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Beef Price Volatility in Turkey: Can Import Policy Affect the Price and Its Uncertainty?

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Abstract

This study aims to examine the monthly volatility of consumer and producer beef prices for Turkey, using both univariate and multivariate models and investigate whether beef imports can stabilize the volatility and high inflation level in beef market. To do so, first we decide on the best volatility model for both consumer and producer beef inflation using a variety of different univariate symmetric and asymmetric GARCH models. Second, we check if the quantity of imported beef is significant in our best volatility model for consumer and producer beef prices. Lastly we compare our univariate analysis with a multivariate DCC-GARCH model. Our results reveal that while univariate GARCH models do not successfully capture the effect of import policy on the producer and consumer beef inflation, multivariate model is superior in illustrating the effect of import policy on beef inflation.

Keywords: beef prices; price volatility; univariate GARCH models; beef import policy; DCC-GARCH model

JEL Code: C32, C58, E31, Q13

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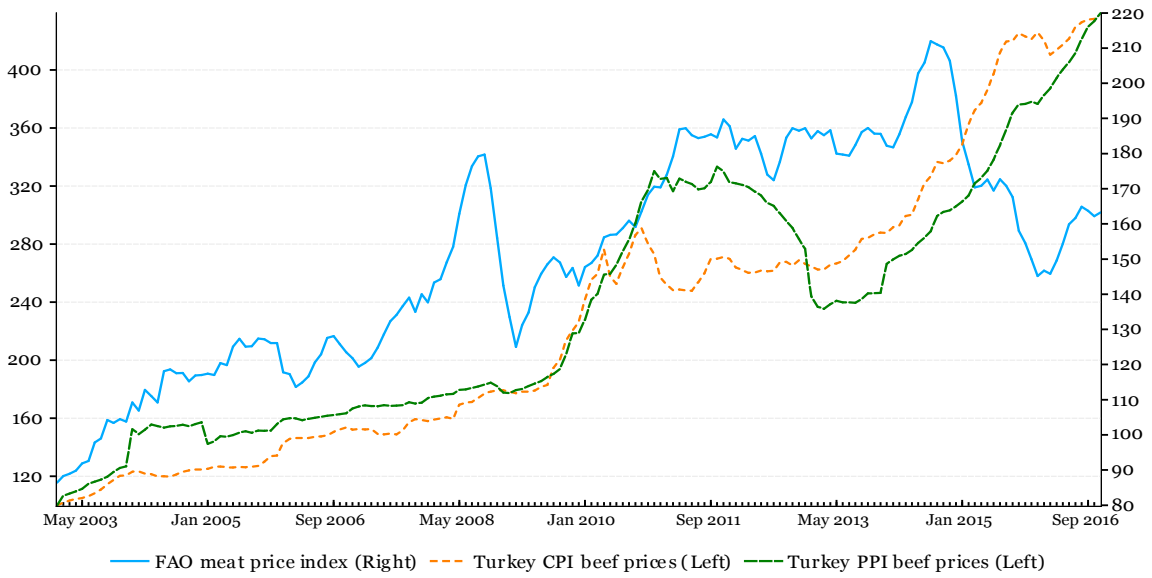
1 Introduction

A significant surge and volatility in food prices remain one of the important issues for policy makers who are concerned about price stability and development, as increasing price and especially price volatility affects the ability of market participants to forecast prices which could have distortionary effects on their welfare, notably in the absence of hedging mechanism.[1] The volatility in food prices can be also detrimental to macroeconomic stability and to the productivity of food producers. As can be seen from Figure 1 over the past decade, international food prices have risen at an ever-increasing pace and generally follow a fluctuating course, with two periods of significant food price spikes:2007-2008 and 2010-2011. These unprecedented price developments have serious welfare implications for low-income families, especially those whose food expenditures are a significant part of their income.

Figure 1: World meat price and Turkish beef prices



FAO Meat Price Index: Computed from average prices of four types of meat, weighted by world average export trade shares for 2002-2004. Commodities include two poultry products, three bovine meat products, three pig meat products, and one ovine meat product. There are 27 price quotations in total used in the calculation of the index. Where more than one quotation exists for a given meat type, a simple average is used.
Source: FAO.ORG and TURKSTAT.

Impact of high agricultural commodity price and price volatility on general price stability in

[1] See Hayenga and DiPietre (1982).

Turkey has been an important concern for the policymakers especially after the country adopted inflation targeting as monetary policy. Livestock breeding in Turkey is known to be around a quarter of agricultural output and beef price surge within the last decade is quite significant and between January 2005 - December 2013 period, retail beef prices rose by 130 percent in Turkey and during the same period CPI food index increased by 118 percent. [2] Although there was a significant price surge in Turkey, Figure 1 shows that Turkish red meat market is not affected from the first global food crisis of 2007-2008.[3] The trend of beef prices in Turkey dissociated from the world prices after August 2014 and although the world prices start to decline, this decline was not transmitted to Turkish beef prices.[4]

The reasons for the volatility and rapid jumps in international food prices have been discussed extensively among policy makers and academics. The literature on agricultural prices suggests a number of factors for volatility and sudden jumps in agricultural prices, e.g. changes in stocks, supply and demand shocks in emerging markets, financial speculation and monetary policy in developed countries. In addition to these, academics and policy makers note that trade policy may also be a part of the problem.[5]

Trade policy is one of the most commonly used stabilization policy by the governments in response to food price volatility or spikes. As a response to international and country price surges some governments intervened to stabilize their domestic prices via imposing/loosening export or import restrictions. Demeke et al. (2009) state that 68 out of 81 countries use trade policy as a stabilization tool against global 2007-2008 food price spike. Anderson and Nelgen (2012) use a panel of 75 countries to show that trade policy is one of the most commonly used policy measure for price stabilization, not only in crisis periods but equally in all the other periods. Gouel (2013) claim that trade policies are fairly countercyclical, i.e. tariffs increase when world prices are low and decrease when they are high. Accordingly, exporting countries tend to restrict exports during price spikes and promote them during price downturns. However, there are mixed findings about the impact of trade policies both for world food prices and domestic food prices of the policy implementing country. Giordani et al. (2016) study the relationship between trade policy and food prices and conclude that trade measures are set in response to increased trade policy implementation by other governments, particularly for important products such as staple foods. They also add that these

[2] See Akbay and Boz (2005) and Özertan et al. (2015).

