https://doi.org/10.17221/260/2020-AGRICECON

The impact of agricultural input costs on food prices in Turkey: A case study

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Citation: Işık S., Özbuğday F.C. (2021): The impact of agricultural input costs on food prices in Turkey: A case study. Agric. Econ. – Czech, 67: 101–110.

Abstract: Food price inflation has been a significant subject of debate in Turkey since food prices soared in 2018. The study examines the linkage between agricultural input prices and food prices in Turkey by using quantitative method approaches with the monthly data spanning from 2015-M01 to 2020-M01. A co-integration analysis is performed using the autoregressive-distributed lag (ARDL) bounds test approach and Maki co-integration test with structural breaks. Additionally, the fully modified ordinary least square (FMOLS), dynamic ordinary least squares (DOLS), and canonical co-integrating regression (CCR) are applied to verify the results of the ARDL approach. The analysis demonstrates a significant, long-running relationship between agricultural input prices and food prices in Turkey. The long-run agricultural input price elasticities are found to be in the range of 1.30–1.36.

Keywords: autoregressive-distributed lag (ARDL); food inflation; fully modified ordinary least square (FMOLS); structural breaks; time series analysis

Turkey has experienced high food prices in recent years. The movement of the consumer price index for food and non-alcoholic beverages (food-CPI) is shown in Figure 1 for Turkey and some European countries. The figure clearly indicates a negative divergence of the levels of food-CPI in Turkey from European countries. The difference has become more evident, especially in recent years. For instance, food-CPI in Turkey increased by 18% in 2018 and 19.5% in 2019 compared to the previous year. In the same years, the increase in food-CPI was just 1.9% and 2% in the European Union (28 countries), respectively.

There can be many different factors that explain the high food prices in Turkey, especially in the last five years (the analysis period of the current study). These factors may be weather conditions, agricultural input costs, currency exchange rates, international trade, population growth, income growth, agricultural policy changes, structural changes, etc. In the 2015–2019 period within Turkey, gross domestic product (GDP) from agriculture increased by 3.5% on average in real terms. Also, the production of many vital products such as wheat, barley, maize, and sugar did not change significantly during that period. Although the production of some other products such as potatoes and onions decreased in some periods, it was not critical for the food-CPI. Therefore, there does not appear to be any significant factor that could reduce agricultural production. As to the demand-side factors such as export, population growth, and income growth, no significant change has been observed in the last five years that could increase food prices in Turkey. However, some significant events occurred in the last period that increased the macroeconomic country risk, such as the failed coup attempt on July 15, 2016, tensions between Turkey and the United States, the threat of terrorism, the 2017 Turkish constitutional referendum, elections, new government system, and

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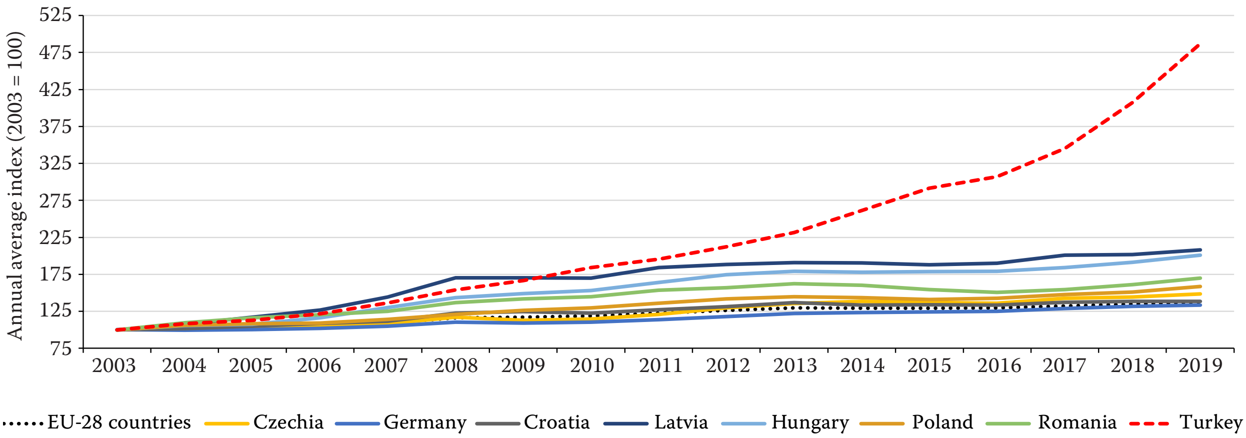

