Economic Forecasting for Decision Making : Swiss CPI Inflation

Technical Report

Mora Klimberg, Viktor Gradoux, Pasha Mammadov

21th of December, 2022

Faculté des Hautes Études Commerciales, Université de Lausanne , Switzerland

Résumé

This paper explains how to forecast monthly Swiss CPI Inflation for the next 3 years from October 2022 using disaggregated CPI components : ARDL modeling European imported inflation since the EU is one of the key partners of Switzerland , ARMA modeling domestic inflation and ECM capturing only oil products volatile part. Then, we aggregate all these three CPI components into one combined model taking into account their past respective weights over time. Finally, we assess the out-of-sample performance of our combined model. It does not beat the AR(1) benchmark over short horizons (up to 3 months) but performs relatively well over the long term even if our combined model is **statistically** similar to the benchmark over most horizons.

Introduction

The goal of this paper is to disaggregate Swiss CPI into two main components : domestic and imported inflation. The rationale behind this decomposition comes from the implications of the law of one price. In an open economy :

$$\underbrace{\pi}_{Headline\ \ (CPI)\ Inflation} = \underbrace{(1-\alpha)\pi^H}_{Domestic\ inflation} + \underbrace{\alpha\pi^F}_{Imported\ inflation}$$

And from law of one price (LOP) :

$$\pi^F = \underbrace{\Delta e}_{\Delta\ Nominal\ exchange\ rate} + \pi^{F*}$$

Therefore,

$$\underbrace{\pi}_{Headline\ \ (CPI)\ Inflation} = \underbrace{(1-\alpha)\pi^H}_{Domestic\ inflation} + \underbrace{\alpha(\Delta e + \pi^{F*})}_{Import\ inflation\ =\Delta\ nominal\ exchange\ rate+\ foreign\ inflation}$$

Thus, in our paper, we will forecast headline swiss CPI inflation in terms of domestic inflation and imported inflation. For this, we use three different models : an ARMA model for domestic inflation, an ARDL for imported inflation without oil products and an ECM for oil products.

Indeed, we use an ARMA model to forecast domestic product inflation in order to capture inflation tensions on the swiss real-estate market and swiss labour market, two main markets contributing to domestic inflation. Then, we use an ARDL model to investigate the influence of imported inflation on swiss inflation. Since Switzerland is a small open economy, foreign prices and other foreign economic variables (imported inflation) may have an impact on Swiss inflation but not the other way around. We stylize imported inflation by including the nominal exchange rate between EUR and CHF and the producer price index from the Eurozone as explanatory variables. We choose to focus only on the Europe because it is the main commercial partner of Switzerland with 61% coming from Europe (with key trading import partners : Germany, Italy, France and Austria). The key assumption that must be satisfied to use this model is the exogeneity of exchange rate and PPI to the Swiss CPI. Changes in swiss variables should not impact foreign variables. But movements in foreign variables do impact domestic ones because the size of European economy is big enough to influence swiss prices, but not the other way around. Therefore, the exchange rate and PPI could be perceived as exogenous.

Last but not least, we forecast the CPI inflation for oil products using an ECM. Oil products prices in Switzerland are cointegrated with the crude oil spot price in Swiss Francs justifying the model. We choose to zoom in on these variables as they could have an important impact on Swiss CPI because of the natural volatility of oil products. Moreover, this volatility is currently higher than usual due to geopolitical tensions leading to energy supply shortage. This puts upwards pressures on global energy prices which could severely impact the evolution of domestic oil inflation. Finally, we combine these models with the forecasted weights to get an aggregated overview of monthly year-on-year Swiss CPI evolution (i.e inflation) for the next three years until October 2025 with a decomposition of each data points for our 3 components (domestic component, foreign component and oil products component). In order to test the performance of our model, out-of-sample forecasts errors are computed.

