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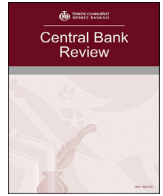
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News impact for Turkish food prices[☆]



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ABSTRACT

Asymmetric volatility is a widely encountered concept particularly in financial series. It refers to the case that “bad news” generates more volatility than “good news” of equal magnitude. In an inflationary environment “bad news” is disclosed as increasing inflation that is expected to generate higher volatility. The present article examines whether unexpected price changes affect the volatility of prices asymmetrically for 90 retail food items of the Turkish consumer price index. These 90 food items have a weight of approximately 20 percent in headline consumer price index (CPI). We employ exponential generalized autoregressive conditional heteroscedastic (EGARCH) model to extract asymmetric volatility, using monthly data between January 2003 and January 2017. Our results reveal that volatility of food prices respond asymmetrically to unexpected price shocks for 62 percent of the retail food items.

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1. Introduction

Food price volatility has become one of the hot topics for researchers and policy makers within the last decade due to its detrimental effect on macroeconomic stability, productivity of food prices and general well-being of consumers. It is well documented that increase in price volatility, which has distortionary effects on the welfare of both consumers and producers, affects the ability of market participants to forecast prices. In an inflationary framework, modelling price volatility inevitably translates into having proper information about inflation uncertainty, where the concept of “uncertainty” is proxied by volatility. There is a vast literature on the relation between inflation and inflation uncertainty, which has gained momentum with the increasing number of central banks implementing inflation targeting regime. The pioneering study in this field is that of Friedman (1977) designating a positive causality between the

level of inflation and inflation uncertainty, with higher inflation leading to greater uncertainty. Ball (1992) formalizes Friedman's argument in the context of an asymmetric information game between the public and the policy maker.¹

Majority of the literature on the relation between inflation and inflation uncertainty employs both symmetric and asymmetric GARCH models. The impact of the news on volatility is captured by asymmetric GARCH models. While most of the studies on asymmetric news impacts in economic literature are on financial markets and other areas of macroeconomics, i.e. foreign exchange markets, there are some major studies that apply symmetric and asymmetric volatility models to inflation and one of those studies is by Kontonikas (2004) who analyses the inflation and inflation uncertainty in UK. His results support the Friedman-Ball hypothesis and he shows that inflation decreases with inflation

* The views expressed herein are those of the authors and do not necessarily represent the official views of the Central Bank of the Republic of Turkey.

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¹ In the light of these two seminal papers, many country and cross-country studies have been conducted on the direction and the sign of the relationship between inflation and inflation uncertainty. For example, Zivkov et al. (2014) analyze 11 Eastern European countries' inflation and find that Friedman's hypothesis is confirmed for countries with flexible exchange rate regimes while refuted for countries with fixed exchange rate regimes. In his study on Turkey's inflation, Karahan (2012) studies the relationship for Turkey between 2002 and 2011 using GARCH type of models whose findings support Friedman's hypothesis.

uncertainty which is asymmetric after the implementation of the inflation-targeting regime in UK. Another study is by [Fountas et al. \(2004\)](#), who analyze inflation and inflation uncertainty for the six European Union countries for the period 1960–1999, taking asymmetry in inflation uncertainty into consideration. While Friedman's hypothesis holds for countries except Germany, the asymmetric terms in their volatility equations are found to be significantly positive and authors discuss that such a result stems from the tough commitment of German monetary authority to price stability.²

Univariate and multivariate GARCH type of models are used in economic literature very frequently to model the agricultural price volatility. [An et al. \(2016\)](#) use a multivariate GARCH model to analyze the volatility, asymmetry and spillovers among wheat and flour prices. [Minot \(2014\)](#) uses GARCH(1,1) model to examine the volatility of 167 food price series from 15 African countries. [Rezitis and Stavropoulos \(2010\)](#) employ several different symmetric, asymmetric and non-linear GARCH models to estimate volatility for the Greek beef market. [Gardebroeck et al. \(2016\)](#) use multivariate GARCH approach to evaluate the time evolution and volatility transmission across corn, wheat and soybean price returns on a daily, weekly and monthly basis. [Ait Sidhoum and Serra \(2016\)](#) employ a multivariate GARCH model to study price transmission between consumer, producer and wholesale prices in the Spanish tomato market.³

The effect of news on volatility is motivated by the pioneering works of [Pagan and Schwert \(1990\)](#) and [Engle and Ng \(1993\)](#). In their study, [Engle and Ng \(1993\)](#) define the news impact curve which measures how new information is incorporated into volatility estimates. The news impact curve depicts the impact of an unexpected shock on next period's volatility such that the impact of good and bad news are reflected on either sides of the curve with different slopes. The closest study to our paper is by [Zheng et al. \(2008\)](#), who analyze the volatility and the news impact with a particular focus on asymmetric news effects for the US food market. Across 45 retail food items, they find that price news destabilizes about a third of the markets such that unexpected price increases contribute more to the price volatility compared to unexpected price decreases.

Global food price and volatility became more remarkable especially after the effects of serious food crisis of 2008 and 2011.⁴ However, in Turkey food prices started to fall after 2011 and in February 2016 food prices dropped to a lowest value experienced after 2010. Shortly after, the food prices in Turkey reached its peak value in January 2017, deviating from historical trends and international food prices significantly. We observe a surge of 7.67 percent between January 2016 and January 2017 in food prices, while annual CPI inflation is found to be 9.22 percent. Since food items have the highest weight in the CPI basket (20.17 percent for year 2017), the path they follow has particular importance for policy makers.⁵ The divergence of domestic food prices in Turkey from international levels is documented by [Akcelik et al. \(2016\)](#). They show that the level of divergence from European Union price levels and their volatility has been

increasing since the global food crisis. [Ogunc \(2010\)](#) also shows that the volatility of the food prices in Turkey, particularly that of unprocessed food items, has been above that of CPI within the last decade.⁶

For Turkey, it is well documented that the path of the unprocessed food items is the main factor behind the quick surge of the food prices.⁷ In this vein, [Atuk and Sevinc \(2010\)](#) state that fresh fruits and vegetables in the CPI basket distinguish from others with their strong seasonality and the accompanying level of high volatility. They suggest that using constant weights would help diminish the volatility of CPI. [Orman et al. \(2010\)](#) also state that unprocessed food items exhibit a more fluctuating pattern compared to other sub-groups in the CPI basket. They attribute this observation to some structural factors such as high level of the dependency of production on climate conditions, high number of intermediaries, uncertainties around public support to agriculture, insufficient level of monitoring by the government, concentration of production in certain regions and fluctuations in external demand.⁸ They conclude that a stable path could be attained by the implementation of medium to long-run policies.

In Turkey, an evaluation committee for food prices was indeed established in 2014 to implement medium to long-run policies, while the official secretariat of the committee was transferred to the Central Bank of Republic of Turkey in December 2016. The "Food Committee" specifically examines every item with increasing price and volatility while presenting policy suggestions for different horizons. Due to their unpredictable and volatile pattern, the Committee closely tracks the prices of unprocessed food items, the prices of fresh fruits and vegetables in particular. The Committee has also designed and employed an early warning mechanism for this purpose.

In this respect, similar to [Zheng et al. \(2008\)](#), this paper examines whether asymmetric news effects exist for 90 retail food items in Turkish food market. We choose 90 food items, which have a share of 19.87 percent in total consumer price index (CPI), out of total number of 129 items under headline CPI of Turkey. These 90 items have a share of 91.3 percent within the food prices of CPI and the choice is made considering data availability, i.e. we eliminate 39 items as they have missing data.⁹ This study is essential as the existence of possible asymmetry in the behaviour of price volatility in the retail food prices of Turkey is so far unknown and such asymmetry in the retail price volatility can help policy makers to take some measures to meet the targets and also give useful information about retail market power. To the best of our knowledge, our paper is the first to observe news impact for the

² Other papers that have results for asymmetric effect on prices include [Zheng et al. \(2008\)](#) and [Rezitis and Stavropoulos \(2010\)](#).

³ Some other studies on price volatility include [Apergis and Rezitis \(2003a,b,c\)](#), [Fousekis and Grigoriadis \(2016\)](#), [Gouel \(2013\)](#), [Jha and Nagarajan \(2002\)](#), [Yang et al. \(2003\)](#) and [Rude and An \(2015\)](#).

⁴ See [FAO \(2016\)](#) for details.

⁵ We observe that, due to their weight in the basket, the changes in the price of certain items such as fresh fruit and vegetables and veal became more prominent in the last couple of years. The price of veal for example rose by 146 percent between January 2009 and January 2017.

⁶ [Ogunc \(2010\)](#) examines the structural problems behind price volatility in Turkey, suggesting that long chains of logistics, vastness of informal economy, structural problems in irrigation, storage and packaging capacities contribute to the high level of volatility in prices. In addition to them, absence of big producers who would not have financial problems in mitigating sudden shocks, insufficient capacity of insurance for farmers and big numbers of sellers in the retail sector are also listed as structural problems leading to highly volatile food prices.

⁷ Close examination of the Central Bank of the Republic of Turkey's (CBRT) inflation reports, summary of monetary policy meetings and open letters written to the government illustrate that the main focus has been the rapid increase in food prices and especially their volatility that are outside the control of CBRT.

⁸ Since 2016 the vulnerability of the unprocessed food items to external demand has been explicitly experienced with the restrictions imposed on Turkish exports of food products to Russia. Even though decreasing exports is considered to have favorable effects on domestic inflation, accompanying fluctuations and increase in volatility have become inevitable.

⁹ Some items like peach do not have price data available for winter as they are only produced and consumed in the summer, therefore we excluded those type of seasonal food items. There are some other items that have been included in the CPI basket just recently and those items are also excluded from the analysis.

subcomponents of CPI inflation. Therefore, present article contributes to the price volatility literature by testing the asymmetry of 90 retail food items employing EGARCH model of Nelson (1991). In line with Friedman-Ball hypothesis, we will suggest that news of high prices to be more stabilizing compared with the news of low prices for the food items that we study.

Our results show that among 90 items, there are 5 items which do not exhibit any time-varying variance all of which belong to mature markets. We also find that out of 56 items for which news effect is detected, 32 of them exhibit asymmetric volatility such that the total weight of these items in the CPI basket amounts to 7 percent. Between these two extremes, there are food items which exhibit time varying volatility with no news effect and with symmetric news effect, respectively. The striking point of the results is the downward sloping news impact curve that is detected for 10 items such as tomato, eggplant and zucchini. We consider that even though the primary focus should be on the items with asymmetric volatility, the case of these items should also not be ignored.

The remainder of the article is organized as follows. Section 2 describes the EGARCH(1,1) model and the news impact employed in this study to test the asymmetry in the volatility of 90 food items. Section 3 gives the detailed summary of the results and their implications. Section 4 concludes.

2. Methodology

Inflation volatility is often claimed to be one of the most important costs of inflation, since it distorts the allocation decision of market players by redistributing wealth between debtors and creditors and by reducing the effectiveness of relative prices in co-ordinating economic actions. In this respect, the importance of a correctly specified volatility model is essential for the valuation of future inflation. Early studies use unconditional volatility measures, i.e. standard deviation of inflation, and such measures have a drawback in the sense that higher variability need not necessarily imply higher uncertainty.¹⁰ Ever since the seminal papers of Engle (1982) and Bollerslev (1986), inflation volatility is proxied by ARCH and subsequent GARCH models.¹¹ There are certain advantages of GARCH type of models to proxy volatility.¹² Contrary to other measures of volatility, GARCH type of models allow the researcher to formally test for constant volatility and asymmetric volatility over the sample period.

In this part of the article we will concern ourselves with EGARCH model to measure volatility and employ news impact analysis. Following Engle and Ng (1993), let y_t be the log difference of food price.¹³ Let F_{t-1} be the past information set containing the realized values of all relevant variables up to time $t - 1$. The relevant expected price change and volatility are the conditional expected value of y_t , given F_{t-1} . These are denoted by $m_t \equiv E(y_t | F_{t-1})$ and $h_t \equiv \text{Var}(y_t | F_{t-1})$. Therefore, the unexpected price change at time t is $\varepsilon_t \equiv y_t - m_t$. In this paper, ε_t is treated as a collective measure of news at time t and opposite to Engle and Ng (1993) a positive ε_t (an unexpected increase in price) suggests the arrival of bad news, while a negative ε_t (an unexpected decrease in price) suggests the

arrival of good news.¹⁴ Given that the predictable volatility is dependent on past news an ARCH(1) model ala Engle (1982) will be:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2$$

where α and ω are constant parameters. Bollerslev (1986) generalizes the ARCH model to the GARCH model, such that a GARCH(1,1) model will be:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}$$

where α , β and ω are constant parameters. Indeed, the GARCH(1,1) model is like an ARMA(1,1) model for the variance and therefore a GARCH model is an infinite order ARCH model. Unfortunately, ARCH and GARCH models cannot capture some important aspects related to the data. The most important aspect not measured with these models is the leverage or asymmetric effect of news.¹⁵

Nelson's 1991 exponential GARCH (EGARCH) model captures such asymmetric effects and the EGARCH(1,1) model can be represented as:

$$\log(h_t) = \omega + \beta \log(h_{t-1}) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{2/\pi} \right] \quad (1)$$

where ω , β , γ and α are constant parameters.¹⁶ Given F_{t-1} , we can examine the implied relation between ε_{t-1} and h_t with the help of the news impact curve and can see the asymmetric effects of increasing and decreasing food prices on the next periods' volatility.¹⁷ Given the EGARCH(1,1) model in Equation (1) we can embed a parametric test for the asymmetry hypothesis, i.e. when $\gamma = 0$ there are symmetric effects and when γ is positive (negative) high (low) price news generates more volatility. We finish describing our methodology by illustrating the mean and error equations given by:

$$y_t = \mu + \sum_{i=1}^k \rho_i y_{t-i} + \varepsilon_t \quad (2)$$

$$\varepsilon_t = \nu_t \sqrt{h_t} \quad (3)$$

where y_t is the first difference of log price, k is the lag length and ν_t is a white noise process with unit variance. The lagged terms in the autoregressive AR(k) process defined by Equation (2) capture the predictable components of the price changes.

