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Is the Food Price Volatility Responsible for Inflation Volatility? An Investigation for Turkey [1]

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Abstract

The purpose of this study is to investigate the impact of food price and its volatility in the overall level and volatility of inflation measured by the consumer price index (CPI). Appropriate GARCH models are estimated for the food and headline inflation in Turkey as tests confirms the presence of volatility for both. Starting with a hybrid new Keynesian type of Phillips Curve, analyses based on ARDL bounds tests, VAR models and ANN all indicate that food-inflation and the change in exchange rate proxied by the US dollar have significant and lasting impact on the level and the volatility of inflation in Turkey. Hence, a policy focus on core inflation should account the food inflation.

Jel Codes: C22, E31, E37

Keywords: Price volatility, food inflation, GARCH, Turkey

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1. Introduction

Food prices are subject to higher volatility in comparison to other commodity groups. Four main factors can potentially explain this phenomenon: Changes in agricultural productivity in between harvests due to agricultural diseases and changes in weather conditions; inelastic demand for agricultural products; the longer time it takes for agricultural products to respond to price changes; and increasing income and population in the world, especially in the developing world. The volatility in prices of agricultural products has global consequences, but the impact is more severe in the developing world. Specifically, the volatility in agricultural prices affects policies such as eradicating hunger and malnutrition, increasing food production, stabilizing consumer prices and improving small farm production. Although the volatility of food prices affects the whole society, the effects are much more strongly felt on the poor due to the much higher share of income devoted to food. Moreover, because basic subsistence necessities are price inelastic for the poor, the share of income spent on basic food staples will increase at the expense of other foodstuff with higher nutritional value.

The unprecedented upward trend in the prices of agriculture and food products in the last decade has led to various social reactions in some countries and initiated a widespread research on the causes of price increases all over the world. There are economic, social, geographical and political reasons for price increases, but these vary from country to country. Common reasons for rise in the level and volatility of food prices include rising energy prices, drought, environmental sensitivities, global warming and speculation.

Rising prices and price volatility have also led to shrinking of world trade volume in food staples, raising a great concern especially for the world’s poor and food importer countries. Turkey has also been affected by developments in the world agriculture and food prices and reflected a trend similar to that of the world. In this sense, the developments taking place in the world oil market have direct effects on the agricultural sector of the country. The prices of fertilizer and diesel oil, for example, which are both oil derivatives and among the most important inputs in agricultural production, are directly affected by fluctuations in world oil prices. Of course, Turkey's own agricultural policies, its overall economic dynamics and imbalances have also effects on food prices and its volatility.

Food prices and their volatilities in the world rose dramatically after the food price crises of 2007-2008 and 2010-2011and nonfood inflation rose quickly in many countries as well. Increase in nonfood inflation after the food price crises underscores the importance of looking at the relationship between food prices and headline inflation and questions whether a focus on nonfood inflation might lead policymakers to underestimate the impact of change in food prices on headline inflation. Rising food prices have been indicated as a major cause of inflation inertia in Turkey in recent years. A surge of 7.67 percent was observed in food prices between January 2016 and January 2017, while annual CPI inflation was found to be 9.22 percent during the same period. For October 2017 though, annual food inflation swelled to 12.5 percent while the CPI inflation was slightly below at 11.9 percent (CBRT, 2018).

Because the food items have the highest weight in the CPI basket (20.17 percent for year 2017), the path they follow has particular importance for policy makers. Atuk and Sevinç (2010) state that fresh fruits and vegetables in the CPI basket are distinguished from others with their strong seasonality and the accompanying level of high volatility. Orman et al. (2010) also state that unprocessed food items exhibit a more fluctuating pattern compared to other sub-groups in the CPI basket. They attribute this observation to some structural factors such as high level of the dependency of production on climate conditions high number of intermediaries, uncertainties around public support to agriculture, insufficient level of monitoring by the government, concentration of production in certain regions and fluctuations in external demand. With the changes in weights in the basket of CPI, the changes in the price of certain items such as fresh fruit and vegetables become more prominent in the food inflation and hence headline inflation.

Food price volatility is an important political and scientific matter, because food price volatility can be damaging to macroeconomic stability and the life conditions of farmers. In light of the discussions above, analyzing the price volatility inevitably leads to the examination of the relationship between food and nonfood inflation. Hence, the purpose of this study is to investigate price volatilities of food versus headline inflation in consumer price index (CPI) and analyze the impact of food inflation on the overall inflation and its volatility. The remaining of the paper is designed as follows: Section 2 gives a description of data used, section 3 provides the theoretical framework and gives the detailed summary of the results and their implications, and finally section 4 concludes.

2. Data

Data is monthly and covers period from 1995M01-2017M10. The Inflation (*Inf*) and food inflation (*FoodInf*) series are calculated using CPI (2004, 2010 base years) data from the Turkish Statistical Institute (TurkStat, 2018(a)). The index numbers following January 2006 are derived using the monthly rate of change in 2003=100 CPI and Food Price Index, excluding alcoholic beverages. We use 12 month percentage changes in the price indexes to calculate both inflation series. The output gap (*GAP*) is calculated from Industrial Production Index (IPI 1994, 2010 base years) from Turkish Statistical Institute (TurkStat, 2018 (b)), using Hodrick-Prescott filter where the two series are joined by the authors taking IPI 2010 as 100. We also use 12 month percentage changes in IPI (*IPI%*Δ) as an alternative measure of output deviation to *GAP*. Dollar Exchange rate (USD) is the effective selling rate of US dollar against TL (TL per dollar) and obtained from the Central Bank of the Republic of Turkey (CBRT, 2018(b)). We use 12 month percentage changes in USD (*USD%*Δ) in the analysis. Finally, we use the 12 month percentage change in the price of Brent oil per barrel (*Brent%*Δ). The series for Brent oil price is obtained from the US Energy Information Administration data base(U.S. Energy Information Administration, 2018).

3. Method and Analyses

We start the analysis by investigating the time series properties of the series we use via ADF unit root tests. The ADF tests were performed starting with the largest model (including trend and intercept) and testing the significance of trend and intercept as well if the null of unit root is not rejected (Dickey-Fuller tests based on OLS F statistic: φ_3 and φ_1 tests). Results reveal that all the variables except *USD%*Δ are I(0) at level. For *USD%*Δ the null of unit root cannot be rejected in all three model (p-value 0.104 for the model without intercept and trend) and the nonexistence of trend and intercept as well cannot be rejected by φ_3 and φ_1 tests as well. However, ADF tests are very sensitive to the number of lags added to the model to account for serial correlation in the error term. Using the alternative Phillips-Perron test which modifies the test statistics via nonparametric method to account for serial correlation, we find that all variables, including *USD%*Δ*,* are I(0) at level. Hence, we conclude that all the variables we use are stationary at level. Results of ADF and P-P tests are given in Table 1.