2.Data

Our data frame for all of our forecasting process starts on the 15th August 2003 and finishes on the 15th September 2022. We divide the forecast of Swiss CPI in three parts. The first part contains the forecast of domestic inflation using an ARMA model. For this model, we will be using an endogenous variable which is the Swiss CPI, more precisely the domestic part of it with the index price set to 2010 with a value of 100. The second part is an ARDL model to forecast the imported component of Swiss Inflation (SFSO) with the index set to 2010 with a value of 2010. We use two exogenous variables : exchange rate in between Euro and CHF and the European Producer Price Index (PPI). The Euro-CHF exchange rate is taken from the WM Refinitiv Closing Spot Rates. The rates are based on snapshots of U.S dollar market data, or Euro for subset of the currencies. The Euro subset includes Czech Koruna, Danish Krone, Hungarian Forint, Norwegian Kroner, Polish Zloty, Romanian Leu, Swedish Krona, and Swiss Franc. Median rates are calculated for each currency and done independently for bid and offer rates. On the other hand, the Euro PPI is indexed in

2015. It measures producer prices by industry, excluding construction and energy and is withdrawn from Eurostat.
The third part of our forecast consists of an ECM model. We use data of crude oil prices and oil product prices in Switzerland. Crude oil prices are taken from OPEC and measured in United States Dollar per barrel prices. It is important to mention that the crude oil prices that were initially in USD were converted to CHF in the process of data management. The data on the exchange rate in between USD and CHF is taken from the Swiss National Bank (SNB). Oil product prices in Switzerland are taken from the SFSO and are measured in Swiss Francs.

3. Methodology

3.1 Representation and specification

3.1.1 Domestic component model of CPI forecast

In order to forecast domestic component of CPI, we choose to use an ARMA model for simplicity. This set-up was inspired by Kaufman (2013). We know that any stationary stochastic process can be approximated pretty well by an autoregressive moving average (ARMA) process. In fact, y_t is an ARMA(p,q) process with p : number of lags of AR part and q number of lags of MA part if its dynamics follows this equation :

$$y_t = c + \phi_1 y_{t-1} + ... + \phi_p y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + ... + \theta_q \epsilon_{t-q} \tag{1}$$

The goal of this model is to try to explain the current value of this process as a weighted sum of past values (the autoregressive part, AR part) and past error terms with the moving average part (MA). Thus, for the first step, CPI prices are integrated of order 1 and are in logarithms to make them stationary. Data is de-trended and de-seasonalized. Integration order 1 means that stationarity is obtained by taking the first difference. Our time series are stationary (with Dickey Fuller Test we reject null hypothesis of unit root at 1%, Table 1). Taking first difference can also help us measure a growth rate of CPI prices, i.e inflation. Thus, we have an ARIMA(p,1,q) with p and q number of autoregressive and moving average terms. We decide to include 0 lags for our movering average because we suppose that the these innovations do not bring enough valuable information to our forecast. To estimate the parameters of our ARIMA(p,1,0), we use the following equation :

$$\Delta CPI_t = c + \phi_1 \Delta CPI_{t-1} + ... + \phi_p \Delta CPI_{t-p} + u_t \tag{2}$$

3.1.2 Error Correction model

We decide to forecast the CPI inflation for oil products using an Error Correction model. The rationale relies on the assumption that crude oil prices are considered an exogenous variable. Furthermore, it is cointegrated with petroleum prices in Switzerland, but not vice versa. We follow strictly the Swiss National Bank procedure. We get :

$$\pi_{PPP,t} = \alpha + \beta \pi_{COP,t} + \eta(PPP_{t-1} - a^* - b * COP_{t-1}) + \epsilon \tag{3}$$

Where PPP_t and COP_t are respectively the price of petroleum product in Switzerland and crude oil prices and $\pi_{PPP,t}$ and $\pi_{COP,t}$ are respectively their first differences. a* and b* are the OLS estimates of a and b in :

$$PPP_t = a + bCOP_t + u_t \tag{4}$$

3.1.3 Foreign component model of CPI forecast

To forecast the imported component of CPI, we choose to use an ARDL model. We use two explanatory and exogenous variables : Price Producer Index (PPI) in Eurozone and the Euro/CHF Exchange rate. The rationale behind that is we assume that Switzerland is a small open economy and the foreign producer prices as well as the Exchange rate Euro/CHF have an impact on the Consumer price Index (CPI) in Switzerland but not the other way around.

