CENTRAL BANK OF
THE REPUBLIC OF AZERBAIJAN

WORKING PAPER
SERIES № 01/2020

FORECASTING MODELS FOR COMPONENTS OF THE CONSUMER PRICE INDEX IN AZERBAIJAN

VUGAR RAHIMOV

Forecasting Models for Components of the Consumer Price Index in Azerbaijan

Vugar Rahimov[1]

The Central Bank of the Republic of Azerbaijan

24 December 2020

Abstract

The paper examines the main determinants of prices of food, non-food, and services components of the consumer basket of Azerbaijani households and provides forecasting models based on those determinants. For this purpose, I build vector autoregression models using quarterly data from 2003Q1 to 2020Q3. I find that the prices of items in the consumer basket are determined by both domestic and foreign factors. World food prices, consumer prices in trading partners, non-oil import weighted nominal effective exchange rate, real GDP, agricultural producer prices and own lags of food prices are main determinants of food prices, while consumer prices in trading partners, non-oil import weighted nominal effective exchange rate, output gap, manufacturing producer prices and own lags of non-food prices are determinants of non-food prices. However, services prices is mainly affected by non-oil import weighted nominal effective exchange rate, M2 (money supply), food consumer prices, non-oil tax, and own lags of services prices. In this paper, I also produce one-, two-, four-, six-, and eight-quarter forecasts for each component, combine the forecasts using corresponding weights and compare their forecasting errors to that of the direct forecasting model. The results show that the combination method has better forecasting performance than that of the direct method.

JEL Classification: E31, E37

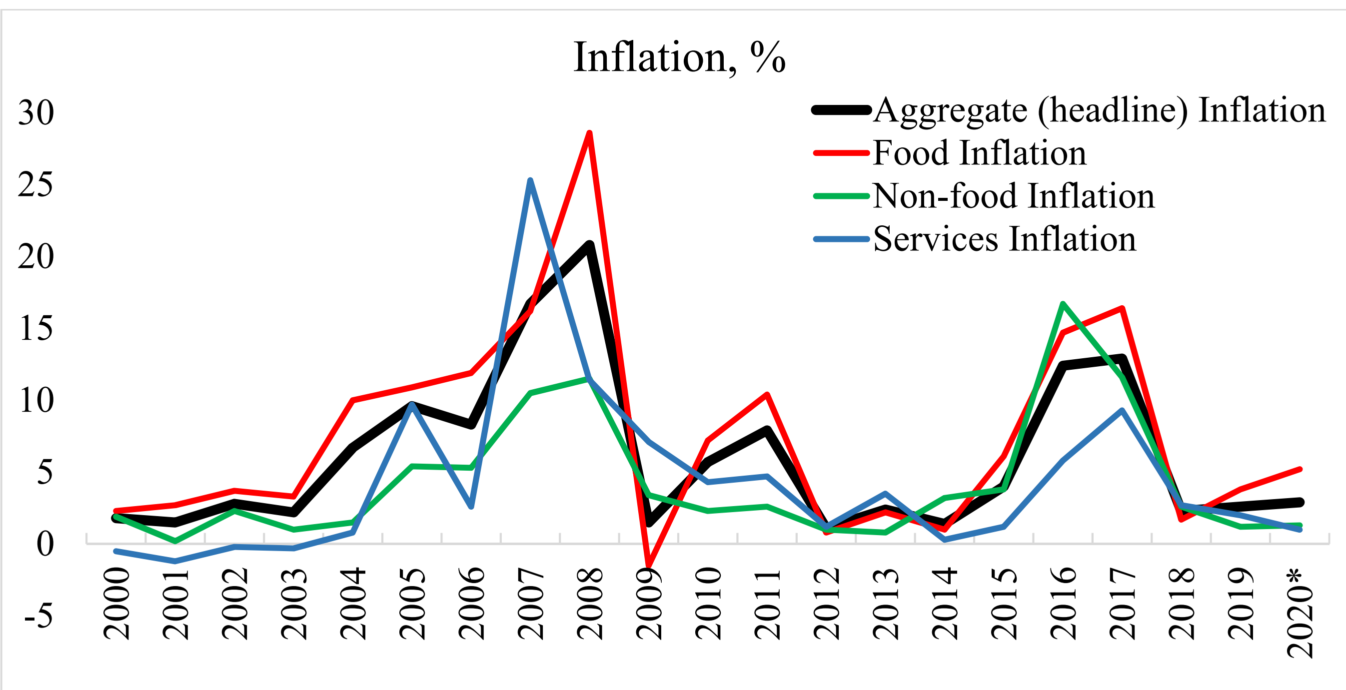
Keywords: consumer price index, inflation, food prices, non-food prices, services prices, forecasting performance

[1] Vugar Rahimov – Research Department, Central Bank of the Republic of Azerbaijan, e-mail: vugar_rahimov@cbar.az

1. Introduction

The implicit inflation target of the Central Bank of the Republic of Azerbaijan (CBAR) is Consumer Price Index (CPI) headline inflation. Therefore, understanding and exploring the inflationary processes and examining the drivers of prices of components in the consumer basket is of great importance for researchers and policymakers. The consumer basket of Azerbaijani households comprises more than 500 items and the weights of the items in the basket are revised once a year based on a survey among households. The components and the weights are defined and approved by the State Statistics Committee of the Republic of Azerbaijan (SSCRA). The SSCRA is also responsible for the collection, compilation, and dissemination of the monthly price changes of the items of the basket. The consumer basket of Azerbaijan is usually divided into three aggregate components, namely food, non-food, and services components. The weights are revised every year but do not change significantly. The food component has the highest weight in the basket. The services and non-food components rank second and third, respectively. **Figure 1** plots aggregate (headline), as well as food, non-food, services inflation dynamics between 2000 and 2020.

Figure 1: Annual average inflation rate of aggregate (headline), food, non-food and services.



Source: The State Statistics Committee of the Republic of Azerbaijan

** The inflation rate for 2020 represents the 3rd quarter.*

The figure shows that inflation in Azerbaijan has been volatile and high until 2009. Annual average inflation accelerates since 2004 and reaches a double-digit level in 2007. However, the food inflation rate has already been 10% in 2004. All components of aggregate inflation were double-digit in 2007-2008. That period is characterized by huge inflows of oil money into Azerbaijan and a sharp increase in budget expenditures, which also boosted aggregate demand in the country. The years 2007-2008 are associated with a dramatic increase in global food prices[2] (30% and 25%, respectively). Higher aggregate demand and the surge in global food prices might explain high food inflation during that period. On the other hand, the increase in income might cause a price increase in non-food and services prices. Furthermore, a significant part of the consumer basket of Azerbaijan consists of administered (regulated) prices. Most of the regulated prices are in the services basket. Meanwhile administered items such as gasoline and diesel belong to the non-food basket. 2007-2008 period is also associated with an increase in the prices of the administered items. For instance, in 2007, the Tariff Council of Azerbaijan increased tariffs for stable network telephones, bus fares, drinking water supply costs, as well as gasoline and diesel prices significantly. Rahimov et al. (2016) calculate that administered prices surged by 57% in 2007. From 2009 to 2015, Azerbaijan has experienced relatively stable and low inflation. The year 2009 has been associated with deflation. This is due to a decline both in international food prices and in local fruits and vegetables. Food inflation reaches a double-digit level in 2011, but aggregate inflation stays at a single-digit level. Since up to 90 percent of export of Azerbaijan is oil and gas, a sharp drop in oil prices in 2014 gave rise to the deterioration of the balance of payments of Azerbaijan. Subsequently, the CBAR devalued Manat in February 2015 and December 2015, which resulted in Manat losing half of its value (from 0.78 AZN/USD at the beginning of 2015 to 1.55 AZN/USD at the end of 2015). Considering that Azerbaijan is a small open economy, and the share of imported products is significantly high in the consumer basket, the effects of devaluations were transmitted to prices in the following years. As expected, the biggest impact of devaluation was on non-food item prices. Since 2018, the inflation has stabilized again.

