal components.[16] The factors are added to the autoregressive block, as shown in equation (7). The relative forecast errors of the resulting DI-ARL model are reported in Table 7 and broadly confirm the results from the predictor models of Table 6. The DI-ARL model augmented with monetary and credit variables clearly dominates the benchmark in the most recent period, although the statistical significance fades away in the short-run for HICPXE and HICPXEF. Constraining the model to a single factor with no lags (DI-AR), the relative forecast errors decrease substantially in the first two evaluation periods (although not enough to achieve a significant improvement over the benchmark model), while for the period 2013-2015 the results improve in terms of significance for HICPXE and HICPXEF. These findings point to a slightly better forecasting performance of more parsimonious models, as found by Stock and Watson (2002b).

We now use the results from Section 3 by loading in the forecasting equation factors estimated using the best predictors excluding monetary and credit aggregates.[17] In a second stage, we estimate the factors using the best predictors plus the six monetary and credit variables. A comparison between the

[15] Our results confirm the view that the relevant predictors of macroeconomic variables are constantly changing over time, particularly as a result of recessions with financial market origins (Ng and Wright, 2013). Exploiting a data-rich environment to form synthetic indicators of many predictors, as we do in this paper, is one of the approaches proposed to provide better forecasts in such a case.

[16] Lenza (2008) computes the synthetic indicators from 35 monetary variables, including M1, M2, M3, some of their subcomponents and loans to the private sectors. He finds that, for the period 2000-2003, gains with respect to the benchmark model are only achieved if monetary variables are combined with alternative variables. From 2003 to 2008 he shows that none of the forecasting models can improve upon the random walk, reflecting a less volatile inflation profile.

[17] It is worth recalling that the best predictors, and hence the factors, change at each period in time t and across forecast horizons h. Moreover, since the first window in Section 3 covers the period February 1980 – January 1990, we need to re-compute for each forecast horizon the combined rank of our predictors also for the periods February 1980 – January $1990-h$.

forecasting properties of the two types of models would provide us with an indication of the relative forecasting power of monetary and credit variables.

Table 8 reports the forecast errors of two DI models (DI-ARL and DI-AR) featuring an autoregressive component plus factors estimated using the 30 best predictors excluding monetary and credit aggregates.[18] As regards HICP, the AR(BIC) model is beaten only in few cases, which are clustered in the most recent period, revealing the difficulty to forecast headline inflation. By contrast, the benchmark model is always outperformed by the model with the 30 best predictors for HICPXE and HICPXEF, except during the crisis period at longer horizons. These results clearly show that the benefits from pre-selecting the predictors are noticeable when forecasting measures of core inflation. The forecasting gains are particularly striking in the most recent period at horizons longer than 12 months, pointing to improved forecastability of core inflation in this period.

In Table 9, we present the relative forecast errors of the DI models with factors estimated using the 30 best predictors and the six monetary and credit variables. The chosen benchmark models are no longer AR(BIC), but those presented in Table 8, namely the DI models with factors estimated using the 30 best predictors excluding the monetary and credit aggregates. A number lower than one indicates that the inclusion of the monetary and credit aggregates in the sub-set of best predictors brings gains compared to a model without these variables. As shown in Table 9, exploiting the information embedded in monetary and credit aggregates on top of that contained in the 30 best predictors leads to forecasting gains in the post-2012 period for HICP inflation at all horizons. The evidence is more mixed for HICPXE: the model with monetary and credit aggregates significantly outperforms the one without only in the DI-AR case. As regards HICPXEF, monetary and credit variables seem to bring useful information for many horizons, but only in one case (24-month horizon) we observe a significant improvement. For the three inflation measures, the accuracy gains are seldom significant in the pre-2008 period, while the performance of the model with monetary and credit variables is generally worse during the crisis period.

These findings are broadly confirmed when we extend the sub-set of best predictors to 50 (Tables 10 and 11). Overall, this evidence highlights the importance of monetary and credit variables in forecasting inflation, even if their information content is diluted in a much broader pool of best predictors. The marginal contribution of monetary and credit aggregates seems to be particularly relevant to the forecast of HICP inflation in the most recent period.

[18] Whenever a monetary or credit aggregate is found among the 30 best predictors, it is excluded from the subset of variables used to compute the factors.

Table 6. Forecasting performance of monetary and credit aggregates (*predictor models*)

			HICP - All items					HICP - Excluding energy					HICP - Excluding energy and food				
			4	8	12	18	24	4	8	12	18	24	4	8	12	18	24
M1	1999:1-2007:12	RMSE	1.00	0.99	1.00	0.99	0.99	1.00	1.01	1.01	1.00	1.01	1.00	1.00	0.97	0.99	1.00
		RMAE	1.00	0.99	1.00	0.99	1.00	1.01	1.01	1.01	1.01	1.01	1.00	1.00	0.98	0.99	1.00
	2008:1-2012:12	RMSE	1.00	0.99	1.00	0.99	1.00	1.00	1.01	1.00	1.01	1.00	1.00	0.98	0.99	1.01	1.01
		RMAE	1.00	0.99	1.02	0.99	1.01	1.00	1.01	1.00	1.00	1.00	1.00	0.98	0.99	1.01	1.02
	2013:1-2015:12	RMSE	1.00	0.91	0.91	0.95	0.88	1.00	1.01	1.00	1.00	0.99	1.01	1.02	1.03	1.02	1.01
		RMAE	0.99	0.94	0.92	0.89	0.84	1.00	1.01	1.00	0.99	0.98	1.01	1.02	1.03	1.02	1.01
M2	1999:1-2007:12	RMSE	0.99	0.99	0.99	1.00	1.00	1.00	1.01	1.01	1.02	1.03	1.00	1.00	1.00	1.02	1.04
		RMAE	0.99	0.99	1.00	1.00	0.99	1.00	1.00	1.01	1.02	1.02	1.01	1.00	0.99	1.03	1.06
	2008:1-2012:12	RMSE	1.01	1.02	1.02	1.02	1.04	1.01	1.01	1.01	1.02	1.03	1.00	1.00	1.00	1.01	1.03
		RMAE	1.01	1.01	1.03	1.03	1.04	1.01	1.01	1.01	1.02	1.04	1.00	1.01	1.00	1.02	1.03
	2013:1-2015:12	RMSE	0.99	0.95	0.97	1.04	0.99	0.99	0.99	0.99	1.00	0.99	1.00	1.00	1.00	1.00	0.99
		RMAE	0.98	0.97	0.97	0.98	0.99	1.00	0.99	0.99	0.99	0.99	1.00	0.99	1.00	0.99	0.99
M3	1999:1-2007:12	RMSE	0.99	0.99	1.00	1.02	1.03	1.00	1.01	1.01	1.09	1.11	1.01	1.02	1.01	1.16	1.19
		RMAE	0.99	1.01	1.01	1.02	1.02	1.00	1.00	1.01	1.06	1.10	1.00	1.02	1.01	1.16	1.23
	2008:1-2012:12	RMSE	1.02	1.02	1.02	1.03	1.07	1.01	1.01	1.02	1.03	1.14	0.99	0.99	1.04	1.13	1.37
		RMAE	1.02	1.03	1.05	1.06	1.06	1.01	1.02	1.03	1.03	1.15	1.00	1.02	1.05	1.20	1.41
	2013:1-2015:12	RMSE	0.98	0.93	0.95	1.03	0.99	0.97	0.96	0.96	0.96	0.96	0.98	0.95	0.92	0.92	0.92
		RMAE	0.97	0.94	0.96	0.97	0.97	0.99	0.96	0.94	0.95	0.95	0.98	0.93	0.91	0.90	0.92
Loans to the private sector	1999:1-2007:12	RMSE	1.01	1.12	1.34	1.46	1.76	1.00	1.09	1.15	1.17	1.25	1.04	1.07	1.17	1.25	1.29
		RMAE	1.00	1.12	1.31	1.46	1.88	1.01	1.08	1.15	1.10	1.14	1.03	1.06	1.15	1.18	1.14
	2008:1-2012:12	RMSE	1.01	1.03	1.06	1.11	1.29	1.01	1.05	1.07	1.17	1.47	0.97	0.98	1.08	1.43	1.88
		RMAE	1.04	1.06	1.12	1.19	1.36	1.02	1.11	1.13	1.22	1.66	0.99	1.00	1.17	1.71	2.30
	2013:1-2015:12	RMSE	0.88	0.80	0.79	0.85	0.87	0.92	0.85	0.83	0.78	0.75	0.94	0.84	0.71	0.66	0.60
		RMAE	0.84	0.77	0.77	0.84	0.84	0.97	0.92	0.82	0.79	0.75	0.93	0.77	0.69	0.63	0.59
Loans to NFCs	2008:1-2012:12	RMSE	1.01	1.02	1.11	1.10	1.05	0.99	1.03	1.06	1.07	1.18	0.99	0.93	0.93	0.88	0.94
		RMAE	1.01	1.05	1.09	1.09	1.01	0.96	1.05	1.03	1.01	1.10	0.97	0.88	0.92	0.88	0.92
	2013:1-2015:12	RMSE	0.90	0.89	0.96	1.13	1.21	0.87	0.78	0.78	0.78	0.80	0.89	0.76	0.76	0.75	0.82
		RMAE	0.88	0.89	0.97	1.14	1.21	0.89	0.75	0.75	0.76	0.79	0.88	0.73	0.74	0.74	0.81
Loans to HHs	2008:1-2012:12	RMSE	1.10	1.15	1.25	1.31	1.24	1.66	1.93	2.15	2.10	1.70	1.28	2.32	2.59	2.66	2.39
		RMAE	1.06	1.17	1.29	1.41	1.35	1.44	1.69	1.93	2.08	1.79	1.27	1.97	2.23	2.64	2.48
	2013:1-2015:12	RMSE	0.92	0.91	0.92	0.95	0.97	0.96	0.94	0.93	0.91	0.84	0.93	0.91	0.88	0.85	0.87
		RMAE	0.91	0.90	0.92	0.95	1.01	0.95	0.92	0.90	0.89	0.84	0.92	0.89	0.86	0.85	0.86

