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Evaluating the Explanatory Power of Behavioral Models in Measuring Food Inflation Uncertainty in Iran: A Confrontation between GARCH and Rational Inattention Models

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ABSTRACT

This study investigates the behavioral roots of persistence in food price inflation volatility and compares its dynamics across urban and rural areas of Iran over the period from April 2003 to January 2026. To this end, a hybrid approach is employed, combining GARCH family models with structural break controls via Fourier trigonometric functions and a semi-parametric model grounded in Rational Inattention theory—which relies on the information flow rate parameter. The findings indicate that the Rational Inattention model, by accounting for information processing capacity constraints, exhibits higher out-of-sample predictive power and explanatory ability-as measured by RMSE and MAE—compared to traditional GARCH and Fourier-GARCH models. The information flow rate in urban areas is estimated to be approximately 2.7 times that of rural areas, indicating a deep information gap between these two markets and the primary cause of stronger volatility persistence in rural regions. Furthermore, based on the Directional Volatility Ratio index, which decomposes variance into upward and downward components, the results reveal that in rural areas, positive price shocks (upward risks) are the main source of uncertainty, whereas in urban areas, volatility stemming from the deflation of price bubbles and mean reversion plays the dominant role in generating fluctuations. Finally, these results underscore the need to upgrade information infrastructure in rural areas and to adopt stabilization policies that account for the distinct behavioral structure of each market.

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Introduction

Inflation has emerged since the 1970s as one of the most serious challenges facing the global economy and a key indicator for evaluating the economic performance of countries (Kun Sek, 2015). In this context, the Iranian economy has experienced one of the most persistent inflationary periods in the world since entering the phase of double-digit inflation in 1971 (Rahmani et al, 2025). From a macroeconomic perspective, high inflation volatility imposes heavy welfare costs by undermining economic activities and intensifying macroeconomic uncertainty (Friedman, 1977; Elder, 2004). Therefore, accurately measuring inflation volatility is vital; however, since it is considered a latent variable, its estimation has always been accompanied by methodological challenges. Among these, food inflation stands out as one of the most vital policy-making concerns due to its direct link to economic welfare. The high share of food expenditures in the budget of urban (23.6%) and rural (37.7%) households (Statistical Center of Iran, 2025) has turned explaining the cause of price volatility persistence in this sector into a research necessity. This importance becomes twofold when severe food price fluctuations, moving beyond a mere economic variable, directly target the food security and public health of society. The continuation of uncertainty in this market can lead to forced changes in consumption patterns and the elimination of essential items from the household basket. Ultimately, it intensifies relative poverty and social inequality, particularly in deprived and rural areas.

The existing literature for estimating inflation volatility has mainly relied on parametric models such as ARCH, GARCH, GARCH-M, and their asymmetric versions. These models have performed acceptably in estimating and forecasting conditional volatility and have been widely used in studies of inflation uncertainty. However, some recent studies indicate that despite their ability to describe the statistical behavior of volatility, these models face limitations in explaining the behavioral origins of volatility persistence, the manner in which information enters expectations, and the gradual response of economic agents to new news (Garcia-Hiernaux et al, 2026). Frequent fluctuations in the price of agricultural products in Iran, in addition to macroeconomic instability, prevent the formation of stable expectations and reduce the incentive for investment (Mehdizadeh Rayen et al., 2022). From this perspective, the fundamental question is not merely measuring volatility, but rather explaining why it persists and why prices respond gradually to market shocks. This has led researchers in recent years to shift their attention from purely econometric approaches toward behavioral and information-based frameworks. One of the most important of these frameworks is the Rational Inattention theory. According to the theoretical framework of the Rational Inattention model, economic agents are unable to react instantaneously to all market signals due to constraints in their information processing capacity and the costly nature of continuously monitoring the news (Garcia-Hiernaux et al, 2026). Consequently, new information to penetrate expectations gradually, and prices to react with a delay to supply and demand shocks; a phenomenon that aligns with the sticky prices hypothesis and leads to the formation of persistent fluctuations and long memory in food inflation (Sims, 2003). Accordingly, understanding the behavioral roots of these fluctuations in urban and rural markets provides an essential foundation for understanding market dynamics.

The literature on measuring inflation volatility has experienced extensive methodological evolutions in recent decades, which can be traced in a historical and evolutionary sequence. The starting point of these studies dates back to the introduction of Autoregressive Conditional Heteroskedasticity (ARCH) models by Engle (1982), which for the first time allowed modeling volatility as a latent variable. Subsequently, Ball (1992), relying on classical theories, theoretically expanded the link between the inflation level and uncertainty. Further along this path, Using Exponential Autoregressive Conditional Heteroskedasticity (EGARCH) models, Barimah (2014) emphasized the importance of incorporating asymmetric effects in the reaction of volatility to positive and negative shocks.

An important step in the specialization of this field was taken by Nahar et al (2021). Focusing on food inflation in West Java, they showed that price fluctuations in this sector, unlike total inflation, possess very high persistence and the phenomenon of volatility clustering. The innovation of their study lay in the use of non-normal probability distributions to prove that due to supply shocks and the seasonal nature of agricultural products, traditional models underestimate the actual risk of food price turmoil. Apergis et al (2021) emphasized the necessity of incorporating structural breaks in the analysis of the causal relationship between inflation and volatility using Fourier functions.

