Journal of Agricultural Science and Technology (JAST), 28(6)
In Press, Pre-Proof Version

Investigating the Effects of Economic Shocks and Price Risk on the Iranian Beef Marketing Margin Using Fourier Approximation

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Abstract

Amid persistent economic shocks over the past decade, this study investigates the influence of price risk on beef marketing margin dynamics in Iran, incorporating structural breaks from April 2014 to March 2024. Price risk was estimated using the GARCH model, and the Fourier approximation was used to evaluate its effects on marketing margins while accounting for non-linear structural shifts. Findings from three estimation frameworks—markup, marketing cost, and relative margin—indicate that retail price risk positively contributes to the total beef marketing margin. In contrast, slaughterhouse-level price risk and slaughtering costs had an adverse effect on the farm-to-wholesale margin. Retail price risk and wholesale-to-retail marketing costs also increased the wholesale-to-retail margin. These results highlight the necessity of reevaluating retail-level price-setting mechanisms and strengthening risk management tools to shield producers from wholesale price volatility.

Keywords: Fourier approximation, Marketing margin, Price risk, Structural break.

Introduction

The marketing margin reflects the difference between the retail price of a product and its price at the farm level, encompassing cumulative costs added as the product moves through processing, packaging, transportation, distribution, and other marketing stages (Elitzak, 1996). Much of the existing literature on marketing margins builds upon the analytical foundation that Gardner (1975) developed, which explores margin behavior under competitive conditions. The framework analyzes the supply and demand dynamics In volatileat both farm and retail levels, highlighting how shifts in retail demand, farm-level supply, and the availability of marketing services shape the marketing margin.

Numerous factors shape marketing margins. From a theoretical standpoint, supply and demand functions—along with their price elasticities—are primary determinants (O'Donnell *et al*., 1999). Incorporating these variables into margin analysis frameworks is critical, especially under uncertainty and price risk conditions, as it enhances model specification and helps capture agents' behavioral responses. Under volatile conditions, the risk responses of marketing

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agents strongly influence their decisions, particularly in agri-food. Gardner (1975) argues that the conduct of marketing firms shapes the farm-to-retail margin. Based on a competitive model, Brorsen *et al.* (1985) showed that when such firms aim to maximize expected utility with low-risk aversion, increased farm-level price volatility reduces the supply of marketing services, lowering the price received by producers and raising consumer prices. Furthermore, increased retail-level price risk tends to widen the marketing margin (Brorsen *et al.*, 1985). These findings imply that higher price risk in beef markets may result in the upward transmission of price gaps to consumers, eroding their purchasing power.

Although risk and uncertainty are often used interchangeably, they carry two distinct economic meanings. Risk refers to events whose probability of occurrence is measurable, while uncertainty, due to insufficient data, has no measurable probability of occurrence (Oskou and Rostami, 2023).

Livestock producers are exposed to two principal types of risk: production and price risk. Production risk stems from stochastic, often natural events—such as droughts, floods, or disease outbreaks—that affect output levels. Price risk, in contrast, arises from unpredictable and significant price fluctuations. Figure 1 illustrates beef prices across different market segments from April 2014 to March 2024. The data reveal heightened price instability following the U.S. withdrawal from the Joint Comprehensive Plan of Action (JCPOA) in May 2018, particularly after removing preferential currency exchange rates in May 2022. These developments have substantially increased producers' exposure to market risk.

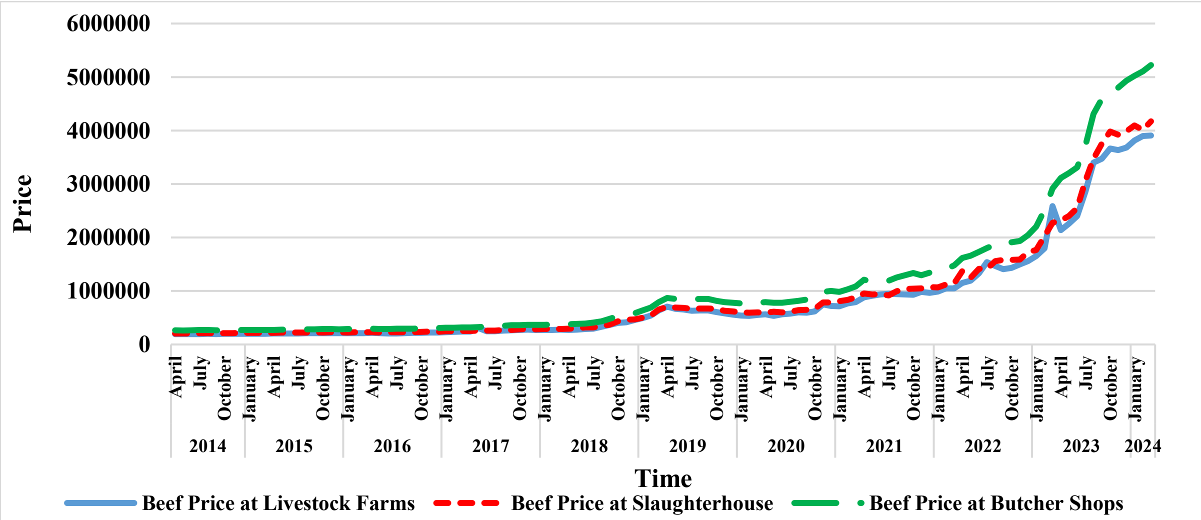

Figure 1. Beef Prices at Different Market Levels from April 2014 to March 2024. Source: Research calculations based on data from the Ministry of Agriculture Jihad.

Figure 2 illustrates the trajectory of the aggregate beef marketing margin. Data from April 2014 to March 2024 reveal notable fluctuations, underscoring the importance of accounting for economic shocks when analyzing margin behavior.

Figure (2) illustrates a gradual increase in the beef marketing margin after the U.S. withdrawal from the Joint Comprehensive Plan of Action (JCPOA) in May 2018, followed by a sharp rise after the elimination of the preferential exchange rate in May 2022.

Incorporating methodologies that capture structural breaks is essential in such analyses. Banerjee *et al.* (2017) stress that ignoring structural breaks in economic data leads to inefficient inferences. Therefore, integrating structural break considerations into marketing margin analysis can assist policymakers in enhancing agricultural market performance and increasing farmers' share in consumer food expenditures.

