The Australian Journal of
Agricultural and
Resource Economics

AARES
AUSTRALASIAN AGRICULTURAL & RESOURCE ECONOMICS SOCIETY

Australian Journal of Agricultural and Resource Economics, 66, pp. 187–215

The role of temperature for seasonal market integration: a case study of poultry in Iran*

Omid Zamani, Thomas Bittmann and
Jens-Peter Loy[†]

Understanding market integration has greatly benefited from analysing and comparing variations in price transmissions. An important source of variation in agricultural markets is seasonal changes in production, consumption and transaction costs. A key factor driving seasonality in agricultural price is temperature, as supply and demand changes are triggered by seasonal temperature differences. In this paper, we study the seasonal variations in vertical price transmission focusing on the asymmetric price adjustment to analyse changes in the market interactions between the stages of the value chain. Our data reveal significant transitory effects of temperature on the price transmission process. Results of a panel threshold model suggest that the farm–wholesale price adjustments to deviations from the market equilibrium are more symmetric at higher temperatures. However, we do not find an effect of temperature on the wholesale–retail price relationship. Our findings can be rationalised with wholesalers making use of their market power to extend their margins in the upstream chain. Wholesaler market power is lower during warm periods, and price adjustment is more symmetric. Concerning the Iranian poultry value chain, our findings imply that temperature-related differences in market interactions should be considered in formulating policy interventions.

Key words: Iran, poultry chain, price transmission, seasonality, temperature.

JEL classifications: Q11, Q13, L13

1. Introduction

Many agri-food markets show seasonal price movements due to variations in supply and demand (Gilbert et al., 2017; Kaminski et al., 2016). Some evidence shows that the seasonal co-movements of prices along vertical chains may cause the margins and market structures to change throughout

* We thank two anonymous referees, the associate editor and Dr. Shyamal Chowdhury for the helpful comments. The authors acknowledge financial support by H. Wilhelm Schaumann Stiftung.

[†] Omid Zamani (e-mail: omid.zamani@thuenen.de) is a research associate at the Thünen Institute of Market Analysis, Bundesallee 63, 38116, Braunschweig, Germany. Department of Agricultural Market Analysis, Institute of Agricultural Economics, Christian-Albrechts-University Kiel, Olshausenstraße 40, 24118 Kiel, Germany. Thomas Bittmann is a postdoctoral research associate at the Department of Agricultural Market Analysis, Institute of Agricultural Economics, Christian-Albrechts-University Kiel, Olshausenstraße 40, 24118 Kiel, Germany. Jens-Peter Loy is a full professor at the Department of Agricultural Market Analysis, Institute of Agricultural Economics, Christian-Albrechts-University Kiel, Olshausenstraße 40, 24118 Kiel, Germany.

doi: 10.1111/1467-8489.12443

seasons. Arnade and Pick (2000: 696) argue: 'in a market which is characterized by seasonality…, it is quite possible to observe oligopoly power during different months of the year'. Similarly, Lundberg et al., (2020) present empirical evidence of seasonal changes in the price transmission rates of several agricultural commodities including the US broiler market.

In this paper, we empirically analyse the seasonal variations of the vertical price relationships in the Iranian poultry market chain. Dealing with seasonality in agricultural commodity markets is generally a complex issue. The literature introduces three major time series models to investigate seasonal effects: (1) deterministic seasonality, (2) stationary stochastic seasonality and (3) seasonal unit roots (Ghysels et al., 2001). In this sense, some related empirical works use seasonal statistical tests such as HEGY-type tests inspired by Hylleberg et al., (1990) and Canova and Hansen (1995). Furthermore, seasonality has been modelled by deterministic fixed dummies defining seasons (e.g. Amikuzuno & von Cramon-Taubadel, 2012; Bittmann & Anders, 2016; Mehta & Chavas, 2008). This is a convincing approach, if the key factors behind seasonal variations are unknown or if specific data are not available. This approach appears to be inaccurate if seasons cannot be identified a priori (Cáceres-Hernández & Martín-Rodríguez, 2017). As Willenbockel (2012) and Hertel and Lima (2020) find, supply shocks and price spikes in the agricultural markets are triggered by temperature changes. Temperature is the most critical factor to ensure quality and to reduce losses of perishable foods during transportation (Aung & Chang, 2014). Transportation and production costs increase with temperature. Official estimations for the Iranian poultry industry show that a significant share of wholesale marginal costs is associated with losses during transportation from farmers to retailers (Fatemiamin & Mortezaie, 2013). Due to the additional production costs, the poultry supply drops during the summer months in Iran (Gilanpour et al., 2012). Thus, poultry prices follow a cyclical pattern with a peak in the summer months (Keshavarz, 2006).

The mark-up between prices and costs is an indicator of market power. Ceteris paribus, in the linear demand case a seasonal increase in (transaction and transportation) costs reduces the gap between prices and costs measured by the Lerner Index. Market power leads to a reduced price transmission rate. In the linear demand case with constant marginal costs, the price transmission elasticity decreases to fifty per cent in the monopoly case compared with 100% under perfect competition (see Bulow & Pfleiderer, 1983). Thus, under market power, seasonal changing transaction costs may lead to seasonal to reduced price transmission elasticities. However, non-linear demand and non-constant marginal costs can change this outcome (Weyl & Fabinger, 2013).

Seasonal price dynamics due to temperature variations may have important marketing and policy implications. The current policy intervention in the Iranian poultry industry, which we discuss in more detail in Section 3, is a buffer stock scheme implemented in 2002. Governmental institutions determine ceiling and floor prices according to the average production costs including a profit margin. The public institutions do not intervene within the floor and ceiling price range. Outside this range, poultry meat is bought and stored. The public interventions can further reinforce the market power of firms in the winter and fall when the poultry meat is usually acquired through a buffer stock scheme. The policy intervention may contrarily affect competition if no accurate prediction is available regarding price dynamics during different periods.

With this paper, we contribute to the existing literature on food price transmission, cost pass-through and seasonal price patterns in several ways. The present study empirically analyses the potential effects of temperature variations on price dynamics in the value chain of the Iranian poultry industry. The analysis primarily aims to shed light on the importance of temperature in predicting seasonal market functioning at the farm, wholesale and retail levels. We model the stable relationship between the prices, yet the relationship may vary with the seasonal fluctuating temperatures. A panel threshold error correction model is employed to a recent high-frequency panel data set of the farm, wholesale, and retail prices for all thirty provinces in Iran over the period from 2010 to 2016. Results indicate incomplete vertical price transmission at the wholesale level and a complete pass-through at the retail level.[1] In line with previous research, we interpret these findings as evidence of wholesaler market power (Hassouneh et al., 2012; Hosseini et al., 2012; Saghaian et al., 2008). The econometric estimates reveal that asymmetric price adjustment from farm to wholesale level decreases with temperature. To put it differently, the ‘rockets and feathers’ phenomenon is more pronounced during periods of low temperatures. Our findings have significant implications for policymakers and provide empirical evidence on the application of weather-related factors to predict the functioning of markets. To our knowledge, this is the first study using temperature as the key factor of seasonal variations in investigating asymmetric vertical price adjustments or cost pass-through. The results allow us to identify seasonal changing market conditions along different stages of the poultry food supply chain.

The paper is structured as follows: In the second section, we review the existing literature on price transmission along the poultry value chain and discuss the potential impact of temperature on prices and price transmission. In Section 3, we describe the general structure of the Iranian poultry market supply chain. Section 4 describes and discusses the data under study. Section 5 presents the empirical model specifications. In Section 6, we present and discuss the empirical estimates. Finally, in Section 7, we summarise our findings and derive policy implications.

[1] The terms vertical price transmission and pass-through are used interchangeably in this paper.

2. Literature review on vertical price transmission

How price signals transmit along the food supply chain is an indicator for the well-functioning of markets (Lloyd, 2017; Rapsomanikis et al., 2006). The extent to which price transmission interacts with explanatory variables has important implications concerning the evaluation of market performance, marketing decisions and policy recommendations. Along with search cost and menu cost, market power is often cited as a cause of asymmetric price transmission (Hassouneh et al., 2012; Lloyd, 2017; Loy et al., 2016; Meyer & von Cramon-Taubadel, 2004; Vavra & Goodwin, 2005). Market power allows market participants to delay price–cost shocks in their favour. For example, wholesalers may delay price decreases, while they push price increases. This particular price adjustment process is called the 'rockets and feathers' phenomenon, which is observed in many studies on agricultural and other commodity markets (e.g. Loy et al., 2014; Peltzman, 2000; Rezitis & Tsionas, 2019; Surathkal & Chung, 2017).

The existing literature has identified several determinants of vertical market integration in the poultry sector. Early works by Bernard and Willett (1996) and Vavra and Goodwin (2005) confirm a significant asymmetric price relationship along the US vertical poultry chain. The authors, however, do not discuss the drivers behind the asymmetric behaviour. Several studies simulate the consequences of bird flu outbreaks on price dynamics in the poultry value chain. Saghaian et al., (2008) and Mutlu Çamoğlu et al., (2015) assess the implications of the avian influenza outbreaks in the Turkish poultry market by focusing on price transmission. They find that retail prices respond more strongly to the outbreak than producer prices. According to the authors, market power can explain the change in retail margins. Applying a regime-dependent model, Acosta et al., (2020) show a similar result for the effects of the highly pathogenic avian influenza outbreak and the antitrust intervention on the vertical integration of the Mexican egg market. Moreover, Park et al., (2008) analyse the effects of livestock disease outbreaks in South Korea and the bovine spongiform encephalopathy outbreaks in the United States on the Korean poultry market. They report that the price transmission process tends to be more asymmetric and the retail-to-wholesale margins expand in reaction to both disease outbreaks. Hassouneh et al., (2012) investigate the potential outcomes of food scarcity for price dynamics along the Egyptian poultry value chain. Using a food safety index as the exogenous transmission variable, they argue that the food scare shock creates a situation in which retailers exert market power to increase their margin.