As can be seen above, Azerbaijan has experienced both volatile and stable inflation dynamics over the past 20 years. Although the components of the consumer basket have different inflation levels, in general, they have followed a similar trajectory. The reactions of CPI components to domestic and foreign economic processes are different. Identifying the causes of price changes of consumer basket components would allow policymakers to mitigate the effects of inflationary processes and help them to conduct adequate policy in response to the processes.

[2] Source: FAO - http://www.fao.org/worldfoodsituation/foodpricesindex/en/

The inflation processes of Azerbaijan have been explored from different aspects before. The prices of components of the consumer basket have also been examined within the exchange rate pass-through (ERPT) context (Rahimov & Jafarova, 2017). However, to the best of my knowledge, comprehensive research on this topic has not been conducted so far. Therefore, this paper contributes to the existing literature by filling the gap in this area. Besides, the paper also compares the forecasting accuracy of the headline inflation forecasting of component methods against the direct inflation forecasting method. Hence, the purpose of the paper is twofold: The first goal is to identify the main determinants of prices of food, non-food, and services components of the consumer basket. Currently, the CBAR has a number of inflation forecasting models. My coauthors and I have constructed one of them[3], which is actively used for direct forecasting purposes. Comparing the performance of forecast, which is produced based on the combination of the components to that of univariate (benchmark) model, as well as to forecasting performance of the direct method would be interesting. Therefore, the second purpose of the paper is to produce forecasts based on the combination of components, combine the forecasts using respective weights and compare forecast errors from component models to forecast errors from the univariate models and the direct inflation forecast model. I employ a vector autoregressive (VAR) model for estimation. The univariate (benchmark) model is based on autoregressive processes. I use quarterly data from 2003 to 2020 (2003Q1-2020Q3).

The study finds that foreign factors play a significant role in the determination of food prices, while non-food prices are mostly exposed to exchange rate shocks. The exchange rate is also an important determinant of services prices. However, the money supply is another significant factor that affects services prices. Another major finding of the paper is that the food inflation forecast made on the food prices model has superior accuracy than the univariate (benchmark) model, while the forecasting performance of non-food and services prices models are not statistically different from the univariate models. Overall, services prices are the most unpredictable component of the consumer basket, which is probably due to the weights of administered items of the component. Finally, the inflation forecast made by combining the forecasts of components has better forecasting accuracy compared to the direct inflation forecasting model.

The rest of the paper is structured as follows. In section two, I review relevant literature regarding the determinants of inflation components. Section three is devoted to data and methodological issues. I present and discuss the results in section four. And section five concludes.

[3] Determinants of Inflation in Azerbaijan. https://uploads.cbar.az/assets/eab8c8c4d73082b4b

2. Literature Review

Determinants of consumer prices differ from country to country, depending on import dependence, energy-fuel prices, exchange rate, infrastructure, level of agricultural production, and seasonal factors. Literature on this topic suggests that there are a lot of factors that form prices in different countries. Rahimov & Jafarova (2017) explore the causes of changes in CPI and its components within the exchange rate pass-through (ERPT) context. Since they identify the shocks in the Cholesky decomposition scheme, most exogenous shocks are identified in the study. The impact of exchange rate changes on the non-food component of the consumer basket is quite high. The degree of ERPT on this component is 0.41. More than 50% of the variation in non-food prices is explained by this factor. The maximum degrees of ERPT on food and services prices are 0.28 and 0.15, respectively. Besides, the researchers find that food prices are also affected by foreign prices (i.e., CPI in trading partners), while the effect of foreign prices on non-food prices is low and on services prices are almost zero.

Baek & Woo (2010) examine the factors affecting U.S. food prices. Using monthly data from 1989 to 2008, they apply Johansen cointegration analysis and vector error correction methodologies for estimation. According to their findings, agricultural commodity prices and exchange rate are the main factors affecting U.S. food prices in both the short and long run. They also show that energy price is a significant factor that explains the behaviors of food prices. However, its impact on U.S. food prices is sizable in the long run, while its effect is little in the short run. It is consistent with the results found by Lambert & Miljkovic (2010). They show that fuel and energy prices play a significant role in food price formation. Farm product prices and wages are underlying factors affecting food prices, too.

Ismaya & Anugrah (2018) attempt to investigate food inflation in terms of expectations: whether backward-looking or forward-looking expectations or combinations of both expectations are better at explaining food prices. They show other demand-supply factor determinants of food inflation. The study covers the period 2008-2017. They find that the inflation model in which both backward-looking and forward-looking expectations are included demonstrates the best performance. Besides, the researchers conclude that rice productivity (which is a staple food in Indonesia), loans to the agricultural sector, money supply (M1), infrastructure (irrigation), climate (El-Nino), and seasonal factors (Ramadan) are significant variables that affect food prices in Indonesia. According to the paper written by Louw et al. (2018), food supply factors cause food inflation in South Africa. They conclude that global and local commodity prices, as well as exchange rate indicators, are dominant factors behind food prices in South Africa. Irz et al. (2013) investigate underlying factors behind food price determination in Finland. They check the long-run relationship between food prices and agricultural commodity prices, energy prices, and labor costs. The study indicates three factors explain half of the variability in food prices in Finland. They conclude that a third of food prices comes from agricultural prices, whereas the impact of energy prices is significant but quantitatively limited.

Alper et al. (2016) describe and investigate the causes of food inflation in Sub-Saharan Africa for 2000-2016 years. They find that, on average, food inflation has been more volatile than non-food inflation during that period. The results indicate that food prices in the region are driven by both external and structural factors: External factors include world food prices, world fuel prices, and exchange rate. Fresh food prices are a major factor contributing to food prices.

The volatility of food prices is also among interesting topics for researchers and policymakers. Kornher & Kalkuhl (2013) examine the food price volatility and its determinants in a group of developing countries. They conduct panel regression estimation using monthly data of more than 50 developing over 2000-2012. The dependent variable is formed from fluctuation in retail and wholesale prices. They find that persistency, that is volatility in the previous period, is one of the main factors that influence price volatility. The impact of international price volatility, production shortfall, and transaction costs also increase domestic price volatility. On the other hand, factors such as the level of food stocks, the functionality of markets, and governance effectiveness help to stabilize prices.

Jacobs & Williams (2014) study the factors that affect inflation in the non-tradable component of CPI, which makes up some 60% of the consumer basket of Australia. They carry out the research through mark-up and Phillips curve specifications. The results from mark-up regression suggest that inflation expectations, unit labor costs, and the output gap are significant variables that explain the behaviors of prices in non-tradable items. Phillips curve approach shows that inflation expectations and unemployment rate have a significant impact on prices. In both models, the effect of import price inflation is positive, however, its effect is not statistically different from zero. Following this study, similar estimations have been conducted by the Chile Unit of the BBVA Research for identifying the determinants of non-tradable inflation of Chile. The results show that inflation expectations and non-tradable unit labor cost variables have positive and significant, while unemployment has a negative and significant effect on the non-tradable inflation of Chile. Unlike in Australia, the impact of import inflation on non-tradable inflation is significant, whereas the coefficient of the output gap is insignificant.

Simwaka et al. (2012) examine whether monetary, exchange rate, and supply-side factors play any roles in driving inflation in Malawi. In this context, they decompose inflation into food and non-food components. According to the results, money supply (M2) and exchange rate changes can predict the non-food inflation of Malawi.