3. Empirical results

In this study, we use monthly retail price data that is publicly

¹⁰ Kontonikas (2004) states that this will be the case only if agents don't possess the relevant information to predict part of the increased variability.

¹¹ There are also survey-based proxies for inflation volatility where dispersion in inflation forecasts of individual respondents are aggregated.

¹² Although not related to inflation, Day and Lewis (1992) show that implied volatility from the Black-Scholes model cannot capture the entire predictable part of future stock price volatility relative to some GARCH and EGARCH models.

¹³ See the unit root tests for price series at the Appendix.

¹⁴ GARCH type of models are mostly used to evaluate financial returns and a positive shock for an asset return is good news, yet it will not be considered good when the prices considered are related to food. Therefore the definition of good news is the opposite of general literature on news impact.

¹⁵ The leverage effect suggests that a symmetry constraint on the conditional variance function in past ε 's is inappropriate.

¹⁶ EGARCH model is asymmetric as the level of $\varepsilon_{t-1}/\sqrt{h_{t-1}}$ is included with a coefficient γ .

¹⁷ See Engle and Ng (1993) for the details and shape of news impact curve. It is important to note that, Engle and Ng (1993) show that the shape of the curve depends on very strict parameter assumptions.

Table 1
Maximum likelihood estimates of EGARCH(1,1).

Food Item	α	t-stat. α	β	t-stat. β	γ	t-stat. γ	LM-stat.
Rice	1.565	11.91	0.31	2.88	-0.08	-0.71	81.44*
Wheat flour	0.812	5.59	0.08	0.39	0.19	1.67	11.14*
Baby food	0.018	0.15	-0.32	-2.62	0.75	11.63	75.93*
Boiled and pounded wheat	0.161	1.78	0.98	106.56	0.18	4.25	3896.00*
Bread	0.510	3.63	0.81	10.99	0.14	1.32	81.42*
Biscuit	-0.293	-1.61	0.00	0.01	0.08	0.39	1.32
Cracker	1.642	13.68	-0.15	-3.79	-0.82	-7.68	161.31*
Wafer	0.872	7.30	-0.21	-2.78	0.47	3.95	73.00*
Cream-cake and patisserie	0.314	2.17	-0.63	-2.29	-0.12	-1.15	11.68**
Cake	-0.028	-1.17	0.91	71.82	0.01	0.20	1789.71*
Dessert	0.316	2.00	-0.63	-2.81	-0.07	-0.87	12.33*
Thin dough	0.399	2.62	0.41	1.07	0.22	2.32	5.00*
Macaroni	-0.088	-1.98	0.98	61.46	0.10	2.03	3281.33*
Wermicelli	-0.070	-1.70	0.98	75.75	0.09	1.91	5237.23*
Cereal	0.205	1.26	-0.36	-1.53	0.43	3.71	6.72*
Veal	-0.014	-0.23	0.93	26.43	0.22	4.29	749.98*
Mutton	0.651	2.96	0.37	2.06	0.01	0.07	5.48*
Poultry	0.216	1.90	0.97	31.42	0.02	0.33	840.78*
Offal	0.067	0.61	0.76	11.40	0.29	3.89	186.23*
Garlic-flavored sausage	0.248	1.35	0.83	7.38	-0.01	-0.23	38.69*
Sausage	-0.441	-2.79	-0.12	-0.87	-0.27	-2.38	4.53*
Salami	-0.134	-4.01	0.94	1009.81	-0.01	-0.31	19318415*
Fresh fish	-0.239	-2.53	0.61	3.48	-0.26	-2.16	14.93*
Milk	-0.279	-1.97	-0.04	-0.12	0.21	1.74	1.67
Yoghurt	0.054	0.83	0.95	41.47	-0.08	-1.42	861.17
White cheese	-0.678	-4.00	0.50	3.13	0.36	3.31	28.62*
Kasar cheese	-0.141	-3.76	0.96	77.35	-0.10	-2.36	3284.81*
Tulum cheese	0.215	2.24	0.92	24.89	-0.24	-3.35	319.01*
Egg	-0.167	-1.49	0.42	1.58	0.25	2.02	6.85*
Butter	0.247	1.52	0.89	10.81	-0.01	-0.06	64.48*
Margarine	0.428	2.94	0.02	0.09	-0.03	-0.29	6.08*
Olive oil	3.038	14.21	-0.02	-0.49	-2.59	-15.30	81.60*
Sun-flower oil	0.209	3.65	0.95	98.37	0.11	2.69	3248.76*
Corn oil	0.188	2.78	0.97	112.34	0.18	3.90	4622.89*
Apple	0.471	2.09	0.68	4.03	0.31	2.71	13.92*
Lemon	1.285	9.15	-0.03	-0.35	-0.63	-6.33	37.44*
Banana	0.339	1.60	0.27	1.30	0.39	3.09	4.98*
Walnut (without shells)	0.609	3.42	-0.40	-1.68	-0.09	-0.78	8.63*
Hazelnut (without shells)	-0.109	-22.21	0.97	1080.23	0.31	9.05	44590098*
Pistachio	0.259	2.89	0.66	6.35	0.33	4.37	62.09*
Peanuts	0.246	1.98	-0.03	-0.25	0.54	5.84	20.98*
Roasted chick-pea	-0.506	-4.92	0.76	13.31	0.69	6.77	530.09*
Sun flower seed	-0.535	-3.84	0.70	7.51	0.58	4.09	397.65*
Pumpkin seed	0.853	4.91	0.40	3.66	0.46	4.18	21.87*
Raisin	0.716	3.64	0.45	4.32	0.03	0.25	39.64*

Note: Lagrange Multiplier statistic computed under the null hypothesis that alpha, beta and gamma are jointly zero.

* Indicates significance at a 5% level or less.

available at Turkish statistics agency (Turkstat). We only use food items that do not have missing data problem and that restricts us to 90 food items under CPI. These 90 food items have a 20 percent of share in CPI. Data for all the food items is available after January 2003, therefore all the EGARCH models are estimated between January 2003 and January 2017 (last available data).¹⁸ Some of the food items under CPI exhibit seasonality and we use TRAMO-SEATS for seasonal adjustment. GARCH type of models require stationary data for estimation, therefore our

data is transformed using logarithmic difference, i.e. $y_t = \ln(p_t/p_{t-1})$.

We choose k lags in the AR(k)-EGARCH(1,1) of each food item so that there does not remain any serial correlation in the residuals of the estimation and we come up with the most parsimonious specification for the mean and variance model illustrated with Equations (2) and (1). In all the cases k up to 4 lags provide good approximation to the data generating process. Additionally, EGARCH(1,1) provides a proper approximation for the time-varying variance as there does not exist any remaining heteroscedasticity in

¹⁸ See the descriptive statistics of the series at the Appendix.

Table 2
Maximum likelihood estimates of EGARCH(1,1) continued.

Item	α	t-stat. α	β	t-stat. β	γ	t-stat. γ	LM-stat.
Sweet green pepper	0.76	4.81	-0.38	-2.12	-0.21	-1.92	17.55*
Green pepper	0.961	5.16	-0.33	-2.01	-0.26	-1.94	19.20*
Tomato	-0.613	-5.43	0.66	9.30	0.56	7.24	115.11*
Zucchini	-0.713	-4.64	0.74	12.23	0.59	6.85	109.74*
Onion	0.087	1.11	0.93	35.57	0.47	5.65	891.85*
Lettuce	-0.277	-3.32	0.86	26.92	0.72	5.20	435.96*
Parsley	0.024	0.15	0.69	11.61	0.88	8.09	124.58*
Eggplant	-0.397	-3.00	0.84	17.89	0.33	2.97	234.34*
Cucumber	0.179	0.78	0.22	0.21	-0.06	-0.40	0.22
Garlic	0.279	2.09	0.22	0.97	-0.42	-3.60	7.79*
Green onion	-0.401	-5.86	0.83	35.25	0.63	5.29	445.91*
Potato	0.674	5.19	0.30	2.45	0.48	4.80	22.04*
Dry bean	0.537	3.72	0.09	0.39	0.15	1.22	9.12*
Chickpea	-0.004	-0.06	0.82	9.45	0.11	1.68	85.74*
Lentils	0.164	1.30	0.90	24.58	0.06	1.00	702.58*
Other pulse	-0.011	-0.07	0.55	5.51	0.54	5.05	28.17*
Canned vegetables	0.911	8.68	-0.25	-1.80	0.04	0.57	49.29*
Tomato sauce	0.670	2.88	0.67	4.89	0.19	2.05	40.99*
Olive	-0.219	-27.51	0.92	69.75	0.13	7.87	1940.20*
Chips and appetizers	0.718	5.68	0.60	6.19	-0.34	-3.14	113.96*
Granulated sugar	0.375	2.81	-0.53	-3.53	0.29	2.67	18.76*
Cube sugar	-0.005	-0.03	-0.66	-5.84	0.30	4.08	56.50*
Jam	0.119	1.91	0.87	16.05	-0.30	-3.49	152.33*
Honey	-0.013	-0.07	-0.03	-0.16	0.53	4.41	6.70*
Grape molasses	0.501	2.45	0.52	6.62	0.29	1.81	47.01*
Halvah	0.160	1.20	0.60	5.09	0.37	3.55	29.67*
Chocolate cream	0.431	2.73	-0.67	-5.37	0.13	1.66	47.61*
Turkish delight	0.330	2.17	-0.36	-1.21	-0.25	-2.82	10.63*
Holiday candy	-0.956	-14.53	0.38	5.58	0.55	6.72	154.80*
Ice-cream	-0.153	-3.84	0.91	42.45	-0.34	-4.63	1397.54*
Condiment-spices	-0.016	-0.29	0.80	19.10	0.50	6.99	617.98*
Salt	0.500	4.31	0.78	6.97	-0.19	-1.62	37.95*
Baking powder	-1.056	-0.59	0.01	0.04	-0.26	-0.25	0.31
Catchup	0.741	3.89	0.43	2.33	0.07	0.55	7.80*
Packaged soup	-1.218	-135.77	0.01	2.43	1.03	126.70	21635.84*
Turkish Coffee	0.360	2.15	-0.24	-1.48	0.47	4.68	21.67*
Ready-made coffee	-1.262	-12.16	0.22	1.52	0.51	7.03	138.14*
Tea	-0.021	-0.17	-0.02	-0.07	0.25	1.91	1.31
Cocoa	-0.433	-3.59	-0.80	-5.81	0.18	1.99	32.82*
Cocoa beverages	-0.018	-0.12	-0.09	-0.22	0.35	2.54	2.17
Water	-0.451	-4.02	0.00	0.02	-3.05	-36.45	4205.91*
Mineral water	0.400	2.39	-0.67	-4.70	0.18	1.88	80.85*
Carbonated fruity beverages	0.822	7.77	0.25	2.57	1.00	9.38	187.14*
Coke	1.035	5.88	0.29	2.43	1.26	8.56	238.32*
Fruit Juice	-0.099	-1696.68	0.97	20537.66	-0.13	-15.91	28000000000*

Note: Lagrange Multiplier statistic computed under the null hypothesis that alpha, beta and gamma are jointly zero.

* Indicates significance at a 5% level or less.

the residuals of the estimated models.¹⁹

Table 1 and Table 2 lists the maximum likelihood estimates of α , β and γ . We use 5 percent level of significance for all the estimated parameters. When we check the significance of the parameters alpha and beta, we observe that most of the time one or the other is statistically significant pointing to existence of time-varying variance in 94 percent of the food items of the CPI.

