Nexus between Energy Consumption and Agricultural Inflation: an Iranian Experience

Niyoosha Naraghi*, Reza Moghaddasi*,[1], and Amir Mohamadinejad*

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ABSTRACT

The purpose of this paper is to examine an empirical method and identify the possible linkage between energy consumption and commodity prices in the context of Iran's agriculture. Different linear and non-linear models are estimated using quarterly data over 26 years from the second quarter of 1991 to the first quarter of 2017. Our results confirm the asymmetric impact of energy consumption shocks on agricultural commodity prices. Results of the Markov switching model show that agricultural prices respond negatively to any shock from energy consumption whereas, the effect of energy consumption on agricultural commodity prices in the high inflation rate regime is less than the low inflation rate regime. The empirical evidence indicates that the probability of remaining in the high inflation rate regime equals 93%, which is more than the other regime. The agricultural inflation rate is low and in 36 seasons and high in 63 seasons. Additionally, this study found an asymmetry in the agricultural price volatilities due to most of the coefficients changing across regimes.

1. INTRODUCTION

Today, the food-energy nexus is a vital issue. Energy in the food production chain is an essential feature of agricultural development and a critical factor in achieving food security.

Energy use in the agricultural sector has increased to respond to the growing demand of the population, the limited supply of cultivated lands, and the desire for high standards of living [1], [2]. In agriculture, energy consumption is divided into two parts: direct and indirect. Direct energy relates to different tasks in the agricultural production process such as land preparation, irrigation, plowing, harvesting, and transportation of agricultural inputs and farm production [3]. Direct energy is the energy consumed in the manufacturing, packaging, and transportation of fertilizers, pesticides, and farm machinery [4], [5].

Therefore, the agricultural sector is heavily dependent on energy which affects agricultural prices. Fluctuation in agricultural price is one of the most critical challenges for policymakers. Rapid rise in food prices has a significant negative impact on social welfare, which is an issue that is more critical in developing countries than in developed countries. According to the Food and Agriculture Organization (FAO) report in 2018, the food world price index increased from 89.6 to 229.9 during the period from 2002 to 2011.

In recent years, many studies were conducted to investigate the contentious issue of the food-energy nexus. The next section provides an overview of recent studies on food and energy prices. Several studies have confirmed the relationship between energy and food prices including Bergmann *et al.* [6], Rezitis [7], Zhang and Qu [8], Byrne *et al.* [9], Belke and Dreger [10], Nazlioglu *et al.* [11], Natanelov *et al.* [12], Jongwanich and Park [13], Kaltalioglu and Soytas [14], Balcombe and Rapsomanikis [15].

Recently, Ueda and Kunimitsu [16] investigated the effect of price changes in fossil fuel resources on world food prices. The findings displayed strong evidence of a relationship between mechanized agriculture sectors (wheat, plant fibers, and fishing) and the world oil sector. Taghizadeh-hesary *et al.* [17] examined the relationships between energy price and food price using the panel vector autoregressive (Panel-VAR) model for the selected Asian nations. Their findings revealed that the price of oil has a significant impact on food prices. Shehu *et al.* [18] demonstrated the asymmetric relationship between oil price shocks and food prices in the short run and long run using a non-linear autoregressive distributed lag analysis in Nigeria. Olasunkanmi and Oladele [19] found strong evidence of the asymmetric effect of oil price changes on agricultural commodity prices in Nigeria using a non-linear autoregressive distributed lag (NARDL) approach. Al-Maadid *et al.* [20] tried to discover a linkage between food and energy prices. The estimation results of a bivariate vector autoregressive-generalized autoregressive conditional heteroscedasticity (VAR-GARCH) (1,1) model showed significant relationships between food and both oil and ethanol prices. Mawejje [21] studied the impact of energy and climate shocks on

*Department of Agricultural Economics, College of Agricultural Sciences and Food Industries, Science and Research Branch, Islamic Azad University, Tehran, Iran.

[1]Corresponding author:
Email: r.moghaddasi@srbiau.ac.ir.

food prices in Uganda. They found a long-term relationship between food prices and energy prices.

McFarlane *et al.* [22] attempted to examine the relationships between oil prices and selected agricultural commodity prices (corn, wheat, and sugar) in the U.S., using a vector autoregressive (VAR) model for two consecutive seven-year periods: 1999-2005 and 2006-2012. They found strong evidence of co-integration between prices in both series. Cabrera and Schulz [23] assessed price and volatility risk originating in linkages between energy and agricultural commodity prices in Germany through an asymmetric dynamic conditional correlation GARCH model. Results showed that prices move together and preserve an equilibrium in the long run while correlations are mostly positive with persistent market shocks. Nwoko *et al.* [24] investigated the impact of oil price on the volatility of food prices in Nigeria by using a VAR model from 2000 to 2013. They found evidence of a positive and significant short-run relationship between oil price and food price volatility. Koirala and Mehlhorn [25] analyzed the dependency between agricultural commodity prices and energy prices and found a high positive correlation and a significant relationship between oil and food prices. Ibrahim [26] used a structural non-linear autoregressive distributed lag (NARDL) model to discover linkages between Malaysia's food and oil prices. Results showed a significant relationship between oil price increases and food prices in the long-run, but there is no linkage between oil price reduction and food prices. Wang *et al.* [27] tried to discover the effect of oil price volatility on agricultural markets. The estimation results from a structural VAR analysis showed that the relationship between agricultural commodity prices and oil price volatility depends significantly on oil supply shocks, aggregate demand shocks or other oil-specific shocks. Sassi [28] investigated the literature on food prices. The results of their research showed that various factors affect the food price, especially the price of energy. Nazlioglu and Soytas [29] analyzed the dynamic correlation between world oil prices and agricultural commodities' prices. They employed panel co-integration and Granger causality methods for a panel of twenty-four agricultural products over 1980-2010. Their results revealed strong support for the role of world oil prices on the prices of several agricultural commodities.