Table 1: ADF and Phillips-Perron Unit Root Tests

	ADF								**P-P**			
	Model A			Model B			Model C		MODEL B		Model C	
Variables	***P***	***t***	ϕ_3	***p***	***t***	ϕ_1	***p***	***t***	***k***	***t***	***K***	***t***
Inf	13	-0.55	2.63	13	**-2.20**	**4.80****	13	**-3.10*****	6	**-3.12****	6	**-3.43*****
FodInf	13	-1.77	2.33	13	-2.02	2.80	13	**-2.31****	7		7	**-3.59*****
GAP	13	**-5.24*****		13	**-5.25*****		13	**-5.27*****	3		3	**-13.3*****
*IPI%*Δ	1	**-4.54*****		1	**-4.53*****		1	**-3.68*****	10		10	**-7.49*****
*USD%*Δ	13	-1.62	1.51	13	-1.6	1.45	13	-1.59	6		6	**-3.73*****
*Brent%*Δ	3	**-4.60*****		3	**-4.55*****		3	**-4.32*****	6		6	**-3.81*****
Critical (****)%1*		-399	8.43		3.46	6.52		-2.57		3.46		-2.57
Values (***)%5*		-3.43	6.34		2.87	4.63		-1.94		2.87		-1.94
(**)%10*		-3.14	5.39		2.57	3.81		-1.62		2.57		-1.62

Models A, B and C of the tests include a constant and a linear trend, a constant, and none, respectively. **p** and **k** are lag lengths selected using SIC for the ADF tests and bandwidth length selected using Barlett kernel for the P-P tests.

Next, we start with a hybrid New Keynesian type of Phillips Curve, and add control variables to the model to identify the significant ones that affect inflation.

$$Inf_t = c + \alpha_1 Inf_{t-1} + \alpha_2 E_t Inf_{t+1} + \alpha_3 GAP_t + \alpha_4 z_{1t} + \alpha_5 z_{2t} + u_t.$$

Where Inf_t is inflation rate at time t, $E_t Inf_{t+1}$ is conditional expectation of inflation in period $t+1$ as of time t, and z_{1t} and z_{2t} are control variables. Under rational expectations $E_t Inf_{t+1} = Inf_{t+1}$, results in Table 2 reveal that *FoodInf* and *USD%*Δ are significant in all cases whereas *GAP Brent%*Δ is not. The results indicate that food inflation and percentage change in US Dollar which proxies the increase in the cost of imports have significant effects on the level of inflation and can potentially affect the volatility of inflation.

Results in Table 2 are very informative regarding the variables that affect inflation but the effects of changes in control variables on inflation may all not be realized contemporaneously. Full impact of changes in regressors on inflation might take quite a long period. Hence, we employ ARDL bounds testing approach to investigate the long run level relationship between inflation and the other variables, and investigate the short and long run dynamics. Table 3 provides the ARDL bounds testing results for the existence of long run level relationship between inflation and the relevant variables.

Table 2: Hybrid New Keynesian Type of Phillips Curve

Dep. Var. *Inf*	**Model1**	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**	**Model7**	**Model8**
C	-0.053 (0.670)	-0.017 (0.897)	-0.061 (0.648)	0.077 (0.574)	-0.023 (0.869)	0.032 (0.823)	-0.017 (0.886)	0.011 (0.937)
Inf(-1)	**0.452** (0.000)	**0.529** (0.000)	**0.499** (0.000)	**0.455** (0.000)	**0.519** (0.000)	**0.503** (0.000)	**0.472** (0.000)	**0.471** (0.000)
Inf(+1)	**0.487** (0.000)	**0.465** (0.000)	**0.503** (0.000)	**0.482** (0.000)	**0.465** (0.000)	**0.498** (0.000)	**0.448** (0.000)	**0.450** (0.000)
GAP	-0.01 (0.469)	0.001 (0.953)	-0.009 (0.052)				-0.0003 (0.986)	
*IPI%*Δ				**-0.025** (0.031)	0.001 (0.913)	-0.002 (0.071)		-0.006 (0.621)
FoodInf	**0.006** (0.000)			**0.066** (0.000)			**0.064** (0.000)	**0.065** (0.000)
*USD%*Δ		**0.017** (0.0013)			**0.017** (0.004)		**0.017** (0.0005)	**0.016** (0.005)

Brent%Δ	0.001 (0.7398)	0.002 (0.397)

The p-values are shown in the parentheses.

Table 3: ARDL Bounds Testing

Dep. Var. Inf	**Dynamic Regressors** **(# = k)**	**VAR Lag Length (AIC)**	**F -Bounds Test** **(Rest. Cons.)**	**Asy. Critical Values**
ARDL-M1	*GAP, FoodInf*	12	2.94	**%1*** ** 4.13-5.00
ARDL-M2	*GAP, USD%Δ*	12	**4.19** **	**%5** ** 3.10-3.87 k=2 **%10*** 2.63-3.35
ARDL-M3	*GAP, Brent %Δ*	12	2.01	
ARDL-M4	*IPI%Δ , FoodInf*	11	2.41	
ARDL-M5	*IPI%Δ , USD%Δ*	4	**5.13*** **	**%1*** ** 3.65-4.66
ARDL-M6	*IPI%Δ , Brent%Δ*	4	0.84	**%5** ** 2.79-3.67 k=3**%10*** 2..37-3.2
ARDL-M7	*GAP, FoodInf, USD%Δ*	12	**3.82** **	
ARDL-M8	*IPI%Δ, FoodInf, USD%Δ*	3	2.73	
ARDL-M9	*FoodInf*	12	**4.003***	**%1*** ** 4.94-5.58
ARDL-M10	*USD%Δ*	7	**5.53** **	**%5** ** 3.62-4.16 k=1**%10*** 3.02-3.51
ARDL-M11	*FoodInf, USD%Δ*	11	**4.58** **	

VAR lag lengths are selected using AIC.

The results in Table 3 show that FoodInf and/or *USD%Δ* are among the dynamic regressors when the bounds tests support the existence of a long-term level relationship. On the other hand, where F-Bounds test values are even below the 10% lower limit values, both *FoodInf* and *USD%Δ* are not among the dynamic regressors. Estimated long-run relationship and the error corrections forms for the cases where F-Bounds tests reject the null of no long-run relationship are presented in Tables A1 through A6 in the Appendix.

Results in Tables A1-A6 indicates that initial contemporaneous short run impacts of increase in *USD%Δ* and *FoodInf* are always positive significant and larger in magnitude than lagged impacts. We do observe some negative and significant lagged terms in general though. For the change in lagged inflation terms, the first lag is always positive, significant and larger in magnitude than other lagged terms. After the first lag, however, some negative and significant coefficients on lagged changes of inflation are present. The error correction coefficients are all negative, significant and fairly small in magnitude, indicating a very slow return to the long-run level relationship when a shock disturbs the long-run equilibrium. In particular, the error correction term magnitudes vary between -0.0276 and -0.434, corresponding a half-life of 16 and 25 months.