For the food items listed in the gray shaded rows of Tables 1 and 2, we cannot observe time-varying variance and this happens for 5 items including biscuit, milk, cucumber, baking

powder and tea.²⁰ With a closer inspection, it can be seen that these 5 food items with constant variance belong mostly to mature markets where competition and entry is difficult with no incentive for extra profit or margin. Therefore, the growth prospect and volatility for these items are more stable in the short-run. The weight of these 5 constant variance food items in the headline CPI amounts to 1.55 percent, whereas it amounts to 7.12 in the food and non-alcoholic beverages' sub-component of

¹⁹ Residual diagnostics of EGARCH(1,1) models are illustrated with Table C.1 and Table C.2 at the Appendix.

²⁰ We declare an item to have constant variance if neither the individual significance nor the joint significance of coefficients are verified. For 5 items listed as constant variance items, α , β and γ are not significant jointly and individually.

Table 3
Effect of news on food price volatility.

Food Item	High price		Low price	
	news $\alpha + \gamma$	t-stat. ($\alpha + \gamma$)	news $\alpha - \gamma$	t-stat. ($\alpha - \gamma$)
Baby food	0.77	5.62	-0.74	-5.37
Boiled and pounded wheat	0.34	4.26	-0.02	-0.13
Cracker	0.83	4.76	2.46	16.86
Wafer	1.34	11.96	0.41	1.94
Thin dough	0.62	3.78	0.18	0.92
Macaroni	0.01	0.24	-0.19	-2.39
Cereal	0.63	2.83	-0.23	-1.31
Veal	0.21	2.84	-0.24	-2.65
Offal	0.36	2.26	-0.23	-2.23
Sausage	-0.71	-3.64	-0.17	-0.88
Fresh fish	-0.50	-2.77	0.02	0.14
White cheese	-0.31	-3.49	-1.04	-3.84
Kasar cheese	-0.24	-3.60	-0.04	-0.83
Tulum cheese	-0.03	-0.22	0.46	3.81
Egg	0.09	0.58	-0.42	-2.27
Olive oil	0.45	3.74	5.63	15.35
Sun-flower oil	0.32	7.14	0.10	1.08
Corn oil	0.37	6.77	0.01	0.09
Apple	0.78	2.98	0.16	0.65
Lemon	0.65	4.76	1.92	9.50
Banana	0.73	3.03	-0.05	-0.20
Hazelnut (without shells)	0.20	5.80	-0.42	-12.09
Pistachio	0.59	4.68	-0.07	-0.67
Peanuts	0.79	6.01	-0.30	-1.70
Roasted chick-pea	0.19	3.59	-1.20	-6.05
Sun flower seed	0.05	0.77	-1.12	-4.07
Pumpkin seed	1.31	6.77	0.39	1.81
Tomato	-0.05	-0.42	-1.18	-7.78
Zucchini	-0.12	-0.94	-1.30	-6.15
Onion	0.56	4.98	-0.38	-3.28
Lettuce	0.44	4.53	-0.99	-4.82
Parsley	0.90	6.36	-0.85	-3.73
Eggplant	-0.07	-0.46	-0.73	-3.70
Garlic	-0.14	-0.81	0.70	3.93
Green onion	0.23	2.71	-1.03	-5.90
Potato	1.15	7.26	0.20	1.17
Other pulse	0.53	2.50	-0.55	-3.47
Tomato sauce	0.86	3.19	0.48	2.09
Olive	-0.09	-4.28	-0.35	-22.81
Chips and appetizers	0.38	4.18	1.06	4.85
Granulated sugar	0.67	3.66	0.09	0.52
Cube sugar	0.29	1.75	-0.30	-1.96
Jam	-0.18	-1.80	0.42	3.74
Honey	0.52	2.23	-0.55	-2.49
Halvah	0.53	3.50	-0.21	-1.11
Turkish delight	0.08	0.44	0.58	3.62
Holiday candy	-0.41	-4.66	-1.50	-12.65
Ice-cream	-0.49	-4.99	0.19	2.89
Condiment-spices	0.49	6.94	-0.52	-4.86
Packaged soup	-0.19	-33.92	-2.25	-138.80
Turkish Coffee	0.83	3.96	-0.11	-0.61
Ready-made coffee	-0.75	-8.93	-1.77	-11.23
Water	-3.50	-45.15	2.60	14.26
Carbonated fruity beverages	1.82	18.71	-0.18	-0.94
Coke	2.29	11.68	-0.22	-0.87
Fruit Juice	-0.23	-28.14	0.03	3.63

CPI. It is remarkable to see that 3 of these food items, i.e. biscuit, milk and tea, are produced in markets with high levels of concentration. Such items could lead to further consideration about the impact of market structure on price determination dynamics.²¹ The last column of Tables 1 and 2 illustrates the Lagrange Multiplier (LM) statistics for a joint significance test of parameters α , β and γ and only 7 food items out of 90 fail the LM test statistics.

The last two columns of Tables 1 and 2 that are shaded in colour red are for food items with both significant γ and LM test statistics. Table 3 lists these items separately with both significant statistics of γ and LM test, i.e. that are shaded red in Tables 1 and 2. In the empirical literature, a significant γ parameter of Equation (1) is usually considered a sign of asymmetric volatility, however we behave conservative and regard items to have asymmetric effect if both the γ and the LM statistic is significant together. Columns one and three of Table 3 shows coefficients for high and low price news respectively. This table is extremely important to observe the asymmetric effect of a decrease and

²¹ See Önder (2016) and Kaynak (2016).

Table 4

Classification of food price variance response.

News effects		No news effects		
Symmetric effects	Asymmetric effects	Insignificant LM statistic	No news effects EGARCH model	Constant variance
Cracker	Baby food	Cocoa beverages	Rice	Biscuit
Wafer	Boiled and pounded wheat		Wheat flour	Milk
Thin dough	Macaroni		Bread	Tea
Olive oil	Veal		Cream-cake and patisserie	Baking powder
Sun-flower oil	Offal		Cake	Cucumber
Corn oil	Egg		Dessert	
Apple	Banana		Wermicelli	
Lemon	Hazelnut (without shells)		Mutton	
Pumpkin seed	Pistachio		Poultry	
Potato	Peanuts		Garlic-flavored sausage	
Tomato sauce	Roasted chick-pea		Salami	
Chips and appetizers	Sun flower seed		Yoghurt	
Granulated sugar	Onion		Butter	
Turkish delight	Lettuce		Margarine	
Sausage	Parsley		Walnut (without shells)	
White cheese	Green onion		Raisin	
Kasar cheese	Other pulse		Sweet green pepper	
Tomato	Cube sugar		Green pepper	
Zucchini	Honey		Dry bean	
Eggplant	Halvah		Chickpea	
Olive	Condiment-spices		Lentils	
Holiday candy	Turkish Coffee		Canned vegetables	
Packaged soup	Carbonated fruity beverages		Grape molasses	
Ready-made coffee	Coke		Chocolate cream	
	Fresh fish		Salt	
	Tulum cheese		Catchup	
	Garlic		Cocoa	
	Jam		Mineral water	
	Ice-cream			
	Water			
	Fruit Juice			
	Cereal			

increase in prices on the next period volatility. For EGARCH(1,1) model the effect of high price news on conditional variance can be quantified by $\alpha + \gamma$ and the effect of low price news can be quantified by $\alpha - \gamma$.

When we examine Table 3 closely, estimated high price and low price effects are 0.21 and -0.24 respectively for veal. If we quantify the effects for veal, we can claim that an unexpected price increase measured by a unit increase in the standardized residual with $\varepsilon_{t-1} > 0$ increases volatility by 21 percent and an unexpected price decrease with $\varepsilon_{t-1} < 0$ decreases volatility by 24 percent. This asymmetric effect for food item veal can be observed clearly from the news impact curve at Appendix D. Appendix D shows that, for veal the news impact curve is upward sloping for high price news and downward sloping for low price news. The asymmetry is sharper for eggs, i.e. high price effects increase the volatility only by 9 percent, yet low price news decrease price by 42 percent.

Unexpectedly, news impact curve is downward sloping for some food items and this is more common for negative shocks. One example is baby food, which has similar high and low price effects but the news impact curve is sloped downwards for the low price news. News impact curve is downward sloping both for the high and low price news for 10 food items, which is quite extraordinary. For these 10 items, i.e. sausages, white cheese, kasar cheese, tomato, zucchini, eggplant, olives, holiday candy, packaged soup and instant coffee, any change in price will decrease volatility. There does not exist any common features of

these 10 food items that will cause their volatility to respond to negative and positive shocks in such an unexpected behaviour.²² Out of 56 food items listed in Table 3, for nearly half of them high price news effects are larger than the low price news effects in absolute values, which means for half of the food items consumers respond disproportionately given the high price news.

Indeed, Table 4 sums up the news impact analysis of all EGARCH(1,1) models estimated for the 90 retail food items. For the food items that takes place in the first column of the table, low price and high price news have the same effect on the price. The 10 shaded items on the first column of the table are food items having negative sloped news impact curve for both high price and low price news.

Considering the price of veal, which is one of the food items in the first column of Table 4, it should be stated that the news effect detected for veal should be examined closely in light of the price increases observed in recent years and the subsequent import decision, to prevent the repercussions of increased uncertainty. As can be seen in the news effect structure of the veal in Appendix D, an unexpected decrease in the price of veal decreases volatility whereas an unexpected increase in price causes a jump of volatility in an almost exponential manner. This vulnerable structure validates the special focus of policy makers to prevent unexpected increases in the price of veal, and similar sensitive items in this category.

The second column of Table 4 have food items with significant news impact and the effect of low price and high price news are asymmetric. A similar pattern is observed for food item egg, such that unexpected price increase in the previous period leads to higher uncertainty compared to unexpected price decrease in

²² It would be interesting to study and find the reason behind this unexpected behaviour, which is beyond the scope of this study.

the same period. It is seen that as the amount of unexpected price decrease gets larger, the impact on volatility gets smaller. Detection of such a structure shows that developments such as the unexpected increase in the price of egg through the end of 2016 should be monitored closely by policy making authorities in order to limit its impact on volatility and further price increases.²³

Items such as apple, onion and potato are also found to exhibit news impact structure and this structure reveals that price declines do not cause any change in volatility whereas price increases definitely contribute to that. In Turkish food market, it is known that some food products are stored either by producers or middlemen to sell them at a higher price in subsequent periods. Since these three items are among those products, it could be suggested that any unexpected decline in the price leads to increase in the stored amount with no impact on price level volatility. In other words, since the actors in those markets already know that their products would be stored in the face of a price decline, any unexpected decline might not end up with increased volatility as all producers (or middlemen) would (surely) wait until the prices recover to a desired level.²⁴

The third column of the table has only one food item that have an insignificant LM test statistics, yet γ for this item is individually significant. For the food items listed on the last two columns of Table 4, either there are no price news effects (fourth column with both insignificant LM test statistics and insignificant asymmetry parameters for the EGARCH model), or there is constant variance (5 food items that are shaded gray in Tables 1 and 2).

The fourth column, i.e. with no news impact but time-varying variance, includes items such as bread, rice, wheat flour, mutton and poultry. It is evident that the first three of these food items are among basic necessity foods, which need further consideration by policy makers. Although the weight of these items amount to 7.2 percent in the headline CPI, it amounts to 33 percent within the food and non-alcoholic beverages' sub-component of CPI.²⁵ Monitoring the volatility of the price of poultry is also a matter of significance since poultry sector is closely connected with the exchange rate and export dynamics along with the high level of imported input materials.²⁶

Because inference in GARCH type of models depends on the correct specification set and the validity of the functions used to represent the conditional mean and the conditional variance we conduct an additional test on asymmetry by employing the regression given as:

$$s_t^2 = \delta_0 + \delta_1 s_{t-1} + \delta_2 s_{t-2} + \delta_3 s_{t-3} + \eta_t \quad (4)$$

where $s_t = (\varepsilon_t/h_t^{1/2})'$ is the predicted standardized residual from Equation (2). A test for any additional symmetry will be a joint significance test for the null hypothesis of $\delta_1 = \delta_2 = \delta_3 = 0$.²⁷

²³ It is publicly known that the sudden increase in the price of egg was triggered by the sudden increase in export demand accompanied by the decline in the demand for eggs from the countries with avian influenza disease. It is also known that the demand for Iranian egg was substantially directed to Turkish egg market.

²⁴ Though this scenario is a valid and vastly observed one in Turkey, how long producers would wait for the prices to recover and at what price they would be satisfied is a question that needs to be examined on a market level. Admittedly, this is out of the scope of this paper.

²⁵ The weight of bread has particular importance with 2.22 percent in the CPI basket and 10 percent in the food and non-alcoholic beverages' basket.

²⁶ It would be plausible to decompose the volatility of the price of poultry as it could be affected by many factors simultaneously.

²⁷ See Enders (2008) for details.

Table 5
Diagnostic regression.