Notes: Green cells indicate that the improvement over the benchmark model (AR(BIC)) is statistically significant at the 10% level. Red cells indicate that the worsening versus the benchmark model (AR(BIC)) is statistically significant at the 10% level. The second column reports the out-of-sample period.

Table 7. Forecasting performance of monetary and credit aggregates (*DI models*)

			HICP - All items					HICP - Excluding energy					HICP - Excluding energy and food				
			4	8	12	18	24	4	8	12	18	24	4	8	12	18	24
DIARL model (monetary and credit aggregates)	1999:1-2007:12	RMSE	1.00	1.02	1.07	1.15	1.15	0.98	1.01	1.03	1.08	1.15	1.02	1.07	1.05	1.19	1.22
		RMAE	1.00	1.03	1.12	1.15	1.10	0.97	0.99	1.00	1.02	1.02	1.01	1.06	1.03	1.13	1.10
	2008:1-2012:12	RMSE	1.02	1.05	1.09	1.13	1.25	1.08	1.19	1.26	1.51	1.62	1.00	1.22	1.60	1.95	2.41
		RMAE	1.05	1.09	1.16	1.21	1.29	1.09	1.20	1.25	1.53	1.74	1.02	1.27	1.73	2.17	2.65
	2013:1-2015:12	RMSE	0.93	0.85	0.83	0.86	0.85	0.94	0.96	0.90	0.80	0.80	0.97	0.94	0.80	0.67	0.63
		RMAE	0.91	0.80	0.80	0.82	0.84	0.98	1.03	0.87	0.78	0.79	0.96	0.86	0.76	0.59	0.62
DIAR model (monetary and credit aggregates), 1 factor	1999:1-2007:12	RMSE	0.99	1.01	1.05	1.07	1.06	0.98	0.98	0.99	0.99	0.99	1.00	1.01	1.00	1.02	1.03
		RMAE	1.00	1.03	1.07	1.09	1.05	0.97	0.98	0.96	0.95	0.94	1.00	1.02	1.01	1.00	1.01
	2008:1-2012:12	RMSE	1.02	1.04	1.06	1.08	1.15	1.03	1.04	1.07	1.13	1.19	0.99	1.05	1.11	1.19	1.27
		RMAE	1.05	1.07	1.13	1.15	1.18	1.05	1.08	1.11	1.14	1.22	1.02	1.11	1.15	1.29	1.38
	2013:1-2015:12	RMSE	0.93	0.85	0.83	0.88	0.90	0.94	0.90	0.85	0.80	0.76	0.97	0.91	0.80	0.73	0.68
		RMAE	0.91	0.80	0.80	0.85	0.87	0.98	0.95	0.81	0.78	0.73	0.96	0.85	0.79	0.67	0.66

Notes: Green cells indicate that the improvement over the benchmark model (AR(BIC)) is statistically significant at the 10% level. Red cells indicate that the worsening versus the benchmark model (AR(BIC)) is statistically significant at the 10% level. The second column reports the out-of-sample period.

Table 8. Forecasting performance of the 30 best predictors *excluding* monetary and credit aggregates (*DI models*)

			HICP - All items					HICP - Excluding energy					HICP - Excluding energy and food				
			4	8	12	18	24	4	8	12	18	24	4	8	12	18	24
DIARL model (30 best predictors)	1999:1-2007:12	RMSE	1.00	0.99	1.12	1.17	1.06	0.94	0.90	0.88	0.83	0.79	0.98	0.89	0.85	0.78	0.75
		RMAE	1.00	0.97	1.15	1.19	1.00	0.94	0.97	0.93	0.86	0.80	0.97	0.91	0.89	0.77	0.74
	2008:1-2012:12	RMSE	1.00	1.02	1.03	1.11	1.17	0.92	0.95	0.97	1.14	1.22	0.96	1.08	1.15	1.54	1.56
		RMAE	0.99	1.00	1.07	1.12	1.15	0.92	0.97	0.96	1.04	1.21	1.00	1.13	1.26	1.72	1.70
	2013:1-2015:12	RMSE	0.98	1.07	0.80	0.98	0.90	0.94	0.91	0.78	0.74	0.65	0.95	0.87	0.65	0.51	0.47
		RMAE	1.00	1.06	0.81	0.99	0.86	0.96	0.96	0.78	0.71	0.65	0.96	0.76	0.62	0.45	0.44
DIAR model (30 best predictors), 1 factor	1999:1-2007:12	RMSE	1.00	1.01	1.03	1.12	1.08	0.96	0.90	0.88	0.83	0.78	0.97	0.90	0.87	0.83	0.73
		RMAE	1.00	1.00	1.05	1.13	1.05	0.96	0.95	0.92	0.86	0.78	0.96	0.92	0.92	0.86	0.72
	2008:1-2012:12	RMSE	1.03	1.02	1.05	1.08	1.15	0.89	0.92	1.00	1.07	1.13	0.87	0.82	0.94	1.34	1.44
		RMAE	1.03	1.02	1.06	1.10	1.12	0.91	0.95	1.01	0.99	1.12	0.88	0.86	0.99	1.49	1.55
	2013:1-2015:12	RMSE	0.98	1.03	1.03	0.97	0.96	0.95	0.93	0.80	0.74	0.75	0.95	0.86	0.66	0.50	0.59
		RMAE	0.98	1.04	1.04	0.95	0.93	0.99	0.97	0.80	0.70	0.75	0.96	0.76	0.65	0.46	0.54

Notes: Green cells indicate that the improvement over the benchmark model (AR(BIC)) is statistically significant at the 10% level. Red cells indicate that the worsening versus the benchmark model (AR(BIC)) is statistically significant at the 10% level. The second column reports the out-of-sample period.