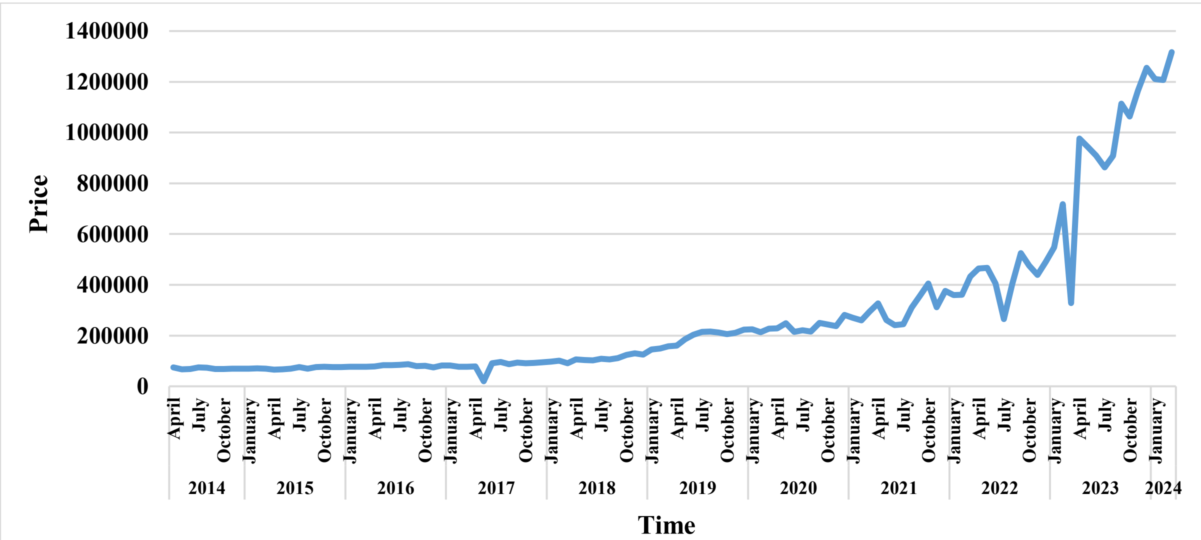

Figure 2. Behavior of the Total Beef Marketing Margin from April 2014 to March 2024. Source: Research calculations based on data from the Ministry of Agriculture Jihad.

A substantial body of literature has investigated the determinants of marketing margins. Using competitive market theory, Gardner (1975) was among the first to systematically evaluate price transmission from farm to retail in agricultural products. His contributions include formulating a foundational framework, identifying drivers of margin variability, and outlining transmission elasticity calculations. Although based on competitive market assumptions, his work remains a cornerstone.

Building on this, Wohlgenant (1985) applied a modified markup model using monthly data from January 1974 to October 1983, incorporating future price expectations. His findings indicated that the lagged marketing margin was a key determinant of beef margins. Holloway

(1991) examined price spreads under imperfect competition by estimating marketing margin functions for eight food categories—including beef, pork, poultry, eggs, dairy, and fruits and vegetables—using U.S. data from 1955 to 1983. His model allowed for variation in the number of firms, ranging from monopoly to perfect competition. The results showed minimal deviations from competitive market outcomes.

Faminow and Laubscher (1991) extended the relative margin model by integrating price risk, applying it to South African maize data from May 1982 to December 1988. Risk was captured through distributed lag specifications of past prices, and dummy variables were included for specific events. Their analysis demonstrated a positive correlation between heightened price risk and wider marketing margins.

Jayne and Myers (1994) explored wheat price volatility and its effects on equilibrium prices and international marketing margins in trade between the U.S. and Japan from January 1972 to February 1986. Using a bivariate GARCH model, they found that increased price risk did not significantly affect U.S. export prices but led to higher Japanese import prices and widened margins—particularly during high-volatility periods in the mid-1970s.

Brester and Musick (1995) investigated market concentration and price risk in lamb marketing margins, dividing the margin into farm-to-wholesale and wholesale-to-retail segments. Using monthly data from January 1980 to June 1992 and estimating via three-stage least squares (3SLS), they found that market concentration had modest but positive effects on margins, while price risk showed a positive and inelastic association with both components.

Finally, Piggott *et al.* (2000) assessed market power in the Australian food marketing chain using data from 1970 to 1997. Their findings aligned with Gardner's (1975) conclusions, reflecting the competitive nature of Australia's agricultural sector.

Given the disruptions of the COVID-19 pandemic in agricultural supply and demand, recent studies—including studies by Hirvonen *et al.* (2021), Lusk *et al.* (2021), and Azzam and Dhoubhadel (2022)— have focused on its impact on marketing margins.

Domestic studies have also addressed price risk and marketing margins. Shahbazi *et al.* (2009), adapting the approach of Brester and Musick (1995), analyzed farm-slaughterhouse and slaughterhouse-retail beef and lamb margins between 1997 and 2003. Price risk, defined as the relative volatility of the 12-month moving average, significantly increased marketing margins—except for the farm-slaughterhouse margin of lamb. *Shahiki Tash et al.* (2016) assessed date marketing margins from 1982 to 2012, incorporating marginal processing costs, market power, and price uncertainty. Their results showed that a 1% rise in price risk increased the marketing margin by approximately 0.07%, all else equal.

Kohansal and Rafiei Darani (2019) applied a geographically weighted regression model to examine marketing margins in the Neyshabour Plain. Data collected from 366 farmers in 2016 through surveys indicated that marketing costs and retail prices positively affected margins, while cultivated areas negatively impacted most regions. Eshghi *et al.* (2022) used a dynamic stochastic general equilibrium (DSGE) model and impulse response functions to analyze how news and technology shocks affected agricultural marketing margins between 1974 and 2014. Positive shocks were found to reduce marketing margins.

Rezvani and Pendar (2025) employed the Brester and Musick (1995) framework to examine lamb marketing margins, incorporating price risk, the COVID-19 shock, and removing preferential exchange rates. The GARCH method was used to estimate price risk, while dummy variables captured the impacts of COVID-19 and currency policy changes. Their findings indicated a negligible positive effect of the pandemic on both farm-wholesale and wholesale-retail margins. Slaughterhouse price risk significantly raised the farm-wholesale margin, and retail price risk increased the wholesale-retail margin.

A literature review reveals that prior studies have overlooked mainly structural breaks when estimating price risk and analyzing its impact on marketing margins. To address this gap, the present study integrates structural breaks into the stationarity testing of variables and the analysis of price risk effects by applying the Fourier approximation. This methodological refinement improves upon earlier research. Considering the country's specific context—including international sanctions, the U.S. withdrawal from the *JCPOA*, and the COVID-19 pandemic—this study seeks to incorporate structural breaks comprehensively at all stages of the empirical investigation.

This neglect of macroeconomic shocks has created a research gap. This is because, in a market like Iran's beef market, the increase in the marketing margin is directly influenced by these major macroeconomic shocks. Ignoring these shocks will lead to inefficient outcomes and misguided policy decisions. This necessity is confirmed by reviewing the behavior of price and marketing margin in Figures (1) and (2).

The main objective of the present research is to analyze the effect of price risk on the beef marketing margin in Iran, considering structural breaks in the time series analysis process. The methodological innovation of this study lies in the application of the Fourier approximation. This method has been used to flexibly and simultaneously incorporate all multiple, unscheduled structural breaks (such as the effect of sanctions, withdrawal from the JCPOA, COVID-19, and the elimination of the subsidized exchange rate) in the variables' stationarity test, the calculation of price risk using the GARCH model, and the final estimation of the risk's effect on the marketing margin. This approach increases the model's validity and accuracy compared to previous studies.