Food Item	F-stat.	
	$H_0 : \delta_1 = \delta_2 = \delta_3 = 0$	p-value
Cracker	0.671	0.571
Wafer	0.015	0.998
Thin dough	0.611	0.609
Fresh fish	1.219	0.305
Tulum cheese	0.314	0.815
Olive oil	0.009	0.999
Sun-flower oil	0.117	0.950
Corn oil	0.380	0.768
Apple	0.340	0.797
Lemon	0.214	0.887
Pumpkin seed	0.255	0.857
Garlic	0.385	0.764
Potato	0.114	0.952
Tomato sauce	0.811	0.490
Chips and appetizers	0.626	0.599
Granulated sugar	0.351	0.789
Jam	0.339	0.797
Turkish delight	0.164	0.920
Ice-cream	1.695	0.170
Water	0.404	0.751
Fruit Juice	1.499	0.217
Baby food	0.311	0.818
Boiled and pounded wheat	0.062	0.980
Macaroni	1.201	0.311
Veal	0.639	0.591
Offal	0.230	0.875
Sausage	1.181	0.319
White cheese	0.123	0.947
Kasar cheese	0.288	0.834
Egg	1.568	0.199
Banana	0.806	0.492
Hazelnut (without shells)	2.351	0.074
Pistachio	0.165	0.920
Peanuts	0.031	0.993
Roasted chick-pea	0.110	0.954
Sun flower seed	0.085	0.968
Tomato	0.168	0.918
Zucchini	1.565	0.200
Onion	0.538	0.657
Lettuce	0.317	0.813
Parsley	1.285	0.282
Eggplant	1.165	0.325
Green onion	0.788	0.502
Other pulse	0.043	0.988
Olive	0.340	0.796
Cube sugar	0.069	0.976
Honey	0.296	0.829
Halvah	0.067	0.978
Holiday candy	0.087	0.967
Condiment-spices	0.147	0.932
Packaged soup	0.062	0.980
Turkish Coffee	0.226	0.878
Ready-made coffee	0.140	0.936
Carbonated fruity beverages	0.059	0.981
Coke	0.119	0.949
Cocoa beverages	0.158	0.925

Rejection of the null hypothesis will indicate there exist remaining asymmetry effects and the model is misspecified. We estimate Equation (4) and conduct an F test for all the items listed in the first two columns of Table 4 (food items that have news effect). Results are listed in Table 5 and only one food item (shaded row) fails the test. Given the results listed in Table 5 we conclude that the AR(k) EGARCH(1,1) model we use are well-specified and the asymmetric effects are fully accounted for 55 of 56 items (hazelnuts are the only exception).

4. Concluding remarks

Inflation and inflation volatility have always been the focus of research for investigators of all kinds with an increasing number of studies produced especially after the two global food price crises occurred within the last decade. In the academic literature, the research on inflation concentrating on three basic features of the dynamics of inflation, i.e. the mean inflation or level of inflation, the permanence of inflation, and the volatility of inflation. While there is a great amount of research on the first two features of inflation, there exist a limited amount of research on the volatility of inflation, particularly for developing countries. Although, policy makers generally make evaluations in terms of first moments, in reality the second moments have also an adverse effect on general economic performance by making the future more uncertain and unpredictable.

During the inflation targeting period of Turkey, deviation from the targets have been mostly explained by unexpected shocks that increase the volatility especially for food prices. In this respect, we think that our study will be a valuable contribution to the literature on the food price volatility. Our results also have significant implications for food markets in light of recent developments that cause inflation to move to double digits, as knowing the asymmetric impact of unexpected shocks to food items may help the policy makers foresee how the prices will respond given an increase or decrease in retail food items listed under the CPI. Especially sub-components of CPI that illustrate time-varying variance should be monitored closely in order to prevent undesired deviations from targeted levels that could stem from changes in volatility.

We believe that, monitoring certain food items that exhibit both time-varying variance and asymmetry could even function as an early warning mechanism for the surveillance of food inflation in particular. In light of the arguments in the literature, it could be stated that the asymmetric structure of volatility observed for some food products, which in our case has around 20 percent in CPI, should be a signal to policy makers.

Appendix A. Descriptive statistics

Table A.1
Descriptive Statistics of Raw Data.

Food Item	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera (J-B)	(J-B) Probability
Rice	1.393	0.362	-0.305	1.878	11.483	0.003
Wheat flour	2.118	0.168	-0.326	2.575	4.256	0.119
Baby food	2.728	0.398	-0.108	2.126	5.709	0.058
Boiled and pounded wheat	1.140	0.347	0.046	1.947	7.868	0.020
Bread	0.600	0.367	-0.285	1.716	13.892	0.001
Biscuit	0.598	0.365	-0.286	1.717	13.894	0.001
Cracker	2.585	0.155	0.646	2.092	17.561	0.000
Wafer	2.947	0.431	0.065	1.786	10.505	0.005
Cream-cake and patisserie	2.876	0.457	-0.115	1.349	19.560	0.000
Cake	1.613	0.355	-0.384	1.744	15.271	0.000
Dessert	2.503	0.509	0.016	1.562	14.570	0.001
Thin dough	0.506	0.355	0.135	1.734	11.808	0.003
Macaroni	3.404	0.343	0.211	1.950	9.019	0.011
Wermicelli	3.143	0.263	0.208	1.664	13.793	0.001
Cereal	3.204	0.277	0.400	1.901	13.004	0.002
Veal	2.364	0.317	0.135	2.141	5.719	0.057
Mutton	0.667	0.243	0.231	1.901	10.003	0.007
Poultry	1.101	0.247	-0.126	1.814	10.359	0.006
Offal	2.326	0.555	-0.561	1.824	18.594	0.000
Garlic-flavored sausage	2.806	0.309	-0.168	1.840	10.272	0.006
Sausage	2.695	0.356	0.066	1.921	8.324	0.016
Salami	-1.509	0.416	-0.101	1.982	7.586	0.023
Fresh fish	3.914	0.190	-0.070	2.287	3.718	0.156
Milk	2.841	0.423	0.123	1.819	10.248	0.006
Yoghurt	1.457	0.310	-0.008	1.433	17.298	0.000
White cheese	2.415	0.402	1.134	3.844	41.250	0.000
Kasar cheese	1.521	0.341	-0.138	1.558	15.168	0.001
Tulum cheese	1.644	0.301	-0.314	1.508	18.453	0.000
Egg	0.546	0.325	-0.243	2.047	8.064	0.018
Butter	0.364	1.137	-0.951	2.549	26.915	0.000
Margarine	1.259	0.283	0.828	2.482	21.181	0.000
Olive oil	3.266	0.497	0.085	1.934	8.206	0.017
Sun-flower oil	3.106	0.499	0.511	2.922	7.389	0.025
Corn oil	0.634	0.353	-0.416	1.713	16.551	0.000
Apple	3.127	0.499	0.309	1.908	11.092	0.004
Lemon	2.205	0.440	0.269	1.996	9.133	0.010
Banana	1.974	0.525	-0.082	1.706	11.984	0.002
Walnut (without shells)	1.857	0.453	-0.028	1.878	8.880	0.012
Hazelnut (without shells)	2.556	0.456	-0.055	1.790	10.400	0.006

(continued on next page)

Table A.1 (continued)

Food Item	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera (J-B)	(J-B) Probability
Pistachio	1.769	0.475	0.091	1.597	14.099	0.001
Peanuts	0.665	0.475	0.021	2.321	3.258	0.196
Roasted chick-pea	0.740	0.508	0.134	2.231	4.671	0.097
Sun flower seed	0.326	0.444	-0.310	2.638	3.627	0.163
Pumpkin seed	0.407	0.457	0.010	2.839	0.185	0.912
Raisin	0.702	0.407	-0.029	1.764	10.775	0.005

Table A.2

Descriptive Statistics of Raw Data Continued.

Food Item	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera (J-B)	(J-B) Probability
Sweet green pepper	-0.150	0.456	-0.005	2.823	0.222	0.895
Green pepper	0.113	0.396	0.059	2.046	6.501	0.039
Tomato	-0.793	0.402	-0.083	1.913	8.507	0.014
Zucchini	0.569	0.479	0.079	2.658	1.000	0.607
Onion	0.320	0.485	-0.152	2.531	2.198	0.333
Lettuce	1.829	0.543	-0.266	2.606	3.080	0.214
Parsley	0.982	0.484	0.247	2.282	5.356	0.069
Eggplant	-0.069	0.501	0.062	2.632	1.062	0.588
Cucumber	1.465	0.459	-0.095	2.267	4.041	0.133
Garlic	1.330	0.507	-0.099	2.049	6.647	0.036
Green onion	1.700	0.194	-0.489	2.205	11.169	0.004
Potato	1.156	0.483	0.028	1.929	8.095	0.017
Dry bean	1.595	0.471	-0.026	1.925	8.154	0.017
Chickpea	1.243	0.371	-0.216	1.830	10.947	0.004
Lentils	1.347	0.343	-0.061	1.579	14.316	0.001
Other pulse	2.266	0.363	-0.258	2.363	4.732	0.094
Canned vegetables	2.705	0.271	0.176	1.650	13.692	0.001
Tomato sauce	0.965	0.264	0.269	1.888	10.749	0.005
Olive	1.091	0.228	0.370	1.961	11.468	0.003
Chips and appetizers	2.087	0.292	0.285	1.810	12.250	0.002
Granulated sugar	2.980	0.425	-0.262	1.808	11.944	0.003
Cube sugar	1.833	0.174	-0.565	1.934	16.986	0.000
Jam	2.111	0.418	-0.336	1.646	16.087	0.000
Honey	2.252	0.410	0.023	1.614	13.533	0.001
Grape molasses	2.355	0.197	0.038	2.346	3.052	0.217
Halvah	1.761	0.282	0.107	2.026	6.998	0.030
Chocolate cream	2.544	0.270	-0.175	2.602	1.975	0.373
Turkish delight	2.433	0.168	0.938	3.130	24.897	0.000
Holiday candy	2.769	0.492	0.323	1.844	12.362	0.002
Ice-cream	-0.062	0.414	-0.041	1.691	12.105	0.002
Condiment-spices	0.149	1.479	-0.225	1.128	26.091	0.000
Salt	1.518	0.263	0.178	1.895	9.481	0.009
Baking powder	2.565	0.258	-0.106	2.412	2.750	0.253
Catchup	-0.003	0.918	2.768	9.518	514.968	0.000
Packaged soup	2.964	0.467	-0.252	1.781	12.249	0.002
Turkish Coffee	3.672	0.221	-0.885	3.369	22.997	0.000
Ready-made coffee	2.449	0.368	0.094	2.278	3.913	0.141
Tea	3.307	0.260	0.309	1.664	15.259	0.000
Cocoa	2.678	0.316	0.113	1.627	13.636	0.001
Cocoa beverages	-1.088	0.242	0.351	2.555	4.860	0.088
Water	0.507	0.282	-0.038	1.746	11.112	0.004
Mineral water	0.639	0.165	-0.341	2.148	8.380	0.015
Carbonated fruity beverages	0.726	0.170	-0.265	2.027	8.650	0.013
Coke	2.773	0.372	-0.155	2.229	4.861	0.088
Fruit Juice	0.784	0.191	0.323	1.784	13.350	0.001

Appendix B. Unit root tests**Table B.1**

Augmented Dickey-Fuller Test Statistics.