Figure 1. Food-CPI in European Union and Turkey (2003 = 100)

Food-CPI – the consumer price index for food and non-alcoholic beverages
Source: Eurostat (2019)

so on. These events had a substantial impact on some economic indicators such as exchange rates, CPI, and the stock market. Thus, we consider that agricultural input prices play a crucial role in food prices as these inputs are heavily dependent on imports and hence on exchange rates.

In the literature, 2006–2008 global food price crisis has raised concerns about the determinants of food prices for academics, researchers, institutions, and other stakeholders, because the United Nations Food and Agriculture Organization (FAO) food price index increased by 37.7% on average in the second half of 2007 compared to the same month of the previous period and reached its highest annual increase of 58% in March 2008 (FAO 2019). Although numerous factors behind this food price crisis have been extensively analyzed in the literature, the temporary imbalance between demand and supply has been generally seen as the cause of these increases (Bukeviciute et al. 2009).

In the literature, there are also country-based studies that investigate the rises in food prices. Davidson et al. (2011) discuss the determinants of U.K. food inflation in a study. The paper uses a co-integrated vector autoregressive (C-VAR) model over the period 1990–2010. They conclude that world raw food prices and the exchange rate are responsible for U.K. food price inflation. Also, unemployment, earnings, and manufacturing costs are less important. On the other hand, oil prices are indirectly important due to their impact on world agricultural commodity prices. Zhang and Law (2010) study the determinants of food price inflation for China using a triangle model with quarterly data of 1996–2009. They state that demand pressures had been more critical than supply-side shocks from a medium-term perspective. Demand pressures include output gap and excess money, while supply-side factors consist of natural disasters, food production costs, and food yields. Using a co-integration analysis and a vector error-correction (VEC) model, Baek and Koo (2010) investigate the impacts of the exchange rate, prices of agricultural commodities, and energy prices on U.S. food prices throughout 1989–2008. They conclude that food prices in the U.S. are affected by agricultural commodity prices and exchange rates in both the short- and long-term. Moreover, energy prices have a significant impact on U.S. food prices in the long run. Lambert and Miljkovic (2010) analyze the main drivers of U.S. food prices using a vector auto-regression (VAR) model and monthly data for January 1970–February 2009. Their findings indicate that farm prices and manufacturing wages are the main determinants of food prices, rather than consumers' income or he price of other inputs like energy. Rangasamy (2011) examines the food price movements in South Africa for the period 1980 to 2008. The study uses a VAR modeling framework and concludes that domestic influences play an important role in South African food price movements. According to the authors, this means that national policy can reduce the food price inflation in South Africa. Ahsan (2011) conducts a study to examine the determinants of food prices in Pakistan using the autoregressive distributed lag model (ARDL) for 1970–2008. That study finds that supply-side factors such as subsidies and world food prices and demand-side factors such as money supply have a significant impact on food prices in Pakistan. Using a lock VAR, Huh and

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Park (2013) investigate the determinants of food prices in developing Asian countries. In the study, 10 variables classified into three blocks as global, regional, and country variables are used. It is shown that regional shocks play a key role in determining domestic food prices, especially in the medium- and long-term, and global shocks do not contribute much to the domestic food prices in developing Asia. The study also claims that the country's own shock largely explains the short-term movements of domestic food prices. Irz et al. (2013) examine the short-term and long-term dynamics of food price formation in Finland by using the VEC model and monthly data throughout 1995–2010. Their results indicate that the main determinants of food prices are farm prices, wages in food retail, and the price of energy. Using a time series analysis, Sasmal (2015) conducts a study examining price increase in India. While the study shows that an increase in *per capita* income and shortage in supply are the essential drivers of food price inflation in the long run, it cannot find a relationship between money supply and agricultural prices in the long run. Norazman et al. (2018) use a VEC model and monthly data from 1991 to 2013 to investigate the main drivers of food inflation in Malaysia. They state that world food commodity prices and real effective exchange rates are the major determinants of food prices.