Table 9. Forecasting performance of the 30 best predictors *including* monetary and credit aggregates (*DI models*)

			HICP - All items					HICP - Excluding energy					HICP - Excluding energy and food				
			4	8	12	18	24	4	8	12	18	24	4	8	12	18	24
DIARL model (30 best predictors augmented)	1999:1-2007:12	RMSE	0.99	1.03	1.00	0.99	1.00	1.01	1.00	1.00	1.04	1.01	1.04	0.98	0.95	1.02	1.02
		RMAE	0.98	1.05	1.01	0.99	1.02	1.01	0.97	0.99	1.02	0.99	1.03	0.97	0.93	1.05	1.01
	2008:1-2012:12	RMSE	1.00	1.05	1.14	1.02	1.07	1.04	1.08	1.13	1.07	1.08	1.03	1.08	1.21	1.12	1.13
		RMAE	1.00	1.05	1.16	1.04	1.11	1.04	1.08	1.13	1.10	1.10	1.02	1.10	1.21	1.11	1.12
	2013:1-2015:12	RMSE	0.97	0.72	0.95	0.82	0.95	1.00	0.97	0.97	0.99	1.06	0.99	1.01	1.05	1.00	0.95
		RMAE	0.93	0.68	0.95	0.81	0.97	1.02	0.98	0.95	0.97	1.03	0.97	1.04	0.98	0.98	0.91
DIAR model (30 best predictors augmented), 1 factor	1999:1-2007:12	RMSE	0.99	1.00	1.03	0.98	0.99	1.00	1.05	1.08	1.09	1.16	1.04	1.07	1.09	1.04	1.19
		RMAE	0.98	1.00	1.03	0.99	1.00	0.99	1.00	1.00	1.07	1.16	1.03	1.06	1.05	1.01	1.20
	2008:1-2012:12	RMSE	0.99	1.03	1.09	1.01	1.02	1.03	1.02	1.04	1.02	1.03	1.02	1.09	1.08	1.05	1.04
		RMAE	0.99	1.04	1.09	1.02	1.04	1.03	1.03	1.05	1.04	1.02	1.02	1.09	1.10	1.05	1.02
	2013:1-2015:12	RMSE	1.00	0.96	0.94	0.83	0.94	0.98	1.00	0.94	0.95	0.86	0.99	1.02	0.94	0.94	0.83
		RMAE	0.99	0.95	0.93	0.83	0.92	1.00	1.01	0.93	0.93	0.83	0.98	1.05	0.91	0.88	0.83

Notes: Green cells indicate that the improvement over the benchmark model (models in Table 8) is statistically significant at the 10% level. Red cells indicate that the worsening versus the benchmark model (models in Table 8) is statistically significant at the 10% level. The second column reports the out-of-sample period.

Table 10. Forecasting performance of the 50 best predictors *excluding* monetary and credit aggregates (*DI models*)

			HICP - All items					HICP - Excluding energy					HICP - Excluding energy and food				
			4	8	12	18	24	4	8	12	18	24	4	8	12	18	24
DIARL model (50 best predictors)	1999:1-2007:12	RMSE	0.99	0.97	1.09	1.11	1.01	0.92	0.89	0.88	0.84	0.81	0.96	0.90	0.80	0.81	0.77
		RMAE	0.98	0.97	1.11	1.12	0.98	0.92	0.95	0.93	0.87	0.83	0.95	0.92	0.85	0.82	0.74
	2008:1-2012:12	RMSE	0.99	0.98	1.04	1.09	1.12	0.96	0.95	1.02	1.13	1.24	0.97	1.03	1.24	1.56	1.65
		RMAE	1.00	0.96	1.04	1.11	1.09	0.96	0.96	1.00	1.04	1.24	1.01	1.07	1.35	1.79	1.76
	2013:1-2015:12	RMSE	0.98	1.01	0.91	1.02	0.95	0.93	0.91	0.80	0.74	0.59	0.96	0.90	0.64	0.51	0.54
		RMAE	0.98	1.04	0.90	1.04	0.91	0.97	0.95	0.81	0.72	0.59	0.95	0.79	0.64	0.44	0.51
DIAR model (50 best predictors), 1 factor	1999:1-2007:12	RMSE	1.00	1.00	1.01	1.05	1.03	0.95	0.89	0.88	0.85	0.82	0.95	0.92	0.86	0.82	0.79
		RMAE	1.00	0.99	1.04	1.05	0.99	0.95	0.95	0.93	0.88	0.83	0.95	0.92	0.91	0.85	0.78
	2008:1-2012:12	RMSE	0.99	0.98	1.05	1.02	1.13	0.92	0.92	1.02	1.03	1.15	0.91	0.78	0.98	1.26	1.46
		RMAE	1.00	0.97	1.05	1.03	1.10	0.95	0.95	1.03	0.98	1.13	0.92	0.80	1.04	1.39	1.55
	2013:1-2015:12	RMSE	0.99	1.05	1.00	0.98	0.97	0.96	0.94	0.81	0.72	0.73	1.01	0.92	0.66	0.51	0.61
		RMAE	0.99	1.06	1.01	0.97	0.96	0.98	0.98	0.80	0.68	0.71	1.00	0.80	0.65	0.45	0.56

Notes: Green cells indicate that the improvement over the benchmark model (AR(BIC)) is statistically significant at the 10% level. Red cells indicate that the worsening versus the benchmark model (AR(BIC)) is statistically significant at the 10% level. The second column reports the out-of-sample period.