Having established the potential link between inflation, food inflation and the percentage change of the exchange rate of US dollar against Turkish Lira, we turn our attention to the volatility of inflation and the volatilities of other variables included in the analysis, namely GAP, IPI%Δ, FoodInf, USD%Δ and Brent%Δ. To test the existence of volatility and to obtain the appropriate GARCH series for each variable once volatility is found to exist, we follow the steps below:

1. Estimate a SARMA (seasonal autoregressive moving average) model using AIC for model selection for each series. Since we have decided that all the series employed are stationary, we estimate SARMA rather that SARIMA (seasonal autoregressive integrated moving average) models.
2. Apply the ARCH-LM test to the residuals of the appropriate SARMA model we select for each series to check whether it has an ARCH effect.
3. Fit the appropriate GARCH model to the residuals of SARMA model based on AIC.
4. Apply the ARCH-LM test to the residuals of GARCH model built to make sure that ARCH effect is removed.
5. Obtain (estimate) GARCH series for each variable, using the proper GARCH model chosen in step 3.

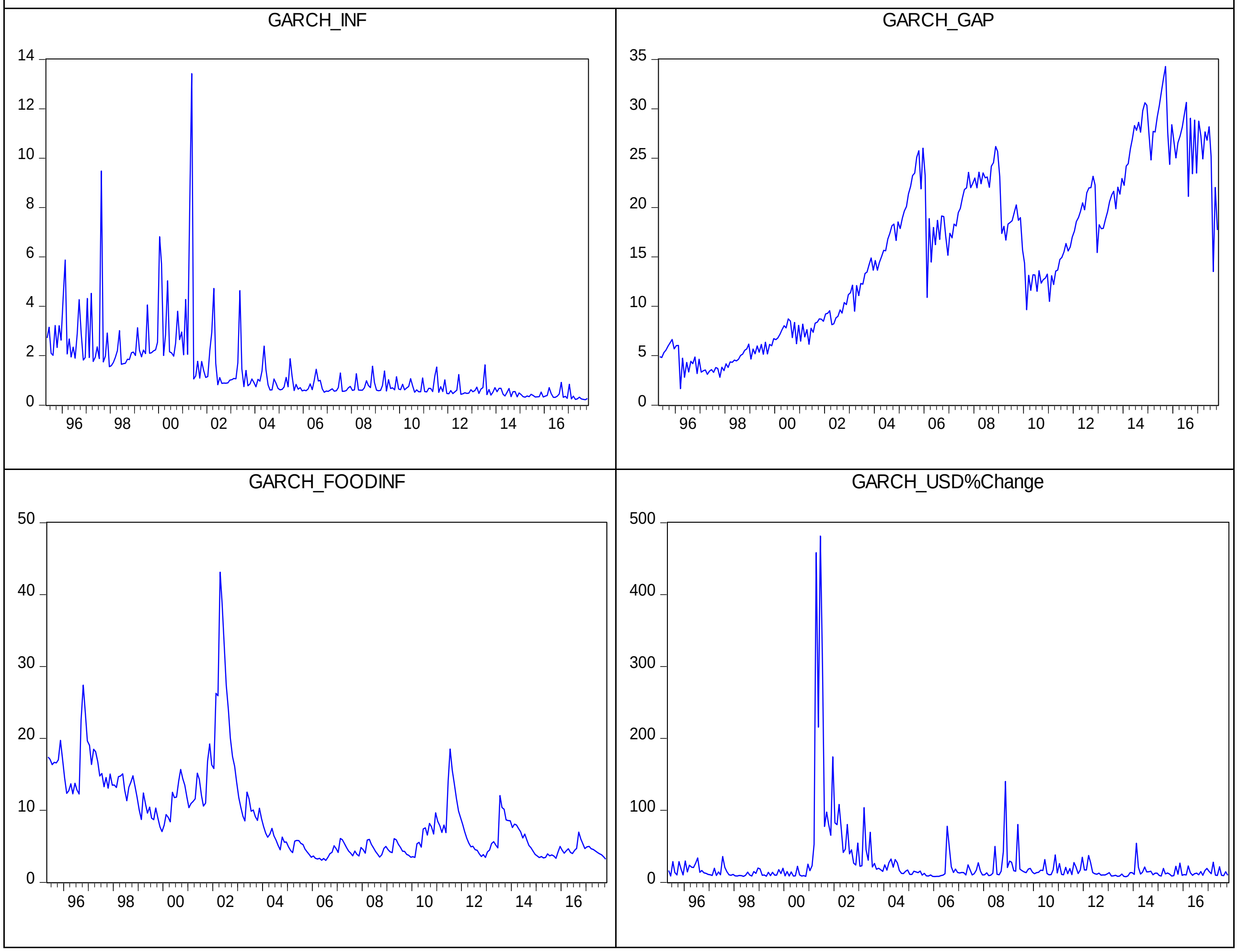
The suitable SARMA and GARCH models chosen for each series are given in Table 4. According to Table 4, volatility is present in all series except the growth of industrial production index (*IPI%Δ)* for which the LM test cannot reject the null of no ARCH effect. Figure 1 below presents the GARCH series obtained from the models in Table 4.

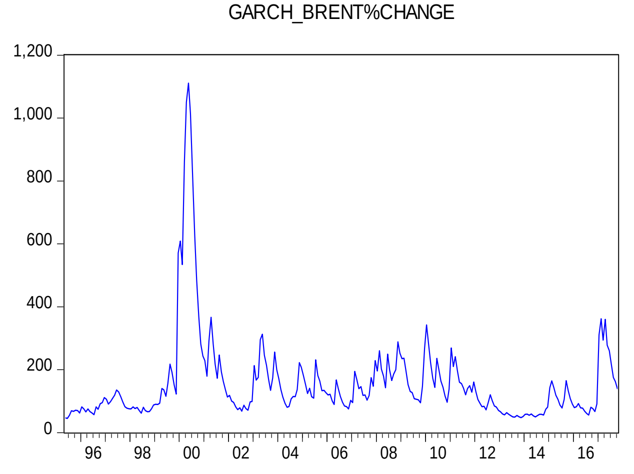
Table 4: SARMA and GARCH Models

Series	SARMA Model	GARCH Model
Inf	**(3,1,12,12)**	**(2,1)**
GAP	**(4, 4, 12, 6)**	**(1, 2)**
IPI%Δ	**(4, 2, 12, 12)**	**No ARCH Effect**

FoodInf	**(4, 4, 12, 12)**	**(1, 1)**
USD%Δ	**(2, 4, 12, 12)**	**(2, 1)**
Brent%Δ	**(4, 3, 6, 12)**	**(1,1)**
In SARMA (p, q, l, k) p, q, l, k are AR, MA, SAR and SMA terms and in GARCH(p, h) p and h are ARCH and GARCH terms in order.		

