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Inflation forecasting and the crisis: assessing the impact on the performance of different forecasting models and methods

Christian Buelens[*]

Abstract: This paper analyses how the accuracy of euro area inflation forecasting models has been affected by the financial and economic crisis. Its first objective is to compare the precision of three representative groups of inflation forecasting models (*rules of thumb and benchmark models; autoregressive moving average models; autoregressive distributed lag models)* under a direct and an indirect approach, respectively. Under the former, the forecasting models contain headline inflation as their dependent variable; under the latter, individual forecasts are generated in a first step for each of the main HICP components, and subsequently aggregated to obtain an indirect forecast of headline inflation. The second objective is to study how the absolute and relative forecasting performances of the models and approaches have been impacted by the economic and financial crisis.

The paper finds that direct forecasting models selected on the basis of a penalty function generally dominate simple rules of thumb and econometric benchmark models. The analysis furthermore suggests that when an appropriate specification for the component-specific models is found, indirect forecasts outperform the corresponding direct forecasts. Nonetheless, in line with the findings from earlier studies, there are insufficient elements to assert a systematic superiority of one of the two approaches. Concerning the second objective, the across-the-board rise in the forecast errors of all models considered, confirms that inflation forecasting has become substantially more difficult after the onset of the crisis. However, the deterioration of the different models has been uneven. Relative to simple econometric models and rules of thumb, the performance of direct autoregressive distributed lag models and of the indirect approach has improved during the crisis.

Keywords: HICP, inflation, forecasting, aggregation, model selection, model evaluation, inflation targeting

JEL Codes: C32, C52, C53, E31, E37, E58

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1. Introduction

Economic agents base many current decisions *inter alia* on their expectation of the future inflation pattern. The views held about future inflation may influence firms' price-setting behaviour or workers' wage-demands, and thereby impact current purchasing power and labour costs; through its effect on the real interest rate and on inflation risk *premia*, the expected inflation rate furthermore influences savings and investment decisions. Inflation forecasts and projections are also often at the heart of economic policy decision-making, as is the case for monetary policy, which in most industrialised economies is mandated to maintain price stability over the medium term. Decision-makers hence need to have a view on the likely future path of inflation when taking measures that are necessary to reach their objective. Yet, while being indispensable to many decision-making agents, forming inflation expectations is generally both complex and costly: indeed, inflation forecasting requires an understanding of economic relationships, econometric modelling tools, access to data and other information.

The first objective of this paper is to assess the forecasting performance of direct and indirect euro area inflation forecasting models. While direct inflation forecasting models contain headline inflation as their dependent variable, indirect forecasts are obtained by aggregating component-specific forecasts, weighted by their share in the Harmonised Index of Consumer Prices (HICP).[1] The models considered in the paper are taken from three different model groups (rules of thumb and benchmark models; autoregressive moving average models; autoregressive distributed lag models), which vary in terms of selection procedure and information included. As such, they are simple but representative illustrations of the more sophisticated models used by forecasters in practice.

The first group of models comprises "low-cost" numerical and econometric benchmark models. As concerns headline inflation, simple numerical benchmarks ("rules of thumb") may in fact offer an alternative to more complex forecasting techniques, and can be adopted by any economic agent at little cost. For example, the prevailing inflation rate or the central bank's inflation target may be used as potential forecasts. Simple econometric models, which are "imposed" on the data, without following a particular selection procedure, are another rapid and inexpensive way of forecasting inflation. Typically, however, forecasters also rely on econometric models that are more complex and not as readily available. The second group of models considered in this paper, consists of autoregressive moving average (ARMA) models picked on the basis of a penalty function (information criterion). For the third group of autoregressive distributed lag (ADL) models, the information set is extended to potential exogenous predictors of inflation.

In a first step the models are applied to headline inflation to generate direct forecasts. All models are subsequently applied separately to the five components to obtain the indirect inflation forecasts. This method requires the specification and selection of one model per component, thus adding a number of intermediate steps, which are not required in the direct approach. While the advantages of indirect relative to direct forecasts are ambiguous from a theoretical point of view (cf. section 2), indirect forecasts are attractive in practice, as they can

[1] The five main components of headline inflation are energy, processed food, unprocessed food, non-energy industrial goods and services. While this breakdown is standard, some authors (e.g. Bermingham and D'Agostino (2010)) also study lower levels of disaggregation.

be associated to more detailed narratives and economic arguments, and avoid inconsistencies between headline inflation and component-specific forecasts.[2]

The paper's second objective is to assess the impact of the large swings in commodity prices observed since 2007, and of the economic and financial crisis, on inflation forecasting. As noted below, it emerges from the literature on inflation forecasting that the performance of a model depends *inter alia* on the estimation and evaluation period. At the current juncture, it is thus particularly interesting to assess to what extent the financial and economic crisis, which itself was preceded by a shock in global food and commodity prices, has impacted the performance of different models and approaches in both absolute and relative terms. Substantial forecast revisions by international institutions and professional forecasters suggest that the traditional approaches have indeed been seriously challenged (table A.1 in the annex illustrates this by way of example, showing different vintages of inflation forecasts made from 2006 onwards for the years 2008 and 2009). The impact of the crisis on the relative performance of different inflation forecasting models and methods is studied by repeating the comparative evaluation for two different sample periods ending before and after the onset of the crisis, respectively.

The remainder of the paper is organised as follows: after a brief review of the literature in the next section, section 3 presents the pattern of euro area inflation developments since 1996. Section 4 introduces the benchmark models considered, as well as the algorithms that are used to select autoregressive and ADL-models. The evaluation of the different models in terms of their forecast accuracy during the crisis is presented in section 5. Section 6 presents the comparative assessment for the pre-crisis period, essentially showing how the conclusions from section 5 would have been different, if the comparison had been performed three years earlier. Section 7 concludes.

2. Literature review

Over the past two decades many central banks around the world have adopted inflation targeting frameworks. Their central feature is a publicly announced quantitative inflation target, typically expressed as a single number or a range, to be met over the medium term (Bernanke and Mishkin, 1997; Hammond, 2011). The main objective of a pre-announced target-level is to anchor inflation expectations and notably to prevent second-round effects in the event of a transitory shock. If credible, it may thus contribute to keeping inflation stable and low. An inflation target also provides a measure by which a central bank's performance can be judged *ex post* by the public: the closer the observed inflation rate and the inflation target are to each other, the better the central bank's track record, and the more compelling is the incentive to trust the central bank as regards the future, by using the target as a forecast *ex ante*.[3] Inflation forecasts represent a key element in an inflation targeting framework. As noted by Svensson (1997), a central bank's control over inflation is imperfect and missing the target may be the consequence of factors outside its command. That said, a central bank

[2] It is also noteworthy that many published forecasts of headline inflation are based on an indirect approach; this is the case notably for the Eurosystem staff's inflation projection exercise and for European Commission forecasts.

[3] The incentive is likely to be even greater, if it can be shown that the inflation target has also outperformed competing alternatives in the past, and adopting the inflation target as an own forecast would consequently have constituted the optimal strategy *ex ante*.

pursuing an explicit inflation target would still set its monetary policy instrument in such a way that its inflation forecast would coincide with the official inflation target; inflation forecasts, which are more controllable than the inflation rate itself, hence become an implicit intermediate target, and as such also shift into the focus of public scrutiny.

In the euro area, the Treaty assigns to monetary policy the primary objective of maintaining price stability. While the European Central Bank (ECB) did not adopt an inflation targeting framework as such, its Governing Council nonetheless provided a quantification of price stability, defined as an annual increase in the HICP below, but close to 2% over the medium term for the euro area as a whole (ECB, 2003). It hence set a reference value, serving concurrently as a yardstick for the assessment of the ECB's past performance, and as a point of orientation for inflation in the future. Diron and Mojon (2005) compare the forecast performance of inflation targets of the euro area and seven inflation targeting countries, to model-based and published inflation forecasts respectively. They find that the central banks' targets generally match or outperform the alternatives considered, and conclude that there are substantial benefits in adopting the stated target as a forecast, in particular over longer horizons.

A number of authors have shown that simple inflation forecasting models have often performed well with respect to more elaborated ones. Fritzer et al. (2002) find that for Austrian inflation, univariate (ARIMA) forecast models outperform multivariate (VAR) models at short horizons; the opposite is however true at more distant horizons (8 to 12 months). Considering a set of univariate and multivariate euro area inflation forecasting models, Hubrich (2005) testifies the good overall performance of the autoregressive model, which even turns out to be the most accurate model at a 12-month forecast horizon. For the US, Stock and Watson (1999) also note the "surprisingly" strong performance of autoregressions and random walk models. Also for the US, Atkeson and Ohanian (2001) evaluate the accuracy of Phillips curve-based inflation forecasting models based on the non-accelerating inflation rate of unemployment. They find that none of three sets of inflation forecasts considered (forecasts published by the Federal Reserve Board, as well as two model-based forecasts), succeeds in systematically outperforming the random walk model used by them as benchmark.

While most economic agents' and observers' ultimate interest in inflation centres on the headline rate, the question whether it should be forecasted directly ('top-down') or indirectly ('bottom-up'), has received a lot of attention among forecasters.[4] Hubrich (2005) reviews theoretical considerations behind the two approaches, noting that the "results from asymptotic theory and small sample simulations do not give a clear answer regarding [their] relative forecast accuracy" (p.122). In the absence of clear theoretical guidance, the judgement thus essentially becomes an empirical one. A number of authors have empirically assessed the relative forecast performance of direct and indirect approaches to forecasting. Overall, their findings do not allow systematically favouring one method over the other, let alone discarding one. Indeed, the findings seem to be sensitive, *inter alia*, to the geographical entity, the types of models considered, the forecast horizon, the data frequency and the transformation of the price index series, as well as the periods chosen for model selection and evaluation. Fritzer et al. (2002) construct two series for Austrian headline inflation by aggregating component-specific inflation forecasts generated by ARIMA and by VAR models, respectively. In the ARIMA case, the indirect approach generally beats the corresponding direct ARIMA

[4] Another indirect way of forecasting, not considered here, would be to forecast individual Member States' series and to aggregate them to obtain a euro area forecast series (see Benalal et al. (2004)).

forecasts. In the VAR case, however, the indirect approach becomes only slightly superior at distant horizons. Moser et al. (2004) find that indirect forecasts for Austrian inflation appear to be somewhat more precise than the best direct inflation forecast considered; their model competition is based on ARIMA, VAR and factor models. Den Reijer and Vlaar (2006), considering AR, VAR and VECM models, find that for the Netherlands the indirect approach is only superior at closer forecasting horizons (up to 7 months). For the euro area, they find that the indirect approach outperforms the direct approach on all forecast horizons evaluated (18 months). Meanwhile, Benalal et al. (2004), considering both univariate and multivariate (VAR, Bayesian VAR and single equation) models, find that for the euro area (as well as for Germany, France, Italy and Spain) the direct HICP forecasts improve upon indirect forecasts for horizons beyond 12 months. For closer horizons their results are however less evident. Hubrich (2005) finds that the indirect approach primes for forecasts of euro area inflation one-month ahead, but that it does not generally improve upon direct forecasts at forecast horizons of 6- or 12-months, which are more relevant from a policy point of view. In a more recent study, Bermingham and D'Agostino (2010) find that aggregating forecasts of inflation components (at different levels of disaggregation) yields more accurate forecast than direct forecasting for both the euro area and US inflation. However, they stress the necessity of specifying an appropriate model for each individual component first.

3. Euro area inflation between 1996 and 2010

3.1 ANNUAL INFLATION PATTERNS

This section provides a brief description of euro area (16 Member States) inflation developments between 1996:01 and 2010:12.[5] Figure A.1 in the annex displays the price level index (in logarithmic transformation), as well as monthly and annual changes respectively for all series. Annual headline inflation, measured by year-on-year changes in the overall harmonised index of consumer prices (HICP), has averaged around 1.9% over the sample period. It steadily declined from 1997 until the introduction of the euro in 1999. It then rebounded and remained broadly stable between the early 2000's and mid-2007, hovering in a range of 1.6% to 3.1%. In the following period and until the end of the sample, inflation was characterised by large swings: it climbed to 4.0% in July 2008, plunged to -0.6% one year later and progressively returned to around 2% by the end of the sample period. These swings were primarily the result of the patterns of global commodity prices, which impacted directly on food and energy inflation in the euro area during that period, and coincided with the "great recession" period triggered by the financial crisis that started in mid-2007 and intensified after the failure of Lehman Brothers in September 2008.

A notable feature of annual euro area inflation developments is that price indices in the different categories have on average grown at a very different speed in the period considered (see table 1). The non-energy industrial goods component, which on average has accounted for almost one third of the consumer basket, is the only category for which prices have grown at an average pace below 2% a year (0.8%). Low inflation in this category most likely reflects the strong external competitive pressures that exist for many manufactured products, as well as quality improvements in the product items covered. At the other extreme, with an average of 4.0% a year, energy prices have grown fastest over the period considered, followed by

[5] The HICP indices are published by Eurostat.

processed food (2.4%) and services (2.2%). Energy inflation has also been the most volatile, with year-on-year rates falling into a 31 percentage point-range, from a high of 17.0% (July 2008) to a low of -14.2% (July 2009). Unprocessed, and to a lesser extent processed food inflation, also oscillated considerably. Annual inflation of services and non-energy industrial goods respectively has evolved in a smoother way, thus lessening the volatility of overall inflation. Services and processed food are the only components which never experienced negative annual price growth, having fallen to respective minima of 1.2% and 0.4%. It is also confirmed that inflation in the core categories – non-energy industrial goods, services and to a lesser extent processed food – generally fluctuates less and within narrower bands. Finally, it is noteworthy that for most components the extreme values in annual inflation occurred after 2007.

Table 1: Descriptive statistics of euro area inflation (1996:01-2010:12)[6]

	Annual inflation (%)					
	cp00	enrgy	foodproc	foodunp	igoodsxe	serv
Mean	1.93	4.03	2.37	2.14	0.76	2.23
Median	2.01	3.33	1.96	1.98	0.76	2.35
Maximum	4.06	17.01	7.20	8.93	1.78	3.35
Minimum	-0.65	-14.25	0.35	-1.65	-0.12	1.18
Range	4.70	31.26	6.85	10.57	1.90	2.17
Std Dev	0.77	6.44	1.46	2.18	0.35	0.52
	Monthly inflation (%)					
	cp00	enrgy	foodproc	foodunp	igoodsxe	serv
Mean	0.16	0.34	0.19	0.18	0.08	0.18
Median	0.18	0.30	0.13	0.16	0.13	0.14
Maximum	1.11	4.10	1.18	3.47	2.48	1.14
Minimum	-0.83	-4.90	-0.12	-1.59	-3.14	-0.75
Range	1.94	8.99	1.31	5.06	5.62	1.89
Std Dev	0.29	1.44	0.22	0.73	0.89	0.37

Source: own calculations based on Eurostat

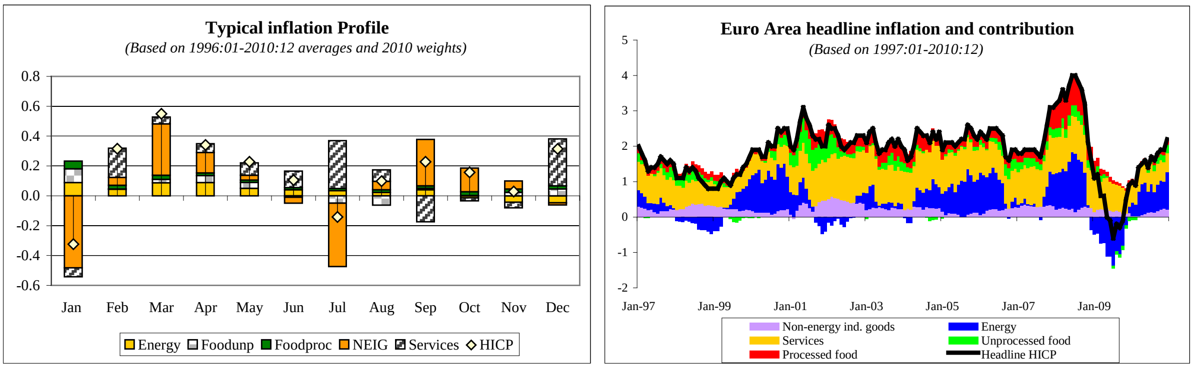
3.2 INTRA-YEAR VARIATION OF INFLATION

Some of the inflation series, in particular non-energy industrial goods and services, display clear seasonal patterns, which shape the profile of monthly headline inflation in proportion to their weight in the HICP. The additional presence of seasonal trends in some of the series also generates a seasonal pattern in annual inflation.

Figure 1 below (left panel) shows the average monthly profile for overall inflation over the sample period (applying the 2010 weights). Monthly headline HICP inflation is positive in most months (+0.16% on average). Notable exceptions are the sales months January and July, when prices have declined on average by 0.32% and 0.14% percent, respectively. Both drops in the price level offset increases of a similar magnitude in the preceding months, i.e. December (+0.31%) and June (+0.10%), respectively. About two thirds of the annual price increases occur in the first half of the year, with March (+0.54%), April (+0.34%) and February (+0.31%) typically being the months with the strongest price increases.

[6] Note that one observation is lost compute monthly inflation and 12 are lost to compute annual inflation.

Figure 1: Breakdown of intra-year inflation profile and contributions to annual inflation



Source: own calculations based on Eurostat

The seasonal plots of monthly inflation for the five components (figure A.2 in the annex) provide additional insights regarding intra-year variation. A seasonal profile is only hardly discernible for energy inflation. Processed food prices typically make a jump in January, which is likely to reflect the scarcity (or unavailability) at that time of the year of certain items included in the index. However, intra-year variation is very low otherwise. In contrast, unprocessed food displays a very pronounced seasonal pattern. Similar to processed food, prices for unprocessed food make a distinctive leap in January, but decline from June to August. The high volatility of monthly inflation can also result from disruptions such as weather-related uncertainties of crop production or animal and vegetal diseases. Non-energy industrial goods prices exhibit the most pronounced seasonal profile, with significant price drops in the sales months January and July. Two interesting developments are worth pointing out: first, monthly price decreases in January and July have become larger over time, while, secondly, the price increases which have followed in March, and in September and October, respectively, have accelerated over the years. This suggests that summer and winter sales may have become more aggressive over time, with firms offering increasingly large discounts, while the following rebound in prices has also become stronger. Services inflation also displays a quite marked intra-year variation, *inter alia* determined by holiday periods.