In recent years, a new current has emerged in the literature that views volatility persistence not merely as a statistical phenomenon, but as a result of the cognitive limitations of agents. Gabaix (2019), by introducing behavioral models, demonstrated how limited attention affects economic decisions. Following this, Mackowiak et al (2023) proved in a study that the rational inattention hypothesis can explain price stickiness and volatility persistence better than traditional models. Garcia-Hiernaux et al (2026), by linking the rational inattention hypothesis to the process of news arrival, presented a model in which the weighting of forecast errors changes based on the optimal attention level of agents. They showed that across different inflation regimes, this behavioral model possesses higher forecasting power compared to GARCH models.

A review of the international literature shows that this field has developed along three main paths: first, the development of conditional variance models for measuring volatility; second, accounting for structural breaks and nonlinear features in inflation behavior; and third, attention to behavioral and informational mechanisms in explaining volatility persistence. However, most existing studies have either focused on the statistical properties of volatility or examined behavioral dimensions. Therefore, the simultaneous integration of structural breaks, volatility dynamics, and information constraints of economic agents—particularly in the food market—has received less attention.

In the domain of domestic research, the analysis of inflation volatility has been pursued focusing on the structural characteristics of the Iranian economy and utilizing conditional variance models extensively. Dahmardeh et al (2009), using GARCH models, while confirming the existence of asymmetric effects, showed that positive price shocks in the Iranian economy have a more long-lasting effect on uncertainty compared to negative shocks. Safdari & Pourshahabi (2011), by employing the EGARCH model, emphasized the high persistence of inflation volatility and its destructive effects on economic growth. With the evolution of measurement tools, Samadi & Majdzadeh tabatabaee (2013) first estimated inflation uncertainty based on the GARCH model and then, using Markov-switching regression, showed that in high-inflation regimes, price fluctuations intensify doubly. Nilchi et al (2023), utilizing Bounded Innovation Propagation GARCH (BIP-GARCH) models, estimated volatility dynamics with higher accuracy than classical models. Continuing this research path, Rezvani et al (2025) investigated the relationship between inflation and inflation volatility by employing the ARCH and GARCH family of models under structural break conditions using Fourier functions.

Despite these advances, the domestic literature has also mainly focused on the statistical description of volatility and has paid less attention to the role of information constraints and behavioral mechanisms in the formation of uncertainty. Furthermore, the simultaneous comparison of classical econometric models and behavioral frameworks in Iran's food market, as well as the distinction between urban and rural areas, has not been examined. Accordingly, the main research gap can be summarized along three axes: first, the predominant focus on aggregate inflation rather than food inflation; second, the neglect of the role of information constraints in explaining volatility persistence; and third, the lack of sufficient empirical evidence regarding differences in volatility dynamics between urban and rural areas. This study aims to cover this gap by analyzing the dynamics of food inflation volatility from the perspective of Rational Inattention theory. The primary innovation of this research lies in a comparative approach; such that volatility dynamics are first estimated through GARCH-family models incorporating Fourier trigonometric functions to control for structural breaks and the seasonality of products, and then its results are compared with the outputs obtained from models based on rational inattention. This methodological contrast makes it possible to determine which approach has greater explanatory power in analyzing the persistence of food inflation volatility in Iran. In addition, the present study employs the Directional Volatility Ratio index. By comparing the contribution of positive and negative price shocks to volatility, this index makes it possible to identify the dominant source of uncertainty and shows whether upside or downside risks play a more prominent role in shaping food market volatility. By decomposing and comparing positive and negative semi-variances under information processing constraints, this index enables the identification of tail risks and directional volatility dynamics—an aspect that has been overlooked in traditional models. Furthermore, the simultaneous focus on urban and rural markets in Iran and comparing the estimation results in these two markets provides a platform for understanding structural differences in volatility dynamics. From the perspective of rational inattention, the difference in the information absorption rate and the weight of the consumption basket in these two societies can lead to differences in volatility persistence and the level of uncertainty. Finally, by comparing different models, this study seeks to identify the most accurate analytical framework for forecasting food price turmoil and providing stabilizing solutions for the table of Iranian households. The research hypotheses are formulated as follows:

- Hypothesis 1: Due to rational inattention constraints, the persistence of food inflation volatility is significantly higher in rural areas than in urban areas.
- Hypothesis 2-A: In rural areas, positive (upside) price shocks contribute more to inflation uncertainty than negative (downside) shocks.
- Hypothesis 2-B: In urban areas, the contribution of positive and negative shocks to inflation uncertainty differs, with price adjustment and correction fluctuations playing a significant role.

Materials and Methods

In this study, a hybrid and comparative approach is used to analyze the dynamics of food price volatility. The core of this approach is based on a semi-parametric volatility model grounded in the Rational Inattention framework. This model assumes that economic agents form their expectations by optimally weighting squared forecast errors. This weighting process is influenced by the news arrival process, which guides the optimal attention level over time and determines inflation volatility. This approach aligns fully with the sticky prices hypothesis, demonstrating that information flow constraints cause prices to react with a delay to supply and demand shocks. Unlike standard approaches in the conditional variance literature, the present methodology incorporates the information arrival rate into the weighting function to generate inflation volatility expectations under the physical probability measure.

To evaluate the accuracy and validity of the behavioral model, volatility is also estimated using conventional parametric GARCH-family models. Parametric models face challenges when dealing with structural instabilities caused by changes in inflation regimes. To address this, we combine conditional heteroskedasticity models with Fourier trigonometric functions to control for structural breaks. This combination allows seasonal effects and regime shifts to be accurately separated from volatility caused by uncertainty, and ultimately, the explanatory power of the model based on rational inattention is compared against GARCH and Fourier-GARCH models.