Item	ADF-test-stat	p-value	Item	ADF-test-stat	p-value
Rice	-2.2668	0.4493	Sweet green pepper	-3.00465	0.1343
Wheat flour	-2.39387	0.3814	Green pepper	-2.99502	0.137
Baby food	-1.60019	0.7891	Tomato	-3.71724	0.024
Boiled and pounded wheat	-1.92207	0.6385	Zucchini	-3.5199	0.0407
Bread	-1.95613	0.6204	Onion	-3.88835	0.0147
Biscuit	-2.79496	0.2013	Lettuce	-4.47978	0.0022
Cracker	-2.02321	0.5841	Parsley	-2.93613	0.1541
Wafer	-2.7306	0.2258	Eggplant	-4.07091	0.0085
Cream-cake and patisserie	-2.88995	0.1685	Cucumber	-3.07379	0.1163

Table B.1 (continued)

Item	ADF-test-stat	p-value	Item	ADF-test-stat	p-value
Cake	-2.81486	0.1941	Garlic	-2.90256	0.1644
Dessert	-2.44001	0.3577	Green onion	-2.8862	0.1698
Thin dough	-2.69016	0.2421	Potato	-2.80479	0.1977
Macaroni	-1.45202	0.8419	Dry bean	-3.04888	0.1223
Wermicelli	-1.45503	0.8409	Chickpea	-2.0398	0.5749
Cereal	-0.88889	0.9539	Lentils	-2.41535	0.3703
Veal	-2.4758	0.3398	Other pulse	-3.10214	0.1093
Mutton	-1.7593	0.7201	Canned vegetables	-2.26524	0.4501
Poultry	-3.00243	0.1348	Tomato sauce	-3.52986	0.0397
Offal	-2.31532	0.423	Olive	-2.60156	0.2803
Garlic-flavored sausage	-1.82098	0.6903	Chips and appetizers	-3.07059	0.1169
Sausage	-2.23353	0.4676	Granulated sugar	-2.64743	0.2601
Salami	-1.58012	0.7969	Cube sugar	-2.08335	0.5509
Fresh fish	-2.56469	0.2971	Jam	-1.83091	0.6854
Milk	-3.13125	0.1026	Honey	-2.04532	0.5719
Yoghurt	-2.81579	0.1938	Grape molasses	-1.26113	0.8936
White cheese	-1.52478	0.8174	Halvah	-2.30857	0.4266
Kasar cheese	-2.89519	0.1668	Chocolate cream	-2.80504	0.1977
Tulum cheese	-2.32776	0.4163	Turkish delight	-1.56504	0.8026
Egg	-2.52317	0.3167	Holiday candy	-2.12464	0.5279
Butter	-2.94184	0.1522	Ice-cream	-1.5885	0.7937
Margarine	-2.41724	0.3693	Condiment-spices	-1.8558	0.6728
Olive oil	-1.00913	0.939	Salt	-2.46117	0.347
Sun-flower oil	-2.8292	0.189	Baking powder	-2.07437	0.5559
Corn oil	-2.46801	0.3436	Catchup	-2.55687	0.3008
Apple	-2.95355	0.1488	Packaged soup	-0.81764	0.9611
Lemon	-2.76271	0.2134	Turkish Coffee	-1.87824	0.6614
Banana	-2.87965	0.1719	Ready-made coffee	-2.17171	0.5018
Walnut (without shells)	-3.02857	0.1277	Tea	-1.35325	0.8708
Hazelnut (without shells)	-2.10649	0.538	Cocoa	-1.23097	0.9003
Pistachio	-2.98142	0.1406	Cocoa beverages	-1.81444	0.6935
Peanuts	-3.06974	0.1171	Water	-1.52067	0.8188
Roasted chick-pea	-2.60146	0.2803	Mineral water	-2.55824	0.3001
Sun flower seed	-2.41657	0.3697	Carbonated fruity beverages	-2.02349	0.5839
Pumpkin seed	-2.48625	0.3346	Coke	-2.25993	0.4531
Raisin	-3.07765	0.1152	Fruit Juice	-1.79915	0.701

Appendix C. Diagnostic tests

Table C.1
Diagnostic Tests of EGARCH models.

Item	Q(1)	Q(1) - p	Q ² (1)	Q ² (1) - p	Q(12)	Q(12) - p	Q ² (12)	Q ² (12) - p
Rice	0.215	0.643	0.646	0.422	10.343	0.411	7.425	0.685
Wheat flour	0.046	0.831	0.147	0.702	9.249	0.509	3.522	0.966
Baby food	2.226	0.136	0.270	0.603	12.138	0.276	6.366	0.784
Boiled and pounded wheat	0.396	0.529	0.008	0.928	6.542	0.768	8.925	0.539
Bread	1.069	0.301	0.012	0.914	11.337	0.332	7.205	0.706
Biscuit	0.056	0.813	0.050	0.823	19.472	0.035	26.550	0.003
Cracker	3.539	0.060	0.197	0.657	11.983	0.286	9.181	0.515
Wafer	0.333	0.564	0.110	0.741	8.861	0.545	3.114	0.979
Cream-cake and patisserie	0.207	0.649	0.020	0.887	9.134	0.519	2.782	0.986
Cake	0.969	0.325	0.019	0.891	9.240	0.510	1.664	0.998
Dessert	0.172	0.678	0.021	0.886	9.669	0.470	13.193	0.213
Thin dough	0.119	0.731	0.029	0.864	9.479	0.487	2.790	0.986
Macaroni	0.311	0.577	0.019	0.892	8.514	0.579	10.503	0.397
Wermicelli	0.104	0.747	0.012	0.913	7.740	0.654	11.356	0.330
Cereal	0.104	0.747	0.273	0.601	3.936	0.950	3.155	0.978
Veal	1.491	0.222	0.081	0.776	13.902	0.178	7.288	0.698
Mutton	0.006	0.939	0.117	0.733	5.986	0.816	7.110	0.715
Poultry	0.077	0.782	0.001	0.976	11.501	0.320	8.868	0.545
Offal	0.007	0.933	0.001	0.971	8.795	0.552	0.453	1.000
Garlic-flavored sausage	1.968	0.161	0.122	0.726	17.684	0.061	2.933	0.983
Sausage	0.519	0.471	0.009	0.926	5.972	0.818	2.591	0.989
Salami	0.378	0.538	0.762	0.383	13.411	0.202	4.080	0.944
Fresh fish	0.320	0.572	0.278	0.598	54.022	0.000	2.465	0.991
Milk	0.168	0.682	0.039	0.843	10.253	0.419	11.667	0.308
Yoghurt	0.247	0.619	0.036	0.849	7.085	0.717	9.944	0.445
White cheese	2.132	0.144	0.000	0.990	9.339	0.500	0.101	1.000
Kasar cheese	0.908	0.341	0.261	0.609	7.009	0.725	15.074	0.129
Tulum cheese	0.819	0.366	0.507	0.476	6.049	0.811	5.130	0.882

(continued on next page)

Table C.1 (continued)

Item	Q(1)	Q(1) – p	Q ² (1)	Q ² (1) – p	Q(12)	Q(12) – p	Q ² (12)	Q ² (12) – p
Egg	0.079	0.778	0.265	0.607	16.741	0.080	5.949	0.820
Butter	0.001	0.977	1.198	0.274	6.812	0.743	9.854	0.453
Margarine	0.356	0.551	0.075	0.784	5.327	0.868	0.944	1.000
Olive oil	0.147	0.702	0.020	0.889	14.256	0.162	0.953	1.000
Sun-flower oil	0.002	0.963	0.032	0.858	4.477	0.923	9.975	0.443
Corn oil	0.789	0.374	0.495	0.482	10.062	0.435	7.369	0.690
Apple	0.075	0.784	0.467	0.494	14.300	0.160	9.636	0.473
Lemon	0.002	0.964	0.000	0.994	20.949	0.021	1.319	0.999
Banana	0.144	0.704	0.074	0.786	23.978	0.008	4.586	0.917
Walnut (without shells)	2.165	0.141	0.254	0.614	5.742	0.836	7.475	0.680
Hazelnut (without shells)	0.391	0.532	11.974	0.001	10.854	0.369	19.781	0.031
Pistachio	1.589	0.207	0.031	0.861	8.831	0.548	2.913	0.983
Peanuts	0.069	0.793	0.016	0.900	7.541	0.674	2.360	0.993
Roasted chick-pea	0.001	0.974	0.236	0.627	11.675	0.307	18.429	0.048
Sun flower seed	0.481	0.488	0.885	0.347	4.932	0.896	1.744	0.998
Pumpkin seed	2.026	0.155	0.131	0.717	14.591	0.148	8.267	0.603
Raisin	0.013	0.909	0.001	0.979	13.280	0.208	2.318	0.993

Note: $Q(n)$ denotes Ljung-Box-Q-Statistics for residuals and $Q^2(n)$ denotes Ljung-Box-Q-Statistics for squared residuals. $-p$ stands for p-values and n is the lag order.

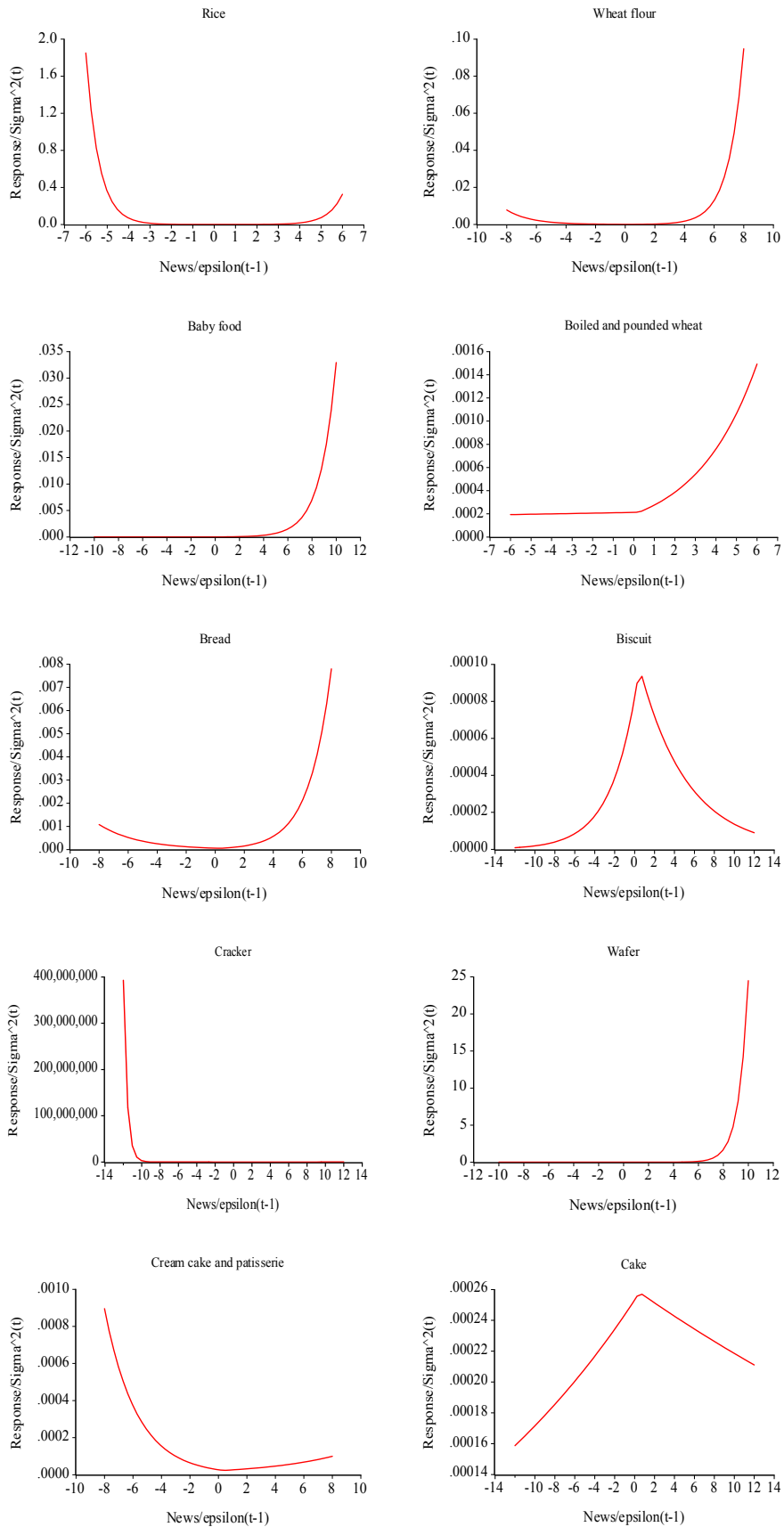
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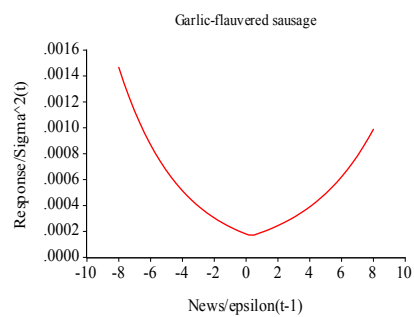
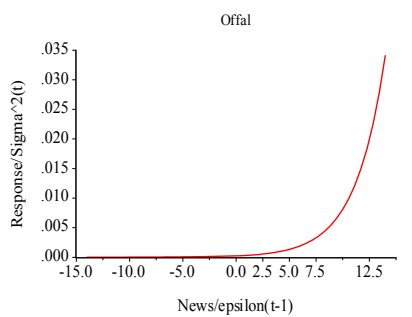
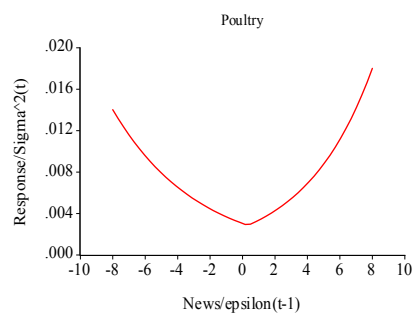
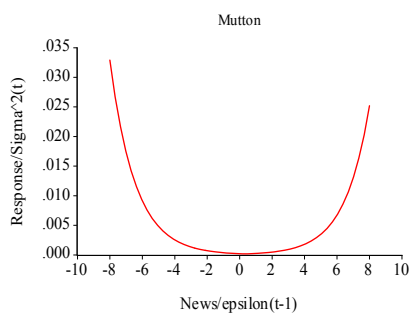
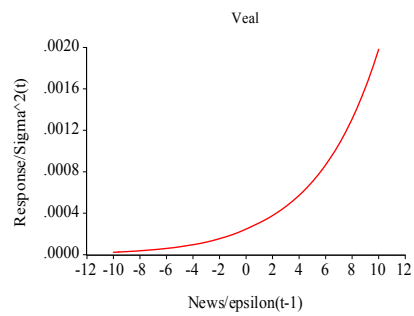
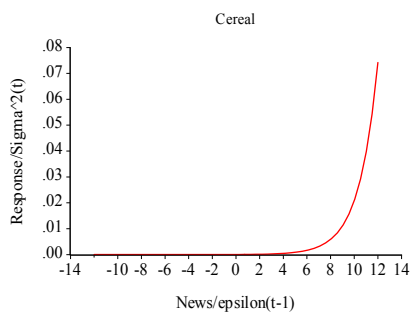
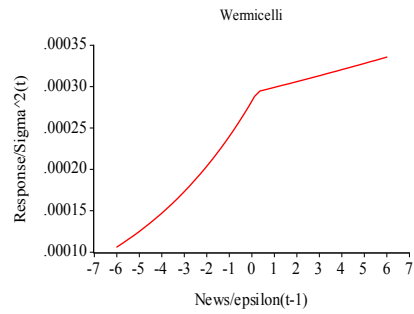
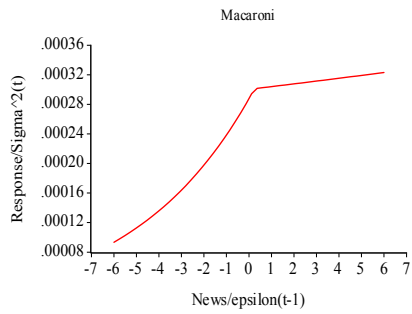
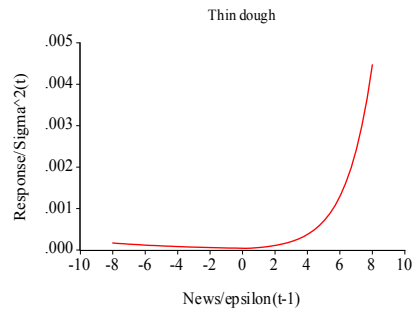
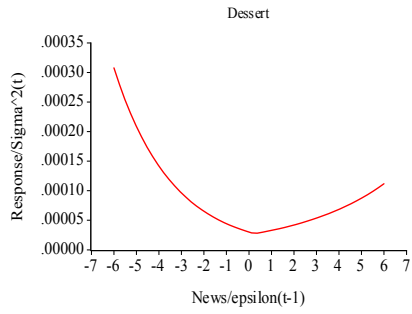
Diagnostic Tests of EGARCH models.

