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News and volatility of food prices

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Financial markets exhibit an asymmetric news effect with unexpected low prices generating more price volatility than 'news' of high prices. The present study examines US food markets for such asymmetric news effects. Analysis of 25 years of monthly data for 45 retail food items shows that price news destabilizes about a third of the markets with unexpected price increases more destabilizing.

I. Introduction

The present article examines whether unexpected price changes or news affects the variance of prices for 45 retail US food items. Price volatility generates losses for consumers and producers as developed by Newberry (1989). The hypothesized link between news and volatility of prices is motivated by the seminal work of Engle and Ng (1993) who develop a news impact curve that measures how new price information is incorporated into volatility. For assets, estimated news impact curves are typically asymmetric with news of low-prices having a larger impact on volatility.

Studies of asymmetric news impacts in the macroeconomic literature include Braun *et al*. (1995) and McKenzie (2002). The most common explanation is the asset leverage effect of Braun *et al*. (1995) and Chen and Wang (2004). McKenzie (2002) attributes the asymmetry in foreign exchange markets to central bank intervention. Other explanations for asymmetry include the reduced serial correlation of prices during periods of high volatility as developed by Shiller (1984), nonsynchronous trading of Lo and MacKinlay (1987), and firm size effects of Chueng and Ng (1992). Attribution theory offers a theoretical background for asymmetric news effects based on risk aversion as in Mizerski (1982), Chang and Kinnucan (1991) and Richards and Patterson (2005).

The extent to which food price news contributes to volatility may have some practical or policy interest. Tomek (2000) notes the variance of farm prices increases from harvest to summer attributing the increase to crop uncertainty during the growing season. Time varying variances are noted in some retail and farm prices. Bénabou and Gertner (1993) note that increased volatility may reduce the incentive for consumer search and magnify retailer market power. Samuelson (2005) notes food and energy are the most volatile components of consumer prices. The importance of price news is emphasized by the recent mad cow scares discussed by Burton and Young (1996), Verbeke and Ward (2001), Lloyd *et al*. (2002), Pennings *et al*. (2002), Jin and Koo (2003), Sanjuán and Dawson (2003), Piggott and Marsh (2004) and McCluskey *et al*. (2005).

Price volatility at the farm level has received attention, for instance by Yang *et al*. (2001), Apergis and Rezitis (2003a), Yang *et al*. (2003) and Bose (2004). Studies of retail price volatility focusing on its transmission through the marketing channel include Kesavan *et al*. (1992), Jha and Nagarajan (2002), Apergis and Rezitis (2003b) and Rezitis (2003).

The present article contributes to this literature with its test of asymmetric volatility. The exponential generalized autoregressive conditional heteroskedastic (EGARCH) model of Nelson (1991) allows a straightforward test of the asymmetry hypothesis.

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The present analysis of 45 food markets suggests that price news exacerbates volatility in a number of markets with news of high-prices more destabilizing.

II. The News Impact Curve

Following Engle and Ng (1993) let y_t be the first difference of the natural log of price. Let F_{t-1} be the past information set containing realized values of all relevant variables. Consumers know the information in F_{t-1} when they make consumption decisions at that time. The expected price change and volatility are the conditional expected value of y_t and the conditional variance of y_t given F_{t-1} denoted $m_t \equiv E(y_t|F_{t-1})$ and $h_t \equiv \text{var}(y_t|F_{t-1})$. The unexpected price change at time t is $\varepsilon_t = y_t - m_t$. Engle and Ng (1993) state that ε_t may be treated as a collective measure of news at time t. If $\varepsilon_t > 0$ (<0) price is higher (lower) than expected. With the maintained hypothesis that predictable volatility depends on past news, the ARCH specification of Engle (1982) is

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \tag{1}$$

where p is the number of lags and α_i and ω are parameters. An implicit assumption is that older news has less impact on current volatility than more recent news, $\alpha_i < \alpha_j$ for $i > j$. News that arrived more than p periods ago has no effect on current volatility.

The GARCH (p, q) model introduced by Bollerslev (1986) generalizes the ARCH (p) model by including the persistence term

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} \tag{2}$$

where q is the number of lags for the lagged variance term and the β_i are coefficients. This GARCH model is an infinite order ARCH model. Most empirical applications use the GARCH(1,1) implying the effect of the shock declines geometrically over time.