In the first step, to estimate volatility, the Generalized Autoregressive Conditional Heteroskedasticity model is used, in which the conditional variance equation is defined as Equation (1):

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

In Equation (1), u_t^2 is the disturbance term or residual of the mean model, σ_t^2 is the conditional variance, p and q are the orders of the ARCH and GARCH components, respectively. Furthermore, β_i and δ_i represent the parameters of conditional variance dynamics. However, given the existence of severe shocks and structural breaks in the Iranian economy, following Teterin et al (2016) an Apergis et al (2021) a Fourier approximation is added to the conditional variance equation to rewrite the Fourier-GARCH model as Equation (2), in which the sine and cosine components are responsible for controlling unknown structural breaks.

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

In Equation (2), T is the total number of observations, K is the Fourier frequency, and $\gamma_{1,1k}$ and $\gamma_{1,2k}$ are the coefficients of the sine and cosine components that model gradual structural changes. Also, all parameters must be positive, and $\sum_{i=1}^{p} \beta_i + \sum_{i=1}^{q} \delta_i$ must be less than one, indicating a mean-reverting process. Equation (2) requires determining the number of Fourier frequencies, which, according to Pascalau et al. (2011), can be done using the Akaike Information Criterion (AIC) or the Schwarz Information Criterion (SIC). In the next stage, to explain the behavioral roots of these fluctuations, the semi-parametric model based on the theory of rational inattention presented by Garcia-Hiernaux et al (2026) is utilized. First, to identify the unpredicted component of inflation, an ARIMA filter is used. Assuming that food inflation (p_t) follows an Autoregressive Integrated Moving Average process:

$$\phi_p(\mathrm{B})(\Delta^d p_t - \mu) = \theta_q(\mathrm{B}) a_t \tag{3}$$

In Equation (3), B is the lag operator, d is the degree of differencing, $\phi_p(\mathrm{B})$ is the autoregressive polynomial of order p, $\theta_q(\mathrm{B})$ is the moving average polynomial of order q, and a_t represents the one-step-ahead forecast error, which is calculated as $a_t = p_t - p_{t|t-1}$. This error can be decomposed as $a_t = Z_t h_t^{1/2}$, where Z_t is a standardized white noise process and h_t is the time-varying conditional variance. In the rational inattention literature, a_t is the "innovation" or shock to which households, due to information processing constraints, react only when it exceeds a certain threshold. Also, μ represents the long-term mean of inflation, which reflects the stable level of expectations. Within the trend-cycle decomposition framework of Beveridge & Nelson (1981), the inflation trend (π_t) is defined as the expected long-run change in the price level. In other words, the inflation trend represents the permanent component of inflation, which is formed based on all available information up to time t and is separated from temporary and transitory fluctuations. Thus, the inflation trend can be defined as follows:

$$\pi_t = \lim_{l\to\infty} \mathbb{E}[p_{t+l}|\mathcal{F}_t] \tag{4}$$

In Equation (4), p_{t+l} is the price level in future period l, and $\mathcal{F}_t$ represents the set of information available to economic agents up to time t. This set includes past values of inflation, forecast errors, observed shocks, and other information used in the expectation formation process. Therefore, π_t represents the permanent or long-run component of inflation, calculated based on the information available at time t. The conditional variance of inflation ($h_{p,t}$) is estimated as the weighted sum of past squared forecast errors:

$$h_{p,t} = \sum_{i=0}^{\infty} \omega_i \, a_{t-i}^2 \tag{5}$$

In this model, the weighting of past shocks (ω_i) is determined based on the rational inattention hypothesis and with the following geometric structure:

$$h_{p,t} = \sum_{i=0}^{\infty} \omega_i \, a_{t-i}^2 \tag{6}$$

φ is the information flow rate parameter (the probability of new news arrival). This parameter indicates how quickly urban and rural households replace old information with new information in their mental calculations. The value of φ lies between zero and one; the closer it is to one, the faster the response to shocks and the greater the focus on recent information. In this framework, news arrival is defined when a_t from Equation (3) exceeds a critical threshold $Z\alpha/_{2}$relative to the unconditional standard deviation σ_a (with $Z\alpha/_{2} = 1.96$ at the 5% significance level), such that $I_t = 1$ if $\left|{}^{a_t}/_{\sigma_a}\right| > Z\alpha/_{2}$, and $I_t = 0$ otherwise. Consequently, I_t is a Bernoulli variable with parameter φ, meaning that $\varphi = P(\left|{}^{a_t}/_{\sigma_a}\right| > Z\alpha/_{2})$ represents the probability of an information shock occurrence and the rate of news arrival in the economy. Therefore, the total number of news arrival events in a sample of size n is defined as $u = \sum_{i=0}^{n-1} I_{t-i}$, which follows a binomial distribution. Since I_t is a Bernoulli variable, its sum over a sample of size n follows a binomial distribution. This parameter represents the speed of expectation updating and the information flow rate among economic agents, and the choice of the threshold $Z\alpha/_{2}$ and significance level α provides the necessary flexibility to adapt to data characteristics. To estimate the parameter φ, the maximum likelihood estimation (MLE) method based on the binomial distribution is used. If n is the total number of observations and j is the number of times the standardized forecast error exceeds a critical threshold (the number of jumps), we have:

$$\hat{\varphi} = {}^{\hat{j}}/_{n} \tag{7}$$

Therefore, the estimated variance is equal to:

$$\hat{h}_{p,t} = \sum_{i=0}^{n-1} \hat{\varphi}(1-\hat{\varphi})^i \, \hat{a}_{t-i}^2 \tag{8}$$