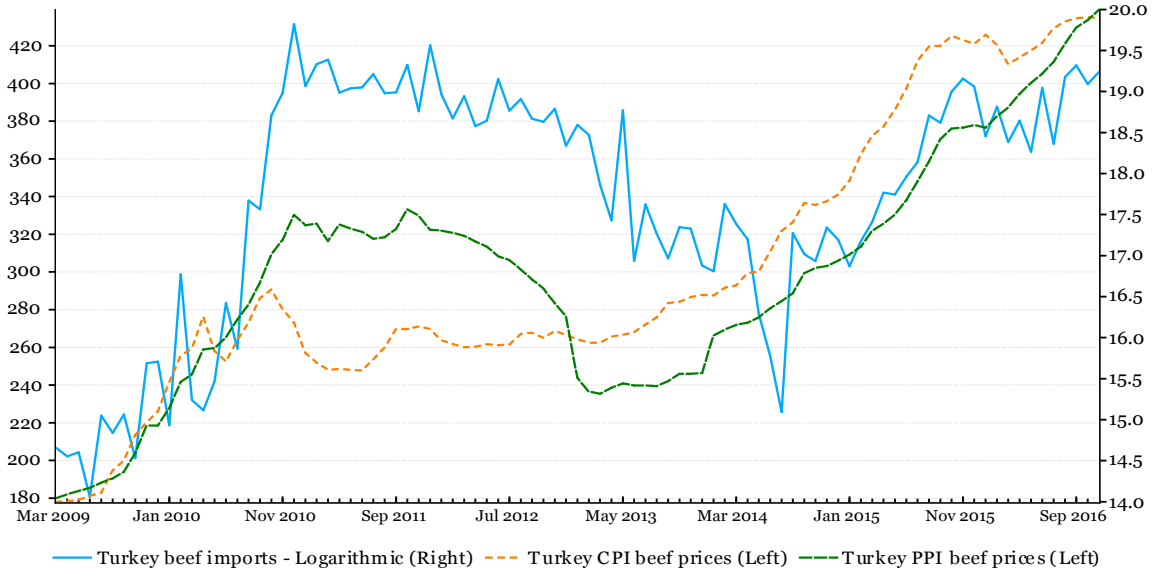
[3] Özertan et al. (2015) claim that restriction of imports during the first global food crisis protected the country prices.

[4] Bilgic and Yen (2014) report that the rapid increase in prices around 2009 led to 30 per cent decrease in per capita red meat consumption.

[5] An et al. (2016) FAO et al. (2011), Giordani et al. (2016), Gouel (2013), Headey (2011), Kornher and Kalkuhl (2013) and Tadasse et al. (2016) are some of the papers about the determinants of food price volatility and the effects of trade on price and price volatility.

measures have significantly contributed to increase staple food prices in 2008-11. Anderson and Nelgen (2012) find that in African countries domestic agricultural prices are on average more volatile with trade policy adjustments and they suggest this may be caused by poor policy timing. Chapoto and Jayne (2009) show that in Eastern and South Africa, countries that adopt trade interventions end up with more volatile and uncertain prices than other countries. Porteous (2012) uses data on maize prices and trade policies in 12 countries in East and Southern Africa to investigate the effects of short-term export bans on agricultural markets and finds that short-term export bans may in fact increase prices and volatility in the implementing country. An et al. (2016) investigate the effect of export restrictions implemented by the Ukranian government on wheat and flour market and find that price volatility increased in both markets during periods of export control.

Figure 2: Beef Imports and Prices



Source: TURKSTAT. .

The empirical literature on the food price literature and the effects of trade policy on agricultural prices for Turkey is still scarce and nearly non-existent especially for beef prices. For Turkey in general, supply-side problems have been highlighted as the main reason for price increases. Common view about beef prices in Turkey argues that the premature culling of dairy herds starting in 2007 led to increased supply of slaughtered animals initially, and depressed wholesale beef prices temporarily, which caused a shortage of cow and calf stocks in the next couple of years. By 2009, the slaughter caused a significant decline in the beef supply in Turkey. Decline in supply coupled with almost no

imports increased beef prices significantly within the 2009-2010 period.[6]

As a response to the increase in beef prices and excess demand, government focused on the import of red meat during periods when there is inadequate supply. In this respect, our study investigates the effect of import policy on the level and volatility of beef prices, with particular focus on constructing volatility series rather than determining causes of fluctuations in meat prices. Before 2010, red meat market in Turkey was nearly closed to the outside world as imports and exports were at a minimal level. However, after 2010, as can be observed via Figure 2 the country started extensive import of red meat to stabilize local prices. In this respect, this study examines the effects of import policy and world meat prices on the beef prices and volatility in Turkey.

Univariate and multivariate GARCH type of models are used in international literature very frequently to model the agricultural price price volatility. An et al. (2016) use VEC-BEKK-GARCH model to analyze the volatility,asymmetry and spillovers among wheat and flour prices and export controls. Minot (2014) uses GARCH(1,1) model to examine 167 food price series from 15 African countries. Rezitis and Stavropoulos (2010) use several different symmetric, asymmetric and non-linear GARCH models to estimate volatility for Greek beef market. Gardebroek et al. (2016) use multivariate GARCH approach to evaluate the time evolution and volatility transmission across corn, wheat and soybean price returns on a daily, weekly and monthly basis. Ait Sidhoum and Serra (2016) employ multivariate GARCH model to study price transmission between consumer, producer and wholesale prices in Spanish tomato market. Hernandez et al. (2014) use world commodity prices and using a multivariate GARCH model conclude that agricultural markets are highly interrelated.

The objective and the contribution of the paper to the literature is twofold. First, this study aims to fill a gap in the existing literature by providing a convenient volatility structure of the Turkey beef prices. We believe that the volatility model choice is crucial to observe spikes and effects of policy shocks. Different univariate GARCH models are employed to observe the best model that fits the consumer and producer beef inflation. We choose beef prices, as it is one of the most problematic and unstable among agricultural prices. Second, given the best volatility structure for consumer and producer beef prices, we aim to explore if import policy in Turkey is effective in reducing price and its volatility in beef market. It is also interesting to see how the results of multivariate model differs from the univariate volatility model results. Price transmissions between consumer and producer prices is really essential for the formation of price dynamics in any given market. Therefore it is really essential to use a multivariate model for policy analysis purpose.

The remainder of the paper is organized as follows. Section 2 illustrates the information related to our dataset used and lists some descriptive statistics that will show us the common problems

[6] See Özertan et al. (2015) for details.

of the raw data employed in this paper. Section 3 describes the univariate GARCH models and multivariate DCC-GARCH model applied in this study to analyze beef price volatility and make inferences about import policy implemented in Turkey along with a detailed summary of the results and their ramifications. Section 4 concludes.

2 Data

Table 1: Descriptive Statistics of Beef Price and Import Series

A. Summary Statistics

Variable	Mean	Std.Dev.	Skewness	Kurtosis	J-B Normality
cpi-beef	2.939	0.427	0.070	1.793	10.274***
ppi-beef	7.749	0.370	0.005	1.866	8.947***
import-beef	15.299	3.828	-1.333	3.989	56.303***

B. Unit Root Tests

	Unit Root Tests	
Variable	ADF	DF-GLS
cpi-beef	-2.459	-2.463
ppi-beef	-1.610	-1.339
import-beef	-2.685	-1.726

C. ARCH LM Heteroscedasticity Tests

Variable	ARCH (1) LM Test	ARCH (12) LM Test
cpi-beef	18850.33***	2025.20***
ppi-beef	5827.25***	408.15***
import-beef	1.20	5.90***

D. Serial Correlation LM Test

Variable	Lag (1) LM Test	Lag (12) LM Test
cpi-beef	7894.60***	616.64***
ppi-beef	4897.64***	383.80***
import-beef	72.30***	18.70***

Number of observations=167.
**Denotes statistical significance at the 99% level. **Denotes statistical significance at the 95% level. *Denotes statistical significance at the 90% level.
For unit root tests: Trend and Intercept included.