As far as Turkey is concerned, Nazlioglu and Soytas (2011) empirically assess the relationship between oil prices, exchange rates, and agricultural commodity prices for the January 1994–March 2010 period. Using the Toda-Yamamoto causality approach and generalized impulse-response analysis, they find that oil prices and exchange rates had a neutral impact on agricultural commodity prices. The current study aims to examine the impact of agricultural input costs on food prices in Turkey by using quantitative method approaches with the monthly data spanning from 2015-M01 to 2020-M01. In doing so, the study employs the agricultural input price index data published for the first time in March 2020 by Turkish Statistical Institute (TurkStat 2020). We use various advanced estimation techniques with significant advantages. The methods we employ can provide efficient results when applied to small samples. Additionally, the ARDL bounds test we use can be applied when the order of integration is purely I(0), purely I(1), or a mixture of both. Furthermore, the other techniques we use [the fully modified ordinary least square (FMOLS), dynamic ordinary least squares (DOLS), and canonical co-integrating regression (CCR)] overcome problems of endogeneity bias and serial correlation (Narayan and Narayan 2004; Alhassan and Fiador 2014; Abu and Staniewski 2019). Accordingly, we obtain robust results that indicate a significant relationship between agricultural input prices and food prices in Turkey. Moreover, retail food prices increase more than agricultural input prices.

DATA, MODEL SPECIFICATION AND METHODS

Data. The monthly data employed in this study consists of the agricultural input price index (AIP) and food and non-alcoholic beverages price index in the consumer prices index (FP). Both sets of data were extracted from the Turkish Statistical Institute (TurkStat) website for the period from January 2015 to January 2020 (TurkStat 2020). The variables were used in logarithmic form and seasonally adjusted with the X-13 ARIMA method developed by the U.S. Bureau of the Census (U.S. Census Bureau 2017).

The AIP with the base year 2015 = 100 was published for the first time by TurkStat in March 2020 (TurkStat 2020). Prior to that, there had been no index showing input prices paid by farmers. This index measured by the Laspeyres formula was prepared according to Eurostat's methodology and regulations and is also suitable for international comparisons. In addition, this index is in Turkish lira, which is the local currency.

The AIP consists of the goods and services (diesel, electricity, fertilizers, pesticides, animal feedingstuffs, etc.) purchased by farmers for use in agricultural production and the goods and services that contribute to agricultural investment [tractors, agricultural equipment, farm buildings (non-residential)]. On the other hand, wage and labor costs, rent, interest payment, and land purchase are not included in the index.

In this context, the study is presumably the first to employ the AIP. Therefore, the results of this study can be expected to make significant contributions to the related literature.

Model specification. This study aims to investigate the impact of agricultural input costs on food prices in Turkey. For this aim, the study estimates the bivariate framework, as expressed in Equation (1).

$$\ln FP_t = \alpha_0 + \alpha_1 \ln AIP_t + \varepsilon_t \quad (1)$$

where: ln – the natural logarithm of the variables; *FP* – the food prices; *AIP* – the agricultural input prices; ε_t – the equation's white noise error term. According to the existing literature, the expected sign of α_1 is positive.

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Methods. A time-series analysis usually begins with unit root tests to investigate the variables' order of integration. Unit root tests that do not take into account structural breaks, such as Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP), are usually used in empirical studies. However, conducting these traditional unit root tests may cause the loss of their power to determine the order of integration of variables in the presence of structural breaks in time series (Perron 1989). Looking at the Turkish economy's development, we can conclude that potential structural breaks occurred in the period 2015–2020. Some examples of those structural breaks include the failed coup attempt on July 15, 2016; tensions between Turkey and the United States because of military operations in Syria, a detained American pastor in Turkey, Turkey's purchase of the S-400 weapons system developed by Russia, and accusing Turkey's Halkbank of violating U.S. sanctions against Iran; the threat of terrorism; 2017 Turkish constitutional referendum and new government system; and so on. Therefore, this study used the Kapetanios (2005) unit root test, which allows up to five structural breaks. Another advantage of the Kapetanios unit root test is that it determines the breakpoints endogenously.