To analyze the asymmetric effect of shocks on urban and rural households, the total variance is decomposed into two positive and negative components:

$$h_{p,t} = \sum_{i=0}^{\infty} \omega_i \, a_{t-i}^2 = \sum_{i=0}^{\infty} \omega_i \, I_{t-i}^- a_{t-i}^2 + \sum_{i=0}^{\infty} \omega_i \, I_{t-i}^+ a_{t-i}^2 = h_{t,\ p}^- + h_{t,\ p}^+ \tag{9}$$

In Equation (9), I_t^- equals one if the forecast error is negative or zero, and I_t^+ equals one if it is positive; otherwise, they are zero. Accordingly, $h_{t,\ p}^+$ and $h_{t,\ p}^-$ represent the positive and negative semi-variances of inflation, respectively. Next, the positive and negative semi-volatilities of inflation are defined as the square root of the corresponding semi-variances:

$$V_{t,\ p}^{+} = \sqrt{h_{t,\ p}^{+}}, \qquad V_{t,\ p}^{-} = \sqrt{h_{t,\ p}^{-}} \tag{10}$$

In Equation (10), $V_{t,\ p}^{+}$ and $V_{t,\ p}^{-}$ represent the semi-volatility arising from positive and negative forecast errors, respectively. Finally, to measure the dominance of upside or downside risks, the Directional Volatility Ratio (DVR) index is calculated as follows:

$$DVR_{t,\ p} = \ln({V_{t,\ p}^{+}}/{V_{t,\ p}^{-}}) \tag{11}$$

Positive values of this index indicate the dominance of upside risks, while negative values indicate the dominance of downside risks in inflation volatility. This index is the main welfare comparison criterion between urban and rural households in this study. The data used in this study include monthly point-to-point food inflation for urban and rural areas of Iran, extracted from the statistical database of the Statistical Center of Iran. The research period covers the interval from April 2003 to January 2026. Furthermore, all estimations and implementations of parametric models (GARCH) and the semi-parametric rational inattention model have been performed using the statistical packages of the R software.

Results and Discussion

Examining the stationarity of variables is an important step in the analysis of time-series variables. Given the monthly frequency of the data, a seasonal unit root test was used to identify unit roots at different frequencies. The results in Table (1) show that the t1 statistic (frequency (0)) is not significant for either the urban or rural food inflation series. This indicates the presence of a non-seasonal unit root in the levels of the variables. However, the results of the other statistics indicate that the null hypothesis of a seasonal unit root is rejected at all seasonal frequencies. On the other hand, due to the presence of structural shocks in the Iranian economy, the Enders & Lee (2012) unit root test was employed.

Table 1- Results of the seasonal unit root test

Frequency	**0**	π	$\pi/2$	$2\pi/3$	$\pi/3$	$5\pi/6$	$\pi/6$
Null Hypothesis	$\pi_1 = 0$	$\pi_2 = 0$	$\pi_3 = \pi_4 = 0$	$\pi_5 = \pi_6 = 0$	$\pi_7 = \pi_8 = 0$	$\pi_9 = \pi_{10} = 0$	$\pi_{11} = \pi_{12} = 0$
Test	t_1	t_2	$F_{3,4}$	$F_{5,6}$	$F_{7,8}$	$F_{9,10}$	$F_{11,12}$
Food inflation of rural households	-2.29	-4.29	21.79	21.94	33.45	21.53	24.58
Food inflation of urban households	-2.19	-4.71	27.86	23.15	39.40	18.33	29.42
Critical Value (10%)	-2.47	-2.48	5.27	5.27	5.27	5.27	5.27
Critical Value (5%)	-2.76	-2.77	6.25	6.25	6.25	6.25	6.25

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

Table 2- Results of the unit root test Using Fourier approximation

Variable	**Optimal Fourier Frequency (k)**	**Test Statistic**
Food inflation of urban households	1	-2.08
Food inflation of rural households	1	-2.15
First difference of food inflation of urban households	1	-10.32***
First difference of food inflation of rural households	1	-10.57***

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

By modeling structural breaks as trigonometric functions, this test possesses higher power in detecting stationarity. Based on the lag selection criterion, the optimal Fourier frequency for both urban and rural food inflation series and their difference was determined to be one. According to Table (2), the test statistic at the level of the variables cannot reject the null hypothesis, but after taking the first difference, both variables become stationary.

In the present study, to first identify the optimal structure of food inflation volatility in urban and rural areas of Iran, various models of the GARCH family were tested. Based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), the GARCH (1, 2) model with a normal distribution was selected as the optimal pattern for explaining conditional heteroskedasticity. In the next step, to incorporate seasonal and cyclical components into the variance equation, a Fourier expansion was utilized. To determine the optimal Fourier frequency, the Fourier-GARCH model was estimated for different frequency values. The results of comparing the AIC and BIC information criteria in Table (3) showed that frequency k = 1 had the lowest values for these criteria in both urban and rural areas, and was therefore selected as the optimal Fourier frequency.

Table 3- Information Criteria (AIC and BIC) for Alternative Fourier Frequencies

Fourier Frequency (k)	AIC-Urban Households	AIC- Rural Households	BIC- Urban Households	BIC- Rural Households
1	5.71	5.88	5.80	5.97
2	5.72	5.90	5.84	6.01
3	5.74	5.91	5.88	6.06
4	5.75	5.92	5.92	6.10
5	5.77	5.94	5.96	6.14

Source: Research Findings

After estimating the Fourier-GARCH (1,2) model, diagnostic tests were performed to ensure model adequacy. The results of the Ljung-Box test indicated that there is no remaining autocorrelation in either the mean or variance. Additionally, the ARCH-LM test confirmed the absence of additional ARCH effects, demonstrating the adequacy of the selected order for the GARCH model. After ensuring the validity of the estimation and passing the diagnostic tests (absence of autocorrelation and ARCH effects in the residuals), the out-of-sample performance of the models was evaluated to select the superior pattern. Given the high noise present in the squared residuals of inflation, forecast error indices serve as the primary evaluation criteria in this study. The results of this evaluation are presented in Table (4). Furthermore, for the rational inattention model, similar diagnostic tests were performed on the model residuals. The results confirmed the absence of significant autocorrelation and ARCH effects in the residuals, indicating the adequacy of this model in extracting the dynamic structure of inflation volatility.

