Forecasting inflation in times of crisis

VAR models performance in forecasting inflation in the eurozone during the post-crisis period

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Abstract

Previous forecasting methods of inflation are presented. In order to investigate and improve the forecasting procedure on inflation around the 2008 recession period in the eurozone, various vector-autoregressive (VAR) models and simple autoregressive (AR) models are specified and compared. First we find that models with first-difference variables are inferior to level variables. Second, the introduction of import price indexes renders the VAR-models unstable thereby hinders forecasting. Third, the classical triangle-VAR and ARIMA model outperform other specifications over longer horizons, but the VAR-model with unemployment, output growth and money aggregate M2 minimizes the root-mean-square forecast error for inflation over short-term forecast, among the analyzed models.

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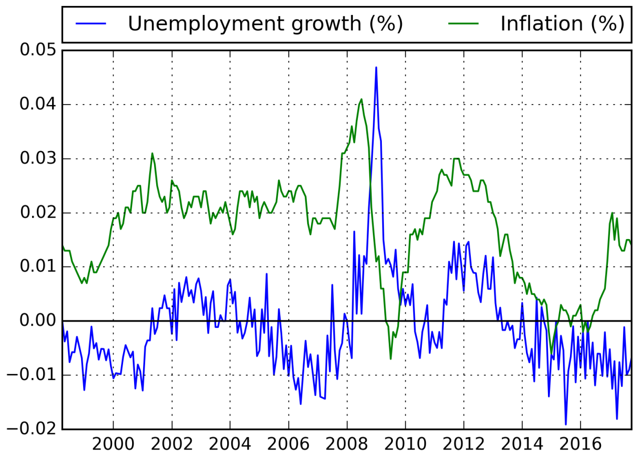
Figure 1: HICP and unemployment growth, ECB data warehouse

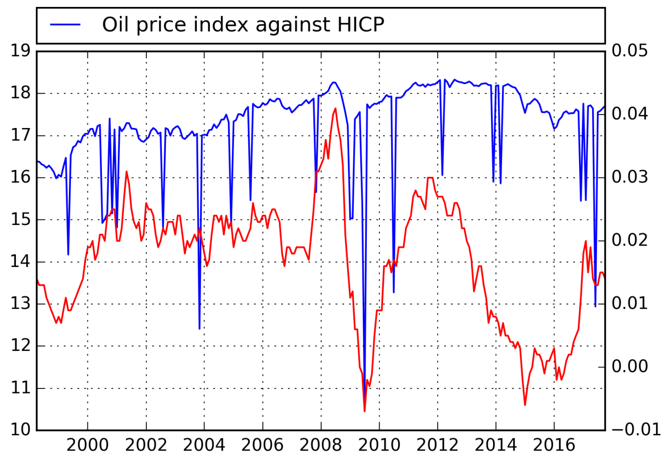


1 Introduction

In recent years, inflation forecasting has been a major challenge for economists and central bankers alike. The perception of the public is that the inflation process is yet another unsolved economic mystery: central bankers have no clear certainty after the breakdown of traditional models like the Phillips curve and economists are essentially the blind leading the blind. In these times of uncertainties the most reliable and thorough analysis was conducted in two papers by Stock and Watson (2008, 2010). The former paper categorizes a variety of approaches used to tackle the inflation forecasting issue, from simple univariate models and random walk to more complex multivariate models with a large number of variables. The latter focuses on Phillips curve-based forecasting during the recession period but gives inconclusive results. The present paper aims to apply a similar analysis to Stock and Watson (2010) with a larger data window for the post-recession period on the eurozone. The relevance of such an analysis arises from the fact that during the 2008 recession, as unemployment rose sharply and output fell, inflation became increasingly volatile, but, despite output growth and quantitative easing by the ECB, stayed within the 4% barrier, as seen in figure 1.

Such a pattern of inflation, seemingly detached from the unemployment, seems to indicate a breakdown of the Philips curve. There has been a lot of speculation around this phenomenon and many pointed at anchoring expectation as its root cause. Notably, Łyziak and Paloviita (2017) in their paper show that anchoring expectations may cause the trade-off unemployment/inflation to break down in the eurozone and thereby hinder modeling inflation and hence monetary policy. However, in the context of stable monetary policy, like the 2% inflation target of the ECB, anchoring expectations do not affect forecasting

Figure 2: Oil prices plotted against HICP, ECB statistical warehouse



because they are already encompassed in the assumption of adaptive expectations, as pointed out by the father of the idea Lucas: "For tile question of the short-term forecasting, or tracking ability of econometric models, we have seen that this conclusion (ed. of monetary policy shifting econometric models) is of only occasional significance." (1976, p. 41). Another factor in the HICP pattern may have been a drop in oil prices of the second semester of 2009. Theoretically, being oil price an important component in the HICP measure, a drop in prices of oil will cause inflation to decrease instantly and subsequently increase, due to reduced production costs and increase in output, as seen in figure 2. However, once again, this is more of concern to monetary policy than inflation forecasting. The issue of exogenous oil price shocks will be addressed later within the models.

The purpose of this paper's analysis is to determine whether Phillips curve-based models still maintain explanatory and predictive power, despite the abnormal monetary policies and the stagflation of the last two decades. To do so, a VAR model, a triangle-based model, and an Autoregressive integrated moving average (ARIMA) model will be determined, theoretically justified, estimated and compared. Despite inconclusive results by Stock and Watson (2008, 2010) regarding the performance of the Phillips curve model on forecasting, the VAR model is expected to outperform the benchmark models due to its efficacy in forecasting under shocks to the dependent variables.

The analysis will be conducted with data from the Eurozone, for the period 1997-2017, thereby restricting the analysis to a specific time period and economic area. Although the result could probably be extended to the rest of the developed world, due to the similar patterns in recent inflation trends, the focus of the analysis remains contingent to the specific economic area. Most importantly, the analysis is strongly time contingent and, although it may provide insights in forecasting for future specific recession periods, it is hardly generalizable to other economic periods.

In this paper, first the relevant literature on Phillips curve forecasting and inflation theory with a focus on adaptive expectations will be presented, then the focus will move towards the model structuring and the variable choice. After the model specification, the data will be analyzed, checked for specific conditions and used to estimate the models. The models will then be evaluated in terms of predictive power and used to forecast inflation.

2 Literature Review

Thus far inflation forecasting in economic empirical research has largely been conducted based on Philips Curve theory or univariate time series models (Stock & Watson, 2008). The most prominent Philips curve-based model is the triangle model, designed by Gordon (1990), that relies on three variables:

$$\pi_{\mathrm{t+1}} = \mu + \alpha^{\mathrm{G}}(L)\pi_{\mathrm{t}} + \beta(L)u_{\mathrm{t+1}} + \gamma(L)z_{\mathrm{t}} + v_{\mathrm{t+1}} \tag{2.1}$$

where π is the inflation rate, u is the (Perry-weighted) unemployment rate and z is a variable for supply shocks. A simpler approach, used as a benchmark for forecasting improvement of other models, is the direct autoregressive (AR) model with a lag length computed with the Akaike information criterion (AIC):

$$\pi^{h}{}_{\mathrm{t+h}} - \pi_{\mathrm{t}} = \mu^{h} + \alpha^{h}(L)\Delta\pi_{\mathrm{h}} + v^{h}{}_{\mathrm{t+h}} \tag{2.2}$$

Stock and Watson (2008) found that "the performance of Philips curve forecasts is episodic" (p. 2), that is the forecasting with Philips curve models improves with respect to a univariate model, for example the AC(AIC) model, only when examining certain periods, such as the mid-90s. Another widespread approach is to forecast inflation with a variety of models and then average the result, for example with Bayesian Model Averaging as in Wright (2003).