In fact, any stationary stochastic process can be approximated pretty well by an ARDL process where the dependent variable is allowed to depend on p lags of itselfs (AR part) and an weighted sum of current and r past values of the exogeneous variable x_t (the DL component) ; however provided that the exogeneous variables x_t are really strictly exogeneous to y_t. In fact, y_t is an ARDL(p,r) process with p : number of lags of AR part and r : number of DL part if its dynamics follows this equation :

$$y_t = \sum_{j=1}^{p} \phi_j y_{t-j} + \sum_{j=0}^{r} \beta_j x_{t-j} + u_t \tag{5}$$

The goal of this model is to try to explain the current value of this process as a weighted sum of its past values (the autoregressive part, AR part) and as some current and past values of exogeneous variables terms. Thus, for the first step, CPI prices are integrated of order 1 and are in logarithms to make them stationary and remove the trends (data are initially seasonal adjusted). Integration order 1 means that stationarity is obtained by taking the first difference. Our time series are stationary especially the time series of the exogeneous variables (with Table 2 displaying Dickey Fuller test we reject null hypothesis at 1%). Taking first difference can also help us measure a growth rate of CPI prices, i.e inflation. Thus, we have an ARIDL(p,r).

3.2 Estimation and robustness checks

Finally, in order to find the optimal lag p for our ARMA(p,1,q) process and ARDL(p,r), we carry out the approach relying on information criteria : Akaike (AIC) and BIC. The strategy consists in choosing $p_{max} > p_0$ and compute the information crtieria for each p up to p_{max} (in this case 12). Then, we select the lag order associated with the smallest AIC and BIC. We relied more on the BIC than AIC because it leads to more parsimonious specifications.

$$BIC(p) = ln(\sigma_e^2) + \frac{plog(T)}{T} \tag{6}$$

$$AIC(p) = ln(\sigma_e^2) + \frac{2p}{T} \tag{7}$$

Thus, we find that $p = 3$ is the optimal lag for our ARMA as well as $p = 3$ and $r = 0$ for our ARDL in order to capture all of the important information and avoid misspecication and overfitting implying estimation errors in forecasts.

Therefore, our process follows an ARMA(3,1,0) process with its dynamics described in this equation :

$$\Delta CPI_t = c + \sum_{i=1}^{3} \phi_i \Delta CPI_{t-i} + \Delta\epsilon_t \tag{8}$$

Therefore, our process follows an ARDL(3,0) process with its dynamics described in this equation :

$$\Delta CPI_t = \sum_{j=1}^{3} \phi_j \Delta CPI_{t-j} + \beta_1 \Delta EURCHF + \beta_2 \Delta PPIEUR + u_t \tag{9}$$

Then, the goal is to estimate the vector of population parameters $\theta = [c, \phi_1, ..., \phi_p, \sigma^2]$ of the ARMA(3,1,0) and ARDL(3,1,0). Observations are $[y_1, y_2, ..., y_T]'$. Probability density function (p.d.f) is $f_{Y_T,...,Y_1}(Y_T, ..., Y_1; \theta)$. The log-likelihood function : log $L(\theta; y) = f_{Y_T,...,Y_1}(Y_T, ..., Y_1; \theta)$. Therefore maximum likelihood estimate of