Figure 1: Estimated GARCH Series





3.1. Transmission Mechanism

To investigate the transmission of shocks to inflation and other variables, we consider a simple two-variable vector autoregression (VAR) model for each variable and inflation, and derive impulse response functions (IRFs), accumulated impulse responses and variance decomposition for inflation.

$$\mathrm{z}_{\mathrm{t}} = c_1 + \sum_{i=1}^{p} \alpha_i^{zz} \mathrm{z}_{\text{t-i}} + \sum_{i=1}^{p} \beta_i^{\pi z} \pi_{\text{t-i}} + \varepsilon_t^z$$

$$\pi_{\mathrm{t}} = c_2 + \sum_{i=1}^{p} \alpha_i^{z\pi} \mathrm{z}_{\text{t-i}} + \sum_{i=1}^{p} \beta_i^{\pi\pi} \pi_{\text{t-i}} + \varepsilon_t^{\pi}$$

Where π is inflation and z is the other variable included in bi-variate VAR model.

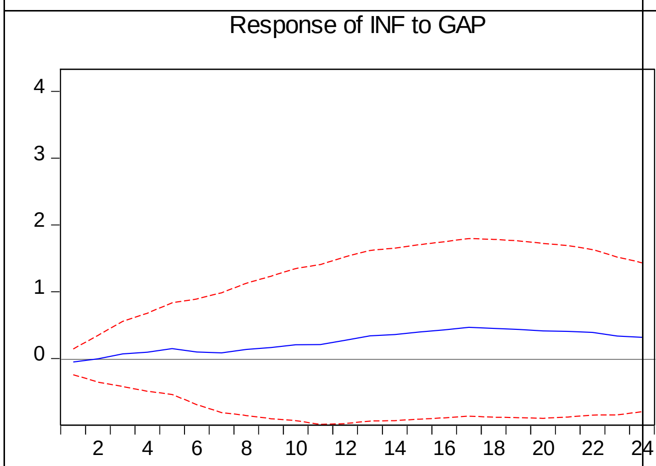
Figure 2 and 3 below presents the results from the bi-variate VAR model. Figure 2 reveals that *GAP*, growth of industrial production (*IPI%*Δ) and the percentage change in the price of Brent oil (*Brent%*Δ) appear to have no significant effect on the level and the variance of inflation. According to Figure 3, on the other hand, shocks to the exchange rate of the US dollar against Turkish Lira (*USD%*Δ) and the food inflation (*FoodInf*) have significant and lasting effects on both the level and variance of inflation. In particular, one standard deviation shock to *USD%*Δ continues to push inflation up significantly for about 18 months. The magnitude of the impact reaches 2.7 points in period 8, and the accumulated impact reaches 43 points within two years while the variance of inflation due to a shock to the exchange rate of the US dollar reaches 75 percent after 2 years.

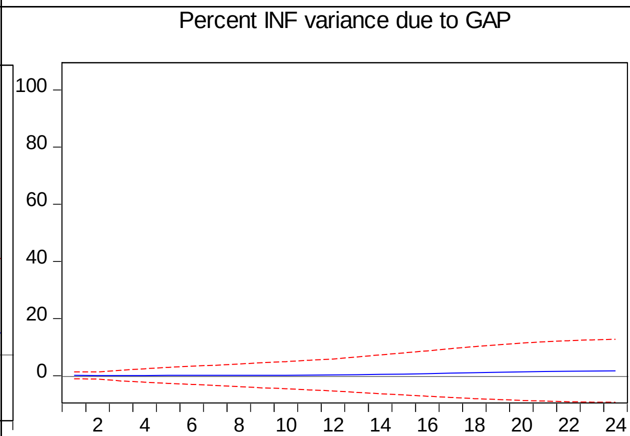
A similar pattern is valid for the impact of the food inflation too, though the magnitudes are smaller to a certain degree. One standard deviation shock to *FoodInf* continues to push inflation up significantly about 13 months, exceeding a year, and the impact on inflation reaches

1.9 points in the 10th period. The accumulated impact of the shock, on the other hand, stretches to 26 points in the 19th month. Further, the variance of inflation due to food inflation initially accounts for almost 56 percent, decreases to 32-33 percent in periods 9 and 10, but remains over 37 percent even after two years. Results from a three equation VAR model with ordering of variables *USD%∆, FoodInf* and *Inf,* indicates that *FoodInf* continues to have significant and lasting effects on the level and variance of inflation, though the effects decrease to a degree.

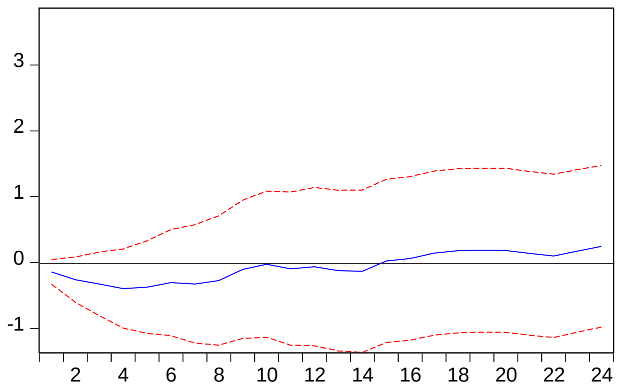
Figure 2: Impact of GAP, IPI%∆ and Brent%∆ on Level and Variance of Inflation