4. Model selection strategy

This section sets out the detailed strategies that are followed to select the models, which will ultimately be evaluated on the basis of their forecast precision. The first sub-section (4.1) introduces the benchmark models; the ARMA and ADL-model selection algorithms are presented in sub-sections 4.2 and 4.3, respectively. All model selection procedures are applied to the headline inflation series for the specification of direct inflation forecasting models. Separately, they are applied to each of the five inflation component series to specify the component-specific models which are the basis of the indirect inflation forecasts.

4.1 RULES OF THUMB AND ECONOMETRIC BENCHMARK MODELS

To obtain a yardstick for judging the forecasting accuracy of candidate models, a group of six benchmark models is considered. It contains four econometric models, including three autoregressive models - AR (1), ARMA (1,1) and AR (12) – and a seasonal average model, setting monthly inflation in a particular month equal to the average inflation observed in that month in the past. For headline inflation, two additional "rules of thumb" are considered: the first is the ECB's definition of price stability, discussed in the survey. For the purpose of this paper, and following Diron and Mojon (2005), the ECB's inflation objective is defined as an annual inflation rate of 1.9% (denoted "ECB-target" in the following). Since the objective of price stability applies to the medium-term, the target should be expected to improve relative to other models as the length of the forecast horizon increases. Target misses at close forecast horizons should accordingly not be ascribed to central bank decisions, as monetary policy has no corrective impact on inflation in the very short-run. The second rule of thumb ("naïve" model) simply corresponds to the year-on-year inflation rate prevailing at the moment the forecast is made; it hence does not take account of temporary factors that may explain the current inflation rate. Nevertheless, the "model" is easy to implement, as it only requires knowledge of current inflation, and also recognises that the last available observation generally constitutes a natural starting point and orientation for any forecast. The naïve approach could even be expected to perform reasonably well at short horizons when there is inflation persistence or at more distant ones when the last available inflation rate is already close to target.

4.2 ARMA-MODEL SELECTION ALGORITHM

Autoregressive forecasting models rely on identifying the data-generating process (DGP) underlying the inflation series. This "essentially agnostic" (Meyler et al. (1998)) way of forecasting is purely mechanical rather than fundamentals-based, and can therefore in some ways be criticised as simplistic. Nonetheless, univariate models have often been found to perform well in short-run inflation-forecasting (see survey), and have the practical advantage that data requirements are limited to the series of interest.

The atheoretical nature of univariate models leaves many liberties when specifying a forecast model. This, however, risks making the selection somewhat arbitrary and non-transparent. Applying a Box-Jenkins model-selection approach could indeed lead to find models with a higher (in-sample and out-of-sample) fit, but would also introduce a large scope of discretion, resulting in different models depending on the individual forecaster (see Meyler et al. (1998) for a discussion). For that reason, it is proposed to pick the models retained for the evaluation stage through an automated selection procedure based on objective selection (information) criteria (cf. Meyler et al. (1998), and Hubrich (2005)). Information criteria essentially differ in the severity by which they sanction the inclusion of additional parameters in a model, relative to its fit. Of the two mainly used criteria – Schwarz (SIC) and Akaike (AIC) – the SIC generally leads to more parsimonious lag orders, while the AIC tends to overfit a model by putting a lower penalty on additional parameters than the SIC (for a discussion see Lütkepohl and Krätzig (2004)). In this paper, a large set of autoregressive models are estimated. Those with the lowest AIC and the lowest SIC, respectively, are retained and carried forward to the out-of-sample simulation exercise.

The order of an autoregressive integrated moving average (ARIMA) process is expressed as (p, d, q)[7], where *p* refers to the number of lags of the dependent variable and *q* to the number of moving average (MA) terms, and *d* is the order of integration of the original series. While *p* and *q* will be determined by the minimum value of the information criterion, the differencing decision is made on the basis of a separate stationarity analysis. The latter, presented in annex 2, has suggested using either the first-differenced series (i.e. monthly inflation)[8] or seasonal

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[7] Seasonal lags and MA terms are not considered here.

[8] The unit root hypothesis is rejected for all first-differenced series by the Philips-Perron test. The ADF-test leads

differences of first-differenced series, for all series. For the present exercise, the first-differenced log series (monthly inflation) is used, i.e. d=1; this is also in line with other authors (e.g. Hubrich, 2005). Since monthly inflation now is the series of interest, the notation ARMA (p, q) will be used in the following.

Four ARMA-specifications are considered. The first sample observation in first-differenced form is 1996:02 and 12 pre-sample observations have to be set aside to allow for a maximum of 12 lags, while ensuring an equal number of observations across all estimations. The models are hence estimated over the samples 1997:02-2010:12 (including the crisis) and 1997:02-2007:12 (pre-crisis), respectively. The basic ARMA specification is given by

(U.1) $A(L)\mu_t = c + B(L)\varepsilon_t$,

where $A(L) = 1 - \alpha_1 L - \cdots - \alpha_p L^p$ and $B(L) = 1 - \beta_1 L - \cdots - \beta_q L^q$, with $p^{\max} = 11$ and $q^{\max} = 11$, and μ_t is the first difference of the log price index series under consideration (i.e. monthly inflation). *L* is the lag-operator. The selection procedure considers only full sets of adjacent lags (i.e. including all lags up to the maximum). Determining *p* and *q* requires the estimation of 144 (*(p+1)*(q+1)*) models for a given selection criterion. Note that pure AR (i.e. q=0) and pure MA (i.e. p=0) models are special cases that are considered under this selection procedure. The second specification, which is obtained by augmenting specification (U.1) by a full set of seasonal dummies (SD)[9], is likely to be particularly relevant for series exhibiting a distinct intra-year pattern. It is expressed as:

(U.2) $A(L)\mu_t = c + \sum_1^{11} \delta_d SD_d + B(L)\varepsilon_t$

As inflation in a particular month may be affected by monthly inflation one year earlier and may be driven by seasonal regularities, specification (U.1) is augmented by the twelfth lag of monthly inflation, becoming

(U.3) $A^{12}(L)\mu_t = c + B(L)\varepsilon_t$,

where $A^{12}(L) = 1 - \alpha_1 L - \cdots - \alpha_p L^p - \alpha_{12} L^{12}$, with $p^{\max} = 11$, and *B(L)* is defined as above. The twelfth lag of the dependent variable is thus explicitly introduced in the regressions, while the choice of p and q is again left to the information criterion. This ARMA "with a hole" is a special case of a (12, q) process, possibly with some intermediate lag coefficients set to zero. A pure AR (12) process is thus also part of the specifications considered. In analogy with specification (U.1), (U.3) is augmented by seasonal dummies, yielding the following specification:

(U.4) $A^{12}(L)\mu_t = c + \sum_1^{11} \delta_d SD_d + B(L)\varepsilon_t$

The order of the processes eventually retained by the algorithm is shown in the tables A.6-A.12 in annex 5.

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to more ambiguous results.

[9] SD is equal to 1 in month *d* and equal to 0 otherwise. As the equation includes a constant, 11 seasonal dummies are included.

4.3 AUTO-REGRESSIVE DISTRIBUTED LAG MODELS

The third group of models exploits structural relationships observed in historical data between inflation and different exogenous variables. These models can be broadly categorised, according the type of exogenous variable included, as cost-push (supply-side) or demand-side models.[10] The former include cost-indicators as potential drivers of inflation and depend mainly on vertical production relations (e.g. energy prices strongly depend on oil prices). The latter are essentially Philips-curve-type relationships, which explain inflation by (deviations in) measures of actual or potential economic activity (e.g. output gap, unemployment, industrial production): low demand leads to excess supply and, as firms need to liquidate their products, to lower pricing power and eventually lower prices – and *vice versa*. Finally, other variables, such as household surveys, may also exhibit leading indicator properties for inflation.

4.3.1 INVESTIGATION OF "RELEVANCE" OF EXOGENOUS VARIABLES

Following Fritzer et al. (2002), an exploratory analysis is performed first, aiming to identify the most relevant exogenous variables among a set of candidates. The selected variables will enter the more refined ADL model-selection process described in the next sub-section.

A total of around 40 exogenous variables are considered here that are of monthly frequency (i.e. no interpolated quarterly data are used), and can be classified in the following broad categories, which can all be expected to drive inflation and/or act as leading indicators: *commodity prices*; *exchange rate*; *industrial production*; *industrial orders*; *surveys*; *labour market*. The individual series are listed in table A.4 (annex 3).

The following “pre-fitting” equations are estimated for the sample period 1997:02 to 2010:12:

$$\text{(B.0)} \quad \pi_t^j = c + \sum_{i=0}^{12} \phi_i \pi_{t-1-i}^j + \sum_{j=0}^{12} \beta_i x_{t-k-j} + \varepsilon_t ,$$

where the j superscript identifies the inflation series and x is the exogenous variable of interest, which in general enters the equation as first-difference of the log-series (for some series the percentage or absolute change is retained). Each equation is estimated for three different displacements (k=1, 6, 12) of the exogenous variable, to assess whether it could constitute a leading indicator for inflation. A contemporaneous equation (with no displacement, i.e. k=0) is also fitted, as a feedback effect from inflation to the exogenous variables used here can be ruled out on conceptual grounds and as such should not give rise to endogeneity concerns. The joint significance of the exogenous variables is tested applying an F-test. Under the null hypothesis it assumes that the coefficients on the exogenous variables (the betas) are jointly equal to zero, such that the equation (B.0) reduces to an AR(12) model.

Table A.5 in the annex 3 reports the F-statistic and the probability value, as well as the goodness of fit of the unrestricted specification, measured by the adjusted coefficient of determination. For headline inflation the pre-fitting equations suggest that commodity prices

[10] Monetary models are another category of models (not considered in this paper; see for example Hofmann, (2006)), which could be used for longer horizons and rest on the idea that money is neutral in the long run, following the Friedman-Schwarz insight that ‘inflation is always and everywhere a monetary phenomenon’. The relationship between monetary growth and inflation has also shaped the Eurosystem’s monetary policy strategy, in which monetary analysis constitutes the second of two pillars (ECB, 2003).

and activity variables (industrial production, orders and employment) are *a priori* relevant leading indicators and significantly improve the fit of the regressions, contrary to exchange rates and consumer surveys (with the exception of expected price trends over the next 12 months).[11]

On the basis of this pre-fitting analysis, the significant exogenous variables, which offer the largest explanatory potential, are carried forward to the actual ADL-model selection. Some variables that are considered particularly important from either a macroeconomic (e.g. commodity prices, exchange rates) or sectoral (e.g. agricultural raw materials in the case of food inflation) perspective, are maintained regardless of this pre-fitting outcome.

4.3.2 ADL-MODEL SELECTION-ALGORITHM

This section describes the selection procedure for ADL-models. The estimated process in its most general form is given by the following ADL-model:

$$\text{(B.1)} \qquad \pi_t^j = c + \sum_{i=0}^{p} \phi_i \pi_{t-1-i}^j + \sum_{j=0}^{q} \beta_j x_{t-j} + \varepsilon_t ,$$

with p^{max}=11 and q^{max}=25, allowing for a lead time of two years; μ and x are defined as in the pre-fitting equation (B.0) above, except that the lag orders p and q are now determined via the penalty function. Adding a full set of seasonal dummies to specification (B.1) yields the following equation:

$$\text{(B.2)} \qquad \pi_t^j = c + \sum_{1}^{11} \delta_d SD + \sum_{i=0}^{p} \phi_i \pi_{t-1-i}^j + \sum_{j=0}^{q} \beta_j x_{t-j} + \varepsilon_t ,$$

The next specification modifies (B.1) by adding the twelfth lag of the dependent variable into the equation:

$$\text{(B.3)} \qquad \pi_t^j = c + \sum_{i=0}^{p} \phi_i \pi_{t-1-i}^j + \pi_{t-12}^j + \sum_{j=0}^{q} \beta_j x_{t-j} + \varepsilon_t$$

Augmenting it by a set of seasonal dummies, yields the following equation:

$$\text{(B.4)} \qquad \pi_t^j = c + \sum_{1}^{11} \delta_d SD + \sum_{i=0}^{p} \phi_i \pi_{t-1-i}^j + \pi_{t-12}^j + \sum_{j=0}^{q} \beta_j x_{t-j} + \varepsilon_t$$

For each inflation series and for each respective exogenous variable, the model is estimated for all combinations of p and q up to their respective maximum, yielding a total of 312 (12*26) models per specification, including a set of pure AR models (i.e. no exogenous variable) and a set of pure distributed lag models (i.e. no lag dependent variable) as special cases. The combination of p and q returning the lowest information criterion is retained for the evaluation stage. The AIC is now used as evaluating criterion, as it imposes a lower penalty on additional variables than the SIC, and thus reduces the probability of dropping the exogenous variable.

[11] An analogous exercise is performed for the five inflation components (available upon request).

Following the strategy described in section 4.2 (ARMA) and 4.3 (ADL) above, carries the risk that a good forecast model is already discarded at the selection stage. To avoid this, all candidate models initially considered could in principle be directly evaluated on their forecasting accuracy - which after all is the ultimate feature of interest - without undergoing this pre-selection stage. However, there are two good reasons to maintain a pre-selection: first, it ensures that the set of candidate models is narrowed down to a more manageable size. Secondly, it screens models according to their fit, ensuring that a meaningful statistical relationship exists between the variables.

5. Evaluation of the forecast accuracy during the crisis

The candidate models picked by the algorithms are evaluated by their out-of-sample accuracy measured by the recursive Root Mean Squared Forecast Error (RMSFE) presented in annex 4. Each forecast horizon is evaluated over 48 observations, i.e. 4 years. The first recursive model is estimated over the sample 1997:02 to 2005:07. The end date of the sample is gradually extended until 2009:06, leaving 18 remaining observations for evaluation purposes.[12] Overall, the evaluation period was relatively calm until the end of 2007, but became more agitated afterwards, when global oil and food prices started to hike and the financial crisis started. Headline inflation between 2005:08 and 2010:12 averaged 1.94%, i.e. close to target, but was very volatile (see table A.2.1 in annex 1 for descriptive statistics of the evaluation period).

5.1 DIRECT FORECASTS OF HEADLINE INFLATION DURING THE CRISIS

Table 2 (left panel) below summarises the accuracy of the main model groups, displaying their average RMSFEs over all 18 forecast horizons, as well as the average RMSFEs for three blocks of six-month forecast horizons. Table A.6 in annex 5 displays the RMSFEs for each of the 18 forecast horizons for all competing headline inflation models. The ADL-model specification (i.e. B.1-B.4) included in the table, is the one yielding the lowest average RMSFE.[13]

[12] One-step-ahead forecasts are thus evaluated over the period 2005:08 to 2009:07, while the 18-step-ahead forecasts are assessed over the 48-month period between 2007:01 and 2010:12.

[13] When evaluating ADL models, a path for the exogenous variables needs to be specified. In this paper the out-of-sample evaluations of the ADL models are based on conditioning assumptions that correspond to the true path of the exogenous variable of interest. While this assumption of perfect foresight is of course very strong and unlikely to be met in practice, it however allows focussing on the particular exogenous variables. With assumption errors thus effectively being ruled out as a source of inflation forecast error, the RMSFEs obtained should be regarded as a lower bound and an indication of the margin of improvement for other models. The results may hence help to focus on those variables that are particularly valuable as inflation predictors.

Table 2: Average RMSFEs of main model categories in crisis-sample (summary)

	Direct forecast				Indirect forecast			
Horizon:	1 to 6	7 to 12	13 to 18	*1 to 18*	1 to 6	7 to 12	13 to 18	*1 to 18*
Benchmarks								
ECB	1,12	1,19	1,19	*1,17*	(-)	(-)	(-)	*(-)*
Naive	0,77	1,60	1,88	*1,42*	(-)	(-)	(-)	*(-)*
AR(1)	0,71	1,17	1,24	*1,04*	0,71	1,17	1,24	*1,04*
ARMA(1,1)	0,69	1,15	1,21	*1,02*	0,70	1,16	1,24	*1,03*
AR(12)	0,79	1,51	1,67	*1,32*	0,60	1,26	1,48	*1,12*
Seas. Dummies	0,57	1,09	1,23	*0,96*	0,57	1,09	1,23	*0,97*
ARMA (*)								
Identical DGP	0,58	1,11	1,26	*0,98*	0,54	1,11	1,31	*0,99*
Component-specific DGP	(-)	(-)	(-)	*(-)*	0,48	1,02	1,20	*0,90*
ADL (oilusd) (*)								
Identical model	0,35	0,75	0,95	*0,68*	0,33	0,70	0,89	*0,64*
Component-specific model	(-)	(-)	(-)	*(-)*	0,32	0,67	0,86	*0,62*
Combination								
	(-)	(-)	(-)	*(-)*	0,28	0,46	0,53	*0,42*

Note: (*) Refers to the model specification generating the lowest RMSFE of the respective model group

For headline inflation, the accuracy of forecasts produced by the ARMA-models selected by an information criterion tends to be comparable to that of benchmark models. In particular, the seasonal dummy-model appears difficult to beat, reflecting the importance of the intra-year inflation pattern. The ECB-target improves in relative terms with the distance of the forecast horizon, dominating all ARMA-models on horizons beyond twelve months, which are more relevant from a monetary policy perspective. The naïve model is rapidly outperformed by the ARMA-models, which is unsurprising in the light of the swings in inflation observed during the evaluation period. Considering ADL-models reveals that the inclusion of commodity prices, in particular of oil prices, considerably reduces the forecast errors over all horizons compared to ARMA and benchmark models. The RMSFE of the model including dollar-denominated oil prices corresponds to around 70% of that of the seasonal-dummy model and to around 60% of the static ECB-target forecast. Industrial production, industrial orders and labour market data also improve the out-of-sample fit, albeit to a lesser extent.