The study examines the co-integration relationship between the variables using the ARDL bounds test developed by Pesaran et al. (2001). However, the test does not determine the breakpoints endogenously, and we do not have a priori information about the number of structural breaks. Therefore, we used the Maki (2012) co-integration test allowing for an unknown number of breaks to determine breakpoints endogenously and to check the result of the ARDL bounds test.

In the Maki (2012) co-integration test, t-statistics are calculated for all possible periods of the breakpoint in a time series. The minimum t-statistic determines the first breakpoint. Then, the test applies the estimated first breakpoint to the sample and searches for the second breakpoint in the same way. Following the above procedure, the process is repeated until k breakpoints have been estimated for each of Models (0, 1, 2, and 3) corresponding to Equations (2–5) respectively:

$$y_t = \mu + \sum_{i=1}^{k} \mu_i D_{i,t} + \beta' x_t + u_t \tag{2}$$

$$y_t = \mu + \sum_{i=1}^{k} \mu_i D_{i,t} + \beta' x_t + \sum_{i=1}^{k} \beta_i' x_t D_{i,t} + u_t \tag{3}$$

$$y_t = \mu + \sum_{i=1}^{k} \mu_i D_{i,t} + \gamma t + \beta' x_t + \sum_{i=1}^{k} \beta_i' x_t D_{i,t} + u_t \tag{4}$$

$$\begin{aligned} y_t = {} & \mu + \sum_{i=1}^{k} \mu_i D_{i,t} + \gamma t + \sum_{i=1}^{k} \gamma_i t D_{i,t} + \beta' x_t + \\ & + \sum_{i=1}^{k} \beta_i' x_t D_{i,t} + u_t \end{aligned} \tag{5}$$

where: $t = 1, 2, \ldots, T$; y_t, $x_t = (x_{1t}, \ldots, x_{mt})$ – observable I(1) variables; u_t – the equilibrium error; γ, γ_i, μ, μ_i, $\beta' = (\beta_1, \ldots, \beta_m)$; $\beta_i' = (\beta_{i1}, \ldots \beta_{im})$ – true parameters; $D_{i,t}$ takes a value of 1 if $t > T_{Bi}$, $i = (1, \ldots, k)$ and of 0 otherwise, where k is the maximum number of breaks and T_{Bi} – the time period of the break.

Equation (2) is the Model (0) with level shifts. Equation (3) denotes the Model (1), which is called the regime-shifts model. Equation (4) is the Model (2) with a trend. Finally, Equation (5) is the Model (3), which constitutes structural breaks of levels, trends, and regressors. Maki's method is based on the Kapetanios (2005) unit root test with structural breaks. The null hypothesis is no co-integration, and the alternative hypothesis is co-integration with i breaks.

The study employs the ARDL Bounds Test developed by Pesaran et al. (2001) to test the long-run and short-run dynamics. In doing so, we estimate the ARDL equation as follows:

$$\begin{aligned} \Delta\ln FP_t = {} & \beta_0 + \sum_{i=1}^{n} \beta_{1i} \Delta\ln FP_{t-i} + \sum_{i=1}^{n} \beta_{2i} \Delta\ln AIP_{t-i} + \\ & + \lambda_1 \ln FP_{t-1} + \lambda_2 \ln AIP_{t-1} + e_t \end{aligned} \tag{6}$$

where: Δ – the first difference operator; e_t – the error term. The error term is assumed to be white noise, normally and identically distributed.

Based on Equation (6), the long-term relationship between agricultural input prices and food prices is investigated via the standard F- and t-statistics. The null hypothesis is no co-integration, and the alternative hypothesis is co-integration.

Additionally, if there is a long-run or co-integrating relationship between the variables, the study estimates the short-run coefficients using the error correction model as follows:

$$\begin{aligned} \Delta\ln FP_t = {} & \gamma_0 + \sum_{j=1}^{n} \gamma_{1i} \Delta\ln FP_{t-i} + \sum_{j=1}^{n} \gamma_{2i} \Delta\ln AIP_{t-i} + \\ & + \psi ECT_{t-1} + \vartheta t \end{aligned} \tag{7}$$

where: ECT_{t-1} – the error correction variable that represents the speed of adjustment to converge back to the long-run equilibrium following a deviation from the short-run equilibrium. It should be between 0 and –1.