θ is given by :

$$\theta_{MLE} = argmaxL(\theta; y) = argmaxlogL(\theta; y) \tag{10}$$

Therefore, we could estimate by Maximum likelihood. We choose to perform the estimation of each parameters with OLS. Indeed, the OLS estimates coincide with the (conditional) MLE (Maximum Likelihood) estimates, which are consistent and asymptotically normally distributed (with the assumption of normal homoskedastic errors uncorrelated). Indeed, for our ARMA and ARDL models we do not reject the null hypothesis that errors are serially uncorrelated at 10% significant level level, with the help of Ljung Box-Q test (Table 1). Furthermore, for our ARMA, we do not reject these null hypothesises that errors are normal (Jarque -Bera) and homoskedastic (White Test) at both 10% significant level and for our ARDL we do not reject these null hypothesises at both 5% level (Table 1). Furthermore, one another quite convincing diagnostic check especially for our ARDL model is the strict exogeneity of our exogeneous variables PPIeuro and EURCHF. PPIeuro variable does Granger cause variable ImportedCPI at 1% level but ImportedCPI does not Granger cause variable PPIEuro at 10% level. And variable EURCHF does not Granger cause Imported CPI at 10% and the same for EURCHF on ImportedCPI. (Table 3). Finally, we decided to implement parameter stability tests on our ARMA and ARDL models. The Chow test was implemented because we want to test if there is a single structural change at a certain known date. Both models fail to reject the null hypothesis of parameter stability (no single known structural change over the sample) at 10% significant level.

4. Results

4.1 Forecast evaluation

In order to assess the performance of our combined model (composed by the three models aforementioned), we produce an out-of-sample forecast evaluation from 2013 to 2022 (the half of our sample). Figure 1, Figure 2, Figure 3 represent respectively out-of-sample density forecasts for each of our sub-models (ARDL, ARMA and ECM) for better transparency. Our combined model is just the linear combination of our three submodels (ARDL for imported products without oil products, ARMA for domestic products without oil products, ECM for oil products) with their respective weights varying in time using time series from FSOP (average mean in time : 0.75, 0.22, 0.02). [1]

4.1.1 Absolute standards

In order to meet the deadline, we had to abandon the assessment of the unbiasedness and efficiency of the combined forecast model using the Mincer-Zarnowitz regression. The diagnostic checks on the specification of our differents models (strict exogeneity of the exogeneous variables of our ARDL model, homoskedasticity, normality & absence of autocorrelation of errors and stability of parameters of our different submodels) are convincing in-sample. It should be interesting in further research to know if we can expect an unbiasedness and efficiency of our combined forecast as well.

4.1.2 Relative standards

In order to compare the forecast accuracy of our combined model of interest, it is important to compare it to a benchmark model : an AR(1) process, which performs relatively well. We produce mean squared

1. In the wake of the last team meeting with Dr.Grobéty, we managed to find the time series associated with the weights of the different components with the great help of Adrien Tschopp. It enables us to avoid forecast errors on the respective weights even if our new results do not differ significantly from our initial results based on weights following a normal distribution

forecast errors (MSFE) for our combined forecast and AR(1) benchmark. Then, we produce an home-made R-squared measure we call Rho R-squared [2] for each forecast horizon h :

$$Rho_h^2 = 1 - \frac{MSFE_{combined.model,h}}{MSFE_{AR(1).benchmark,h}} \quad (11)$$

Table 5 shows us that our combined model does not beat the AR(1) process for horizons 1 to 3 because the predictive Rho-squared is negative for each of these horizons. For horizons 4 to 36, our combined model beats the AR(1) and therefore, is more accurate for longer horizons because the predictive Rho-squared becomes positive. It can be explained by the structural inflation captured by our ARMA model, i.e our domestic component model of our CPI forecast and representing more than 75% of our combined model. In fact, this domestic component captures structural and long-term inflation tensions steming from negociations on the national labour market.