Table 11. Forecasting performance of the 50 best predictors *including* monetary and credit aggregates (*DI models*)

			HICP - All items					HICP - Excluding energy					HICP - Excluding energy and food				
			4	8	12	18	24	4	8	12	18	24	4	8	12	18	24
DIARL model (50 best predictors augmented)	1999:1-2007:12	RMSE	1.00	1.03	0.97	0.97	0.95	1.03	0.99	0.98	1.03	0.97	1.00	0.97	1.01	0.98	0.94
		RMAE	1.00	1.03	0.97	0.96	0.94	1.02	0.99	0.98	1.02	0.98	0.99	0.96	0.98	1.00	0.97
	2008:1-2012:12	RMSE	1.01	1.07	1.04	1.01	1.03	1.06	1.05	1.09	1.03	1.06	1.01	1.09	1.14	1.08	1.10
		RMAE	1.01	1.10	1.05	1.01	1.04	1.04	1.06	1.09	1.04	1.08	1.01	1.10	1.15	1.06	1.09
	2013:1-2015:12	RMSE	0.95	0.92	0.97	0.91	0.85	1.01	1.01	0.98	1.00	0.99	0.99	0.99	1.01	0.97	0.87
		RMAE	0.93	0.90	0.96	0.89	0.87	1.02	1.00	0.94	1.01	0.95	1.01	1.00	1.00	0.94	0.85
DIAR model (50 best predictors augmented), 1 factor	1999:1-2007:12	RMSE	1.00	1.03	1.04	1.01	1.02	1.02	1.07	1.10	1.15	1.15	1.05	1.07	1.13	1.17	1.13
		RMAE	1.00	1.04	1.04	1.02	1.05	1.02	1.02	1.03	1.11	1.13	1.04	1.06	1.08	1.10	1.18
	2008:1-2012:12	RMSE	1.00	1.02	1.01	1.01	1.02	1.00	1.02	1.01	1.01	1.03	1.00	1.08	1.02	1.08	1.01
		RMAE	1.00	1.02	1.03	1.01	1.04	0.98	1.02	1.01	1.03	1.03	1.01	1.09	1.02	1.09	1.01
	2013:1-2015:12	RMSE	0.99	0.98	0.97	0.94	0.97	0.97	0.99	0.96	0.95	0.89	0.99	0.99	1.01	0.96	0.87
		RMAE	0.99	0.97	0.97	0.94	0.96	1.01	1.01	0.96	0.93	0.89	0.98	1.00	1.00	0.93	0.91

Notes: Green cells indicate that the improvement over the benchmark model (models in Table 10) is statistically significant at the 10% level. Red cells indicate that the worsening versus the benchmark model (models in Table 10) is statistically significant at the 10% level. The second column reports the out-of-sample period.

5. Concluding remarks

This paper has shed new light on the information content of monetary and credit aggregates for future price developments in the euro area. We find strong variation in the information content of monetary and credit aggregates over time. Using techniques aimed at identifying targeted predictors, we show that monetary and credit aggregates are very often selected among the top predictors of inflation, with their predictive power compared to other predictors generally improving in the post-2012 period. An out-of-sample forecasting exercise indicates that, when monetary and credit aggregates are loaded directly in the forecasting equation, the additional gains over the benchmark model are generally high and significant across all horizons and HICP components only in the most recent period. When the forecasts are computed using factor-augmented regressions based on the best predictors, we confirm that monetary and credit variables are statistically useful to forecast inflation, even if their information content is diluted in a much broader pool variables. The marginal contribution of monetary and credit aggregates seems to be particularly relevant to the forecast of HICP inflation in the post-2012 period. Overall, our results confirm the need to continue to carry out the monetary analysis in the assessment of the risks to price stability within the Eurosystem.

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Appendix. The data

Table 1A. Data description

Description	Start date	Transformation
Monetary and credit aggregates		
M1, notional stock	Jan-80	Delta log
M2, notional stock	Jan-80	Delta log
M3, notional stock	Jan-80	Delta log
Loans to the private sector, notional stock, adjusted for sales and securitisation	Jan-83	Delta log
Loans to non-financial corporations, notional stock, adjusted for sales and securitisation	Jan-97	Delta log
Loans to households, notional stock, adjusted for sales and securitisation	Jan-97	Delta log
Industrial production		
Total (excl. constr.)	Jan-80	Delta log
Total (incl. constr.)	Jan-85	Delta log
Total (excl. constr. and MIG energy)	Jan-91	Delta log
Manufacturing	Jan-80	Delta log
Construction	Jan-85	Delta log
Manufacture of food products - NACE Rev2	Jan-91	Delta log
Manufacture of textiles - NACE Rev2	Jan-91	Delta log
Manufacture of wearing apparel - NACE Rev2	Jan-85	Delta log
Manufacture of leather and related products - NACE Rev2	Jan-85	Delta log
Manufacture of wood and of products of wood and cork	Jan-91	Delta log
Manufacture of paper and paper products - NACE Rev2	Jan-91	Delta log
Manufacture of chemicals and chemical products - NACE Rev2	Jan-91	Delta log
Manufacture of rubber and plastic products - NACE Rev2	Jan-91	Delta log
Manufacture of other non-metallic mineral products - NACE Rev2	Jan-91	Delta log
Manufacture of basic metals - NACE Rev2	Jan-91	Delta log
Manufacture of fabricated metal products	Jan-91	Delta log
Manufacture of electrical equipment - NACE Rev2	Jan-91	Delta log
Manufacture of machinery and equipment n.e.c. - NACE Rev2	Jan-91	Delta log
Manufacture of other transport equipment - NACE Rev2	Jan-91	Delta log
All buildings	Jan-88	Delta log
All Civil engineering Works	Jan-88	Delta log
MIG Intermediate Goods Industry - NACE Rev2	Jan-80	Delta log
MIG Capital Goods Industry - NACE Rev2	Jan-80	Delta log
MIG Durable Consumer Goods Industry - NACE Rev2	Jan-80	Delta log
MIG Non-durable Consumer Goods Industry - NACE Rev2	Jan-80	Delta log
Consumer goods industry - NACE Rev2	Jan-80	Delta log
MIG Energy - NACE Rev2	Jan-80	Delta log
MIG Energy excluding NACE Rev.2 Sections D and E	Jan-85	Delta log
Industrial new orders		
MIG intermediate goods	Jan-96	Delta log
MIG capital goods	Jan-95	Delta log
MIG consumer goods	Jan-95	Delta log
MIG non-durable consumer goods	Jan-00	Delta log
MIG durable consumer goods	Jan-00	Delta log
Total manufacturing	Jan-95	Delta log
Total manufacturing (except heavy transport equipment)	Jan-96	Delta log
Total manufacturing domestic	Jan-98	Delta log
Total manufacturing non-domestic	Jan-95	Delta log
Turnover indices		
Manufacturing - NACE rev2	Jan-80	Delta log
Wholesale and retail trade; repair of motor vehicles and motorcycles - NACE rev2	Jan-99	Delta log
Retail trade including fuel	Jan-95	Delta log
MIG capital goods industry - NACE Rev2	Jan-80	Delta log
MIG durable consumer goods industry - NACE Rev2	Jan-93	Delta log
MIG non-durable consumer goods industry - NACE Rev2	Jan-94	Delta log
Retail trade excluding fuel	Jan-80	Delta log
Retail sale of food	Jan-95	Delta log
Retail sale of non-food products (except fuel) - NACE Rev2	Jan-95	Delta log
Retail sale of textiles	Jan-95	Delta log
Retail sale of non-food products including fuel - NACE Rev2	Jan-95	Delta log
Retail sale in non-specialised stores -	Jan-98	Delta log
Retail sale in non-specialised stores with food	Jan-98	Delta log
Retail trade turnover, deflated, total including motor vehicles	Jan-95	Delta log
Retail sale in non-specialised stores, deflated	Jan-98	Delta log
Retail sale in non-specialised stores with food, deflated	Jan-98	Delta log
Retail trade excluding fuel, deflated	Jan-80	Delta log
Retail sale of food, deflated	Jan-95	Delta log
Retail sale of non-food products (except fuel), deflated	Jan-95	Delta log
Retail sale of textiles, deflated	Jan-95	Delta log
Retail sale of audio and video equipment; hardware, deflated	Jan-95	Delta log