Du *et al.* [30] assessed the linkage between the volatility of crude oil prices and agricultural commodity markets using Bayesian Markov Chain Monte Carlo methods over ten years from 1998 to 2009. Their findings indicated the recent oil price shocks appear to have triggered sharp price changes in agricultural commodity markets, especially in the corn and wheat markets. Alghalith [31] attempted to examine the impact of the oil price on the food price by annual time series data (1974–2007) of Trinidad and Tobago. Results showed that increasing oil production leads to a reduction in food prices.

On the other hand, some research shows that there is no direct linkage between oil and agricultural commodity prices (*e.g.* Pindyck and Rotemberg [32], Abbott *et al.* [33], Gilbert [34], Zhang *et al.* [35],). For example, Gardebroek and Hernandez [36] shed light on the effect of oil price volatility on agricultural markets in the United States between 1997 and 2011. The estimation results from a multivariate GARCH approach showing that change in U.S. corn price does not depend on energy price change. Jiranyakul [37] failed to indicate the long-run relation between oil price fluctuation on consumer prices in Thailand. Abdulaziz *et al.* [38] found that negative oil price fluctuation has no significant effect on food prices. More recently, Meyer *et al.* [39] found evidence of a significant long term and positive linkage between oil price increases and food prices using a non-linear panel autoregressive distributed lag (ARDL) model. But they showed that there is no relationship between oil price decreases and food prices.

In this study, we investigated the impact of energy consumption, especially oil and its derivatives, on agricultural price inflation in Iran. According to a British Petroleum (BP) report [40] in 2018, the total primary energy consumption in Iran was around 285.7 million tonnes of oil equivalent (MTOE). In comparison to 2017, the growth rate was approximately 3.2%, and it was also compared to the last ten years (2007-2017) and average annual growth rate was approximately 5 %. This comparison shows an increase in the consumption trends during recent years. According to Iran's Ministry of Energy (ME) reports [41] in 2016, the share of the agriculture sector in Iran's total energy consumption was 4%, as shown in Figure 1.
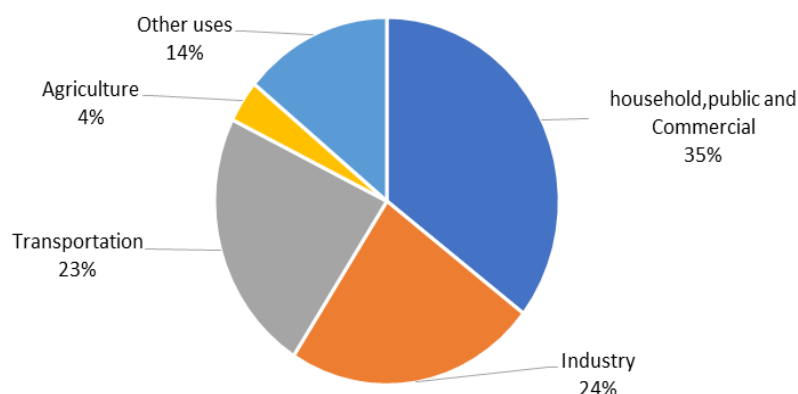

Fig. 1. The share of energy consumption of different sectors in Iran (EBSI, 2016).

Agriculture is an essential sector to the Iranian economy with a share of about 10% of gross domestic product, 18% of employment, and more than 15% of non-oil exports [42]. Therefore, the fluctuation in the price of agricultural commodities plays a significant role in inflation. Inflation is a major challenge for policymakers in Iran, and a single-digit inflation rate was one of the critical targets of the Iranian economy in recent years.

The agricultural price index is the most crucial tool for measuring inflation in the economy. High inflation is not a new phenomenon in Iran. With an annual average increase of 17.5%, the consumer price index rose from 0.056 to 109.6 from 1970 to 2017. Due to subsidy reform, international sanctions, and world price volatilities in food and oil markets, the inflation rate of agricultural commodity prices in Iran rose from 0.33% in 1991 to 25% in 2017. Hence, the analysis of high inflation determinants in Iran is useful for policymakers and contributes to a better design of policies.