In these papers, the effects of seasonality on the price transmission process are not considered. In one of the first studies, Goodwin et al., (2002) estimate the role of mechanical refrigeration adoption on the US butter price transmission. The study suggests that mechanical refrigeration adoption has a significant impact on both temporal and spatial market integration by mitigating the impact of temperature-induced seasonality. Mehta and Chavas (2008) find evidence of seasonality in price transmission in the Brazilian coffee market. The impact of seasonality differs along the stages of the coffee value chain. Bittmann and Anders (2016) report a higher speed of adjustment of retail prices in the fall due to a change in input composition and seasonal changing market conditions in the Canadian retail sector. Amikuzuno and von Cramon-Taubadel (2012) analyse seasonality in spatial price adjustment among regional tomato markets in Ghana. They find that changing sources of supply between major production areas over the year is the main reason for seasonal asymmetries in price transmission. As storage may dampen seasonal differences in production, seasonal patterns are more likely to occur for perishable products (Amikuzuno & von Cramon-Taubadel, 2012). For example, due to the perishability of the product traders may delay the transmission of price increases to prevent the risk of spoilage during warm seasons (Kim & Ward, 2013). In recent work, Lundberg et al., (2020) analyse seasonal patterns in the price transmission process of the US broiler market applying a frequency-domain framework. The authors suggest that seasonality in the price transmission process is significantly driven by changes in transportation costs.

Transportation costs between farmers and wholesalers are significant in the case of the Iranian poultry chain (Fatemiamin & Mortezaie, 2013; Hosseini et al., 2015). Some of the transaction costs are due to ice(berg) transport costs, which are directly related to temperature (Bosker & Buringh, 2020; Glaeser & Kohlhase, 2004; Irarrazabal et al., 2015).[2] Poultry production is highly affected by temperature (Meremikwu et al., 2013; Shakeri et al., 2020; Vieira et al., 2019).There is a significant relationship between elevated temperature during hot seasons and poultry losses, due to mortality and heat stress in transit from farmer to wholesaler (Mitchell & Kettlewell, 2009; dos Santos et al., 2020). These cost increases in the summer periods may drive up seasonal price dynamics especially for perishable products such as fresh poultry meat.

Due to the significant role of the poultry market for food security in Iran, price transmission analysis in this market has always been an important topic for Iranian agricultural economists (e.g. Hosseini et al., 2012; Hosseini et al., 2008; Moghaddasi & Nuroozi, 2010; Pishbahar et al., 2019; Shadmehri, 2014). Market integration has been investigated in this market using various techniques and data sets. Although all studies communally emphasise market integration along the Iranian poultry chain, their findings are mixed in terms of integration level and asymmetry direction. Shadmehri (2014) reports that the retail index price responds symmetrically to changes in farm prices. Many other studies find asymmetric price adjustments in the same market (e.g.

[2] Iceberg transport costs are an important concept in modern trade and economic geography models. A certain proportion of transported goods is assumed to ‘melt in transit’ (Boskers and Buringh, 2020).

Hosseini et al., 2012; Hosseini et al., 2008; Moghaddasi & Nuroozi, 2010; Pishbahar et al., 2019). Market power at the wholesale level is often highlighted as the primary source of asymmetry in the Iranian poultry industry (Gilanpour et al., 2012; Hosseini et al., 2012; Zamani et al., 2019). Despite many debates in the media, there is little empirical evidence on the degree of seasonal changing market integration in the poultry supply chain. Rasouli et al., (2011) find evidence of seasonality in spatial market integration, while Pishbahar et al., (2015) do not find seasonal patterns in the price dynamic between input costs and farm prices.

3. The poultry market in Iran

The Iranian poultry industry has a substantial role in food security by providing the primary source of protein for the country's population. Official reports indicate that in 2019, more than 2.73 million metric tonnes of poultry meat are produced by 16 thousand commercial broiler farmers (Iranian Agricultural Ministry, 2020). From the demand perspective, the per capita consumption of poultry meat has expanded significantly during the last decades and reached 33 kg per capita in 2019 (Iranian Agricultural Ministry, 2020). Poultry meat production is majorly used to cover domestic demand. The share of exports (4.5 thousand tonnes) and imports (2.8 thousand tonnes) of total supply is less than one per cent (United Nation Trade Statistics, 2019). More than 90 per cent of the market supply consists of highly perishable poultry meat, which normally has a shelf life of one or two weeks (Iranian Agricultural Ministry, 2018). The retail chain is dominated by numerous small-scale stores. Official statistics indicate that the market concentration is significantly higher at the wholesale and processor levels. For 2016, the number of commercial broiler slaughterhouses is 243 with an annual slaughtering capacity of 1.8 billion pieces (Alimalayeri, 2018). Moreover, large wholesalers often own slaughterhouses (Hosseini et al., 2012). The combined margin of wholesalers and slaughterhouses is estimated at 65.7% compared to retailers and producers with 15 and 9.3%, respectively (Khaledi et al., 2010). Thus, wholesalers are likely to exert market power over retailers (Gilanpour et al., 2012). Figure 1 presents the different stages involved in the typical poultry value chain in Iran including the point of price data observation.

Adopted in 2002, the most recent public intervention in the poultry market consists of a buffer stock scheme and a Market Regulation Commission (MRC). This policy scheme aims at stabilising prices in the poultry value chain (Gilanpour et al., 2012). Authorised by the institution of the presidency, the MRC annually (or in face of severe shocks to the market) proposes a price bound, which is estimated according to production costs (including an 8% margin for producers). Within the proposed bounds, there is no market intervention. If the price exceeds the bounds, a public–private company, known as State Livestock Affairs Logistics (SLAL), buys poultry

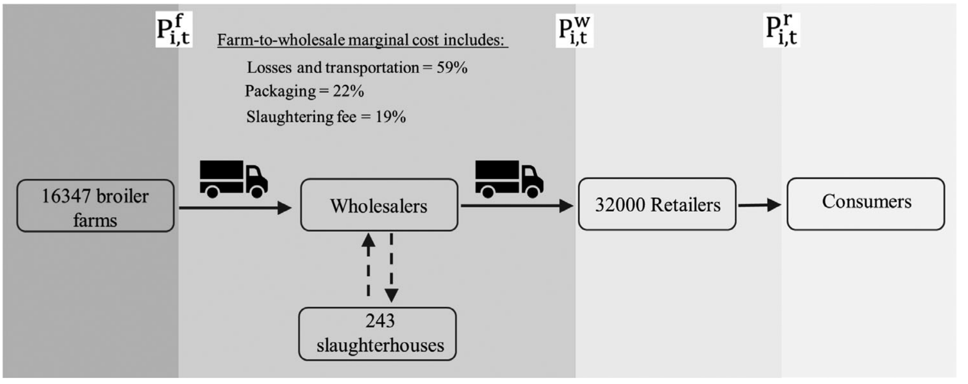


Figure 1 Iranian poultry value chain.
Note: The figure presents Iran's poultry value chain. Retail ($P^r_{i,t}$), wholesale ($P^w_{i,t}$) and farm ($P^f_{i,t}$) prices are defined in the next section.
Source: Own representation based on data from the Iran Ministry of Agriculture (2020). The number of retailers (butcher's shops) is retrieved from: www.senf.ir

meat from the market in the winter and resells frozen poultry meat in the summer. Apart from supermarkets, frozen poultry is supplied through seasonal outlets launched by the Ministry of Agriculture and Local Municipalities.

According to a survey by the Statistical Center of Iran (2015), 54 per cent of the total production is concentrated in seven provinces. Besides, 66 per cent of the slaughtering capacity (about 100 slaughterhouses) is located in eight provinces, while only 47 per cent of the poultry production is located in these provinces (Hosseini et al., 2012). During different seasons, productions of either poultry meat or live birds are transported from the regions with a better production condition to other regions. Accordingly, transport losses and costs are key factors to decide whether live birds are slaughtered and transported to demand regions or whether live birds are transported to the slaughterhouses of other regions. Although the transport costs of live birds are lower than those of poultry meat, the induced transport losses are higher for live birds. In 2013, the average transportation costs of poultry meat were about 9 per cent higher than transportation costs of live birds (Iran Road Maintenance & Transportation Organization, 2013).

4. Data

We employ two data sets in this study. First, a weekly panel data set on fresh poultry meat prices at three subsequent stages of the chain (retail, wholesale and farm level) is compiled. The price series are collected from the spot markets by State Livestock Affairs Logistics (2017). Retail and wholesale price series are deflated using the consumer price index. The farm prices are deflated by the producer price index (PPI). An analogous strategy has been applied by Bukeviciute et al., (2009) and Kalkuhl et al., (2016) to analyse agricultural price dynamics[3]. All prices are presented per kilogram of fresh poultry meat. The panel data set covers prices for 30 provinces starting with the third week of April 2010 through the second week of June 2016, summing up to 9,720 observations (324 weeks for 30 regions) for each variable.

Second, this study makes use of monthly temperature data from the Iran Meteorological Organization. The panel data set on temperature covers 2220 observations (74 months for 30 regions). Iran has diverse climate conditions over regions. Appendix 2 presents the average temperature of individual regions. To show the variations in prices at the farm, wholesale and retail levels, Figure 2 reports the evolution of average prices from 2010 through 2016.

All three-price series co-move closely. The average retail margin is considerably lower than the wholesale margin. The relative wholesale margin covers 85% of the entire chain margin, while the retail margin is only 15 per cent on average.

Table 1 presents summary statistics of the main variables used in this analysis, including deflated prices, relative margin at different stages of the poultry chain, temperature, consumer price index and producer price index. As shown, the main variables are decomposed into between- and within-region variations with corresponding minimum and maximum values. The statistics make clear that real prices show substantially greater within variation than between variations. This means that differences in prices are larger over time compared with the cross-sectional differences. Overall, we observe sufficient variation to estimate price transmission patterns and identify the role of seasonal variation.

We are interested in measuring the stochastic panel properties of each price series. The purpose is to ensure the price series are compatible to initiate statistical testing in an error correction framework. We first carry out a cross-sectional dependence test proposed by Pesaran (2021) to identify the appropriate unit root and cointegration tests. Pesaran (2021) documents that the proposed tests have good small sample properties. The rejection of the null hypothesis implies that the panel members are cross-sectional-dependent. As presented in Table 2, we find a clear indication of cross-sectional dependence for all price series.

Cross-correlation implies that some movements over time are similar to all products. We therefore separate prices into common and regional components. Pesaran (2006) approximates unobserved factors in terms of cross-sectional averages to eliminate the differential effects of unobserved common factors. For example, Zamani et al., (2019) and Bittmann et al., (2020) also use this approach. We follow this procedure and use the average prices over all panels to estimate a country-wide price component. The differences

[3] Note that we got similar results when we use the CPI to deflate all price series. There is only a small change in the constant term.