Decomposing consumer basket into tradable and non-tradable components, Hargreaves et al. (2006) model New Zealand inflation. Their estimations show that non-tradable inflation can be well explained by inflation expectations and the output gap, while drivers of tradables inflation are inflation expectations, output gap, and imported inflation. Following their approach, Tallman & Zaman (2017) model goods and services inflation separately. Phillips curve relationship approach – where the relationship between unemployment and services inflation - is applied to model services inflation. However, univariate unobserved components with a stochastic volatility model is used for modeling goods items of inflation. As a next step, they compare the forecasting performance of the combination of components to that of benchmark aggregate models. Root mean squared errors from the combination of components models are smaller than benchmark models, suggesting that the combination model has superior performance.

3. Data and Methodology

3.1. Data

I use quarterly data over the period 2003Q1 and 2020Q3. All the variables have been taken on monthly basis. Since the quarterly series is included in the econometric models, I have converted the monthly series into quarterly series (See **Table A1**).

Both domestic and foreign variables have been used for modeling the food, non-food, and services CPI of Azerbaijan. It is worth noting that, I have employed different combinations of variables. But in this section, I present only significant ones. Data on **food CPI, non-food CPI**, and **services CPI** are collected from the SSCRA. Data on **world food prices** are taken from the IMF Primary Commodity Prices database on monthly basis. World food prices series is adjusted for the U.S. CPI. Data on **trading**

partners' CPI are provided by the internal database of the CBAR and are publicly available on the webpages of respective statistical agencies of partner countries. Trading partners' CPI series is constructed using data of 15 trading partners[4].

As I have already mentioned above, since a significant part of consumer products including food products are imported, what happens in the exchange rate also changes the dynamics of food prices. Since there has not been variation in the bilateral exchange rate of Manat against USD for a long period (from 2008 until February 2015 and from 2017 until the end of the study period), including USD/AZN or vice versa into model would not allow me to identify the impacts of the exchange rate. To overcome this issue, I employ nominal effective exchange rate variable, which is constructed using the trade-weighted bilateral exchange rate of Manat against 15 trading partners (including Euro). The CBAR statistics produces different NEER series based on oil export-, import-weighted trade and non-oil export-, import-weighted trade, separately. Therefore, I consider that **non-oil import weighted NEER** is appropriate in this case. When the exchange rate issue is discussed, it is worth emphasizing the way how Azerbaijani NEER is expressed. The exchange rate can be constructed by two methodologies: either the amount needed to buy one unit of a foreign currency or the amount of foreign currency for one unit of domestic currency. The CBAR calculates NEER as $(basket\ of\ foreign\ currencies)/AZN$ methodology. Hence, increase in the value of the exchange rate means appreciation of Manat.

Of course, one should think about domestic factors that are potential drivers of food prices. For that purpose, I check the effects and significance of the producer price index (PPI), as well as its different sub-components. I find that **agricultural PPI** is a relevant indicator for that purpose. This series is collected and compiled by the SSCRA and published on monthly basis. As a demand factor, I consider **real GDP growth** of Azerbaijan, which is reported on quarterly basis by the SSCRA.

Non-food consumer prices are also determined by both foreign and domestic factors. Particularly, the non-food component of the consumer basket is the most affected one by foreign products. In fact, Azerbaijan imports almost all of the cars and their parts, machinery, pharmaceutical and medicinal drugs, a large share of home appliances and consumer electronics, and clothes. So, as in the food prices, I use **trading partners' CPI** provided by the CBAR. **Non-oil import weighted NEER** is another variable I have included in the model. Switching to domestic variables, I use the **output gap** indicator that is computed with Hodrick-Prescott filter based non-oil GDP. **Manufacturing PPI** is another potential factor that might

[4] Eurozone is treated as a single entity.

influence of prices of the non-food component. Therefore, I use that variable in the estimation.

Table 1: Augmented Dickey-Fuller unit root tests

Variable	Level		First differences	
	t-statistic	Status	t-statistic	Status
Food CPI (2002=100)	-0.26	Non-stationary	-5.39***	Stationary
Non-food CPI (2002=100)	-0.48	Non-stationary	-2.81*	Stationary
Services CPI (2002=100)	-1.26	Non-stationary	-6.74***	Stationary
World food prices (2002=100)	-2.58	Non-stationary	-5.74***	Stationary
CPI in trading partners (2002=100)	-1.22	Non-stationary	-5.73***	Stationary
N.o.i.w NEER (2002=100)	-1.59	Non-stationary	-3.35**	Stationary
Real GDP (based on 2005 prices)	-1.29	Non-stationary	-8.74***	Stationary
Agricultural PPI (2002=100)	-1.49	Non-stationary	-5.98***	Stationary
Output gap	-3.12	Stationary	-	Stationary
Manufacturing PPI (2002=100)	0.14	Non-stationary	-7.31***	Stationary
M2	-0.82	Non-stationary	-3.95***	Stationary
Non-oil tax	-1.38	Non-stationary	-8.47***	Stationary

Regarding services prices, the role of foreign factor exists though it is not as much as in other components. Thus, **non-oil import weighted NEER** is used as a determinant of services prices. I also use **M2 (broad money)** which is published by the CBAR. Thus, **food CPI** is used as well. Another significant determinant variable is **non-oil tax** variable. This is the amount of tax collection in the non-oil sector.

I add a dummy variable for food (for the periods 2007Q4-2008Q2 and 2009Q1) and services prices (for the periods 2005Q1, 2007Q1 and 2009Q3) models for the periods where structural breaks are observed.

All variables of the models are seasonally adjusted with X-12 methodology. I apply an Augmented Dickey-Fuller unit root test procedure and find out that all variables are non-stationary in level. So, I take the first difference and check the stationarity again. Results show that those variables are stationary in the first difference. Hence all variables exhibit I(1) (See **Table 1**). Therefore, I use all variables in the log-difference form.

3.2. Methodology

I employ vector autoregression (VAR) methodology to carry out the estimations. The general form of VAR equations is specified as follows:

$$y_t = \sum_{i=1}^{p} A_i y_{t-i} + \sum_{j=0}^{q} A_j x_{t-j} + u_t \qquad (1)$$

where y_t is a $kx1$ vector of k variables, A_i is a kxk dimensional matrix of parameters, A_j is kxn matrix of coefficients of exogenous variables, x is $nx1$ vector of exogenous variables, u_t is $kx1$ vector of error terms. According to the above model, each variable is explained by the lagged values of all the endogenous variables and current and lagged values of the exogenous variables in the system. There is no contemporaneous relationship among the endogenous variables.

For the identification of shocks, I use the Cholesky decomposition scheme. In this scheme, the first variable does not respond to structural shocks of other variables. The second contemporaneously responds to structural shocks of itself and the variable before it. In this manner, the latest variable contemporaneously responds to all other variables, whereas none of the variables respond it structural shocks of the last variable.

Thus, in Cholesky decomposition identification, I list the variables from most exogenous one to endogenous shocks in the following lower triangular matrix.

Food prices

$$\begin{pmatrix} \mu_t^{wfp} \\ \mu_t^{tpcpi} \\ \mu_t^{neer} \\ \mu_t^{gdp} \\ \mu_t^{agriPPI} \\ \mu_t^{foodcpi} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \end{pmatrix} \begin{pmatrix} \varepsilon_t^{foreignfood} \\ \varepsilon_t^{foreignprice} \\ \varepsilon_t^{er} \\ \varepsilon_t^{demand} \\ \varepsilon_t^{agrishocks} \\ \varepsilon_t^{foodprice} \end{pmatrix}$$

where, μ_t^{wfp}, μ_t^{tpcpi}, μ_t^{neer}, μ_t^{gdp}, $\mu_t^{agriPPI}$, $\mu_t^{foodcpi}$ stand for world food prices, CPI in trading partners, non-oil import weighted NEER, GDP, agricultural PPI and food CPI respectively, while $\varepsilon_t^{foreignfood}$, $\varepsilon_t^{foreignprice}$, ε_t^{er}, ε_t^{demand}, $\varepsilon_t^{agriprices}$, $\varepsilon_t^{foodprice}$ are world food prices, foreign price, exchange rate, real GDP, agricultural and food inflation shocks, respectively.