Another major issue in Philips curve-based forecasts is modeling expected inflation, that is going from survey responses on the direction of inflation to quantitative data. Various approaches are possible, the most common being the probability approach, which assumes that consumers have a probability function over the expected inflation rate and vary in the probability chosen to model their responses. Notably, Carlson and Parkin (1975) argued in favor of using a normal distribution as the probability function. On the other hand, advocates of rational expectations theory argue that agents form expectations rationally and adapt them based on experienced and available information on inflation. In light of this hypothesis, it seems incorrect to model inflation expectations as exogenous. In support of this approach, Malmendier and Nagel (2009) found that "When forming macroeconomic expectations, individuals put a higher weight on realizations of macroeconomic data experienced during their lifetimes compared with other available historical data" (p. 3). This result implies that individuals from different age groups have different expectations based on their lifetime experience, but on a macroeconomic level, these differences get canceled out and only the expectation of the median consumer is relevant. Another major implication of the paper is that, in the context of the Philips curve-based models discussed so far, inflation expectations would be endogenous. Other papers dealt with possible exogenous determinants of expectations, notably Heinemann and Ullrich (2006) who analyzed the inflation expectations changes contingent to a change in anti-inflation attitudes from the Bundesbank to the ECB, after the Maastricht Treaty. In their empirical analysis they find “that the regime change did not have a strong and lasting impact on the formation of inflation expectations” (p. 1). This result further validates a more endogenous approach towards inflation expectation modeling, in this case among financial markets.

Other prominent papers heavily criticized Philips curve-based forecasts. Famously, Atkeson and Ohanian (2001) conducted a thorough empirical analysis comparing naive random-walk forecasting models for inflation against the models aforementioned in this literature review, and found that “for the last 15 years, economists have not produced a version of the Phillips curve that makes more accurate inflation forecasts than those from a naive model” (p. 10). Furthermore, they add that “given the weak theoretical and empirical underpinnings of the various incarnations of the Phillips curve, we conclude that the search for yet another Phillips curve-based forecasting model should be abandoned” (p. 10). These results heavily undermine the most widespread methods and models used in inflation forecasting, yet do not provide alternative methods. Further validation of criticism on this type of forecasting has been centered around the unreliability and small predictive power of the individual indicators and variable used in forecasting. Namely, Cecchetti et al. (2000) analyzed with simple statistics the performance of various variables like exchange rate, interest rates, money growth and unemployment and concluded that “ No single indicator in our simple statistical framework clearly and consistently improved autoregressive projections ” (p. 5).

Despite these criticisms, this paper will try and analyze a specific time period with Phillips curve-based forecast models in light of the theoretical bases that underpin the models and the positive performance of these models in specific time periods. Nonetheless, the sword of Damocles represented by the empirical limitations and shortcoming of the models needs to be acknowledged and kept in mind throughout the analysis. In light of the literature presented, in the next section the core VAR model will be theoretically justified and structured and the benchmark models will be selected.

3 The models

3.1 VAR model

The model of choice for this analysis is the vector autoregression model. The model is defined as:

$$Y_{\text{t}} = A + B_{\text{t-1}}\ Y_{\text{t-1}} + ... + B_{\text{t-p}}\ Y_{\text{t-p}} + u_{\ \text{t}} \tag{3.1}$$

where:

$$Y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}$$

that is a vector of n endogenous variables. A is the constants matrix, B is the coefficient matrix and u is the error matrix. We further assume that $E(u_{\mathrm{t}}) = 0, E(u_{\mathrm{t}}u_{\mathrm{t}}') = \Omega$ and $E(u_{\mathrm{t}}u_{\mathrm{s}}) = 0$
The subscripts p refers to the number of lags and t to the time.

Since its introduction by Sims (1980), the VAR model has been widely used in macroeconomic, and specifically inflation, analysis by both central bankers in the Federal reserve and ECB and economists, due to its versatility and the possibility to model simultaneous causality among time periods and various different variables.

3.2 Phillips curve

The core of the VAR-models of the paper will be an expectations-augmented Phillips curve. The empirical relevance of the Phillips curve has been debated widely since its introduction by Samuelson and Solow (1960). The theoretical fundamentals and the short-term nature of the correlation are well known, although the mechanisms and causality direction of the relation has been since debated. Notably Phelps (1967) argues that as output increases beyond the natural level, unemployment decreases, bargaining power of workers increases, thereby increasing wages and producing higher prices to protect profits by employers. In general, especially when the Phillips curve is used for empirical analysis and long-term forecasting, the model is integrated with other theoretical determinants of inflation for example import prices, long-run inflation or money growth. More recently, on its relevance on inflation forecasting, Stock and Watson (2008) argue that "The results here suggest that, if times are quiet (...) then in fact one is better off using a univariate forecast than introducing additional estimation error by making a multivariate forecast. But if the economy is near a turning point (...) then knowledge of that large unemployment gap would be useful for inflation forecasting." (p.32, 2008). For the Eurozone during the analyzed period, it can be argued that the economy is in a turning point due to the imbalances on the unemployment level and money growth as a result of the 2008 financial crisis. In the euro-area, according to Assenmacher-Wesche and Gerlach (2006), the core determinants of inflation, at low frequency, appear to be money and output growth. For this reason, the first VAR model (referred to as *simple*) will be composed of the three standard Phillips curve variables, unemployment (u), the growth of the monetary aggregate M2 (m) and HICP (π).

The VAR(p) model will be then defined as follows:

$$\begin{pmatrix} \pi_t \\ m_t \\ u_t \end{pmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \begin{bmatrix} \beta_{1,t-1} \\ \beta_{2,t-1} \\ \beta_{3,t-1} \end{bmatrix} \begin{pmatrix} \pi_{t-1} \\ m_{t-1} \\ u_{t-1} \end{pmatrix} + ... + \begin{bmatrix} \beta_{1,t-p} \\ \beta_{2,t-p} \\ \beta_{3,t-p} \end{bmatrix} \begin{pmatrix} \pi_{t-p} \\ m_{t-p} \\ u_{t-p} \end{pmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} \tag{3.2}$$

In a second model specification (referred to as *extended*), the model will be integrated with a variable that represents the medium- and high-frequency determinant of low inflation, output grow (o):

$$\begin{pmatrix} \pi_t \\ m_t \\ u_t \\ o_t \end{pmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{bmatrix} + \begin{bmatrix} \beta_{1,t-1} \\ \beta_{2,t-1} \\ \beta_{3,t-1} \\ \beta_{4,t-1} \end{bmatrix} \begin{pmatrix} \pi_{t-1} \\ m_{t-1} \\ u_{t-1} \\ o_{t-1} \end{pmatrix} + ... + \begin{bmatrix} \beta_{1,t-p} \\ \beta_{2,t-p} \\ \beta_{3,t-p} \\ \beta_{4,t-p} \end{bmatrix} \begin{pmatrix} \pi_{t-p} \\ m_{t-p} \\ u_{t-p} \\ o_{t-p} \end{pmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} \tag{3.3}$$

In support of these theoretical arguments for the Phillips curve, for the analyzed period, table 1 shows that there seems to be empirical evidence for a negative relation between the two variables. Although these are simple regressions that do not prove any negative causality, they do indicate a specific correlation during the analyzed time frame and further support the use of the Phillips curve as a framework for the VAR model.