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As alternatives to the ARDL model, the study employs three other estimation techniques to investigate the long-run elasticities for the variables. These are the FMOLS of Phillips and Hansen (1990), DOLS of Stock and Watson (1993), and CCR of Park (1992).

The ARDL, FMOLS, DOLS, and CCR methods have significant advantages. For instance, these methods can provide efficient results when applied to small samples. In addition, the ARDL bounds test can be applied when the order of integration is purely I(0), purely I(1), or a mixture of both. Moreover, the FMOLS, DOLS, and CCR techniques overcome problems of endogeneity bias and serial correlation (Narayan and Narayan 2004; Alhassan and Fiador 2014; Abu and Staniewski 2019).

RESULTS AND DISCUSSION

To investigate the variables' order of integration, the Kapetanios (2005) unit root test, which allows five structural breaks and determines the break dates endogenously, was employed. Under this unit root test there are three models: Model (A), (B), and (C). However, Sen (2003a) states that Model C should be preferred when the breakpoint is treated as unknown. In his other study, Sen (2003b) also shows that Model C provides more reliable results. Therefore, Model C was specified as appropriate in this study. The results of the Kapetanios (2005) unit root test are reported in Table 1.

The test statistics clearly show that both *FP* and *AIP* have the same order of integration, which is I(1). Therefore, conducting the Maki (2012) co-integration test allowing for an unknown number of breaks has become possible to decide whether there is a long-term relationship between the variables. Table 2 summarizes the result of the Maki co-integration test.

According to the results in Table 2, there is a long-term relationship between food prices and agricultural input prices with structural breaks for Model (0), Model (1), and Model (3). Considering the break dates determined by the co-integration test, two dates come to the fore: October 2017 and October 2018. Therefore, these dates are included in subsequent models as dummy variables.

Table 1. The result of Kapetanios (2005) unit root test with endogenous structural breaks

Variable	Test-statistics	Critical values (%)			Break dates
		1	5	10	
ln*FP*	−7.688	−9.039	−8.343	−8.016	2017-M08, 2016-M06, 2019-M04, 2018-M02, 2016-M12
ln*AIP*	−5.090	−7.401	−7.006	−6.686	2017-M04, 2019-M07, 2016-M07
Δln*FP*	−8.848**	−9.039	−8.343	−8.016	2018-M10, 2017-M03, 2018-M03, 2019-M04, 2015-M10
Δln*AIP*	−8.965***	−7.401	−7.006	−6.686	2018-M06, 2017-M06, 2016-M10

***, **Significance level at 1% and 5%, respectively; Model C, which allows structural breaks in intercept and deterministic trend, is used; Δ – the first difference operator; *AIP* – agricultural input prices; *FP* – food prices
Source: The critical values are obtained from Kapetanios (2005); own calculation based on TurkStat (2020)

Table 2. The result of Maki (2012) co-integration test with endogenous structural breaks

Model	Test-statistics	Critical values (%)			Break dates
		1	5	10	
Model (0)	−5.261**	−5.776	−5.230	−4.982	2015-M05, 2016-M06, 2017-M06, 2018-M10
Model (1)	−7.882***	−6.193	−5.699	−5.449	2016-M07, 2017-M10, 2018-M03, 2018-M10, 2019-M08
Model (2)	−4.866	−6.915	−6.357	−6.057	2017-M06, 2018-M05, 2018-M09, 2018-M12, 2019-M07
Model (3)	−7.072***	−6.620	−6.100	−5.845	2017-M10, 2018-M10

***, **Presence of the co-integration relationship between the variables at the significance level of 1% and 5%, respectively
Source: The critical values are obtained from Maki (2012); own calculation based on TurkStat (2020)

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In October 2017, the deteriorating relationship between the U.S. and Turkey was decisive for the Turkish economy. Both the U.S. and Turkey mutually suspended visa applications on October 8, 2017, after the arrest of a U.S. consulate employee in Turkey. The rising tension led to adverse effects on the domestic markets in Turkey. In just one day (October 9), the Turkey Stock Market (BIST 100 Index) dropped by 2.73%. The U.S. dollar/Turkish lira exchange rate rose by 3.24%. Furthermore, the compound interest rateof 2-year benchmark bond increased by 51 basis points.