Impulse Response Functions	**Variance Decomposition**

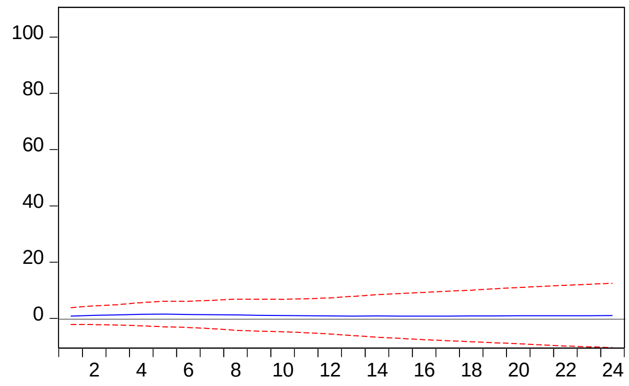




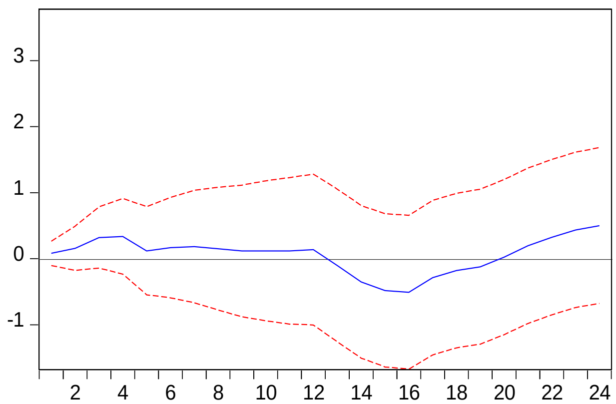
Response of INF to INDUSTRY%CHANGE



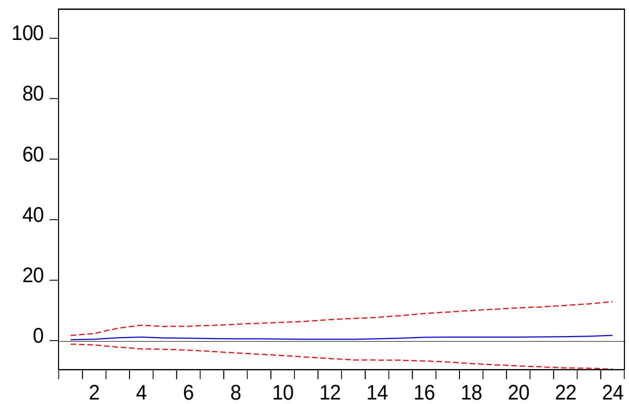
Percent INF variance due to INDUSTRY%CHANGE



Response of INF to BRENT%CHANGE



Percent INF variance due to BRENT%CHANGE

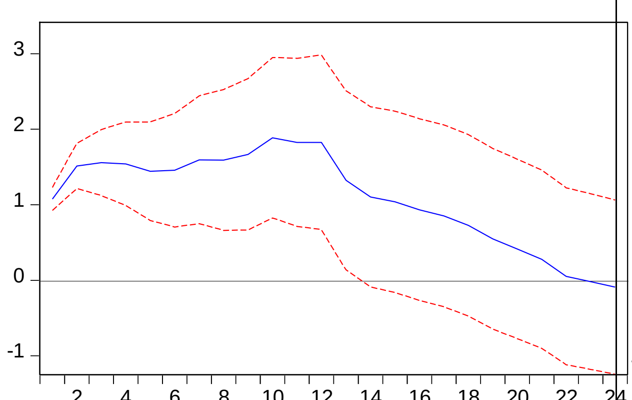


VAR lag lengths are 15 for GAP model and 14 for others, and based on AIC.

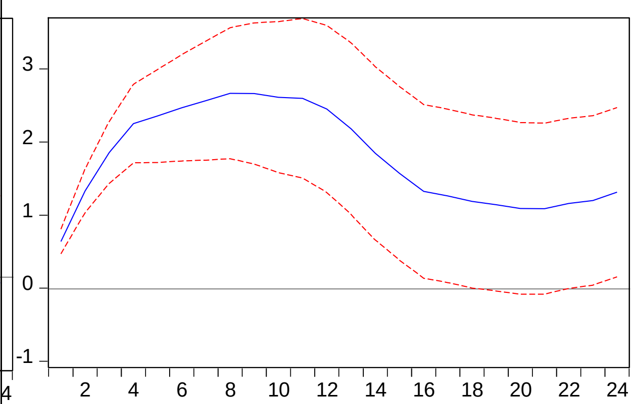
Figure 3: Impact of FoodInf and USD%Δ on Level and Variance of Inflation

Impulse Response Function

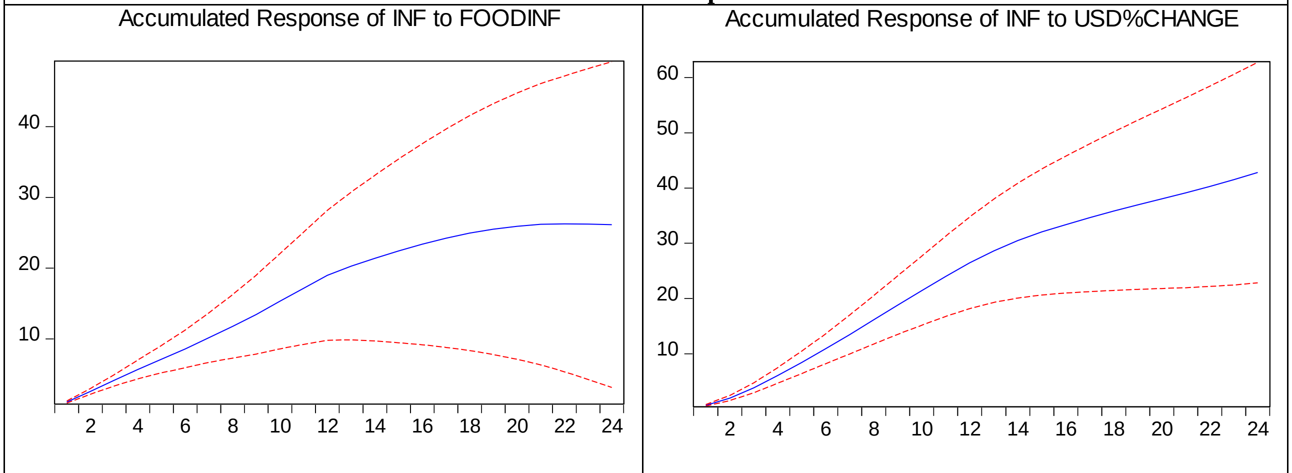
Response of INF to FOODINF



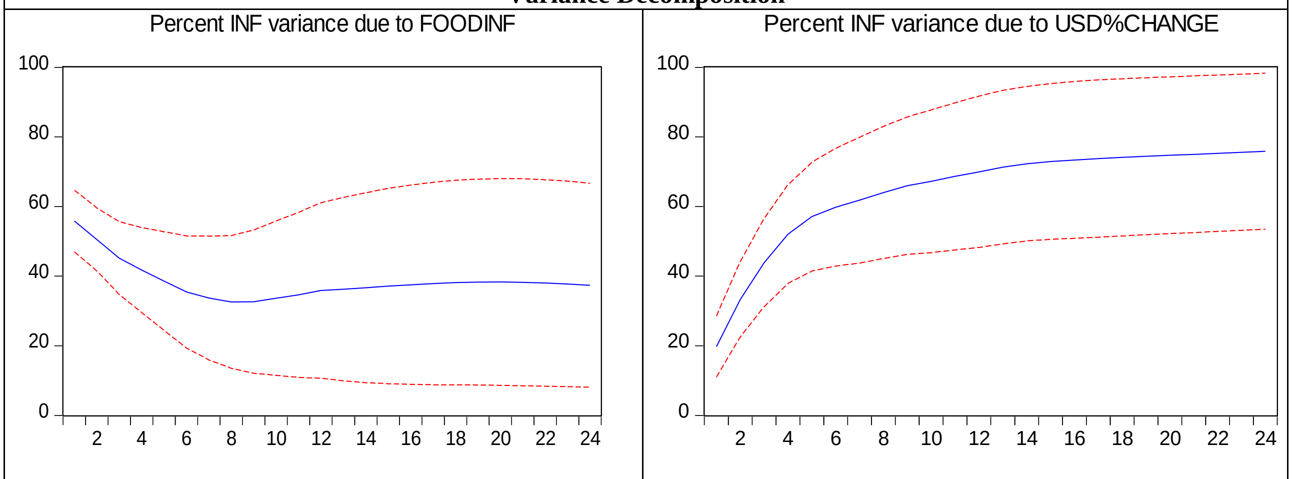
Response of INF to USD%CHANGE



Accumulated Responses



Variance Decomposition



VAR lag lengths are 14 for both food inflation (FoodInf)and USD% Change(USD%Δ)models and based on AIC.