The contribution of this research to the value chain's policy-making and planning is very prominent: from the policy-making perspective, the results of this research, by accurately measuring the share of price risk in the expansion of the marketing margin, provide an operational tool for reviewing and reforming current market regulation policies (such as supportive pricing or government interventions in imports and exports).Also, from the planning perspective, this study helps planners and economic actors, by better understanding the way price risk is transferred from the farm to the consumer, to identify the weaknesses and bottlenecks in the chain and take necessary measures to improve market performance and increase the farmers' share of the final price.

Methodology

Given the volatility in meat production and pricing, alongside policymakers' concerns regarding beef price fluctuations, this study investigates the behavior of aggregate beef marketing margins. The analysis applies the markup, marketing cost, and relative margin models, integrating price risk based on the approach of Faminow and Laubscher (1991). To evaluate the effects of price risk on farm-to-wholesale and wholesale-to-retail margins, the framework developed by Brester and Musick (1995) is employed.

The selection of the approaches by Faminow and Laubscher (1991) and Brester and Musick (1995) is due to their provision of a stable and reference theoretical framework for the analysis of the marketing margin. To account for the complexities and risks inherent in the beef value chain, which classical models are incapable of modeling, the research innovation lies in combining these standard frameworks with advanced time series econometrics techniques. This integration enables the incorporation of price risk and both sharp and gradual structural breaks (using the Fourier approximation).

Analyzing the influence of price risk on marketing margins requires, as a first step, testing the stationarity of variables and calculating price uncertainty. In the presence of structural breaks, standard unit root tests—such as the Dickey-Fuller test—fail to capture non-linear shifts adequately.

Since Iran's economic time series data are susceptible to sharp and gradual structural breaks (arising from economic crises and policy interventions), and given the use of monthly data that raises the likelihood of seasonal unit roots, the current research utilizes the unit root test developed by Enders and Lee (2012) based on the Fourier component. This test takes into account both cyclical patterns and structural breaks and delivering efficient stationarity results irrespective of the number of structural breaks and the nature of the seasonal unit roots (Apergis *et al.*, 2021)

This test is based on the Lagrange Multiplier (LM) principle, initially developed by Schmidt and Phillips (1992) and Amsler and Lee (1995). Accordingly, the null hypothesis of equation (1) is estimated following this LM-based framework (Apergis *et al.*, 2021):

$$\Delta y_t = \rho y_{t-1} + c_1 + c_2 t + c_3 \sin\left(\frac{2\pi kt}{T}\right) + c_4 \cos\left(\frac{2\pi kt}{T}\right) + e_t \quad (1)$$

n Equation (1), k denotes the frequency parameter and Δ is the first-difference operator. Empirically, incorporating high values of k is not feasible within a regression framework, as excessive frequency components reduce degrees of freedom and increase the risk of overfitting. Therefore, selecting an appropriate frequency is essential. To determine the optimal value of k, Equation (1) is estimated for all integer values within the range $1 \leq k \leq 5$. The model that minimizes the sum of squared residuals is selected as the optimal specification. Using the estimated coefficients $\tilde{\gamma}_0$, $\tilde{\gamma}_1$, and $\tilde{\gamma}_2$, a detrended series is subsequently constructed according to Equation (2).

$$\tilde{S}_t = y_t - \tilde{\psi} - \tilde{\gamma}_0 t - \tilde{\gamma}_1 \sin\left(\frac{2\pi kt}{T}\right) - \tilde{\gamma}_2 \cos\left(\frac{2\pi kt}{T}\right); \quad t = 2, \ldots, t \quad (2)$$

In Equation (2), Ψ is defined according to Equation (3), and y_1 denotes the first observation of y_t.

$$\tilde{\psi} = y_1 - \tilde{\gamma}_0 - \tilde{\gamma}_1 \sin\left(\frac{2\pi kt}{T}\right) - \tilde{\gamma}_2 \cos\left(\frac{2\pi kt}{T}\right) \quad (3)$$

The null hypothesis of a unit root ($\theta = 0$) is tested using the LM statistic based on Equation (4):

$$\Delta y_t = \theta S_{t-1} + d_0 + d_1 \Delta \sin\left(\frac{2\pi kt}{T}\right) + d_2 \Delta \cos\left(\frac{2\pi kt}{T}\right) + u_t \quad (4)$$

Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model to model time-varying volatility. Under an ARCH specification, the conditional variance depends on the squared residuals of prior periods (Oğurlu, 2014). An ARCH(p) model is formulated as follows:

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{p} \beta_i \, u_{t-i}^2 \tag{5}$$

For the process to exhibit stationarity (mean reversion), all parameters must be positive, and the sum of β_i must be less than one. The null hypothesis of no ARCH effects is tested against the presence of conditional heteroskedasticity.

Bollerslev (1986) extended the ARCH model by proposing the Generalized ARCH (GARCH) model, in which conditional variance also depends on its lags (Brooks, 2008). The GARCH (p, q) model is expressed as:

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{p} \beta_i \, u_{t-i}^2 + \sum_{i=1}^{q} \delta_i \, \sigma_{t-i}^2 \tag{6}$$

For stationarity, all parameters in Equation (6) must be positive, and the sum of $\sum_{i=1}^{p} \beta_i + \sum_{i=1}^{q} \delta_i$ must be less than one. Several studies emphasize that disregarding structural breaks in conditional variance modeling can yield inaccurate estimates, as economic time series are frequently exposed to such breaks (Li and Enders, 2017). To address this issue, the current study applies a Fourier approximation following the approach of *Teterin et al.* (2016), allowing for structural breaks within the variance equation. Thus, Equation (6) is extended as follows:

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{p} \beta_i \, u_{t-i}^2 + \sum_{i=1}^{q} \delta_i \, \sigma_{t-i}^2 + \sum_{k=1}^{n} \gamma_{1,1k} \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \gamma_{1,2k} \, cos\left(\frac{2\pi kt}{T}\right) \tag{7}$$

The number of Fourier frequencies *n* is determined using information criteria such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC), as recommended by Pascual *et al.* (2011).

Price risk was estimated as the Conditional Volatility of prices. To select the model, various structures, including symmetric and asymmetric models (EGARCH and TGARCH), were examined. The final selection of the superior model was based on the minimum values of the Akaike and Bayesian criteria, as well as the validation of model adequacy through the Ljung-Box and ARCH-LM diagnostic tests.

If the series are non-stationary, testing for co-integration becomes necessary to avoid spurious regression. Banerjee *et al.* (2017) proposed a Fourier-based Autoregressive Distributed Lag (ARDL) co-integration test, formulated as:

$$\Delta y_t = \mathrm{d(t)} + \alpha y_{t-1} + \acute{\beta} x_{t-1} + \acute{\delta} \Delta x_t + \varepsilon_t \tag{8}$$

In Equation (8), β and δ are n×1 vectors of coefficients, and x_t is the vector of explanatory variables. The deterministic component *d(t)* is defined in Equation (9), where *k* denotes the frequency, *q* is the number of Fourier terms, and *T* is the sample size.

$$\mathrm{d(t)} = \theta_0 + \sum_{k=1}^{n} \theta_{1,k} \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{q} \gamma_{2,k}\, cos\left(\frac{2\pi kt}{T}\right) \tag{9}$$

The null hypothesis of no co-integration (α = 0) is tested against the alternative (α < 0). The test statistic is expressed as:

$$t_{ADL}^{F} = \frac{\hat{\alpha}}{se(\hat{\alpha})} \tag{10}$$

Here, $\hat{\alpha}$ is the estimated coefficient from Equation (8), and se($\hat{\alpha}$) is its standard error. Following the methodology of Enders and Lee (2012), the maximum F-statistic is used to detect nonlinear trends and determine the optimal value of *K*.