Another important date for structural breaks is October 2018. The Turkish economy had a challenging year in 2018. In the June 24 elections, the new government system called the "Presidential System of Government" came into effect. Moreover, the event of American Evangelical Pastor Andrew Brunson held in jail in Turkey led to one of the gravest crises in the history of Turkey-U.S. relations. The pastor was indicted on charges of espionage and links to terror groups in Turkey. However, the U.S. asked for the pastor's release and announced that it would impose sanctions if not released. In August, the U.S. imposed sanctions on two Turkish ministers who had played a role in Brunson's detention and doubled tariffs on steel and aluminum imported from Turkey. Turkey responded with retaliatory sanctions to these sanctions. All of these caused a deterioration in the leading economic indicators in Turkey. In the first eight months of 2018, the Turkish lira depreciated by 41%. The Turkish economy, which grew by 7.4% in the first quarter of the year, contracted by 2.8% in the last quarter. CPI reached its peak in October 2018 with 25%. Also, food prices increased by about 30% in that month.

We re-examine the co-integration relationship between the variables with the ARDL bounds test using the dummy variables for 2017-M10 and 2018-M10. The results are reported in Table 3.

The ARDL bounds test for co-integration involves the *F*-bounds test and *t*-bounds test. Both the calculated *F*-statistic and *t*-statistic are higher than upper bounds I(1) critical values at the significance level of 1% and 5%, respectively. These results clearly

Table 3. The results of bounds test for co-integration

	Critical values (%)		
	1	5	10
Panel A: *F*-bounds test			
Lower bounds I(0)	6.84	4.94	4.04
Upper bounds I(1)	7.84	5.73	4.78
F-statistic		8.49***	
Panel B: *t*-bounds test			
Lower bounds I(0)	–3.43	–2.86	–2.57
Upper bounds I(1)	–3.82	–3.22	–2.91
t-statistic		–3.54**	
Panel C: Diagnostic tests			
R^2		0.996	
Adjusted R^2		0.9955	
F-statistic		1 771.085 (0.00)	
Jarque-Bera		0.908 (0.64)	
Breusch-Pagan-Godfrey for heteroskedasticity		1.677 (0.14)	
Breusch-Godfrey Lagrange multiplier test	[1]: 1.730 (0.195), [2]: 0.853 (0.433), [3]: 0.741 (0.533), [4]: 0.550 (0.700), [5]: 0.457 (0.806), [6]: 0.539 (0.776), [7]: 0.508 (0.823), [8]: 0.462 (0.876), [9]: 0.705 (0.701), [10]: 0.620 (0.788), [11]: 0.552 (0.855), [12]: 0.791 (0.657)		

***, **Presence of the co-integration relationship between the variables at the significance level of 1% and 5%, respectively; the optimal lag length: (4, 0); the optimal lag length for the autoregressive-distributed lag model was chosen based on the Akaike information criterion (AIC); case III: unrestricted intercept and no trend (*k* – the number of exogenous variables; *k* = 1) critical values are obtained from Pesaran et al. (2001); dummy variables were added for the 2017-M10 and 2018-M10; [·] – the diagnostics tests order; (·) – the *P*-values

Source: Own calculation based on TurkStat (2020)

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indicate that the food prices and agricultural input prices in Turkey have a long-run or co-integrating relationship over the analysis period of 2015-M01 to 2020-M01. Also, the results of the bounds test confirm the results of the Maki (2012) test. Since the co-integration relationship is determined between variables used in the model, we can estimate the long-term coefficients and error correction terms from short-run dynamics. These are shown in Table 4.

Long term ARDL estimation results reveal that agricultural input prices are highly effective on food prices. In other words, a 1% increase in agricultural input prices increases food prices by 1.36%. Table 4 also indicates the error correction term, which is the speed of adjustment to converge back to the long-run equilibrium. As expected, this is between 0 and –1, and highly significant. A significant error correction term also indicates the existence of a long-run relationship between the variables. In the short-run, the system is converging to the long-run equilibrium at a rate of 34.1%.