Table 1: Phillips curve regression

	(1) HICP 1997-2007	(2) HICP 2008-2017
Unemployment growth %	-0.393***	-0.591***
	(-9.16)	(-10.61)
_cons	0.0546***	0.0731***
	(13.15)	(14.48)
N	235	107

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.3 Money growth and output gap

Other dependent variables are used in the VAR model, namely the Money growth (m) and, only in the extended model, the output gap growth (o). There is a strong theoretical and empirical basis supporting the inclusion of these variables. Firstly, the idea that the inflation trend arises exclusively from a discrepancy between the quantity of money and the quantity of output is a long-lasting fundamental pillar of the monetarist economic theory. Notably Friedman (1968) argues that monetary policy should be used as a stabilizer and in principle central banks should not deviate from a moderate and constant growth of the monetary base because this will certainly cause long-run inflation.

This idea is reflected in the equation of exchange defined by Irving Fisher in 1911: $MV_T = PT$; where given a constant velocity of money and amount of transactions an increase in money quantity necessarily leads to an increase in price. Empirically, Assenmacher-Wesche and Gerlach (2006) found that in the euro-area, despite the significance of deviation from the trend in the short-run caused by import price, exchange rates and oil shocks, in the long-run the core fundamentals of inflationary trends are money growth and the output gap. In light of this, it seems reasonable to include money growth and output gap in the VAR-model and expect them to help forecast the long-run inflation trend.

3.4 Adaptive expectations

The role of consumers' expected inflation on monetary policy and on inflation forecasting has been central in recent research, as shown previously. The modeling choice for these expectations and their relation to actual inflation is a difficult and rather arbitrary task. Results from Malmendier and Nagel (2009) have shown that consumers in developed countries base their expectation on lifetime experience and on their economic literacy. Furthermore, Łyziak and Paloviita (2017) have shown how consumers expectations, in times of low inflation and in the context of credible central banks, show an anchoring effect. Based on these results, this paper will model expected inflation (π^{e}) as an adaptive process, where consumers update their expected inflation based on the error in their previous time periods expectations:

$$\pi^{\mathrm{e}}{}_t = \pi^{\mathrm{e}}{}_{\text{t-1}} + \beta(\pi_{\text{t-1}} - \pi^{\mathrm{e}}{}_{\text{t-1}}) \tag{3.3}$$

$$\pi^{\mathrm{e}}{}_t = (1-\beta)\pi^{\mathrm{e}}{}_{\text{t-1}} + \beta(\pi_{\text{t-1}}) \tag{3.4}$$

By reiterating:

$$\pi^{\mathrm{e}}{}_t = (1-\beta)^p \pi^{\mathrm{e}}{}_{\text{t-p}} + \beta[\sum_{n=1}^{p} (1-\beta)^{n-1}\ \pi_{\text{t-n}}] \tag{3.5}$$

Where p is the number of periods in the median consumer economic life, $\pi^{\mathrm{e}}{}_{\text{t-p}}$ is an initial inflation expectation and β is the learning rate.

This simple equation models expected inflation as an AR(p) model where consumers form expectations based on lifetime experience, in line with Malmendier and Nagel (2009) results, and can result in fragile anchoring expectations, due to sustained periods of low volatility, as found by Łyziak and Paloviita (2017). The model is in line with the median consumer attitude towards expectations, arising from survey results in the EU; the median consumer's opinion is not informed, rather he expects short-term prices to grow at a rather constant level. Assuming equation 3.5 results, expectations are solely determined by past inflation behavior during the consumer's lifetime and, at a macroeconomic level, the relevance of expectations in forecasting is reflected entirely in the actual inflation level (HICP).

3.5 Estimation and forecasting

Before estimating the model, firstly, the time series will be checked for stationarity and trend-stationarity with the Dickey–Fuller test. For the purpose of this analysis, non-stationarity is not regarded as a problem, following Sims (1980) and Fanchon and Wendel (1992). Furthermore, differencing within the VAR model generates other types of issues like hindering forecasting power over a long-term horizon. Secondly, the number of lags (p) will be determined by the the Akaike information criteria (AIC). Following this, the model parameters will be estimated using data from June 1998 to December 2007. The estimated model will then be used to forecast HICP for the period January 2008 to November 2017. The forecasting procedure will follow an iterated multi-step (IMS) as described by Clark and McCracken (2013). In lag order notation, the VAR model is

$$Y_t = A + B(L)Y_{t-1} + u_t \tag{3.6}$$

where Y is a vector of variables and is equivalent to

$$\begin{aligned} Y_t &= (A, B_1, ..., B_p)(1, Y\prime_t, ..., Y\prime_{t-m+1})\prime + u_t \\ &= \lambda x_{t-1} + \epsilon_t \\ &= (x\prime_{t-1} \otimes I_n)vec(\lambda) + u_t \end{aligned}$$

then, assuming that the model errors u_t form a martingale difference sequence, the τ-step forecast is $\widehat{Y}_{t+\tau} = i\prime\ (A + B_1\widehat{Y}_{t+\tau-1} + ... + B_p\widehat{Y}_{t+\tau-p})$ where $i\prime$ is a vector with element 0 or 1 depending on the variable(s) of interest. Intuitively this approach computes a value to the first step forecast and iterates that computation in the second step forecast and so on, thereby computing a τ-step forecast.

3.6 Benchmark model

The computed forecast will then be compared by means of AIC and minimum root-mean-squared error (RMSE) with a VAR model based on the Gordon triangle model (2.1) and an ARIMA model (referred to as *benchmark models*). The choice of these two model is mainly based on theoretical grounds, as suggested by Stock and Watson (2008). The ARIMA model is defined, in terms of inflation π as follows>

$$(1 - \sum_{i=1}^{p} \alpha_i L^i)\pi_t = (1 + \sum_{i=1}^{q} \theta_i L^i)\epsilon_t \tag{3.8}$$

Intuitively, the left hand side of the equation represents an autoregression of inflation on its own lag (p) and the right hand side a regression error computed as a linear combination of past error terms (hence q is the order of the moving average model).

To simplify the comparison and to repurpose it for forecasting, the Gordon model (2.1) will be reconstructed as a VARX model. It will be defined as follows:

$$y_t = \delta + \sum_{i=1}^{p} \sigma_i y_{t-i} + \sum_{i=0}^{s} \Theta_i Z_{t-i} + u_t \tag{3.7}$$

where $y_t = \begin{pmatrix} \pi_t \\ u_t \end{pmatrix}$ and the exogenous component Z_{t-i} is a vector of the oil shocks as defined in Gordon (1990) and section 3.5.