To analyze the effect of price risk on the aggregate beef marketing margin, three margin models are specified based on the framework developed by Faminow and Laubscher (1991):

$$MM = \alpha_0 + \alpha_1 P_R + \alpha_2 KH + \alpha_3 Risk_{PR} \tag{11}$$

$$MM = \beta_0 + \beta_1 Q + \beta_2 KH + \beta_3 Risk_{PR} \tag{12}$$

$$MM = \gamma_0 + \gamma_1 P_R + \gamma_2 P_R Q + \gamma_3 KH + \gamma_4 Risk_{PR} \tag{13}$$

In Equations (11) to (13), MM denotes the aggregate farm-to-retail marketing margin, P_R is the retail price, *KH* represents the marketing cost index, $Risk_{PR}$ indicates retail price risk, and *Q* refers to the quantity of product supplied. Equation (11) defines the markup model, Equation (12) the marketing cost model, and Equation (13) the relative margin model.

These models are reformulated using a Fourier approximation to capture abrupt and gradual structural breaks, as shown in Equations (14) to (16).

compared to traditional techniques for determining break dates and seasonal dummy variables, because the Fourier approximation, due to its sinusoidal nature, offers greater flexibility and can simultaneously incorporate multiple non-linear structural breaks with unknown timing into the modeling. The optimal number of frequencies (k) was determined using the AIC or BIC.

The number of Fourier frequencies is selected based on information criteria such as the AIC or the BIC.

$$MM = \alpha_0 + \alpha_1 P_R + \alpha_2 KH + \alpha_3 Risk_{PR} + \sum_{k=1}^{n} \delta_{1k} \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \delta_{2k}\, cos\left(\frac{2\pi kt}{T}\right) \tag{14}$$

$$MM = \beta_0 + \beta_1 Q + \beta_2 KH + \beta_3 Risk_{PR} + \sum_{k=1}^{n} \gamma_{1k} \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \gamma_{2k} \, cos\left(\frac{2\pi kt}{T}\right) \tag{15}$$

$$M = \gamma_0 + \gamma_1 P_R + \gamma_2 P_R Q + \gamma_3 KH + \gamma_4 Risk_{PR} + \sum_{k=1}^{n} \mu_{1k} \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \mu_{2k} \, cos\left(\frac{2\pi kt}{T}\right) \tag{16}$$

Following the methodology of Brester and Musick (1995), two marketing margin equations—farm-to-wholesale and slaughterhouse-to-retail—are estimated simultaneously using the 3SLS method.

$$MM_{FW} = \alpha_0 + \alpha_1 P_w + \alpha_2 P_w Q_R + \alpha_3 K + \alpha_4 Risk_{Pw} + \sum_{k=1}^{n} \delta_{1k} \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \delta_{2k} \, cos\left(\frac{2\pi kt}{T}\right) \tag{17}$$

In Equation (17), M_{FW} denotes the farm-to-wholesale marketing margin, P_w is the slaughterhouse-level price, Q_R refers to the quantity of output produced, K represents the slaughtering cost index, and $Risk_{PR}$ indicates price risk at the slaughterhouse level.

Equation (18) is then specified to examine changes in the wholesale-to-retail marketing margin.

$$M_{WR} = \beta_0 + \beta_1 P_R + \beta_2 P_R Q_R + \beta_3 H + \beta_4 Risk_{PR} + \sum_{k=1}^{n} \delta_{1k} \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \delta_{2k} \, cos\left(\frac{2\pi kt}{T}\right) \tag{18}$$

In Equation (18), M_{WR} refers to the wholesale-to-retail marketing margin, P_R denotes the retail price, Q_R represents the quantity produced, H captures the marketing cost index from wholesale (slaughterhouse) to retail, and $Risk_{PR}$ indicates retail-level price risk.

Each of these equations is estimated using the 3SLS method. Since slaughterhouses often engage in processing, a single firm may influence both the farm-to-wholesale and wholesale-to-retail margins. This structure can result in contemporaneous correlation among the residuals in Equations (17) and (18). As the exogenous variables differ across the two equations, a systems estimation approach produces more efficient results (Brester and Musick, 1995).

The Hausman test is applied to evaluate potential simultaneity bias. Specifically, it tests for the endogeneity of slaughterhouse-level beef prices in Equation (17) and retail-level beef prices in Equation (18).

In addition to the Hausman Test, which examines the endogeneity of variables, the Sargan Test was also utilized to assess the validity and exogeneity of the Instrumental Variables used in the 3SLS estimation. The null hypothesis of this test is that the instrumental variables are valid and exogenous.

This study utilizes monthly time series data from April 2014 to March 2024 (with 120 observations) to examine the determinants of the marketing margin and there is no time gap. Beef price data at the live cattle, slaughterhouse, and retail levels were obtained from the Livestock Affairs Support Company. Data on carcass weight and marketing cost indices—including slaughtering and preservation against spoilage—were sourced from the Statistical Center of Iran and the Central Bank of Iran, which release these figures monthly.

The Marketing Cost Index was calculated according to the official and weighted methodologies of the Central Bank. All price variables and marketing margins used in the study have been converted and adjusted to real prices using the Consumer Price Index (CPI) for the meat subgroup, which is published by the Central bank.

Results and Discussion

Price risk was first calculated at the slaughterhouse and retail levels to examine the effect of price risk on marketing margins and follow the frameworks of Faminow and Laubscher (1991) and Brester and Musick (1995). GARCH modeling requires a preliminary check for stationarity. Figures 1 and 2 show the autocorrelation functions (ACF) for beef prices at the wholesale and retail levels, respectively. Based on these figures, the gradual decay of the autocorrelation function for beef prices at both levels indicates an I(0) process and non-stationarity in these time series.

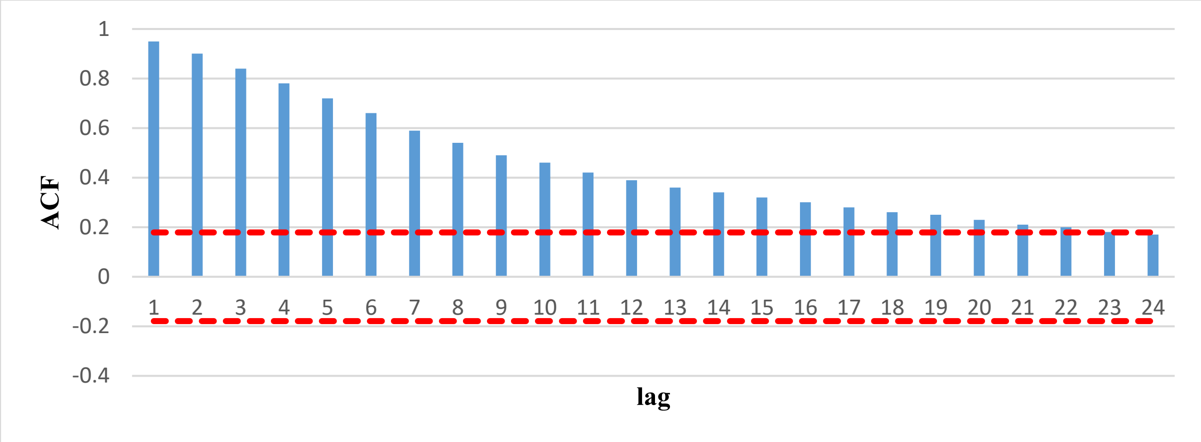

Figure 1. Autocorrelation Function (ACF) of Beef Price at Wholesale Level.