An ME report in 2016 compared the energy consumption of industry and agriculture in Iran between 1991 and 2016, a period of 25 years. Overall, the energy consumption of industry was far higher than the energy consumption of agriculture and the energy consumption trend has fluctuated in recent decades in Iran (Figure 2). As Figure 2 shows, the agricultural sector's energy use has increased in 1994, 1998, 2003, and over the years 2005–2011. The ME report also shows that both the agricultural price and energy consumption have been highly volatile throughout the whole-time frame. In addition, there is an inverse correlation between agriculture and energy; as energy consumption decreases, agricultural prices increase (Figure 2).
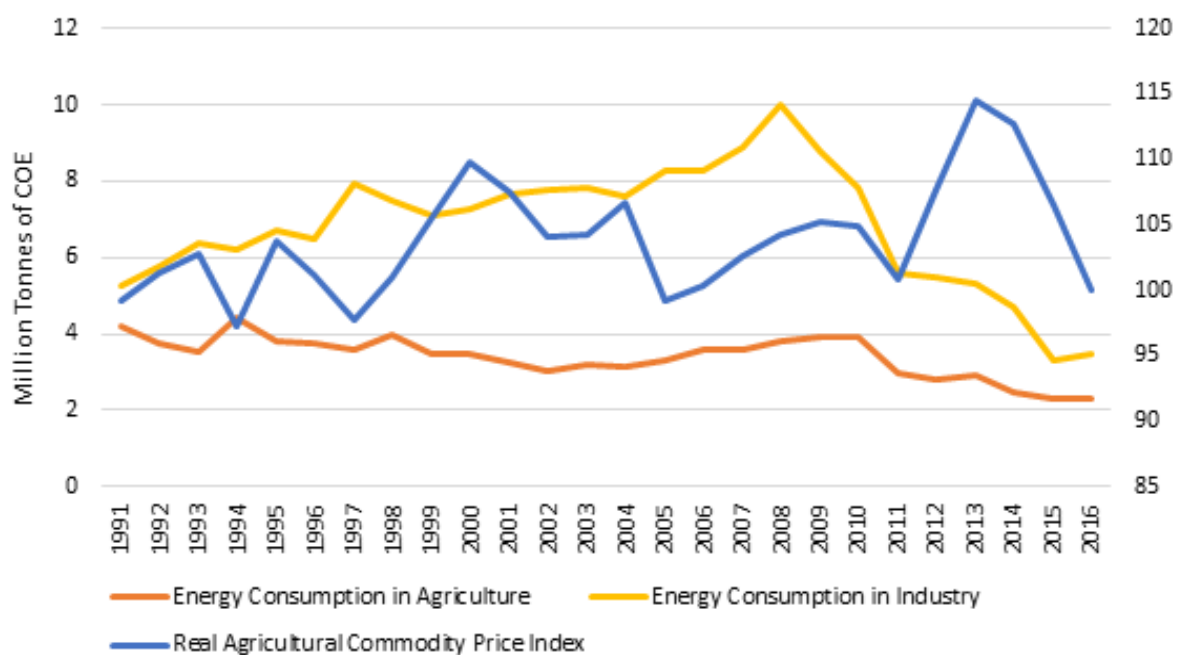

Fig. 2. Energy consumption of industry, energy consumption of agriculture and agricultural commodity prices index in Iran over the period 1991-2016 (million ton of crude oil equivalent (COE)) - (EBSI, 2016).

Considering global market interactions, international sanctions, increasing demand due to growing population, drought and desertification, oil price fluctuations, reducing global food production, and increasing the price of agricultural inputs, the essential and strategic agricultural sector of Iran has been facing severe challenges. Since in the current world-economy, import plays an important role in production, growth, and economic development, production is strongly under the influence of factors that affect imports. There are restrictions on producing some required agricultural inputs, such as fertilizers and pesticides. Half of which are supplied through imports. On the other hand, given that the petrochemical and agricultural sectors are most dependent on oil, oil price fluctuations can affect the price of agricultural commodity prices.

Our literature review shows a distinct lack of research on modeling and analyzing the linkage between agricultural input price shock, especially energy and agricultural commodity prices in Iran. A review of empirical research shows that linear models have been used in most studies that could not show the asymmetric impact of energy price on the food price, so that non-linear models should be used. The Markov switching model is a popular non-linear time-series model that involves multiple equations and can characterize the time-series behaviors in different regimes. This model is suitable for describing correlated data that exhibit distinct dynamic patterns during different periods.

Considering the sensitivity of food security and the impact of agricultural input, the main objective of this paper is to develop an economic model and to gain reliable insight into energy consumption behavior on agricultural inflation, by using the Markov Switching Approach.

2. MATERIALS AND METHODS

2.1 Markov Switching Model

Non-linear models assume that the behavior of variables is different in varying situations. The speed at which we see these changing variables in non-linear models are divided into two main groups. In one group, the changing situation is done slowly and smoothly (*e.g.*, smooth transition autoregressive (STAR) and artificial neural network (ANN) models). In other group, the transition is done quickly, which we see in the Markov switching model.

The Markov switching model is one of the non-linear time series models proposed by Hamilton [43]. This model assumes that there are m regimes for the time series variable y_t, which is specified by unobservable variable s_t. A Markov switching autoregressive model (MS-AR) of regimes with an AR process of order p is written as follows;

$$y_t = \begin{cases} c_1 + \alpha_1 y_{t-1} + \varepsilon_1, & s_t = 1 \\ c_2 + \alpha_2 y_{t-1} + \varepsilon_2, & s_t = 2 \end{cases} \quad (1)$$

Where $u_t \approx N(0, \sigma^2)$ and s_t is resulted by the Markov chain with n regimes that is independent of u_t in all of the time. The autoregressive parameters, the intercept, and heteroskedasticity of this model are dependent on the regime at time t. The hidden process s_t follows a first-order ergodic Markov chain. It means that the probability for regime 1 to happen at time t depends solely on the regime at time $t-1$.

In Equation 1, the transition probability from one regime to another regime is calculable in the form of conditional probabilities, where p_{ij} represents the transition, as defined below:

$$P(s_1, s_2, \dots s_{t-1}) = P(s_{t-1} = i) = p_{ij} \quad (2)$$

In Equation 2, p is a one-step transition probability, which indicates the transition probability from i to j. The probability of switching is captured in the matrix P, known as a transition matrix.

$$P = \begin{bmatrix} P(s_{t-1} = 1) & P(s_{t-1} = 2) \\ P(s_{t-1} = 1) & P(s_{t-1} = 2) \end{bmatrix} \quad (3)$$
$$= [p_{11} \ p_{12} \ p_{21} \ p_{22}]$$

Where the $p_{11} + p_{12} = 1$ and $p_{21} + p_{22} = 1$

Therefore, p_{12} is the transition probability from regime 1 to regime 2, and p_{21} indicates transition probability from regime 2 to regime 1. Also, p_{11} and p_{22} show the stability probability of regime 1 and 2, respectively.