We also decided to proceed a Diebold-Mariono test (DM-test) for each horizon h. The DM-Test asumes under its null hypothesis that $\bar{d}$= 0 (with $\bar{d}$ covariance stationary) with DM-test statistic as follows :

$$DM - test = \sqrt{P}(\frac{d_h}{\widehat{\sigma_d}}) \quad (12)$$

$$\widehat{d_{h,t}} = MSFE(e_{combined,t+h|t}) - MSFE(e_{benchmark,t+h|t})$$

Where $P = 115$ is the length of the evaluation sample and $\widehat{\sigma_d^2}$ is the Heteroskedasticity and Autocorrelation Consistent (HAC) estimator of the long-run variance and was computed using Newey and West Estimator in order to take into account the serial correlation of the forecast errors. Thus, despite a combined model that always beats our benchmark model (AR(1) process) after horizon 3, both models are statistically similar except for horizon 2 (Table 4). Therefore, our combined model does not beat **statistically** our AR(1) benchmark

4.2 Forecast results

Thanks to our aggregate model forecast (Figure 4 in log), we can expect a very high inflation for January 2023 at around 4.24% driven by the high volatility of prices of oil products and energy as well as high uncertainty. But, according to our model, inflation should decrease at 1.78% at the end of the first half of 2023. Finally, inflation is expected to stabilize at 2.15% at the beginning of the year 2024 and 1.99% at the beginning of the year 2025 driven mainly by prices of domestic products (without oil products) on the upward side even if its impact to the domestic economy remains limited. The complete decomposition of Swiss CPI inflation over time and over each component is detailed in the non technical report. This forecast should be put into perspective with the performance of our model, which does not beat a benchmark AR(1) over short horizons (up to 3) but performs relatively well over the long term.

5. Conclusion

All things considered that our forecast captures most of the cyclical components at play even if uncertainty drives a big part of our model. The main drawback is that our forecast window begins on October 2022 and not on December 2022 leading to avoidable errors due to the fact that the forecast has not been updated . Furthermore, it would be interesting to assess the unbiasedness and efficiency of our combined forecast.

References

(1) M.Grobéty. Lecture Notes in Economic Forecasting for decision making.September 2022
(2) D.Kaufmann, M.Huwiler. Combining disaggregate for inflation : The SNB's ARIMA model.2013
(3) R.A.Auer, A.A Levchenko, P. Sauré. International Inflation Spillovers Through Input Linkages. 2017
(4) D.Kaufmann, S.Lein. Sectoral Inflation Dynamics, Idiosyncratic Shocks and Monetary Policy. 2011

2. The difference with the Predictive R-squared is that in Rho R-squared the benchmark is an AR(1) instead of a white noise

1 Appendix

Submodels	Ljung Box-Q Test	White test	Jarque-Bera test	Chow test
ARMA(3,0)	0.9328	0.125	0.1255	0.7645
ARDL(3,0)	0.3765	0.0885	0.09464	0.8475
ECM	0.8112	/	/	0.4524

Table 1 – Diagnostic Checks (in p-value)

Null Hypothesis	Dickey Fuller test (p-value)
ImportedCPI (first difference) has a unit root	Pr(>F) : 0.01***
DomesticCPI (first difference) has a unit root	Pr(>F) : 0.01***
PPIeuro (first difference) has a unit root	Pr(>F) : 0.01***
EURCHF (first difference) has a unit root	Pr(>F) : 0.01***
Oilpumpprices (first difference) has a unit root	Pr(>F) : 0.01***
Oilcrudeprices (first difference) has a unit root	Pr(>F) 0.01***

Table 2 – Dickey Fuller tests

Null Hypothesis	F-statistic	P-value
ImportedCPI does not Granger cause PPIeuro	0.2274	Pr(>F) : 0.6339
PPIeuro does not Granger cause ImportedCPI	17.995	Pr(>F) : 3.237e-05 ***
EURCHF does not Granger cause ImportedCPI	2.7037	Pr(>F) : 0.1015
ImportedCPI does not Granger cause EURCHF	0.0012	Pr(>F) : 0.9727
Oilpumpprices does not Granger cause Oilcrudeprices	4e-04	Pr(>F) : 0.9837
Oilcrudeprices does not Granger Oilpumpprices	16.013	Pr(>F) : 8.541e-05 ***