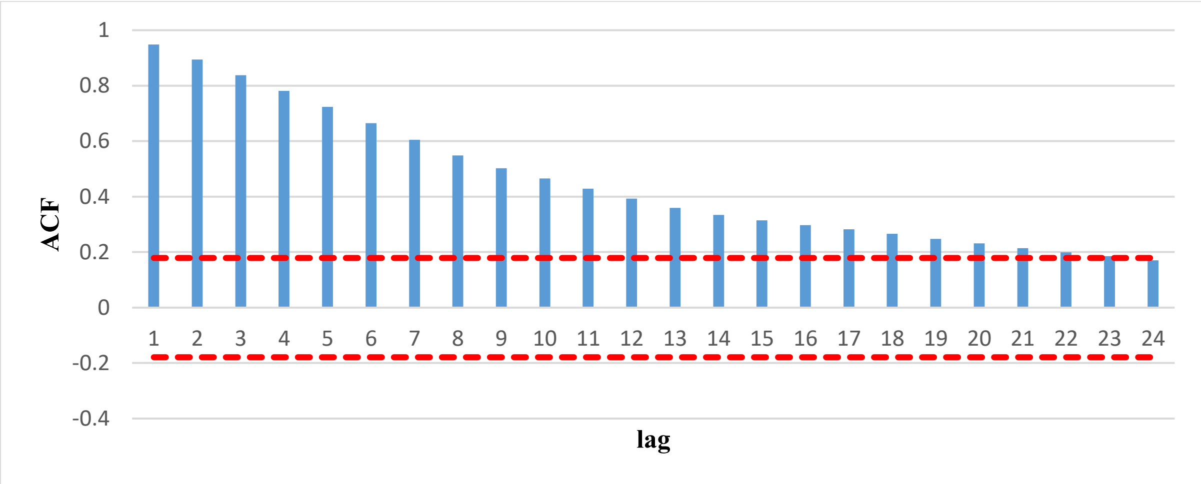

Figure 2. Autocorrelation Function (ACF) of Beef Price at Retail Level.

Given multiple economic shocks, the unit root test proposed by Enders and Lee (2012) was applied. As reported in Table 1, the null hypothesis of a unit root could not be rejected at levels; however, it was rejected at first differences for beef prices at both slaughterhouse and retail levels, indicating that the variables become stationary after differencing.

Table 1. Unit Root Test Results for Slaughterhouse and Retail Prices.

Variable	Optimal k	Test Statistic
Beef Price at Slaughterhouse	1	2.86
First Difference of Beef Price at Slaughterhouse	4	5.17^{***}
Retail Beef Price	1	3.18
First Difference of Retail Beef Price	4	3.87^{**}

Source: Research Findings (*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively) (Critical values are provided in Andres and Lee (2012)).

The second stage involves selecting the appropriate ARIMA structure. To determine the most suitable orders (p,q) for the AR and MA components in the ARIMA model, the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) analysis were utilized. In Figures 3 and 4, the PACF function for beef prices at both the wholesale and retail levels was plotted up to 24 lags. The initial significant spikes in the PACF plot were considered as preliminary guidance for determining the maximum potential number of lags for the AR and MA components. Taking this initial guidance into account, a set of ARIMA(p,d,q) models with various values of p and q (ranging from 0 to 2, given the nature of economic data and to avoid excessive model complexity) were estimated for each time series. For the final selection of the best model in this study, the Akaike Information Criterion (AIC) statistic was employed to choose the appropriate model. This criterion considers both the goodness-of-fit to the data and the complexity of the model (the number of estimated parameters). The model showing the lowest AIC value among the set of estimated models for each time series is selected as the final and superior model.

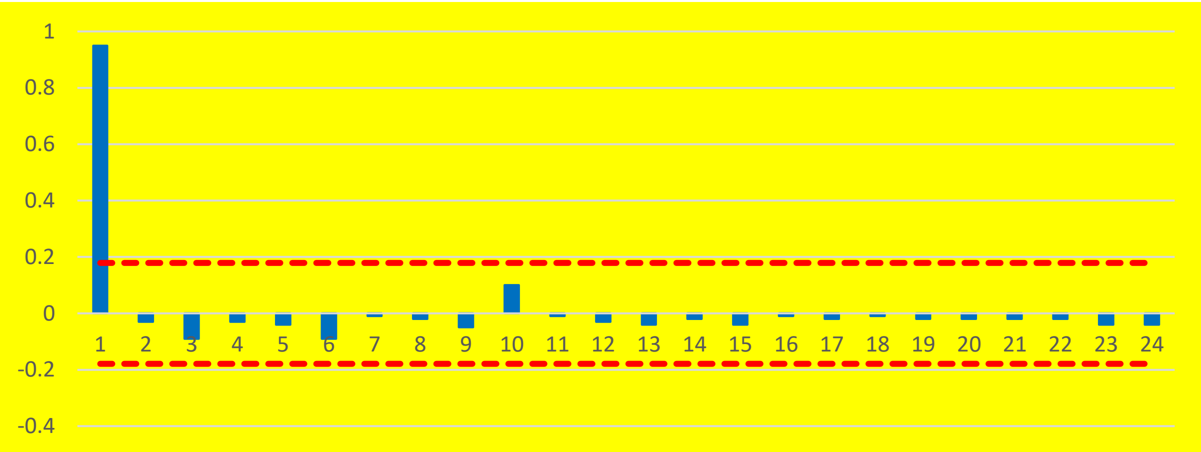

Figure 3. Partial Autocorrelation Function (PACF) of Beef Price at Wholesale Level.