The Markov switching model is categorized into different types depending on which part of the autoregressive model is regime-dependent and affected. In economic studies, what gets the most attention involves four varieties of Markov-switching models:

MSM   Markov-switching mean,
MSI   Markov-switching intercept term,
MSA   Markov-switching autoregressive parameter,
MSH   Markov-switching heteroskedasticity.

A summary of Markov models is given in Tables 1 and 2 [44].

Consequently, based on economic theories and empirical observations, some economic variables have non-linear behavior that can be modeled as mentioned earlier the Markov switching model is estimated by methods such as Maximum Likelihood Estimation (MLE), Expectation-Maximization (EM), and Gibbs Sampling Approach. To select the best-fitting model from the above examples, the following strategy is used:

- Using the Akaike Information Criterion (AIC) for determining the optimal number of lags for variables
- Comparing the estimates of a variety of specifications in the Markov switching models based on three features:1) the highest number of significant coefficients (especially regime-dependent components), 2) the most amount of the maximum likelihood function, 3) the least amount of minimum variance for error terms.

Table 1. Types of Markov-switching models.

Name of the model	Equation	Error Terms Distribution	Regime-dependent parameters
MSM(m)-AR(p)	$\Delta y_t - \mu(s_t) = \sum_{i=1}^{p} \alpha_i (\Delta y_{t-i} - \mu(s_{t-i})) + \varepsilon_t$	$\varepsilon_t \sim IID(0, \sigma^2)$	Mean
MSI(m)-AR(p)	$\Delta y_t = c(s_t) + \sum_{i=1}^{p} \alpha_i (\Delta y_{t-i}) + \varepsilon_t$	$\varepsilon_t \sim IID(0, \sigma^2)$	Intercept term
MSH(m)-AR(p)	$\Delta y_t = c + \sum_{i=1}^{p} \alpha_i (\Delta y_{t-i}) + \varepsilon_t$	$\varepsilon_t \sim IID(0, \sigma^2(s_t))$	Heteroskedasiticity
MSA(m)-AR(p)	$\Delta y_t = c + \sum_{i=1}^{p} \alpha_i (s_t)(\Delta y_{t-i}) + \varepsilon_t$	$\varepsilon_t \sim IID(0, \sigma^2)$	Autoregressive Parameters

Table 2. Types of Markov-switching autoregressive models.

		MSM		MSI	
		Mean varying	Mean invariant	Intercept varying	Intercept invariant
Autoregressive Parameters invariant	Heteroskedasiticity invariant	MSM-AR	Linear MAR	MSI-AR	Linear AR
	Heteroskedasiticity varying	MSMH-AR	MSH-MAR	MSIH-AR	MSH-AR
Autoregressive Parameters varying	Heteroskedasiticity invariant	MSMA-AR	MSA-MAR	MSIA-AR	MSA-AR
	Heteroskedasiticity varying	MSMAH-AR	MSAH-MAR	MSIAH-AR	MSAH-AR

2.2 BDS Test of Non-linearity

The non-parametric BDS test was developed to investigate the serial correlation and non-linear structure in a time series based on the total correlation by Brock *et al.* [45]. In this method, the scalar time series x_t, which has N-lengths and m-dimensions, is considered, and the new series of X_t creates as $X_t \in R^m$, $X_t = (X_t, X_{t-\tau}, ..., x_{t-(m-1)\tau})$. In the null hypothesis situation of time series x_t, the BDS statistic for $m > 1$ is defined as:

$$BDS_{m.M}(r) = \sqrt{M} \, \frac{c_m(r) - c_1^r(r)}{\sigma_{m.M}(r)} \qquad (4)$$

Where $M = N - (m\text{-}1)$, τ shows the number of surrounded point in m-dimensional space, r is the radius of the sphere with the center X_i and $c_m(r)$ is constant values that presented by Grassberger and Procaccia [46]. Thus, the null and alternative hypothesis of the BDS test for discovering non-linearity is as follows;

H₀: the series are linearly dependent
H₁: the series are not linearly dependent.

Additionally, this test is used as a suitable identification tool to distinguish between linear and non-linear models. Thus, if the analysis is performed on the residual of linear models, the test hypotheses are as follows (For more detailed information about this test, see the Wang *et al.* [47] report):

H₀: The linearity of the time series process
H₁: the series are not linearly dependent.

Following the above theoretical model, we employ below an empirical econometric model (Equation 5) to estimate the effects of energy consumption fluctuations and other factors on agricultural commodity prices.

$$API_t = a_{s_t} + \beta_1 PPI_{s_t} + \beta_2 FPI_{s_t} + \beta_3 EC_{s_t} + \varepsilon_t \qquad (5)$$

Where API indicates agricultural commodity prices index, PPI and FPI represent pesticide prices index and fertilizer prices index, respectively, and EC denotes energy consumption of regime s at time t.

To estimate this equation, we will run a MS-AR model and some preliminary tests, such as a unit root test and a stability test, are employed to ensure the reliability of MS-AR estimation results.

2.3 Data

In Iran, energy prices do not fluctuate much since Iran's energy market is overly centralized and controlled by the government. However, based on the demand function, there is a negative one-to-one relationship between energy consumption and its price. Hence, we used the energy consumption database instead of the energy price in this study.