Next, the study assesses the stability of the long-run relationship between the variables depending on cumulative sum (CUSUM) and cumulative sum of the square (CUSUM) tests proposed by Brown et al. (1975). These tests are based on the cumulative sum of recursive residuals. If the graphs of CUSUM and CUSUM-squared statistics stay within the critical bounds at a 5% significance level, we conclude that the estimates are stable. The results of these tests are shown in Figure 2. Both CUSUM and CUSUM-squared tests do not indicate evidence of any significant structural instability for the estimated parameters of the ARDL (4, 0) model.

The FMOLS, DOLS, and CCR approaches were also used in the study to check the robustness of long-term elasticities obtained from the ARDL model. Table 5 reports the outcomes of these alternative techniques.

As seen in Table 5, the results of the FMOLS, DOLS, and CCR support the results of the ARDL long-run model. According to these three alternative approaches, a 1% increase in agricultural input prices increases food prices between 1.30% and 1.33% at the 1% level. This means that food prices increase more than agricultural input costs. These results can be explained in three ways.

The first explanation can be related to competition in the food supply chain, especially in the retail industry. The top five supermarket chains in terms of the total number of branches in Turkey are A101, BİM, ŞOK, Migros, and Ekomini. These firms can play a dominant role in the industry by preventing price competitiveness. They can see an increase in input costs as an opportunity for a price increase.

The second reason can be related to the analysed period. Our analysed period is five years (61 months) because the data of the agricultural input price index published by Turkstat is available from January 2015. The available data is sufficient for our analysis. However,

Table 4. Results of short-run and long-run coefficients from the autoregressive-distributed lag model (dependent variable: ln*FP*)

Variables	Coefficient	Standard error	*t*-statistics	*P*-values
Panel A: Short run results				
$\Delta \ln FP_{t-1}$	0.337***	0.116	2.913	0.005
$\Delta \ln FP_{t-2}$	–0.297**	0.114	–2.611	0.012
$\Delta \ln FP_{t-3}$	0.204*	0.112	1.824	0.074
$\Delta \ln AIP$	0.463***	0.115	4.042	0.000
Δdum (2017-M10)	–0.016	0.010	–1.670	0.101
Δdum (2018-M10)	–0.018*	0.009	–1.950	0.057
ECT_{t-1}	–0.341***	0.096	–3.537	0.001
Panel B: Long run results				
$\ln AIP$	1.359***	0.132	10.316	0.000
Dum (2017-M10)	–0.047*	0.026	–1.830	0.073
Dum (2018-M10)	–0.054	0.035	–1.534	0.131
Constant	–0.563	0.610	–0.923	0.360

***, **, *Significance level of 1, 5, and 10%, respectively; Δ – the first difference operator; *AIP* – agricultural input prices; dum – dummy variables; ECT_{t-1} – the error correction term; *FP* –food prices

Source: Own calculation based on TurkStat (2020)