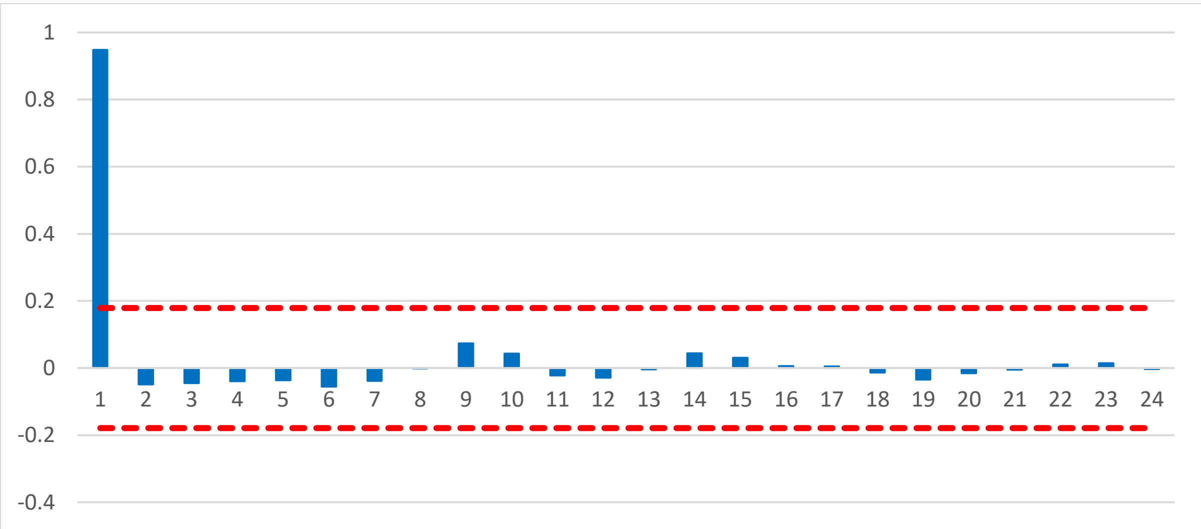

Figure 4. Partial Autocorrelation Function (ACF) of Beef Price at Retail Level.

The ARIMA(2,1,2) model was optimal for retail beef prices, and ARIMA(2,1,0) for slaughterhouse prices. Tests for ARCH effects confirmed conditional heteroskedasticity at the

1% level, validating the use of ARCH-GARCH models. Additional diagnostic tests confirmed the absence of serial autocorrelation and the normality of residuals.

To ensure that the model residuals are truly white noise (i.e., that they contain no significant autocorrelation), the Ljung-Box test was performed on the residuals. Table 2 presents the results of this test for the best- fitting model. As shown in Table 2, the P-values for the Ljung-Box statistic are greater than 5 percent (0.05) across all lags. This means that we cannot reject the null hypothesis of the absence of autocorrelation. Therefore, the test results indicate that the residuals of the estimated ARIMA model exhibit white noise behavior, and no significant autocorrelation pattern was found in them.

Table 2 - Ljung-Box Test for White Noise in ARIMA Model Residuals.

Variable	Ljung-Box	p-value
Beef Price at Slaughterhouse	29.33	0.40
Retail Beef Price	36.73	0.13

Based on coefficient significance and model selection criteria, the ARCH-GARCH(2,1) specification was adopted for slaughterhouse prices. Table 3 reports the estimated coefficients. The optimal value for the Fourier frequency parameter, k, was determined by minimizing both the Akaike Information Criterion (AIC) and the Residual Sum of Squares (RSS). In both cases, k=2 provided the most parsimonious and best-fitting model, which was adopted.

Table 3. Results of the ARCH-GARCH (2,1) Model.

Variable	Coefficient	Z-statistic
Intercept	1372.9**	54.15
AR(1)	-0.19	-0.83
AR(2)	-0.48***	-2.66
MA(1)	0.30**	2.01
MA(2)	0.78***	5.28
Variance Equation		
Intercept	56786.8	0.03
u_{t-1}^2	0.27***	44.15
u_{t-2}^2	-0.35***	-91.22
σ_{t-1}^2	0.15***	30.0
$\sin\left(\frac{2\pi kt}{T}\right)$	-4697.9	-0.004
$\cos\left(\frac{2\pi kt}{T}\right)$	-29.4***	-0.00004

Source: Research Findings (*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively) (Optimal k=2).

An ARCH-GARCH(2,1) model was selected for retail price volatility. The model results are presented in Table 4.

To determine the value of, k, all integer values from k=1 to k=5 were estimated, and based on the minimization of the Akaike Information Criterion (AIC) and the Residual Sum of Squares (RSS), the optimal value k=3 was selected as the most appropriate and parsimonious model.

Price uncertainty at both market levels was calculated using conditional variances derived from these models.

It should be noted that the selected models for beef prices at both the wholesale and retail levels are statistically stable. This means that the sum of the coefficients for the ARCH and GARCH terms in the variance equation is less than one, which confirms the stationarity of the conditional variance process.

Table 4. Results of the ARCH-GARCH (2,1) Model.

Variable	Coefficient	Z-statistic
AR(1)	-0.20^{***}	-2.76
AR(2)	-0.44^{***}	-5.25
MA(1)	0.53^{***}	10.58
MA(2)	0.87^{***}	19.69
Variance Equation		
Intercept	74732.2	0.96
u_{t-1}^2	0.85^{***}	5.88
u_{t-2}^2	-0.99^{***}	-5.49
σ_{t-1}^2	1.13^{***}	56.25
$\sin\left(\frac{2\pi kt}{T}\right)$	-735.55	-0.001
$\cos\left(\frac{2\pi kt}{T}\right)$	-154.47^{***}	-3.85

Source: Research Findings (*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively) (Optimal k=3).

To evaluate the adequacy of the estimated ARCH-GARCH models, diagnostic tests were performed on the residuals. The Ljung-Box test, with a P-value of 0.513 (for Q-statistic = 0.57), confirms the absence of serial autocorrelation. Furthermore, the ARCH-LM test, with a P-value of 0.947 (for LM-statistic = 0.57), supports the null hypothesis of ARCH effects in the residuals.

Before estimating Equations (14)–(16), the Enders and Lee (2012) unit root test were applied to all variables. As shown in Table 5, all series were found to be stationary at first difference.

Table 5. Unit Root Test Results for Marketing Margin Variables (Faminow and Laubscher (1991) Model).

Variable	Optimal k	Test Statistic
Beef Marketing Margin (MM)	1	-1.44
First Difference of Marketing Margin	4	-7.61^{***}
Marketing Cost Index (KH)	4	-0.35
First Difference of Marketing Cost Index	3	-8.16^{***}
Retail Meat Price Risk (RISK)	1	-1.97
First Difference of Retail Meat Price Risk	4	-7.31^{***}
Quantity of Product Supplied (Q)	3	-2.48
First Difference of Quantity of Product Supplied	3	-10.73

Source: Research Findings (*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively) (Critical values are provided in Andres and Lee (2012)).

Given the non-stationarity of variables at levels, the ARDL co-integration test with Fourier approximation assessed the long-run relationships in the markup, marketing cost, and relative margin models. As shown in Table 6, the null hypothesis of no co-integration was rejected.

Table 6. Co-integration Test Results.

model	Optimal k	Co-integration Test Statistic
mark-up model	3	9.93***
marketing cost model	1	9.42***
relative margin model	3	10.24***

Source: Research Findings (*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively) (Critical values are provided in Banerjee *et al*. (2017)).