5.2 INDIRECT FORECASTS OF HEADLINE INFLATION DURING THE CRISIS

Indirect headline inflation forecasts are obtained by aggregating forecasts of each of the five components (generated by some component-specific models), weighted by their share in the HICP in the relevant year. The aggregated inflation series obtained through this indirect approach are then also evaluated by the RMSFE. While a large number of combinations of component-forecasts are possible, six sets of aggregation are considered here: i) aggregations of forecasts produced by the four econometric benchmark models; ii) an aggregation of forecasts obtained by imposing the data-generation process of the most accurate direct ARMA-model on all series; iii) an aggregation of ARMA forecasts, allowing for a component-specific data-generation processes; iv) an aggregation of ADL-forecasts using dollar-denominated oil prices as an explanatory variable for all components, imposing the same model on all series; v) an aggregation of ADL-forecasts based on dollar-denominated oil prices, now allowing for component-specific specifications; vi) an aggregation of those forecasts, which have given rise to the lowest average RMSFE for each component, i.e. allowing for component-specific models with different exogenous variables. Aggregations i), ii) and iv) thus fit an identical model to each individual series, as to the headline series; the other aggregations consider true component-specific models.

Before turning to the evaluation of the aggregated series, the results of the forecasting models for the individual inflation components are briefly commented in this paragraph. The candidate models for the respective components and their average RMSFEs over all 18 forecast period, and the average RMSFEs over three blocks of six-month horizons are reported in tables A.8 to A.12 in the annex. The results show that the components attributed to core inflation, which are less volatile and exhibit stronger regularities, also have the highest out-of-sample fit. This is well-illustrated by the non-energy industrial goods and services series on the one hand, which have the smallest forecast errors, and by the energy series on the other, which has the largest. In the case of *energy* inflation, the highest forecast accuracy – albeit low by the standards of the other components – is achieved by an ADL-model that includes oil prices.[14] For *processed food* inflation, the ADL-model including the euro-dollar exchange rate produces the smallest forecast errors.[15] For *unprocessed food* inflation, the highest forecast accuracy is obtained by including activity variables and industrial order data, which dominate commodity prices, such as agricultural raw materials and cereals. The strong seasonal regularities observed for *non-energy industrial goods* inflation generally facilitate the forecasting of this series, as is confirmed by the generally low RMSFEs relative to other inflation series. Adding exogenous variables can in some cases (e.g. industrial production or labour market variables) reduce the forecast errors even further, albeit only marginally. For *services* inflation, the forecast accuracy of the simple seasonal-dummy model is similar to that of the best ARMA-models picked by the algorithm. An ADL-model that includes the unemployment rate slightly improves the out-of-sample fit with respect to benchmarks and ARMA-models.

The RMSFEs obtained by the indirect approach are reported in table 2 (right panel) and in more detail at the bottom of table A.6 in the annex. Except for the AR (12) model, indirect forecasts based on benchmark models do not yield better forecasts than the corresponding direct forecast. The indirect forecast obtained from applying the DGP of the best direct model to all component-series, does not improve upon the direct forecast overall: while the forecast accuracy is slightly higher up to six-months ahead, it deteriorates over horizons further than 12 months away. In contrast, when allowing for differentiated component-specific DGPs, the indirect approach clearly outperforms the best direct ARMA-model. This supports the conclusion of Bermingham and D'Agostino (2010), who stress the importance of specifying an appropriate model for each component. Indirect forecast resulting from ADL-models including oil prices dominate the corresponding direct approach, regardless of whether an identical model is imposed or component-specific models are fitted. The final aggregation, which is effectively a multivariate forecasting set-up, relies on dollar-denominated oil prices (energy), the exchange rate (processed food), industrial production of consumer goods (unprocessed food and non-energy industrial goods) and the unemployment rate (services). It generates a lower average RMSFE than all direct and indirect approaches considered: the average RMSFE corresponds to 36% of that of the ECB-target and 30% of that of the naïve

[14] Interestingly, dollar-denominated oil prices constitute a better predictor for energy inflation in the euro area than euro-denominated oil prices (the same holds for headline inflation).

[15] It is also worth noting that the agricultural raw materials price index is not retained by the ADL algorithm. While the unprocessed food price index is retained by the algorithm, the resulting model does not yield better forecasts.

model. Relative to the best direct forecast (ADL-model including dollar-denominated oil prices), the average RMSFE corresponds to 63%. This aggregation also improves in relative terms with the length of the forecast horizon: while for the six months ahead, the average RMSFE of the indirect approach represents around 80% of that of the best direct model, it drops to around 56% on horizons that are between 13 and 18 months ahead.

6. Evaluation of the forecast accuracy before the economic and financial crisis

The evaluation period in section 5 has to a large extent coincided with the financial and economic crisis. As the latter is likely to have impacted the conclusions, the validity and robustness of the latter for other periods may thus *a priori* be questioned. Indeed, the large swings in global oil and food prices after 2007 and the disruptions in economic activity caused by the crisis itself had a major impact on the euro area inflation profile, as illustrated in section 3, but also on private and public institutions' forecasts, which had to be significantly revised (cf. table A.1). To assess the robustness of the results over time, this section considers how the forecasting performance of the models considered above would have been different – in both absolute and relative terms – if the selection and evaluation process had been carried out before the start of the crisis.

To assess the pre-crisis forecasting accuracy, the last three years of the sample are dropped, and the model selection algorithms described in section 4 are run over the sample 1997:02 to 2007:12. Maintaining an evaluation period of 48 months, the first recursive sample ends in 2002:07, while the last sample runs until 2006:06.[16] While average headline inflation between 2002:08 and 2007:12 was on average somewhat higher than during the evaluation period considered in section 5, namely at 2.17%, the volatility, measured by the range or the standard deviation, was considerably lower (see table A.2.2 in the annex). On average, inflation in all categories with the exception of energy was higher in the pre-crisis evaluation period. Meanwhile, inflation volatility was lower for all components, except for unprocessed food and non-energy industrial goods inflation.

6.1 DIRECT FORECASTS OF HEADLINE INFLATION PRE-CRISIS

Table 3 (left panel) summarises the performance of the main model groups, showing their average RMSFEs for the entire evaluation period and for three six-month periods. Table A.7 in the annex displays the pre-crisis RMSFEs of the benchmarks and all selected direct headline inflation models. The ADL-models reported in the table correspond to the specification (B.1-B.4) that yielded the lowest average RMSFE. The precise specifications of the models evaluated before the crisis are consequently not necessarily the same as the ones evaluated during the crisis.[17]

[16] One-month ahead forecasts are assessed over the period 2002:08 to 2006:07, while the 18-month forecast horizon is evaluated over the period 2004:01 to 2007:12.

[17] It is noteworthy that some exogenous variables may be retained by the algorithm in one period, but not in the other. In the case of processed food inflation for example, agricultural raw materials prices would have been included in an ADL-model prior to the crisis, but not thereafter.

Table 3: Average RMSFEs of main model categories in pre-crisis-sample (summary)

	Direct forecast				Indirect forecast			
Horizon:	1 to 6	7 to 12	13 to 18	*1 to 18*	1 to 6	7 to 12	13 to 18	*1 to 18*
Benchmarks								
ECB	0,34	0,32	0,34	*0,33*	(-)	(-)	(-)	*(-)*
Naive	0,29	0,36	0,36	*0,34*	(-)	(-)	(-)	*(-)*
AR(1)	0,44	0,52	0,39	*0,45*	0,47	0,55	0,38	*0,47*
ARMA(1,1)	0,42	0,49	0,38	*0,43*	0,47	0,55	0,32	*0,45*
AR(12)	0,31	0,35	0,35	*0,34*	0,29	0,35	0,33	*0,32*
Seas. Dummies	0,30	0,40	0,42	*0,37*	0,31	0,40	0,40	*0,37*
ARMA (*)								
Identical DGP	0,28	0,35	0,37	*0,33*	0,30	0,48	0,55	*0,44*
Component-specific DGP	(-)	(-)	(-)	*(-)*	0,28	0,36	0,34	*0,33*
ADL (oilusd) (*)								
Identical model	0,22	0,26	0,23	*0,24*	0,22	0,30	0,31	*0,28*
Component-specific model	(-)	(-)	(-)	*(-)*	0,21	0,26	0,24	*0,24*
Combination								
	(-)	(-)	(-)	*(-)*	0,20	0,23	0,25	*0,23*

Note: (*) Refers to the model specification generating the lowest RMSFE of the respective model group

Comparing the forecast accuracy of the different models highlights the relatively strong performance of the ECB-target. On average it dominates all benchmark and ARMA-models, essentially due to its good performance over horizons beyond 8 months. It is also interesting to note that, contrary to other models, the forecast errors of the ECB-target remain stable and even decline with the length of the forecast horizon, consistent with the medium-term character of the price stability objective.[18] Finally, the ECB-target also performs reasonably well compared to ADL-models, in particular at more distant forecasting horizons. The average RMSFE of the best direct model, an ADL-model including oil prices, corresponds to 72% of the ECB-targets' RMSFE. Overall, this would have supported the conclusion of Diron and Mojon (2005) that the ECB-target constitutes a good rule of thumb over medium-term horizons. In general, the performance of the other benchmark models was also relatively strong compared to ARMA and ADL-models selected on the basis of the penalty function. The naive model, for example, performed comparatively well at horizons below 12 months, owing to the stability of inflation during that period. These results corroborate the conclusions of other studies (cf. survey) stressing the good performance of simple inflation forecasting models.

6.2 INDIRECT FORECASTS OF HEADLINE INFLATION PRE-CRISIS

Indirect forecasts for the pre-crisis period are obtained from the same six aggregation sets as in section 5.2; their RMSFEs are displayed in table 3 (right panel) and in more detail at the bottom of table A.7 in the annex.[19] Again, the indirect forecasts produced by the benchmark models cannot outperform their corresponding direct equivalent. Also in line with the results of the crisis period, the ARMA-based indirect approach leads to lower forecast errors than the direct equivalent, on the condition that component-specific DGPs are allowed. In contrast to the crisis period, indirect forecasts based on ADL-models including oil prices cannot

[18] The rise in the RMSFE for forecasts beyond 16 months can essentially be attributed to the strong pick-up in inflation at the end of the sample in 2007, which does not impact on the evaluation of closer forecast horizons.

[19] The evaluations of the forecasting models for the individual inflation components are reported in tables A.8 to A.12 in the annex.

outperform their direct equivalent. Imposing an identical model on all components actually increases the size of the forecast errors with respect to the direct approach, while the aggregation of forecasts of component-specific models produces comparable results to those of the direct model.

The indirect inflation forecast obtained from the best component-specific models, allowing for the inclusion of exogenous variables,[20] yields an average RMSFE that is only marginally below that of the best direct model. The better performance of the indirect inflation forecast is essentially due to the better performance for horizons up to 12 months ahead. It should also be considered in the light of the strong underlying assumptions: in particular, it requires the knowledge of the path of three exogenous variables, while the best direct approach "only" requires the knowledge of oil prices. The aggregation of the best component-specific forecasts outperforms the rules of thumb (ECB-target and naïve), but by a narrower margin than during the crisis: the average RMSFE is about 70% of that of the numerical benchmarks.

6.3 HOW DID THE CRISIS AFFECT THE ABSOLUTE AND RELATIVE FORECASTING ACCURACY?

Table 4 reports the ratio of the pre-crisis average RMSFE to the crisis average RMSFE for comparable models. A value below 100% indicates that forecast errors of the given model group were lower before the start of the crisis. Comparing the forecast accuracy of the different groups of direct and indirect headline inflation models in both evaluation periods reveals that all of them have deteriorated after the outbreak of the crisis, confirming the impression that inflation forecasting has in general become more difficult in that period. This is particularly well-illustrated by the rules of thumb and the benchmark models whose precision significantly worsened: for example, the average RMSFE of the naïve model rose from 0.34 before the crisis to 1.42, implying that taking the current inflation rate as an inflation forecast yielded four times larger errors with the crisis. The ECB-target forecast also worsened significantly with the crisis, as the average RMSFE increased from 0.33 to 1.17.

[20] Dollar-denominated oil prices (energy and non-energy industrial goods); exchange rate (processed food); euro-denominated oil prices (unprocessed food); services inflation is best modelled by an ARMA models including seasonal dummies.

Table 4: Pre-crisis average RMSFEs relative to crisis average RMSFEs (in %)

	Direct forecast				Indirect forecast			
Horizon:	1 to 6	7 to 12	13 to 18	*1 to 18*	1 to 6	7 to 12	13 to 18	*1 to 18*
Benchmarks								
ECB	29,9	26,7	28,4	*28,3*	(-)	(-)	(-)	*(-)*
Naive	37,5	22,4	19,3	*23,8*	(-)	(-)	(-)	*(-)*
AR(1)	62,6	44,1	31,8	*43,4*	66,3	46,9	30,8	*44,9*
ARMA(1,1)	61,1	42,3	31,1	*42,1*	67,6	47,3	25,7	*43,2*
AR(12)	39,1	23,0	21,0	*25,4*	47,8	27,9	22,4	*29,0*
Seas. Dummies	52,7	36,3	34,3	*38,7*	54,6	36,5	32,8	*38,5*
ARMA (*)								
Identical DGP	48,3	31,2	28,9	*33,6*	55,0	43,0	42,2	*44,8*
Component-specific DGP	(-)	(-)	(-)	*(-)*	58,2	34,8	28,1	*36,0*
ADL (oilusd) (*)								
Identical model	61,3	34,6	24,8	*34,7*	66,7	42,9	34,8	*43,3*
Component-specific model	(-)	(-)	(-)	*(-)*	67,8	38,2	27,2	*38,1*
Combination								
	(-)	(-)	(-)	(-)	72,2	49,1	46,6	*53,1*

Note: (*) Refers to the model specification generating the lowest RMSFE of the respective model group

Compared to the benchmark models the weakening of more sophisticated models (i.e. ADL and aggregations) has been relatively contained; as a consequence the rewards from investing in them, rather than relying on simple models have increased. Put the other way round, the attractiveness of resorting to simple rules of thumb has fallen with the crisis: evaluated during the crisis, the average RMSFE of the dollar-denominated oil-price ADL-model (based on the assumption of perfect foresight of the path of the exogenous variable), accounted for 59% of the RMFSE of the ECB-target model. Before the crisis, the corresponding value was 72%. Relative to the average RMSFE of the naïve model, the RMSFE of the oil-price ADL-model declined from 70% before the crisis to 48% during the crisis. Note that the relative worsening of benchmarks is not a consequence of the average inflation level during the two respective evaluation periods (it was further away from the ECB-target in the pre-crisis period), but of the more irregular inflation profile.

A look at the forecasts for the individual inflation components confirms that the deterioration of forecasting models was broad-based, and not limited to one particular component (see tables A.8-A.12). While in the case of *energy* inflation, the accuracy of the ADL-model including dollar-denominated oil prices only deteriorated marginally with the crisis, for *processed food*, all model groups produced substantially lower average RMSFEs before the crisis. This is not surprising, given that this category was particularly affected by the global food price shock starting in 2007. For *unprocessed food*, the results are mixed: ADL-models including oil and energy variables performed best before the crisis, while models that include activity variables produced more accurate forecasts during the crisis. *Services* inflation forecasting models have also deteriorated, regardless of the model category. For *non-energy industrial goods* inflation, ARMA-models actually generated more accurate forecasts during the crisis.

7. Conclusion

This paper has analysed how the financial and economic crisis has affected inflation forecasting in the euro area. Specifically, three groups of inflation forecasting models (*rules of thumb and benchmark models; autoregressive moving average models; autoregressive distributed lag models)* were evaluated under two distinct forecasting approaches: under the first one, the models were applied directly to headline inflation, while under the second one, component-specific forecasts were generated first and subsequently aggregated to obtain an indirect forecast of headline inflation.

The paper's first objective has been to compare the accuracy of different inflation forecasting models. Regarding the direct ones, it finds that ARMA-models determined via a penalty function generally perform at least as well as econometric benchmark models or rules of thumb. Adding exogenous explanatory data in an ADL-setting in many cases improves the forecast precision further. The best direct forecasts are obtained when including oil prices, which play a key role in explaining and predicting inflation. The gains obtained from relying on ADL-models are particularly large during the crisis period. As far as the indirect approach is concerned, the forecasts are generally at least as accurate as those generated by the direct method. However, the magnitude of the gains depends much on what precisely is being aggregated: indeed, it is only once appropriate specifications for the component-specific ARMA or ADL-models have been found, that the indirect forecasts dominate the corresponding direct model. Indirect forecasts perform best when the information set is widened, allowing different exogenous explanatory variables to enter in each component-specific model. It should however be noted that in the pre-crisis period the best indirect forecasts only marginally beat the best direct forecasts, and that this can partly be related to the strong conditioning assumptions. Yet, even if a systematic superiority of the indirect forecasting approach would be difficult to assert on the mere basis of the results of this paper, its use in practice nonetheless seems fully warranted and justifies further work on the refinement of component-specific models.

An important lesson from the literature has been that the forecasting accuracy of models is sensitive to the period in which they are estimated and evaluated, and that conclusions regarding their merit may consequently be short-lived. The second objective of the paper has been to illustrate this time-sensitivity and to gauge the impact of the crisis by repeating the comparative assessment over two different sample periods. The rise in forecast errors of all models, confirms that inflation forecasting has become substantially more difficult after the onset of the crisis. However, the deterioration of the different models has been uneven: in general, the performance of slightly more elaborated models – i.e. ARMA- and ADL-models selected on the basis of a penalty function – and in particular of indirect forecasts, has improved during the crisis relative to simple econometric benchmarks or rules of thumb. Indeed, while the model comparison during the pre-crisis period would have backed the conclusions of earlier studies emphasising the virtues of simple models – including the central bank's inflation target – the comparative evaluation during the crisis would cast doubts on those very same conclusions.

Future analysis on the specification of inflation forecasting models will need to take into account the distortions caused by the commodity price swings and by the crisis after 2007. If the choice of the forecasting model is made on the basis of past observations, e.g. by performing an out-of-sample evaluation as in this paper, the question will arise how inflation data from the crisis should be included in the model estimation, but also whether it seems right to use the crisis as an evaluation period.