As noted by Engle and Ng (1993) a drawback of (1) and (2) is the implicit assumption that low-or high-price news has symmetric effects. The exponential GARCH or EGARCH model of Nelson (1991) relaxes this assumption,

$$\ln(h_t) = \omega + \beta \ln(h_{t-1}) + \gamma \left(\frac{\varepsilon_{t-1}}{h_{t-1}^{1/2}} \right) + \alpha \left[\left(\frac{|\varepsilon_{t-1}|}{h_{t-1}^{1/2}} \right) - \left(\frac{2}{\pi} \right)^{1/2} \right] \tag{3}$$

where ω, β, γ, and α are coefficients with asymmetry captured by γ. If $\gamma = 0$ there are symmetric effects but if γ is positive (negative) high (low) price news generates more volatility. The EGARCH model embeds a parametric test of the asymmetry hypothesis.

The news impact curve of Engle and Ng (1993) is based on (2) and (3). Comparing the GARCH(1,1) and EGARCH(1,1) models with one lag, the relation between ε_{t-1} and h_t is the news curve relating past news to current volatility and measuring how new information is incorporated into volatility.

Graphs of the GARCH(1,1) and EGARCH(1,1) models in Fig. 1 highlight key differences. First, the news impact curve implied by the GARCH model is symmetric with respect to the centering point $\varepsilon_{t-1} = 0$ while the graph for the EGARCH model is skewed right implying high-price news produces more volatility. The graph illustrates $\gamma > 0$ and for $\gamma < 0$ there would be left skew.

A second difference is the EGARCH curve rises faster than the GARCH curve moving away from the origin, implying that 'big news' is more destabilizing in the EGARCH model than in the GARCH model. This feature is due to the functional forms with the exponential EGARCH tending to overtake the quadratic GARCH as they extrapolate beyond the minimum point at $\varepsilon_{t-1} = 0$.

Glosten *et al.* (1993) relax this magnification feature of the EGARCH model in the Glosten model $h_t = \omega + \beta h_{t-1} + \alpha \varepsilon_{t-1}^2 + \gamma S_{t-1}^- \varepsilon_{t-1}^2$ where $S_t^- = 1$ if $\varepsilon_t < 0$ and $S_t^- = 0$ otherwise. There is little difference between present estimates of this GJR model and the EGARCH (1,1) as presented.

The model is completed by mean and error equations,

$$y_t = \mu + \sum_{i=1}^{k} \rho_i y_{t-k} + \varepsilon_i \tag{4}$$

$$\varepsilon_t = v_t h_t^{1/2} \tag{5}$$

where y_t is the first difference of log price, k is the lag length, and v_t is a white noise process with unit variance. The lagged terms in the autoregressive AR(k) process (4) capture the predictable components of price change. The error term ε_t reflects a random component or shock. The conditional variance of the shock in (5) h_t forms the basis for the dependent variable in (3).

III. Empirical Results

The present data of monthly retail food prices from 1980 to 2004 is from the US Bureau of Labor