Table 7 presents the eatimation results for markup results, marketing cost, and relative margin models. In the markup model, the retail price of beef, retail-level price risk, and the marketing cost index are all positively associated with the marketing margin. Among these, the retail price exhibits a statistically significant effect. The estimated elasticity indicates that a 1% increase in retail beef price leads to a 0.98% rise in the marketing margin. However, the margin's responsiveness to both price risk and the cost index is modest.

In the marketing cost model, the marketing margin responds positively and significantly to the marketing cost index and retail-level price risk. The corresponding elasticities suggest that a 1% increase in the cost index raises the margin by 1.07%, while a 1% increase in price risk increases the margin by 0.19%. The quantity supplied exerts a negative and significant effect, consistent with theoretical expectations, and the elasticity estimates confirm that the margin is inelastic concerning supply.

Although the calculated elasticity for beef retail price risk in the marketing cost model appears to be small in magnitude, it holds significant economic importance. This positive and significant coefficient indicates price risk is transmitted to the final consumer through an increase in the marketing margin.

The relative margin model shows that retail price, the total value of beef supplied at the retail level, the marketing cost index, and retail price risk positively affect the marketing margin. The retail price exerts the most pronounced influence among these variables, with an estimated elasticity of 0.98.

These findings align with the theoretical predictions of Brorsen *et al.* (1985), who reported that higher price risk at the retail level tends to expand the marketing margin. This implies that greater sensitivity of the margin to retail price risk contributes to a wider price gap transmitted to consumers, thereby reducing their purchasing power.

Across all three models, the coefficient of retail price risk is positive and consistent with economic theory. Its effect is statistically significant in the marketing cost and relative margin models. Similarly, the marketing cost index shows the expected sign in all specifications, although its impact is statistically significant only in the marketing cost model.

The results obtained from estimating the marketing margin patterns for beef show significant alignment with global findings regarding the transmission of price risk. Specifically, the positive and significant effect of price risk on the marketing margin is in agreement with the study by Faminow and Laubscher (1991), which was conducted on the South African maize market. Furthermore, the findings of this research are consistent with the conclusion of Jayne and Myers concerning the international wheat trade between the United States and Japan, which confirmed the positive impact of increased risk on the expansion of marketing margins. These alignments suggest that the increase in the marketing margin is a common behavioral pattern across various agricultural markets, enabling middlemen to transfer uncertainty to the consumer.

Table 7. Estimation Results of Equations (14), (15) and (16).

	Variable	Coefficient	T-statistic	elasticity
mark-up model	P_R	0.59***	40.07	0.98
	KH	5.20	0.32	0.03
	$Risk_{PR}$	0.18	0.01	0.012
$DW = 2.13 \quad R^2 = 0.99$				
marketing cost model	Q	-4.83***	-2.80	-0.14
	KH	2029***	28.54	1.07
	$Risk_{PR}$	2.04***	3.54	0.19
$DW = 2.12 R^2 = 0.99$				
relative margin model	P_R	0.59***	40.28	0.98
	$P_R Q$	0.00009	1.04	0.036
	KH	17.41	0.21	0.009
	$Risk_{PR}$	0.17**	2.39	0.011
$R^2 = 0.99 \quad DW = 2.02$				

Source: Research Findings (*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively). The estimated model includes Fourier components. However, the parameters of these components are not reported here in the interest of table clarity, due to their non-elastic and non-interpretable nature.

Unit root tests were applied to all variables before estimating the Brester and Musick (1995) models. As shown in Table 8, each series becomes stationary after first differencing.

Table 8. Unit Root Test Results for Marketing Margin Variables (Brester and Musick (1995) Model).

Variable	Optimal k	Test Statistic
Beef Farm-Wholesale Marketing Margin (M_{FW})	1	-0.93
First Difference of Beef Farm-Wholesale Marketing Margin	5	-12.63***
Beef Wholesale-Retail Marketing Margin (M_{WR})	1	-2.14
First Difference of Beef Wholesale-Retail Marketing Margin	4	-9.81***
Slaughtering Marketing Cost Index (K)	4	-1.35
First Difference of Slaughtering Marketing Cost Index	3	-11.69***
Marketing Cost Index from Wholesale to Retail Level (H)	1	-2.45
First Difference of Slaughtering Marketing Cost Index	3	-10.17***
Slaughterhouse Cattle Price Risk ($Risk_{PW}$)	3	-2.18
First Difference of Slaughterhouse Cattle Price Risk	3	-11.81***

Source: Research Findings (*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively) (Critical values are provided in Andres and Lee (2012)).

Given the non-stationarity at levels, co-integration was tested using the ARDL approach with a Fourier approximation. Results in Table 9 confirm the existence of long-run relationships in both the farm-wholesale and wholesale-retail models, mitigating concerns about spurious regression.

Table 9. Co-integration Test Results.

Model	Optimal k	Co-integration Test Statistic
Farm-Wholesale Marketing Margin Model	1	9.73***
Wholesale-Retail Marketing Margin Model	3	8.13***

Source: Research Findings (*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively) (Critical values are provided in Banerjee *et al.* (2017)).

The Hausman test was conducted for the beef price variables in Equations (17) and (18) to assess potential endogeneity. Table 10 reports statistically significant test statistics, confirming the endogenous nature of prices at both the slaughterhouse and retail levels. Therefore, a systems-based estimation is appropriate.

Table 10. Hausman Endogeneity Test Results.

Variable	Coefficient	T-statistic
Beef Price at Slaughter Level	-0.62***	4.79
Beef Price at Retail Level	0.22***	6.89

Source: Research Findings (*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively).

Estimation results for the two-equation system are presented in Table 11. For the farm-to-wholesale margin, the beef price and the total value of meat produced at the slaughterhouse level positively and significantly affect the margin. In contrast, the slaughtering cost index and slaughterhouse-level price risk exert a negative and significant influence. Elasticity estimates indicate that this margin is elastic concerning the slaughterhouse price—specifically, a 1% increase in this variable leads to a 1.17% rise in the margin. The effects of cost and risk variables are statistically significant but economically minor.

At the wholesale-to-retail level, the value of meat supplied to retail markets ($P_R \times Q_R$) has a significant inverse effect on the margin. Meanwhile, the retail price, meat spoilage protection cost index, and price risk contribute positively. The margin's responsiveness to these variables is inelastic. A 1% increase in the spoilage protection index raises the margin by 0.73%, while a 1% increase in retail price and retail price risk results in 0.64% and 0.026% increases in the wholesale-retail marketing margin, respectively.

The 3SLS model substitutes the endogenous variables with a combination of predetermined explanatory variables used as instruments. To evaluate the validity of the instrumental variables used in the 3SLS estimation, the Sargan Test was employed. The null hypothesis of this test is the exogeneity and validity of the instrumental variables. The calculated P-value for the Sargan statistic is 0.11. Since this value is greater than the significance level of 0.05, the null hypothesis is not rejected. This result confirms the validity of the chosen instrumental variables in the model and affirms the correctness of the marketing margin model estimation using the 3SLS method.