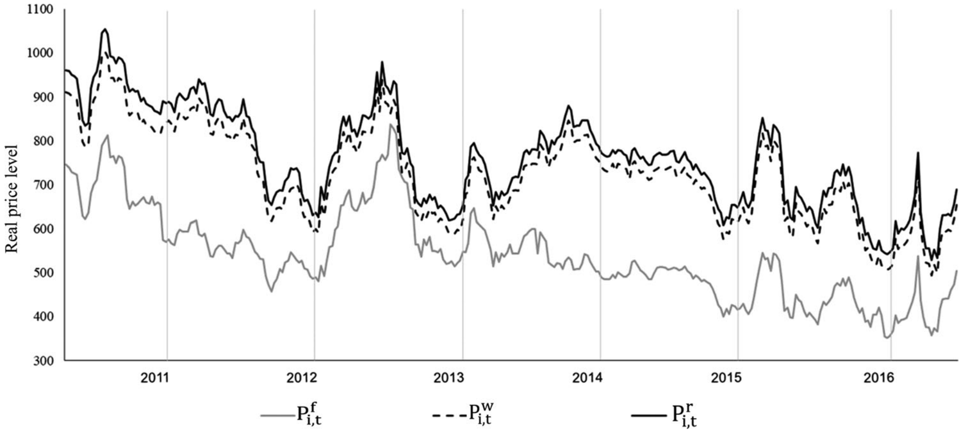


Figure 2 Evolution of regional average real prices of poultry chain during 2010–2016.
Note: The graph presents the weekly evolution of the average real prices in retail, wholesale and farm levels between 2010 and 2016. The vertical axis presents the average prices (Rial per kg), and the horizontal axis presents the weeks. The grid lines are in the month of March.
Source: Own representation based on data from State Livestock Affairs Logistics (2017).

Table 1 Descriptive statistics of prices and the margins over the period of 2010 to 2016

Measure	Definition	Mean	Min.	Max.	Std.D
Real retail price					
$P^{r}_{i,t}$	Overall	760.503	450.159	1190.133	119.322
	Between		709.800	811.418	21.758
	Within		488.222	1165.268	117.388
Real wholesale price					
$P^{w}_{i,t}$	Overall	723.126	347.342	1109.473	115.339
	Between		678.011	759.105	19.168
	Within		344.940	1105.530	113.789
Real farm price					
$P^{f}_{i,t}$	Overall	539.747	303.512	987.800	105.430
	Between		518.237	564.270	9.594
	Within		296.547	963.277	105.007
Relative wholesale–retail margin					
$RM^{r-w}_{i,t}$	Overall	0.049	0.000	0.565	0.023
	Between		0.018	0.079	0.014
	Within		−0.001	0.569	0.018
Relative farm–wholesale margin					
$RM^{r-w}_{i,t}$	Overall	0.253	−0.965	0.458	0.086
	Between		0.199	0.284	0.019
	Within		−0.972	0.462	0.084
Temperature (degree Celsius)					
$Temp_{i,t}$	Overall	17.594	−6.900	39.600	9.820
	Between		10.536	27.462	4.211
	Within		−2.069	32.528	8.904

Note: All price series are deflated, using official price indices. The prices are based on Iranian Rial per Kg of poultry meat. The average retail, wholesale and farm nominal prices are 52,777, 50,200 and 35,427 Rial per Kg, and are equal to 2.00, 1.91 and 1.35 USD per Kg, respectively. We employ an average exchange rate for 2010–2016 [IRR: 0.000038 USD]. Overall variation is the movements over time and regions. Within variation denotes the movements over time. Between variation denotes the movements across regions.
Source: Own calculation based on data from State Livestock Affairs Logistics (2017) and Iran Meteorological Organization (2017).

Table 2 Cross-sectional dependence tests

Variable	Pesaran's CD test
$lnP^{f}_{i,t}$	354.437***
$lnP^{w}_{i,t}$	345.387***
$lnP^{r}_{i,t}$	347.308***
$Temp_{i,t}$	369.390***

Note: The table shows test statistics of Pesaran (2021) cross-sectional dependence test. The null hypothesis is that there is no cross-sectional dependence. $^{***}P < 0.01$, $^{**}P < 0.05$ and $^{*}P < 0.1$ denote the significance level at which the null is rejected.
Source: Own calculation based on data from State Livestock Affairs Logistics (2017) and Iran Meteorological Organization (2017).

between the individual and the average prices represent the regional-specific component.

In the presence of cross-sectional dependence, second-generation unit root tests are preferred as they take cross-sectional dependence into account. However, the situation is different when cross-sectional dependence is caused by common dynamic factors, which are non-stationary. We calculated the cross-sectional means as follows: $\ln\overline{\mathrm{P}}^{\mathrm{r}}_{\mathrm{t}} = \frac{1}{n}\sum_i \ln\mathrm{P}^{r}_{i,t}$; $\ln\overline{\mathrm{P}}^{\mathrm{w}}_{\mathrm{t}} = \frac{1}{n}\sum_i \ln\mathrm{P}^{\mathrm{w}}_{i,t}$; $\ln\overline{\mathrm{P}}^{\mathrm{f}}_{\mathrm{t}} = \frac{1}{n}\sum_i \ln\mathrm{P}^{\mathrm{f}}_{i,t}$. The augmented Dickey–Fuller unit root test is applied to these components. As shown in Table 3, cross-sectional means of the price series are indeed non-stationary.Moreover, we performed the same procedure for temperature. The results indicate a stationary process for temperature in levels.

We also apply panel unit root tests on the demeaned data proposed by Hadri (2000), considering possible heteroscedasticity of the errors. The test indicates that at least some of the demeaned panels contain a unit root (see Table 4). However, all the first differences of demeaned prices are found to be stationary with and without trend and constant.

Table 3 Unit root tests on cross-sectional means

Variable	ADF test
Average of $lnP^{r}_{i,t}$	−0.552
Average of $lnP^{w}_{i,t}$	−0.527
Average of $lnP^{f}_{i,t}$	−0.581
Average of $Temp_{i,t}$	−2.690***
Average of $\Delta lnP^{r}_{i,t}$	−10.370***
Average of $\Delta lnP^{w}_{i,t}$	−10.469***
Average of $\Delta lnP^{f}_{i,t}$	−16.452***
Average of $\Delta Temp_{i,t}$	–

Note: The table shows the results of the augmented Dickey–Fuller (ADF) test on the logs of cross-sectional means. The null hypothesis is that the time series is non-stationary. $^{***}P < 0.01$, $^{**}P < 0.05$ and $^{*}P < 0.1$ denote the significance level at which the null is rejected. Maximum lag length is chosen by the Schwartz criterion. Δ denotes the first difference operator. As the temperature is stationary in levels, we did not apply the test to the first differenced variable.
Source: Own calculation based on data from State Livestock Affairs Logistics (2017) and Iran Meteorological Organization (2017).

Table 4 Panel unit root test

Variable	Hadri test
$lnP^{f}_{i,t}$	104.717***
$\Delta lnP^{f}_{i,t}$	−4.523
$lnP^{w}_{i,t}$	106.004***
$\Delta lnP^{w}_{i,t}$	−5.162
$lnP^{r}_{i,t}$	109.622***
$\Delta lnP^{r}_{i,t}$	−5.104
$Temp_{i,t}$	−3.604

Note: The table shows the results of the panel unit root test by Hadri (2000), which is robust to heteroscedasticity. The null hypothesis is that the panel is stationary. $^{***}P < 0.01$, $^{**}P < 0.05$ and $^{*}P < 0.1$ denote the significance level at which the null is rejected. Δ denotes the first difference operator. All panels were demeaned prior to testing. As the temperature is stationary in levels, we did not apply the test to the first differenced panel.
Source: Own calculation based on data from State Livestock Affairs Logistics (2017) and Iran Meteorological Organization (2017).

For the price panels, the common factors are responsible for the non-stationarity. Idiosyncratic prices, that is the time series without the common factor, are also to some extent non-stationary. This means that some regions may deviate from the market average in the long term. A panel with a factor structure is not stationary if a common factor is not stationary and/or the individual components are not stationary (Breitung & Das, 2008). Therefore, it is assumed that the price panel is non-stationary. In the first differences, all variables are tested stationary. This implies that all series are likely to be integrated of order 1 (i.e. I(1)).

For the temperature panel, we cannot reject the hypothesis of stationarity. This has important implications for the interpretation of the temperature variable in the long- run. Stationary variables may be included in the long-run relationship, but the effect on other variables is transitory. Thus, we model a stable relationship between the prices, yet the relationship may vary with the seasonal fluctuating temperature. Accordingly, we also include the temperature panel in the tests for cointegration.

We use the panel cointegration test by Westerlund (2007) to examine long-run relationships between price series. Westerlund proposed four test statistics for panel cointegration that are based on structural dynamics and thus do not assume any common-factor restriction (Persyn & Westerlund, 2008). As shown in Table 5, the test statistics reject the null hypothesis of no panel cointegration at 1% significance for all test statistics of both price modelling.

In our analysis, we estimate the price transmission process for two consecutive chains: farm–wholesale and retail–wholesale price relationships. This estimation strategy is motivated by bivariate maximum eigenvalue and trace tests for individual regions. We run vector autoregression (VAR) separately for each region to identify the number of cointegration vectors. In most cases, there are two cointegration relationships (as shown in Appendix 3). A similar strategy is suggested by Santeramo and von Cramon Taubadel (2016), and Ahmed (2018).

Table 5 Panel cointegration tests of wholesale and retail equations

	Farm→Wholesale		Wholesale → Retail	
	Group mean tests		Group mean tests	
	G_t	G_a	G_t	G_a
Statistic value	-2.558^{***}	-15.252^{***}	-4.078^{***}	-58.667^{***}
	Panel tests		Panel tests	
	P_t	P_a	P_t	P_a
Statistic value	-13.926^{***}	-15.134^{***}	-22.687^{***}	-57.029^{***}

Note: The table reports Westerlund (2007) cointegration tests of retail–wholesale and wholesale–farmgate relationships including temperature as the third variable with the null hypothesis of no cointegration. Hypothesis testing is based on bootstrapped confidence intervals. $^{***}P < 0.01$, $^{**}P < 0.05$ and $^{*}P < 0.1$ denote the significance level at which the null is rejected.
Source: Own calculation based on data from State Livestock Affairs Logistics (2017) and Iran Meteorological Organization (2017).