Table 3: Lag selection

Lag	AIC value	Lag	AIC value
With output o		Without output o	
14	-28.1699	14	-30.2232
15	-28.0742	15	-30.1652
16	-28.4641	16	-30.2595
17	-28.7498	17	-30.3081
18	-29.6711*	18	-30.4407*

Lag	AIC value
Gordon VARX model	
5	-22.2533
6	-22.2875
7	-22.4294*
8	-22.3603
9	-22.2835

Table 2: Stability condition

VARX-Gordon	
Eigenvalues	Modules
.9790615 + .07253431i	.981745
.9790615 - .07253431i	.981745
.8685662	.868566
.5908123 + .6363828i	.868356
.5908123 - .6363828i	.868356
.3742212 + .7566517i	.844135
.3742212 - .7566517i	.844135
-.5093792 + .5857605i	.776262
-.5093792 - .5857605i	.776262
-.7554968 + .1658979i	.773497
-.7554968 - .1658979i	.773497
-.3316225 + .6359827i	.71725
-.3316225 - .6359827i	.71725
.6801097	.68011
All modules line within the unit circle	

VAR - extended (Lags 18)	
Eigenvalues	Modules
1.062495 + .1352754i	1.07107***
1.062495 - .1352754i	1.07107***
1.054362	1.05436***
.5910043 + .8049708i	.998631
.5910043 - .8049708i	.998631
Only the first 5 eigenvalues in decreasing order are reported	
At least one module is bigger than 1	

VAR - simple (Lags 18)	
Eigenvalues	Modules
1.027331	1.02733***
1.004366 + .1678158i	1.01829***
1.004366 - .1678158i	1.01829***
.983339 + .07646328i	.986307
.983339 - .07646328i	.986307
Only the first 5 eigenvalues in decreasing order are reported	
At least one module is bigger than 1	

ARIMA(4,1,2)	
Eigenvalues	Modules
.7413526 + .5611223i	.929764
.7413526 - .5611223i	.929764
.2136643	.213664
All modules lie within the unit circle.	

3.7 Alternative specifications and selection procedure

Various other theoretical specifications have been taken into consideration. Within the VAR-model framework, various combinations of the aforementioned variables and first-difference import prices were considered. Furthermore, the standard Gordon model and an AR(1) were also tested for significance. As seen in table 4 the Gordon standard models are the only models with lower AIC values than the VAR-Gordon model and the ARIMA(p,d,q) model. Despite this, these model are not taken into consideration as benchmark models because the VAR - Gordon model would just be an alternative specification that facilitates comparison with the estimated VAR models. The choice hence is to trade off some AIC fitness of the model for easier comparability. Regarding the alternative specifications of the VAR model, they were the ones that achieved lowest AIC values. The exceptions are reported in table 4, in particular the simpler models with $HICP$ and m or u have lower AIC values but are of little use because of the small number amount of variables. The import price index was excluded because it causes instability of the VAR model at any lag length. Furthermore, it is important to notice that it does not make sense to compare different models based on the AIC value if they do not share the same dependent component. Hence the AIC value, in this case, can be compared among VAR models and among AR(p), Gordon-standard and ARIMA models. The decision to exclude certain specifications and models based on the AIC value, which measures likelihood of fit, and not the root-mean-square forecasting error (RMSFE), which measures forecasting power, reflects a more theoretical based approach to forecasting, that is more focused on causal and logical relationships among variables, in order to obtain a model as general as possible. It might have been possible to solely specify models based on predictive power over the analyzed specific sample, but that would have had defeated the purpose of judging the model as a whole and not only its accuracy over this limited time period.

3.8 Data

The monthly growth of the Harmonized Index of Consumer Prices (HICP) is used as representative of inflation; data for unemployment (u) and the M2 aggregate (m) is also monthly and computed on the Euro19 countries; similarly output growth (o) will be approximated with the monthly percentage change in industrial output of mining and quarrying, manufacturing, electricity, gas, steam and air conditioning supply and construction as retrieved from Eurostat. All the aforementioned data were retrieved from the ECB statistical data warehouse. The supply-shock (z) will be modeled, as in Gordon (1990), by a dummy variable that takes a value 1 if shocks of the oil prices exceed 5% and unemployment (u) is the monthly weighted average of unemployment in the Euro19 countries. These statistics are retrieved respectively from the OECD data and Eurostat.

Table 4: AIC values and stability of all tested models

Var and benchmark models used during the analysis			
Variables/Model	Lags	AIC value	Stability condition
VAR simple	14	-3194.609	Stable
VAR extended	11	-2897.417	Stable
VAR - Gordon	7	-2470.295	Stable
ARIMA(p,d,q)	4,1,2	-1110.648	Stable

Alternative models and specifications for benchmarks			
Variables/Model	Lags	ΔAIC	Stability condition
AR	1	8.867	Stable
Gordon standard	2	-16.28	Stable
Gordon standard	1	-5.738	Stable

Alternative models and specifications for estimated VAR			
Variables/Model	Lags	ΔAIC	Stability condition
VAR (HICP, m)	1	-902.345	Stable
VAR (HICP, u)	13	-423.271	Stable
First diff. VAR all	2	515.984	Stable
First diff. imp.	2	-742.285	Unstable

[1] *The lag selection and instability analysis for the Benchmark and VAR models is treated in section 4.2. The lag selection and instability of other specifications is reported in appendix B.*

4 Model estimation and empirical results

4.1 Diagnostic of variables

In order to test for stationarity, an augmented Dickey-Fuller test is applied. This test, developed by Dickey and Fuller (1979), fits the equation $\Delta y = \alpha + \beta_{t-p} y_{t-1} + ... + \beta_{t-p} y_{t-p} \epsilon_{t-1}$ where the lag-length p is determined with the AIC criterion as before. testing the null-hypothesis that $H0 : \beta_i = 0 \; \forall i$ (i.e. the time series has a unit-root, hence it cannot be inferred that it was generated by a stationary process). As seen in table 5, the null-hypothesis can be rejected only in the case of output growth (o). This is in line with figure 4, 3 and 5, where the graphical analysis suggests that the other variables are indeed non-stationary.

Table 5: Augmented Dickey–Fuller unit-root test

	m	o	u	hicp
Lag length	33	1	38	17
Z(t)	-2.573	-17.902	-2.061	-2.147
MacKinnon approximate p-value	(0.2757)	(0.0000)	(0.2604)	(0.2852)
N	234			

4.2 Model estimation

First the simple VAR model with endogenous variables π, u and m is estimated. The number of lags (p) is first determined through the AIC, which selects the VAR(p) model with the lowest AIC value computed as $AIC_p = 2k - 2ln(\hat{L}_p)$ where k is the number of estimated parameters, in this case three, and $\hat{L}$ is the value of the maximum likelihood function. As seen in table 3, the selected lowest AIC value is obtained with $p = 18$. The same result arises after including an endogenous output variable (o) in the extended VAR model. For the VARX-Gordon model (3.7) the AIC lag selection suggests a $p_{Gordon} = 7$ After estimating the VAR model, it is necessary to run diagnostics on the model before forecasting. The main necessary feature for postestimation is the stability condition. In order to test for this, the companion matrix A is computed as well as the modules of its eigenvalues. As shown by Lütkepohl (2005), if the modules lie within the unit circle the VAR is stable. The condition is met only for $p_{\pi,m,u,o} = 14$ in the o-including model and is met for $p_{\pi,m,u} = 11$ in the o-excluding model therefore the number of lag will be adapted accordingly. On the other hand, the stability condition is met by the VARX-Gordon model. The aforementioned results are reported in table 2. For the ARIMA model the AIC selection criteria suggests a $(p, d, q) = (4, 1, 2)$. The benchmark models estimate are reported in table 7 and 8 and the VAR models estimate are reported in table 9. It is important to notice that for the sake of forecasting, especially for a VAR model, the coefficient estimate is not informative and impossible to interpret.