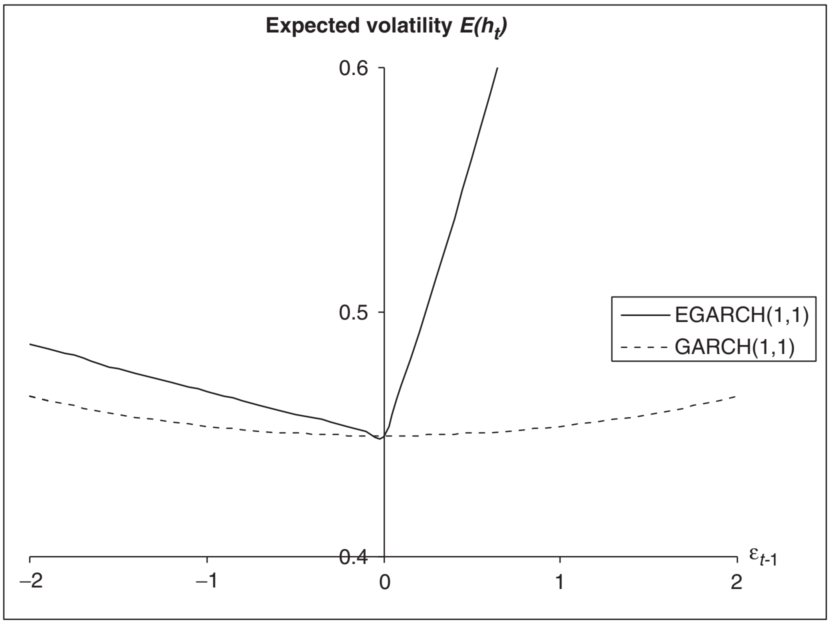

Fig. 1. The news impact curves of the GARCH(1, 1) model and EGARCH(1, 1) model
Notes: EGARCH(1,1) curve corresponds to equation:

$$\ln(h_t) = -0.8 + \ln(h_{t-1}) + 0.45(\varepsilon_{t-1}/h_{t-1}^{1/2}), h_{t-1} = 1, \quad \text{when } \varepsilon_{t-1} > 0$$

$$\ln(h_t) = -0.8 + \ln(h_{t-1}) + 0.04(\varepsilon_{t-1}/h_{t-1}^{1/2}), h_{t-1} = 1, \quad \text{when } \varepsilon_{t-1} < 0$$

GARCH(1,1) curve corresponds to equation:

$$h_t = -0.55 + h_{t-1} + 0.004(\varepsilon_{t-1}^2), h_{t-1} = 1$$

Statistics for 45 food items that account for the bulk of the US Consumer Price Index (CPI). Prices for items with limited data availability are excluded as are prices for different package sizes of items such as sugar, coffee and cola. The most representative package size is chosen. The sample yields 300 observations but with incomplete reporting actual sample sizes in some instances are less, most notably pork with 80 and broccoli, cola and wine with 110.

The EGARCH model requires a stationary data generating process and the Dickey and Fuller (1981) test for unit roots is

$$\Delta \ln p_t = a + b\Delta \ln p_{t-1} + cT + e_t \tag{6}$$

where T is a unit step variable. These test results (available upon request) indicate that each log series is difference stationary in (4), $y_t = \ln(p_t/p_{t-1}) = \Delta \ln p_t$. For 19 products, however, both b and c are significant at the 5% level and the dependent variable in (4) is set to $y_t = \Delta \ln p_t - cT$ to remove the trend.

The system (3)–(5) is an AR(k)-EGARCH(1,1) model with the autoregressive parameter k selected to produce the most parsimonious specification for (3) using Box–Jenkins strategy. An AR(1) or AR(2) provides good approximation to the data generating processes. Maximum likelihood estimates of α, β, and γ are in Table 1. The 5% significance level is used unless indicated otherwise.

There is evidence of time varying variance with either α or β significant for 40 of the 45 items. The exceptions are cola, eggs, ground beef, peanut butter and sirloin steak and their constant variance is evidence of mature markets. The parameter α in (3) is significant for 25 items (55% of the sample) indicating news effects on volatility, and the parameter γ is significant for 23 (51%) of the items indicating asymmetric news effects.

A joint test for the significance of ARCH/GARCH effects in the three parameters α, β, and γ is provided by the Lagrange Multiplier (LM) statistic reported in the last column of Table 1. These LM effects are insignificant for 16 items (36%). The LM test has low power in the sense of high probability of a Type II error of failing to reject a false null hypothesis. It is not intuitive for a significant asymmetry effect of γ