5. Empirical model

Based on recent studies, we estimate a reduced-form model of price transmission for the farm–wholesale and wholesale–retail relationships (e.g. Rezitis & Tsionas, 2019; Surathkal & Chung, 2017). Our modelling approach allows us to compare the results between the stages of the poultry chain with different characteristics, which may respond differently to the temperature variations. Let $\mathrm{lnP}^{\mathrm{r}}_{\mathrm{i,t}}$, $\mathrm{lnP}^{\mathrm{w}}_{\mathrm{i,t}}$ and $\mathrm{lnP}^{\mathrm{f}}_{\mathrm{i,t}}$ be the natural logs of retail, wholesale and farmgate prices; let $i = 1\ldots N$ be the different regions, and $t = 1\ldots \mathrm{T}$ be the time (week). Following the two-step cointegration approach proposed by Engle and Granger (1987), we first estimate the long-run relationship between wholesale and farmgate and wholesale and retail prices, respectively, considering temperature (i.e. $\mathrm{Temp}_{\mathrm{i,t}}$) as shown in equation (1):

$$\ln P^{*}_{i,t} = \alpha^{j}_{1} + \alpha^{j}_{2}\ln P^{**}_{i,t} + \alpha^{j}_{3}\mathrm{Temp}_{i,t} + \alpha^{j}_{4}\mathrm{Temp}_{i,t}\mathrm{lnP}^{**}_{i,t} + \mathrm{ECT}^{j}_{i,t} \tag{1}$$

For $j = 1$, the equation gives the long-run relationship between wholesale and farmgate ($\mathrm{lnP}^{*=\mathrm{w}}_{\mathrm{i,t}}$; $\mathrm{lnP}^{**=\mathrm{f}}_{\mathrm{i,t}}$), and for $j = 2$, we have wholesale and retail prices ($\mathrm{lnP}^{*=\mathrm{r}}_{\mathrm{i,t}}$; $\mathrm{lnP}^{**=\mathrm{w}}_{\mathrm{i,t}}$). Assuming cointegration holds between price series, the coefficient α^{j}_{2} is the (long-run) price transmission elasticity. The coefficient α^{j}_{1} indicates time-invariant unobserved differences in supply chain characteristics across regions, which can be interpreted as a measure for the size of transaction costs of moving poultry from wholesalers to retailers and from farmers to wholesalers, respectively.

We model the stable relationship between the prices, yet the relationship may vary with the seasonal fluctuating temperature. Given that the constant term can be interpreted as the average margin between consecutive chains, α^{j}_{3}

denotes the average change in the margin due to a temperature change. Additionally, the price interaction coefficients, that is α_4^j, represent the impact of temperature on the price transmission rate in the long-run relationship.

After estimating the long-run equilibrium, the error correction model allows us to compare asymmetries in the speed of adjustment among different stages of the supply chain. To do so, we split the associated error correction terms ($ECT_{i,t}^j$) into positive (when $ECT_{i,t}^j \geq 0$) and negative (when $ECT_{i,t}^j < 0$) deviations from equilibrium.

A positive error correction term in equation 1 ($j = 1$) indicates that wholesale prices are above equilibrium and farmgate prices are below equilibrium. When the error correction term is negative, wholesale prices are below equilibrium and farmgate prices are above equilibrium.

A positive error correction term in equation 1 ($j = 2$) indicates that retail prices are above equilibrium and wholesale prices are below equilibrium. A negative error correction indicates that retail prices are below equilibrium and wholesale prices are above equilibrium.

Following Hansen (1999), we specify the panel threshold ECMs for each price equation including the threshold value τ for temperature (see equation 2). To distinguish the coefficients in each regime statistically, we defined $I_{i,t}$ as an indicator function, which equals one if the temperature is above the threshold τ, that is $Temp_{i,t} \geq \tau$, and zero otherwise.

$$\text{Farm} \rightarrow \text{Wholesale}\left(j=1; \Delta\ln P_{it}^{*=w}; k=1\right);$$
$$\text{Wholesale} \rightarrow \text{Farm}\left(j=1; \Delta\ln P_{it}^{*=f}; k=2\right)$$

$$\text{Retail} \rightarrow \text{Wholesale}\left(j=2; \Delta\ln P_{it}^{*=r}; k=3\right);$$
$$\text{Wholesale} \rightarrow \text{Retail}\left(j=2; \Delta\ln P_{it}^{*=w}; k=4\right)$$

$$\begin{aligned}\Delta\ln P_{it}^{*} = \gamma_0^{k,+} ECT_{i,t-1}^{j,+} + \gamma_1^{k,-} ECT_{i,t-1}^{j,-} + \gamma_2^{k,+} I_{i,t-1} ECT_{i,t-1}^{j,+} \\ + \gamma_3^{k,-} I_{i,t-1} ECT_{i,t-1}^{j,-} + \cdots + \rho_i^k + \nu_{it}^k\end{aligned} \tag{2}$$

Δ is a difference operator. Additional lags of first differenced dependent and independent variables are added according to information criteria. ρ_i^k are time-invariant unobserved factors, and ν_{it}^k are error terms of the second stage. As mentioned, $ECT_{i,t}^1$ is the error correction term of the first-stage regression for the wholesale–farm chain (i.e. $j = 1$), and $ECT_{i,t}^2$ is the error correction terms for the retail–wholesale chain (i.e. $j = 2$), respectively. Error correction implies that prices move in the opposite direction of the long-run equilibrium.

Thus, the coefficients of adjustment are expected to be negative for $j = 1$, $k = 1$; $j = 2$, $k = 3$ and expected to be positive for $j = 1$, $k = 2$; $j = 2$, $k = 4$ in equation (2). Ignoring the effect of temperature on price transmission for a moment, the coefficients $\gamma_0^{1,+}(\gamma_1^{1,-})$ indicate the speed of adjustment towards long-run equilibrium when the wholesale margins are above (below) the farm–wholesale equilibrium and temperature is below the threshold (i.e. $Temp_{i,t} < \tau$). The negative sign means that wholesale prices are declining in response to changes in farmgate prices. Similar interpretations apply to the coefficients in the other equations. Table 6 gives an overview of the meaning of the main coefficients with expected signs.

Due to the wholesale market power in the Iranian poultry chain, we expect the 'rockets and feathers' effect in price adjustment at the wholesale level, that is $\gamma_0^{1,-} > \gamma_0^{1,+}$ and $\gamma_0^{2,-} < \gamma_0^{2,+}$. This implies that price decreases are delayed from upstream to downstream resulting in extended wholesale margins. When the retail (wholesale) price is below (above) equilibrium, wholesalers' margins increase, when deviations from equilibria are adjusted faster (slower), that is $\gamma_0^{3,-} > \gamma_0^{3,+}$ and $\gamma_0^{4,-} < \gamma_0^{4,+}$.

We identify temperature as a key factor behind the seasonal price and production movements of the poultry meat industry. Production and

Table 6 Overview of main coefficients in the second stage

Variable	Meaning	Implication	Coef.	Sign of EC	Rockets and feathers in favour of wholesalers	More symmetric adjustment
$ECT_{i,t}^{1+}$	Wholesale price above equilibrium	Wholesale price falls (j = 1, k = 1)	$\gamma_0^{1,+}$	−	$\gamma_1^{1,-} < \gamma_0^{1,+}$	$\gamma_2^{1,+} < 0$
	Farm price below equilibrium	Farm price rises (j = 1, k = 2)	$\gamma_0^{2,+}$	+		$\gamma_3^{1,-} > 0$
$\mathrm{ECT}_{\mathrm{i,t}}^{1-}$	Wholesale price below equilibrium	Wholesale price rises (j = 1, k = 1)	$\gamma_1^{1,-}$	−	$\gamma_1^{2,-} > \gamma_0^{2,+}$	$\gamma_2^{2,+} > 0$
	Farm price above equilibrium	Farm price falls (j = 1, k = 2)	$\gamma_1^{2,-}$	+		$\gamma_3^{2,-} < 0$
$ECT_{i,t}^{2+}$	Retail price above equilibrium	Retail price falls (j = 2, k = 3)	$\gamma_0^{3,+}$	−	$\gamma_1^{3,-} > \gamma_0^{3,+}$	$\gamma_2^{3,-} < 0$
	Wholesale price below equilibrium	Wholesale price rises (j = 2, k = 4)	$\gamma_0^{4,+}$	+		$\gamma_3^{3,+} > 0$
$ECT_{i,t}^{2-}$	Retail price below equilibrium	Retail price rises (j = 2, k = 3)	$\gamma_1^{3,-}$	−	$\gamma_1^{4,-} < \gamma_0^{4,+}$	$\gamma_2^{4,-} > 0$
	Wholesale price above equilibrium	Wholesale price falls (j = 2, s 4)	$\gamma_1^{4,-}$	+		$\gamma_3^{4,+} < 0$

Note: The table shows the interpretation of the main coefficients and variables in equation 2.
Source: Own representation.

transportation costs increase with temperature. The interaction terms between the dummy variable and the deviation from equilibrium capture the change in the speed of adjustment when the temperature is above the threshold. For instance, if we differentiate the error correction in equation 2 ($j = 1$, $k = 1$) for positive and negative deviations, we obtain:

$$\frac{\partial \Delta \ln P^{w}_{it}}{\partial ECT^{1,+}_{i,t-1}} = \gamma^{1,+}_{0} + \gamma^{1,+}_{2} I_{t-1} \tag{3}$$

$$\frac{\partial \Delta \ln P^{w}_{it}}{\partial ECT^{1,-}_{i,t-1}} = \gamma^{1,-}_{1} + \gamma^{1,-}_{3} I_{t-1} \tag{4}$$

During summer, production and transportation costs increase. Poultry losses due to mortality and heat stress in transit from farm to wholesaler increase (Mitchell & Kettlewell, 2009; dos Santos et al., 2020), which affects mainly the wholesalers' marginal costs (Fatemiamin & Mortezaie 2013). We hypothesise that in order to avoid losses from spoilage, wholesalers react faster to decreasing farm prices ($\gamma^{1,+}_{1} < 0$) and delay farm gate price increases ($\gamma^{1,-}_{1} > 0$). The asymmetry goes down if the sign of interactions goes in different directions of the main effects: $\gamma^{1,+}_{3} > 0; < \gamma^{1,-}_{2} < 0$. A more symmetric adjustment, for example for rising wholesale prices (when the price is below the equilibrium), is obtained by differentiating equation (4) with respect to the threshold indicator yielding the interaction with regard to negative deviations:

$$\frac{\partial \Delta \ln P^{w}_{i,t}}{\partial ECT^{1,-}_{i,t-1} \partial I_{t-1}} = \gamma^{1,-}_{3} < 0 \tag{5}$$

When the temperature is above the threshold, the speed of adjustment increases by $|\gamma^{1,-}_{3}| \times 100$ per cent.