3.2. Artificial Neural Network Results

The VAR analysis above identifies also identifies the exchange rate and the food inflation as variables significantly affecting the level and volatility of inflation in Turkey. We complete the analysis by presenting the results of Artificial Neural Network (ANN) algorithms applied to estimate inflation and the volatility of inflation (*GARCH_INF*) obtained above. Here we only present the results from the ANN models that only include FoodInf, *USD%*Δ and their first and second lags in the input layer (6 covariates) in estimating the inflation.

Similarly, we fit an ANN model to the *GARCH_INF* series estimated from the GARCH model above and use the volatilities of *USD%*Δ(GARCH_USD%Δ) and the food inflation(*GARCH_FoodInf*) and their first and second lags in the input layer(6 covariates again). For both models we have one hidden layer with 4 nodes and 1 output layer with one node. Figure 4 illustrates the structure of ANN models estimated.

Figure 4: ANN Structure of models for Inflation and Volatility of Inflation

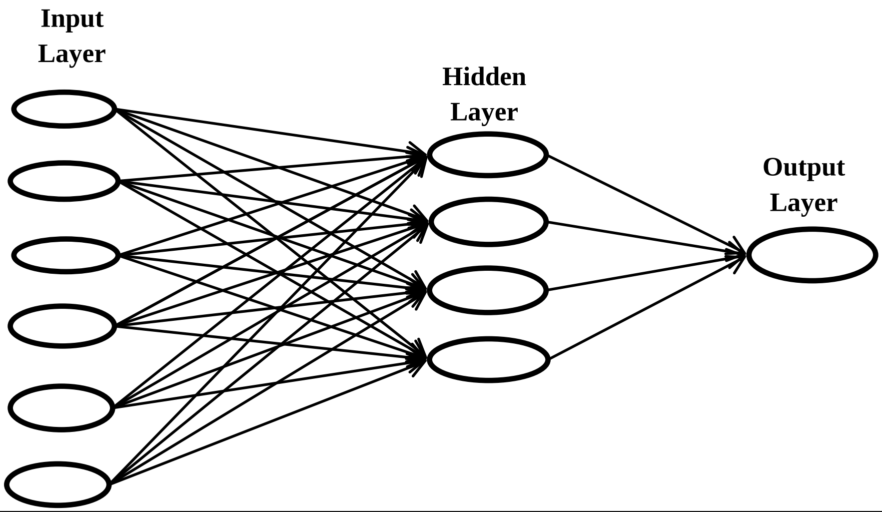
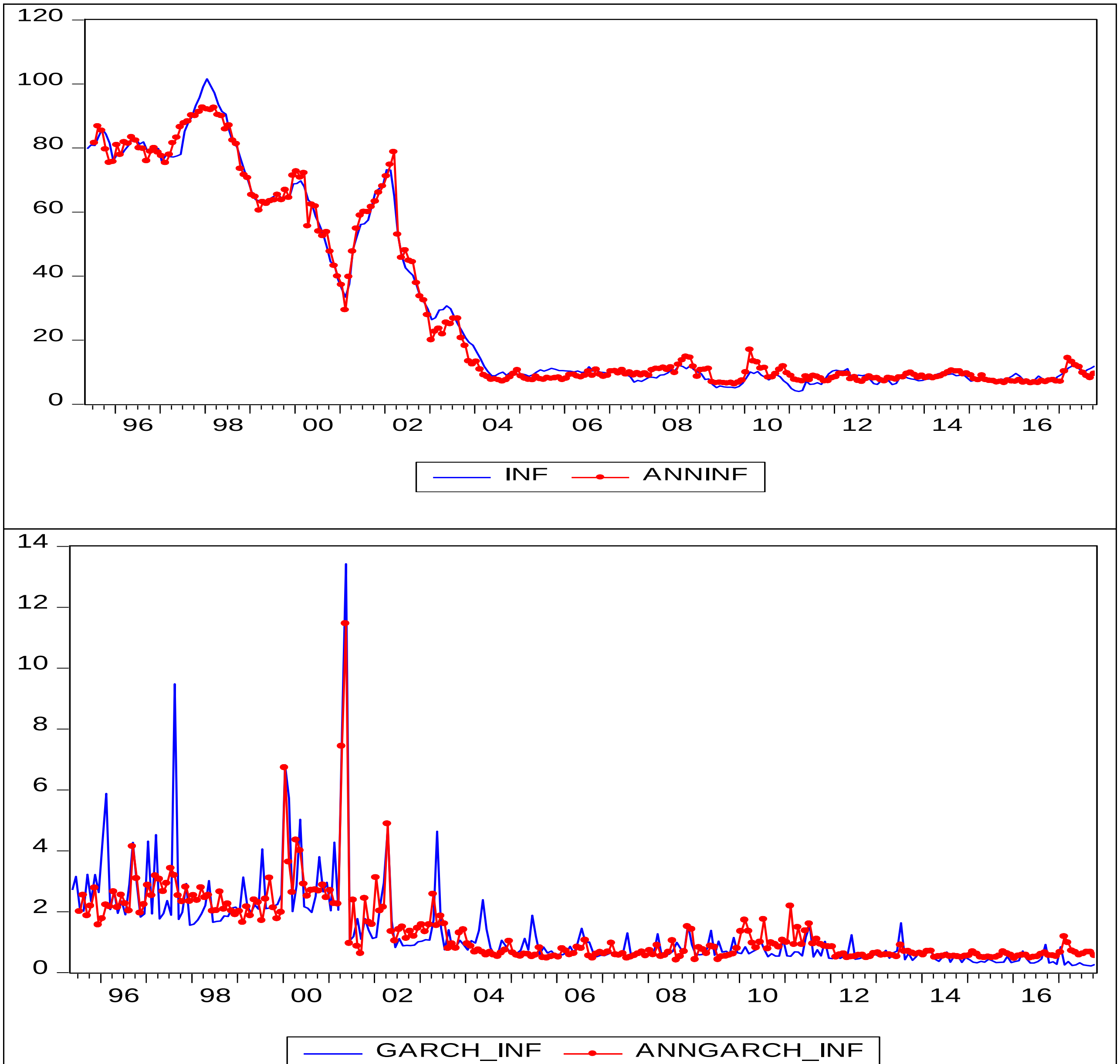