Retail sale of non-food products including fuel , deflated	Jan-95	Delta log
Total industry, domestic	Jan-95	Delta log
Total industry excl. construction and MIG energy, domestic	Jan-95	Delta log
MIG intermediate goods industry, domestic	Jan-95	Delta log
MIG capital goods industry, domestic	Jan-91	Delta log
MIG durable consumer goods industry, domestic	Jan-91	Delta log
MIG non-durable consumer goods industry, domestic	Jan-95	Delta log
Consumer goods industry, domestic	Jan-95	Delta log
Total industry, non-domestic	Jan-95	Delta log
Total industry excl. construction and MIG energy, non-domestic	Jan-95	Delta log
MIG intermediate goods industry, non-domestic	Jan-95	Delta log
MIG capital goods industry, non-domestic	Jan-95	Delta log
MIG durable consumer goods industry, non-domestic	Jan-91	Delta log
MIG non-durable consumer goods industry, non-domestic	Jan-95	Delta log
Consumer goods industry, non-domestic	Jan-95	Delta log
Wholesale trade, except of motor vehicles and motorcycles	Jan-00	Delta log
Accommodation and food service activities	Jan-00	Delta log
Building permits		
Dwellings, one-dwelling buildings	Jan-95	Delta log
Dwellings, two- and more dwelling buildings	Jan-95	Delta log
Sq. meters of useful floor area or alt. size measure, all buildings	Jan-00	Delta log
Sq. meters of useful floor area or alt. size measure, all residential buildings	Jan-00	Delta log
Sq. meters of useful floor area or alt. size measure, one-dwelling buildings	Jan-00	Delta log
Sq. meters of useful floor area or alt. size measure, two- and more dwelling buildings	Jan-00	Delta log
Sq. meters of useful floor area or alt. size measure, all non-Residential Buildings	Jan-95	Delta log
Car registrations		
New passenger car registration	Jan-90	Delta log
New commercial vehicles	Jan-90	Delta log
New heavy commercial vehicles	Jan-90	Delta log
New light commercial vehicles	Jan-90	Delta log
Trade (extra euro area)		
Trade balance, value	Jan-00	Delta level
Import, value	Jan-00	Delta log
Import, volume index	Jan-00	Delta log
Export, value	Jan-00	Delta log
Export, volume index	Jan-00	Delta log
Capital goods, import, value	Jan-00	Delta log
Capital goods, import, volume index	Jan-00	Delta log
Capital goods, export, value	Jan-00	Delta log
Capital goods, export, volume index	Jan-00	Delta log
Intermediate goods, import, value	Jan-00	Delta log
Intermediate goods, import, volume index	Jan-00	Delta log
Intermediate goods, export, value	Jan-00	Delta log
Intermediate goods, export, volume index	Jan-00	Delta log
Consumer goods, import, value	Jan-00	Delta log
Consumer goods, import, volume index	Jan-00	Delta log
Consumer goods, export, value	Jan-00	Delta log
Consumer goods, export, volume index	Jan-00	Delta log
Consumption goods (consumer goods and cars and petrol), import, value	Jan-00	Delta log
Consumption goods (consumer goods and cars and petrol), import, volume index	Jan-00	Delta log
Consumption goods (consumer goods and cars and petrol), export, value	Jan-00	Delta log
Consumption goods (consumer goods and cars and petrol), export, volume index	Jan-00	Delta log
Labour market		
Unemployment rate, total	Jan-93	Delta level
Unemployment rate, female	Jan-83	Delta level
Unemployment rate, male	Jan-83	Delta level
Unemployment rate, 25 and over	Jan-83	Delta level
Unemployment rate, under 25	Jan-83	Delta level
Unemployment rate, female, 25 and over	Jan-83	Delta level
Unemployment rate, male, 25 and over	Jan-83	Delta level
Unemployment rate, female, under 25	Jan-93	Delta level
Unemployment rate, male, under 25	Jan-83	Delta level
Indicator of negotiated wage rates	Jan-91	Level
Indicator of negotiated wage rates, total excluding bonuses	Jan-91	Level
Surveys		
Markit Composite - employment	Jul-98	Level
Markit Composite - input prices	Jul-98	Level
Markit Composite - new orders	Jul-98	Level
Markit Composite - outstanding business	Nov-02	Level
Markit Composite - output	Jul-98	Level
Markit Composite - prices charged	Nov-02	Level
Markit Composite - productivity	Jan-98	Level
Markit Construction - availability of subcontractors	Jan-00	Level
Markit Construction - employment	Jan-00	Level
Markit Construction - input prices	Jan-00	Level

Markit Construction - new orders	Jan-00	Level
Markit Construction - output	Jan-00	Level
Markit Construction - quality of subcontractors	Jan-00	Level
Markit Construction - quantity of purchases	Jan-00	Level
Markit Construction - rates charged by subcontractors	Jan-00	Level
Markit Construction - supplier delivery times	Jan-00	Level
Markit Construction - use of subcontractors	Jan-00	Level
Markit Manufacturing - employment	Jun-97	Level
Markit Manufacturing - input prices	Jun-97	Level
Markit Manufacturing - new orders	Jun-97	Level
Markit Manufacturing - new export orders	Jun-97	Level
Markit Manufacturing - outstanding business	Nov-02	Level
Markit Manufacturing - output	Jun-97	Level
Markit Manufacturing - purchasing manager index	Jun-97	Level
Markit Manufacturing - prices charged	Nov-02	Level
Markit Manufacturing - productivity	Jan-98	Level
Markit Manufacturing - quantity of purchases	Jun-97	Level
Markit Manufacturing - supplier delivery times	Jun-97	Level
Markit Manufacturing - stocks of finished goods	Jun-97	Level
Markit Manufacturing - stocks of purchases	Jun-97	Level
Markit Retail trade survey - actual sales versus previous month	Jan-04	Level
Markit Retail trade survey - employment	Jan-04	Level
Markit Retail trade survey - gross margins	Jan-04	Level
Markit Retail trade survey - prices paid for goods	Jan-04	Level
Markit Retail trade survey - stock of purchased goods	Jan-04	Level
Markit Retail trade survey - value of ordered goods for resale	Jan-04	Level
Markit Services - employment	Jul-98	Level
Markit Services - input prices	Jul-98	Level
Markit Services - new business	Jul-98	Level
Markit Services - outstanding business	Jul-98	Level
Markit Services - business activity	Jul-98	Level
Markit Services - prices charged	Jul-98	Level
Markit Services - productivity	Jan-98	Level
ECFIN Business climate indicator	Jan-85	Level
ECFIN Consumer survey - financial situation over last 12 months	Jan-85	Delta level
ECFIN Consumer survey - financial situation over next 12 months	Jan-85	Level
ECFIN Consumer survey - general economic situation over last 12 months	Jan-85	Level
ECFIN Consumer survey - general economic situation over next 12 months	Jan-85	Level
ECFIN Consumer survey - price trends over last 12 months	Jan-85	Level
ECFIN Consumer survey - price trends over next 12 months	Jan-85	Level
ECFIN Consumer survey - unemployment expectations over next 12 months	Jan-85	Level
ECFIN Consumer survey - major purchases at present	Jan-85	Level
ECFIN Consumer survey - major purchases over next 12 months	Jan-85	Level
ECFIN Consumer survey - savings over next 12 months	Jan-85	Level
ECFIN Consumer survey - statement on financial situation of household	Jan-85	Level
ECFIN Consumer survey - consumer confidence indicator	Jan-85	Level
ECFIN Construction survey - trend of activity compared with preceding months, Construction of buildings	Jan-93	Level
ECFIN Construction survey - trend of activity compared with preceding months, civil engineering	Jan-93	Level
ECFIN Construction survey - trend of activity compared with preceding months, specialised construction activities	Jan-96	Level
ECFIN Construction survey - trend of activity compared with preceding months, total	Jan-85	Level
ECFIN Construction survey - assessment of order books, construction of buildings	Jan-93	Level
ECFIN Construction survey - assessment of order books, civil engineering	Jan-91	Level
ECFIN Construction survey - assessment of order books, specialised construction activities	Jan-93	Level
ECFIN Construction survey - assessment of order books, total	Jan-85	Level
ECFIN Construction survey - employment expectations for the months ahead, construction of buildings	Jan-93	Level
ECFIN Construction survey - employment expectations for the months ahead, civil engineering	Jan-96	Level
ECFIN Construction survey - employment expectations for the months ahead, specialised construction activities	Jan-96	Level
ECFIN Construction survey - employment expectations for the months ahead, total	Jan-85	Level
ECFIN Construction survey - price expectations for the months ahead, construction of buildings	Jan-93	Level
ECFIN Construction survey - price expectations for the months ahead, civil engineering	Jan-96	Level
ECFIN Construction survey - price expectations for the months ahead, specialised construction activities	Jan-93	Level
ECFIN Construction survey - price expectations for the months ahead, total	Jan-85	Delta level
ECFIN Construction Survey - limits to production - none, total	Jan-85	Level
ECFIN Construction Survey - limits to production - insufficient demand, total	Jan-85	Delta level
ECFIN Construction Survey - limits to production - weather conditions, total	Jan-85	Level
ECFIN Construction Survey - limits to production - shortage of labour force, total	Jan-85	Level
ECFIN Construction Survey - limits to production - shortage of material and/or equipment, total	Jan-85	Level
ECFIN Construction Survey - limits to production - other factors, total	Jan-85	Level
ECFIN Construction Survey - limits to production - financial constraints, total	Jan-91	Delta level
ECFIN Construction survey - construction confidence indicator, construction of buildings	Jan-93	Level
ECFIN Construction survey - construction confidence indicator, civil engineering	Jan-96	Level