https://doi.org/10.17221/260/2020-AGRICECON

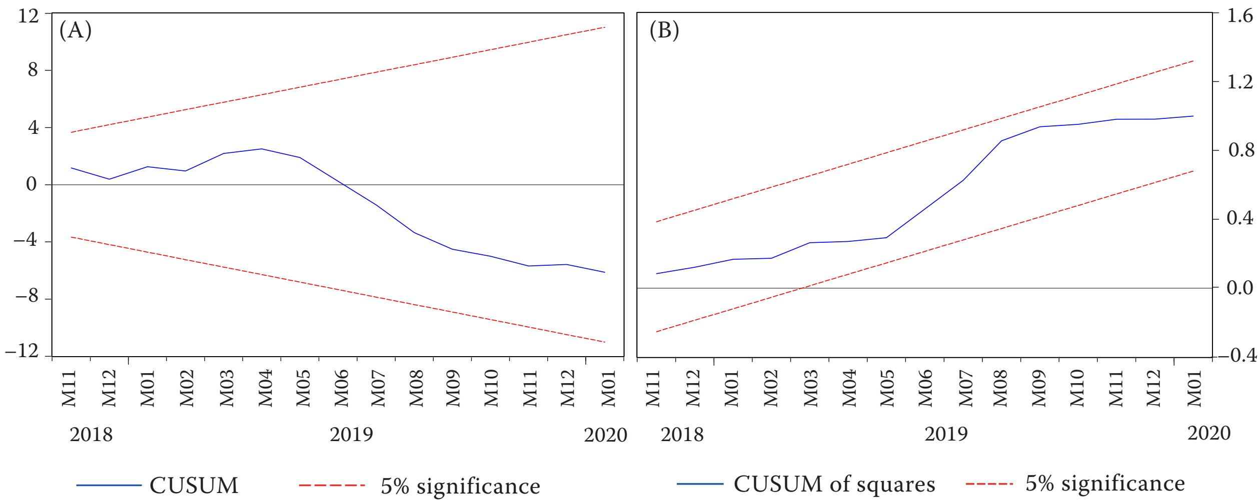

Figure 2. Results of (A) cumulative sum (CUSUM) and (B) cumulative sum of the square (CUSUMSQ) test
Source: Own calculation based on TurkStat (2020)

in further studies with more data, the elasticity coefficient may decrease the the analysed period extends.

Finally, factors that increase agricultural input costs may also increase other costs in the supply chain. For instance, an increase in oil prices can cause increases in both agricultural production costs and transportation costs. Thus, retail food prices can increase more than agricultural input prices.

Table 5. Results of alternative approaches (dependent variable: ln*FP*)

Variables	Coefficient	Standard error	*t*-statistics	*P*-values
Panel A: FMOLS (fully modified least squares)				
ln*AIP*	1.327***	0.071	18.741	0.000
Dum (2017-M10)	–0.067***	0.017	–3.950	0.000
Dum (2018-M10)	–0.022	0.017	–1.326	0.190
Constant	–0.421	0.329	–1.278	0.206
Jarque-Bera		1.364 (0.506)		
Panel B: DOLS (dynamic least squares)				
ln*AIP*	1.298***	0.087	14.943	0.000
Dum (2017-M10)	–0.055***	0.020	–2.744	0.008
Dum (2018-M10)	–0.022	0.024	0.919	0.362
Constant	–0.283	0.403	–0.703	0.485
Jarque-Bera		0.854 (0.652)		
Panel C: CCR (canonical cointegrating regression)				
ln*AIP*	1.325***	0.072	18.475	0.000
Dum (2017-M10)	–0.066***	0.017	–3.974	0.000
Dum (2018-M10)	–0.022	0.017	–1.254	0.215
Constant	–0.412	0.333	–1.236	0.222
Jarque-Bera		1.313 (0.519)		

***, **, *Significance level of 1, 5, and 10%, respectively; the Newey-West estimation method in our regressions is employed to obtain heteroskedasticity and autocorrelation-consistent standard errors; the DOLS estimation does not include the lags and leads based on the Schwarz information criterion; *AIP* – agricultural input prices; dum – dummy variables; *FP* – food prices; (·) – the *P*-values
Source: Own calculation based on TurkStat (2020)

https://doi.org/10.17221/260/2020-AGRICECON

CONCLUSION

The paper investigates the impact of agricultural input costs on retail food prices in Turkey by using various quantitative methods. In doing so, we employed the agricultural input price index published for the first time in March 2020 by TurkStat and the food price index in CPI for the period from January 2015 to January 2020.

The empirical analyses, taking into account the structural breaks, have clearly demonstrated that agricultural input costs have a significant impact on food prices. Moreover, the ARDL, FMOLS, DOLS, and CCR methods have presented robust results showing that a percentage increase in agricultural input prices increases food prices between 1.30% and 1.36%. This means that food prices increase more than agricultural input costs. This finding can be explained in three ways. The first explanation can be related to competition in the retail industry. The first five supermarket chains can play a dominant role in the industry by preventing price competitiveness. They can see an increase in input costs as an opportunity for a price increase. The second reason can be related to the analysis period. In further studies with more data, the elasticity coefficient may decrease since the analysis period extends. Finally, factors that increase agricultural input costs may also increase other costs in the supply chain. Thus, retail food prices can increase more than agricultural input prices.

In short, this study with robust results states that agricultural input prices play a pivotal role in Turkey's food prices. Thus, food price stability can be achieved by preventing the increase in agricultural input costs. Also, the adverse impacts of high food prices on the economy and poor citizens can be eliminated by stable food prices.

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Received: July 1, 2020
Accepted: January 30, 2021