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Annex 1: Inflation forecasts and presentation of data

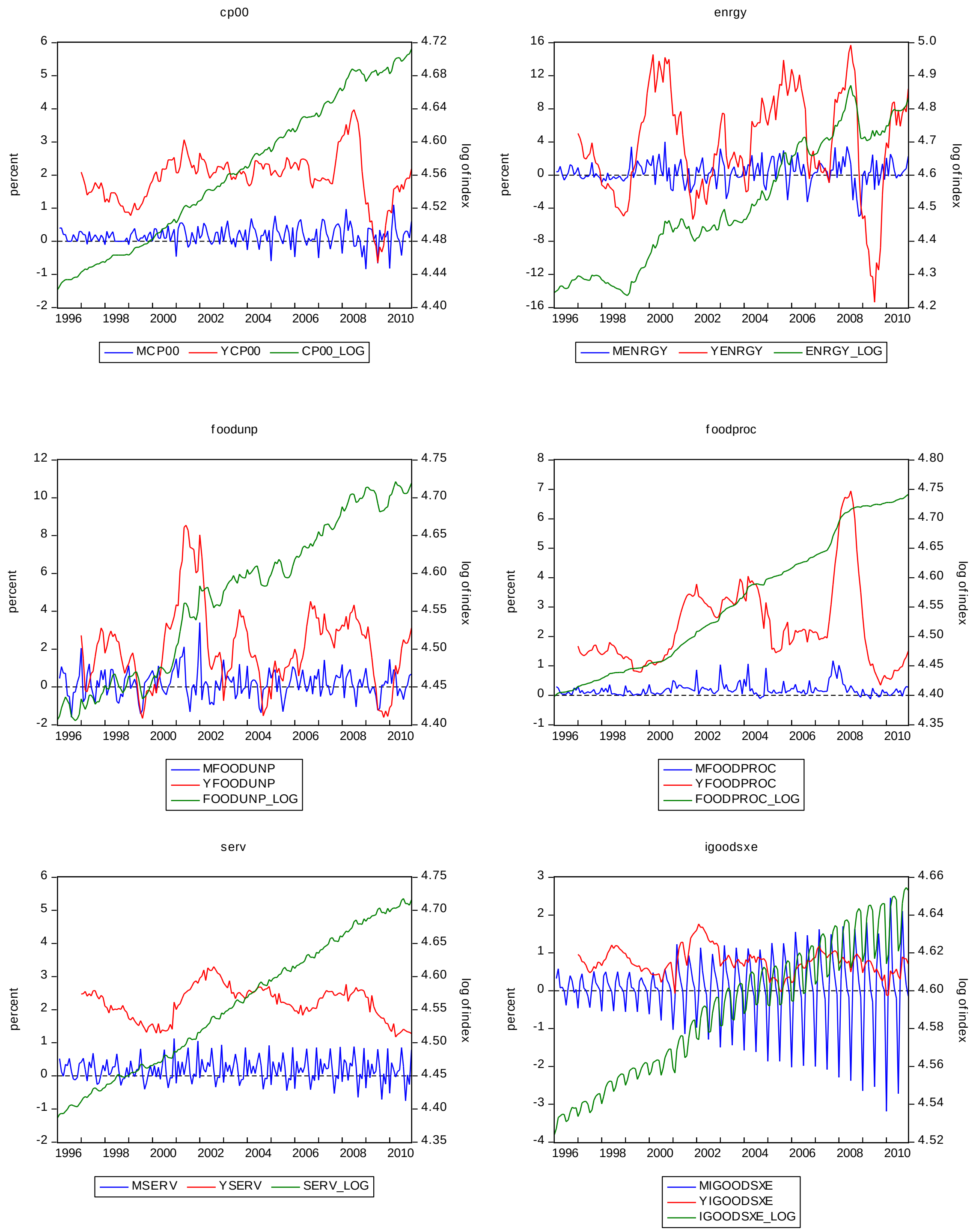
Table A.1: Inflation forecasts for 2008 and 2009 by ECB/Eurosystem, European Commission and Survey of Professional Forecasters

ECB and Eurosystem staff macroeconomic projections for the euro area (*)		
	2008	2009
December 2006	1,9	
March 2007	2,0	
June 2007	2,0	
September 2007	2,0	
December 2007	2,5	1,8
March 2008	2,9	2,1
June 2008	3,4	2,4
September 2008	3,5	2,6
December 2008	3,3	1,4
March 2009		0,4
June 2009		0,3
September 2009		0,4
December 2009		0,3
European Commission Spring and Autumn forecasts		
	2008	2009
Autumn (Nov 2006)	1,9	
Spring (May 2007)	1,9	
Autumn (Nov 2007)	2,1	2,0
Spring (April 2008)	3,2	2,2
Autumn (Oct 2008)	3,5	2,2
Spring (May 2009)		0,4
Autumn (Nov 2009)		0,3
Survey of Professional Forecasters		
	2008	2009
November 2006	1,9	
May 2007	1,9	
October 2007	2,0	2,0
May 2008	3,1	2,1
October 2008	3,4	2,2
May 2009		0,5
October 2009		0,3
Average inflation	3,3	0,3

Note: (*) The figure refers to the mid-point of the published forecast. June and December forecasts are prepared by ECB and Eurosystem staff. March and September forecasts are propared by ECB staff.

Source: ECB Monthly Bulletin, various editions.

Figure A.1. HICP indices, annual and monthly inflation; overall and by component (1996:01-2010:12)



Note: the graphs display the patterns of monthly inflation ("m" prefix), annual inflation ("y" prefix), on the left y-axis, and the logarithm of the price index, on the right y-axis.

Figure A.2. Intra-year pattern of monthly inflation; overall and by component (1996:01-2010:12)

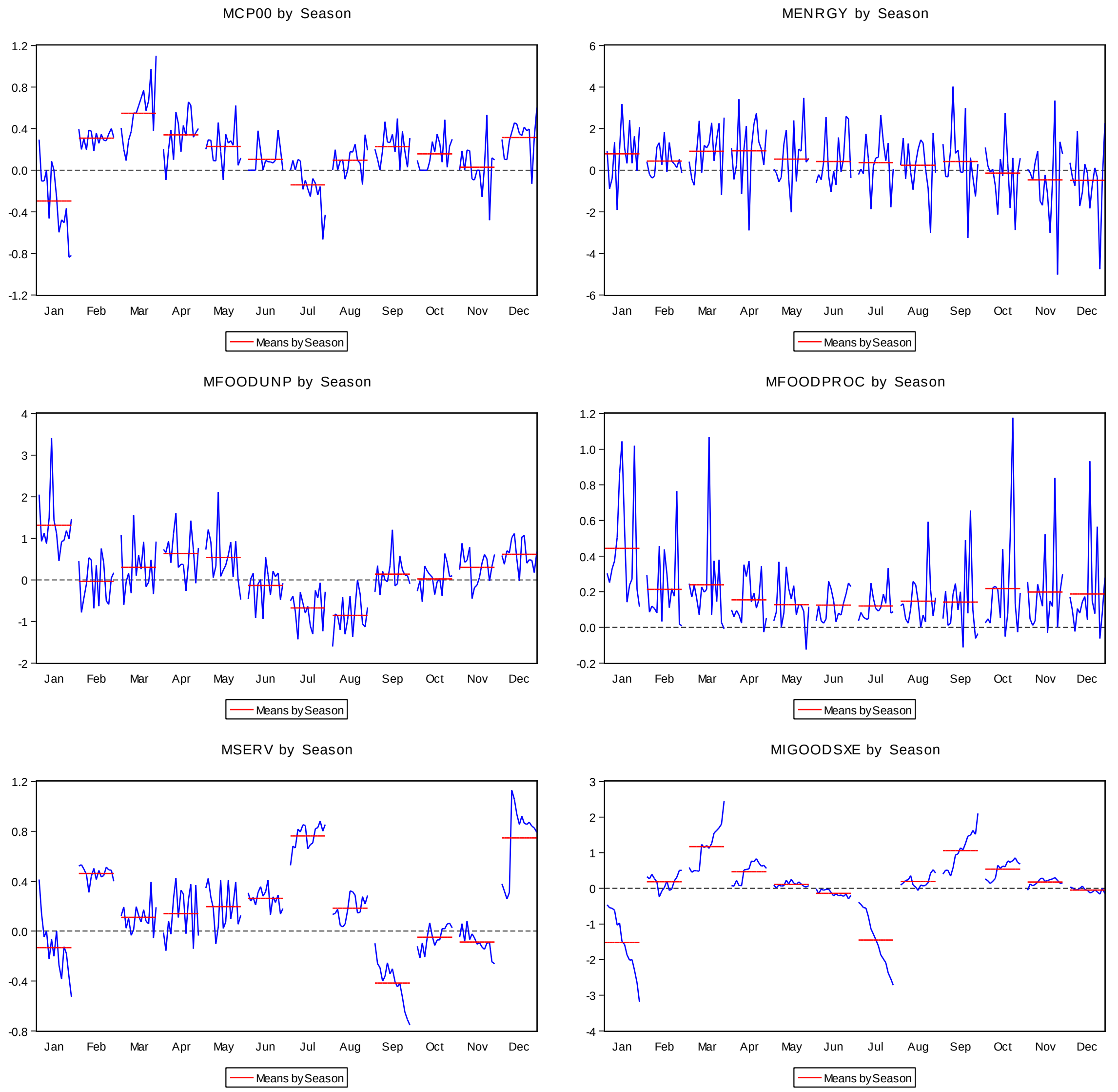


Table A.2.1: Descriptive statistics – crisis evaluation period (2005:08-2010:12)

	cp00	enrgy	foodproc	foodunp	igoodsxe	serv
Annual inflation (%)						
Mean	1.94	4.71	2.56	2.10	0.66	2.09
Median	1.92	7.22	2.02	2.53	0.72	2.12
Maximum	4.06	17.01	7.20	4.63	1.18	2.81
Minimum	-0.65	-14.25	0.35	-1.60	-0.12	1.18
Range	4.70	31.26	6.85	6.23	1.30	1.62
Std Dev	1.07	7.81	1.97	1.67	0.30	0.45
Monthly inflation (%)						
	cp00	enrgy	foodproc	foodunp	igoodsxe	serv
Mean	0.17	0.34	0.21	0.18	0.10	0.16
Median	0.24	0.43	0.13	0.12	0.21	0.15
Maximum	1.11	3.53	1.18	1.47	2.48	0.89
Minimum	-0.83	-4.90	-0.12	-1.23	-3.14	-0.75
Range	1.94	8.43	1.31	2.70	5.62	1.64
Std Dev	0.38	1.75	0.25	0.58	1.23	0.43

Source: own calculations based on Eurostat

Table A.2.2: Descriptive statistics – pre-crisis evaluation period (2002:08-2007:12)

	cp00	enrgy	foodproc	foodunp	igoodsxe	serv
Annual inflation (%)						
Mean	2.17	5.39	2.75	1.86	0.74	2.46
Median	2.15	6.03	2.67	1.66	0.79	2.51
Maximum	3.07	14.93	5.10	4.63	1.33	3.35
Minimum	1.61	-2.04	1.45	-1.52	-0.02	1.84
Range	1.45	16.97	3.64	6.15	1.35	1.51
Std Dev	0.29	4.52	0.84	1.46	0.31	0.33
Monthly inflation (%)						
	cp00	enrgy	foodproc	foodunp	igoodsxe	serv
Mean	0.19	0.50	0.25	0.17	0.09	0.19
Median	0.25	0.45	0.15	0.23	0.16	0.15
Maximum	0.77	3.41	1.18	1.45	1.64	0.94
Minimum	-0.60	-3.21	-0.11	-1.36	-2.06	-0.53
Range	1.37	6.62	1.30	2.81	3.70	1.47
Std Dev	0.29	1.45	0.28	0.61	0.94	0.38

Source: own calculations based on Eurostat

Annex 2: Stationarity analysis

Table A.3 Augmented Dickey-Fuller (ADF) test – Sample: 1997:02-2012:02

ADF-test	Deterministic term	No. of lagged differences		cp00	enrgy	foodproc	foodunp	igoodsxe	serv	*Critical values* *1%*	*5%*	*10%*
log	constant and trend		0	-3,09	-2,38	-2,16	-2,36	-7,99	-3,75	*-4,01*	*-3,44*	*-3,14*
			1	-3,4	-3,02	-2,34	-3,38	-14,17	-3,12			
			2	-3,17	-3,16	-2,65	-3,24	-10,85	-3			
			3	-2,85	-3,22	-2,79	-3,28	-9,82	-1,81			
		SIC		-3,93	-3,02	-2,65	-3,86	-3,29	-3,81			
		AIC		-3,33	-3,02	-3,03	-3,86	-2,54	-3,81			
Monthly changes (d1)	constant		0	-11,64	-9,71	-8,49	-9,78	-10,84	-15,46	*-3,47*	*-2,88*	*-2,58*
			1	-9,55	-7,47	-5,48	-8,39	-14,15	-10,5			
			2	-8,85	-6,42	-4,66	-7,21	-13,2	-12,32			
			3	-8,58	-5,93	-4,23	-6,6	-26,81	-10,84			
		SIC		-2,91	-9,71	-5,48	-2,55	-3,19	-0,85			
		AIC		-3,21	-9,71	-2,89	-2,86	-3,19	-0,85			
Annual changes (d12)	constant		0	-2,09	-2,08	-1,35	-2,11	-3,45	-1,83	*-3,47*	*-2,88*	*-2,58*
			1	-2,65	-2,78	-2,19	-2,79	-3,72	-0,81			
			2	-3,06	-2,94	-2,91	-3,19	-2,97	-0,83			
			3	-2,92	-3,28	-2,92	-3,23	-2,7	-1,02			
		SIC		-2,55	-2,77	-2,32	-2,79	-3,38	-2,67			
		AIC		-2,55	-2,77	-2,32	-2,67	-3,73	-2,21			
d1d12	constant		0	-10,28	-9,84	-8,15	-9,94	-12,22	-20,67	*-3,47*	*-2,88*	*-2,58*
			1	-7,1	-7,52	-5,24	-7,42	-11,23	-10,8			
			2	-6,64	-5,98	-4,89	-6,32	-9,36	-7,31			
			3	-5,24	-5,06	-3,78	-5,96	-9,2	-5,44			
		SIC		-5,97	-6,16	-4,25	-9,94	-4,47	-20,67			
		AIC		-5,97	-6,16	-4,25	-5,11	-4,47	-3,1			

Philips-Peron (PP) test – Sample: 1997:02-2012:02

PP-test	Deterministic term	cp00	enrgy	foodproc	foodunp	igoodsxe	serv	*Critical values* *1%*	*5%*	*10%*
log	constant and trend	-3,08	-2,86	-2,4	-2,89	-7,31	-3,68	*-4,01*	*-3,44*	*-3,14*
Monthly changes (d1)	constant	-12,23	-9,7	-9,17	-9,81	-15,06	-20,43	*-3,47*	*-2,88*	*-2,58*
Annual changes (d12)	constant	-2,75	-2,93	-2,44	-2,74	-3,68	-1,6	*-3,47*	*-2,88*	*-2,58*
d1d12	constant	-10,42	-9,99	-8,87	-9,94	-21,02	-19	*-3,47*	*-2,88*	*-2,58*

Annex 3: Pre-selection of exogenous variables

Table A.4: List of exogenous variables and abbreviations

	Commodity prices
oileur	World, Energy, Oil, Crude Oil - North Sea (Brent), Dated, Close, EUR
oilusd	World, Energy, Oil, Crude Oil - North Sea (Brent), Dated, Close, USD
hwwieur	Euro Zone, HWWI, Total Index, Average, EUR
hwwixeneur	Euro Zone, HWWI, Total Index excluding Energy, Average, EUR
hwwiarm	World, HWWI, Agricultural Raw Materials Index, Average, EUR
hwwicer	World, HWWI, Cereals Index, Average, EUR
hwwicoal	World, HWWI, Coal Index, Average, EUR
hwwicoil	World, HWWI, Crude Oil Index, Average, EUR
hwwienrm	World, HWWI, Energy Raw Materials Index, Average, EUR
hwwifood	World, HWWI, Food Index, Average, EUR
hwwiind	World, HWWI, Industrial Raw Materials Index, Average, EUR
hwwiiost	World, HWWI, Iron Ore and Steel Scrap Index, Average, EUR
hwwinfm	World, HWWI, Non-ferrous Metals Index, Average, EUR
hwwiseed	World, HWWI, Oilseeds and Oils Index, Average, EUR
hwwitex	World, HWWI, Textile Fibres Index, Average, EUR
hwwiexen	World, HWWI, Total Index excluding Energy, Average, EUR
hwwi	World, HWWI, Total Index, Average, EUR
	Exchange rate
eurusd	Euro Zone, Spot Rates, EUR/USD, Close, USD
eer21	Euro Zone, ECB, EER-21 Nominal Effective Exchange Rate Index, Euro 16, EUR
eer41	Euro Zone, ECB, EER-41 Nominal Effective Exchange Rate Index, Euro 16, EUR
reer21	Euro Zone, ECB, EER-21 Real CPI Effective Exchange Rate Index, Euro 16, EUR
reer41	Euro Zone, ECB, EER-41 Real CPI Effective Exchange Rate Index, Euro 16, EUR
	Industrial production
iptotencon	Eurostat, Euro Zone, Production, Overall, NACE Rev.2 B_C_X_MIG_NRG, Total, excluding construction and energy, Cal Adj, Index, EUR, 2005=100
iptotcon	Eurostat, Euro Zone, Production, Overall, NACE Rev.2 B-D, Total, excluding construction, Cal Adj, Index, EUR, 2005=100
iptoten	Eurostat, Euro Zone, Production, Overall, NACE Rev.2 B-D_F, Industry including construction, Cal Adj, Index, EUR, 2005=100
ipcapg	Eurostat, Euro Zone, Production, Aggregates, NACE Rev.2 MIG_CAG, Capital goods, Cal Adj, Index, EUR, 2005=100
ipconsg	Eurostat, Euro Zone, Production, Aggregates, NACE Rev.2 MIG_COG, Consumer goods, Cal Adj, Index, EUR, 2005=100
ipintgds	Eurostat, Euro Zone, Production, Aggregates, NACE Rev.2 MIG_ING, Intermediate goods, Cal Adj, Index, EUR, 2005=100
ipener	Eurostat, Euro Zone, Production, Aggregates, NACE Rev.2 MIG_NRG_X_E, Energy, Cal Adj, Index, EUR, 2005=100
	Industrial orders
iocapg	Eurostat, Euro Zone, New Orders, Aggregates, NACE Rev.2 MIG_CAG_ORD, Capital goods, Index, EUR, 2005=100
ioconsd	Eurostat, Euro Zone, New Orders, Aggregates, NACE Rev.2 MIG_DCOG_ORD, Consumer durables, Index, EUR, 2005=100
iointg	Eurostat, Euro Zone, New Orders, Aggregates, NACE Rev.2 MIG_ING_ORD, Intermediate goods, Index, EUR, 2005=100
	Surveys
hhfinsit12	DG ECFIN, Euro Zone, Consumer Surveys, Financial situation of households over next 12 months, SA
hhecosit12	DG ECFIN, Euro Zone, Consumer Surveys, General economic situation over next 12 months, SA
majpur12	DG ECFIN, Euro Zone, Consumer Surveys, Major purchases over next 12 months, SA
pritre12	DG ECFIN, Euro Zone, Consumer Surveys, Price trends over next 12 months, SA
sav12	DG ECFIN, Euro Zone, Consumer Surveys, Savings over next 12 months, SA
	Labour market
uetot_lm	Eurostat, Euro Zone, Unemployment, Overall, Total
uer_lm	Eurostat, Euro Zone, Unemployment, Rate, Total