The monthly price data on producer prices for cattle, consumer prices for veil and cattle imports are collected from Turkish Statistical Institute (Turkstat).Producer prices for cattle are under the agricultural prices in Turkey and there are three series under the agricultural producer prices for cattle,i.e. cross cattle, culture cattle and domestic cattle. We use the prices for cross cattle for

our analysis as this category has the highest share in imports and in consumption that is around 40 percent.[7] The sample contains 167 observations running from January 2003 to November 2016. Our sample is restricted by the availability of import data.

Table 1 lists the descriptive statistics of the beef price and import series used in the empirical model of this study. Panel A lists the summary statistics and Panel B illustrates the unit root test results.[8] As can be seen in the summary statistics table, price and import series are not stationary, leading us to use all the series in logarithmic difference (growth rate) form. Panel C and D exhibit the changing variance and correlation structure of the raw dataset. The Lagrange multiplier (LM) test for serial correlation up to order 12 clearly indicates the presence of serial correlation for all of our series and the LM test for ARCH with 12 lags, also points to changing variance (heteroskedasticity). The evidence of conditional heteroscedasticity in our series lends support to the use of GARCH type of models to capture the time-varying volatility behaviour of the data series. It should also be noted that beef price and import series do not include seasonality.[9]

3 Empirical methodology

3.1 Univariate GARCH models

Uncertainty or volatility of inflation is often claimed to be one of the most important costs of inflation, since it distorts the workings of the price system and leads to allocational inefficiencies by generating losses for consumers and producers. In this part of the paper we will concern ourselves with univariate models to measure volatility. In this framework, the methodology to measure univariate volatility is based on a seminal paper by Engle (1982) who propose to model conditional variance with the Autoregressive Conditional Heteroscedasticity (ARCH) processes that use past disturbances to model the variance of series. The vast majority of empirical applications of ARCH models have studied financial time series such as asset prices. Although the use of GARCH models, developed by Bollerslev (1986) and Taylor (1987), is more commonly associated with finance literature, the first applications of the procedure were to model quarterly inflation.[10] These type of volatility models are becoming very popular among different areas of empirical macroeconomics

[7] Culture cattle is similar to cross cattle and we conducted our analysis using culture cattle category too and got qualitatively very similar results, therefore we will not presents the results with culture cattle. Domestic cattle has a share of around 13 percent in total live cattle in Turkey and we leave that category out of our analysis. Monthly import data is the quantity imported in Turkish Liras.

[8] Appendix B illustrates two other unit root test results for possible structural breaks. See Zivot and Andrews (1992) and Perron (1997) for details.

[9] We use Stata/SE 14.2 and EViews 9.5 Enterprise Edition for all of our analysis in this paper.

[10] See Engle (1982) and Engle (1983).

and within the agricultural prices literature.[11]

There are other methods that can be used to measure price volatility, of which the most employed two are the cross-sectional dispersion of individual forecasts from surveys or a moving standard deviation of the inflation.[12] Yet GARCH techniques are very useful to measure uncertainty due to some technical advantages: First, we can test if the movement in the conditional variance of inflation is statistically significant over time. Second, while many proposed volatility models impose the assumption that the conditional volatility is affected symmetrically by positive and negative innovations, we can test for asymmetric volatility using EGARCH models. Third, by using GARCH type of models we can simultaneously estimate the mean and the conditional variance equation of inflation using maximum likelihood methods and include different exogenous variables into the mean and variance equations to analyze the effects of the policy related variables that we believe has a crucial impact on inflation and its volatility.

Let us consider a univariate time series y_t given in Equation 1. If ψ_{t-1} is the information set available at time $t-1$, in its simplest form we can illustrate GARCH(1,1), i.e. Equation 3 as:

$$y_t = E[y_t|\psi_{t-1}] + \varepsilon_t \tag{1}$$

$$E[\varepsilon_t] = 0 \quad E[\varepsilon_t \varepsilon_s] = 0, \quad \forall t \neq s$$

$$\varepsilon_t = z_t \sigma_t \tag{2}$$

$$z_t \sim (i.i.d.) \quad E(z_t) = 0, \quad Var(z_t) = 1$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{3}$$

where $E[.|.]$ denotes the conditional expectation operator and ε_t is the disturbance term. σ_t is a time-varying, positive and measurable function of the information set at time $t-1$. Indeed GARCH(1,1) model in Equation 3 is effectively an ARMA(1,1) model for the conditional variance.

One of the primary restrictions of GARCH models is that they enforce a symmetric response of volatility to positive and negative shocks. This arises since the conditional variance in Equation

[11] Hamilton (2008) discusses about the possible implications of ignoring second moments conducting empirical macroeconomics. The most important implication is about making inference in a classical sense, which will be invalid when the second moments are not included into consideration. Another point about the importance of GARCH technique is that, if any variable exhibits conditional heteroscedasticity, conducting a simple OLS will produce unbiased but inefficient coefficients. Indeed Engle (1982) shows that by using ARCH, the efficiency gain can be very important when there exist a significant time varying heteroscedasticity.

[12] We do not aim to compare different classes of volatility measures in this paper as that approach is beyond what we aim to focus on. Saying that, we try different measures of volatility,i.e. stochastic volatility and realized volatility to measure uncertainty related to beef prices and although we get quantitatively different results we prefer not report our results here due to the fact that there is not a crucial difference in terms of policy repercussions.

3 is a function of the magnitudes of the lagged residuals and not their signs (in other words, by squaring the lagged error in Equation 3, the sign is lost. However, higher than expected inflation, i.e. "bad news", may generate more uncertainty about future than lower than expected inflation, i.e. "good news". If such asymmetries exist, then conventional symmetric ARCH and GARCH models will provide misleading estimates of inflation uncertainty. We will use two popular asymmetric formulations: threshold GARCH (TGARCH) model proposed by Glosten et al. (1993) and exponential GARCH (EGARCH) model proposed by Nelson (1991).[13]

There are various ways to express the conditional variance equation for EGARCH(1,1) model, but one possible specification can be given by:

$$log\sigma_t^2 = \omega + \alpha|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}| + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta log\sigma_{t-1}^2 \tag{4}$$

Asymmetry given by γ is called the leverage effect and when $\gamma < 0$ "negative shocks" imply a higher next period conditional variance than "positive shocks" of the same sign. Impact is asymmetric if $\gamma \neq 0$. Within an inflationary perspective, we expect the leverage effect to be positive in which "bad news", a rise in inflation, implies a higher next period conditional variance than "good news" of the same sign.