ECFIN Construction survey - construction confidence indicator, specialised construction activities	Jan-96	Level
ECFIN Construction survey - construction confidence indicator, total	Jan-85	Level
ECFIN Economic sentiment indicator	Jan-85	Level
ECFIN Industry survey - production trend observed in recent months, consumer goods	Jan-85	Level
ECFIN Industry survey - production trend observed in recent months, durable consumer goods	Jan-85	Level
ECFIN Industry survey - production trend observed in recent months, intermediate goods	Jan-85	Level
ECFIN Industry survey - production trend observed in recent months, capital goods	Jan-85	Level
ECFIN Industry survey - production trend observed in recent months, non-durable consumer goods	Jan-91	Level
ECFIN Industry survey - production trend observed in recent months, total	Jan-85	Level
ECFIN Industry survey - assessment of order-book levels, consumer goods	Jan-85	Level
ECFIN Industry survey - assessment of order-book levels, durable consumer goods	Jan-85	Level
ECFIN Industry survey - assessment of order-book levels, intermediate goods	Jan-85	Level
ECFIN Industry survey - assessment of order-book levels, capital goods	Jan-85	Level
ECFIN Industry survey - assessment of order-book levels, non-durable consumer goods	Jan-85	Level
ECFIN Industry survey - assessment of order-book levels, total	Jan-85	Level
ECFIN Industry survey - assessment of export order-book levels, consumer goods	Jan-85	Level
ECFIN Industry survey - assessment of export order-book levels, durable consumer goods	Jan-85	Level
ECFIN Industry survey - assessment of export order-book levels, intermediate goods	Jan-85	Level
ECFIN Industry survey - assessment of export order-book levels, capital goods	Jan-85	Level
ECFIN Industry survey - assessment of export order-book levels, non-durable consumer goods	Jan-91	Level
ECFIN Industry survey - assessment of export order-book levels, total	Jan-85	Level
ECFIN Industry survey - assessment of stocks of finished products, consumer goods	Jan-85	Level
ECFIN Industry survey - assessment of stocks of finished products, durable consumer goods	Jan-85	Level
ECFIN Industry survey - assessment of stocks of finished products, intermediate goods	Jan-85	Level
ECFIN Industry survey - assessment of stocks of finished products, capital goods	Jan-85	Level
ECFIN Industry survey - assessment of stocks of finished products, non-durable consumer goods	Jan-91	Level
ECFIN Industry survey - assessment of stocks of finished products, total	Jan-85	Level
ECFIN Industry survey - production expectations for the months ahead, consumer goods	Jan-85	Level
ECFIN Industry survey - production expectations for the months ahead, durable consumer goods	Jan-85	Level
ECFIN Industry survey - production expectations for the months ahead, intermediate goods	Jan-85	Level
ECFIN Industry survey - production expectations for the months ahead, capital goods	Jan-85	Level
ECFIN Industry survey - production expectations for the months ahead, non-durable consumer goods	Jan-91	Level
ECFIN Industry survey - production expectations for the months ahead, total	Jan-85	Level
ECFIN Industry survey - selling price expectations for the months ahead, consumer goods	Jan-85	Level
ECFIN Industry survey - selling price expectations for the months ahead, durable consumer goods	Jan-85	Level
ECFIN Industry survey - selling price expectations for the months ahead, intermediate goods	Jan-85	Level
ECFIN Industry survey - selling price expectations for the months ahead, capital goods	Jan-85	Level
ECFIN Industry survey - selling price expectations for the months ahead, non-durable consumer goods	Jan-91	Level
ECFIN Industry survey - selling price expectations for the months ahead, total	Jan-85	Level
ECFIN Industry survey - employment expectations for the months ahead, consumer goods	Jan-85	Level
ECFIN Industry survey - employment expectations for the months ahead, durable consumer goods	Oct-93	Level
ECFIN Industry survey - employment expectations for the months ahead, total	Jan-85	Level
ECFIN Industry survey - industrial confidence indicator, total	Jan-85	Level
ECFIN Retail trade survey - present business situation	Jan-85	Level
ECFIN Retail trade survey - assessment of stocks	Jan-85	Level
ECFIN Retail trade survey - orders placed with suppliers	Feb-85	Level
ECFIN Retail trade survey - expected business situation	Jan-85	Level
ECFIN Retail trade survey - employment expectations	Apr-85	Level
ECFIN Retail Trade Survey - selling price expectations for 3 months ahead	May-03	Level
ECFIN Retail trade survey - retail confidence indicator	Jan-85	Level
ECFIN Service survey - assessment of the business climate	Apr-95	Level
ECFIN Service survey - evolution of demand in recent months	Apr-95	Delta level
ECFIN Service survey - evolution of demand expected in the months ahead	Apr-95	Delta level
ECFIN Service survey - evolution of employment in recent months	Apr-95	Delta level
ECFIN Service survey - evolution of employment expected in the months ahead	Oct-96	Delta level
ECFIN Services survey - selling price expectations for 3 months ahead	Apr-03	Level
ECFIN Service survey - service confidence indicator	Apr-95	Level
Eurocoin, coincident indicator of business cycle	Jan-88	Level
ZEW Economic situation current	Jan-99	Level
ZEW Economic situation future (6 months)	Jan-99	Level
ZEW Inflation rate future (6 months)	Feb-99	Level
ZEW Short-term interest rate future (6 months)	Dec-91	Level
OECD Business tendency surveys (construction), Business situation - Activity, Tendency	Jan-85	Level
OECD Business tendency surveys (construction), Confidence indicators, Composite indicators	Jan-85	Level
OECD Business tendency surveys (construction), Employment, Future tendency	Jan-85	Level
OECD Business tendency surveys (construction), Order books, Level	Jan-85	Level
OECD Business tendency surveys (construction), Selling prices, Future tendency	Jan-85	Delta level
OECD Business tendency surveys (retail trade), Business situation - Activity, Future tendency	Jan-85	Level
OECD Business tendency surveys (retail trade), Business situation - Activity, Tendency	Jan-85	Level
OECD Business tendency surveys (retail trade), Confidence indicators, Composite indicators	Jan-85	Level
OECD Business tendency surveys (retail trade), Employment, Future tendency	Apr-85	Level
OECD Business tendency surveys (retail trade), Order intentions or Demand, Future tendency	Feb-85	Level
OECD Business tendency surveys (retail trade), Volume of stocks, Level	Jan-85	Level
OECD Business tendency surveys (manufacturing), Confidence indicators, Composite indicators	Jan-85	Level
OECD Business tendency surveys (manufacturing), Employment, Future Tendency	Jan-85	Level