Source: Ecowin

Table A.5: Leading indicator analysis for headline inflation (1997:02-2010:12)

cp00	F-stat	p-value	R-bar2	F-stat	p-value	R-bar2	F-stat	p-value	R-bar2	F-stat	p-value	R-bar2
	k=0			k=1			k=6			k=12		
Commodity prices												
dln_oileur	8.66	0.00	0.63	5.61	0.00	0.56	3.49	0.00	0.50	1.43	0.15	0.41
dln_oilusd	8.02	0.00	0.64	5.67	0.00	0.58	3.40	0.00	0.51	1.56	0.11	0.43
dln_hwwieur	9.60	0.00	0.67	5.71	0.00	0.58	2.95	0.00	0.49	1.14	0.34	0.41
dln_hwwixeneur	3.79	0.00	0.52	3.42	0.00	0.51	1.50	0.13	0.43	0.66	0.80	0.38
dln_hwwiarm	1.86	0.04	0.45	2.17	0.01	0.46	1.37	0.18	0.42	1.02	0.44	0.40
dln_hwwicer	3.39	0.00	0.51	3.31	0.00	0.51	1.55	0.11	0.43	1.02	0.44	0.40
dln_hwwicoal	4.02	0.00	0.53	3.90	0.00	0.53	1.48	0.13	0.43	1.88	0.04	0.45
dln_hwwicoil	7.78	0.00	0.63	5.25	0.00	0.57	3.16	0.00	0.50	1.06	0.40	0.40
dln_hwwienrm	8.22	0.00	0.64	5.55	0.00	0.58	3.21	0.00	0.50	1.14	0.34	0.41
dln_hwwifood	2.80	0.00	0.49	2.82	0.00	0.49	1.41	0.16	0.42	0.93	0.52	0.40
dln_hwwiind	3.13	0.00	0.50	2.54	0.00	0.47	1.38	0.18	0.42	0.88	0.58	0.39
dln_hwwiiost	3.38	0.00	0.51	3.28	0.00	0.50	3.32	0.00	0.51	1.38	0.18	0.42
dln_hwwinfm	3.01	0.00	0.49	1.95	0.03	0.45	1.10	0.36	0.41	0.66	0.79	0.38
dln_hwwiseed	1.80	0.05	0.44	1.95	0.03	0.45	1.22	0.27	0.41	1.27	0.24	0.42
dln_hwwitex	1.81	0.05	0.44	1.84	0.04	0.44	1.24	0.26	0.41	0.54	0.89	0.37
dln_hwwiexen	3.31	0.00	0.51	2.95	0.00	0.49	1.24	0.26	0.41	0.66	0.80	0.38
dln_hwwi	9.02	0.00	0.65	5.70	0.00	0.58	3.01	0.00	0.50	1.08	0.38	0.41
Exchange rate												
dln_eurusd	1.35	0.19	0.42	1.64	0.08	0.43	0.79	0.67	0.39	0.91	0.54	0.40
dln_eer21	1.13	0.34	0.41	1.43	0.16	0.42	0.61	0.84	0.38	1.01	0.45	0.40
dln_eer41	1.11	0.36	0.41	1.40	0.17	0.42	0.63	0.82	0.38	0.91	0.54	0.40
dln_reer21	1.20	0.28	0.41	1.42	0.16	0.42	0.58	0.87	0.38	0.93	0.52	0.40
dln_reer41	1.15	0.33	0.41	1.37	0.18	0.42	0.58	0.86	0.38	0.88	0.58	0.39
Industrial production												
dln_iptotencon	5.57	0.00	0.58	5.62	0.00	0.58	4.43	0.00	0.55	4.41	0.00	0.55
dln_iptotcon	6.00	0.00	0.59	6.29	0.00	0.60	5.15	0.00	0.57	5.11	0.00	0.58
dln_iptoten	6.23	0.00	0.60	6.35	0.00	0.60	5.24	0.00	0.57	5.41	0.00	0.58
dln_ipcapg	6.44	0.00	0.60	6.34	0.00	0.60	5.41	0.00	0.58	4.91	0.00	0.57
dln_ipconsg	4.38	0.00	0.54	4.42	0.00	0.54	4.94	0.00	0.56	5.02	0.00	0.57
dln_ipintgds	5.87	0.00	0.59	5.56	0.00	0.58	4.41	0.00	0.55	4.61	0.00	0.56
dln_ipener	4.32	0.00	0.54	4.77	0.00	0.56	4.60	0.00	0.55	5.23	0.00	0.58
Industrial orders												
dln_iocapg	5.26	0.00	0.57	5.21	0.00	0.57	2.80	0.00	0.49	3.10	0.00	0.50
dln_ioconsd	4.73	0.00	0.55	4.42	0.00	0.54	3.04	0.00	0.50	2.97	0.00	0.50
dln_iointg	4.72	0.00	0.55	4.99	0.00	0.56	2.39	0.01	0.47	2.28	0.01	0.47
Surveys												
plv_hhfinsit12	0.62	0.83	0.38	0.63	0.82	0.38	1.01	0.45	0.40	0.82	0.64	0.39
plv_hhecosit12	0.82	0.63	0.39	0.83	0.63	0.39	1.38	0.18	0.42	1.08	0.39	0.41
plv_majpur12	1.62	0.09	0.43	1.66	0.08	0.43	1.07	0.39	0.40	1.11	0.35	0.41
plv_pritre12	1.79	0.05	0.44	1.73	0.06	0.44	1.68	0.07	0.44	0.75	0.72	0.39
dlv_sav12	1.32	0.21	0.42	1.31	0.22	0.42	1.36	0.19	0.42	1.56	0.11	0.43
Labour market												
dln_uetot_lm	3.40	0.00	0.51	2.54	0.00	0.47	2.98	0.00	0.50	4.28	0.00	0.55
dln_uer_lm	4.35	0.00	0.54	2.75	0.00	0.48	3.02	0.00	0.50	4.08	0.00	0.54

Note: the adjusted coefficient of determination of the (restricted) AR(12) model is 0.39. "dln" is the first difference of the logarithmic series; "dlv" is the first difference of the original series; "plv" is the percentage change of the original series.

Annex 4: Recursive Root Mean Squared Forecast Error

The forecast accuracy of a model *m* can be measured by the standard recursive Root Mean Squared Forecast Error (RMSFE) in a simulated out-of-sample forecast exercise. The RMSFE is obtained by first splitting the sample (of length *N*) into two parts: the model is fitted to the first subsample (of length *N*-*n*), running up to month *t*, and the series is then forecasted "out-of-sample". The forecast errors – the difference between the expectation of annual inflation at time $t+h$ conditional on the information at time *t*,[21] and the actual value of annual inflation – are then computed over the second (shorter) sub-sample (of length *n*) and stored.[22] The maximum number of comparable forecasts thus corresponds to the number of remaining observations in the second sub-sample. For a given forecast horizon, the RMSFE is given by the following expression:

$$RMSFE(h)^m = \left(\sum_t^T \left(\hat{\pi}^m_{t+h}\Big|_t - \pi_{t+h} \right)^2 / T \right)^{1/2},$$

Where $\hat{\pi}^m_{t+h}$ is the annual inflation forecast generated by candidate model *m*, at an *h*-month horizon, conditional on the information or assumptions at time *t*. π_{t+h} is the actual inflation rate at time $t+h$, while *T* represents the number of observations over which the model is evaluated.

The first sub-sample is recursively extended by one observation, and the estimation and comparison procedure above is repeated. While the first sub-sample thus gradually approaches the size of the full sample, the maximum comparable forecast horizon is reduced by one period at each step and thus approaches zero. More generally, for an h-step-ahead forecast, there will be n-h+1 possible forecast observations.[23] If a model is to be evaluated up to *h* steps ahead, the last recursive estimation should yield *h* comparable forecasts, implying that the last *h* available observations will not be used for the recursive estimation but only for evaluation purposes. This also implies that the same number of observations, $T\ (=n-h_{max}+1)$, is used to compute the RMSFE at each forecast horizon. In this paper, the evaluation period (*T*) is set to 48 months (i.e. 4 years), and the maximum forecast horizon (h_{max}) is set to 18 months.

[21] If the model contains exogenous variables, the forecast needs to be conditioned on a specific path assumed for the latter beyond time t.

[22] Models are compared on how accurately they predict *annual* inflation, which is the natural yardstick for inflation. This implies that forecasts obtained from models that are based on other transformations of the original price level series first need to be transformed into annual price changes.

[23] Starting with a given sub-sample, one will obtain n possible one-step-ahead forecasts, n-1 two-step ahead forecasts etc. and one n-step-ahead forecast.

Annex 5: Results

Table.A.6: RMSFEs for evaluation sample including crisis

				Direct forecasts																					
Horizon:				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	1 to 6	7 to 12	13 to 18	*1 to 18*
Benchmarks																									
ECB				1,03	1,08	1,12	1,15	1,17	1,18	1,18	1,19	1,19	1,19	1,19	1,19	1,19	1,19	1,19	1,18	1,18	1,19	1,12	1,19	1,19	*1,17*
Naive				0,31	0,51	0,70	0,87	1,04	1,18	1,31	1,44	1,57	1,68	1,77	1,84	1,89	1,90	1,90	1,89	1,86	1,84	0,77	1,60	1,88	*1,42*
AR(1)				0,37	0,57	0,72	0,81	0,87	0,90	1,02	1,12	1,19	1,22	1,23	1,24	1,24	1,24	1,24	1,24	1,23	1,23	0,71	1,17	1,24	*1,04*
ARMA(1,1)				0,37	0,56	0,70	0,79	0,85	0,89	1,01	1,10	1,17	1,19	1,20	1,22	1,22	1,22	1,22	1,21	1,21	1,20	0,69	1,15	1,21	*1,02*
AR(12)				0,31	0,53	0,74	0,91	1,06	1,17	1,29	1,40	1,49	1,57	1,64	1,69	1,70	1,71	1,69	1,68	1,64	1,61	0,79	1,51	1,67	*1,32*
Seas. Dummies				0,26	0,41	0,54	0,64	0,73	0,81	0,91	1,00	1,08	1,14	1,19	1,24	1,24	1,24	1,24	1,23	1,23	1,23	0,57	1,09	1,23	*0,96*
Univariate (AIC)		AR	MA																						
	U.1	10	6	0,31	0,48	0,66	0,81	0,94	1,01	1,11	1,20	1,26	1,33	1,36	1,39	1,38	1,38	1,35	1,33	1,31	1,29	0,70	1,27	1,34	*1,11*
	U.2	8	9	0,27	0,44	0,60	0,71	0,83	0,92	1,05	1,19	1,30	1,40	1,48	1,56	1,57	1,56	1,55	1,52	1,47	1,40	0,63	1,33	1,51	*1,16*
	U.3	10	9	0,30	0,50	0,70	0,85	1,00	1,12	1,23	1,34	1,43	1,50	1,54	1,57	1,56	1,55	1,53	1,52	1,49	1,46	0,75	1,43	1,52	*1,23*
	U.4	5	6	0,26	0,42	0,57	0,66	0,74	0,82	0,91	1,00	1,09	1,16	1,21	1,26	1,27	1,27	1,27	1,27	1,25	1,24	0,58	1,11	1,26	*0,98*
Univariate (SIC)		AR	MA																						
	U.1	10	6	0,31	0,48	0,66	0,81	0,94	1,01	1,11	1,20	1,26	1,33	1,36	1,39	1,38	1,38	1,35	1,33	1,31	1,29	0,70	1,27	1,34	*1,11*
	U.2	7	5	0,24	0,42	0,56	0,67	0,78	0,86	0,97	1,08	1,16	1,24	1,31	1,37	1,38	1,38	1,38	1,37	1,35	1,32	0,59	1,19	1,36	*1,05*
	U.3	0	0	0,29	0,48	0,66	0,80	0,95	1,07	1,19	1,31	1,43	1,53	1,62	1,69	1,72	1,73	1,73	1,72	1,69	1,66	0,71	1,46	1,71	*1,29*
	U.4	5	6	0,26	0,42	0,57	0,66	0,74	0,82	0,91	1,00	1,09	1,16	1,21	1,26	1,27	1,27	1,27	1,27	1,25	1,24	0,58	1,11	1,26	*0,98*
ADL	Specification	Y-lags	X-lags																						
oileur	B.3	7	6	0,19	0,28	0,36	0,41	0,48	0,52	0,61	0,70	0,79	0,87	0,93	1,00	1,02	1,04	1,05	1,06	1,04	1,05	0,37	0,82	1,04	*0,74*
oilusd	B.3	7	9	0,19	0,27	0,34	0,38	0,44	0,48	0,56	0,64	0,72	0,80	0,86	0,92	0,93	0,95	0,95	0,96	0,94	0,94	0,35	0,75	0,95	*0,68*
hwwieur	B.3	7	6	0,19	0,27	0,35	0,38	0,43	0,45	0,53	0,62	0,70	0,77	0,82	0,88	0,90	0,92	0,93	0,93	0,93	0,94	0,34	0,72	0,92	*0,66*
hwwixeneur	B.1	6	2	0,31	0,44	0,56	0,63	0,68	0,71	0,79	0,87	0,94	0,99	1,03	1,08	1,09	1,12	1,13	1,13	1,14	1,14	0,55	0,95	1,12	*0,88*
hwwiarm	B.3	6	0	0,25	0,42	0,56	0,67	0,77	0,84	0,94	1,04	1,14	1,21	1,27	1,32	1,32	1,32	1,31	1,29	1,27	1,25	0,59	1,16	1,29	*1,01*
hwwicer	B.1	8	9	0,32	0,44	0,57	0,64	0,69	0,70	0,75	0,81	0,84	0,86	0,86	0,87	0,87	0,87	0,89	0,90	0,90	0,89	0,56	0,83	0,89	*0,76*
hwwicoal	B.1	6	19	0,33	0,44	0,53	0,60	0,65	0,66	0,75	0,84	0,90	0,94	0,96	0,98	0,97	0,96	0,95	0,95	0,95	0,94	0,54	0,90	0,95	*0,79*
hwwicoil	B.3	7	6	0,19	0,28	0,36	0,41	0,47	0,52	0,60	0,69	0,78	0,86	0,92	0,99	1,01	1,03	1,04	1,05	1,03	1,04	0,37	0,80	1,03	*0,74*
hwwienrm	B.3	7	9	0,19	0,28	0,36	0,40	0,47	0,51	0,58	0,67	0,76	0,85	0,91	0,98	1,00	1,02	1,02	1,03	1,02	1,02	0,37	0,79	1,02	*0,73*
hwwifood	B.1	8	9	0,31	0,46	0,61	0,69	0,75	0,77	0,84	0,92	0,96	0,98	0,99	1,00	1,00	1,00	1,00	1,01	1,01	1,00	0,60	0,95	1,00	*0,85*
hwwiind	B.3	6	0	0,24	0,39	0,52	0,61	0,71	0,78	0,88	0,98	1,08	1,16	1,22	1,28	1,29	1,29	1,29	1,28	1,27	1,25	0,54	1,10	1,28	*0,97*
hwwiiost	B.1	7	16	0,32	0,48	0,57	0,63	0,66	0,68	0,76	0,83	0,87	0,89	0,92	0,96	0,99	1,02	1,03	1,05	1,06	1,06	0,55	0,87	1,03	*0.82*
hwwinfm	B.3	6	0	0,24	0,38	0,51	0,60	0,70	0,77	0,88	0,98	1,08	1,16	1,23	1,29	1,30	1,30	1,29	1,29	1,27	1,26	0,53	1,10	1,29	*0,97*
hwwiseed	B.4	6	9	0,26	0,42	0,55	0,63	0,71	0,76	0,83	0,92	1,01	1,07	1,11	1,15	1,14	1,14	1,13	1,12	1,10	1,09	0,55	1,01	1,12	*0,90*
hwwiexen	B.3	6	2	0,24	0,38	0,51	0,59	0,68	0,73	0,83	0,92	1,01	1,09	1,14	1,20	1,21	1,22	1,22	1,21	1,21	1,20	0,52	1,03	1,21	*0,92*
hwwi	B.3	7	6	0,19	0,28	0,35	0,38	0,44	0,47	0,55	0,63	0,72	0,79	0,85	0,91	0,93	0,96	0,96	0,97	0,97	0,97	0,35	0,74	0,96	*0,68*
eurusd	B.3	6	n.a.	0,25	0,41	0,56	0,66	0,76	0,83	0,93	1,03	1,12	1,19	1,25	1,30	1,29	1,29	1,28	1,27	1,25	1,24	0,58	1,14	1,27	*0,99*
iptotencon	B.1	11	9	0,27	0,44	0,60	0,71	0,81	0,85	0,90	0,92	0,94	0,95	0,97	0,99	0,97	0,98	0,97	0,95	0,91	0,88	0,61	0,94	0,94	*0,83*
iptotcon	B.2	6	8	0,25	0,42	0,58	0,70	0,81	0,87	0,94	0,98	1,03	1,06	1,08	1,09	1,06	1,05	1,01	0,97	0,92	0,89	0,61	1,03	0,98	*0,87*
iptoten	B.3	6	1	0,24	0,40	0,54	0,65	0,75	0,82	0,91	1,00	1,09	1,16	1,21	1,25	1,24	1,24	1,22	1,20	1,16	1,14	0,57	1,10	1,20	*0,96*
ipcapg	B.2	8	8	0,25	0,42	0,57	0,68	0,78	0,83	0,89	0,92	0,95	0,98	0,99	1,00	0,99	0,99	0,97	0,95	0,92	0,90	0,59	0,96	0,95	*0,83*
ipconsg	B.3	6	6	0,25	0,41	0,56	0,65	0,77	0,84	0,95	1,05	1,14	1,22	1,29	1,34	1,34	1,34	1,33	1,31	1,27	1,25	0,58	1,17	1,31	*1,02*
ipintgds	B.2	11	10	0,26	0,43	0,58	0,68	0,76	0,80	0,87	0,95	1,05	1,14	1,23	1,31	1,33	1,35	1,34	1,32	1,26	1,22	0,59	1,09	1,30	*0,99*
ipener	B.3	6	13	0,26	0,44	0,59	0,68	0,78	0,82	0,88	0,95	1,04	1,11	1,16	1,19	1,18	1,17	1,15	1,13	1,11	1,09	0,59	1,05	1,14	*0,93*
iocapg	B.2	0	7	0,25	0,38	0,50	0,58	0,67	0,71	0,76	0,81	0,87	0,91	0,94	0,98	0,98	0,97	0,94	0,92	0,88	0,86	0,52	0,88	0,93	*0,77*
ioconsd	B.1	8	12	0,28	0,48	0,66	0,83	0,96	1,04	1,14	1,20	1,24	1,27	1,31	1,34	1,34	1,34	1,33	1,33	1,32	1,31	0,71	1,25	1,33	*1,10*
iointg	B.1	6	19	0,28	0,42	0,56	0,64	0,68	0,70	0,74	0,76	0,80	0,84	0,87	0,89	0,89	0,90	0,92	0,94	0,95	0,97	0,55	0,81	0,93	*0,76*
hhfinsit12	B.3	6	3	0,25	0,41	0,56	0,66	0,76	0,83	0,93	1,03	1,13	1,21	1,27	1,32	1,32	1,32	1,31	1,30	1,27	1,26	0,58	1,15	1,30	*1,01*
hhecosit12	B.3	6	n.a.	0,25	0,41	0,56	0,66	0,76	0,83	0,93	1,03	1,12	1,19	1,25	1,30	1,29	1,29	1,28	1,27	1,25	1,24	0,58	1,14	1,27	*0,99*
majpur12	B.1	8	3	0,34	0,52	0,69	0,82	0,92	0,97	1,07	1,15	1,20	1,23	1,24	1,25	1,23	1,22	1,22	1,22	1,22	1,20	0,71	1,19	1,22	*1,04*
pritre12	B.3	6	0	0,25	0,41	0,55	0,64	0,74	0,80	0,90	0,99	1,09	1,16	1,23	1,29	1,32	1,34	1,36	1,37	1,37	1,37	0,56	1,11	1,35	*1,01*
sav12	B.3	6	1	0,24	0,40	0,54	0,63	0,71	0,77	0,85	0,94	1,02	1,09	1,13	1,17	1,16	1,16	1,14	1,13	1,11	1,10	0,55	1,03	1,13	*0,91*
uetot_lm	B.3	6	0	0,24	0,38	0,50	0,58	0,67	0,72	0,80	0,87	0,95	1,01	1,06	1,09	1,08	1,08	1,08	1,08	1,06	1,05	0,51	0,96	1,07	*0,85*
uer_lm	B.3	6	0	0,23	0,37	0,50	0,58	0,66	0,72	0,80	0,87	0,95	1,01	1,06	1,09	1,08	1,09	1,09	1,09	1,07	1,06	0,51	0,96	1,08	*0,85*
				Indirect forecasts																					
Agg-AR(1)				0,36	0,57	0,73	0,83	0,88	0,89	1,00	1,11	1,19	1,24	1,24	1,24	1,24	1,24	1,24	1,24	1,23	1,23	0,71	1,17	1,24	*1,04*
Agg-ARMA(1,1)				0,36	0,58	0,73	0,81	0,86	0,85	0,96	1,08	1,18	1,23	1,25	1,24	1,24	1,25	1,25	1,25	1,24	1,23	0,70	1,16	1,24	*1,03*
Agg-AR(12)				0,23	0,38	0,54	0,68	0,82	0,93	1,04	1,14	1,23	1,31	1,39	1,47	1,49	1,50	1,50	1,49	1,47	1,45	0,60	1,26	1,48	*1,12*
Agg-Seas. Dummies				0,27	0,43	0,56	0,64	0,73	0,80	0,90	1,00	1,09	1,15	1,19	1,24	1,24	1,24	1,24	1,23	1,23	1,23	0,57	1,09	1,23	*0,97*
Agg-ARMA (identical)				0,21	0,36	0,52	0,62	0,72	0,82	0,92	1,00	1,07	1,15	1,21	1,28	1,31	1,32	1,32	1,32	1,31	1,30	0,54	1,11	1,31	*0,99*
Agg-ARMA (component-specific)				0,20	0,32	0,45	0,54	0,65	0,74	0,82	0,92	0,99	1,07	1,13	1,19	1,20	1,21	1,21	1,20	1,20	1,20	0,48	1,02	1,20	*0,90*
Agg-oilusd (identical)				0,16	0,23	0,31	0,36	0,44	0,49	0,56	0,62	0,67	0,73	0,79	0,84	0,86	0,88	0,89	0,90	0,91	0,91	0,33	0,70	0,89	*0,64*
Agg-oilusd (component-specific)				0,16	0,21	0,29	0,34	0,42	0,47	0,53	0,60	0,65	0,70	0,75	0,80	0,82	0,85	0,86	0,87	0,89	0,89	0,32	0,67	0,86	*0,62*
Agg-multivariate (component-specific)				0,16	0,21	0,28	0,31	0,36	0,38	0,39	0,42	0,45	0,48	0,50	0,53	0,53	0,53	0,53	0,53	0,53	0,54	0,28	0,46	0,53	*0,42*