For the TGARCH(1,1) model, the conditional variance of Equation 3 is given by:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1}^- + \beta\sigma_{t-1}^2 \tag{5}$$

$$I_{t-1}^- = \begin{cases} 1 & \text{if } \varepsilon_t < 0 \\ 0 & \text{otherwise} \end{cases}$$

where "positive shocks" $\varepsilon_{t-1} > 0$ and "negative shocks" $\varepsilon_{t-1} < 0$ have different effects. When $\gamma = 0$ in Equation 5, the model reduces to GARCH(1,1).

The GARCH models are estimated using a maximum likelihood (ML) approach and the normal distribution is by far the most widely used distribution in the estimation of GARCH type of models. Given that the mean equation is expressed as in Equation 1, the log-likelihood function of the

[13] TGARCH model is sometimes named as GJR model in the literature. The difference is that TGARCH model of Zakoian (1994) models the conditional standard deviation instead of the conditional variance.

standard normal distribution of z_t in Equation 2 is given by:

$$LL_T = -\frac{1}{2}\sum_{t=1}^{T}[ln(2\pi) + ln(\sigma_t^2) + (z_t^2)] \tag{6}$$

where T is the number of observations.

Most financial/non-financial time-series often exhibit non-normality patterns, i.e. excess kurtosis and skewness.[14] It may be expected that excess kurtosis and skewness displayed by the residuals of conditional heteroskedasticity models will be reduced when a more appropriate distribution is used, therefore we utilize student-t distribution in this study.[15] For a student-t distribution of z_t in Equation 2, the log likelihood is given by:

$$LL_T = ln[\Gamma(\frac{\upsilon+1}{2})] - ln[\Gamma(\frac{\upsilon}{2})] - \frac{1}{2}ln[\pi(\upsilon-2)] - \frac{1}{2}\sum_{t=1}^{T}[ln\sigma_t^2 + (1+\upsilon)ln(1+\frac{z_t^2}{\upsilon-2})] \tag{7}$$

where T is the number of observations, υ is the degrees of freedom, $2 < \upsilon \leq \infty$ and $\Gamma(.)$ is the gamma function. When $\upsilon \to \infty$, we have the normal distribution, so that the smaller υ, the fatter the tails.

3.1.1 Results and Discussion

Our empirical work begins with estimating the univariate conditional means represented by Equation 1 and the conditional variances represented by Equation 3, Equation 4 and Equation 5 for consumer and producer beef inflation.[16] Our strategy for modelling conditional mean is to search over alternative $AR(k)$ models by varying the k parameter from 0 to 12 until we get rid of the serial correlation represented in Table 1 and get robust residual diagnostic tests. We employ the same procedure for the conditional variance and choose a convenient $GARCH(p,q)$ process till we get rid of the heteroscedasticity problem. Table 2 provides the estimation results along with their diagnostics. We estimate the models' parameters with monthly data from January 2003 to November 2016. Also, as we assume that z_t innovations in Equation 2 follow a student-t distribution, we report the estimates of the tail parameters.

[14] Non-normality pattern in our dataset can be observed form the normality test illustrated in Table 1.

[15] See Appendix A.

[16] Table 1 illustrates that our producer and consumer price series are not stationary, therefore throughout the paper we will conduct all our estimation procedures using logarithmic difference (growth rate/inflation) of price series.

Table 2: Univariate GARCH Results

	Monthly CPI-Beef Inflation			Monthly PPI-Beef Inflation		
	GARCH	**TGARCH**	**EGARCH**	**GARCH**	**TGARCH**	**EGARCH**
A.Conditional Mean	**Equation 1**	**Equation 1**	**Equation 1**	**Equation 1**	**Equation 1**	**Equation 1**
α_0	0.003***	0.004***	0.004***	0.004***	0.004***	0.004***
$ar(1)$	0.386***	0.351***	0.388***	0.434***	0.411***	0.380***
$ar(2)$	0.131*	0.148**	0.123*			
$ar(3)$					0.102***	
$ar(4)$	-0.119**	-0.103*	-0.028			
$ar(12)$				0.05	-0.115***	0.056
B.Conditional Variance	**Equation 3**	**Equation 5**	**Equation 4**	**Equation 3**	**Equation 5**	**Equation 4**
ω	0.000	0.000	-0.186	0.000	0.000***	-1.827**
$arch(1)$	0.374	0.513	-0.062	0.639***	0.785	0.640**
$garch(1)$	0.546***	0.632***	0.974***		0.466***	0.182
$garch(2)$					-0.152***	0.625***
γ		-0.517	0.271***		-0.271	0.166
υ	3.378***	3.310***	3.300***	2.989***	3.086***	2.463***
C.Selection Criteria	LL=453.682	LL=455.359	LL=455.968	LL=422.865	LL=426.299	LL=424.768
AIC	-5.502	-5.511	-5.518	-5.427	-5.406	-5.400
BIC	-5.350	-5.339	-5.347	-5.328	-5.209	-5.222
MAE	0.0004	0.0003	0.0002	0.0005	0.0022	0.0007
MAPE	1.833	0.950	0.574	1.164	98.084	1.760
RMSE	0.00054	0.00043	0.00036	0.00116	0.00230	0.00115
D. Residual Diagnostics						
$Q(1)$	0.520	0.199	1.066	0.009	0.164	0.141
$Q(12)$	15.807	13.638	16.184	13.694	10.893	15.687
$Q^2(1)$	0.331	0.374	0.090	0.170	0.193	0.090
$Q^2(12)$	5.642	4.664	4.964	5.694	6.181	10.406

***Denotes statistical significance at the 1% level. **Denotes statistical significance at the 5% level. *Denotes statistical significance at the 10% level.
$Q(12)$ and $Q^2(12)$ are the Box-Pierce statistics for serial correlations of up to 12 orders in residuals and squared residuals from our estimations

GARCH-in-Mean (GARCH-M) model ala Engle et al. (1987) can be represented by introducing the conditional variance or standard deviation into the conditional mean equation. An example of a GARCH-M model can be given by a specification:

$$y_t = E[y_t|\psi_{t-1}] + \delta\sigma_t + \varepsilon_t \tag{8}$$

where we add $\delta\sigma_t$ to mean equation represented previously by Equation 1. If δ is positive and statistically significant, then increased risk, in our case increased inflation, given by an increase in conditional variance, leads to a rise in the mean return. In some empirical applications, the conditional variance term, σ^2_{t-1} appears directly in the conditional mean equation and in our case we employ the square root form of σ^2_{t-1} and the term is contemporaneous. We can observe the

GARCH in mean results in Table 3 and inflation uncertainty does not seem to have any effect on the inflation level.