As in Hansen (1999), the optimal thresholds are determined and tested by using a bootstrap method. The thresholds are estimated within a fixed-effect framework using the code by Wang (2015). We estimate equations (1) and (2) with mean group (MG), fixed-effect (FE) and random-effect (RE) estimators. The equations above represent the data-generating processes that can be estimated by a fixed-effect estimator. The MG-type estimators follow a two-step procedure. In the first step, N individual ordinary least squares (OLS) regressions are estimated. The coefficients are then averaged across panel members. Thus, in contrast to the classical fixed-effect estimator, slope coefficients may differ across panel members. On the one hand, this represents a very flexible specification without restricting assumptions about (near) homogeneous long- or short-run relationships and the danger of misspecification. On the other hand, the MG estimator ignores cross-sectional dependence across panel members, which is present in our panel data as shown in the previous section. The intercept in each regression represents the regional fixed effects that account for unobserved heterogeneity between panel members. As Pirotte (1999) and Pesaran and Smith (1995) indicate a mean group estimator provides consistent estimates of the parameters' averages with a large cross section. Because MG estimation ignores cross-sectional variation, we also show results of fixed-effect and random-effect estimations to check for the robustness of the results. As a further robustness check, we use fully modified OLS (FMOLS) to control for distortions that may be induced by the potential endogeneity of regressors (Pedroni, 2000; Phillips & Hansen, 1990).

6. Results

We first evaluate the long-run price transmission elasticities. As shown in Appendix 4, the price transmission rate at the wholesale-farm level is 69% meaning that the wholesale price responds incompletely to the changes in the farmgate prices (costs). This is consistent with the findings in Hassouneh et al., (2012) for the Egyptian poultry chain and Saghaian et al., (2008) for the Turkish poultry chain. The price transmission elasticities decrease from downstream (final consumer) to upstream (farm chain).

Note that we also apply a threshold search model to the long–long price transmission relationship. However, we do not find a significant threshold effect of temperature. This means that the impact of temperature on price transmission is linear in the long run. This is reflected by the model specification in equation 1, which includes temperature as additional variable and an interaction term. The estimated coefficients are shown in Table 7.[4] The effect of temperature on the price transmission elasticity and constant in the farm–wholesale relationship is highly significant across estimates, and it is rather negligible in the wholesale–retail relationship. On the one hand, our findings show that the price transmission elasticity at the wholesale level is significantly lower as temperature increases. On the other hand, the average wholesale–farmgate margin increases at elevated temperatures. The constant in the wholesale–retail (farm–wholesale) long-run price equilibrium regression can be interpreted as a measure for the size of transaction costs of moving poultry from wholesalers to retailers (from farmer to wholesalers). The interaction term is negative (wholesale/farmer) indicating that the price transmission elasticity decreases with temperature. This means that cost increases are passed on to a lesser degree when the temperature rises. Given the average temperature (i.e. 17.59°C), the farmgate–wholesale margin expands by 49% as temperature increases. The interaction term is small for

[4] The results of different estimators are quite robust. We also apply FMOLS for robustness check. The results are available upon request.

Table 7 Estimates of long-run equilibrium along the poultry chain

Regressor	Farm→Wholesale			Wholesale →Retail		
	Log wholesale price ($\ln P^{W}_{i,t}$)			Log retail price ($\ln P^{r}_{i,t}$)		
	FE	RE	MG	FE	RE	MG
Const.	1.4609*** (0.1040)	1.4635*** (0.1040)	1.338*** (0.0962)	0.3620*** (0.0589)	0.3622*** (0.0607)	0.2769*** (0.0452)
$TEMP_{i,t-1}$	0.0412*** (0.0042)	0.0412*** (0.0043)	0.0452*** (0.0037)	−0.0046* (0.0025)	−0.0046* (0.0025)	−0.0050*** (0.0012)
$lnP^{w}_{i,t}$	–	–	–	0.9525*** (0.0090)	0.9524*** (0.0089)	0.9646*** (0.0068)
$lnP^{f}_{i,t}$	0.8143*** (0.0167)	0.8138*** (0.0167)	0.8342*** (0.0156)	–	–	–
$lnP^{w}_{i,t} \times TEMP_{i,t-1}$	–	–	–	0.0007* (0.0004)	0.0007* (0.0004)	0.0008*** (0.0070)
$lnP^{f}_{i,t} \times TEMP_{i,t-1}$	−0.0065*** (0.0007)	−0.0065*** (0.0007)	−0.0072*** (0.0006)	–	–	–
Observations	9,720	9,720	9,720	9,720	9,720	9,720
Number of id	30	30	30	30	30	30
R^2 overall	0.6903	0.6903		0.9828	0.9828	
R^2 within	0.2572	0.2610		0.7333	0.7333	
R^2 between	0.6782	0.6783		0.9745	0.9745	
Average R^2			0.7140			0.9785

Note: The table reports the mean group (MG), fixed-effect (FE) and random-effect (RE) estimated coefficients of the long-run equilibrium relationship. The independent variable is the logarithm of the wholesale price for the farm→wholesale equation and the retail price for wholesale→retail equation, respectively. Outlier-robust means of parameter coefficients across groups are reported in parentheses for the MG estimator and robust standard errors for the other two estimators. ***$P < 0.01$, **$P < 0.05$ and *$P < 0.1$ denote the significance level at which the null is rejected.

Source: Own calculation based on data from State Livestock Affairs Logistics (2017) and Iran Meteorological Organization (2017).

the wholesale–retail price relationship, which means that increases in transaction costs are not passed on to the retailers.[5]

The Akaike information criterion (AIC) is applied to determine appropriate lag lengths of the model specification of short-term price adjustments. Based on the AIC, we set the lag length to $p = q=3$ for both price modelling. Table 8 presents the estimation results of the threshold error correction models for the relationships between retail, wholesale and farmgate prices.

Appendix 4 shows the estimate of time constant price adjustment, that is without the temperature variable. We find evidence for the ‘rockets and feathers’ pattern at the wholesale–farm level. Wholesale prices adjust faster in response to negative deviations from the long-run equilibrium than positive deviations. These findings are robust across estimated models and are in line with the previous studies on price dynamics of food and agricultural commodities (e.g. Hassouneh et al., 2012; Loy et al., 2016; Peltzman, 2000; Richards et al., 2014). In contrast, we find the reverse of the ‘rockets and feathers’ effect at the retail–wholesale level.

Our findings can be rationalised with wholesalers making use of their market power to extend their margins in the upstream chain (Goodwin & Piggott, 2001; Hassouneh et al., 2012; Surathkal & Chung, 2017). As wholesalers may exert market power over retailers, retail (wholesale) prices adjust faster (more slowly) in response to positive deviations from the long-run retail–wholesale equilibrium than negative deviations. Further, shocks are adjusted faster at the retail–wholesale level.

We now turn to the threshold effects of temperature on the price adjustment rates. Significant interaction terms of error correction terms imply that temperature influences price adjustment from farm to wholesale. Ceteris paribus, when the temperature is above 30.20 degrees Celsius, the wholesale price is adjusted faster in response to negative farm price changes. This is in line with Kim and Ward (2013) who argue that traders respond to price increases sluggishly to avoid sales reductions leading to spoilage. In periods of high temperature, the risk of losses for the wholesaler is likely to be more pronounced due to transportation (see dos Santos et al., 2020). Thus, wholesaler market power is lower during warm periods and price adjustment is more symmetric. Our findings are in line with Gilbert et al., (2017) and Lundberg et al., (2020) who report that weather-induced seasonality is an important factor, especially for perishable products. In contrast, the interaction terms of temperature are insignificant in retail–wholesale equations. A possible explanation for this outcome is that transportation costs and thus the main channel of weather-induced seasonality is less important at the wholesale–retail level. To clarify our results, we present the asymmetric speed of adjustment below and above the estimated thresholds ($\tau = 30.20$) in Table 9.

[5] In line with the described results, the signs are the opposite for the retail–wholesale relationship. Note that the size of the coefficient is rather small in economic terms.

Table 8 Estimates of price adjustment between three stages of the poultry chain

Regressor	Farm → Wholesale			Wholesale → Farm			Wholesale → Retail			Retail → Wholesale		
	$\Delta \ln P^{w}_{i,t}$			$\Delta \ln P^{f}_{i,t}$			$\Delta \ln P^{r}_{i,t}$			$\Delta \ln P^{w}_{i,t}$		
	FE	RE	MG	FE	RE	MG	FE	RE	MG	FE	RE	MG
$[TEMP_{i,t} < \tau]$												
$ECT^{+}_{i,t-1}$	−0.1401***	−0.1400***	−0.1413***	0.1527***	0.1525***	0.1518***	−0.5253***	−0.5055***	−0.4486***	0.5600***	0.5393***	0.4765***
	(0.0109)	(0.0105)	(0.0100)	(0.0111)	(0.0107)	(0.0107)	(0.0768)	(0.0779)	(0.0450)	(0.0842)	(0.0853)	(0.0499)
$ECT^{-}_{i,t-1}$	−0.2139***	−0.2117***	−0.1963***	0.2181***	0.2156***	0.1999***	−0.1947***	−0.2009***	−0.2784***	0.1851***	0.1943***	0.2785***
	(0.0193)	(0.0191)	(0.0128)	(0.0122)	(0.0117)	(0.0118)	(0.0582)	(0.0437)	(0.0403)	(0.0582)	(0.0434)	(0.0451)
$[TEMP_{i,t} \geq \tau]$												
$ECT^{+}_{i,t-1} \times I_{i,t-1}$	−0.1013***	−0.0947***	−0.0224	0.0962***	0.0912***	0.0956***	0.0062	0.0066	−0.0092	0.0750	0.0701	0.1431
	(0.0190)	(0.0159)	(0.0198)	(0.0208)	(0.0202)	(0.0206)	(0.0721)	(0.0717)	(0.0556)	(0.0791)	(0.0523)	(0.1088)
$ECT^{-}_{i,t-1} \times I_{i,t-1}$	−0.0333*	−0.0376**	−0.0475**	0.0113	0.0145	−0.0006	0.0044	0.0001	−0.0458	−0.0156	−0.0061	0.0173
	(0.0183)	(0.0163)	(0.0235)	(0.0149)	(0.0145)	(0.0361)	(0.0481)	(0.0394)	(0.0450)	(0.0421)	(0.0378)	(0.0522)
Threshold (τ)	30.20			28.00			28.00			27.20		
Observations	9,600	9,600	9,600	9,600	9,600	9,600	9,600	9,600	9,600	9,600	9,600	9,600
Number of id	30	30	30	30	30	30	30	30	30	30	30	30
R^2 overall	0.6804	0.6804		0.6286	0.6286		0.9286	0.9286		0.9311	0.9314	
R^2 within	0.6806	0.6806		0.6288	0.6288		0.9289	0.9289		0.9314	0.9311	
R^2 between	0.0038	0.0032		0.0356	0.0351		0.0721	0.0757		0.0014	0.0007	
Average R^2			0.7203			0.6869			0.9524			0.9577

Note: The thresholds are estimated according to the threshold fixed-effect model in equation 2. The table reports the mean group (MG), fixed-effect (FE) and random-effect (RE) estimated coefficients of the dynamic short-run equation defined in equation 2. The indicator variable is one if the temperature exceeds the threshold, $I_{i,t-1} = (TEMP_{i,t-1} \geq \tau)$ and zero otherwise. Outlier-robust means of parameter coefficients across groups are reported in parentheses for the MG estimator and robust standard errors for the other two estimators. $^{***}P < 0.01$, $^{**}P < 0.05$ and $^{*}P < 0.1$ denote the significance level at which the null is rejected.
Source: Own calculation based on data from State Livestock Affairs Logistics (2017) and Iran Meteorological Organization (2017).