In my identification scheme, I assume that *world food prices* is the most exogenous shock. It means that it can have a contemporaneous effect on the rest of the variables; none of the other variable shocks in the model has a contemporaneous effect on world food prices. World food prices can transmit local food prices through two channels. One is that it can affect food prices in our trading partners and through those partners, import prices will change. The second channel might be an export channel. When food prices increase (decline), it will also drive up (down) local prices through the export channel.

I include *trading partners' CPI* to capture the effects of price shocks in the trading partners. Since world food prices do not reflect all foreign price shocks, I have decided to include CPI in trading partners. Purchasing Power Parity Hypothesis implies that price differences among trading partners shape the exchange rate in the long run. Therefore, Rahimov & Jafarova (2017) note that *"By including this variable, we can net out the influence of trade partners' CPI on the exchange rate."*

Non-oil import weighted NEER is included to find out exchange rate shocks on food prices. *Real GDP* is used to capture the effects of increase in income on food prices. Another significant variable, agricultural PPI, is used to reflect the impact of local agricultural producer prices on food prices. And *food prices* is also included to capture the effects abovementioned on it.

Non-food prices

$$\begin{pmatrix} \mu_t^{tpcpi} \\ \mu_t^{neer} \\ \mu_t^{outputgap} \\ \mu_t^{manufacturingppi} \\ \mu_t^{nonfoodcpi} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & \mathrm{a}_{22} & 0 & 0 & 0 \\ a_{31} & \mathrm{a}_{32} & \mathrm{a}_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{pmatrix} \begin{pmatrix} \varepsilon_t^{foreignfood} \\ \varepsilon_t^{er} \\ \varepsilon_t^{outputgap} \\ \varepsilon_t^{manuf.price} \\ \varepsilon_t^{nonfoodprice} \end{pmatrix}$$

where, μ_t^{tpcpi}, μ_t^{neer}, μ_t^{gap}, $\mu_t^{manufacturingppi}$, $\mu_t^{nonfoodcpi}$ stand for CPI in trading partners, non-oil import weighted NEER, output gap, manufacturing PPI and non-food CPI respectively, while $\varepsilon_t^{foreignfood}$, ε_t^{er}, $\varepsilon_t^{output\ gap}$, $\varepsilon_t^{manuf.price}$, $\varepsilon_t^{nonfoodprice}$ foreign price, exchange rate, output gap, prices in manufacturing sector and non-food inflation shocks, respectively.

In non-food shock identification scheme, *CPI in trading partners* is ordered first as it is the most exogenous shock. This variable captures foreign price shocks. *Non-oil import weighted NEER* measures the effects of exchange rate shocks on local non-food prices. Since a significant share of non-food items is imported, its response to exchange rate shock is expected to be high.

Output gap is used to play the demand factor role. This variable is extracted from the real non-oil output, as the revenue from oil do not directly flow into the economy. Therefore, gap of non-oil GDP better serves my interest. Another supply shock is *manufacturing prices*. The motivation I use this variable is that manufacturing products correspond to non-food component of the consumer basket and what happens in that sector directly affects consumer prices. *Non-food CPI* variable is included to capture the effects of other shocks.

Services prices

$$\begin{pmatrix} \mu_t^{neer} \\ \mu_t^{m2} \\ \mu_t^{foodcpi} \\ \mu_t^{tax} \\ \mu_t^{servicescpi} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & \mathrm{a}_{22} & 0 & 0 & 0 \\ a_{31} & \mathrm{a}_{32} & \mathrm{a}_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{pmatrix} \begin{pmatrix} \varepsilon_t^{er} \\ \varepsilon_t^{money} \\ \varepsilon_t^{foodprice} \\ \varepsilon_t^{tax} \\ \varepsilon_t^{servicesprice} \end{pmatrix}$$

where, $\boldsymbol{\mu_t^{neer}}$, $\boldsymbol{\mu_t^{m2}}$, $\boldsymbol{\mu_t^{foodcpi}}$, $\boldsymbol{\mu_t^{tax}}$, $\boldsymbol{\mu_t^{servicescpi}}$ stand for non-oil import weighted NEER, M2 (broad money), tax and services CPI respectively, while $\boldsymbol{\varepsilon_t^{er}}$, $\boldsymbol{\varepsilon_t^{fiscal}}$, $\boldsymbol{\varepsilon_t^{foodprice}}$, $\boldsymbol{\varepsilon_t^{tax}}$, $\boldsymbol{\varepsilon_t^{servicesprice}}$ are exchange rate, money supply, food inflation, tax and services inflation shocks, respectively.

In the shock identification scheme of the model, *non-oil import weighted NEER* variable is included as a first variable. Despite the services component of the consumer basket is usually considered non-tradable, some items in this basket are tradable. For instance, airfare, ship transport, cross-border train ticket costs are exposed to exchange rate changes, as these items are priced in foreign currency (mostly Euro). Besides, there can be a correlation between domestic and international tourism costs due to exchange rates. For example, if tourism abroad is costly because of exchange rate depreciation, local tourism prices such as the cost of hotels and recreational areas can also increase. That is why I try to measure exchange rate shocks.

I use *M2* (*broad money*) as an important variable for services prices. Referring to Huseynov & Ahmadov (2013), I might assume that it is a fiscal shock. The authors show that fiscal shocks cause 90% of the M2 of Azerbaijan. Later Rahimov et al. (2016) use M2 as fiscal shocks.

Since some items of services basket are related to hotel, restaurants, cafes services, changes in food prices directly affect the costs of these sectors. Therefore, it is reasonable to include *food prices* into the model. Another cost factor would be *taxes*. When tax rates/collection increase, it can be transmitted into services prices. And the last variable in the identification scheme is the services CPI variable.

To compare forecasting accuracies of the models, I make one-, two-, four-, six- and eight-period forecasts and conduct out-of-sample analysis. I estimate the model from the beginning until 2012Q4. Later the forecasts are made for h-periods (i.e., one-, two-, four-, six-, and eight-periods). In this manner, each time the estimation period is recursively extended by one quarter, and h-step forecasts are produced. The process is repeated until the end of study period. Then I calculate the root mean squared errors (RMSEs). The RMSE is given as follows:

$$RMSE_{m,h} = \sqrt{\frac{1}{T}\sum_{i=1}^{T}(y_t - \hat{y}_t^{m,h})^2} \tag{2}$$

Where y_t denotes actual inflation rate at period t at the forecast evaluation period, while $\hat{y}_t^{m,h}$ is *h-period* ahead inflation forecast for period t for model m (i.e., benchmark and VAR models). To find the forecasting performance of VAR model, I calculate the ratio of RMSEs between VAR and benchmark models. Likewise, RMSE of component model is expressed as ratio between component combination and direct forecasting model. Hence, the ratio less than unity indicates lower errors and better model performance.

However, lower ratio does not necessarily mean that its forecasting performance is better. To test the significance of the differences, I apply Diebold-Mariano (DM) (Diebold & Mariano, 1995) test. Define d_τ as follows:

$$d_\tau = g\left(e_\tau^{(2)}\right) - g\left(e_\tau^{(1)}\right), \tag{3}$$

where

$$e_\tau^{(i)} = y_{\tau+h} - \hat{y}_{t+1|\tau}, \tag{4}$$

for models $i = 1, 2$, and g is a generic loss function $(g(e)) = e^2$.
Then, the DM test is defined as follows:

$$DM = \sqrt{n}\frac{\bar{d}}{\sigma_d}, \tag{5}$$

where

$$\bar{d} = \frac{1}{n}\sum_{\tau=t}^{T+n-1} d_\tau, \tag{6}$$

and σ_d is the estimator of the variance of $\bar{d}$. The null hypothesis of the DM test is that the two models have the same RMSE.