Table 3: Univariate GARCH-M Results

	Monthly CPI-Beef Inflation			Monthly PPI-Beef Inflation		
	GARCH-M	**TGARCH-M**	**EGARCH-M**	**GARCH-M**	**TGARCH-M**	**EGARCH-M**
A.Conditional Mean	**Equation 8**	**Equation 8**	**Equation 8**	**Equation 8**	**Equation 8**	**Equation 8**
α_0	0.007	0.007	-0.022	0.008	-0.002	0.015
$ar(1)$	0.377***	0.347***	0.430***	0.400***	0.399***	0.355***
$ar(2)$	0.127*	0.141*	0.156**			
$ar(3)$					0.067*	
$ar(4)$	-0.124**	-0.108*	-0.021			
$ar(12)$				0.050	0.038	0.045
σ_t	0.000	0.000	-0.003*	0.001	0.000	0.001
B.Conditional Variance	**Equation 3**	**Equation 5**	**Equation 4**	**Equation 3**	**Equation 5**	**Equation 4**
ω	0.000	0.000	-0.497***	0.000	0.000	-1.550*
$arch(1)$	0.359	0.500	-0.103	0.605***	1.808	0.637*
$garch(1)$	0.577***	0.641***	0.932***		0.379***	0.202
$garch(2)$					-0.116***	0.639
γ		-0.500	0.329***		-0.712	0.219
υ	3.266***	3.206***	3.176***	2.918	2.356***	2.418***
C.Selection Criteria	LL=453.779	LL=455.368	LL=457.455	LL=420.834	LL=429.602	LL=425.063
AIC	-5.491	-5.498	-5.524	-5.387	-5.436	-5.390
BIC	-5.320	-5.308	-5.334	-5.269	-5.219	-5.193
MAE	0.0005	0.0003	0.0005	0.0004	1.2362E+33	0.0010
MAPE	2.188	1.031	0.646	0.918	3.46469E+36	2.544
RMSE	0.0006	0.0004	0.0006	0.0011	8.07338E+33	0.0013
D. Residual Diagnostics						
$Q(1)$	0.532	0.2473	0.822	0.277	0.0192	0.277
$Q(12)$	15.597	13.745	19.799	16.614	12.830	16.614
$Q^2(1)$	0.317	0.360	0.090	0.067	0.165	0.067
$Q^2(12)$	5.537	4.630	20.132	11.699	8.164	11.699

***Denotes statistical significance at the 1% level. **Denotes statistical significance at the 5% level. *Denotes statistical significance at the 10% level.
$Q(12)$ and $Q^2(12)$ are the Box-Pierce statistics for serial correlations of up to 12 orders in residuals and squared residuals from our estimations

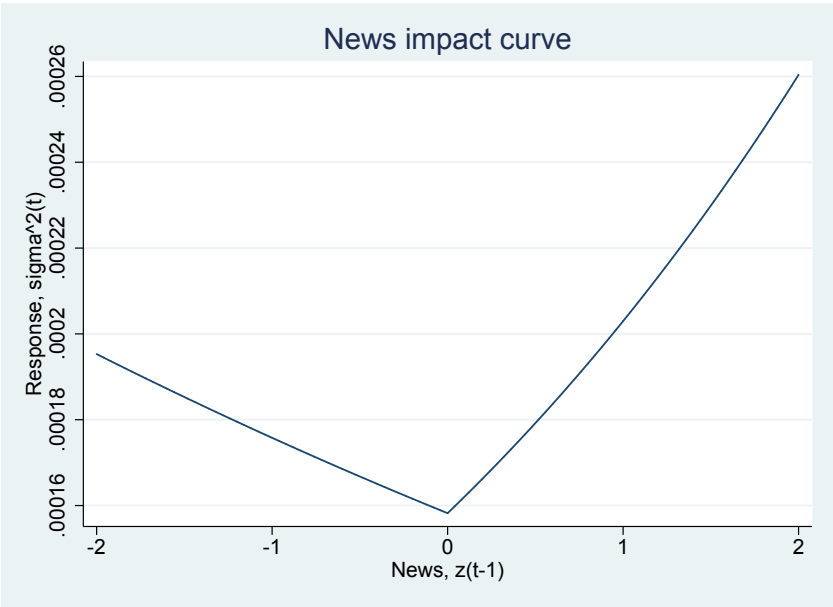
A pictorial representation of the degree of asymmetry of volatility to positive and negative shocks is given by the news impact curve introduced by Pagan and Schwert (1990) and we can observe it via Figure 3. The news impact curve plots the next-period volatility,i.e. σ^2_{t-1} that would arise from various positive and negative values of ε_{t-1} given an estimated model.[17] Figure 3 is the news impact curve for EGARCH model of CPI beef inflation with coefficients given in Table 2. The news impact figure illustrates that the increase in inflation, "bad news" or "positive shock" in our case, affects the inflation volatility in the next term more than a "'negative shock" of the same

[17]The curves are drawn by using the estimated conditional variance equation for the model under consideration, with its given coefficient estimates, and with the lagged conditional variance. Then, successive values of ε_{t-1} are used in the equation to determine what the corresponding values of σ^2_t derived from the model would be.

magnitude.

For a GARCH model the news impact curve will be symmetric, i.e. for a GARCH model Figure 3 will take a symmetric "V" shape. Yet, with the help of an EGARCH model we can successfully observe whether an increase in inflation, i.e. bad news or positive shock, increases the volatility more one period after the shock happened compared to a decrease in inflation, i.e. good news or negative shock. In Figure 3, for the negative z_{t-1} of the x-axis (negative shocks), the news impact curve has a smaller slope when compared to the positive z_{t-1} of the x-axis (positive shocks), which means an increase in inflation will increase the volatility (y-axis) more than a decrease in inflation.

Figure 3: News Impact Curve (EGARCH model / CPI-beef Inflation)



We estimate 6 models for CPI-beef price inflation and 6 models for PPI-beef inflation and we choose one to use for policy analysis. Engle and Patton (2001) claim that a volatility model should be able to forecast volatility. Therefore we use combination of Akaike and Bayesian Information Criteria (AIC and BIC) and evaluate in-sample forecasting performance of the conditional volatility models using their associated root mean squared error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) statistics. The statistics associated with the conditional

volatility are constructed as:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\sigma_{a,t}^2 - \sigma_{f,t}^2)^2}$$

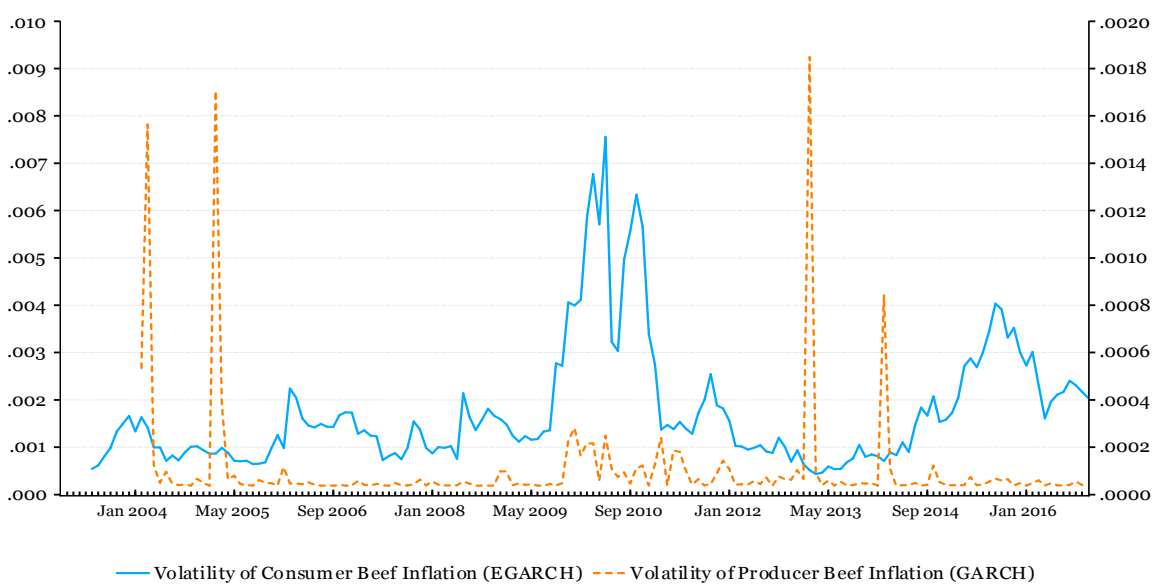
$$MAE = \frac{1}{T}\sum_{t=1}^{T}|\sigma_{a,t}^2 - \sigma_{f,t}^2|$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\frac{|\sigma_{a,t}^2 - \sigma_{f,t}^2|}{\sigma_{a,t}^2}$$