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

Item	α		β		γ		LM statistic[a]
Apples	0.23*	(2.35)[b]	0.87*	(21.1)	0.21*	(3.45)	22.9*
Bacon	0.27*	(2.74)	0.67*	(5.38)	0.18*	(2.76)	25.6*
Bananas	0.09	(1.94)	0.98*	(55.2)	0.05	(1.42)	2.58
Bread	0.24*	(4.47)	−0.87*	(−16.3)	−0.07*	(−2.23)	21.6*
Broccoli	0.01	(0.21)	0.53*	(2.47)	0.37	(0.99)	2.01
Butter	0.26*	(5.33)	0.99*	(154.7)	−0.05	(−1.17)	15.3*
Cabbage	0.01	(1.46)	0.88*	(11.8)	0.03*	(2.30)	6.92
Carrots	0.25	(1.94)	0.55*	(3.92)	0.26*	(3.08)	14.2*
Celery	−0.26*	(−2.13)	0.82*	(12.5)	0.17*	(2.37)	2.12
Cheese, American	0.13	(1.31)	0.93*	(25.0)	−0.15	(−1.95)	7.36
Cheese, cheddar	0.39*	(4.88)	0.97*	(60.7)	−0.13	(−1.83)	44.9*
Chicken	0.28*	(3.72)	0.39*	(3.17)	0.42*	(5.94)	37.0*
Chuck roast	0.46*	(2.87)	0.12	(0.28)	−0.03	(−0.19)	13.8*
Coffee	0.98*	(6.04)	0.11	(0.84)	0.32*	(2.38)	49.1*
Cola	0.17	(0.64)	0.39	(0.80)	−0.19	(−1.31)	6.34
Cookies	0.24*	(6.44)	−0.93*	(−78.3)	−0.02*	(−2.54)	8.05*
Cucumbers	−0.43*	(−2.84)	0.41*	(2.73)	0.35*	(3.18)	2.94
Eggs	0.28	(1.61)	0.52	(0.78)	0.04	(0.49)	5.30
Flour	0.02	(0.40)	0.97*	(95.2)	−0.11*	(−3.87)	4.26
Ground beef	−0.04	(−0.18)	−0.03	(−0.11)	−0.21*	(−2.12)	7.61
Grapefruit	−0.17*	(−2.79)	0.82*	(22.1)	0.39*	(5.79)	8.24*
Ham	0.48*	(2.47)	−0.28	(−1.19)	−0.14	(−1.44)	1.49
Ice cream	0.12	(1.32)	0.99*	(104.8)	−0.05*	(−2.96)	14.3*
Lemons	0.00	(−0.31)	−0.61*	(−2.03)	0.11	(0.87)	11.3*
Lettuce	0.06	(0.79)	0.76*	(12.7)	0.26*	(3.47)	11.4*
Milk	0.27*	(3.87)	0.97*	(52.7)	0.00	(0.00)	33.8*
Orange juice	0.47*	(3.48)	0.52*	(3.15)	0.07	(0.81)	19.2*
Onions	0.01	(0.61)	0.67*	(7.91)	0.44*	(2.99)	14.3*
Peanut butter	0.25	(1.62)	0.35	(1.12)	0.21	(1.48)	9.87*
Pork	0.11	(1.05)	0.96*	(34.0)	−0.23*	(−2.64)	2.03
Potatoes	0.05	(0.78)	0.86*	(16.5)	0.42*	(4.41)	20.7*
Potato chips	0.01	(0.92)	0.98*	(122.7)	−0.06*	(−2.11)	39.2*
Rice	0.31*	(2.53)	−0.21	(−0.57)	−0.03	(−0.34)	9.59*
Round roast	0.21*	(3.04)	0.95*	(26.8)	−0.06	(−1.31)	24.0*
Sausage	0.11	(0.60)	0.72*	(4.52)	−0.12	(−1.80)	1.96
Spaghetti	0.46*	(3.12)	−0.06	(−0.13)	0.01	(0.05)	10.4*
Steak, round	0.47*	(3.76)	0.77*	(6.72)	0.07	(0.98)	26.5*
Steak, sirloin	−0.00	(−0.23)	0.62	(1.27)	0.13	(1.02)	3.25
Steak, T-bone	0.11	(1.72)	−0.88*	(−20.5)	−0.11*	(−2.66)	14.6*
Sugar	0.47*	(4.35)	0.93*	(31.6)	−0.001	(−0.02)	86.6*
Tomatoes	0.16*	(2.15)	0.88*	(19.1)	0.26*	(3.67)	18.1*
Tuna	0.43*	(3.09)	0.85*	(9.13)	0.06	(0.98)	23.4*
Turkey	−0.37*	(−4.70)	0.70*	(7.54)	−0.25*	(−3.20)	2.96
Wine	1.12*	(5.45)	0.69*	(6.49)	0.40*	(2.94)	81.4*
Yogurt	0.27*	(2.51)	0.99*	(67.7)	−0.07	(−1.57)	5.99

Notes: [a]Lagrange Multiplier statistic computed under the null hypothesis that α, β, and γ are jointly zero.
[b]Numbers in parenthesis are asymptotic t-ratios.
* indicates significance at the 5% level or less.

with insignificant ARCH/GARCH effects as occurs for cabbage, celery, cucumbers, flour, pork and turkey. To err on the conservative side, asymmetry is considered significant only if γ and the LM statistic are jointly significant.