Table.A.7: RMSFEs for pre-crisis evaluation sample

												Direct forecasts													
Horizon:				1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	1 to 6	7 to 12	13 to 18	*1 to 18*
Benchmarks																									
ECB				0,34	0,34	0,34	0,34	0,33	0,33	0,33	0,32	0,31	0,31	0,31	0,31	0,31	0,31	0,31	0,33	0,36	0,40	0,34	0,32	0,34	*0,33*
Naive				0,18	0,24	0,30	0,33	0,34	0,34	0,34	0,35	0,34	0,35	0,37	0,40	0,39	0,38	0,36	0,35	0,35	0,36	0,29	0,36	0,36	*0,34*
AR(1)				0,29	0,41	0,49	0,51	0,49	0,46	0,52	0,58	0,58	0,55	0,48	0,38	0,37	0,37	0,37	0,38	0,41	0,44	0,44	0,52	0,39	*0,45*
ARMA(1,1)				0,29	0,40	0,47	0,49	0,47	0,44	0,49	0,55	0,55	0,52	0,45	0,36	0,36	0,36	0,35	0,36	0,40	0,43	0,42	0,49	0,38	*0,43*
AR(12)				0,20	0,27	0,32	0,35	0,35	0,35	0,35	0,36	0,36	0,35	0,34	0,33	0,33	0,34	0,34	0,35	0,37	0,39	0,31	0,35	0,35	*0,34*
Seas. Dummies				0,18	0,27	0,33	0,34	0,34	0,33	0,36	0,40	0,41	0,41	0,40	0,41	0,41	0,40	0,40	0,41	0,44	0,47	0,30	0,40	0,42	*0,37*
Univariate (AIC)		AR	MA																						
	U.1	10	10	0,23	0,29	0,35	0,37	0,38	0,38	0,41	0,41	0,41	0,42	0,39	0,37	0,35	0,36	0,37	0,37	0,40	0,43	0,34	0,40	0,38	*0,37*
	U.2	7	8	0,18	0,25	0,32	0,35	0,35	0,36	0,37	0,38	0,41	0,43	0,43	0,43	0,42	0,41	0,42	0,42	0,44	0,45	0,30	0,41	0,43	*0,38*
	U.3	10	11	0,20	0,26	0,33	0,37	0,39	0,38	0,41	0,44	0,42	0,42	0,42	0,42	0,43	0,46	0,45	0,44	0,44	0,47	0,32	0,42	0,45	*0,40*
	U.4	2	11	0,18	0,27	0,35	0,39	0,41	0,42	0,45	0,50	0,53	0,53	0,53	0,51	0,49	0,48	0,48	0,45	0,43	0,42	0,34	0,51	0,46	*0,44*
Univariate (SIC)		AR	MA																						
	U.1	9	7	0,25	0,32	0,39	0,41	0,43	0,42	0,42	0,44	0,42	0,43	0,41	0,38	0,37	0,38	0,37	0,36	0,39	0,41	0,37	0,42	0,38	*0,39*
	U.2	2	2	0,18	0,26	0,32	0,34	0,33	0,33	0,36	0,39	0,39	0,39	0,39	0,39	0,40	0,40	0,40	0,39	0,41	0,44	0,29	0,39	0,40	*0,36*
	U.3	0	0	0,19	0,26	0,32	0,35	0,35	0,34	0,36	0,39	0,38	0,38	0,37	0,36	0,36	0,36	0,36	0,36	0,36	0,37	0,30	0,37	0,36	*0,35*
	U.4	2	2	0,18	0,25	0,31	0,32	0,31	0,30	0,31	0,35	0,36	0,37	0,34	0,34	0,32	0,34	0,34	0,37	0,40	0,42	0,28	0,35	0,37	*0,33*
ADL	Specification	Y-lags	X-lags																						
oileur	B.4	7	1	0,16	0,19	0,24	0,26	0,26	0,25	0,26	0,28	0,28	0,29	0,29	0,29	0,28	0,27	0,27	0,27	0,29	0,31	0,23	0,28	0,28	*0,26*
oilusd	B.4	7	1	0,15	0,19	0,23	0,24	0,24	0,24	0,24	0,26	0,26	0,27	0,27	0,25	0,24	0,23	0,22	0,22	0,24	0,26	0,22	0,26	0,23	*0,24*
hwwieur	B.3	6	1	0,17	0,21	0,26	0,28	0,27	0,27	0,28	0,31	0,31	0,31	0,31	0,30	0,29	0,29	0,27	0,27	0,28	0,30	0,24	0,30	0,28	*0,28*
hwwixeneur	B.2	4	1	0,19	0,24	0,29	0,32	0,34	0,33	0,34	0,35	0,33	0,32	0,32	0,32	0,32	0,32	0,32	0,32	0,34	0,37	0,29	0,33	0,33	*0,32*
hwwiarm	B.2	6	1	0,19	0,23	0,28	0,30	0,32	0,31	0,32	0,34	0,33	0,32	0,33	0,35	0,35	0,35	0,35	0,35	0,37	0,39	0,27	0,33	0,36	*0,32*
hwwicer	B.4	6	6	0,18	0,23	0,28	0,30	0,32	0,33	0,37	0,41	0,44	0,47	0,50	0,53	0,54	0,54	0,54	0,53	0,54	0,55	0,28	0,45	0,54	*0,42*
hwwicoal	B.2	4	4	0,21	0,25	0,29	0,31	0,32	0,31	0,34	0,37	0,37	0,38	0,39	0,39	0,39	0,40	0,39	0,39	0,40	0,41	0,28	0,37	0,40	*0,35*
hwwicoil	B.4	7	1	0,16	0,20	0,24	0,26	0,26	0,26	0,26	0,28	0,29	0,30	0,30	0,30	0,29	0,29	0,29	0,29	0,31	0,33	0,23	0,29	0,30	*0,27*
hwwienrm	B.4	7	1	0,16	0,20	0,24	0,26	0,25	0,25	0,25	0,28	0,28	0,29	0,29	0,29	0,28	0,29	0,28	0,28	0,30	0,32	0,23	0,28	0,29	*0,27*
hwwifood	B.4	11	6	0,18	0,20	0,24	0,24	0,24	0,24	0,27	0,31	0,33	0,34	0,35	0,35	0,35	0,36	0,36	0,36	0,36	0,38	0,22	0,32	0,36	*0,30*
hwwiind	B.4	2	8	0,17	0,23	0,28	0,30	0,31	0,31	0,32	0,34	0,33	0,33	0,33	0,35	0,35	0,34	0,34	0,34	0,36	0,39	0,27	0,33	0,35	*0,32*
hwwiiost	B.2	4	1	0,19	0,26	0,31	0,33	0,34	0,34	0,34	0,33	0,30	0,29	0,28	0,29	0,29	0,29	0,28	0,29	0,32	0,35	0,29	0,31	0,30	*0,30*
hwwinfm	B.4	6	0	0,17	0,23	0,27	0,30	0,30	0,30	0,31	0,32	0,31	0,31	0,31	0,31	0,31	0,29	0,28	0,30	0,35	0,40	0,26	0,31	0,32	*0,30*
hwwiseed	B.4	11	6	0,18	0,21	0,25	0,25	0,25	0,24	0,27	0,31	0,34	0,35	0,35	0,37	0,36	0,37	0,37	0,38	0,39	0,40	0,23	0,33	0,38	*0,31*
hwwitex	B.2	4	n.a.	0,20	0,25	0,30	0,32	0,33	0,33	0,34	0,35	0,34	0,34	0,34	0,34	0,35	0,35	0,35	0,36	0,38	0,41	0,29	0,34	0,36	*0,33*
hwwiexen	B.2	4	1	0,19	0,24	0,29	0,32	0,33	0,33	0,33	0,34	0,33	0,31	0,31	0,31	0,32	0,32	0,32	0,33	0,35	0,38	0,28	0,32	0,34	*0,31*
hwwi	B.3	6	1	0,17	0,21	0,26	0,27	0,27	0,27	0,27	0,30	0,31	0,31	0,30	0,29	0,28	0,28	0,28	0,27	0,28	0,31	0,24	0,30	0,28	*0,27*
eurusd	B.4	6	n.a.	0,17	0,22	0,27	0,30	0,31	0,31	0,33	0,35	0,36	0,36	0,38	0,39	0,39	0,39	0,39	0,40	0,43	0,46	0,26	0,36	0,41	*0,35*
eer21	B.4	6	n.a.	0,17	0,22	0,27	0,30	0,31	0,31	0,33	0,35	0,36	0,36	0,38	0,39	0,39	0,39	0,39	0,40	0,43	0,46	0,26	0,36	0,41	*0,35*
eer41	B.2	4	1	0,19	0,24	0,29	0,32	0,33	0,33	0,34	0,35	0,33	0,32	0,33	0,33	0,33	0,33	0,33	0,34	0,36	0,40	0,28	0,33	0,35	*0,32*
reer21	B.4	6	n.a.	0,17	0,22	0,27	0,30	0,31	0,31	0,33	0,35	0,36	0,36	0,38	0,39	0,39	0,39	0,39	0,40	0,43	0,46	0,26	0,36	0,41	*0,35*
reer41	B.2	4	1	0,20	0,25	0,30	0,32	0,34	0,33	0,35	0,36	0,34	0,34	0,34	0,35	0,35	0,35	0,35	0,36	0,39	0,42	0,29	0,35	0,37	*0,33*
iptotencon	B.2	11	11	0,17	0,24	0,28	0,30	0,30	0,29	0,30	0,32	0,34	0,35	0,35	0,36	0,36	0,36	0,35	0,35	0,38	0,41	0,27	0,34	0,37	*0,32*
iptotcon	B.2	6	13	0,16	0,22	0,26	0,28	0,29	0,29	0,30	0,31	0,32	0,32	0,34	0,36	0,35	0,35	0,36	0,37	0,41	0,45	0,25	0,33	0,38	*0,32*
iptoten	B.2	6	16	0,18	0,25	0,32	0,36	0,37	0,37	0,36	0,36	0,33	0,33	0,35	0,39	0,39	0,39	0,38	0,38	0,41	0,45	0,31	0,35	0,40	*0,35*
ipcapg	B.2	6	11	0,17	0,22	0,27	0,29	0,30	0,30	0,31	0,32	0,32	0,33	0,35	0,36	0,36	0,35	0,36	0,38	0,42	0,46	0,26	0,33	0,39	*0,33*
ipconsg	B.2	4	4	0,17	0,23	0,28	0,31	0,32	0,32	0,34	0,35	0,35	0,35	0,36	0,37	0,37	0,37	0,37	0,39	0,42	0,45	0,27	0,35	0,39	*0,34*
ipintgds	B.2	11	17	0,18	0,25	0,29	0,31	0,31	0,30	0,31	0,34	0,36	0,38	0,39	0,40	0,39	0,39	0,38	0,38	0,39	0,43	0,27	0,36	0,39	*0,34*
ipener	B.2	10	15	0,19	0,25	0,29	0,31	0,31	0,30	0,31	0,34	0,35	0,35	0,35	0,33	0,30	0,30	0,29	0,30	0,33	0,36	0,27	0,34	0,31	*0,31*
iocapg	B.2	10	11	0,19	0,25	0,30	0,31	0,31	0,29	0,30	0,33	0,35	0,37	0,37	0,38	0,37	0,37	0,37	0,36	0,36	0,38	0,28	0,35	0,37	*0,33*
ioconsd	B.2	4	11	0,18	0,24	0,29	0,31	0,32	0,32	0,34	0,35	0,35	0,36	0,36	0,37	0,36	0,36	0,36	0,38	0,40	0,43	0,28	0,35	0,38	*0,34*
iointg	B.2	4	12	0,18	0,23	0,27	0,29	0,30	0,30	0,32	0,34	0,33	0,35	0,36	0,37	0,38	0,37	0,37	0,37	0,40	0,42	0,26	0,35	0,38	*0,33*
hhfinsit12	B.2	4	n.a.	0,20	0,25	0,30	0,32	0,33	0,33	0,34	0,35	0,34	0,34	0,34	0,34	0,35	0,35	0,35	0,36	0,38	0,41	0,29	0,34	0,36	*0,33*
hhecosit12	B.2	4	n.a.	0,20	0,25	0,30	0,32	0,33	0,33	0,34	0,35	0,34	0,34	0,34	0,34	0,35	0,35	0,35	0,36	0,38	0,41	0,29	0,34	0,36	*0,33*
majpur12	B.2	4	11	0,21	0,27	0,33	0,35	0,37	0,37	0,38	0,39	0,38	0,38	0,39	0,41	0,42	0,42	0,44	0,45	0,46	0,47	0,32	0,39	0,44	*0,38*
pritre12	B.2	6	0	0,20	0,24	0,27	0,28	0,29	0,28	0,30	0,31	0,30	0,29	0,29	0,29	0,30	0,30	0,31	0,31	0,33	0,34	0,26	0,30	0,31	*0,29*
sav12	B.2	4	0	0,19	0,25	0,30	0,32	0,33	0,33	0,34	0,35	0,34	0,33	0,34	0,34	0,34	0,35	0,35	0,36	0,38	0,40	0,28	0,34	0,36	*0,33*
uetot_lm	B.4	6	n.a.	0,17	0,22	0,27	0,30	0,31	0,31	0,33	0,35	0,36	0,36	0,38	0,39	0,39	0,39	0,39	0,40	0,43	0,46	0,26	0,36	0,41	*0,35*
uer_lm	B.4	6	n.a.	0,17	0,22	0,27	0,30	0,31	0,31	0,33	0,35	0,36	0,36	0,38	0,39	0,39	0,39	0,39	0,40	0,43	0,46	0,26	0,36	0,41	*0,35*
												Indirect forecasts													
Aggregation																									
Agg-AR(1)				0,29	0,43	0,53	0,57	0,54	0,47	0,53	0,61	0,63	0,61	0,52	0,39	0,37	0,36	0,36	0,37	0,40	0,43	0,47	0,55	0,38	*0,47*
Agg-ARMA(1,1)				0,29	0,44	0,54	0,56	0,54	0,45	0,52	0,61	0,64	0,61	0,53	0,37	0,32	0,31	0,30	0,31	0,33	0,36	0,47	0,55	0,32	*0,45*
Agg-AR(12)				0,16	0,24	0,30	0,34	0,34	0,34	0,34	0,37	0,37	0,36	0,34	0,35	0,34	0,33	0,32	0,31	0,33	0,36	0,29	0,35	0,33	*0,32*
Agg-Seas. Dummies				0,20	0,29	0,36	0,36	0,34	0,32	0,36	0,41	0,43	0,42	0,40	0,39	0,39	0,39	0,39	0,39	0,42	0,45	0,31	0,40	0,40	*0,37*
Agg-ARMA (identical)				0,16	0,23	0,31	0,35	0,37	0,38	0,39	0,44	0,46	0,49	0,52	0,55	0,54	0,53	0,52	0,53	0,58	0,62	0,30	0,48	0,55	*0,44*
Agg-ARMA (component-specific)				0,15	0,23	0,30	0,33	0,33	0,34	0,35	0,36	0,35	0,35	0,35	0,37	0,35	0,33	0,31	0,31	0,35	0,38	0,28	0,36	0,34	*0,33*
Agg-oilusd (identical)				0,14	0,18	0,23	0,26	0,26	0,26	0,25	0,28	0,29	0,32	0,33	0,34	0,33	0,31	0,30	0,29	0,31	0,33	0,22	0,30	0,31	*0,28*
Agg-oilusd (component-specific)				0,13	0,18	0,22	0,25	0,25	0,25	0,24	0,26	0,25	0,26	0,26	0,27	0,26	0,25	0,23	0,20	0,22	0,25	0,21	0,26	0,24	*0,24*
Agg-multivariate (component-specific)				0,13	0,17	0,21	0,23	0,24	0,24	0,23	0,23	0,22	0,22	0,23	0,23	0,23	0,23	0,22	0,23	0,27	0,31	0,20	0,23	0,25	*0,23*