where T is the number of in-sample forecast data points, $\sigma_{a,t}^2$ and $\sigma_{f,t}^2$ are the realized and forecasts of volatility respectively. As a general rule, smaller forecast error statistics imply superior forecasting ability.

Panel C of Table 2 and Table 3 lists the AIC, BIC and forecast performance criteria of models estimated for CPI-beef and PPI-beef inflation and Figure 4 illustrates the best model for estimated conditional variance of CPI and PPI-beef inflation.

Figure 4: Best Univariate Conditional Variance Models for Beef Inflation



As can be inspected from Figure 4, consumer beef inflation is much more volatile compared to producer beef inflation, with severe spikes around the second half of 2009 and first half of 2010.

Producer prices have four spikes, two of which we think is related to announcements of import restriction.

Table 4 gives us a chance to observe the effect of import policy on the level and volatility of beef prices as we insert the import quantity in the mean and variance equations of volatility models we choose with the help of AIC, BIC and forecast performance criteria, which we think will best represent the uncertainty for consumer and producer beef inflation respectively. The first column of the table lists the parameters of the best volatility model estimated for CPI-beef prices, i.e. EGARCH model. In the second column, we report the results for the best volatility model for CPI that includes beef import quantity. With the help of these results we want to analyze whether the government import policy is effective in stabilizing the volatility of consumer beef inflation.[18] Second column of Table 4 points out to a significant volatility reducing effect of imports on consumer prices. We conduct the same analysis for producer beef inflation, yet we can not observe a significant effect of import policy both for both producer inflation and inflation volatility. Column 4 and column 5 of the table display that the coefficient of beef import quantity is not significant neither in mean nor in volatility equation for producer prices.

[18] We do not report the results where we include the import quantity in the mean equation of best model for consumer beef prices as the coefficient of import variable is not significant for lags up to 12.

Table 4: Univariate models with import quantity incorporated

Models	CPI-Beef EGARCH Best Model	CPI-Beef EGARCH +IMPORT (in Variance)	PPI-Beef GARCH Best Model	PPI-Beef GARCH +IMPORT (in Mean)	PPI-Beef GARCH +IMPORT (in Variance)
A.Conditional Mean					
α_0	0.004***	0.006***	0.004***	0.003***	0.004
$ar(1)$	0.388***	0.351***	0.434***	0.463***	0.414***
$ar(2)$	0.123*	0.115*			
$ar(4)$	-0.028	-0.074			
$ar(12)$			0.046	0.040	0.043
Δimp_{t-3}				0.000	
B.Conditional Variance					
ω	-0.186	-0.429	0.000	0.000	0.000
$arch(1)$	-0.062	0.045	0.639***	0.672***	0.623***
$garch(1)$	0.974***	0.954***			
γ	0.271***	0.217***			
Δimp_{t-2}		0.134**			
Δimp_{t-3}					-0.000***
Δimp_{t-6}		-0.203***			
υ	3.300***	3.583***	2.990***	3.057***	2.999***
LL	455.968	455.928	422.865	425.411	423.948
AIC	-5.518	-5.562	-5.427	-5.447	-5.428
BIC	-5.347	-5.350	-5.328	-5.329	-5.310
C. Residual Diagnostics					
$Q(1)$	1.066	0.665	0.009	0.028	0.000
$Q(12)$	16.184	13.540	13.694	11.205	12.855
$Q^2(1)$	0.090	0.896	0.170	0.163	0.220
$Q^2(12)$	4.964	2.111	5.694	5.287	11.654

***Denotes statistical significance at the 1% level. **Denotes statistical significance at the 5% level. *Denotes statistical significance at the 10% level.
$Q(12)$ and $Q^2(12)$ are the Box-Pierce statistics for serial correlations of up to 12 orders in residuals and squared residuals from our estimations.
Δimp variable represents the logarithmic difference of beef import quantity (in terms of TL amount).

3.2 Multivariate DCC-GARCH model

The second model we use to analyze the volatility of consumer and producer beef prices, price volatility and the effect of import policy on beef market is the DCC-GARCH(1,1) model of Engle (2002), which provides a convenient way to model the dynamic processes of conditional variances and conditional covariances simultaneously. Similar to GARCH-type processes for modeling condi-

tional variances, the current values of conditional covariances are related to their lagged values and lagged squared innovations in the model. However, in DCC-GARCH model, conditional covariances are modeled as nonlinear functions of the conditional variances.

There are two major advantages of using this model over the univariate GARCH type of models. First, in the univariate models we present previously for consumer and producer inflation we analyze the dynamics of each price on its own. On the other hand, in multivariate model we use a reduced form VAR for the mean equation, where we can see the transmission of producer to consumer prices and vice versa. Another major advantage of using this model is that it enables us to detect the possible changes in conditional correlations over time between consumer and producer inflation.

To get the volatility and dynamic correlation of consumer and producer beef prices, we will utilize the following DCC-GARCH(1,1) model:

$$\begin{aligned}
\Delta Y_t &= \Theta \Delta X_t + \varepsilon_t \\
\varepsilon_t &\sim N(0, H_t) \quad t = 1, ..., T \\
\varepsilon_t &= H_t^{\frac{1}{2}} \upsilon_t \\
\upsilon_t &\sim N(0, 1) \\
H_t &= D_t^{\frac{1}{2}} R_t D_t^{\frac{1}{2}} \\
R_t &= diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}} \\
Q_t &= (1 - \lambda_1 - \lambda_2) R + \lambda_1 \varepsilon_{t-1} \varepsilon_{t-1}^{'} + \lambda_2 Q_{t-1}
\end{aligned} \tag{9}$$

where Equation 9 is a reduced-form Vector Autoregression process (VAR), $D_t = diag(h_{it})$ is a 2×2 matrix containing the time varying standard deviations from univariate GARCH(1,1) models and $R_t = \{\rho_{ij}\}_t$ is a correlation matrix containing conditional quasicorrelations for $i, j = 1, 2$.