4. Results

4.1. Stability tests and Impulse responses

In this section, I report the stability tests and results of the impulse response analysis. I have already discussed above, all variables are I(1). Therefore, VAR models are estimated in the log first differences. Different information criteria suggest 1, 2, 4 lags in the model. However, I use standard two lags in the VAR models. First thing is to test the stability of the VAR model. Therefore, I apply diagnostics test. The test result is presented in **Figure A2**. Results for all models show that VAR (2) satisfies stability condition as the inverted roots of the model lie inside the unit circle.

The impulse responses are expressed as reactions of the food, non-food and services to one standard shocks of other variables, respectively. Solid lines represent accumulated impulse responses, while red dotted lines are one standard error confidence bands.

Figure A3 shows that the impacts of the shocks of all variables on food prices are immediate and significant. The effect of world food prices on local food prices is positive. Pass-through reaches the highest degree in the 2nd quarter. Consumer prices in trading partners has also a positive effect on food prices as expected. The response of food prices to exchange rate shocks is negative. However, pass-through is slower and it peaks in the 6th quarter. Taking into account, positive shock means appreciation in this model, this result is intuitive. Demand shock has a positive shock on food prices. When the real GDP goes up, people tend to increase demand and it gives rise to an increase in prices. Another inflationary shock is producer prices in agricultural products. Although its effect is immediate, it is also limited.

Figure A4 presents the impulse response functions of non-food prices. As in food prices, the response of non-food prices to foreign price shock is positive. The figure suggests that the response becomes significant immediately after the shock and the highest pass-through occurs in the sixth quarter. Institutively, the response to exchange rate shock is negative and significant. It takes about two years to fully reflect on prices. The effect of output gap shocks is positive. It was controversial whether output gap shock is supply or demand shock. It seems output gap shock represents demand shock, as prices respond positively when output gap goes up. The impact of manufacturing prices shock is positive. However, its effect is tiny and stays significant for two quarters.

Figure A5 reports impulse responses of services prices. Since most non-tradable items are in the services component of the consumer basket, the role of exchange rate shocks on services prices is smaller compared to that of other components. The impulse response analysis reveals that money supply shocks influence services prices. In other components of the consumer basket, this kind of shock did not have significant effects on them. Thus, the response of services prices to money supply shock is positive, although it turns significant from the second quarter on. The response of services prices to food prices shock is also positive. As I have already discussed in the Data section, an increase in food prices might influence catering items of services component. Therefore, I consider this outcome reasonable. Another positive effect comes from taxes. When tax collection goes up, it can be due to either increase in tax rates or an improvement in tax administration. In both cases, the costs of business increase.

4.2. Variance decomposition

To reveal the relative effects of variables, a variance decomposition analysis is undertaken to determine the percentage of changes in each of the variables that are attributable to variations or shocks to all variables in the system.

According to **Table A2**, initially, the largest part of food price variance is explained by its innovations. The contribution of lagged food prices is 63% within the first quarter. However, the contribution decreases gradually and from the fourth quarter on it makes up only 38% of variation in the food consumer prices. The table shows that exchange rate shocks also play a significant role in determination of food prices. It immediately affects food prices and the contribution of NEER to food prices is 22% after the first quarter. The result indicates that foreign prices – world food prices and CPI in trading partners - have also high importance in explaining variation in food prices. Starting from the third period, these two shocks explain more than one-fourth of the variation in food prices. GDP accounts for 5% of food price variation after the third quarter, while this is 9-10% for agricultural PPI.

Table A3 shows that the variation in the prices of non-food items is mainly explained by its own lags and the exchange rate. Especially, the contribution of its lags is highest in the first two quarters. After one year, NEER accounts for about 40% of the variation of non-food prices. The share of CPI in trading partners is about 10% after three quarters and it increases gradually. Output gap socks explain about 3-5 percent of the variation in non-food prices. Manufacturing prices shocks have the lowest explanatory power with only 2-3 percent contribution.

Variance decomposition of the shocks to services prices is presented in **Table A4**. According to the decomposition, three-fourth of variation is explained by its innovations. In the first two quarters, shocks of exchange rate are also high. From the third quarter on, the share of services prices shocks goes down significantly, and the contributions of shocks of other variables increase. One year after shock, services prices still explain half of the variation, while one-fifth of the variation comes from exchange rate. Besides, M2 and food CPI each account for 10% and 9% after 4 quarters, respectively. Non-oil tax variable has the lowest contribution.

4.3. Forecast errors

In the next step, I calculate forecast errors of food, non-food, and services prices models based on the determinants and compare each of them against autoregressive (benchmark) model. Recursive forecasting schemes for one-, two-, four-, six- and eight-period forecasts are used for that purpose. Relative root mean squared errors are calculated for each period (See **Table 2**) and their significance are checked (**Table 4**).

The forecasting performance of the VAR model for food prices is better than the univariate model except for all periods. However, the DM test shows that this difference is statistically significant in only two-, four-, six- and eight-period forecasts. Regarding the non-food price model, the VAR model performs slightly better than the benchmark model up to six forecast periods. Nevertheless, as the DM test suggests that is not statistically different from zero except for the two-quarter forecast, meaning that multivariate model has better accuracy at only two-period forecast. The benchmark model of services prices has better accuracy than the VAR model except for one-quarter forecast. However, none of those forecast differences are statistically significant.

Table 3 gives relative forecasting errors of inflation forecasts based on combination of components and direct forecasting methods. The former method means combining the forecasts of component models and making aggregate forecasting using corresponding weights, while direct method is the forecasting of aggregate headline inflation directly. The results suggest that the forecasts, which are produced based on the combination of component forecasts, have better forecasting performance than the direct aggregate forecasting method for all periods, however, only up to six-period forecasts are statistically significant as the DM test indicates. However, eight-quarter forecast performances do not differ significantly.

Table 2: Relative RMSEs of benchmark (AR) and VAR models for Components

Models	Forecast periods (quarters)				
	1p	2p	4p	6p	8p
Relative forecast error of food price model					
Benchmark	1.00	1.00	1.00	1.00	1.00
VAR	0.97	0.84	0.87	0.77	0.81
Relative forecast error of non-food price model					
Benchmark	1.00	1.00	1.00	1.00	1.00
VAR	0.96	0.83	0.95	1.00	1.02
Forecast error of services price model					
Benchmark	1.00	1.00	1.00	1.00	1.00
VAR	0.99	1.07	1.08	1.07	1.01

Table 3: Relative RMSEs of Forecast based on Direct and Component methods

Models	Forecast periods (quarter)				
	1p	2p	4p	6p	8p
Direct method	1.00	1.00	1.00	1.00	1.00
Components method	0.76	0.71	0.75	0.86	1.05

Table 4: Significance of the comparison of forecast errors

Forecast periods (quarter)					
	1p	2p	4p	6p	8p
Food (AR-VAR)	0.33	0.1*	0.07*	0.00***	0.00***
Non-food (AR-VAR)	0.37	0.08*	0.27	0.49	0.43
Services (AR-VAR)	0.47	0.33	0.20	0.16	0.44
Aggregate (Direct-component)	0.02**	0.00***	0.01**	0.1*	0.33

5. Conclusion

The goal of this paper is twofold: (i) it empirically attempts to identify main determinants of prices of the components of the consumer basket of Azerbaijan and, (ii) it compares forecasting accuracies of the combination of those models to forecasting accuracy of the direct method. For this purpose, I use quarterly data over the period 2003Q1-2020Q3 and employ VAR models. I show that the prices in Azerbaijan are shaped by both domestic and foreign determinants. Especially, the contribution of foreign factors on prices of food and non-food components, in which there a lot of imported items, is large. However, it has also some effects on services prices.