Figure 3: Money aggregate M2, Euro-area 1997-2017

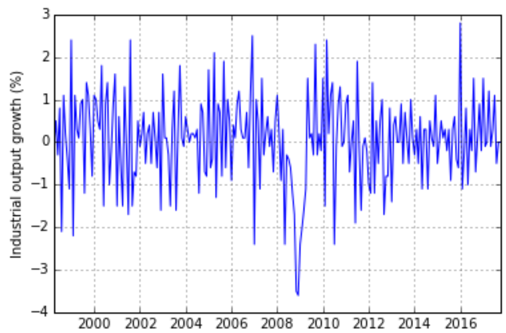


Figure 4: Output, Euro-area 1997-2017

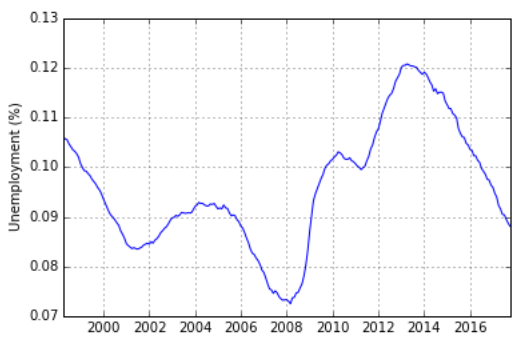
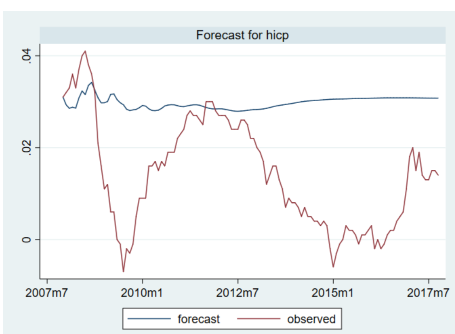


Figure 5: Unemployment, Euro-area 1997-2017

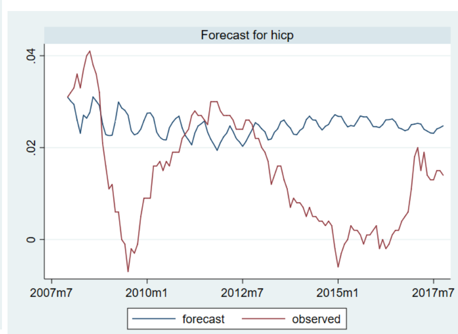
4.3 Forecasting

The first forecast is a long-term forecast with 118 monthly steps from December 2007 to October 2017. As seen in figure 6 the simple VAR-model (i.e. the o-excluding) predicted at the beginning of the crisis an initial upward disturbance of inflation and a later stabilization at around 3%. The extended model, thanks to the inclusion of output growth (o), gave a better prediction of the seasonality component of inflation and did detect a higher volatility that then would stabilize in late-2016/early-2017. Furthermore, by comparing the VAR models to the benchmark models (figure 7) we can see that the former predicted, in general, a higher volatility and the latter a more stable and systematically lower (around 2%) inflation. Overall, just by graphical analysis, it is clear that the models performed really badly in predicting the abnormal behavior of inflation and underestimated the effects of the 2008 crisis on price growth. From a RMSE prospective, as seen in table 6, the benchmark models outperform the VAR model and the extended model improves forecasting on the simple model. Secondly, we conducted a medium-term forecasting and a short-term forecasting of 36 and 12 monthly steps, as seen in figures 8 to 11. The graphical analysis leads to a similar conclusion as for long-term forecasting namely that the benchmark models predict a lower and less volatile inflation. The most interesting result arises in comparing the Root-mean-square error over the medium-term and short-term period. In table 6 we can see that over the medium-term forecast the difference in forecast accuracy decreases between VAR and benchmark models and on short-term forecasting the VAR models perform better than benchmark models

Figure 6: VAR models, long-term forecasting

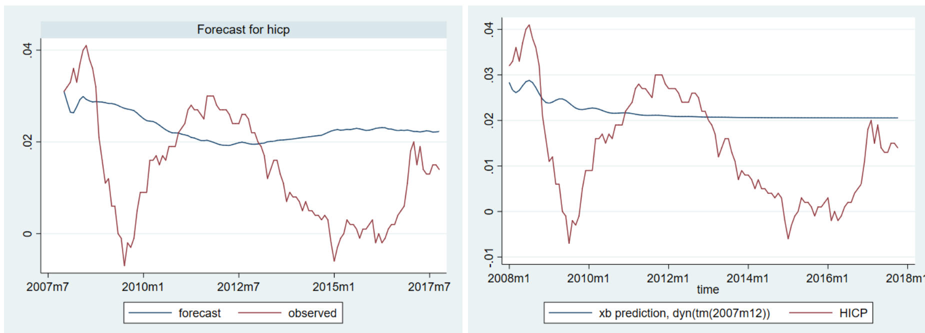


(a) Simple VAR



(b) Extended VAR

Figure 7: Benchmark models, long-term forecasting

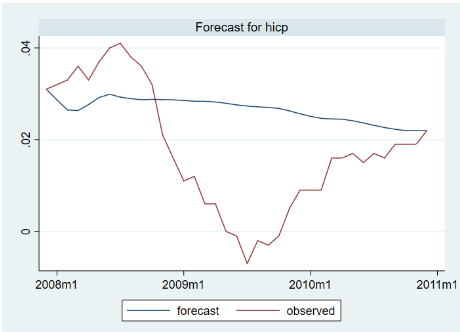


(a) VAR-Gordon model *(b) ARIMA*

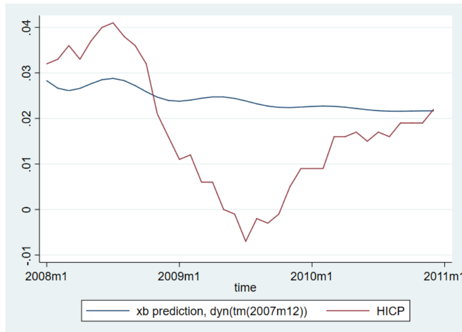
Figure 8: VAR models, medium-term forecasting