The very high coefficient of determination (R^2) (99 percent) in the marketing margin models (Tables 7 and 11) is expected, given the nature of the monthly/seasonal time series price data and the use of Fourier components. the use of the Fourier approximation allows the model to accurately absorb the regular seasonal and cyclical fluctuations present in the data, which constitute the majority of the variance. This does not necessarily indicate overfitting, but rather demonstrates the model's success in controlling for the cyclical and seasonal effects. furthermore, the stability of the results, the absence of autocorrelation, and the cointegration results provide greater confidence regarding the validity of the model structure.

The positive and significant effect of increased price risk on both the farm-wholesale margin and the wholesale-retail margin is consistent with the findings of Bresnahan and Musick's (1995) study, which linked the increase in risk to the expansion of the margin. This global behavioral pattern, which involves transferring the costs of uncertainty to the marketing margin, has also been confirmed in domestic studies by Shahbazi *et al.* (2009) and Razvani and Pendar (2025).

Table 11. Estimation Results of Equations (17) and (18).

	Variable	Coefficient	T-statistic	elasticity
farm-to-wholesale marketing margin	P_W	0.59***	17.82	1.17
	$P_W Q_R$	0.0005	0.60	0.02
	K	-164.85***	-2.96	0.15
	$Risk_{PW}$	-57.5***	-3.11	-0.06
$DW = 2.13$ $R^2 = 0.99$				
wholesale -to- retail marketing margin	P_R	0.13***	6.20	0.64
	$P_R Q_R$	-0.0005**	-2.64	-0.37
	H	460.45***	3.96	0.73
	$Risk_{PR}$	0.12**	2.65	0.026
$DW = 2.12$ sargan test P-Value=0.11 $R^2 = 0.97$				

Source: Research Findings (*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively). The estimated model includes Fourier components. However, the parameters of these components are not reported here in the interest of table clarity, due to their non-elastic and non-interpretable nature.

Conclusions

This study investigated the influence of price risk on beef marketing margins in Iran over the period April 2014 to March 2024, accounting for structural breaks arising from significant macroeconomic shocks, including the U.S. withdrawal from the JCPOA, the COVID-19 pandemic, and the elimination of preferential exchange rates. A Fourier-based approach was applied in the unit root testing and in estimating conditional volatility using the GARCH model to capture abrupt and gradual structural changes.

The elasticity estimates from the markup and relative margin models show that the total marketing margin is most responsive to retail beef prices, with elasticities of 0.98. In contrast, the marketing cost model reveals a stronger sensitivity to the marketing cost index. Retail-level price risk exhibits a positive and statistically significant effect on the margin in the marketing cost and relative margin models. However, the overall magnitude of this effect remains modest, indicating that only large fluctuations in price risk lead to significant changes in marketing margins.

The negative elasticity associated with slaughtering costs reflects producers' diminished bargaining power relative to slaughterhouses, which compels them to accept lower prices as processing costs increase. The contrast between the negative impact of wholesale-level risk on upstream margins and the positive impact of retail risk on downstream margins illustrates a clear case of asymmetric price risk transmission in the beef supply chain. This asymmetry likely reflects market concentration at downstream levels, the structure of government price controls, and the limited availability of risk mitigation tools for upstream producers. While the present study offers robust insights into the asymmetric transmission of price risk along the Iranian beef supply chain, several limitations merit consideration. First, the analysis relies primarily on aggregate time-series data, which may mask heterogeneous behaviors across geographic regions, producer scales, or marketing structures. Incorporating micro-level data could enable more granular insights into risk transmission mechanisms and actor-specific vulnerabilities. Second, although the models account for structural breaks, institutional and policy variables—such as government interventions in pricing or supply chain coordination—were not explicitly integrated. Future research could extend the modeling framework by incorporating institutional quality indicators, risk preferences of supply chain actors, and inter-market linkages, including informal or cross-border trade flows. Additionally, exploring non-linear or regime-switching dynamics may yield a deeper understanding of how risk transmission evolves under extreme market conditions. The positive association between retail price risk and the expansion of marketing margins highlights the need to revisit pricing frameworks and regulatory mechanisms at the retail level. Policy interventions should prioritize transparency and incorporate multi-stakeholder governance structures in price-setting. A possible approach could be the implementing of dynamic pricing models that integrate risk-adjusted benchmarks. Enhancing regulatory oversight is equally essential to curtail opportunistic increases in profit margins during episodes of heightened price volatility. Simultaneously, addressing the negative consequences of wholesale price volatility on producers necessitates greater institutional support for adopting risk management instruments. Expanding access to tools such as futures contracts, price insurance schemes, and stabilization funds would provide essential protection for livestock farmers. Moreover, strengthening producer organizations can improve bargaining power across the supply chain, particularly in negotiations with slaughterhouses and wholesale intermediaries.

Instead of focusing on establishing expensive futures markets (due to the lack of necessary exchange infrastructure and the high cost of livestock standardization), the priority should be placed on facilitating access to and improving existing price insurance schemes (such as guaranteed minimum price coverage) and assessing the feasibility of creating price stabilization funds for livestock products. Furthermore, strengthening producer organizations is essential to enhance their bargaining power in negotiations with slaughterhouses and wholesale intermediaries.

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بررسی اثر تکانه‌های اقتصادی و ریسک قیمت بر رفتار حاشیه بازاریابی گوشت گاو در ایران با استفاده از تقریب فوریه

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چکیده

با توجه به بروز انواع تکانه‌ها در اقتصاد کشور در دهه گذشته و تأثیر این تکانه‌ها بر سطوح مختلف قیمت گوشت گاو، پژوهش حاضر به بررسی اثر ریسک قیمت بر رفتار حاشیه بازاریابی گوشت گاو با لحاظ شکست‌های ساختاری در بازه زمانی فروردین 1393 تا اسفند 1402 پرداخته است. از این رو در پژوهش حاضر برای در نظر گرفتن شکست‌های ساختاری در آزمون ایستایی متغیرها، محاسبه ریسک قیمت با استفاده از روش GARCH و همچنین بررسی اثر ریسک قیمت بر حاشیه بازاریابی از تقریب فوریه استفاده شده است. نتایج برآورد سه الگوی اضافه‌بها، هزینه بازاریابی و حاشیه نسبی بیانگر اثر مثبت ریسک قیمت خرده‌فروشی بر حاشیه کل بازاریابی گوشت گاو است. نتایج همچنین بیانگر اثر منفی دو متغیر ریسک قیمت در سطح کشتارگاه و هزینه کشتار برحاشیه بازاریابی مزرعه- عمده‌فروشی و اثر مثبت ریسک قیمت خرده‌فروشی و هزینه بازاریابی از عمده‌فروشی تا خرده‌فروشی بر حاشیه بازاریابی عمده‌فروشی- خرده‌فروشی گوشت گاو است. بنابراین با توجه به نتایج پژوهش، ایجاد سامانه‌های جامع و به روز برای جمع‌آوری و انتشار اطلاعات قیمت گوشت گاو در سطوح مختلف بازار، تشویق دامداران به استفاده از ابزارهای مدیریت ریسک از جمله بیمه و قراردادهای آتی و همچنین تقویت و حمایت از تشکل‌های دامدارن و تولیدکنندگان برای افزایش قدرت چانه‌زنی دامدارن پیشنهاد می‌شود.