Table 4- Out-of-sample performance comparison of food inflation volatility forecasting models

Region	Evaluation Index	Rational Inattention	GARCH (1,2)	Fourier GARCH (1,2)
Urban	RMSE	198.85	205.93	218.58
	MAE	84.53	89.84	103.01
Rural	RMSE	253.91	266.09	311.21
	MAE	96.54	116.90	153.49

Source: Research Findings

According to the results in Table (4), the Rational Inattention model succeeded in achieving the lowest forecast error values (RMSE and MAE) in both urban and rural regions. This indicates that models based on information processing constraints possess higher persistence and generalizability when confronting new data compared to purely statistical models (GARCH) and models based on mathematical cycles (Fourier-GARCH). Another important point in Table (4) is the difference in error levels between the two regions. It is observed that the error values across all patterns are systematically higher for rural areas than for urban areas, indicating greater volatility and higher difficulty in forecasting fluctuations in rural environments compared to urban ones.

To explain the cause of the differences in model forecast accuracy and to investigate the behavioral roots of urban and rural differences, the internal parameters of the superior pattern were extracted, the results of which are reported in Table (5). The results in this table clearly explain the structural differences between the two regions. The value of the information flow rate parameter (φ) for urban areas (0.0764) is calculated to be approximately 2.7 times that of rural areas (0.0285). This finding shows that economic agents in urban areas absorb new information at a faster rate. In fact, the higher forecast error in rural areas is completely consistent with the lower information processing speed in these regions shown in Table (5); because more severe rational inattention in villages challenges and delays the process of forecasting future volatility.

It should be noted that DVR is a derived index calculated from the estimated conditional variance and is not directly estimated as a model parameter. This index measures the degree of asymmetry in the response of volatility to positive and negative shocks. In this framework, a negative value of the DVR index in urban areas indicates that uncertainty is primarily generated through downward shocks and rapid price adjustment processes, while a positive value close to zero in rural areas suggests relative symmetry in the response to shocks and a slight dominance of upward shocks. Therefore, the difference in DVR index values between the two regions reflects structural heterogeneity in the transmission of inflationary shocks and expectation adjustment patterns in urban and rural areas.

Table 5- Estimated parameters of the Rational Inattention model

	Urban Food Inflation	**Rural Food Inflation**
Rate of Information Flow (φ)	0.0764	0.0285
Directional Volatility Ratio (DVR)	-0.174	0.0013

Source: Research Findings

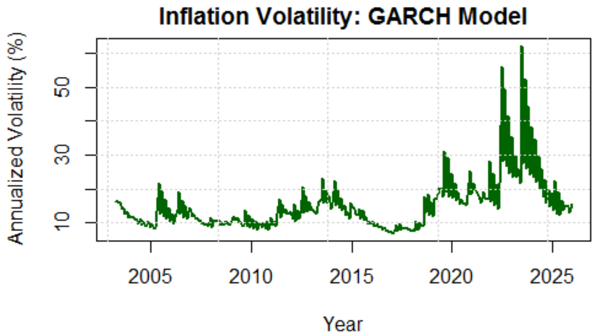
To better understand the fundamental differences between the studied patterns, the volatility extracted by all three models is plotted in Figures (1) and (2). Examining the volatility trend in Figure (1) reveals that all three studied patterns succeeded in identifying periods of turmoil and volatility clusters in urban inflation. The GARCH and Fourier-GARCH models exhibit highly similar behavior in urban areas and show high sensitivity to short-term fluctuations. The lack of a significant difference between these two patterns in Figure (1) confirms the fact that Fourier components play a less prominent role in urban areas compared to rural ones, and turmoil predominantly follows autoregressive processes.

By comparing the volatility trends estimated by the GARCH and Fourier-GARCH models, it can be observed that the temporal pattern of volatility in the two models is almost identical, and the peaks and troughs are similarly reproduced in both time series. This behavioral overlap indicates that adding Fourier components does not create a significant change in the overall structure of volatility, and the dynamics of volatility are primarily explained by the GARCH structure. Therefore, the role of cyclical components in explaining inflation volatility in the examined data is limited, and the main part of volatility behavior arises from clustering effects and variance persistence in the GARCH model. In both urban and rural areas, the rational inattention model exhibits smoother behavior, capturing only the main trend of volatility.

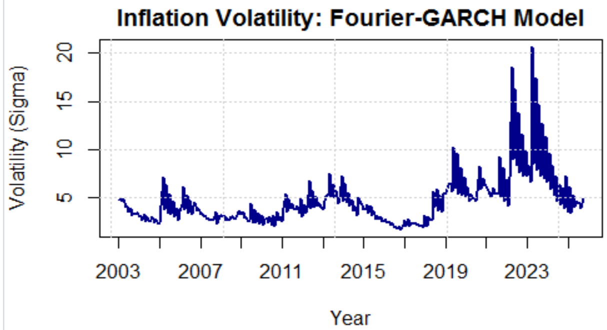
Due to constraints on information processing speed, this model avoids instantaneous reactions to transitory noise and, with a slight delay, incorporates only persistent shocks into the variance estimation. In this study, shocks are defined as random deviations of the time series from its conditional trend, which are observable in the form of ARIMA model residuals and conditional volatilities extracted from GARCH and rational inattention models. This "noise filtering" feature is the primary explanation for the superiority of this model in out-of-sample forecast error indices.