Table 5: Results of ANN Inflation and ANN Inflation Volatility Models					
Dependent Variable: *Inf*			**Dependent Variable:** *GARCH_Inf*		
Variables	**Relative Importance**	**Normalized Importance**	**Variables**	**Relative Importance**	**Normalized Importance**
FoodInf	0.36	100.0%	*GARCH_FoodInf*	0.31	100.0%
FoodInf(-1)	0.25	67.9%	*GARCH_FoodInf(-1)*	0.12	37.8%
FoodInf(-2)	0.06	15.2%	*GARCH_FoodInf(-2)*	0.05	16.8%
USD%Δ	0.15	41.0%	*GARCH_USD%Δ*	0.18	58.3%
USD%Δ(-1)	0.12	34.5%	*GARCH_USD%Δ(-1)*	0.28	91.6%
USD%Δ(-2	0.07	18.1%	*GARCH_USD%Δ(-2*	0.07	23.0%
∑*FoodInf*=**0.66;** ∑ *USD%Δ*=**0.34**			∑*GARCH_FoodInf*=**0.47;** ∑ *GARCH_USD%Δ*=**0.53**		

Full perceptron for both ANN models, including parameter estimates (weights) are not given here for the sake of conserving space. The relative importance of variables for each model, however, are presented in Table 5. Figure 5 illustrates that ANN models provide a fairly good fit for *GARCH_INF* model measured by a correlation coefficient of over 85% and a much better fit for *Inf* model with a correlation coefficient of over 99%.

Figure 5: Fits of ANN Inflation and Inflation Volatility Models



Correlation(Inf, ANNInf)= 0.996025; Correlation(GARCH_Inf, ANNGARCH_Inf)= 0.856892

Estimating additional models with other variables and their lags, we find only *Brent%*Δ and its lags have some importance in explaining inflation (slightly over 10%, including lags). We also find the volatility of percentage change in the price of Brent oil (GARCH_ *Brent%*Δ) and its lags have somewhat larger importance in explaining the volatility of inflation (over 20 percent, including lags). However, *FoodInf* and *USD%*Δ and their lags maintain their relative importance in explaining inflation and similarly their volatilities continue to maintain their importance in explaining the volatility of inflation. Further, none of the other ANN models estimated perform as high as the models given in Table 5 and Figure 5, as measured by the correlation coefficients of "actual" and "fitted" values.

4. Conclusion

In this paper, we attempted to investigate the role of food-inflation on the level and volatility of inflation in Turkey. Whether a shock to food prices propagate into headline inflation is important for policy purposes. If the shocks to food prices do not transmit into headline inflation, monetary policy responses to shocks are unlikely to be efficient. Although food price shocks tend to be greater and more volatile, if these shocks dissipate fast they will not have significant effect on inflation. Therefore, it is important for policy purposes as to whether the shocks to food inflation are transmitted into general inflation. The evidence from the results obtained in this paper so far tend to suggest so. Even though food inflation data series appears to be stationary, its first order autoregressive coefficient is near unity, and a simple autocorrelation analysis indicate that shocks to food inflation are very persistent and remain significant for over five years and the magnitude is over 0.5 for almost three years. A hybrid type new Keynesian Phillips Curve, ARDL bounds tests, VAR and ANN analyses all indicate that food-inflation and the change in exchange rate of US dollar against TL. have significant impact on the level and the volatility of inflation in Turkey. Hence, a policy focus on core inflation should account food inflation.

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APPENDIX

Table A1: ARDL-M2				
Estimated Long-Run Relationship Coefficients, ARDL (2, 0, 6)				
Regressor	**Coefficient**	**Std. Error**	**t –Statistic**	**P – Value**
Constant	1.317	4.500	0.293	0.770
GAP	0.127	0.538	0.236	0.814
USD%Δ	**0.867**	0.100	8.670	0.000
Error Correction Representation of ARDL (2, 0, 6)				
Regressor	**Coefficient**	**Std. Error**	**t –Statistic**	**P - Value**
DInf(-1)	**0.425**	0.053	8.019	0.000
DUDS%Δ	**0.101**	0.014	7.214	0.000
DUDS%Δ(-1)	**0.031**	0.016	1.938	0.050
DUDS%Δ(-2)	0.011	0.016	0.688	0.498
DUDS%Δ(-3)	**0.019**	0.013	1.462	0.134
DUDS%Δ(-4)	**-0.037**	0.013	-2.846	0.004
DUDS%Δ(-5)	0.004	0.012	0.333	0.764
ecm(-1)	**-0.028**	0.006	-4.667	0.000
ARDL lag lengths are selected using AIC				

Table A2: ARDL-M5				
Estimated Long-Run Relationship Coefficients, ARDL (2, 0, 6)				
Regressor	**Coefficient**	**Std. Error**	**t –Statistic**	**P - Value**
Constant	**1.147**	**4.714**	-0.243	0.808
IPI%Δ	0.468	0.38	1.227	0.22
USD%Δ	**0.890**	0.094	9.4	0.00
Error Correction Representation of ARDL (2, 0, 6)				
Regressor	**Coefficient**	**Std. Error**	**t –Statistic**	**P - Value**
DInf(-1)	**0.419**	0.053	7.840	0.000
DUDS%Δ	**0.102**	0.014	7.421	0.000
DUDS%Δ(-1)	**0.031**	0.016	1.953	0.052
DUDS%Δ(-2)	0.011	0.015	0.741	0.459
DUDS%Δ(-3)	0.020	0.013	1.567	0.118
DUDS%Δ(-4)	**-0.035**	0.013	-2.772	0.006
DUDS%Δ(-5)	0.003	0.012	0.236	0.813
ecm(-1)	**-0.030**	0.007	-4.480	0.000
ARDL lag lengths are selected using AIC				