Table 9 Speed of adjustment above and below temperature thresholds

Speed of adjustment	Farm→ Wholesale			Wholesale→ Retail		
	$TEMP_{i,t-1} < \tau$		$TEMP_{i,t-1} \geq \tau$	$TEMP_{i,t-1} < \tau$		$TEMP_{i,t-1} \geq \tau$
Average temperature	15.81		32.81	14.73		31.28
$ECT^{+}_{i,t-1}$	−0.1401	↑	−0.2414	−0.5253	=	−0.5253
$ECT^{-}_{i,t-1}$	−0.2139	↑	−0.2472	−0.1947	=	−0.1947
$\lvert ECT^{+}_{i,t-1} - ECT^{-}_{i,t-1} \rvert$	0.0738	↓	0.0058	0.3306	=	0.3306

Note: The table shows the speed of adjustment back to equilibrium according to the fixed-effect results in Table 8.
Source: Own calculation based on data from State Livestock Affairs Logistics (2017) and Iran Meteorological Organization (2017).

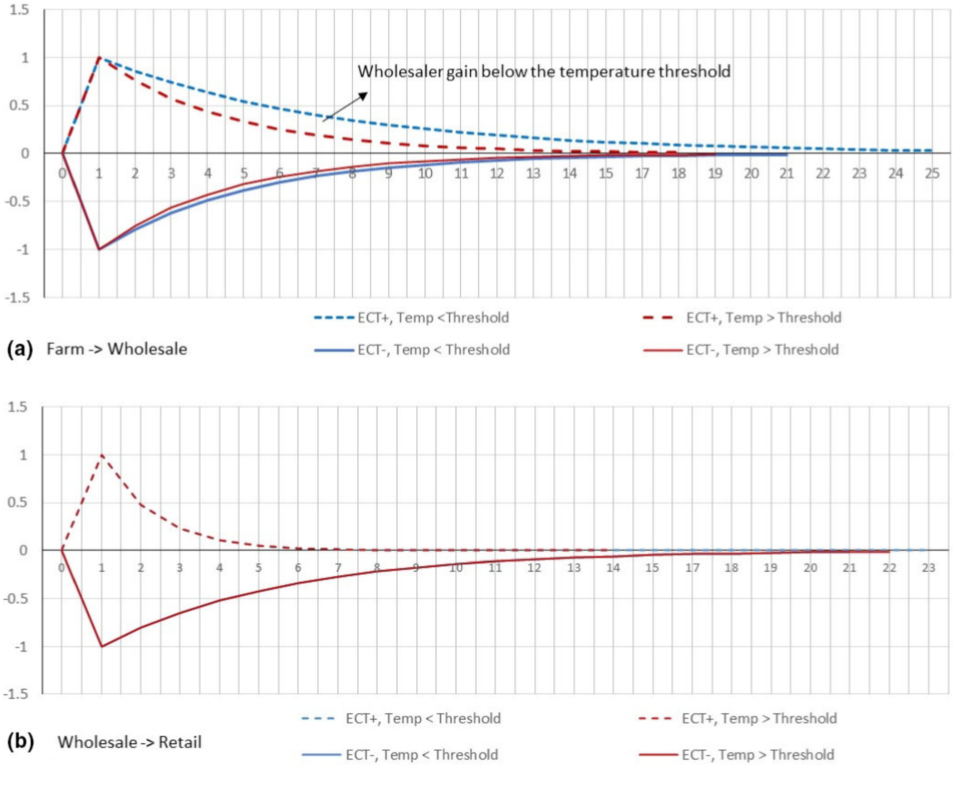


Figure 3 Response functions of wholesale (upper panel) and retail (lower panel) prices to positive and negative price changes above and below thresholds.
Source: Own calculation based on the fixed-effect results in Table 9[Colour figure can be viewed at wileyonlinelibrary.com]

Wholesale prices react more symmetrically to price changes above the threshold. Additionally, the speed of adjustments in price decreases (increases) is significantly lower (higher) during colder periods. This outcome again highlights that temperature variations may influence transportation and processing costs. As a result, price transmission varies seasonally.

Figure 3 simulates the response function of wholesale and retail prices to positive and negative shocks above and below the thresholds. As shown, the gap between adjustment rates above the threshold represents a gain for the wholesaler, which shrinks as temperature goes above 30.20 degrees Celsius during hot seasons.

7. Concluding remarks

Many agricultural and food markets show seasonal variations in supply and demand, which can lead to changes in market functioning and market interactions. The present study empirically analyses seasonal variations of vertical price relationships in the Iranian poultry supply chain. The analysis primarily aims to shed light on the importance of temperature as a key determinant for agricultural production and transportation in predicting the functioning of wholesale and retail markets. We investigate the price transmission processes along the consecutive value chain.

In the long-run, the wholesale prices react incompletely to the changes in farmgate price, while the price transmission rate at the wholesale–retail level is significantly higher. Our results show that temperature is a key variable in the farm–wholesale price transmission equation. However, temperature only plays a minor role in wholesale–retail price transmission. In the long-run, transaction costs due to the additional losses and transportation contribute to price and margin changes. As Lundberg et al., (2020) find, the effects of seasonality on the price transmission process may be driven by changes in transportation or transaction costs over seasons. However, it remains unclear to what extent the extra transaction costs add to the price dynamics. Unfortunately, we do not have detailed information on the potential seasonal losses; thus, we are unable to explicitly disentangle the effects of transaction costs and market power in the dynamics of margins.

In the short run, retail (wholesale) prices adjust faster (more slowly) in response to positive deviations from the long-run retail–wholesale equilibrium than negative deviations. Inversely, wholesale prices adjust more slowly in reaction to positive deviations from the long-run wholesale–farmgate equilibrium. This pattern is called the ‘rockets and feathers’ phenomenon and can be explained by wholesalers making use of their market power to extend the margins in the upstream chain. Additionally, the price adjustment between farmgate and wholesale prices becomes more symmetric when the temperature is above 30.20 degrees Celsius. In line with Kim and Ward (2013), wholesale price adjustment is more symmetric in periods of high temperatures, which can be interpreted as weaker market power due to the additional risk of losses during transportation and storage.

This research could be extended by gathering the actual costs of transportation between markets. Besides, it would be useful to verify whether our results hold for other products, for example red meat and milk. A potential limitation of our analysis is related to the role of public intervention in seasonal price dynamics. As laid out in Section 3, the Iranian government intervenes in the poultry market to stabilise seasonal prices. The intervention may change the seasonality of price dynamics. Further, poultry export and import volumes may be regulated according to seasonal changes. Official data show that the average poultry export volumes are higher during fall and winter (Iran's Customs Administration, 2020). Our analysis suggests that trade policies aligned with seasonal domestic price dynamics may improve the functioning of markets.

In this paper, we focus on supply-side effects caused by temperature fluctuations. However, there may also be demand-side factors affecting downstream chains, that is retailers. Further studies could investigate other determinants of seasonal patterns in agricultural and food price series, such as the seasonal supply of inputs. Future work may also benefit from including data on the institutional structure of the Iranian poultry market in the estimation, as suggested by Acosta et al., (2020) and by one of the reviewers of this paper.

References

Acosta, A., Barrantes, C. & Ihle, R. (2020) Animal disease outbreaks and food market price dynamics: Evidence from regime-dependent modelling and connected scatterplots. *Australian Journal of Agricultural and Resource Economics*, 64, 960–976.

Ahmed, O. (2018) Vertical price transmission in the Egyptian tomato sector after the Arab Spring. *Applied Economics*, 50, 5094–5109.

Alimalayeri, F. (2018). Investigating the situation of poultry and cattle slaughterhouses in Iran, Agricultural Economic Planning, and Rural Development Research Institute, Iran's Ministry of agriculture. [in Persian]

Amikuzuno, J. & von Cramon-Taubadel, S. (2012) Seasonal variation in price transmission between tomato markets in Ghana. *Journal of African Economies*, 21, 669–686.

Arnade, C. & Pick, D. (2000) Seasonal oligopoly power: The case of the US fresh fruit market. *Applied Economics*, 32, 969–977.

Aung, M.M. & Chang, Y.S. (2014) Temperature management for the quality assurance of a perishable food supply chain. *Food Control*, 40, 198–207.

Bernard, J.C. & Willett, L.S. (1996) Asymmetric price relationships in the US broiler industry. *Journal of Agricultural and Applied Economics*, 28, 279–289.

Bittmann, T. & Anders, S. (2016) Seasonal asymmetries in wholesale–retail cost pass-through. *Applied Economics Letters*, 23, 1065–1068.

Bittmann, T., Loy, J.P. & Anders, S. (2020) Product differentiation and cost pass-through: Industry-wide versus firm-specific cost shocks. *Australian Journal of Agricultural and Resource Economics*, 64, 1184–1209.

Bosker, M. & Buringh, E. (2020) Ice (berg) transport costs. *The Economic Journal*, 130, 1262–1287.

Breitung, J. & Das, S. (2008) Testing for unit roots in panels with a factor structure. *Econometric Theory*, 24, 88–108.

Bukeviciute, L., Dierx, A., Ilzkovitz, F. & Roty, G. (2009) Price transmission along the food supply chain in the European Union (No. 698-2016-47870).

Bulow, J.I. & Pfleiderer, P. (1983) A note on the effect of cost changes on prices. *Journal of Political Economy*, 91, 182–185.

Cáceres-Hernández, J.J. & Martín-Rodríguez, G. (2017) Evolving splines and seasonal unit roots in weekly agricultural prices. *Australian Journal of Agricultural and Resource Economics*, 61, 304–323.