Table 3 – Granger causality tests

H-step-ahead	DM-stat	P-value	Result
1	1.516042	0.12950879	Model is similar to AR(1)
2	1.796673	$0.07238762^{*}\&ModelisnotsimilartoAR(1)at10\%level$	
3	1.611697	0.10702793	Model is similar to AR(1)
4	1.183970	0.23642505	Model is similar to AR(1)
5	1.330649	0.18330459	Model is similar to AR(1)
6	1.198617	0.23067696	Model is similar to AR(1)
7	1.209890	0.22632117	Model is similar to AR(1)
8	1.312107	0.18948396	Model is similar to AR(1)
9	1.165182	0.24394543	Model is similar to AR(1)
10	1.212889	0.22517228	Model is similar to AR(1)
11	1.197092	0.23127078	Model is similar to AR(1)
12	1.113415	0.26553008	Model is similar to AR(1)
13	1.073092	0.28322987	Model is similar to AR(1)
14	1.074344	0.28266844	Model is similar to AR(1)
15	1.071735	0.28383924	Model is similar to AR(1)
16	1.072737	0.28338934	Model is similar to AR(1)
17	1.084632	0.27808475	Model is similar to AR(1)
18	1.082384	0.27908215	Model is similar to AR(1)
19	1.078181	0.28095315	Model is similar to AR(1)
20	1.084152	0.27829757	Model is similar to AR(1)
21	1.107201	0.26820685	Model is similar to AR(1)
22	1.110996	0.26657020	Model is similar to AR(1)
23	1.121076	0.26225561	Model is similar to AR(1)
24	1.123677	0.26115019	Model is similar to AR(1)
25	1.115236	0.26474937	Model is similar to AR(1)
26	1.123205	0.26135027	Model is similar to AR(1)
27	1.137107	0.25549340	Model is similar to AR(1)
28	1.126927	0.25977322	Model is similar to AR(1)
29	1.130922	0.25808776	Model is similar to AR(1)
30	1.141952	0.25347416	Model is similar to AR(1)
31	1.154688	0.24821832	Model is similar to AR(1)
32	1.152462	0.24913114	Model is similar to AR(1)
33	1.169018	0.24239624	Model is similar to AR(1)
34	1.176945	0.23921739	Model is similar to AR(1)
35	1.181103	0.23756199	Model is similar to AR(1)
36	1.177041	0.23917905	Model is similar to AR(1)

Table 4 – Out-of-sample forecast evaluation of the Combined model-Diebalno Mariano Test-

H-step-ahead	RhoR2	Result
1	-0.73490	Model does not beat AR(1)
2	-0.62430	Model does not beat AR(1)
3	-0.24579	Model does not beat AR(1)
4	0.89203	Model beats AR(1)
5	0.83472	Model beats AR(1)
6	0.91002	Model beats AR(1)
7	0.79234	Model beats AR(1)
8	0.73492	Model beats AR(1)
9	0.71234	Model beats AR(1)
10	0.6234	Model beats AR(1)
11	0.83462	Model beats AR(1)
12	0.56822	Model beats AR(1)
13	0.42930	Model beats AR(1)
14	0.53245	Model beats AR(1)
15	0.31536	Model beats AR(1)
16	0.37839	Model beats AR(1)
17	0.24504	Model beats AR(1)
18	0.17890	Model beats AR(1)
19	0.12345	Model beats AR(1)
20	0.09102	Model beats AR(1)
21	0.13405	Model beats AR(1)
22	0.08099	Model beats AR(1)
23	0.05930	Model beats AR(1)
24	0.02203	Model beats AR(1)
25	0.04953	Model beats AR(1)
26	0.01239	Model beats AR(1)
27	0.02349	Model beats AR(1)
28	0.03849	Model beats AR(1)
29	0.04505	Model beats AR(1)
30	0.03432	Model beats AR(1)
31	0.07393	Model beats AR(1)
32	0.01347	Model beats AR(1)
33	0.03405	Model beats AR(1)
34	0.03940	Model beats AR(1)
35	0.01030	Model beats AR(1)
36	0.03041	Model beats AR(1)