Table A3: ARDL-M7

Regressor	Coefficient	Std. Error	t –Statistic	P - Value
Estimated Long-Run Relationship Coefficients, ARDL (10, 0, 11, 5)				
Constant	0.043	0.215	0.199	0.842
FOODINF	**0.741**	0.112	6.586	0.000
USD%Δ	**0.244**	0.096	2.530	0.012
Error Correction Representation of ARDL (10, 0, 11, 5)				
Regressor	**Coefficient**	**Std. Error**	**t –Statistic**	**P - Value**
DInf(-1)	**0.254**	0.061	5.695	0.000
DInf(-2)	**0.197**	0.064	2.374	0.018
DInf(-3)	-0.029	0.043	0.116	0.908
DInf(-4)	0.080	0.043	0.812	0.418
DInf(-5)	**0.120**	0.043	2.459	0.015
DInf(-6)	**-0.188**	0.043	-2.651	0.009
DInf(-7)	-0.043	0.043	-2.625	0.009
DInf(-8)	0.064	0.042	0.546	0.586
DInf(-9)	**-0.137**	0.030	-1.519	0.130
DFoodInf	**0.316**	0.028	-2.303	0.022
DFoodInf(-1)	**-0.046**	0.027	-1.927	0.055
DFoodInf(-2)	**-0.076**	0.018	19.282	0.000
DFoodInf(-3)	0.029	0.027	-3.194	0.002
DFoodInf(-4)	-0.009	0.028	-4.017	0.000
DFoodInf(-5)	**-0.045**	0.010	-4.346	0.000
DFoodInf(-6)	0.036	0.061	5.695	0.000
DFoodInf(-7)	-0.019	0.064	2.374	0.018
DFoodInf(-8)	0.007	0.043	0.116	0.908
DFoodInf(-9)	**0.062**	0.043	0.812	0.418
DFoodInf(-10)	**-0.047**	0.043	2.459	0.015
DUSD%Δ	**0.061**	0.043	-2.651	0.009
DUSD%Δ(-1)	0.038	0.043	-2.625	0.009
DUSD%Δ(-2)	-0.011	0.042	0.546	0.586
DUSD%Δ(-3)	-0.003	0.030	-1.519	0.130
DUSD%Δ(-4)	**-0.033**	0.028	-2.303	0.022
ecm(-1)	**-0.043**	0.027	-1.927	0.055
ARDL lag lengths are selected using AIC				

Table A4: ARDL-M9

Estimated Long-Run Relationship Coefficients, ARDL (12, 3)

Regressor	Coefficient	Std. Error	t –Statistic	P – Value
Constant	-2.042	2.288	-0.892	0.373
FOODINF	**0.968**	0.057	1.672	**0.000**
Error Correction Representation of ARDL (12, 3)				
Regressor	**Coefficient**	**Std. Error**	**t –Statistic**	**P – Value**
DInf(-1)	**0.345**	0.061	5.695	0.000
DInf(-2)	**0.151**	0.064	2.374	0.018
DInf(-3)	0.005	0.043	0.116	0.908
DInf(-4)	0.035	0.043	0.812	0.418
DInf(-5)	**0.105**	0.043	2.459	0.015
DInf(-6)	**-0.114**	0.043	-2.651	0.009
DInf(-7)	**-0.113**	0.043	-2.625	0.009
DInf(-8)	0.023	0.042	0.546	0.586
DInf(-9)	-0.045	0.030	-1.519	0.130
DInf(-10)	**-0.065**	0.028	-2.303	0.022
DInf(-11)	**-0.051**	0.027	-1.927	0.055
DFoodInf	**0.356**	0.018	19.282	0.000
DFoodInf(-1)	**-0.087**	0.027	-3.194	0.002
DFoodInf(-2)	**-0.110**	0.028	-4.017	0.000
ecm(-1)	**-0.042**	0.010	-4.346	0.000
ARDL lag lengths are selected using AIC				

Table A5: ARDL-M10

Estimated Long-Run Relationship Coefficients, ARDL (3, 6)				
Regressor	**Coefficient**	**Std. Error**	**t –Statistic**	**P – Value**
Constant	**1.789**	4.474	0.400	0.689
USD%∆	**0.863**	0.100	8.612	0.000
Error Correction Representation of ARDL (3, 6)				
Regressor	**Coefficient**	**Std. Error**	**t –Statistic**	**P – Value**
DInf(-1)	**0.386**	0.060	6.487	0.000
DInf(-2)	0.089	0.059	1.504	0.134
DUDS%∆	**0.102**	0.014	7.390	0.000
DUDS%∆(-1)	**0.037**	0.016	2.275	0.024
DUDS%∆(-2)	0.006	0.016	0.385	0.700
DUDS%∆(-3)	0.013	0.014	0.977	0.330
DUDS%∆(-4)	**-0.039**	0.013	-3.003	0.003
DUDS%∆(-5)	-0.001	0.012	-0.047	0.963
ecm(-1)	**-0.028**	0.006	-4.307	0.000
ARDL lag lengths are selected using AIC				

Table A6: ARDL-M11

Regressor	Coefficient	Std. Error	t –Statistic	P-Value
Estimated Long-Run Relationship Coefficients, ARDL (10, 11, 5)				
Constant	-1.181	1.892	-0.624	0.533
FOODINF	**0.743**	0.112	6.620	0.000
USD%Δ	**0.241**	0.096	2.518	0.013
Error Correction Representation of ARDL (10, 11, 5)				
Regressor	**Coefficient**	**Std. Error**	**t –Statistic**	**P – Value**
DInf(-1)	**0.253**	0.059	4.312	0.000
DInf(-2)	**0.197**	0.061	3.250	0.001
DInf(-3)	-0.028	0.058	-0.491	0.624
DInf(-4)	0.080	0.056	1.428	0.155
DInf(-5)	**0.120**	0.053	2.288	0.023
DInf(-6)	**-0.189**	0.053	-3.568	0.000
DInf(-7)	-0.043	0.054	-0.801	0.424
DInf(-8)	0.064	0.039	1.639	0.103
DInf(-9)	**-0.137**	0.036	-3.774	0.000
DFoodInf	**0.316**	0.016	19.636	0.000
DFoodInf(-1)	**-0.046**	0.025	-1.840	0.067
DFoodInf(-2)	**-0.076**	0.025	-3.028	0.003
DFoodInf(-3)	0.029	0.024	1.208	0.228
DFoodInf(-4)	-0.009	0.024	-0.388	0.698
DFoodInf(-5)	**-0.045**	0.023	-1.940	0.054
DFoodInf(-6)	0.036	0.023	1.547	0.123
DFoodInf(-7)	-0.019	0.023	-0.810	0.419
DFoodInf(-8)	0.007	0.022	0.338	0.735
DFoodInf(-9)	**0.062**	0.022	2.846	0.005
DFoodInf(-10)	**-0.047**	0.014	-3.342	0.001
DUSD%Δ	**0.061**	0.009	6.876	0.000
DUSD%Δ(-1)	**0.038**	0.010	3.686	0.000
DUSD%Δ(-2)	-0.011	0.011	-1.009	0.314
DUSD%Δ(-3)	-0.003	0.011	-0.317	0.751
DUSD%Δ(-4)	**-0.033**	0.010	-3.185	0.002
ecm(-1)	**-0.043**	0.010	-4.183	0.000

ARDL lag lengths are selected using AIC