I find that world food prices, consumer prices in trading partners, non-oil import weighted NEER, real GDP growth, agricultural PPI, and own lags (inertia) of food prices are the main determinants of food prices. The direction of responses of food prices to shocks of the determinants is intuitive and significant. Impulse responses to world food prices, CPI in trading partners, real GDP, agricultural PPI, and food prices shocks are positive, while to NEER shocks are negative. Variance decomposition shows that more than 40 percent of variation in food prices are explained by foreign prices and exchange rate shocks. The food inflation forecast produced by this model has superior forecasting performance than that of benchmark models. However, the differences are significant starting from the two-period forecasts.

Non-food prices are shaped by CPI in trading partners, non-oil import weighted NEER, output gap, manufacturing PPI, and own lags (inertia) of itself. Non-food prices show positive reactions to prices in trading partners, output gap, manufacturing prices and own lags. Its response to NEER is negative. About 45-50% of variations (after three quarters) in non-food prices are explained by foreign CPI and exchange rate. The contribution of output gap and manufacturing prices together is 6%. The rest of the variation is explained by itself. The forecasting performance of this model is at least as accurate as the benchmark model. It is even better at the two-period horizon forecast.

Results indicate that non-oil import weighted NEER, M2, food CPI, non-oil tax and its own lags (inertia) can be considered as main determinants of services CPI. Only deflationary factor on services CPI is the appreciation of the exchange rate. NEER accounts for one-fifth of the variation in services prices. Variance decomposition suggests that unlike in other components model, explanation of shocks by itself remain high in all periods. The forecasting performance of this model fails to beat the univariate model. In general, services prices are the most unpredictable component of the consumer basket. It can be attributed to the share of administered prices which is regulated by the government. Since it is impossible to forecast when the Tariff Council will make a decision on regulated items, the forecast errors are high.

Finally, I try to find an answer to whether the direct method or the combination of components method is better to make aggregate headline inflation. For this purpose, I have compared their forecasting abilities. First, using corresponding weights I combine the forecasts of components inflation and produce aggregate inflation for one-, two-, four-, and eight quarters. Then I calculate the RMSEs of the component model and direct forecasting model, which has been constructed by the CBAR researchers. The results show that the combination of components model has better forecasting accuracy than the direct model for six-period forecasts.

To conclude, I think this model can be used for forecasting purposes. Particularly, the dynamics of food prices can be accurately captured by the variables that I have used. Of course, there is room for future research, as well. Modeling core inflation (headline inflation less seasonal factors and administered items) would improve the forecasting abilities of models. Exposing of these factors and items to unexpected events and changes creates uncertainties in the models. However, since the main objective of the CBAR is to achieve stable headline inflation, I have preferred to make forecasts for headline inflation.

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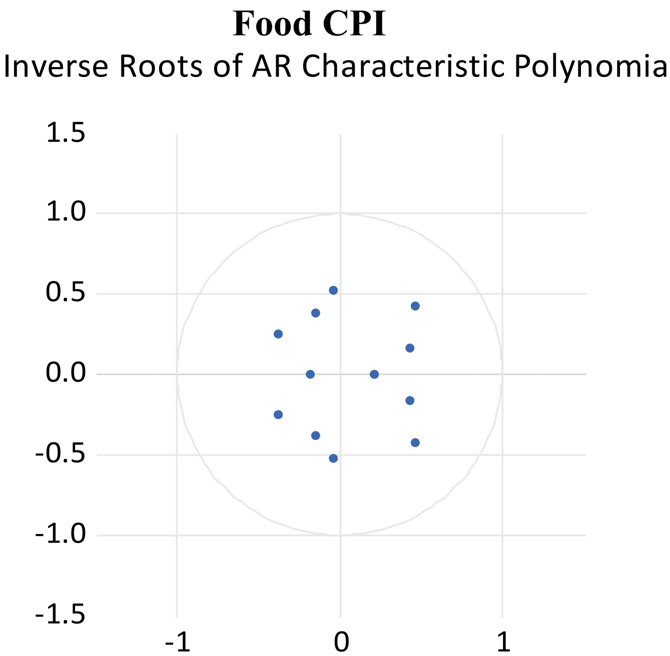
APPENDIX

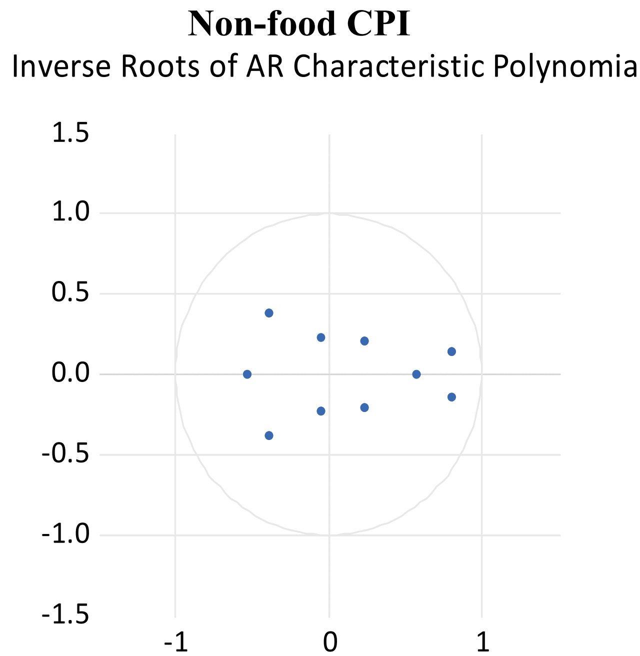
Table A1: Summary statistics*

Variables	Obs	Mean	Median	Std	Max	Min
Food CPI	**71**	2.0	1.7	2.7	11.5	-6.3
Non-food CPI	**71**	1.1	0.6	1.3	4.7	-0.9
Services CPI	**71**	1.3	0.9	2.6	15.6	-2.9
World food prices	**71**	0.2	-0.1	4.7	11.2	-20.9
CPI in trading partners	**71**	1.5	1.5	0.6	3.1	0.6
N.o.i.w NEER	**71**	0.1	0.2	5.4	12.1	-22.1
Real GDP growth	**71**	3.4	2.6	8.1	24.3	-22.8
Agricultural PPI	**71**	1.5	1.4	3.3	9.5	-7.0
Output gap	**71**	0.2	-0.2	2.8	6.4	-5.2
Manufacturing PPI	**71**	1.9	1.2	4.7	20.1	-9.5
M2	**71**	5.4	5.7	8.5	28.5	-26.2
Non-oil tax	**71**	3.3	3.1	16.0	55.0	-27.6

** All variables are expressed in terms of growth.*

Figure A2: VAR (2) stability tests





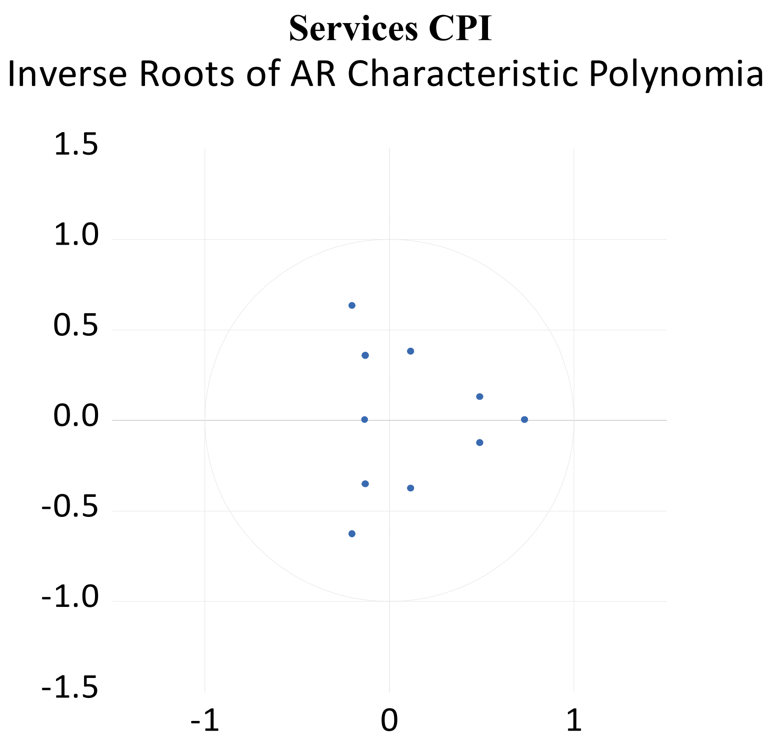


Figure A3. Response to Cholesky One S.D. Innovations ± 1 S.E.