To gain a deeper understanding of the reaction of economic agents to volatility, the dynamic trend of the DVR index, which represents the ratio of expected variance to actual variance, is presented in Figures (3) and (4).

a. Extracted volatility of food inflation in urban areas using the GARCH model



b. Extracted volatility of food inflation in urban areas using the GARCH-Fourier model



c. Extracted volatility of food inflation in urban areas using the rational inattention model

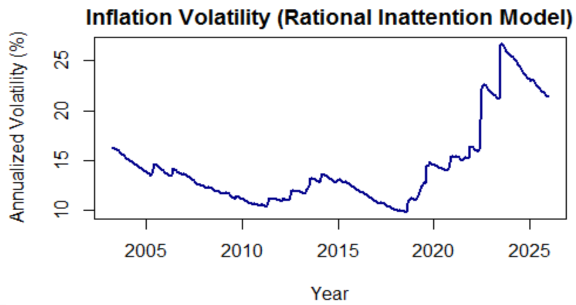


Fig. 1- Comparison of estimated food inflation volatility trends in urban areas

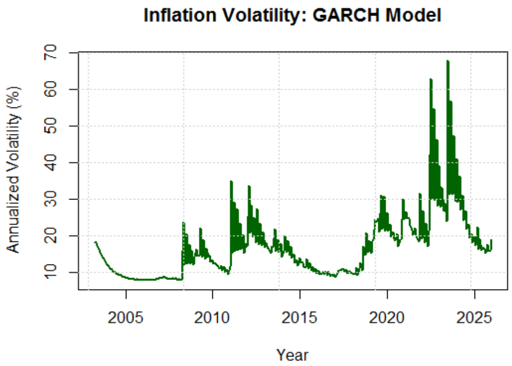
Examining the dynamic index of the DVR in the two urban and rural regions reveals key differences in how information is processed: in urban areas, the fluctuations of the DVR index have intensified, particularly in recent years. The presence of deep ups and downs shows that in urban environments, due to the higher speed of information flow, economic agents react more intensely to fluctuations and are constantly adjusting their expectations. Sudden spikes in this chart reflect periods when actual volatility suddenly exceeded expectations.

Despite experiencing fluctuations, the rural DVR chart experiences relative stability around the zero line over longer periods. This is consistent with the low information flow rate parameter; meaning that in villages, volatility expectations possess greater stickiness and are less affected by instantaneous turmoil. In fact, rural agents react only to large and persistent shocks, which has resulted in a smoother trend in the rural DVR index compared to the urban one.

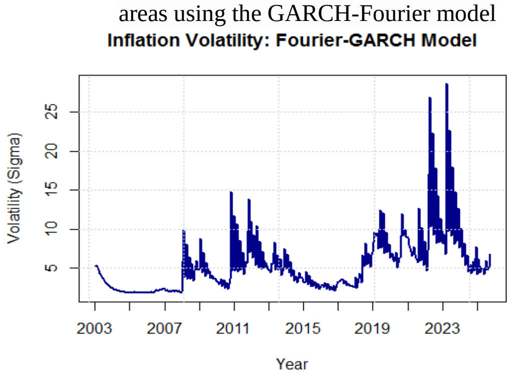
To investigate more precisely the contribution of each volatility component to the total uncertainty in the market, the shares of positive and negative half-volatilities are presented separately in Figures (5) and (6). In urban areas, the results obtained from variance decomposition show that, contrary to initial expectations, downward fluctuations play a dominant role (more than 50%) in generating total uncertainty. This finding, which has led to a negative DVR index in this market, indicates that in urban environments, due to greater information transparency and faster news processing speed by agents, price shocks are corrected more rapidly and revert toward the mean after reaching a peak. In fact, uncertainty in cities stems more from "price bubble deflation" and sharp reversals following upward shocks, a behavior that is completely consistent with the characteristics of more competitive markets and extensive access to information flow in urban areas.

The chart for rural areas reveals a deep structural difference from urban areas; in this market, positive or upward fluctuations account for the dominant share of over 50% in the total variance. This confirms the second research hypothesis in rural areas and indicates that in these regions, upward price shocks are the main cause of uncertainty and tension in the household basket. From the perspective of Rational Inattention theory, the low speed of information processing in villages causes prices to tend toward stickiness after an increase, and the price correction process (downward volatility) occurs with a much greater delay compared to cities. This situation has led to a positive rural DVR index, reflecting the greater vulnerability of rural welfare to upward risks in food prices.

a. Extracted volatility of food inflation in rural areas using the GARCH model



b. Extracted volatility of food inflation in rural areas using the GARCH-Fourier model



c. Extracted volatility of food inflation in urban areas using the rational inattention model