Table.A.8: RMSFE of energy models; crisis and pre-crisis evaluation sample

Energy															
Crisis								Pre-crisis							
Horizon:				1 to 6	7 to 12	13 to 18	*1 to 18*	Horizon:				1 to 6	7 to 12	13 to 18	*1 to 18*
Benchmarks								**Benchmarks**							
AR(1)				4,43	7,74	8,30	6,83	AR(1)				2,91	4,80	5,53	4,41
ARMA(1,1)				4,45	7,71	8,29	6,82	ARMA(1,1)				2,87	4,76	5,51	4,38
AR(12)				4,86	8,99	9,63	7,83	AR(12)				2,93	4,92	5,77	4,54
Seas. Dummies				4,24	7,62	8,27	6,71	Seas. Dummies				2,82	4,72	5,56	4,37
Univariate (AIC)		AR	MA					**Univariate (AIC)**		AR	MA				
	U.1	9	9	4,70	8,46	8,91	7,36		U.1	6	8	3,54	5,53	5,85	4,97
	U.2	2	11	5,47	10,59	10,75	8,94		U.2	8	10	3,02	5,32	6,05	4,80
	U.3	4	11	5,43	9,37	9,08	7,96		U.3	8	9	3,41	5,21	6,05	4,89
	U.4	9	7	4,92	7,96	8,69	7,19		U.4	10	7	2,95	5,51	5,96	4,81
Univariate (SIC)		AR	MA					**Univariate (SIC)**		AR	MA				
	U.1	5	9	4,77	8,04	8,62	7,15		U.1	6	8	3,54	5,53	5,85	4,97
	U.2	1	0	4,14	7,59	8,28	6,67		U.2	2	4	2,93	4,85	5,55	4,44
	U.3	2	1	4,43	7,88	8,58	6,96		U.3	6	4	3,06	4,94	5,75	4,58
	U.4	1	0	4,04	6,96	7,42	6,14		U.4	1	1	2,89	5,04	5,93	4,62
ADL	Specification	Y-lags	X-lags					**ADL**	Specification	Y-lags	X-lags				
oileur	B.4	2	12	1,95	3,29	3,62	2,96	oileur	B.3	0	12	1,57	2,05	2,24	1,95
oilusd	B.4	0	12	1,69	2,40	2,66	2,25	oilusd	B.3	0	16	1,67	2,43	2,56	2,22
hwwieur	B.2	5	12	1,74	2,67	2,94	2,45	hwwieur	B.1	5	12	1,49	1,82	1,89	1,73
hwwicoil	B.4	2	12	1,96	3,09	3,38	2,81	hwwicoil	B.3	0	14	1,65	1,95	1,99	1,86
hwwienrm	B.4	3	12	1,83	2,76	3,01	2,53	hwwienrm	B.3	0	14	1,63	1,91	1,91	1,82
hwwi	B.2	5	12	1,79	2,71	3,00	2,50	hwwi	B.1	5	12	1,46	1,78	1,89	1,71
eurusd	B.4	1	n.a.	4,04	6,96	7,42	6,14	eurusd	B.3	1	n.a.	2,83	4,73	5,57	4,38
iptotencon	B.4	1	n.a.	4,04	6,96	7,42	6,14	iptotencon	B.3	1	n.a.	2,83	4,73	5,57	4,38
iptotcon	B.4	1	1	3,91	5,96	5,66	5,18	iptotcon	B.3	1	n.a.	2,83	4,73	5,57	4,38
iptoten	B.4	1	1	3,91	6,04	5,72	5,22	iptoten	B.3	1	n.a.	2,83	4,73	5,57	4,38
ipcapg	B.4	1	n.a.	4,04	6,96	7,42	6,14	ipcapg	B.3	1	n.a.	2,83	4,73	5,57	4,38
ipconsg	B.4	1	n.a.	4,04	6,96	7,42	6,14	ipconsg	B.3	1	n.a.	2,83	4,73	5,57	4,38
ipintgds	B.4	1	0	4,28	7,41	7,54	6,41	ipintgds	B.3	1	n.a.	2,83	4,73	5,57	4,38
ipener	B.4	1	1	3,94	6,38	6,67	5,66	ipener	B.4	11	2	2,84	4,31	4,95	4,03
iocapg	B.2	1	7	4,10	5,84	5,01	4,99	iocapg	B.1	1	7	2,73	4,50	5,39	4,21
ioconsd	B.4	1	0	4,15	7,24	7,69	6,36	ioconsd	B.3	1	0	2,81	4,74	5,58	4,38
iointg	B.4	1	2	3,29	4,64	5,17	4,37	iointg	B.3	2	2	2,67	4,45	5,18	4,10
uetot_lm	B.4	1	n.a.	4,04	6,96	7,42	6,14	uetot_lm	B.3	1	n.a.	2,83	4,73	5,57	4,38
uer_lm	B.4	1	0	3,87	6,37	6,57	5,60	uer_lm	B.3	1	n.a.	2,83	4,73	5,57	4,38

Table.A.9: RMSFE of processed food models; crisis and pre-crisis evaluation sample

Processed food															
Crisis								Pre-crisis							
Horizon:				1 to 6	7 to 12	13 to 18	*1 to 18*	Horizon:				1 to 6	7 to 12	13 to 18	*1 to 18*
Benchmarks								**Benchmarks**							
AR(1)				0,78	1,88	2,31	1,66	AR(1)				0,52	0,86	0,96	0,78
ARMA(1,1)				0,75	1,83	2,23	1,60	ARMA(1,1)				0,59	1,08	1,39	1,02
AR(12)				0,84	2,24	2,94	2,01	AR(12)				0,53	0,90	1,16	0,86
Seas. Dummies				0,85	1,92	2,31	1,69	Seas. Dummies				0,47	0,83	0,96	0,75
Univariate (AIC)		AR	MA					**Univariate (AIC)**		AR	MA				
	U.1	11	9	0,82	2,17	2,81	1,93		U.1	10	1	0,54	0,88	1,04	0,82
	U.2	9	10	0,82	2,03	2,58	1,81		U.2	5	5	0,54	0,99	1,28	0,94
	U.3	5	9	0,84	2,10	2,67	1,87		U.3	10	9	0,55	0,93	1,12	0,87
	U.4	10	2	0,78	1,92	2,48	1,73		U.4	11	11	0,61	1,11	1,35	1,02
Univariate (SIC)		AR	MA					**Univariate (SIC)**		AR	MA				
	U.1	4	2	0,74	1,83	2,28	1,62		U.1	3	1	0,59	1,04	1,17	0,93
	U.2	1	1	0,75	1,91	2,45	1,70		U.2	5	5	0,54	0,99	1,28	0,94
	U.3	5	1	0,83	2,17	2,78	1,93		U.3	4	3	0,56	0,86	1,00	0,81
	U.4	1	1	0,75	1,94	2,56	1,75		U.4	1	5	0,60	1,18	1,57	1,11
ADL	Specification	Y-lags	X-lags					**ADL**	Specification	Y-lags	X-lags				
oileur	B.4	10	n.a.	0,78	1,98	2,59	1,78	oileur	B.1	9	n.a.	0,54	0,87	0,99	0,80
oilusd	B.4	10	n.a.	0,78	1,98	2,59	1,78	oilusd	B.1	9	n.a.	0,54	0,87	0,99	0,80
hwwieur	B.4	10	n.a.	0,78	1,98	2,59	1,78	hwwieur	B.1	9	n.a.	0,54	0,87	0,99	0,80
hwwixeneur	B.4	10	0	0,76	1,91	2,53	1,73	hwwixeneur	B.1	9	n.a.	0,54	0,87	0,99	0,80
hwwiarm	B.4	10	n.a.	0,78	1,98	2,59	1,78	hwwiarm	B.1	9	1	0,54	0,90	1,04	0,83
hwwicer	B.4	10	0	0,75	1,84	2,41	1,66	hwwicer	B.1	9	0	0,54	0,88	1,00	0,81
hwwienrm	B.4	10	n.a.	0,78	1,98	2,59	1,78	hwwienrm	B.1	9	n.a.	0,54	0,87	0,99	0,80
hwwifood	B.4	10	0	0,75	1,87	2,47	1,69	hwwifood	B.1	9	0	0,53	0,85	0,97	0,78
hwwiseed	B.4	10	0	0,75	1,86	2,45	1,69	hwwiseed	B.1	9	2	0,50	0,75	0,86	0,70
hwwi	B.4	10	n.a.	0,78	1,98	2,59	1,78	hwwi	B.1	9	n.a.	0,54	0,87	0,99	0,80
eurusd	B.1	2	1	0,71	1,72	2,15	1,52	eurusd	B.3	2	1	0,46	0,73	0,82	0,67
eer21	B.1	10	n.a.	0,78	1,98	2,59	1,78	eer21	B.1	2	1	0,51	0,79	0,86	0,72
reer21	B.1	10	n.a.	0,78	1,98	2,59	1,78	reer21	B.1	2	1	0,51	0,78	0,84	0,71
iptotencon	B.4	10	n.a.	0,78	1,98	2,59	1,78	iptotencon	B.1	9	5	0,56	0,88	1,01	0,81
iptotcon	B.1	10	0	0,76	1,91	2,50	1,72	iptotcon	B.3	9	n.a.	0,50	0,90	1,15	0,85
iptoten	B.4	10	0	0,76	1,91	2,50	1,73	iptoten	B.1	9	5	0,56	0,89	1,04	0,83
ipcapg	B.4	10	n.a.	0,78	1,98	2,59	1,78	ipcapg	B.1	9	5	0,55	0,89	1,07	0,84
ipconsg	B.1	10	0	0,78	1,96	2,56	1,76	ipconsg	B.1	9	5	0,54	0,88	1,03	0,81
ipintgds	B.4	10	n.a.	0,78	1,98	2,59	1,78	ipintgds	B.1	9	5	0,57	0,89	0,99	0,81
ipener	B.2	10	n.a.	0,78	1,98	2,59	1,78	ipener	B.4	2	0	0,47	0,74	0,88	0,70
iocapg	B.1	9	0	0,75	1,94	2,58	1,76	iocapg	B.3	9	0	0,50	0,90	1,16	0,85
ioconsd	B.4	10	0	0,78	1,96	2,57	1,77	ioconsd	B.1	9	4	0,55	0,90	1,07	0,84
iointg	B.3	10	0	0,76	1,93	2,54	1,74	iointg	B.1	9	0	0,55	0,88	1,00	0,81
uetot_lm	B.3	10	0	0,78	1,96	2,44	1,73	uetot_lm	B.4	10	1	0,50	0,89	1,07	0,82
uer_lm	B.3	10	0	0,77	1,95	2,49	1,74	uer_lm	B.2	2	0	0,46	0,76	0,97	0,73
foodunp	B.2	9	0	0,79	2,03	2,62	1,81	foodunp	B.1	9	0	0,50	0,81	0,92	0,74

Table A.10: RMSFE of unprocessed food models; crisis and pre-crisis evaluation sample

Unprocessed food

Crisis

Horizon:				1 to 6	7 to 12	13 to 18	*1 to 18*
Benchmarks							
AR(1)				1,21	1,92	1,88	*1,67*
ARMA(1,1)				1,20	1,90	1,87	*1,66*
AR(12)				1,07	1,90	2,04	*1,67*
Seas. Dummies				0,94	1,73	1,86	*1,51*
Univariate (AIC)		AR	MA				
	U.1	10	11	1,06	1,83	1,92	*1,60*
	U.2	2	3	0,94	1,73	1,87	*1,51*
	U.3	9	9	1,01	1,82	1,91	*1,58*
	U.4	4	5	0,97	1,72	1,87	*1,52*
Univariate (SIC)		AR	MA				
	U.1	7	8	1,14	1,83	1,91	*1,63*
	U.2	2	3	0,94	1,73	1,87	*1,51*
	U.3	0	1	1,07	1,95	2,14	*1,72*
	U.4	2	4	0,95	1,75	1,89	*1,53*
ADL	Specification	Y-lags	X-lags				
oileur	B.3	1	8	1,14	1,98	2,12	*1,75*
oilusd	B.3	1	8	1,23	2,14	2,29	*1,88*
hwwieur	B.4	0	8	1,25	2,08	2,19	*1,84*
hwwixeneur	B.2	1	8	0,97	1,69	1,76	*1,47*
hwwiarm	B.2	1	10	1,09	1,76	1,61	*1,49*
hwwicer	B.1	11	1	1,07	1,67	1,71	*1,48*
hwwienrm	B.3	0	8	1,20	2,06	2,21	*1,82*
hwwifood	B.4	1	n.a.	0,93	1,71	1,84	*1,49*
hwwiseed	B.4	1	8	0,86	1,54	1,68	*1,36*
hwwiexen	B.4	1	n.a.	0,93	1,71	1,84	*1,49*
hwwi	B.4	0	8	1,28	2,13	2,25	*1,89*
eurusd	B.4	1	n.a.	0,93	1,71	1,84	*1,49*
eer21	B.4	1	n.a.	0,93	1,71	1,84	*1,49*
reer21	B.4	1	n.a.	0,93	1,71	1,84	*1,49*
iptotencon	B.2	5	13	0,72	2,05	2,82	*1,87*
iptotcon	B.2	5	14	0,78	2,12	3,47	*2,12*
iptoten	B.1	5	14	0,86	1,89	3,62	*2,12*
ipcapg	B.1	5	13	0,72	1,13	1,82	*1,22*
ipconsg	B.1	1	10	0,74	1,26	1,42	*1,14*
ipintgds	B.3	1	9	1,66	2,71	2,47	*2,28*
ipener	B.4	2	1	0,93	1,74	1,90	*1,52*
iocapg	B.1	5	13	0,72	1,13	1,82	*1,22*
ioconsd	B.2	5	15	0,93	1,36	1,47	*1,25*
iointg	B.4	1	20	1,18	1,82	2,76	*1,92*
uetot_lm	B.3	1	4	0,70	1,05	0,96	*0,90*
uer_lm	B.3	1	5	0,65	1,03	1,04	*0,91*