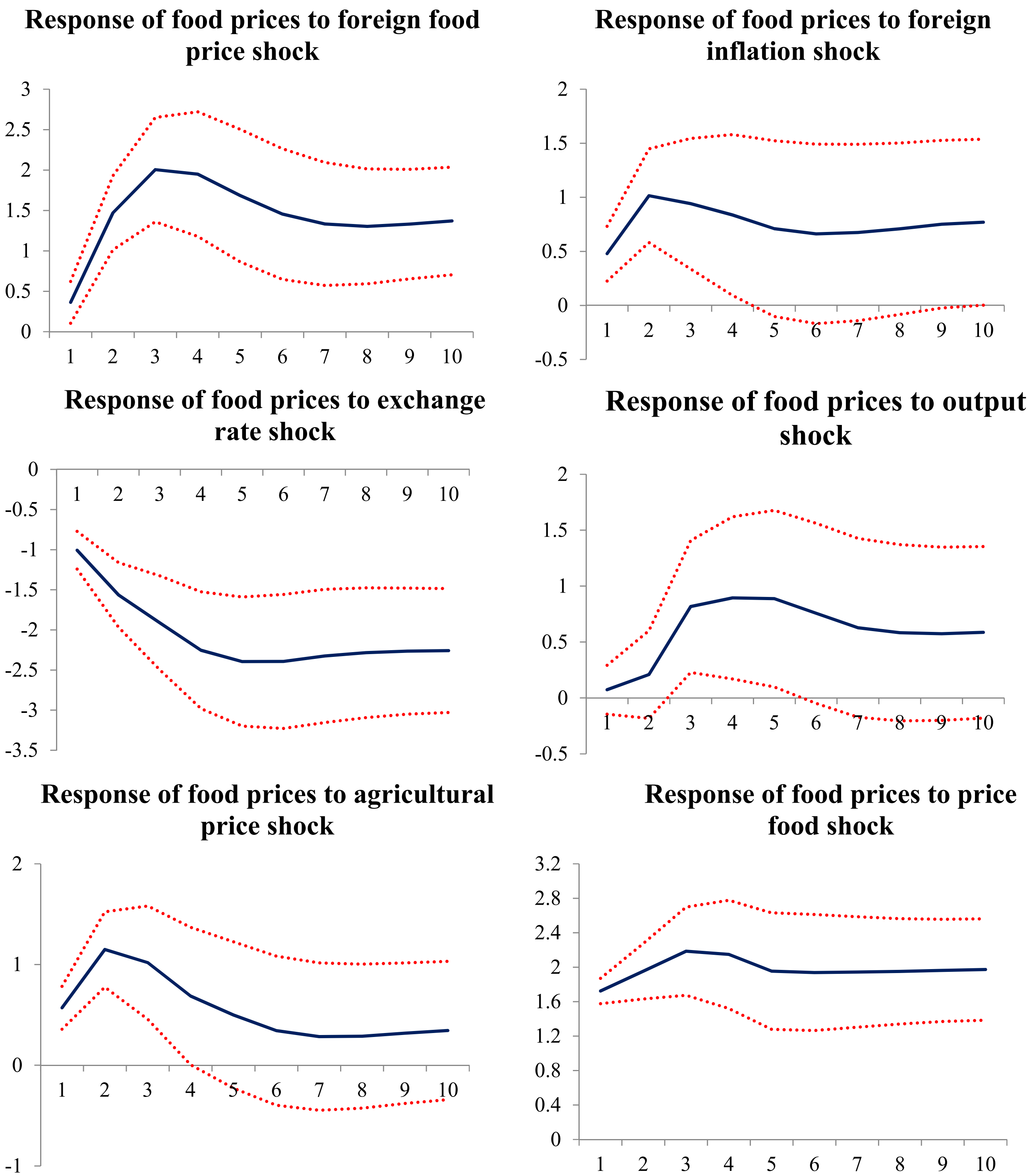
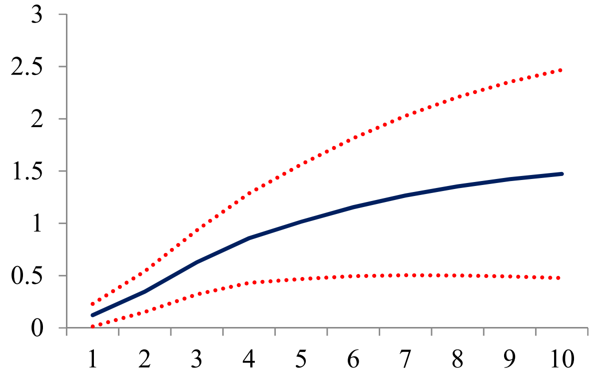
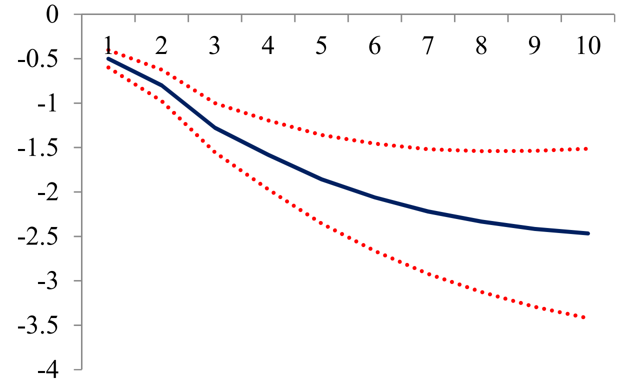


Figure A4. Response to Cholesky One S.D. Innovations ± 1 S.E.

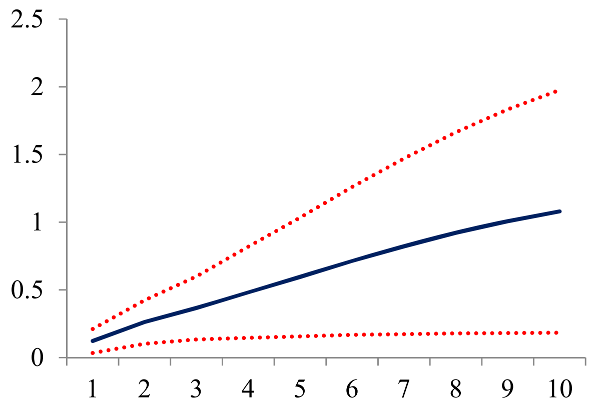
Response of non-food prices to foreign price shock



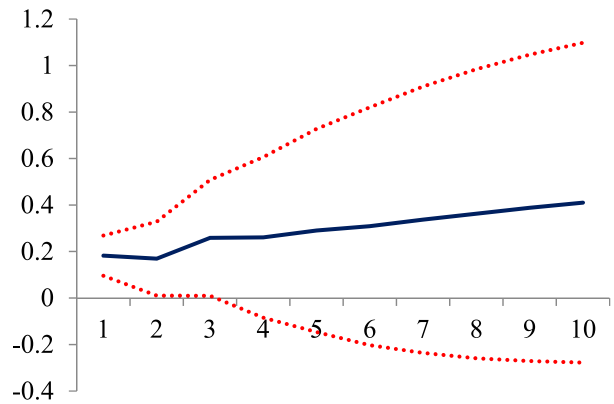
Response of non-food prices to exchange rate shock