3.2.1 Results and Discussion

Table 5, Table 6 and Table 7 displays the results for DCC-GARCH model. Panel A of Table 5 has an additional row related to the contemporaneous effect of producer prices on consumer prices that can not be captured by univariate models. In Table 5, we can not only observe the significant volatility dynamics of consumer and producer inflation but also observe significance of time varying conditional correlation of producer and consumer inflation. We also have the opportunity of observing the transmission of contemporaneous and lagged effects of each series. Table 6 gives us the results of DCC-GARCH model where we include the import quantity only in the mean equation and as can be observed from the panel A of the table, imports have significant

but very small effect on the mean level of producer beef inflation.

Table 5: DCC-GARCH model of CPI and PPI beef prices

A. Mean Model Estimates (Reduced form VAR)		
Dependent Variable : Δcpi	Estimate	Std. Dev.
constant	0.002	0.001
Δcpi_{t-1}	0.155	0.097
Δcpi_{t-2}	0.089	0.102
Δcpi_{t-4}	**-0.212**	0.076
Δppi	**0.551**	0.153
Dependent Variable : Δppi	Estimate	Std. Dev.
constant	**0.006**	0.002
Δppi_{t-3}	**0.072**	0.040
Δppi_{t-5}	0.044	0.037
Δcpi_{t-1}	**0.325**	0.065
Δcpi_{t-2}	**0.274**	0.064
B. Variance Estimates	Estimate	Std. Dev.
ω_1	**0.000**	0.000
ω_1	**0.000**	0.000
α_{11}	**0.390**	0.236
α_{22}	**1.144**	0.469
β_{11}	–	–
β_{22}	–	–
ρ_{12}	**-0.595**	0.165
λ_1	**0.230**	0.061
λ_2	**0.647**	0.070
χ^2 test for $\lambda_1 = \lambda_2$	**284.680**	p-val =0.000
LL	821.726	
C. Residual Diagnostics	BP stat*	p-value
$Q(1)$	1.833	0.176
$Q(12)$	10.708	0.554
$Q^2(1)$	0.059	0.807
$Q^2(12)$	13.378	0.342

Bold parameters are statistically significant. *BP represents Box-Pierce statistics.

Table 7 gives us the results of DCC-GARCH model where we include the import quantity only in the variance equation and as can be observed from the panel B of the table, imports have significant effect on the volatility of both the producer and consumer beef inflation and the sign of the effect is negative. What is more interesting is that the beef import policy affects producer inflation volatility more than the consumer inflation volatility which is in line with expectations.

Table 6: DCC-GARCH model with imports in the mean equation

A. Mean Model Estimates (Reduced form VAR) Imports in Mean		
Dependent Variable : Δcpi	Estimate	Std. Dev.
constant	-0.001	0.003
Δcpi_{t-4}	**-0.237**	0.062
Δppi	**1.031**	0.713
$\Delta import_{t-2}$	-0.0003	0.003
Dependent Variable : Δppi	Estimate	Std. Dev.
constant	**0.006**	0.002
Δppi_{t-3}	**0.036**	0.021
Δppi_{t-5}	0.020	0.025
Δcpi_{t-1}	**0.334**	0.070
Δcpi_{t-2}	**0.260**	0.066
$\Delta import_{t-1}$	**-0.001**	0.000
B. Variance Estimates	Estimate	Std. Dev.
ω_1	**0.001**	0.000
ω_2	**0.001**	0.000
α_{11}	0.248	0.154
α_{22}	**0.382**	0.076
β_{11}	**-0.099**	0.050
β_{22}	**-0.097**	0.015
ρ_{12}	**-0.872**	0.048
λ_1	**0.306**	0.072
λ_2	**0.498**	0.094
χ^2 test for $\lambda_1 = \lambda_2$	**169.430**	p-val =0.000
LL	826.737	
C. Residual Diagnostics	BP stat	p-value
$Q(1)$	1.972	0.160
$Q(12)$	14.426	0.274
$Q^2(1)$	0.034	0.954
$Q^2(12)$	23.995	0.029

Bold parameters are statistically significant. *BP represents Box-Pierce statistics.

Table 7: DCC-GARCH model with imports in the variance equation

A. Mean Model Estimates (Reduced form VAR) Imports in Variance		
Dependent Variable : Δcpi	Estimate	Std. Dev.
constant	0.000	0.003
Δcpi_{t-1}	**0.175**	0.105
Δcpi_{t-2}	-0.003	0.102
Δcpi_{t-4}	**-0.233**	0.067
Δppi	**0.902**	0.189
Dependent Variable : Δppi	Estimate	Std. Dev.
constant	**0.004**	0.002
Δppi_{t-3}	**0.064**	0.027
Δppi_{t-5}	**0.093**	0.047
Δcpi_{t-1}	**0.236**	0.084
Δcpi_{t-2}	**0.257**	0.083
B. Variance Estimates	Estimate	Std. Dev.
ω_1	**-7.148**	0.288
ω_2	**-7.521**	0.114
α_{11}	-0.023	0.023
α_{22}	0.002	0.028
β_{11}	**-0.312**	0.136
β_{22}	–	–
$\Delta import^{11}_{t-1}$	**-0.061**	0.021
$\Delta import^{22}_{t-1}$	**-0.232**	0.081
ρ_{12}	**-0.781**	0.092
λ_1	**0.154**	0.047
λ_2	**0.687**	0.069
χ^2 test for $\lambda_1 = \lambda_2$	**284.930**	p-val =0.000
LL	821.489	
C. Residual Diagnostics	BP stat	p-value
$Q(1)$	0.995	0.318
$Q(12)$	10.875	0.540
$Q^2(1)$	0.038	0.846
$Q^2(12)$	22.689	0.051

Bold parameters are statistically significant. *BP represents Box-Pierce statistics.

4 Concluding Remarks

The remarkable surge in beef prices observed in Turkey in 2009 resulted with a zero tariff policy on beef imports in April 2010 along with the special privilege of importing at that rate given to Meat and Milk Board. Since then, the authorities allowed imports at a zero tariff policy on a necessity

basis although there have been debates around the effectiveness of this policy. While the main point of contention is around the future of domestic cattle breeders, there are also discussions on the extent at which the import policy change affects the course of beef prices. Due to the inflation-targeting regime implemented by the Central Bank of the Republic of Turkey, there emerges an inevitable concern on any factor that might affect the success of the policy on prices. Therefore, this study is very important, in a way that it tries to measure quantitative effect of imports on prices and price volatility.

In this framework, there are two significant research questions investigated in this study. First we try to see what kind of GARCH model best represents the Turkish consumer and producer beef inflation volatility for the period between January 2003 and November 2016. The second question we explore is whether the quantity of imported meat can serve its purpose and decrease the inflation level for producer and consumer beef inflation and stabilize the uncertainty measured by volatility in the beef market.

Among 6 different univariate GARCH models, we find that an asymmetric EGARCH model fits best for consumer beef inflation and a symmetric GARCH model is the best fitting model for the producer beef inflation volatility. In all the 6 univariate GARCH models, we find that volatility does not appear to affect the mean level of inflation. The parameters related to the variance equation for both consumer and beef producer inflation are highly significant and the consumer inflation is much more volatile compared to the producer inflation for the Turkish beef market.