(a) Simple VAR *(b) Extended VAR*

Figure 9: Benchmark models, medium-term forecasting

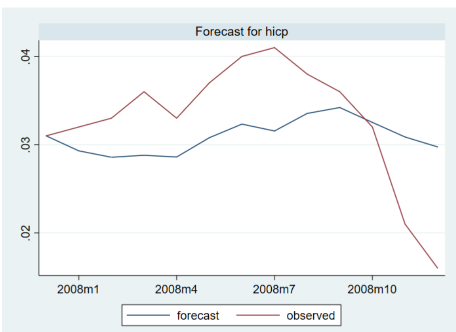


(a) VAR-Gordon model

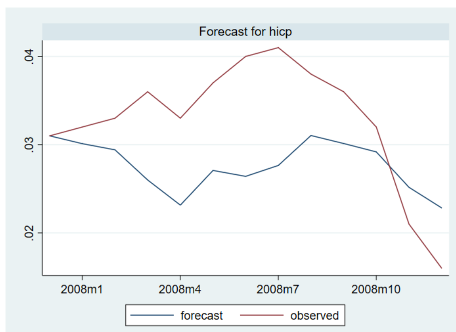


(b) ARIMA

Figure 10: VAR models, short-term forecasting

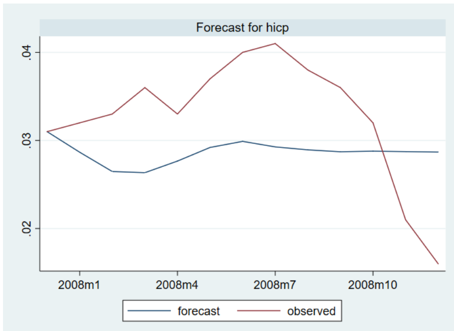


(a) Simple VAR

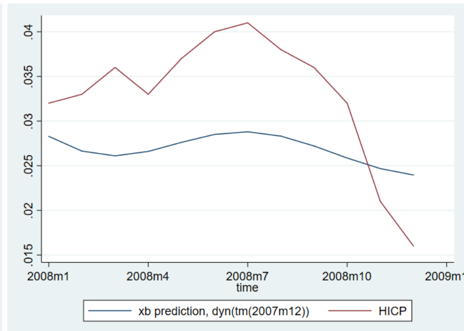


(b) Extended VAR

Figure 11: Benchmark models, short-term forecasting



(a) VAR-Gordon model



(b) ARIMA

Table 6: Root-mean-square errors

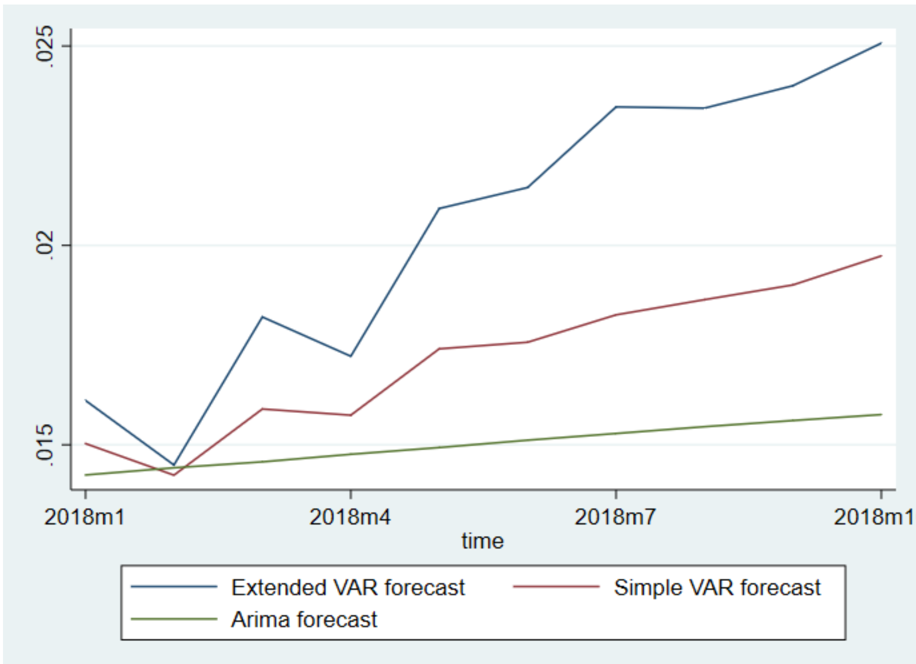
Gordon-VAR	Simple VAR	Extended VAR	ARIMA
Long-term forecast			
0.162619531*	0.215469209	0.176311124	0.145820919
Medium-term forecast			
0.09655579	0.107382489	0.092732102	0.083628703*
Short-term forecast			
0.029021084	0.024384932*	0.028814462	0.029122268

5 Conclusion

The conducted analysis gave valuable insight into the forecasting procedure involving VAR models. The root-mean-square error analysis, which focuses on the forecasting accuracy, shows over longer forecasting horizons the ARIMA model clearly outperforms all the VAR models; among the VAR models the Gordon-based model outperforms the other VAR models. On the other hand, the VAR model performs really well on short-term forecasting compared to a simple ARIMA model. We may infer that in the long-run inflation assumes a more structural behavior with less influence from determinant variables but over shorter horizons the analyzed variables play a bigger role in determining high-frequency variations. It is particularly interesting to notice how the estimated VAR models predicted the decrease in inflation after 7 months that then materialized and on the contrary, the benchmark models forecast a more stable inflation (figure 10 and 11). It is possible that by introducing a high-frequency business cycle related variable like industrial output growth (o), the short-term movements in income, hence demand pulled inflation, can be better predicted than with simple unemployment (u) which requires a longer horizon to materialize. Despite the correct short-term predicted trend, the magnitude of this decrease is not grasped by the model, perhaps because of the global scale of the crisis and consequential significant exogenous effects on inflation. On the other hand, the benchmark models effectively forecast the medium- and long-term new structural trend of inflation, just below 2%, whether the estimated VAR models forecast a return to the pre-crisis long-run trend in the 2.5%-3% range. This may indicate that the discrepancy arises from the strong theoretical dependency of inflation in the long run on money aggregates level (m), long-run structural inflation and exogenous shocks in oil prices (z). Then adding high and medium frequency variables like unemployment (u) or output (o) just distorts the long-run level of inflation (note that the ARIMA model in the long-run performs much better than the Gordon model, as seen in Table 6). It is also important to stress that the period of analysis is an abnormal period for inflation, due to the financial crisis and the unconventional monetary policy applied by the ECB. From this point of view, the short-term performance of the VAR-models is remarkable in predicting 12 monthly forecasting points. Another important aspect to consider is that the ECB achieved stable inflation around 2% since its founding in 1998 and, as pointed out by Lack (2006), this creates a conservative bias on variable interactions in the VAR model that may hinder its forecasting ability during high volatility periods. Despite this, the VAR models did outperform the ARIMA model during 2008, which was a high volatility period.

The analysis, in conclusion, provided an empirical basis for specifying the appropriate forecasting model in times of uncertainty, knowing only data points from periods of stable inflation. The research can certainly be extended by including different types of forecasting models and variables. In particular, the analysis did not touch on Bayesian-VAR models which have been prominent in recent research. Nevertheless, this paper provided further evidence in support of using VAR models for short-term forecasting and ARIMA models for long-term forecasting, and evidence on the variable choice. Given these results, it can be informative to forecast future inflation given the whole estimation period 1998-2017. Figure 12 displays the 12-month forecast from January 2018, using the simple and extended VAR models and the ARIMA model. It is interesting to notice that the VAR forecasts are in line with the ECB one-year projections on HICP (ECB, 2017). This similarity highlights the relevance and centrality of the models discussed so far and suggests a reasonable degree of accuracy. It is definitely not the case that the puzzle of inflation forecasting has been solved but there is no reason to stop tackling the problem. Just because less sophisticated models in the long-run are the best forecasters of inflation it would be a mistake to settle on these. If anything the aforementioned results stress the importance of using different models for different time horizons.