Response of non-food prices to output gap shock



Response of non-food prices to manufacturing price shock



Response of non-food prices to non-food prices shock

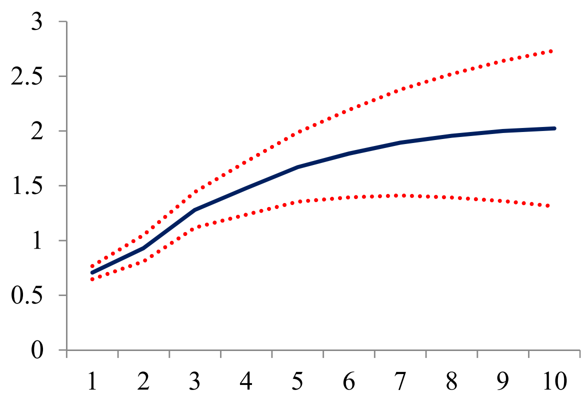
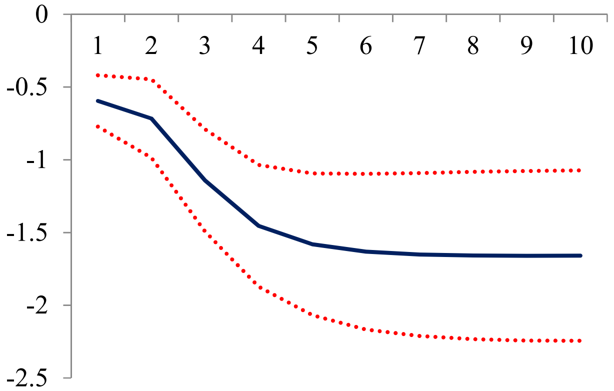
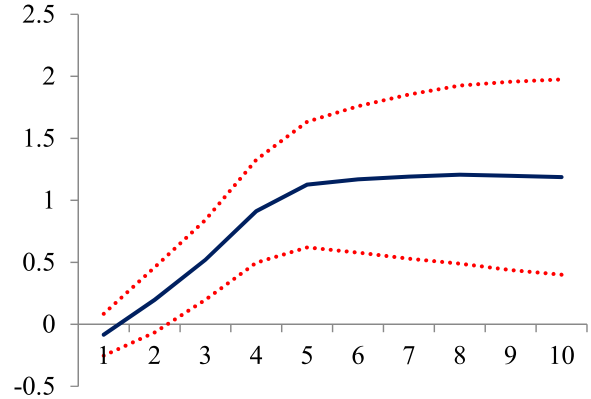


Figure A5. Response to Cholesky One S.D. Innovations ± 1 S.E.

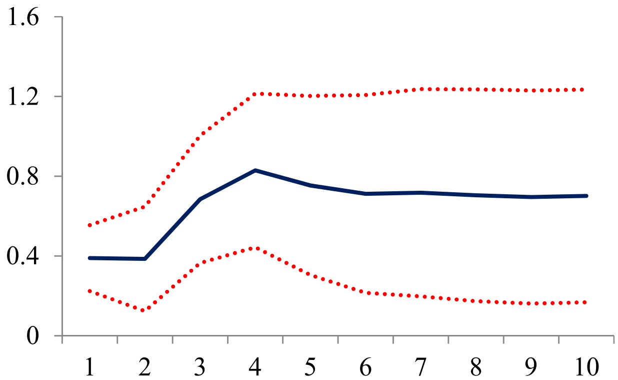
Response of services prices to exchange rate shock



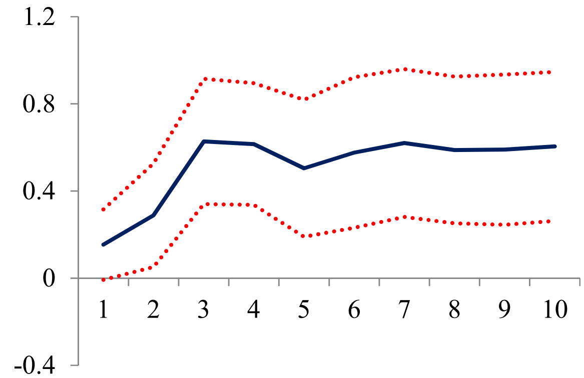
Response of services prices to money supply shock



Response of services prices to food prices shock



Response of services prices to tax shock



Response of services prices to services prices shock

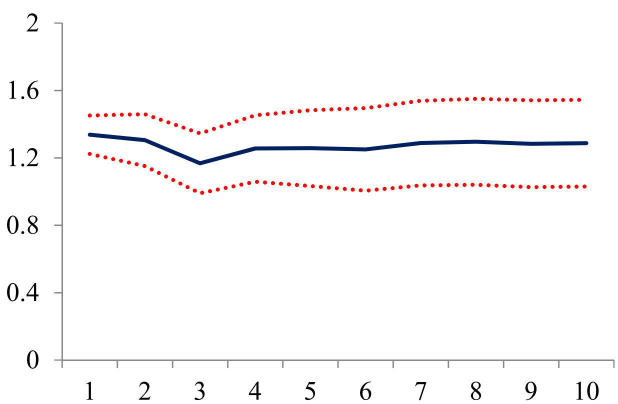


Table A2: Variance decomposition of the shocks to Food prices

Period	WFPI	TP CPI	NEER	Real GDP	Agricultural PPI	Food CPI
1	2.8	4.9	21.7	0.1	7.0	63.5
2	19.7	7.5	19.2	0.3	9.6	43.7
3	21.2	6.7	18.6	5.1	8.7	39.7
4	20.6	6.7	19.5	5.0	9.8	38.4
5	21.0	6.7	19.3	4.9	10.1	38.0
6	21.4	6.7	19.1	5.0	10.2	37.6
7	21.4	6.6	19.1	5.2	10.2	37.5
8	21.4	6.6	19.1	5.2	10.2	37.5
9	21.4	6.7	19.1	5.2	10.2	37.4
10	21.4	6.7	19.1	5.2	10.2	37.4
Cholesky ordering: WFPI, TP CPI, NEER, Real GDP, Agricultural PPI, Food CPI						

Table A3: Variance decomposition of the shocks to Non-food prices

Period	TP CPI	NEER	Output gap	Manufacturing PPI	Non-food CPI
1	1.8	30.8	1.9	4.1	61.4
2	6.4	33.3	3.4	3.3	53.6
3	9.8	38.6	3.1	2.8	45.7
4	11.8	39.6	3.5	2.5	42.6
5	12.2	40.5	3.9	2.3	41.1
6	12.6	40.7	4.5	2.3	39.9
7	12.9	40.8	4.9	2.3	39.1
8	13.0	40.7	5.3	2.3	38.7
9	13.1	40.6	5.7	2.2	38.4
10	13.2	40.5	5.9	2.2	38.2
Cholesky ordering: TP CPI, NEER, Output gap, Manufacturing PPI, Non-food CPI					

Table A4: Variance decomposition of the shocks to Services prices

Period	NEER	M2	Food CPI	Non-oil Tax	Services CPI
1	15.2	0.3	7.1	1.1	76.3
2	15.1	3.5	6.8	1.6	73.0
3	18.8	6.5	8.5	5.2	61.0
4	20.3	10.4	8.5	4.8	56.0
5	20.2	11.6	8.4	5.2	54.6
6	20.2	11.6	8.5	5.3	54.4
7	20.2	11.6	8.4	5.4	54.4
8	20.2	11.6	8.4	5.4	54.4
9	20.2	11.6	8.4	5.4	54.4
10	20.2	11.6	8.4	5.4	54.4
Cholesky ordering: NEER, M2, Food CPI, Non-oil Tax, Services CPI					