OECD Business tendency surveys (manufacturing), Finished goods stocks, Level	Jan-85	Level
OECD Business tendency surveys (manufacturing), Order books, Level	Jan-85	Level
OECD Business tendency surveys (manufacturing), Production, Future Tendency	Jan-85	Level
OECD Business tendency surveys (manufacturing), Production, Tendency	Jan-85	Level
OECD Business tendency surveys (manufacturing), Selling prices, Future tendency	Jan-85	Level
OECD Business tendency surveys (manufacturing), Export order books or demand, Level	Jan-85	Level
OECD Business tendency surveys (services), Business situation - Activity, Tendency, Future tendency	Apr-95	Level
OECD Business tendency surveys (services), Confidence Indicators, Composite Indicators	Apr-95	Level
OECD Business tendency surveys (services), Demand evolution, Future tendency	Apr-95	Delta level
OECD Business tendency surveys (services), Demand evolution, Tendency	Apr-95	Delta level
OECD Business tendency surveys (services), Employment, Future tendency	Oct-96	Delta level
OECD Business tendency surveys (services), Employment, Tendency	Apr-95	Delta level
OECD Consumer opinion surveys, Confidence indicators, Composite indicators	Jan-80	Level
OECD Consumer opinion surveys, Economic Situation, Future tendency	Jan-85	Level
OECD Consumer opinion surveys, Consumer prices (inflation), Future tendency	Jan-85	Level
Coincident and leading indicators		
OECD Leading Indicator, CLI, amplitude adjusted	Jan-80	Level
The Conference Board Coincident Economic Index (CEI)	Jan-87	Delta log
The Conference Board Leading Economic Index (LEI)	Jan-87	Delta log
ECB Growth cycle indicator (GCI, see de Bondt and Hahn, 2014)	Jan-80	Level
ECB Euro area-wide leading indicator (ALI, see de Bondt and Hahn, 2014)	Jan-80	Level
Exchange rates		
US dollar/Euro spot rate	Jan-99	Delta log
Euro area-19 countries vis-a-vis the EER-19 group of trading partners	Jan-93	Delta log
Euro area-19 countries vis-a-vis the EER-18 group of trading partners	Jan-93	Delta log
Euro area-19 countries vis-a-vis the EER-38 group of trading partners	Jan-93	Delta log
Euro area-19 countries vis-a-vis the EER-12 group of trading partners	Sep-81	Delta log
Euro area-19 countries vis-a-vis the REER-19 group of trading partners, CPI deflated	Jan-93	Delta log
Euro area-19 countries vis-a-vis the REER-18 group of trading partners, CPI deflated	Jan-93	Delta log
Euro area-19 countries vis-a-vis the REER-38 group of trading partners, CPI deflated	Jan-93	Delta log
Euro area-19 countries vis-a-vis the REER-12 group of trading partners, CPI deflated	Jan-93	Delta log
Euro area-19 countries vis-a-vis the REER-19 group of trading partners, PPI deflated	Jan-95	Delta log
Euro area-19 countries vis-a-vis the REER-18 group of trading partners, PPI deflated	Jan-95	Delta log
Euro area-19 countries vis-a-vis the REER-12 group of trading partners, PPI deflated	Jan-93	Delta log
Financial markets		
Euro 1-year Inflation Linked Interest Rate Swap	Mar-05	Delta level
Euro 2-year Inflation Linked Interest Rate Swap	Mar-05	Delta level
Euro 3-year Inflation Linked Interest Rate Swap	Mar-05	Delta level
Euro 4-year Inflation Linked Interest Rate Swap	Mar-05	Delta level
Euro 5-year Inflation Linked Interest Rate Swap	Mar-05	Delta level
Euro 6-year Inflation Linked Interest Rate Swap	Mar-05	Delta level
Euro 7-year Inflation Linked Interest Rate Swap	Mar-05	Delta level
Euro 8-year Inflation Linked Interest Rate Swap	Mar-05	Delta level
Euro 9-year Inflation Linked Interest Rate Swap	Mar-05	Delta level
Euro 10-year Inflation Linked Interest Rate Swap	Mar-05	Delta level
Citigroup Economic Surprise Index, Eurozone	Jan-03	Level
Excess bond premium, non-financial	Jan-99	Delta level
Excess bond premium, financial	Jan-99	Delta level
Euro area 2-year Government Benchmark bond yield	Jan-99	Delta level
Euro area 3-year Government Benchmark bond yield	Jan-99	Delta level
Euro area 5-year Government Benchmark bond yield	Jan-99	Delta level
Euro area 7-year Government Benchmark bond yield	Jan-99	Delta level
Euro area 10-year Government Benchmark bond yield	Jan-99	Delta level
Euro area 10-year Government Benchmark bond yield, GDP weighted	Jan-99	Delta level
Euro area 30-year Government Benchmark bond yield	Jan-99	Delta level
Composite Indicator of Sovereign Stress (SovCISS)	Sep-00	Delta log
Sovereign spread DE-IT	Feb-94	Delta level
Slope of the bond yield curve, 10-year gov. benchmark bond yield minus 3-month Euribor	Jan-99	Delta level
Euribor 1-month	Dec-98	Delta level
Euribor 1-year	Dec-98	Delta level
Euribor 2-month	Dec-98	Delta level
Euribor 2-week	Oct-01	Delta level
Euribor 3-month	Dec-98	Delta level
Euribor 6-month	Dec-98	Delta level
Euribor 9-month	Dec-98	Delta level
Euribor Spot week	Dec-98	Delta level
Eonia	Jan-99	Delta level
Eurex Generic 1st `RX` Future - Implied bond volatility	Jun-93	Delta log
European Monetary Union Corporate Non-financial A, Merrill Lynch Bond Index	Jan-96	Delta level
European Monetary Union Corporate Non-financial AA, Merrill Lynch Bond Index	Jan-96	Delta level
European Monetary Union Corporate Non-financial AAA, Merrill Lynch Bond Index	Jan-96	Delta level
European Monetary Union Corporate Non-financial BBB, Merrill Lynch Bond Index	Jan-96	Delta level
European Monetary Union Corporate Financial A, Merrill Lynch Bond Index	Jan-96	Delta level
European Monetary Union Corporate Financial AA, Merrill Lynch Bond Index	Jan-96	Delta level
European Monetary Union Corporate Financial AAA, Merrill Lynch Bond Index	Jan-96	Delta level