Figure 12: Forecast from December 2017



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Appendix A Graphs

Figure 13: First difference of M2, Euro-area 1997-2017

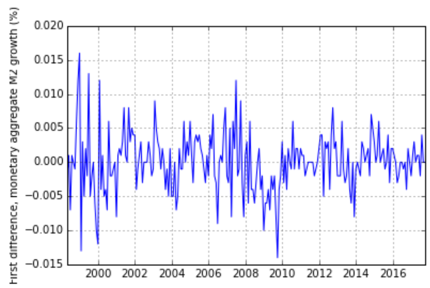
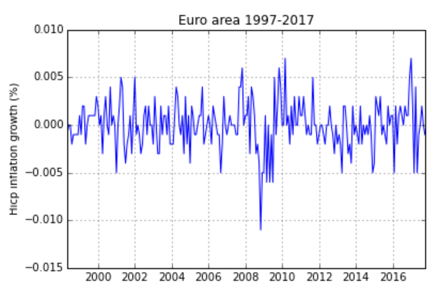


Figure 14: First difference of output, Euro-area 1997-2017

Figure 15: First difference of HICP, Euro-area 1997-2017



Appendix B Tables

Table 7: VAR-Gordon model estimate

	HICP	Unemployment
L.HICP	0.994***	0.00881
L2.HICP	-0.185	-0.0281
L3.HICP	-0.0499	0.0153
L4.HICP	0.0171	-0.154
L5.HICP	0.0263	-0.0325
L6.HICP	0.130	0.0428
L7.HICP	-0.107	-0.0438**
L.u	-0.661	1.249***
L2.u	-0.169	0.154
L3.u	2.186**	-0.477***
L4.u	-0.812	-0.154
L5.u	-0.450	0.473***
L6.u	-0.699	0.0537
L7.u	0.519	-0.319***
z	0.000226	-0.0000304

Table 8: ARIMA model estimate

	(1) First difference HICP
HICP	
Constant	0.000125
	(0.69)
ARMA	
L.ar	1.696***
	(16.69)
L2.ar	-1.181***
	(-7.81)
L3.ar	0.185
	(1.96)
L.ma	-1.716***
	(-95.51)
L2.ma	1.000
	(.)
sigma	
Constant	0.00187***
	(15.22)
Observations	116

Table 9: Var simple and extended, estimated coefficients

Model	Simple	Extended
HICP		
L.HICP	0.943	1.103
	(9.92)	(12.03)
L2.HICP	-0.156	-0.324
	(-1.16)	(-2.51)
L3.HICP	-0.121	-0.0681
	(-0.91)	(-0.58)
L4.HICP	0.0181	0.0515
	(0.13)	(0.45)
L5.HICP	0.0502	-0.139
	(0.37)	(-1.26)

L6.HICP	0.173 (1.28)	0.323 (2.93)
L7.HICP	-0.112 (-0.81)	-0.200 (-1.71)
L8.HICP	-0.0355 (-0.25)	0.0797 (0.63)
L9.HICP	0.135 (0.99)	-0.000517 (-0.00)
L10.HICP	-0.0214 (-0.16)	0.0452 (0.35)
L11.HICP	-0.174 (-1.76)	0.228 (1.96)
L12.HICP		-0.607 (-5.40)
L13.HICP		0.286 (2.35)
L14.HICP		0.00341 (0.04)
L.m2	0.00117 (0.03)	-0.0178 (-0.39)
L2.m2	-0.0663 (-1.16)	0.00163 (0.03)
L3.m2	0.0947 (1.66)	0.0343 (0.54)
L4.m2	0.0161 (0.29)	-0.0122 (-0.19)
L5.m2	-0.122 (-2.25)	-0.112 (-2.04)
L6.m2	0.0577 (1.03)	0.197 (3.45)
L7.m2	0.0283 (0.49)	-0.0303 (-0.51)

L8.m2	-0.0147 (-0.26)	-0.0601 (-1.02)
L9.m2	-0.00334 (-0.05)	0.0863 (1.44)
L10.m2	-0.0462 (-0.73)	-0.108 (-1.91)
L11.m2	0.0487 (1.12)	0.0335 (0.58)
L12.m2		0.188 (3.07)
L13.m2		-0.237 (-3.67)
L14.m2		0.0255 (0.57)
L.u	-0.895 (-1.53)	0.184 (0.35)
L2.u	0.125 (0.13)	-0.553 (-0.74)
L3.u	2.238 (2.50)	2.365 (3.00)
L4.u	-1.141 (-1.18)	-1.753 (-2.11)
L5.u	-0.495 (-0.53)	-0.929 (-1.13)
L6.u	-0.432 (-0.44)	1.863 (2.20)
L7.u	1.223 (1.27)	-0.865 (-0.99)
L8.u	-0.232 (-0.23)	-0.721 (-0.84)
L9.u	-1.449 (-1.52)	-0.802 (-0.94)

L10.u	1.522 (1.57)	2.957 (3.66)
L11.u	-0.609 (-0.99)	-2.267 (-2.68)
L12.u		-0.771 (-0.93)
L13.u		1.878 (2.19)
L14.u		-0.597 (-1.08)
L.o		0.000224 (0.93)
L2.o		-0.000437 (-1.51)
L3.o		-0.000435 (-1.34)
L4.o		-0.0000680 (-0.21)
L5.o		0.000792 (2.54)
L6.o		-0.00000284 (-0.01)
L7.o		0.000513 (1.63)
L8.o		0.000463 (1.35)
L9.o		0.000686 (1.78)
L10.o		0.000928 (2.22)
L11.o		0.000885 (2.02)

L12.o		0.00111 (2.61)
L13.o		0.000627 (1.86)
L14.o		0.000960 (4.07)
Constant	0.0198 (2.78)	0.00577 (0.70)
m2		
L.HICP	0.295 (1.50)	0.0477 (0.23)
L2.HICP	-0.392 (-1.41)	-0.135 (-0.47)
L3.HICP	-0.192 (-0.70)	-0.0747 (-0.29)
L4.HICP	0.535 (1.91)	0.334 (1.32)
L5.HICP	-0.378 (-1.35)	-0.159 (-0.65)
L6.HICP	-0.00300 (-0.01)	-0.122 (-0.50)
L7.HICP	0.376 (1.30)	0.441 (1.69)
L8.HICP	-0.385 (-1.31)	-0.500 (-1.78)
L9.HICP	-0.0537 (-0.19)	-0.0954 (-0.33)
L10.HICP	-0.251 (-0.91)	-0.149 (-0.52)
L11.HICP	0.604 (2.95)	0.264 (1.02)
L12.HICP		0.398 (1.60)

L13.HICP		-0.216 (-0.80)
L14.HICP		0.107 (0.53)
L.m2	1.023 (11.16)	1.041 (10.26)
L2.m2	0.119 (1.00)	0.00567 (0.04)
L3.m2	-0.164 (-1.39)	-0.0582 (-0.41)
L4.m2	0.0693 (0.61)	0.0710 (0.50)
L5.m2	-0.377 (-3.35)	-0.238 (-1.94)
L6.m2	0.487 (4.19)	0.346 (2.72)
L7.m2	0.00960 (0.08)	-0.0493 (-0.37)
L8.m2	-0.387 (-3.30)	-0.199 (-1.52)
L9.m2	0.220 (1.71)	0.0575 (0.43)
L10.m2	-0.140 (-1.06)	0.0116 (0.09)
L11.m2	0.0714 (0.80)	0.0306 (0.24)
L12.m2		-0.401 (-2.95)
L13.m2		0.428 (2.98)
L14.m2		-0.0688