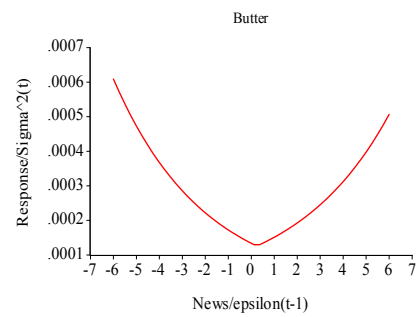
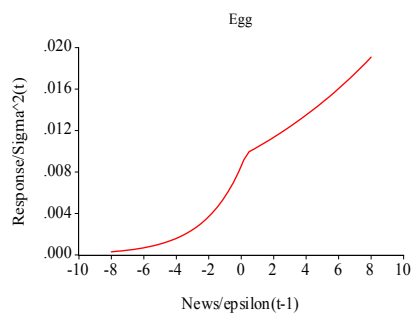
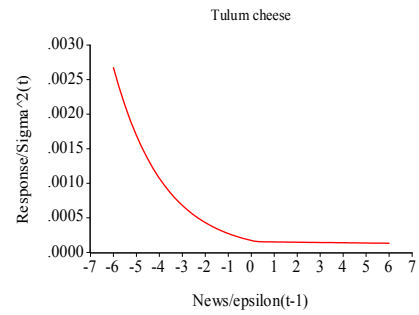
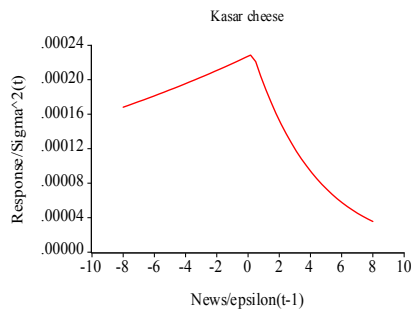
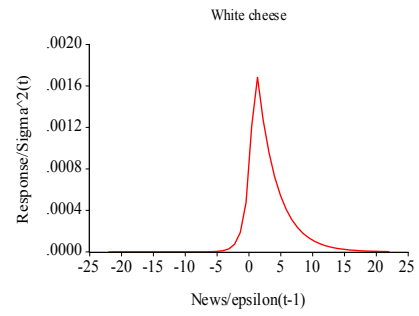
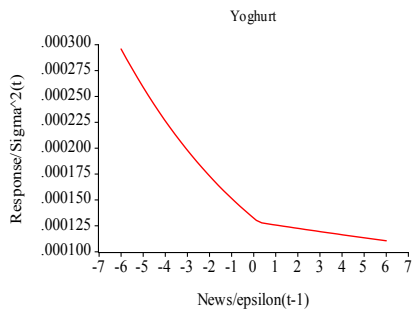
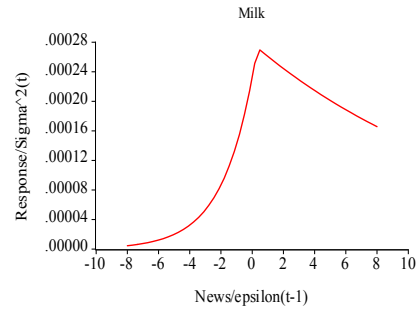
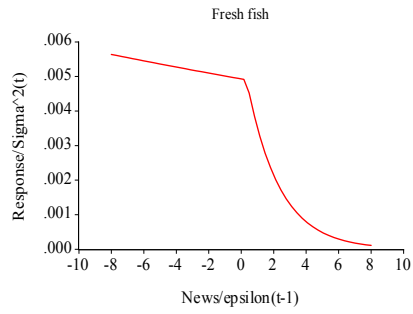
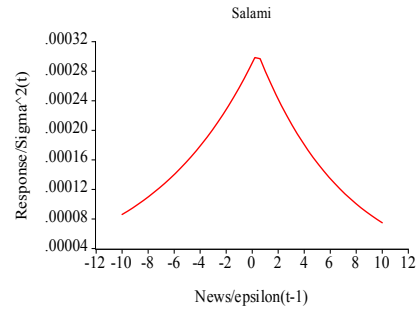
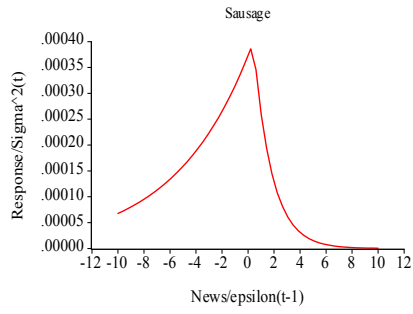
Item	Q(1)	Q(1) – p	Q ² (1)	Q ² (1) – p	Q(12)	Q(12) – p	Q ² (12)	Q ² (12) – p
Sweet green pepper	1.200	0.273	0.997	0.318	26.753	0.003	13.089	0.219
Green pepper	0.318	0.573	0.597	0.440	21.947	0.015	10.071	0.434
Tomato	1.555	0.212	0.348	0.555	17.755	0.059	7.048	0.721
Zucchini	0.446	0.504	0.007	0.933	35.018	0.000	6.368	0.783
Onion	1.239	0.266	0.238	0.625	18.686	0.044	4.224	0.937
Lettuce	0.517	0.472	0.580	0.446	10.573	0.392	12.579	0.248
Parsley	0.269	0.604	0.252	0.616	18.033	0.054	8.839	0.547
Eggplant	0.002	0.968	0.030	0.862	51.129	0.000	5.204	0.877
Cucumber	0.138	0.710	0.000	0.988	23.334	0.010	6.879	0.737
Garlic	0.344	0.558	0.012	0.914	15.840	0.104	5.463	0.858
Green onion	0.495	0.482	1.860	0.173	18.901	0.042	19.526	0.034
Potato	1.047	0.306	0.207	0.649	11.705	0.305	7.049	0.721
Dry bean	1.960	0.161	0.001	0.976	6.331	0.787	0.807	1.000
Chickpea	0.281	0.596	0.683	0.409	10.964	0.360	2.797	0.986
Lentils	1.815	0.178	0.003	0.958	11.706	0.305	5.555	0.851
Other pulse	0.020	0.889	0.009	0.926	6.048	0.811	1.593	0.999
Canned vegetables	0.283	0.595	0.087	0.768	12.694	0.241	2.540	0.990
Tomato sauce	0.045	0.833	0.180	0.671	10.118	0.430	6.501	0.772
Olive	2.787	0.095	1.035	0.309	26.946	0.003	13.507	0.197
Chips and appetizers	0.036	0.849	0.252	0.616	10.087	0.433	7.143	0.712
Granulated sugar	2.170	0.141	0.013	0.911	15.558	0.113	6.477	0.774
Cube sugar	0.132	0.717	0.921	0.337	11.973	0.287	12.364	0.261
Jam	0.582	0.445	0.000	0.992	16.116	0.096	5.645	0.844
Honey	0.289	0.591	0.120	0.729	6.186	0.799	3.676	0.961
Grape molasses	2.614	0.106	0.021	0.886	11.601	0.313	2.067	0.996
Halvah	0.381	0.537	0.000	0.984	7.404	0.687	1.740	0.998
Chocolate cream	0.046	0.831	0.000	0.990	6.230	0.796	4.607	0.916
Turkish delight	1.553	0.213	0.896	0.344	21.666	0.017	7.939	0.635
Holiday candy	2.848	0.091	0.001	0.981	21.228	0.020	0.964	1.000
Ice-cream	0.046	0.831	0.035	0.851	6.578	0.765	3.219	0.976
Condiment-spices	3.511	0.061	0.369	0.544	7.025	0.723	2.429	0.992
Salt	0.017	0.897	0.001	0.979	11.236	0.339	3.763	0.957
Baking powder	1.740	0.187	0.002	0.961	1.796	0.998	0.067	1.000
Catchup	0.260	0.610	0.036	0.850	6.402	0.780	3.998	0.947
Packaged soup	0.395	0.530	0.003	0.954	0.882	1.000	0.030	1.000
Turkish Coffee	2.016	0.156	0.215	0.643	8.873	0.544	1.633	0.998
Ready-made coffee	2.009	0.156	0.002	0.964	5.985	0.817	0.320	1.000
Tea	0.102	0.750	0.000	0.993	6.038	0.812	7.888	0.640
Cocoa	0.036	0.850	0.003	0.953	19.257	0.037	1.094	1.000
Cocoa beverages	0.122	0.727	0.024	0.878	15.158	0.126	10.739	0.378
Water	1.486	0.223	0.011	0.918	6.904	0.734	0.082	1.000
Mineral water	0.435	0.509	0.417	0.519	12.162	0.274	3.252	0.975
Carbonated fruity beverages	0.127	0.722	0.050	0.823	8.557	0.575	1.086	1.000
Coke	0.058	0.810	0.002	0.962	3.685	0.960	0.488	1.000
Fruit Juice	0.008	0.928	0.287	0.592	13.255	0.210	7.295	0.697