To examine the linkage between energy consumption and agricultural commodity prices in Iran, we used the seasonal data over the period 1991:2 to 2017:1. The seasonal data are used in this research, including the agricultural commodity price index (API), pesticide price index (PPI), fertilizer price index (FPI), and energy consumption (EC) from 1991 to 2017. The data was extracted from several official documents of the Central Bank of the Islamic Republic of Iran (CBI) [48] and reports of the Ministry of Energy (ME).

The descriptive statistics of the variables during 1991-2017 showed that (API) has a mean of 103.7, with a maximum of 121.4, while the minimum is only 67.26. The pesticide price index (PPI) has a high volatility based on its high standard deviation. It reaches a maximum of 234.18, while the minimum is only 72.79. The fertilizer price index (FPI) has a volatility of 32.29 with a maximum and minimum of 173.41 and 9.58, respectively. Finally, the energy consumption (EC) volatility of 0.136 million tonnes COE denotes some shocks between 1991-2017. Also, EC ranges from 0.56 to 1.117 million tonne COE. The summary of descriptive statistics is found in Table 3.

3. RESULTS AND DISCUSSION

Due to use of time series data, it is necessary to check the stationarity of variables. But there has been increasing concern that the Dickey-Fuller test, which is derived under a linear setting, may fail to reject the null of a unit root when applied to a non-linear but stationary time series. As mentioned earlier, we performed a common non-linear unit root test (Kapetanios, Shin and Shell (KSS) [49], Zivot and Andrews [50], Lee and Strazicich [51]). The results are presented in Tables 4, 5 and   6.

Table 3. Descriptive statistics of data during 1991-2017.

Variable	Symbol	Unit	Mean	Maximum	Minimum	Std. Dev
Agricultural Price Index	API	-	103.7	121.4	67.26	6.29
Pesticide Price Index	PPI	-	131.8	234.18	72.79	33.27
Fertilizer Price Index	FPI	-	69.9	173.41	9.58	32.29
Energy Consumption	EC	Million tone COE	0.85	1.117	0.56	0.136

Note: COE= Crude Oil Equivalent

Table 4. KSS unit root tests results.

Series	Autocorrelation Degree	t-KSS	t-statistic	Probability
API	1	3.03	1.68	0.0026*
PPI	7	-1.97	1.9	0.049*
FPI	9	-0.9	1.9	0.036
EC	12	4.80	1.9	0.000*

Source: Authors' estimates using Eviews10
Note: * denote significance at 5% level
All variables are in natural logarithm

Table 5. Result of Zivot and Andrews one-break test.

Series	Lags included*	t-statistics	Break season
API	8	-4.70*	2005:2
PPI	0	-4.61*	1995:3
FPI	0	-4.59*	2009:4
EC	9	-4.32*	2010:2

Source: Authors' estimates using Eviews10
Note: All variables are in natural logarithm
* Lags for the difference of the series selected via t-test
*, ** and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

Table 6. Result of Lee and Strazicich two-break test.

Series	t-statistics	Breaks	
API	-5.46**	2001:1	2014:1
PPI	-5.16**	1995:1	1997:2
FPI	-4.82**	2004:1	2011:2
EC	-4.88**	2011:2	2013:3

Source: Authors' estimates using Eviews10
Note: All variables are in natural logarithm
* and ** denote statistical significance at 10% and 5% levels, respectively.

The results in Table 4 show that the API, PPI, and EC series reject the null hypothesis, *i.e.*, they all are non-linear trend stationary, while FPI implies it is a stationary series.

The results of applying the unit root test by the Zivot and Andrews and Lee and Strazicich methods in consideration of the structural break for the variables studied are presented in Tables 5 and 6.

The results for the Zivot and Andrew unit root test are presented in the Table 5. These results suggest that we can reject the null of unit root API, PPI, FPI, and EC at a 10% significance level, implying that all 4 variables considered in this study are stationary with one structural break at levels.

Table 6 presents the results for the Lee and Strazicich unit root test. These results suggest that we can reject the null of unit root API, PPI, FPI, and EC at a 5% significance level, implying that all four variables considered in this study are stationary with two structural breaks at levels.

Next, we perform a test of non-linearity on the residuals of the linear ARMA following [45]. As shown in Table 7, the null hypothesis is rejected and it indicates that the structure of the model is non-linear. Therefore, the BDS test confirms the presence of non-linearity in the residuals. In the final step, the model estimation is extracted using the non-linear Markov switching model.

For this purpose, the model used different lags and regimes by applying OxMetrics software. The values of information criteria such as SBIC, HQ, AIC, and the log-likelihood ratio were compared. However, this study employs both the Akaike information criterion (AIC) and the log-likelihood ratio for model selection. Again, arguably the ACI is one of the most widely used criteria by researchers such as Pan [52], Psaradakis and Spagnolo [53], Manera and Cologni [54], Cavicchioli [55], and Mendy and Widodo [56].

Finally, a model with the lowest AIC is the appropriate regime. Table 8 compares the appropriateness of the variously Markov switching models, with different lags and regimes. Applying

different specification measures on the previously mentioned Table 8, such as the Log-likelihood and Akaike information criteria, one can identify the best-suited Markov-switching model estimation between the

10 different samples. The selected model was MS (2)-AR (5) with the lowest AIC of (-4.068) and the highest log-likelihood of (221.372).

Table 7. Result of BDS test.

Dimension	Prob	Z-statistics	Std. Error	BDS Statistic
2	0.00	8.302	0.007	0.061
3	0.00	11.618	0.011	0.136
4	0.00	12.926	0.014	0.182
5	0.00	14.510	0.014	0.214
6	0.00	16.761	0.014	0.241

Source: Authors' estimates using Eviews10

Table 8. Results of MS models estimation regime.