European Monetary Union Corporate Financial BBB, Merrill Lynch Bond Index	Jan-96	Delta level
VSTOXX volatility index	Feb-00	Delta log
Financial market liquidity indicator, composite indicator	Jan-99	Delta level
Stock market index, Germany	Jan-80	Delta log
Stock market index, Spain	Jan-87	Delta log
Stock market index, France	Jul-87	Delta log
Stock market index, Italy	Jan-98	Delta log
Interest rates on new loans to non-financial corporations	Jan-80	Delta level
Interest rates on new loans to households for house purchase	Jan-80	Delta level
Interest rates on new loans to households for consumption	Jan-80	Delta level
Interest rate on Loans to non-financial corporations up to an amount of EUR 1 million	Jan-80	Delta level
Interest rate on loans to non-financial corporations over an amount of EUR 1 million	Jan-80	Delta level
Overnight deposits rate, non-financial corporations	Jan-80	Delta level
Overnight deposits rate, households and non-profit institutions serving households	Jan-80	Delta level
Deposits from households with agreed maturity up to 2 years	Jan-80	Delta level
Deposits from non-financial corporations with agreed maturity up to 2 years	Jan-80	Delta level
Deposits from households redeemable at notice up to 3 months	Jan-80	Delta level
Producer price indices		
Total (excl. construction)	Jan-91	Delta log
Total (excl. construction and MIG energy)	Jan-91	Delta log
MIG Intermediate Goods Industry - NACE Rev2	Jan-91	Delta log
MIG Capital Goods Industry - NACE Rev2	Jan-91	Delta log
MIG Durable Consumer Goods Industry - NACE Rev2	Jan-91	Delta log
MIG Non-durable Consumer Goods Industry - NACE Rev2	Jan-85	Delta log
Consumer goods industry - NACE Rev2	Jan-91	Delta log
Construction input prices	Jan-93	Delta log
Construction costs, labour costs	Jan-00	Delta log
Construction costs, material prices	Jan-90	Delta log
Commodity prices		
Brent crude oil 1-month forward, fob (free on board) per barrel	May-85	Delta log
Gold price	Jan-80	Delta log
ECB Commodity Price index, import weighted, food	Jan-96	Delta log
ECB Commodity Price index, import weighted, non-food	Jan-96	Delta log
ECB Commodity Price index, import weighted, total non-energy commodity	Jan-96	Delta log
ECB Commodity Price index, use-weighted, food	Jan-96	Delta log
ECB Commodity Price index, use-weighted, non-food	Jan-96	Delta log
ECB Commodity Price index, use-weighted, total non-energy commodity	Jan-96	Delta log
Farm-gate and wholesale market prices in euro	Dec-96	Delta log
World market prices of raw materials, index total	Apr-96	Delta log
World market prices of raw materials, index total excluding energy	Apr-96	Delta log
World market prices of raw materials, food and tropical beverages	Apr-96	Delta log
World market prices of raw materials, cereals	Apr-96	Delta log
World market prices of raw materials, oilseeds and oil	Apr-96	Delta log
World market prices of raw materials, beverages, sugar and tobacco	Apr-96	Delta log
World market prices of raw materials, industrial raw materials	Apr-96	Delta log
World market prices of raw materials, agricultural raw materials	Apr-96	Delta log
World market prices of raw materials, spinning material	Apr-96	Delta log
World market prices of raw materials, wood pulp, NBSK pulp	Apr-96	Delta log
World market prices of raw materials, non-ferrous metals	Apr-96	Delta log
World market prices of raw materials, iron ore, scrap	Apr-96	Delta log
World market prices of raw materials, energy	Apr-96	Delta log
World market prices of raw materials, coal	Apr-96	Delta log
World market prices of raw materials, crude oil	Apr-96	Delta log
Baltic DRY Index (BDI) - Historical close	Jan-85	Delta log
Import prices		
Import prices, manufacturing	Jan-04	Delta log
Import prices, total industry (excluding construction)	Jan-05	Delta log
Import prices, total industry excluding construction and MIG energy	Jan-04	Delta log
Import prices, MIG intermediate goods industry	Jan-05	Delta log
Import prices, MIG capital goods industry	Jan-00	Delta log
Import prices, MIG durable consumer goods industry	Jan-00	Delta log
Import prices, MIG non-durable consumer goods industry	Jan-05	Delta log
Import prices, consumer goods industry	Jan-05	Delta log
Import prices, consumer goods industry excluding food and tobacco	Jan-05	Delta log
Import prices, MIG energy	Jan-05	Delta log
Import prices, manufacturing	Jan-04	Delta log
Import prices, total industry (excluding construction)	Jan-05	Delta log
Import prices, total industry excluding construction and MIG energy	Jan-04	Delta log
Other variables		
Expected default frequency within one year, non-financial corporations	Jan-92	Delta level
Expected default frequency within one year, financial institutions	Jan-92	Delta level
United States, M1	Jan-80	Delta log
United States, M2	Jan-80	Delta log
United States, Treasury bill rate	Jan-80	Delta level
United States, 10-year government bond yield	Jan-80	Delta level

United States, 3-year government bond yield	Jan-80	Delta level
United States, CPI	Jan-80	Delta log
United States, industrial production	Jan-80	Delta log
United States, employment	Jan-80	Delta log
Standard and Poor's 500 Composite Index	Jan-80	Delta log
Chicago Board Of Exchange (CBOE) SPX Volatility VIX	Oct-93	Delta log
US dollar, United States Corporate A, Merrill Lynch Bond Index	Dec-88	Delta level
US dollar, United States Corporate AA, Merrill Lynch Bond Index	Dec-88	Delta level
US dollar, United States Corporate AAA, Merrill Lynch Bond Index	Dec-88	Delta level
US dollar, United States Corporate BBB, Merrill Lynch Bond Index	Dec-88	Delta level
US dollar, United States Corporate Financial A Merrill Lynch Bond Index	Dec-04	Delta level
US dollar, United States Corporate Financial AA Merrill Lynch Bond Index	Dec-04	Delta level
US dollar, United States Corporate Financial AAA Merrill Lynch Bond Index	Dec-04	Delta level
US dollar, United States Corporate Financial BBB Merrill Lynch Bond Index	Dec-04	Delta level
US dollar, United States Treasury 7-10-year, Merrill Lynch Bond Index	Nov-87	Delta level
Markit Composite - output, US	Jul-97	Level
Markit Composite - output, extra euro area	Jul-98	Level
MarkitManufacturing - purchasing manager index, US	Jan-80	Level
MarkitManufacturing - purchasing manager index, extra euro area	Jan-98	Level
Citigroup Economic Surprise Index, United States	Jan-03	Level

Notes: The variables reported in the table refer to the euro area unless specified otherwise.

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