Canova, F. & Hansen, B.E. (1995) Are seasonal patterns constant over time? A test for seasonal stability. *Journal of Business & Economic Statistics*, 13, 237–252.

Engle, R.F. & Granger, C.W. (1987) Co-integration and error correction: Representation, estimation, and testing. *Econometrica: Journal of the Econometric Society*, 55, 251–276.

Fatemiamin, S.R. & Mortezaie, A. (2013) Strategic plan of food processing supply chain. Iran's Ministry of Industry, Mine and Trade, Tehran, Iran. [In Persian].

Ghysels, E., Osborn, D.R. & Rodrigues, P.M. (2001) Seasonal nonstationarity and near-nonstationarity. A Companion to Theoretical Econometrics, 655–677.

Gilanpour, O., Kohansal, M.R., Permeh, Z. & Esmailipur, E. (2012) Investigation of government intervention in the chicken meat market. *Iranian Journal of Trade Studies*, 63, 137–168 [in Persian].

Gilbert, C.L., Christiaensen, L. & Kaminski, J. (2017) Food price seasonality in Africa: Measurement and extent. *Food Policy*, 67, 119–132.

Glaeser, E.L. & Kohlhase, J.E. (2004) *Cities, regions and the decline of transport costs*. In Fifty Years of Regional Science. Berlin, Heidelberg: Springer, pp. 197–228.

Goodwin, B.K., Grennes, T.J. & Craig, L.A. (2002) Mechanical refrigeration and the integration of perishable commodity markets. *Explorations in Economic History*, 39, 154–182.

Goodwin, B.K. & Piggott, N.E. (2001) Spatial market integration in the presence of threshold effects. *American Journal of Agricultural Economics*, 83, 302–317.

Hadri, K. (2000) Testing for stationarity in heterogeneous panel data. *The Econometrics Journal*, 3, 148–161.

Hansen, B.E. (1999) Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of econometrics*, 93, 345–368.

Hassouneh, I., Radwan, A., Serra, T. & Gil, J.M. (2012) Food scare crises and developing countries: the impact of avian influenza on vertical price transmission in the Egyptian poultry sector. *Food Policy*, 37, 264–274.

Hertel, T.W. & de Lima, C.Z. (2020) Climate impacts on agriculture: Searching for keys under the streetlight. *Food Policy*, 101954.

Hosseini, S.A., Malari, M.K. & Sydabadi, H.R. (2015) Determination of the share of cost-effective price per kilogram of broilers by using a multi-criteria decision analysis in Tehran province. *Iranian Journal of Animal Production*, 17, 51–58 [In Persian].

Hosseini, S.S., Nikoukar, A. & Dourandish, A. (2012) Price Transmission analysis in Iran chicken market. *International Journal of Agricultural Management and Development*, 2, 243–253.

Hosseini, S.S., Salami, H.A. & Nikoukar, A. (2008) Price transmission model for Iranian chicken industry. *Iranian Journal of Agricultural Economics*, 2, 1–21 [in Persian].

Hylleberg, S., Engle, R.F., Granger, C.W. & Yoo, B.S. (1990) Seasonal integration and cointegration. *Journal of Econometrics*, 44, 215–238.

Iran Meteorological Organization (2017) *Regional meteorological data*. Retrieved from http://irimo.ir/en

Iran Road Maintenance & Transport Organization (2013) *Annual report on average transportation costs*. Retrieved from http://rmto.ir/en

Iran's Customs Administration (2020) *Annual report*. Retrieved from http://www.irica.gov.ir/en.

Iran's Ministry of Agriculture (2020) *Annual statistics*. Retrieved from https://www.maj.ir/english.

Irarrazabal, A., Moxnes, A. & Opromolla, L.D. (2015) The tip of the iceberg: a quantitative framework for estimating trade costs. *Review of Economics and Statistics*, 97, 777–792.

Kalkuhl, M., Von Braun, J. & Torero, M. (2016) *Food price volatility and its implications for food security and policy*. Springer Nature, p. 626.

Kaminski, J., Christiaensen, L. & Gilbert, C.L. (2016) Seasonality in local food markets and consumption: evidence from Tanzania. *Oxford Economic Papers*, 68, 736–757.

Keshavarz, G.H. (2006) Calendar effects in prices fluctuation (case study of chicken, egg and read meat prices in Iran). *Economic Research Journal.*, 73, 295–328 [in Persian].

Khaledi, M., Shokat Fadaei, M. & Nekoofar, F. (2010) Investigating the efficiency of chicken market in Iran (case study: Karaj city). *Economics and Agricultural Development*, 24, 448–455 [in Persian].

Kim, H. & Ward, R.W. (2013) Price transmission across the US food distribution system. *Food Policy*, 41, 226–236.

Lloyd, T. (2017) Forty years of price transmission research in the food industry: Insights, challenges and prospects. *Journal of Agricultural Economics*, 68, 3–21.

Loy, J.P., Holm, T., Steinhagen, C. & Glauben, T. (2014) Cost pass-through in differentiated product markets: a disaggregated study for milk and butter. *European Review of Agricultural Economics*, 42, 441–471.

Loy, J.P., Weiss, C.R. & Glauben, T. (2016) Asymmetric cost pass-through? Empirical evidence on the role of market power, search and menu costs. *Journal of Economic Behavior & Organization*, 123, 184–192.

Lundberg, C., Skolrud, T., Adrangi, B. & Chatrath, A. (2020) Oil price pass through to agricultural commodities. *American Journal of Agricultural Economics*, 103, 721–742.

Mehta, A. & Chavas, J.P. (2008) Responding to the coffee crisis: What can we learn from price dynamics? *Journal of Development Economics*, 85(1–2), 282–311.

Meremikwu, V.N., Ibekwe, H.A. & Essien, A. (2013) Improving broiler performance in the tropics using quantitative nutrition. *World's Poultry Science Journal*, 69, 633–638.

Meyer, J. & von Cramon-Taubadel, S. (2004) Asymmetric price transmission: a survey. *Journal of Agricultural Economics*, 55, 581–611.

Mitchell, M.A. & Kettlewell, P.J. (2009) *Welfare of poultry during transport–a review*. In Poultry Welfare Symposium (pp. 90–100). Cervia: Association Proceeding.

Moghaddasi, R. & Nuroozi, G. (2010) Investigating price transmission process in meat market of Mazandaran. *Iranian Journal of Trade Studies*, 56, 177–194 [in Persian].

Mutlu Çamoğlu, S., Serra, T. & Gil, J.M. (2015) Vertical price transmission in the Turkish poultry market: The avian influenza crisis. *Applied Economics*, 47, 1106–1117.

Park, M., Jin, Y.H. & Bessler, D.A. (2008) The impacts of animal disease crises on the Korean meat market. *Agricultural Economics*, 39, 183–195.

Pedroni, P. (2000) Fully modified OLS for heterogeneous cointegrated panels. *Advances in Econometrics*, 15, 93–130.

Peltzman, S. (2000) Prices rise faster than they fall. *Journal of Political Economy*, 108, 466–502.

Persyn, D. & Westerlund, J. (2008) Error-correction–based cointegration tests for panel data. *The STATA Journal*, 8, 232–241.

Pesaran, M.H. (2021) General diagnostic tests for cross-sectional dependence in panels. *Empirical Economics*, 60, 13–50.

Pesaran, M.H. (2006) Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74, 967–1012.

Pesaran, M.H. & Smith, R. (1995) Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68, 79–113.

Phillips, P.C. & Hansen, B.E. (1990) Estimation and inference in models of cointegration: A simulation study. *Advances in Econometrics*, 8, 225–248.

Pirotte, A. (1999) Convergence of the static estimation toward the long run effects of dynamic panel data models. *Economics Letters*, 63, 151–158.

Pishbahar, E., Ferdousi, R. & Asadolahpour, F. (2015) Price Transmission in the Market of Chicken Meat: Autoregressive Switching Markov Models (MSAR) [in Persian]. *Iranian Journal of Agricultural Economics and Development Research*, 50, 1–17.

Pishbahar, E., Ferdousi, R. & Asadolahpour, F. (2019). Price transmission of chicken: Usage of Vector Autoregressive Markov Switching (MSVAR) approach. *Iranian Journal of Agricultural Economics*, 9, 55–72. [in Persian]

Rapsomanikis, G., Hallam, D., Conforti, P. & (2006) Market integration and price transmission in selected food and cash crop markets of developing countries: review and applications. In S. Alexander, (eds.), *Agricultural Commodity Markets and Trade*. Food and Agriculture Organization of the United Nations, 187–217.

Rasouli, B.Z., Dashty, G. & Ghahramanzadeh, M. (2011) Seasonal unit root tests, an application for poultry meat in Iran. *Animal Science Researches (Agricultural Science).*, 21, 81–91 [In Persian].

Rezitis, A.N. & Tsionas, M. (2019) Modeling asymmetric price transmission in the European food market. *Economic Modelling*, 76, 216–230.

Richards, T.J., Gómez, M.I. & Lee, J. (2014) Pass-through and consumer search: An empirical analysis. *American Journal of Agricultural Economics*, 96, 1049–1069.

Saghaian, S.H., Ozertan, G. & Spaulding, A.D. (2008) Dynamics of Price Transmission in the Presence of a Major Food Safety Shock: Impact of H5N1 Avian Influenza on the Turkish Poultry Sector. *Journal of Agricultural and Applied Economics*, 40, 1015–1031.

Santeramo, F.G. & von Cramon-Taubadel, S. (2016) On perishability and Vertical Price Transmission: empirical evidences from Italy. *Bio-based and Applied Economics Journal*, 5, 200–212.

dos Santos, V.M., Dallago, B.S., Racanicci, A.M., Santana, Â.P., Cue, R.I. & Bernal, F.E. (2020) Effect of transportation distances, seasons and crate microclimate on broiler chicken production losses. *PLoS One*, 15, e0232004.

Shadmehri, M.T.A. (2014) Price transmission mechanism in the Iran chicken market using the TECM, ECM-EG and GETS Models. *Asian Journal of Research in Business Economics and Management*, 4, 213–225.

Shakeri, M., Oskoueian, E., Le, H.H. & Shakeri, M. (2020) Strategies to combat heat stress in broiler chickens: unveiling the roles of selenium, vitamin E and vitamin C. *Veterinary Sciences*, 7, 71.

Statistical Center of Iran (2015) Annual statistics on poultry producers. https://www.amar.org.ir/english

Surathkal, P. & Chung, C. (2017) Retail price responses to changes in wholesale prices in the US beef industry: differences among quality grades and primal cuts. *Applied Economics*, 49, 5512–5522.