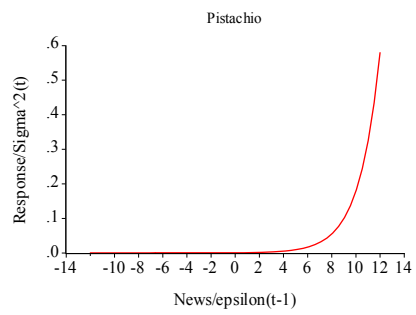
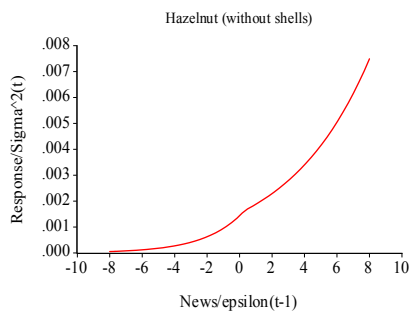
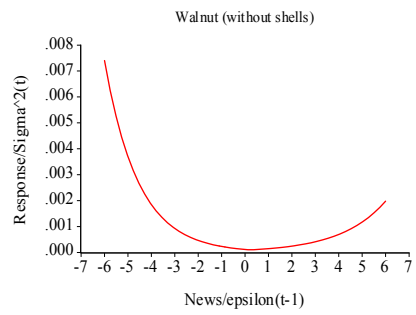
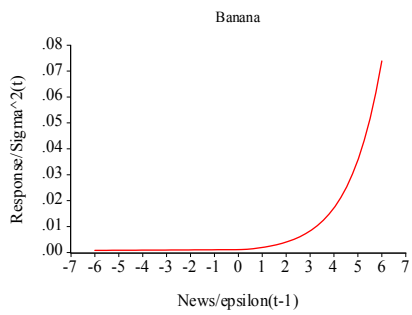
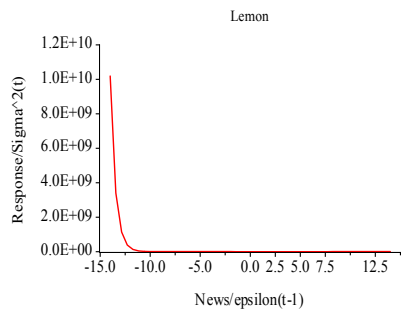
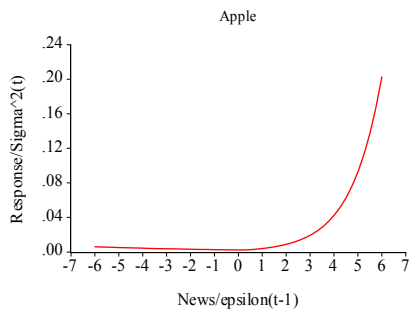
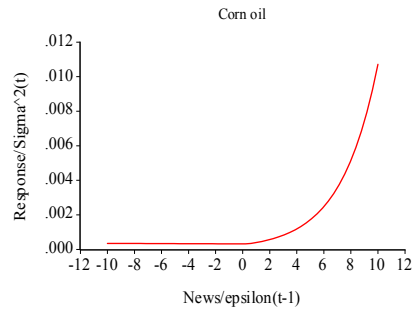
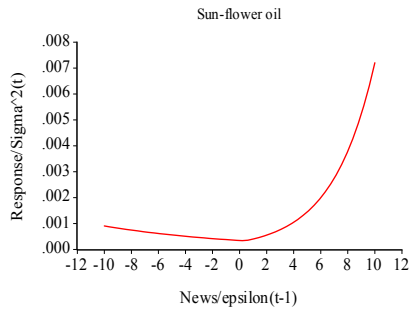
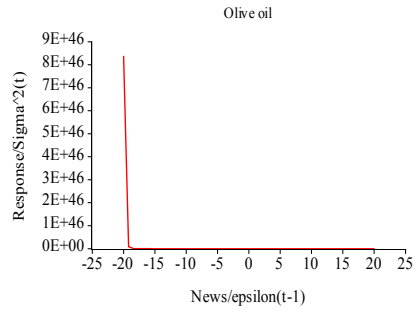
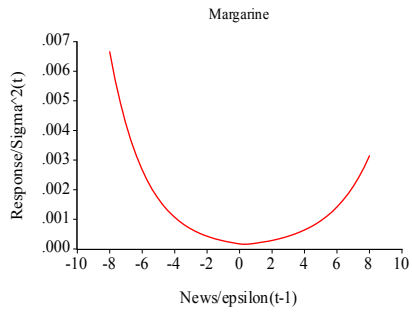
Note: $Q(n)$ denotes Ljung-Box-Q-Statistics for residuals and $Q^2(n)$ denotes Ljung-Box-Q-Statistics for squared residuals. $-p$ stands for p-values and n is the lag order.

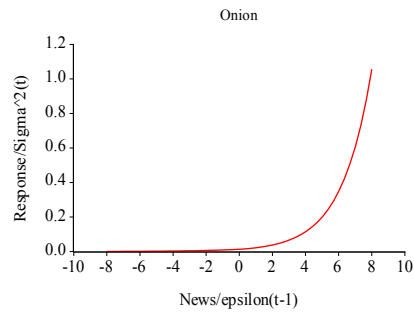
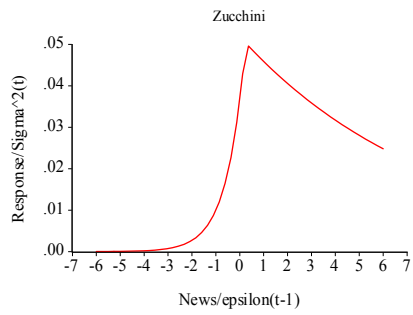
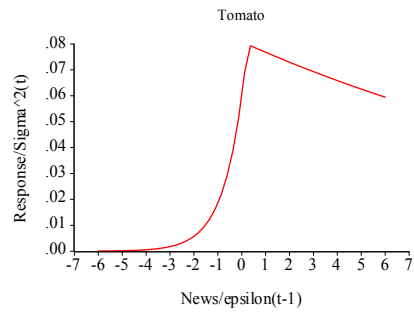
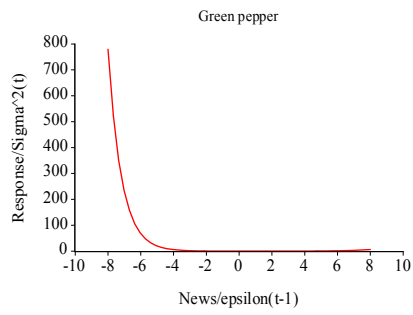
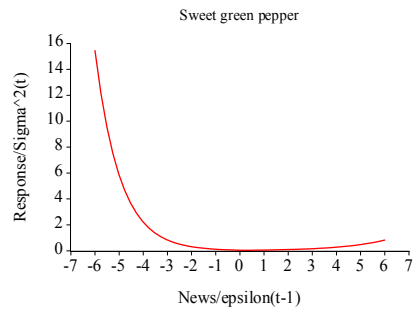
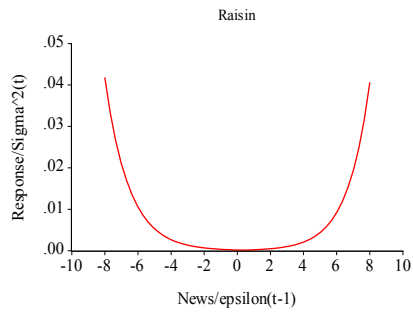
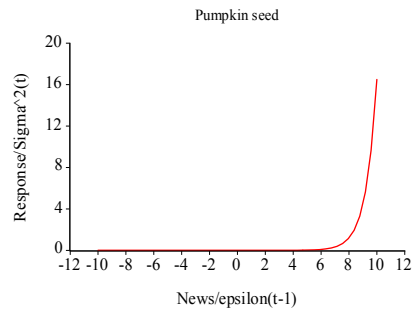
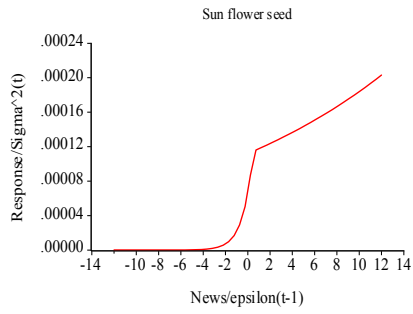
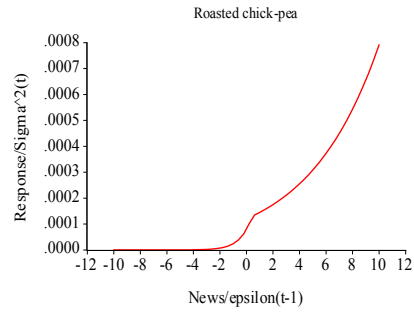
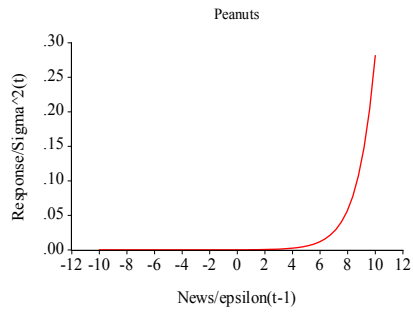
Appendix D. News impact curves

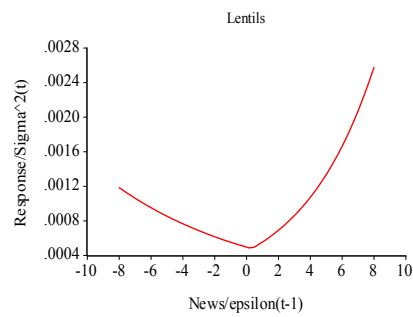
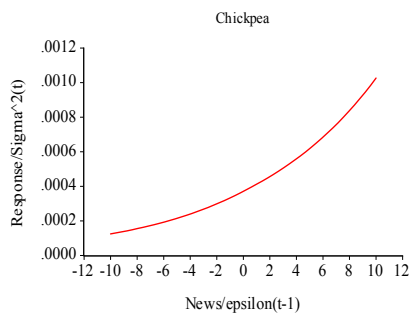
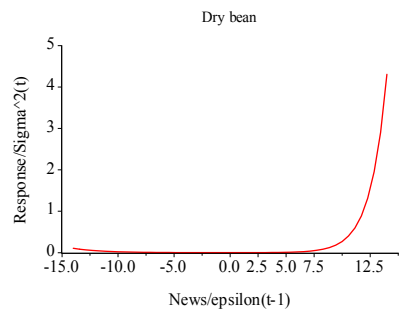
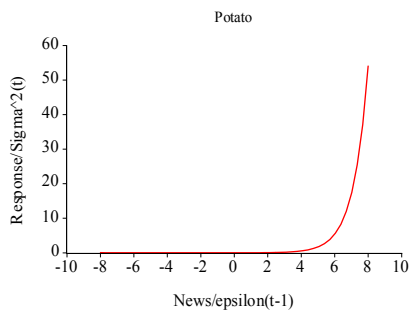
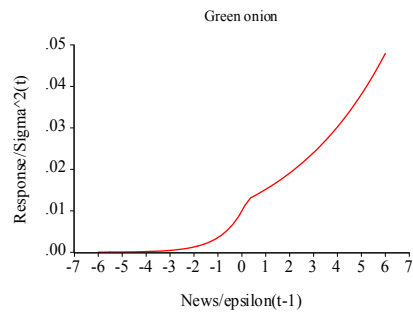
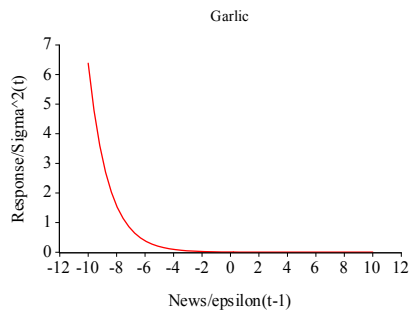
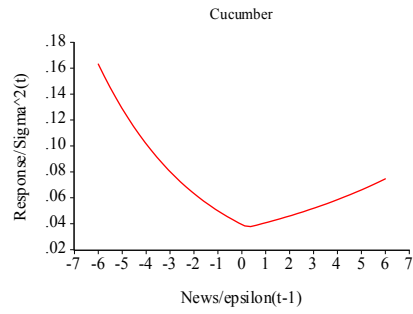
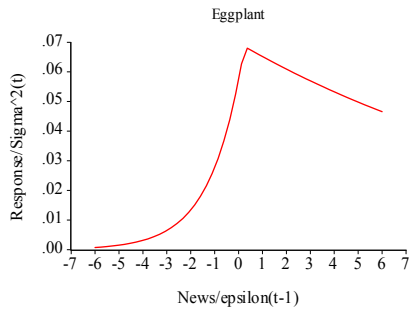
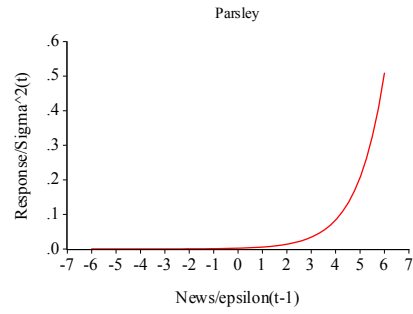
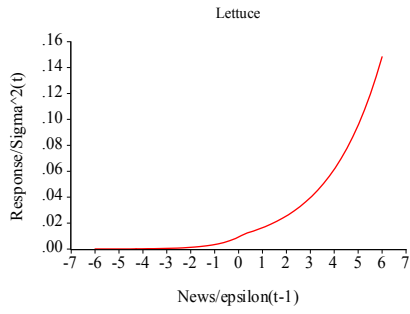