These unexpected results we obtain from the univariate GARCH models directed us to use a multivariate DCC-GARCH model where we can include the transmission between producer and consumer inflation into the dynamics of the model. The results we obtain from the multivariate model tell us a different story, in which import policy is significant in producer beef inflation although the coefficient is very small. The coefficient of imports are also significant with a negative sign in both the consumer and producer inflation volatility. In fact, the results we get from the multivariate model is in line with our expectations since the privilege to import with zero tariff has been given to Meat and Milk Board in Turkey, which functions as a significant producer in the beef market.

For the second question which focuses on the impact of import policy change on beef prices, we find out that the quantity of imported beef mainly decreases the volatilities of inflation series while it has negligible impact on the level of producer beef inflation. Although the decrease in uncertainty is a desired result for policy makers, the small impact of imports on the level of inflation might not help alleviate the concerns about the effectiveness of the policy. Indeed, the small impact of imports on the level of inflation might lead to the conclusion that the policy is not effective. Yet,

the graphical depiction shows that import policy change has helped curb the increase in consumer beef prices, which is ultimately important for a central bank conducting inflation targeting. Even though our results do not present very strong evidence for such a curbing, the slowdown in consumer beef prices can still be considered a factor that could allow policy makers to regulate the market on a necessity basis. We believe that correct determination of the periods of "necessity" is crucial here since the insignificant impact of imports on the levels of inflation could be manifested in the short run if the market players start to consider the import policy merely as a bluff of the policy makers.

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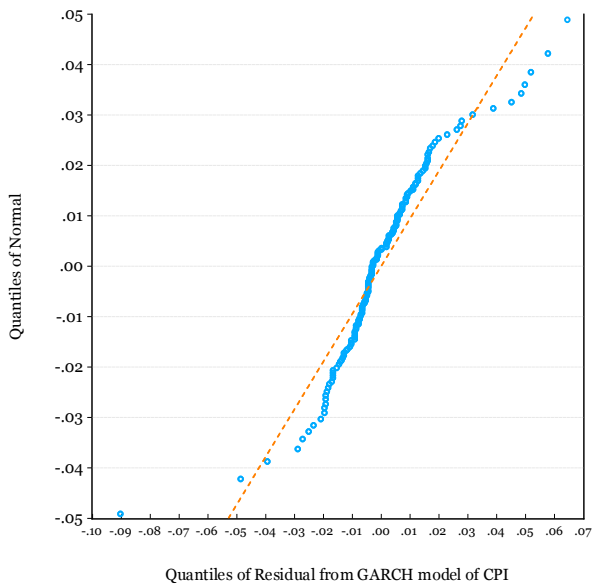
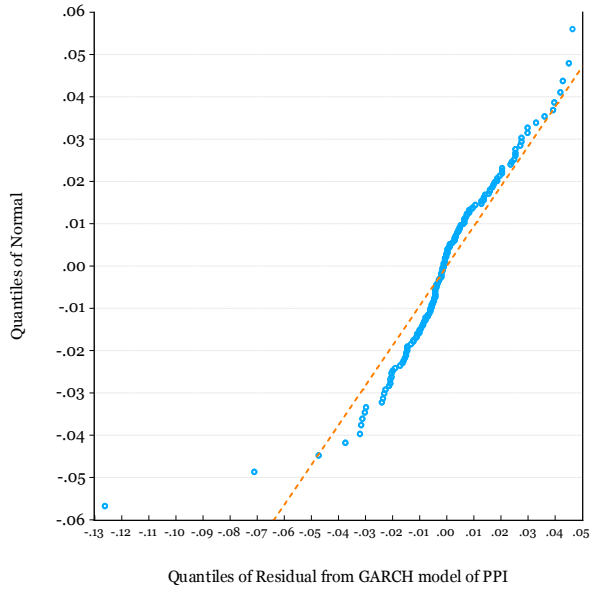
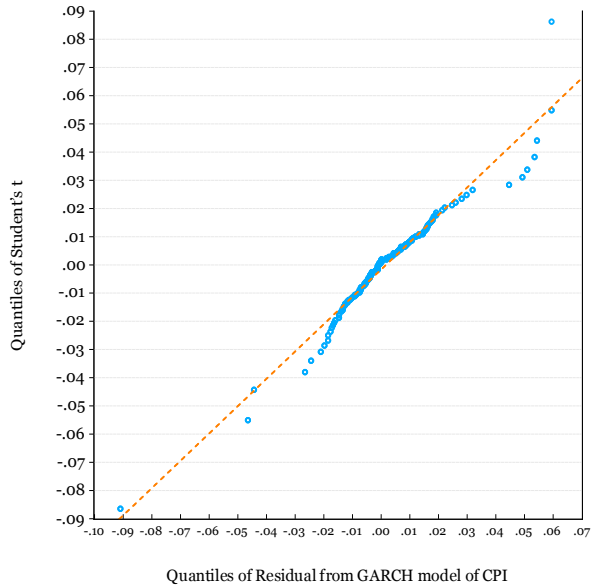
Appendix A

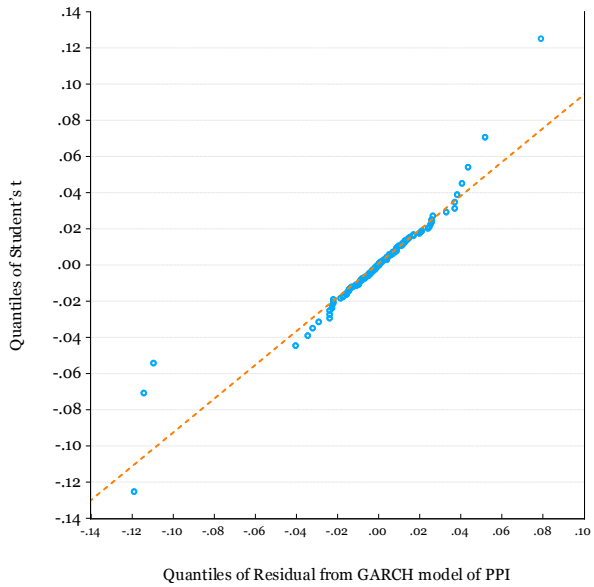
Normal (gaussian) Distribution Assumption





Student-t (fat tailed) Distribution Assumption





Appendix B

*Unit root tests considering structural breaks**

A. Zivot-Andrews variables	t-stat	1% crit. val.	5% crit. val.	10% crit. val.
cpi-beef	-4.63	-5.57	-5.08	-4.82
ppi-beef	-3.62			
import-beef	-3.99			
B. Perron variables	**t-stat**	**1% crit. val.**	**5% crit. val.**	**10% crit. val.**
cpi-beef	-3.29	-6.32	-5.59	-5.29
ppi-beef	-3.61			
import-beef	-4.52			

* See Zivot and Andrews (1992) and Perron (1997) for details of the unit root tests.

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