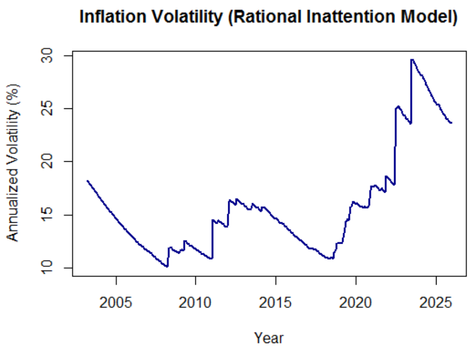


Fig. 2- Comparison of estimated food inflation volatility trends in rural areas

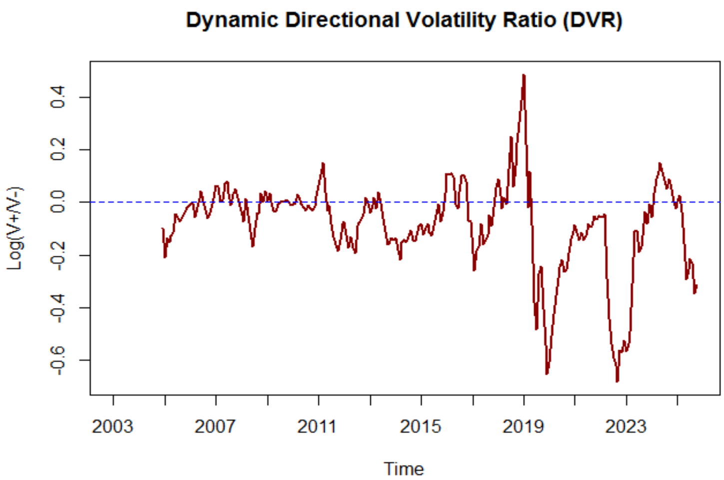


Fig. 3- Dynamic analysis of the DVR index for urban food inflation

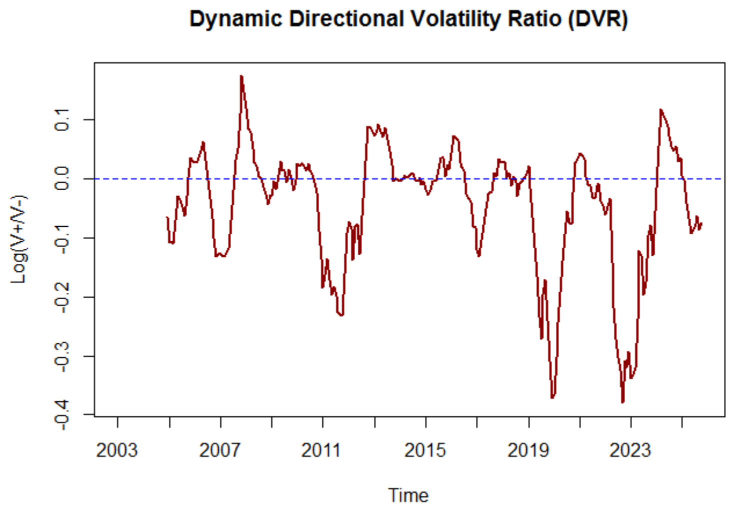


Fig. 4- Dynamic analysis of the DVR index for rural food inflation

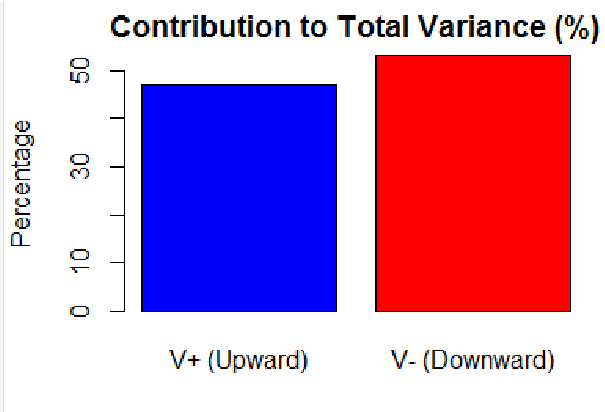


Fig. 5- Dynamic analysis of positive and negative volatilities in urban food inflation

In line with the final explanation of the findings, the research hypotheses are examined based on the empirical evidence obtained from the Rational Inattention model. Regarding the first hypothesis, the estimation results of the information flow rate parameter showed that the speed of news processing in urban areas is significantly higher than in rural areas. The low speed of information absorption in rural areas indicates that new information is reflected in economic expectations and decisions with greater delay; such that economic agents in the rural environment, due to perceptual limitations and higher market monitoring costs, exhibit a slower reaction to new information and changes. Therefore, the first research hypothesis, concerning the difference in information processing speed between urban and rural areas, is confirmed.

In analyzing the second hypothesis, the results of the DVR index reveal a structural difference in the nature of uncertainty between the two markets. In rural areas, the dominance of positive semi-volatilities (a share exceeding 50%) and the positive value of the DVR index indicate that upward price shocks have a greater share in shaping food inflation uncertainty. This finding suggests that price increases affect the expectations and perception of uncertainty among rural households more than price decreases; hence, the research hypothesis 2-A is confirmed. In contrast, in urban areas, the DVR index shows a negative value, indicating the dominance of negative semi-volatilities in the uncertainty structure of this market. This result implies that in urban environments, price decreases and price corrections following periods of increase play a more prominent role in shaping uncertainty. Therefore, the research hypothesis 2-B is also confirmed. Overall, the results show that the main source of food inflation uncertainty in rural areas primarily originates from upward price shocks, while in urban areas it primarily originates from downward shocks and price corrections.