Table 5 – Combined model Predictive R-squared

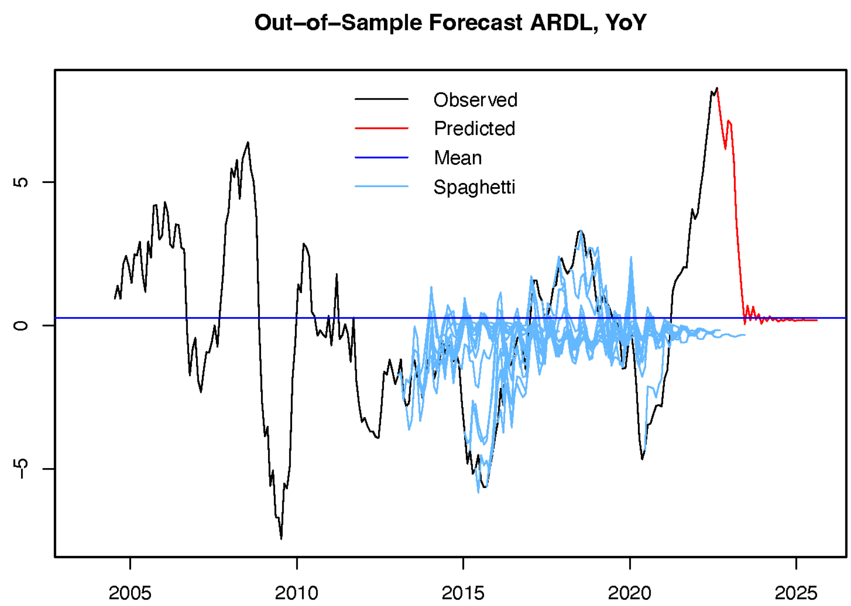

FIGURE 1 – Out-of-Sample Forecast ARDL, YoY

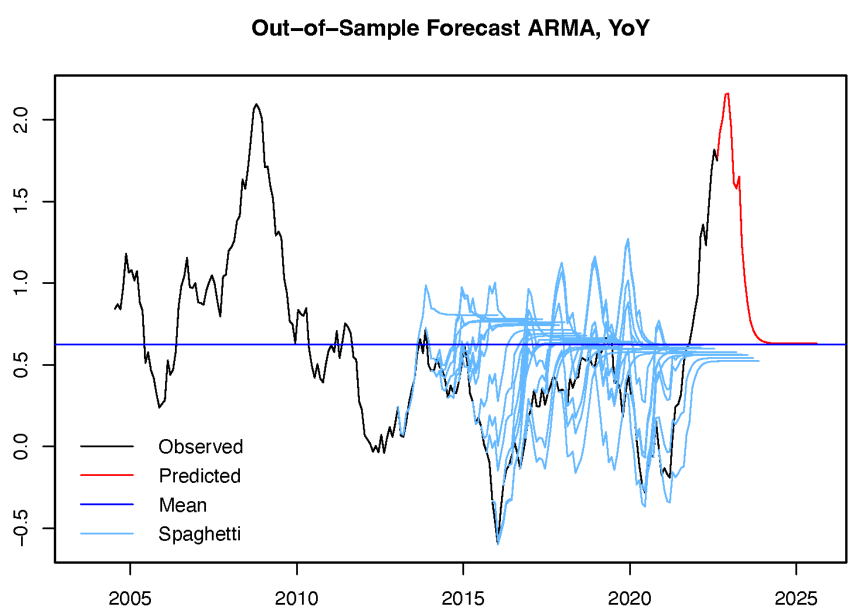