Number of regimes	Model [MS-AR]	Number of lags	Log likelihood	AIC
	MS(2)-AR(1)	1	189.580	-3.46
	MS(2)-AR(2)	2	206.335	-3.77
2	MS(2)-AR(3)	3	209.411	-3.829
	MS(2)-AR(4)	4	211.905	-3.898
	MS(2)-AR(5)	5	221.372*	-4.068*
	MS(3)-AR(1)	1	215.939	-3.998
	MS(3)-AR(2)	2	221.210	-4.044
3	MS(3)-AR(3)	3	217.298	-3.884
	MS(3)-AR(4)	4	218.510	-3.870
	MS(3)-AR(5)	5	220.943	-3.998

Source: Author's estimates using PcGive in OxMetrics 7
[Note the asterisk * denotes the chosen model]

Table 9. Determination the optimal type of Markov switching model.

MS-AR(5)	AIC	
	Regime 2	Regime 3
MSI-AR(5)	-3.423	-3.745
MSMH-AR(5)	-3.647	-3.568
MSIA-AR(5)	-4.119	-4.027
MSMA-AR(5)	-3.436	-3.442
MSIH-AR(5)	-4.119	-4.025
MSIAH-AR(5)	-4.126*	-4.060
MSAH-AR(5)	-3.972	-4.054

Source: Author's estimates using PcGive in OxMetrics 7
[Note the asterisk * denotes the chosen model]

As noted in the research method section, the Markov-Switching model has the various types that each of these is a particular component of the regime-dependent equation. Therefore, to choose the best type, the Akaike information criterion was used, and the model with the minimum value was selected as the optimal model. The Akaike information criteria for each type of Markov Switching are reported in Table 9. The selected model was MSIAH (2)- AR (5) with the lowest AIC of (-4.129) and the highest log-likelihood of (226.418).

After model estimation and selection, the model MSIAH (2)- AR (5) was then tested for serial correlation, ARCH, and normality (see Table 10). The portmanteau test concluded that the error terms are not serially correlated. The ARCH test reported no issues of homogeneity of the variance of the error term. Finally, the normality test indicates that the residuals were found

to be normally distributed. Also, the LR test indicated that the hypothesis of linearity could be rejected in favor of a model a Markov switching model.

According to this model, the period of the Markov switching model estimation is classified into two regimes. In Table 10, the parameters of the MS model are estimated using maximum likelihood estimation. Approximately, all the estimated coefficients of the MSIAH (2) - AR (5) model are found to be significant at the conventional level. As such, it is hard to make economic interpretation using the regime dependent intercepts. Since the LR-test $\chi 2$ is equal to 39.750 and the p-value of DAVIES statistic is less than 0.05, the non-linear relationship between the variables was confirmed.

Table 10 shows the estimation results of the parameters of the model. It indicates the fluctuations in agricultural prices during the period can be divided into

two regimes: low inflation rate and high inflation rate. The intercept of the first regime is 3.36, indicates a low inflation rate, and the intercept of the second regime that equals 4.75 indicates a high inflation rate. The results show that most of the coefficients have changed by changing the regime. In the first regime (low inflation rate), PPI, FPI, and EC have affected the API, and in the second regime (high inflation regime), only PI and EC have influenced API. Furthermore, the energy consumption (EC) variable is statistically significant in all regimes. There is a negative correlation between the agricultural price index and energy consumption in both regimes that the effect of energy in the first regime is stronger than other regimes. Therefore, the results confirm that the impact of EC on API is asymmetrical. This finding is in line with Olasunkanmi and Oladele [19], Shehu *et al.* [18], and Pal and Taghizadeh-hesary *et al.* [17]. They found the asymmetric impact of energy price shocks on food price. In regime 1, the EC coefficient is negative and equal to -0.128, which is statistically significant at the 95% level and indicates an increase in EC lead to a decrease in API. In other words, if the energy consumption increases by one percent, the agriculture price will decrease by an average of 0.128 % during the period, assuming all other conditions are without change. Also, in regime 2, the coefficient of EC is negative and equal to -0.067, which is statistically significant at the 95% level and indicates a decrease in API due to an increase in EC. We can say, if the energy consumption increases by one percent, the agriculture

price will decrease by an average of -0.067 % during the survey period 1991-2017, assuming that all other conditions are without change. Thus, the model corresponds to theoretical expectations, which imply that agriculture prices are affected by inputs, excluding fertilizer prices index at the second regime.

An interesting part of Table 10 is the transition probabilities matrix that presents the probability of transition from one regime at time t to another regime at time t+1. The results of the transition probabilities show that there is a high probability of remaining in the same regime. Considering the results of the transition probabilities, we can say that if there is low inflation rate in one period, the probability that this low rate will continue in the next period is 87%. Correspondingly, when the system is in the second regime, there is a 93% probability of remaining in the second regime or a probability of 7% switching to the first. This shows that only an extreme event can switch the regimes to each other. Further, the estimated transition probabilities are less than one that indicates none of the regimes are permanent. The number of episodes of regime 1 is less than the other regime during the period 1991(2) to 2017(1).

Moreover, considering the estimation result of Table 10, one important policy implemented over the period 1991-2017 was the policy of eliminating subsidies for agricultural inputs that have been implemented in Iran since 2011, which has occurred in the high inflation rate regime.

Table 10. Estimation results of MSIAH(2) – AR (5) model for the period 1991(2) – 2017(1).