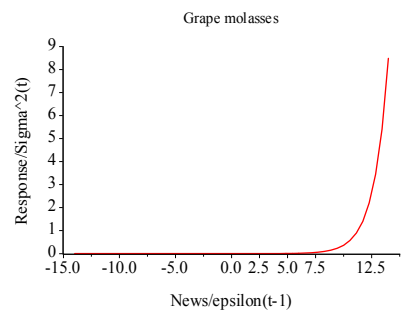
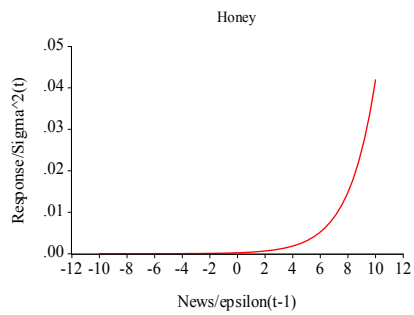
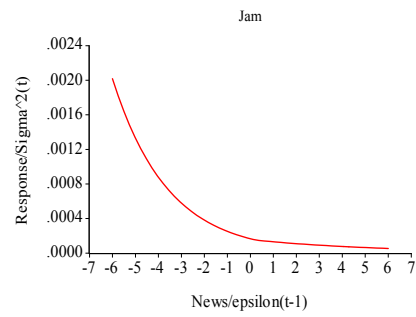
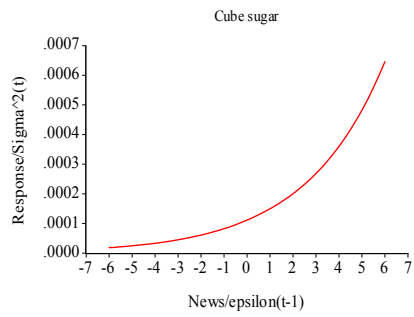
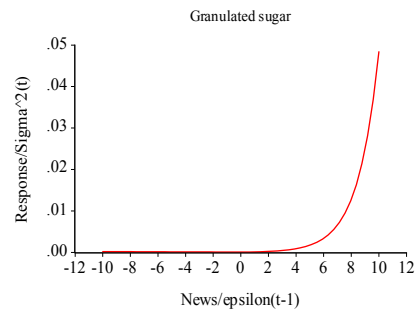
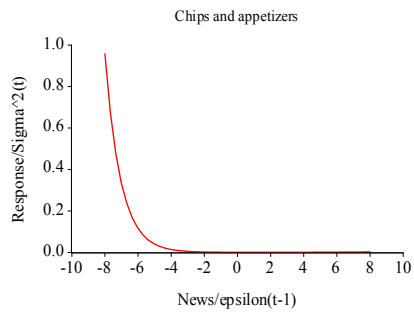
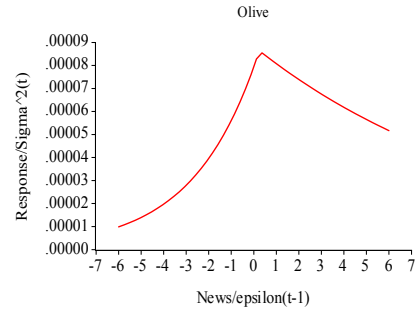
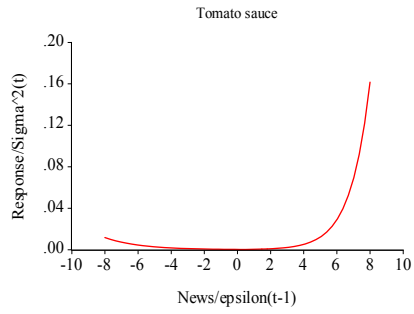
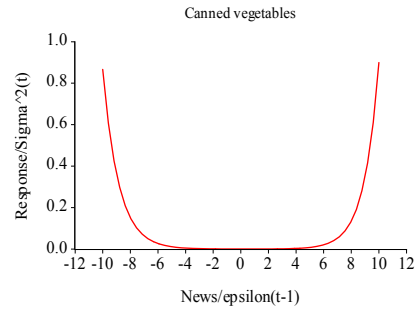
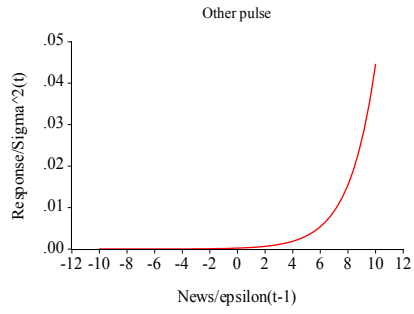


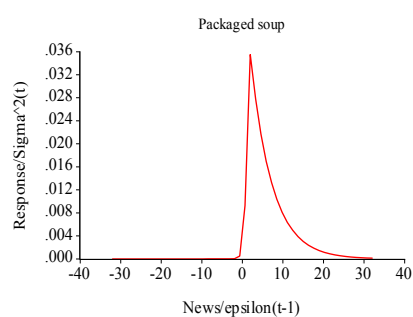
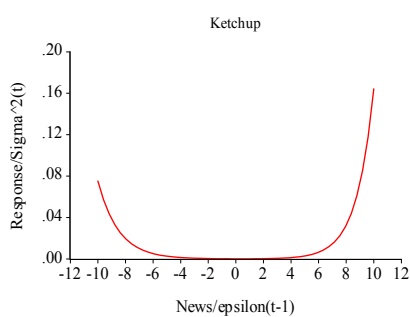
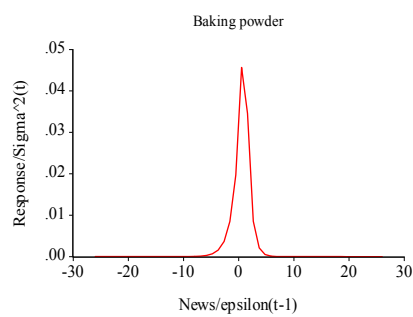
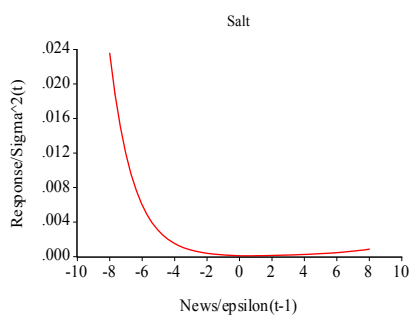
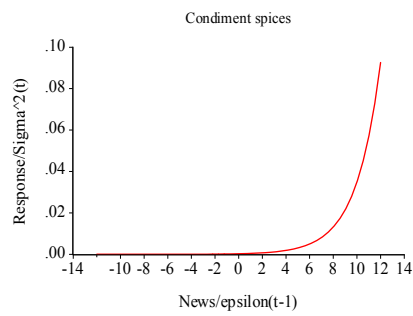
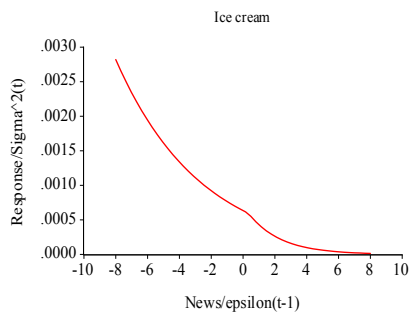
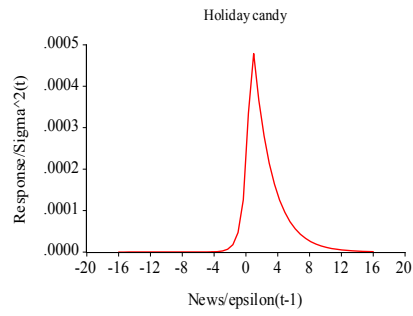
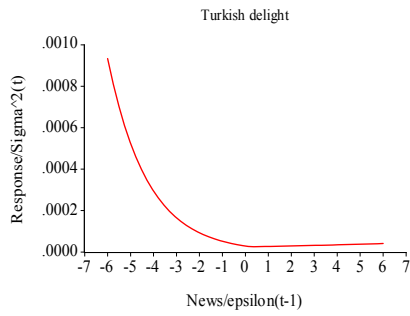
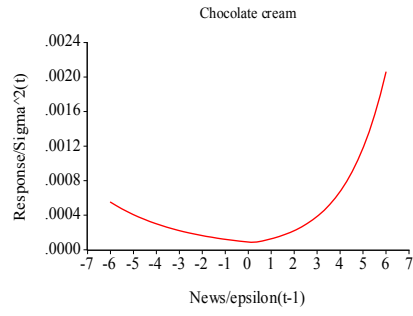
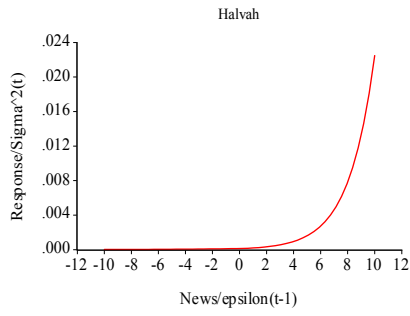


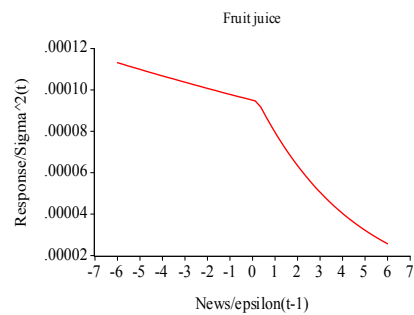
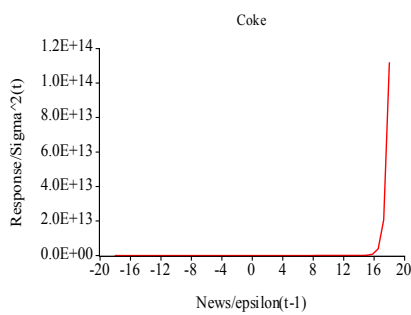
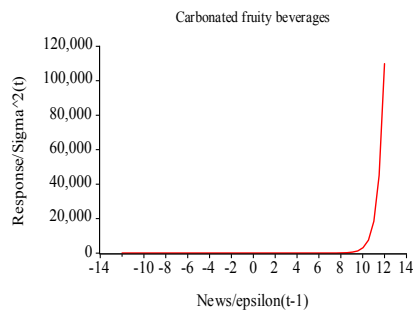
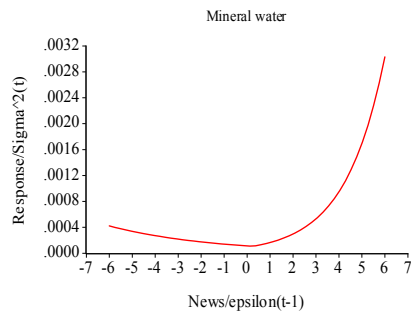
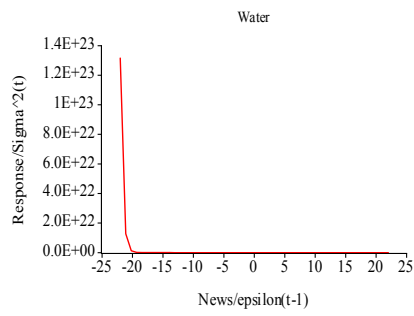
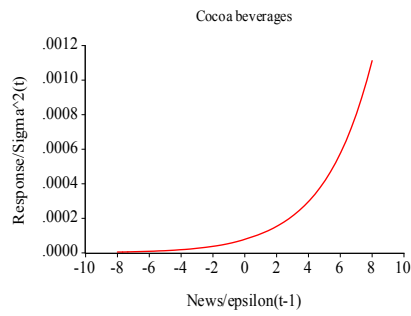
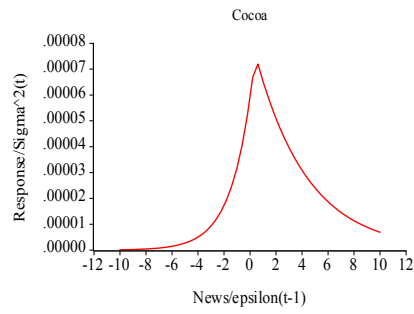
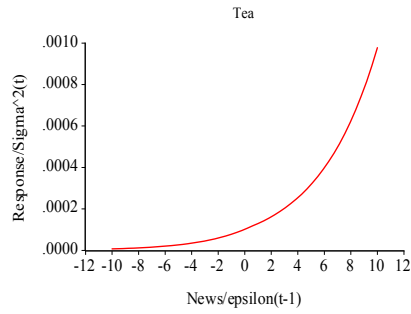
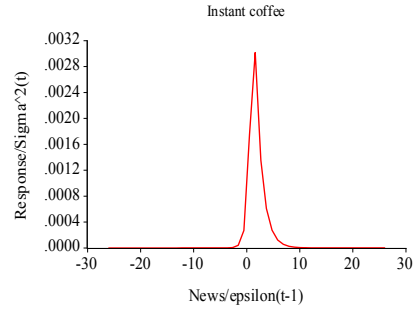
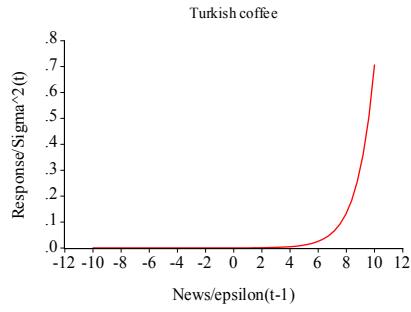












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