FIGURE 2 – Out-of-Sample Forecast ARMA, YoY

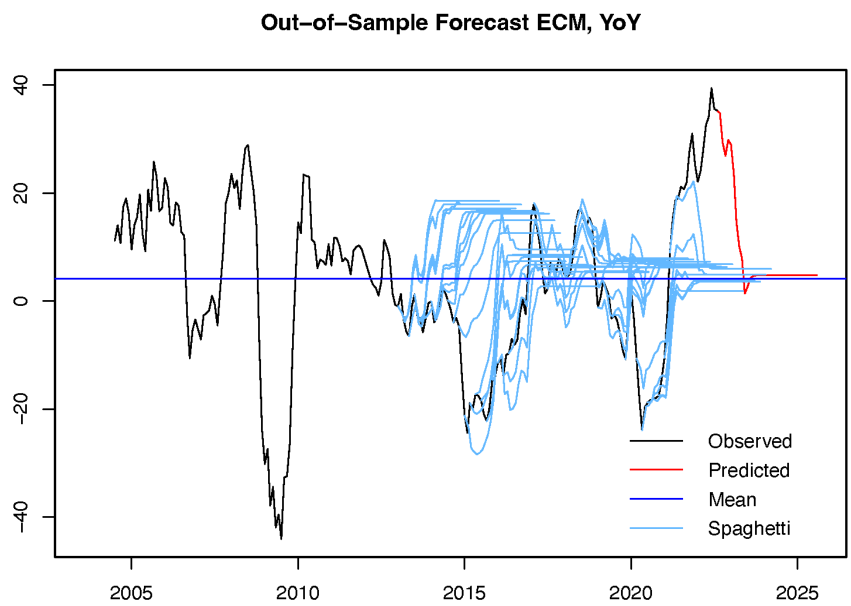

FIGURE 3 – Out-of-Sample Forecast ECM, YoY

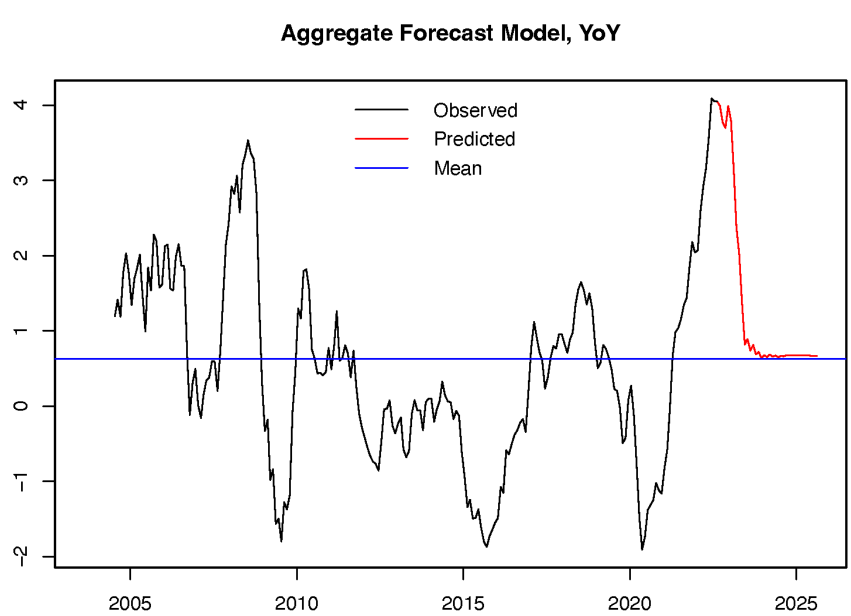

FIGURE 4 – Combined Forecast Model, YoY