Regime-dependent intercepts	Regime 1		Regime 2	
	Coefficient	P-value	Coefficient	P-value
Constant	3.361**	0.000	4.754**	0.000
Autoregressive coefficients				
API(-1)	0.719**	0.000	0.638**	0.000
API(-2)	-0.384**	0.001	-0.315**	0.003
API(-4)	-0.144**	0.025	0.195**	0.038
API(-5)	-0.140**	0.001	-0.518**	0.000
Variables				
PPI	0.151**	0.000	-0.026*	0.058
FPI	0.072**	0.000	-0.002	0.838
EC	-0.128**	0.001	-0.067**	0.014
Variances				
σ^2	0.015	0.0019	0.024	0.002
Log likelihood		224.248		
AIC		-4.126		
LR-test χ2		39.750 (0.000)		
DAVIES		0.000		
Portmanteau test χ2 (12 lags)		19.236 (0.069)		
Normality test χ2		0.268 (0.874)		
ARCH 1-1 test		0.0047 (0.45)		
Transition probability		Regime 1		Regime 2
Regime 1		0.874		0.07
Regime 2		0.126		0.93

Source: Author's estimates using PcGive in OxMetrics 7
Note: All variables are in natural logarithm
* and ** denote statistical significance at 10% and 5% levels, respectively.

Coupled with this policy, successive droughts have also happened in this period. This is why the coefficient of pesticide price has not been positive in the high inflation rate regime, as the agricultural price rose due to decreasing production. The successive droughts periods are as follows 1993(1)-1999(3), 2003(2)-2008(2), as well as 2011(1)-2013(2) [see Table 11].

Based on the expected duration in Table 11, the first regime has an average duration of 9 quarters while the other regime has 15.75 quarters duration. It implies that during the period 1991-2017, the agricultural inflation rate was low and high in the 36 seasons and the 63 seasons, respectively. Therefore, agricultural inflation has mostly had fluctuations in a high inflation rate.

To further assist with the interpretation of the MSIAH (2) - AR (5) model, in Figure 3, the first panel shows the evolution of the agricultural prices index, while Figure 4 denotes the filtered, smoothed, and predicted probabilities of being in two regimes, respectively. From Figure 4, it can be observed that the second regime dominates the first regime, which confirms the statistical analysis reported in Table 11.

The estimation results showed that the Markov Switching model (the non-linear method) provides a better fit than the linear method since it allows us to investigate the non-linear behavior of agricultural commodity prices relative to input prices, especially energy consumption.

Furthermore, the results of MS-AR model confirmed that the agricultural prices index is influenced by pesticide prices index, fertilizer prices index, and energy consumption, all of which have a significant negative or positive effect on the agricultural prices index. Also, the probability of remaining in the high inflation rate is more than the low inflation rate. Therefore, it can be concluded that there is an asymmetry in the agricultural price index fluctuations.

Table 11. Regime classification: episodes of two regimes from 1991(2) to 2017(1) (smoothed probabilities).

Period			Total
Regime 1	Quarters	Average Probability	
1992(3)-1992(4)	2	0.974	
1999(3)-2003(1)	15	0.949	36 quarters (36.36%) with an average
2008(3)-2010(4)	10	0.990	duration of 9 quarters.
2013(3)-2015(3)	9	0.994	
Regime 2			
Period	Quarters	Average Probability	
1993(1)-1999(2)	26	0.989	
2003(2)-2008(2)	21	0.868	63 quarters (63.64%) with an average
2011(1)-2013(2)	10	0.991	duration of 15.75 quarters.
2015(4)-2017(1)	6	0.950	

Source: Authors' estimates using PcGive in OxMetrics 7
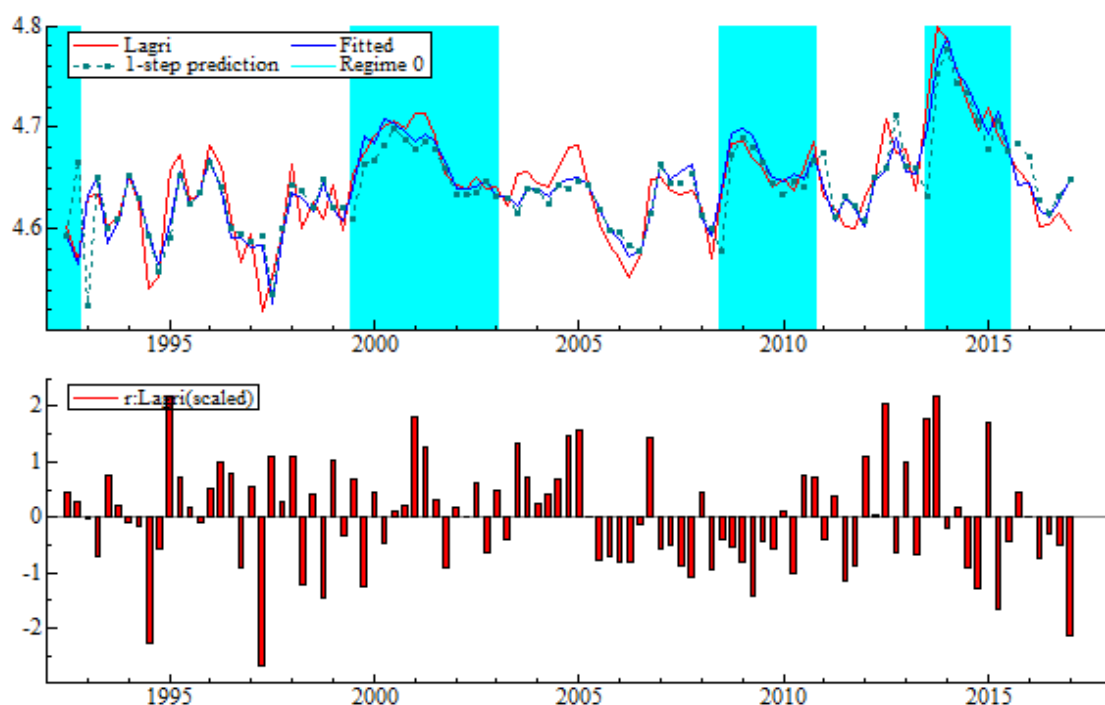