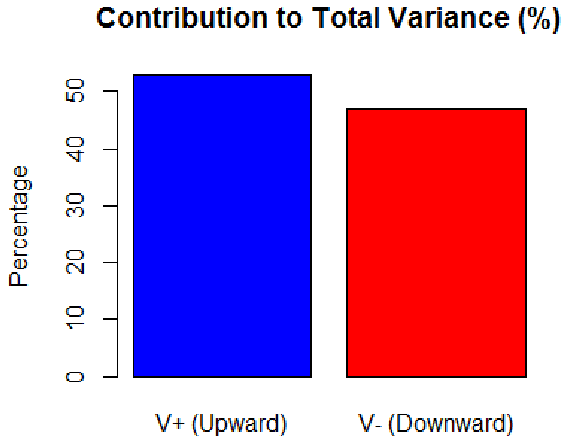


Fig. 6- Dynamic analysis of positive and negative volatilities in rural food inflation

Conclusion and Policy Implications

The present study was conducted with the objective of investigating the dynamics of food inflation volatility in Iran through the lens of Rational Inattention theory. The results demonstrated that unlike traditional conditional variance models—which view volatility merely as a statistical process—behavioral models possess higher predictive and explanatory power by accounting for constraints on information processing capacity. The findings align with the study by Garcia-Hiernaux et al (2026); as in both studies, the Rational Inattention model succeeded in explaining volatility persistence beyond GARCH family models. However, the innovation of this study relative to Garcia-Hiernaux et al (2026) was identifying the information gap between urban and rural communities; specifically, it was revealed that the information flow rate is significantly lower in rural areas, leading to the formation of long memory and more severe volatility persistence in the rural household basket. Furthermore, contrary to the findings of Dahmardeh et al (2009), who considered positive shocks as the main cause of uncertainty across the entire Iranian economy, this study utilized the DVR index to show that this rule does not hold true in urban areas, where downward fluctuations (bubble deflation) play the dominant role in creating uncertainty. Based on the findings, the following recommendations are proposed to stabilize the food market:

- Given the low speed of information processing in rural areas, it is recommended that the government develop online information infrastructure and establish transparent pricing systems for agricultural products to reduce the "market monitoring cost" for rural residents, thereby allowing prices to reach equilibrium with less delay.
- Considering the dominance of upward risks in rural areas, it is essential to activate support mechanisms such as electronic food vouchers and strategic food reserves, prioritizing deprived and rural areas, to neutralize the impact of positive price shocks on the food security of these households.
- It is suggested that policy-making institutions utilize models based on rational inattention to forecast uncertainty instead of relying on classical models; because these models better predict the precise timing of market reactions to new shocks by identifying the attention threshold of agents.
- One of the limitations is the use of aggregated data for urban and rural areas. Since the economic structure, access to information, consumption patterns, and the degree of market integration differ across metropolises, medium-sized cities, and small towns, it is recommended that in

future research, food inflation data be collected and analyzed at more disaggregated geographical levels. Such an approach would enable a more precise identification of regional differences in information flow rates, volatility persistence, and expectation behavior, and could help improve the predictive power of rational inattention models and volatility models.

Author Contributions

The first author was responsible for the conceptualization, study design, and drafting the original manuscript. The second author carried out the data collection and software-based analysis. The third author supervised the entire project and provided administrative and scientific oversight.

Data Availability Statement

"Not applicable"

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Ethical considerations

The authors avoided data fabrication, falsification, plagiarism, and misconduct.

Conflict of interest

The author declares no conflict of interest.

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ارزیابی قدرت تبیین مدل‌های رفتاری در سنجش نااطمینانی تورم مواد غذایی ایران؛ تقابل الگوهای GARCH و بی‌توجهی عقلانی

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کلیدواژه‌ها:
بی‌توجهی عقلانی، توابع مثلثاتی فوریه، شاخص نسبت نوسان جهت‌دار، شکست ساختاری، نوسانات تورم مواد غذایی.

چکیده

در پژوهش حاضر به واکاوی ریشه‌های رفتاری پایداری نوسانات تورم مواد غذایی و مقایسه پویایی‌های نوسان در مناطق شهری و روستایی ایران طی بازه زمانی فروردین ۱۳۸۲ تا دی ۱۴۰۴ پرداخته شده است. در این راستا، از یک رویکرد ترکیبی شامل مدل‌های خانواده GARCH با کنترل شکست‌های ساختاری از طریق توابع مثلثاتی فوریه و مدل نیمه‌پارامتریک مبتنی بر نظریه بی‌توجهی عقلانی (مبتنی بر نرخ جریان اطلاعات) استفاده شده است. یافته‌های پژوهش با استفاده از شاخص‌های ارزیابی RMSE و MAE نشان می‌دهد، مدل بی‌توجهی عقلانی به دلیل لحاظ کردن محدودیت ظرفیت پردازش اطلاعات، قدرت پیش‌بینی برون‌نمونه‌ای و تبیین‌کنندگی بالاتری نسبت به الگوهای سنتی GARCH و Fourier-GARCH دارد. بر اساس نتایج، نرخ جریان اطلاعات در مناطق شهری حدود ۲/۷ برابر مناطق روستایی برآورد شده است که نشان‌دهنده‌ی شکاف اطلاعاتی عمیق میان این دو بازار و علت اصلی پایداری شدیدتر نوسانات در مناطق روستایی است. همچنین، براساس شاخص نسبت نوسان جهت‌دار که حاصل تفکیک واریانس به دو جزء صعودی و نزولی است، نتایج حاکی از آن است که در مناطق روستایی، تکانه‌های مثبت قیمت (ریسک صعودی) منبع اصلی نااطمینانی هستند، در حالی که در مناطق شهری، نوسانات ناشی از تخلیه حباب‌های قیمتی و بازگشت به میانگین سهم غالب را در ایجاد نوسانات ایفا می‌کنند. در نهایت، این نتایج بر ضرورت ارتقای زیرساخت‌های اطلاع‌رسانی در مناطق روستایی و اتخاذ سیاست‌های ثبات‌بخش متناسب با ساختار رفتاری هر بازار تأکید دارد.

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