		(-0.69)
L.u	-3.262 (-2.69)	-3.139 (-2.65)
L2.u	5.323 (2.76)	4.870 (2.93)
L3.u	1.824 (0.98)	0.986 (0.56)
L4.u	-7.267 (-3.63)	-3.546 (-1.92)
L5.u	0.597 (0.31)	-0.150 (-0.08)
L6.u	5.721 (2.81)	0.742 (0.39)
L7.u	-2.677 (-1.33)	0.0254 (0.01)
L8.u	-3.447 (-1.66)	-0.967 (-0.51)
L9.u	2.751 (1.39)	1.523 (0.80)
L10.u	3.222 (1.61)	-0.696 (-0.39)
L11.u	-2.871 (-2.25)	-0.230 (-0.12)
L12.u		3.837 (2.09)
L13.u		-4.733 (-2.49)
L14.u		1.451 (1.18)
L.o		-0.00138 (-2.57)
L2.o		-0.00171

		(-2.67)
L3.o		-0.00101 (-1.40)
L4.o		-0.000320 (-0.45)
L5.o		-0.0000818 (-0.12)
L6.o		0.000273 (0.42)
L7.o		0.000194 (0.28)
L8.o		0.000710 (0.93)
L9.o		0.000954 (1.12)
L10.o		0.000603 (0.65)
L11.o		0.000339 (0.35)
L12.o		-0.000568 (-0.60)
L13.o		0.000241 (0.32)
L14.o		-0.000246 (-0.47)
Constant	0.00942 (0.64)	0.00156 (0.09)
u		
L.HICP	0.00255 (0.17)	0.00322 (0.20)
L2.HICP	-0.0268 (-1.24)	0.000449 (0.02)
L3.HICP	0.0111	-0.00511

	(0.52)	(-0.25)
L4.HICP	0.0144 (0.66)	0.0324 (1.62)
L5.HICP	-0.0337 (-1.54)	-0.0495 (-2.56)
L6.HICP	0.0456 (2.08)	0.0355 (1.83)
L7.HICP	-0.0753 (-3.35)	-0.0519 (-2.52)
L8.HICP	0.0427 (1.86)	-0.000263 (-0.01)
L9.HICP	-0.0299 (-1.36)	-0.000503 (-0.02)
L10.HICP	0.0128 (0.59)	-0.0174 (-0.77)
L11.HICP	0.0124 (0.78)	0.0447 (2.19)
L12.HICP		-0.0218 (-1.11)
L13.HICP		-0.0355 (-1.66)
L14.HICP		0.0323 (2.02)
L.m2	-0.00677 (-0.95)	0.00683 (0.85)
L2.m2	0.00931 (1.01)	-0.0111 (-0.98)
L3.m2	-0.00478 (-0.52)	-0.0125 (-1.12)
L4.m2	-0.00754 (-0.85)	0.00321 (0.29)
L5.m2	0.0164	0.00517

	(1.87)	(0.53)
L6.m2	-0.0195 (-2.15)	-0.0177 (-1.76)
L7.m2	0.0116 (1.25)	0.00712 (0.68)
L8.m2	0.00276 (0.30)	0.00528 (0.51)
L9.m2	-0.0223 (-2.23)	-0.00842 (-0.80)
L10.m2	0.0171 (1.66)	0.00358 (0.36)
L11.m2	-0.00533 (-0.76)	0.00421 (0.42)
L12.m2		-0.00517 (-0.48)
L13.m2		0.0217 (1.91)
L14.m2		-0.0114 (-1.43)
L.u	1.242 (13.15)	0.961 (10.27)
L2.u	0.106 (0.70)	0.287 (2.18)
L3.u	-0.451 (-3.11)	-0.425 (-3.07)
L4.u	-0.184 (-1.18)	-0.227 (-1.55)
L5.u	0.475 (3.12)	0.421 (2.90)
L6.u	0.188 (1.19)	0.315 (2.11)
L7.u	-0.491	-0.363

	(-3.14)	(-2.37)
L8.u	-0.0394 (-0.24)	-0.152 (-1.00)
L9.u	0.166 (1.07)	0.194 (1.29)
L10.u	0.238 (1.52)	0.133 (0.94)
L11.u	-0.283 (-2.85)	-0.158 (-1.06)
L12.u		-0.0424 (-0.29)
L13.u		0.254 (1.68)
L14.u		-0.258 (-2.64)
L.o		-0.0000538 (-1.27)
L2.o		0.0000589 (1.16)
L3.o		0.0000280 (0.49)
L4.o		-0.0000398 (-0.70)
L5.o		-0.000133 (-2.42)
L6.o		-0.000171 (-3.29)
L7.o		-0.000223 (-4.02)
L8.o		-0.000285 (-4.71)
L9.o		-0.000325

		(-4.81)
L10.o		-0.000299 (-4.07)
L11.o		-0.000227 (-2.95)
L12.o		-0.000121 (-1.62)
L13.o		-0.0000337 (-0.57)
L14.o		0.0000177 (0.43)
Constant	0.00405 (3.53)	0.00702 (4.87)
o		
L.HICP		77.38 (2.14)
L2.HICP		-109.1 (-2.15)
L3.HICP		75.08 (1.63)
L4.HICP		-7.427 (-0.17)
L5.HICP		48.57 (1.12)
L6.HICP		-15.16 (-0.35)
L7.HICP		-117.7 (-2.55)
L8.HICP		152.1 (3.05)
L9.HICP		-102.4 (-1.98)
L10.HICP		-28.29

			(-0.56)
L11.HICP			94.69 (2.07)
L12.HICP			-35.56 (-0.80)
L13.HICP			64.36 (1.34)
L14.HICP			-87.85 (-2.46)
L.m2			-52.65 (-2.93)
L2.m2			43.16 (1.70)
L3.m2			34.12 (1.36)
L4.m2			-41.26 (-1.65)
L5.m2			17.50 (0.81)
L6.m2			1.130 (0.05)
L7.m2			-11.23 (-0.48)
L8.m2			25.91 (1.12)
L9.m2			-9.697 (-0.41)
L10.m2			85.93 (3.86)
L11.m2			-90.58 (-4.01)
L12.m2			-20.35

		(-0.85)
L13.m2		0.415 (0.02)
L14.m2		35.59 (2.00)
L.u		-312.5 (-1.49)
L2.u		-125.9 (-0.43)
L3.u		482.2 (1.55)
L4.u		260.6 (0.79)
L5.u		-709.6 (-2.19)
L6.u		5.462 (0.02)
L7.u		501.8 (1.46)
L8.u		0.0768 (0.00)
L9.u		11.71 (0.03)
L10.u		-200.9 (-0.63)
L11.u		-216.7 (-0.65)
L12.u		450.2 (1.38)
L13.u		181.4 (0.54)
L14.u		-315.8

		(-1.45)
L.o		-0.685 (-7.23)
L2.o		-0.681 (-5.99)
L3.o		-0.129 (-1.02)
L4.o		-0.137 (-1.08)
L5.o		0.0422 (0.34)
L6.o		-0.0562 (-0.48)
L7.o		0.0191 (0.15)
L8.o		-0.00973 (-0.07)
L9.o		-0.124 (-0.82)
L10.o		-0.303 (-1.84)
L11.o		-0.540 (-3.13)
L12.o		-0.264 (-1.58)
L13.o		-0.268 (-2.01)
L14.o		-0.0668 (-0.72)
Constant		-1.952 (-0.60)
Observations	106	103

t statistics in parentheses