Fig. 3. Graphical representation of the regime probabilities.
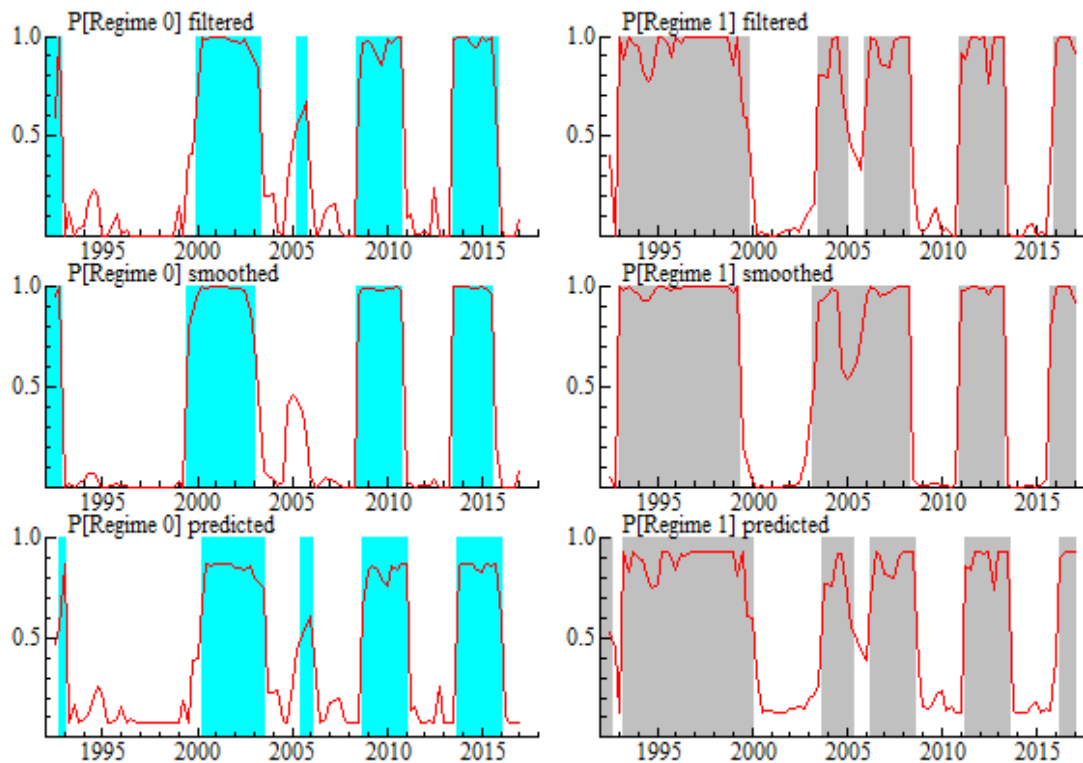
Fig. 4. Graphical representation of the types of transition probabilities.

4. CONCLUSION

In general, the asymmetry in price fluctuations has led to pay more attention to non-linear models for extracting and examining price transmission and the relationship between different markets. The Markov switching model is one of the most popular non-linear models used in this field. This study investigated the relationship between agricultural input price, especially energy consumption, and the Iranian agricultural inflation during the period 1991 (2) - 2017 (1). To that end, the model was estimated using the Markov switching model (MSIAH (2) – AR (5)). Furthermore, to detect the impact of energy on agricultural prices, we employed energy consumption data. From the estimation results, the following conclusions can be drawn:

- First, based on the result of the BDS test and the LR-test χ2, the non-linear model is preferred over the linear model for analyzing the relationship between agricultural input prices and agricultural inflation.
- Second, the estimation results are consistent with theoretical foundations illustrating the importance of input prices and energy consumption on agricultural commodity prices. As with most experimental studies reviewed, this study has also shown energy consumption has a negative impact on agricultural commodity prices. In other words, it can be contended that during the study period, agricultural input prices have been influential factors on agricultural commodity prices.
- Third, the findings revealed that the low inflation rate and high inflation rate regimes are stable and that only extreme events can switch regimes.
- Fourth, the results of the MS model showed that the effect of input prices on agricultural inflation is different in regimes. In the case of energy, the impact of energy consumption on agricultural commodity prices in the high inflation rate regime is less than the low inflation rate regime because the elimination of energy subsidies policy has been applied in the second regime (high inflation rate). Thus, the results indicate the asymmetric impact of energy consumption shocks on agricultural commodity prices.
- Finally, a plot of the smoothed probability was able to report the timing of regimes of agricultural commodity prices index corresponding to major government intervention, environment, and other shocks. The effect of agricultural input prices on agricultural commodity prices indicates that Iranian agriculture is significantly affected by changes in input prices. In this study, changes in input prices were caused by various shocks, such as the elimination of energy subsidies and drought. Therefore, it can be concluded that the elimination of energy subsidies and drought were, directly and indirectly, able to affect agricultural inflations through the price of inputs.

In conclusion, planners and policymakers must pay attention to this asymmetry in agricultural commodity price volatility to increase the price stability in agriculture as much as possible by appropriate policy tools.

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