State Livestock Affairs Logistics of Iran (2017) Weekly data set. http://www.iranslal.com/old/index.php/en

United Nation Trade Statistics (2019) Annual statistics. https://comtrade.un.org/

Vavra, P. & Goodwin, B. (2005). Analysis of Price Transmission Along the Food Chain, OECD Food, Agriculture and Fisheries Papers, No. 3, OECD Publishing, Paris.

Vieira, F.M.C., Groff, P.M., Silva, I.J.O., Nazareno, A.C., Godoy, T.F., Coutinho, L.L. et al. (2019) Impact of exposure time to harsh environments on physiology, mortality, and thermal comfort of day-old chickens in a simulated condition of transport. *International journal of biometeorology*, 63, 777–785.

Wang, Q. (2015) Fixed-effect panel threshold model using Stata. *The Stata Journal*, 15, 121–134.

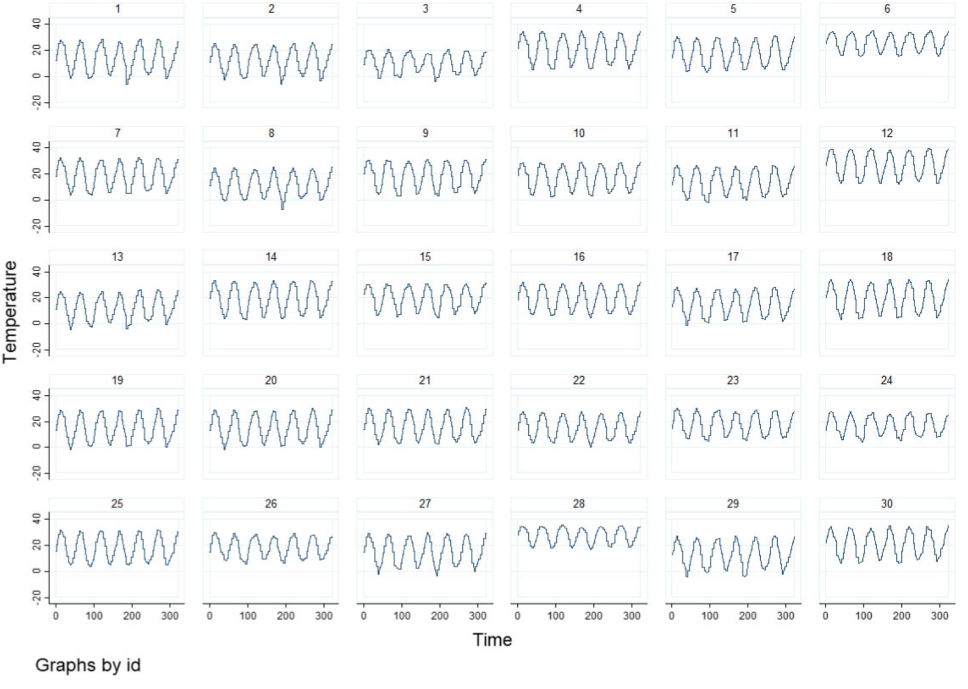
Westerlund, J. (2007) Testing for error correction in panel data. *Oxford Bulletin of Economics and Statistics*, 69, 709–748.

Weyl, E.G. & Fabinger, M. (2013) Pass-through as an economic tool: Principles of incidence under imperfect competition. *Journal of Political Economy*, 121, 528–583.

Willenbockel, D. (2012) Extreme weather events and crop price spikes in a changing climate: Illustrative global simulation scenarios. Oxfam International.

Zamani, O., Bittmann, T. & Loy, J.P. (2019) Demand peaks and cost pass-through: The case of Iran's poultry market. *Agribusiness*, 35, 657–674.

Appendix A
Regional variations in temperature during 2010–2016. [Colour figure can be viewed at wileyonlinelibrary.com]



Note: The graphs show changes in temperature during the sample period across regions (id).
Source: Own calculation based on data from Iran Meteorological Organization (2017).

Appendix B
Regional average temperature (degree Celsius) over the period of 2010 to 2016

Province	Temperature		
	Mean	Min	Max
Azerbaijan-e-Sharghi	13.86290	−5.8	28.5
Azerbaijan-e-Gharbi	12.34722	−5.9	25.9
Ardebil	10.53642	−4.2	21
Esfahan	21.11512	5.4	35.2
Ilam	17.4463	3.3	31.2
Bushehr	26.0892	15.3	35.1
Tehran	18.97222	3.7	32.4
Chaharmahal-o-Bakhtiari	12.04753	−6.9	25.2
Khorasan-e-Razavi	18.75741	3.2	31.2
Khorasan-e Jonubi	17.37284	2.9	29.3
Khorasan-e Shomali	14.03889	−1.6	26.7
Khuzestan	27.07284	12.5	39.6
Zanjan	12.52901	−4.1	26.4

Appendix B. *(Continued)*

Province	Temperature		
	Mean	Min	Max
Semnan	19.36574	3.3	33.6
Sistan-o-Baluchestan	20.04383	5	31.5
Fars	19.38549	4.5	32.3
Ghazvin	14.96451	−0.9	28.2
Ghom	19.67222	3.6	34.1
Kurdistan	15.06574	−1.6	30
Kerman	17.39877	3.5	29.7
Kermanshah	16.47068	2.1	30.8
Kohgiluyeh-o-Boyer-Ahmad	15.41204	0.2	27.9
Golestan	18.05617	4.9	30.3
Gilan	16.98179	4.2	27.6
Lorestan	17.8892	3.8	31.8
Mazandaran	18.24691	5.7	29.5
Markazi	15.0787	−3.1	29.6
Hormozgan	27.46235	16.5	35.4
Hamedan	12.89722	−4.1	27.1
Yazd	21.24691	6	35.2

Note: The table shows summary statistics of the temperature variable across different regions.
Source: Own calculation based on data from Iran Meteorological Organization (2017).

Appendix C
Number of cointegration relations for individual regions

Province	Lag (AIC)	Max-Eig	Trace
Azarbaijan-e-Sharghi	3	2	2
Azarbaijan-e-Gharbi	2	2	2
Ardebil	4	2	2
Esfahan	4	1	1
Ilam	4	2	2
Bushehr	7	1	1
Tehran	6	0	2
Chaharmahal-o-Bakhtiari	4	1	1
Khorasan-e-Razavi	3	2	2
Khorasan-e Jonubi	4	1	1
Khorasan-e-Shomali	2	2	2
Khuzestan	2	2	2
Zanjan	2	2	2
Semnan	2	1	2
Sistan-o-Baluchestan	7	0	0
Fars	6	2	2
Ghazvin	4	0	1
Ghom	5	0	0
Kurdistan	3	1	1
Kerman	2	2	2
Kermanshah	6	2	2
Kohgiluyeh-o-Boyer-Ahmad	5	0	0
Golestan	3	2	2

Appendix C. *(Continued)*

Province	Lag (AIC)	Max-Eig	Trace
Gilan	3	1	2
Lorestan	3	2	2
Mazandaran	2	2	2
Markazi	2	2	2
Hormozgan	1	2	2
Hamedan	3	1	1
Yazd	2	0	0

Note: The table shows the number of cointegration relationships for different regions. The model variables in each model are real retail, wholesale, and farm prices. Lag selection is based on the AIC criterion.
Source: Own calculation based on data from State Livestock Affairs Logistics (2017) and Iran Meteorological Organization (2017).

Appendix D
Long-run and short-run estimates without temperature

Estimates of the long-run equilibrium						
Regressor	Farm→Wholesale			Wholesale →Retail		
	Log wholesale price ($lnP^{W}_{i,t}$)			Log retail price ($lnP^{r}_{i,t}$)		
	FE	RE	MG	FE	RE	MG
Const.	2.2362*** (0.0659)	2.2361*** (0.0667)	2.369*** (0.0693)	.2798*** (0.0548)	.2799*** (0.0563)	.2296*** (0.0474)
$lnP^{w}_{i,t}$	–	–	–	0.9651*** (0.0083)	0.9651*** (0.0083)	0.9727*** (0.0070)
$lnP^{f}_{i,t}$	0.6910*** (0.0105)	0.6910*** (0.0105)	0.6915*** (0.0108)	–	–	–

Regressor	Estimates of short-run price adjustment											
	Farm →Wholesale			Wholesale →Farm			Wholesale →Retail			Retail → Wholesale		
	$\Delta \ln P^{w}_{I,t}$			$\Delta \ln P^{f}_{I,t}$			$\Delta \ln P^{r}_{I,t}$			$\Delta \ln P^{w}_{I,t}$		
	FE	RE	MG	FE	RE	MG	FE	RE	MG	FE	RE	MG
$ECT^{+}_{i,t-1}$	−0.1443***	−0.1438***	−0.1451***	0.1516***	0.1509***	0.1494***	−0.6673***	−0.6594***	−0.4848***	0.7192***	0.7105***	0.5329***
	(0.0101)	(0.0098)	(0.0092)	(0.0111)	(0.0109)	(0.0098)	(0.0669)	(0.0655)	(0.0438)	(0.0885)	(0.0885)	(0.0524)
$ECT^{-}_{i,t-1}$	−0.2206***	−0.2189***	−0.1935***	0.2292***	0.2272***	0.2022***	−0.2612***	−0.2654***	−0.3390***	0.2606***	0.2683***	0.3588***
	(0.0186)	(0.0208)	(0.0113)	(0.0119)	(0.0119)	(0.0101)	(0.0419)	(0.0382)	(0.0344)	(0.0424)	(0.0384)	(0.0361)

Note: (i) The table reports the mean group (MG), fixed-effect (FE) and random-effect (RE) estimated coefficients of the long-run equilibrium relationship. The independent variable is the logarithm of the wholesale price for the farm→wholesale equation and the retail price for wholesale→retail equation, respectively. Robust standard errors for the other two estimators. ***$P < 0.01$, **$P < 0.05$ and *$P < 0.1$ denote the significance level at which the null is rejected. Source: Own calculation based on data from State Livestock Affairs Logistics (2017) and Iran Meteorological Organization (2017). (ii) The thresholds are estimated according to the linear fixed-effect model in equation 2. The table reports the mean group (MG), fixed-effect (FE) and random-effect (RE) estimated coefficients of the dynamic short-run equation defined in equation 2. Outlier-robust means of parameter coefficients across groups are reported in parentheses for the MG estimator and robust standard errors for the other two estimators. ***$P < 0.01$, **$P < 0.05$ and *$P < 0.1$ denote the significance level at which the null is rejected. Source: Own calculation based on data from State Livestock Affairs Logistics (2017) and Iran Meteorological Organization (2017).