Pre-crisis

Horizon:				1 to 6	7 to 12	13 to 18	*1 to 18*
Benchmarks							
AR(1)				1,32	1,80	1,63	*1,58*
ARMA(1,1)				1,31	1,77	1,64	*1,57*
AR(12)				1,10	1,73	1,78	*1,54*
Seas. Dummies				0,92	1,51	1,67	*1,36*
Univariate (AIC)		AR	MA				
	U.1	10	9	1,14	1,76	1,71	*1,54*
	U.2	3	11	1,13	2,07	2,11	*1,77*
	U.3	10	9	1,17	1,78	1,83	*1,59*
	U.4	3	11	1,23	2,27	2,32	*1,94*
Univariate (SIC)		AR	MA				
	U.1	10	9	1,14	1,76	1,71	*1,54*
	U.2	2	2	0,97	1,56	1,68	*1,41*
	U.3	0	1	1,10	1,81	1,93	*1,61*
	U.4	2	3	0,98	1,52	1,68	*1,39*
ADL	Specification	Y-lags	X-lags				
oileur	B.3	0	11	0,76	0,98	1,14	*0,96*
oilusd	B.3	0	8	0,86	1,23	1,35	*1,15*
hwwieur	B.3	0	11	0,77	1,08	1,27	*1,04*
hwwixeneur	B.3	1	n.a.	0,94	1,52	1,66	*1,37*
hwwiarm	B.4	0	11	0,89	1,52	1,65	*1,36*
hwwicer	B.3	1	n.a.	0,94	1,52	1,66	*1,37*
hwwienrm	B.3	0	11	0,74	0,98	1,12	*0,95*
hwwifood	B.3	1	n.a.	0,94	1,52	1,66	*1,37*
hwwiseed	B.4	1	5	1,02	1,81	2,02	*1,62*
hwwiexen	B.3	0	8	0,95	1,61	1,82	*1,46*
hwwi	B.3	0	11	0,74	1,01	1,18	*0,98*
eurusd	B.3	1	n.a.	0,94	1,52	1,66	*1,37*
eer21	B.3	0	11	0,93	1,48	1,54	*1,32*
reer21	B.3	1	n.a.	0,94	1,52	1,66	*1,37*
iptotencon	B.1	5	14	0,99	1,49	1,66	*1,38*
iptotcon	B.1	5	14	0,95	1,45	1,60	*1,33*
iptoten	B.3	1	18	1,11	1,55	1,69	*1,45*
ipcapg	B.2	5	14	1,11	1,56	1,67	*1,45*
ipconsg	B.2	1	10	0,94	1,42	1,48	*1,28*
ipintgds	B.1	5	14	0,93	1,58	1,81	*1,44*
ipener	B.2	1	13	1,11	1,82	1,92	*1,62*
iocapg	B.3	1	1	0,92	1,46	1,62	*1,34*
ioconsd	B.2	5	14	1,13	1,44	1,48	*1,35*
iointg	B.1	5	14	0,98	1,54	1,75	*1,43*
uetot_lm	B.3	1	n.a.	0,94	1,52	1,66	*1,37*
uer_lm	B.3	1	n.a.	0,94	1,52	1,66	*1,37*

Table A.11: RMSFE of non-energy industrial goods models; crisis and pre-crisis evaluation sample

Non-energy industrial goods

Crisis

Horizon:				1 to 6	7 to 12	13 to 18	*1 to 18*
Benchmarks							
AR(1)				1,53	1,62	0,33	*1,16*
ARMA(1,1)				1,51	1,60	0,33	*1,15*
AR(12)				0,17	0,28	0,32	*0,26*
Seas. Dummies				0,64	0,70	0,30	*0,54*
Univariate (AIC)		AR	MA				
	U.1	11	11	0,18	0,29	0,30	*0,26*
	U.2	8	5	0,17	0,28	0,30	*0,25*
	U.3	7	10	0,19	0,27	0,30	*0,25*
	U.4	11	7	0,19	0,28	0,30	*0,26*
Univariate (SIC)		AR	MA				
	U.1	11	5	0,19	0,29	0,30	*0,26*
	U.2	5	5	0,15	0,26	0,29	*0,24*
	U.3	6	0	0,16	0,29	0,33	*0,26*
	U.4	6	0	0,14	0,27	0,32	*0,24*
ADL	Specification	Y-lags	X-lags				
oileur	B.4	6	0	0,13	0,26	0,31	*0,23*
oilusd	B.4	6	0	0,13	0,26	0,32	*0,24*
hwwieur	B.4	6	0	0,13	0,26	0,31	*0,23*
hwwiarm	B.3	11	1	0,16	0,26	0,28	*0,23*
hwwicoal	B.4	6	n.a.	0,14	0,27	0,32	*0,24*
hwwicoil	B.3	11	0	0,16	0,25	0,28	*0,23*
hwwienrm	B.3	11	0	0,16	0,26	0,28	*0,23*
hwwiind	B.3	11	n.a.	0,17	0,27	0,29	*0,24*
hwwiiost	B.3	11	n.a.	0,17	0,27	0,29	*0,24*
hwwinfm	B.4	6	n.a.	0,14	0,27	0,32	*0,24*
hwwitex	B.3	11	10	0,18	0,26	0,29	*0,25*
hwwiexen	B.3	11	n.a.	0,17	0,27	0,29	*0,24*
hwwi	B.3	11	0	0,16	0,25	0,28	*0,23*
eurusd	B.4	11	16	0,17	0,28	0,32	*0,26*
eer21	B.2	11	24	0,18	0,24	0,25	*0,22*
eer41	B.3	11	5	0,18	0,27	0,29	*0,25*
reer21	B.3	11	5	0,18	0,27	0,29	*0,24*
reer41	B.4	6	n.a.	0,14	0,27	0,32	*0,24*
iptotencon	B.4	6	n.a.	0,14	0,27	0,32	*0,24*
iptotcon	B.3	11	n.a.	0,17	0,27	0,29	*0,24*
iptoten	B.3	11	n.a.	0,17	0,27	0,29	*0,24*
ipcapg	B.4	6	n.a.	0,14	0,27	0,32	*0,24*
ipconsg	B.1	11	9	0,17	0,22	0,21	*0,20*
ipintgds	B.3	11	n.a.	0,17	0,27	0,29	*0,24*
ipener	B.1	11	5	0,17	0,27	0,29	*0,24*
iocapg	B.3	11	n.a.	0,17	0,27	0,29	*0,24*
ioconsd	B.3	11	n.a.	0,17	0,27	0,29	*0,24*
iointg	B.2	6	1	0,16	0,29	0,33	*0,26*
hhfinsit12	B.3	11	n.a.	0,17	0,27	0,29	*0,24*
majpur12	B.4	6	n.a.	0,14	0,27	0,32	*0,24*
pritre12	B.4	6	0	0,14	0,27	0,32	*0,24*
sav12	B.3	11	n.a.	0,17	0,27	0,29	*0,24*
uetot_lm	B.4	6	0	0,13	0,24	0,25	*0,21*
uer_lm	B.4	6	0	0,13	0,24	0,24	*0,21*

Pre-crisis

Horizon:				1 to 6	7 to 12	13 to 18	*1 to 18*
Benchmarks							
AR(1)				1,22	1,31	0,40	*0,98*
ARMA(1,1)				1,20	1,29	0,38	*0,96*
AR(12)				0,18	0,34	0,39	*0,30*
Seas. Dummies				0,55	0,60	0,34	*0,50*
Univariate (AIC)		AR	MA				
	U.1	11	8	0,25	0,55	0,60	*0,47*
	U.2	10	11	0,21	0,37	0,38	*0,32*
	U.3	9	11	0,18	0,35	0,41	*0,31*
	U.4	9	10	0,17	0,32	0,36	*0,28*
Univariate (SIC)		AR	MA				
	U.1	11	8	0,25	0,55	0,60	*0,47*
	U.2	5	5	0,17	0,31	0,35	*0,28*
	U.3	7	7	0,17	0,30	0,34	*0,27*
	U.4	5	7	0,16	0,31	0,36	*0,28*
ADL	Specification	Y-lags	X-lags				
oileur	B.1	6	5	0,17	0,26	0,27	*0,23*
oilusd	B.1	6	5	0,16	0,25	0,27	*0,23*
hwwieur	B.1	11	5	0,18	0,28	0,28	*0,25*
hwwiarm	B.1	11	5	0,19	0,34	0,39	*0,30*
hwwicoal	B.1	6	1	0,16	0,30	0,35	*0,27*
hwwicoil	B.1	6	5	0,17	0,26	0,26	*0,23*
hwwienrm	B.1	6	5	0,17	0,27	0,26	*0,23*
hwwiind	B.4	6	n.a.	0,17	0,32	0,37	*0,29*
hwwiiost	B.3	11	4	0,20	0,31	0,31	*0,27*
hwwinfm	B.4	6	n.a.	0,17	0,32	0,37	*0,29*
hwwitex	B.1	6	1	0,17	0,31	0,35	*0,27*
hwwiexen	B.4	6	n.a.	0,17	0,32	0,37	*0,29*
hwwi	B.1	11	5	0,18	0,28	0,28	*0,25*
eurusd	B.3	11	4	0,20	0,36	0,40	*0,32*
eer21	B.3	11	4	0,19	0,35	0,39	*0,31*
eer41	B.3	11	4	0,18	0,33	0,36	*0,29*
reer21	B.3	11	4	0,20	0,36	0,40	*0,32*
reer41	B.3	11	4	0,19	0,35	0,38	*0,31*
iptotencon	B.1	6	4	0,16	0,31	0,36	*0,28*
iptotcon	B.1	6	4	0,16	0,30	0,35	*0,27*
iptoten	B.2	6	4	0,17	0,32	0,39	*0,29*
ipcapg	B.4	6	n.a.	0,17	0,32	0,37	*0,29*
ipconsg	B.1	6	4	0,16	0,31	0,36	*0,27*
ipintgds	B.1	6	4	0,17	0,31	0,36	*0,28*
ipener	B.3	7	n.a.	0,16	0,31	0,36	*0,28*
iocapg	B.1	6	4	0,18	0,31	0,36	*0,28*
ioconsd	B.3	6	8	0,22	0,38	0,42	*0,34*
iointg	B.1	6	4	0,17	0,31	0,35	*0,27*
hhfinsit12	B.1	6	0	0,17	0,31	0,36	*0,28*
majpur12	B.3	11	3	0,17	0,30	0,34	*0,27*
pritre12	B.1	6	n.a.	0,17	0,31	0,36	*0,28*
sav12	B.3	11	0	0,17	0,31	0,35	*0,28*
uetot_lm	B.3	7	0	0,16	0,29	0,33	*0,26*
uer_lm	B.4	6	n.a.	0,17	0,32	0,37	*0,29*

Table A.12: RMSFE of services models; crisis and pre-crisis evaluation sample

Services

Crisis

Horizon:				1 to 6	7 to 12	13 to 18	*1 to 18*
Benchmarks							
AR(1)				0,50	0,56	0,51	*0,52*
ARMA(1,1)				0,44	0,50	0,50	*0,48*
AR(12)				0,23	0,41	0,56	*0,40*
Seas. Dummies				0,18	0,36	0,50	*0,35*
Univariate (AIC)		AR	MA				
	U.1	9	11	0,26	0,41	0,52	*0,40*
	U.2	10	6	0,18	0,37	0,51	*0,35*
	U.3	11	11	0,23	0,41	0,54	*0,39*
	U.4	10	9	0,20	0,40	0,53	*0,38*
Univariate (SIC)		AR	MA				
	U.1	9	11	0,26	0,41	0,52	*0,40*
	U.2	10	6	0,18	0,37	0,51	*0,35*
	U.3	0	4	0,24	0,45	0,64	*0,44*
	U.4	5	6	0,20	0,38	0,52	*0,37*
ADL	Specification	Y-lags	X-lags				
oileur	B.3	11	0	0,20	0,38	0,51	*0,36*
oilusd	B.3	11	0	0,20	0,39	0,52	*0,37*
hwwieur	B.3	11	2	0,20	0,37	0,50	*0,36*
hwwixeneur	B.3	11	n.a.	0,19	0,36	0,49	*0,35*
hwwiarm	B.3	11	0	0,19	0,36	0,47	*0,34*
hwwicoil	B.3	11	2	0,20	0,38	0,50	*0,36*
hwwienrm	B.3	11	2	0,20	0,38	0,51	*0,36*
hwwifood	B.3	11	n.a.	0,19	0,36	0,49	*0,35*
hwwiind	B.3	11	n.a.	0,19	0,36	0,49	*0,35*
hwwinfm	B.3	11	n.a.	0,19	0,36	0,49	*0,35*
hwwiseed	B.3	11	n.a.	0,19	0,36	0,49	*0,35*
hwwitex	B.3	11	n.a.	0,19	0,36	0,49	*0,35*
hwwiexen	B.3	11	n.a.	0,19	0,36	0,49	*0,35*
hwwi	B.3	11	2	0,20	0,38	0,51	*0,37*
eurusd	B.3	11	0	0,18	0,34	0,46	*0,33*
eer21	B.3	11	0	0,18	0,34	0,45	*0,32*
eer41	B.3	11	0	0,18	0,34	0,46	*0,33*
reer21	B.3	11	0	0,18	0,34	0,45	*0,32*
reer41	B.3	11	0	0,18	0,34	0,45	*0,32*
iptotencon	B.2	11	15	0,31	0,52	0,60	*0,48*
iptotcon	B.4	5	12	0,27	0,68	0,97	*0,64*
iptoten	B.3	11	n.a.	0,19	0,36	0,49	*0,35*
ipcapg	B.2	9	15	0,30	0,57	0,71	*0,53*
ipconsg	B.3	8	5	0,18	0,32	0,45	*0,32*
ipintgds	B.2	8	15	0,31	0,57	0,64	*0,51*
ipener	B.4	7	n.a.	0,18	0,38	0,54	*0,37*
iocapg	B.4	7	0	0,19	0,40	0,57	*0,39*
ioconsd	B.3	11	1	0,20	0,41	0,55	*0,39*
iointg	B.2	5	24	0,29	0,45	0,47	*0,40*
uetot_lm	B.4	8	17	0,26	0,53	0,69	*0,49*
uer_lm	B.4	7	10	0,22	0,34	0,41	*0,32*

Pre-crisis

Horizon:				1 to 6	7 to 12	13 to 18	*1 to 18*
Benchmarks							
AR(1)				0,45	0,46	0,28	*0,40*
ARMA(1,1)				0,40	0,43	0,32	*0,38*
AR(12)				0,20	0,34	0,40	*0,31*
Seas. Dummies				0,16	0,25	0,30	*0,23*
Univariate (AIC)		AR	MA				
	U.1	11	7	0,24	0,32	0,33	*0,30*
	U.2	10	8	0,15	0,25	0,31	*0,23*
	U.3	9	9	0,18	0,26	0,31	*0,25*
	U.4	11	5	0,13	0,23	0,30	*0,22*
Univariate (SIC)		AR	MA				
	U.1	11	7	0,24	0,32	0,33	*0,30*
	U.2	10	6	0,15	0,25	0,30	*0,23*
	U.3	0	4	0,18	0,35	0,47	*0,33*
	U.4	5	5	0,12	0,21	0,28	*0,20*
ADL	Specification	Y-lags	X-lags				
oileur	B.4	7	0	0,15	0,26	0,30	*0,24*
oilusd	B.4	7	0	0,15	0,26	0,32	*0,24*
hwwieur	B.4	7	0	0,15	0,27	0,31	*0,24*
hwwixeneur	B.3	11	n.a.	0,15	0,27	0,35	*0,26*
hwwiarm	B.3	11	n.a.	0,15	0,27	0,35	*0,26*
hwwicoil	B.4	7	0	0,15	0,26	0,30	*0,23*
hwwienrm	B.4	7	0	0,15	0,26	0,30	*0,24*
hwwifood	B.3	11	1	0,15	0,28	0,36	*0,26*
hwwiind	B.3	11	n.a.	0,15	0,27	0,35	*0,26*
hwwinfm	B.3	11	n.a.	0,15	0,27	0,35	*0,26*
hwwiseed	B.4	7	1	0,15	0,29	0,35	*0,26*
hwwitex	B.3	11	n.a.	0,15	0,27	0,35	*0,26*
hwwiexen	B.3	11	n.a.	0,15	0,27	0,35	*0,26*
hwwi	B.4	7	2	0,15	0,28	0,33	*0,25*
eurusd	B.3	11	n.a.	0,15	0,27	0,35	*0,26*
eer21	B.3	11	0	0,14	0,23	0,26	*0,21*
eer41	B.3	11	0	0,14	0,24	0,30	*0,23*
reer21	B.3	11	0	0,14	0,23	0,26	*0,21*
reer41	B.3	11	0	0,14	0,24	0,28	*0,22*
iptotencon	B.3	6	5	0,15	0,27	0,33	*0,25*
iptotcon	B.1	11	11	0,16	0,25	0,33	*0,25*
iptoten	B.1	7	15	0,17	0,24	0,34	*0,25*
ipcapg	B.1	11	11	0,19	0,26	0,33	*0,26*
ipconsg	B.3	6	5	0,15	0,25	0,31	*0,24*
ipintgds	B.3	7	5	0,15	0,26	0,33	*0,25*
ipener	B.2	11	17	0,15	0,25	0,32	*0,24*
iocapg	B.4	7	0	0,16	0,29	0,34	*0,26*
ioconsd	B.3	11	5	0,18	0,28	0,29	*0,25*
iointg	B.3	7	12	0,19	0,31	0,39	*0,30*
uetot_lm	B.3	11	n.a.	0,15	0,27	0,35	*0,26*
uer_lm	B.3	11	n.a.	0,15	0,27	0,35	*0,26*