Table 2 lists these significant items along with coefficients for high- and low-price news. In the EGARCH(1,1) model the effect of high-price news on conditional variance is $\alpha+\gamma$ and the low-price effect is $\alpha-\gamma$. For apples, estimated effects are 0.44 and 0.02. An unexpected price increase measured by a unit increase in the standardized residual $|\varepsilon_{t-1}|/h_{t-1}^{1/2}$ with $\varepsilon_{t-1}>0$ increases volatility 44%. In contrast, an unexpected price decrease with $\varepsilon_{t-1}<0$ increases volatility 2%. For apples, the news impact curve is upward sloping for both high-and low-price news with high-price news more destabilizing.

Table 2. Effect of news on monthly retail food price volatility

Food item	High-price news ($\alpha + \gamma$)	Low price news ($\alpha - \gamma$)
Apples	0.44	0.02
Bacon	0.45	0.09
Bread	0.17	0.31
Carrots	0.51	−0.01
Chicken	0.70	−0.14
Coffee	1.30	0.66
Cookies	0.22	0.26
Grapefruit	0.22	−0.56
Ice cream	0.07	0.17
Lettuce	0.32	−0.26
Onions	0.45	−0.43
Potatoes	0.47	−0.37
Potato chips	−0.05	0.07
Steak, T-bone	0.00	0.22
Tomatoes	0.42	−0.10
Wine	1.52	0.72
Mean (μ_i)	0.45	0.04
SD $(\mathrm{sd})_i$	0.41	0.35
Sample size (n_i)	16	16
t-Value under null hypothesis that means are equal:[a] 3.04		

Notes: [a]Calculated with $t = (\mu_1 - \mu_2)/(Psd \cdot N)$ where $N = (1/n_1 + 1/n_2)^{1/2} = 0.353$ and $Psd = 0.381$ is the pooled estimate of the common SD computed using the formula in Spurr and Bonin (1973, p. 297).

The mean effect for the 16 items for high-price news is 0.45 and for low-price news 0.04. The t-value computed under the null hypothesis that the mean responses are equal is 3.06, and the mean news impact curve for these 16 items mimics apples. The mean conceals variation across items and a number of anomalies but illustrates the asymmetry in Fig. 1. The EGARCH(1,1) curve in Fig. 1 corresponds to equations $\ln(h_t) = -0.8 + \ln h_{t-1} + 0.45\varepsilon_{t-1}/h_{t-1}^{1/2}$ when $\varepsilon_{t-1} > 0$, and $\ln(h_t) = -0.8 + \ln(h_{t-1}) + 0.04(\varepsilon_{t-1}/h_{t-1}^{1/2})$ when $\varepsilon_{t-1} < 0$ given $h_{t-1} = 1$. The symmetric GARCH(1,1) curve corresponds to $h_t = -0.55 + h_{t-1} + 0.004(\varepsilon_{t-1}^2)$.

High-price news for T-bone steaks has no effect on price volatility, but low-price news has a pronounced effect of 0.22. T-bone price surprises are different from other beef cuts, and ice cream is similar to T-bones. Regular consumers of T-bone steaks and ice cream might be insensitive to high-price news but potential consumers are sensitive to unexpected low-prices.

There are instances of downward-sloping news impact curves but this is more common for low-price news. For onions, the coefficient of high-price news is 0.45 and the low-price coefficient is −0.43 implying that an unexpected jump in the retail price has a destabilizing effect while an unexpected fall stabilizes price. There is a similar pattern for carrots, chicken, grapefruit, lettuce, potatoes and tomatoes. The market responds to unexpected price increases but does not notice unexpected price declines. When these prices jump unexpectedly the markets attract attention, but with an unexpected fall in price there is decreased volatility.

For 10 of the 16 items in Table 2 coefficients of high-price news are larger than the absolute values of the low-price news coefficients, consistent with the hypothesis that consumers respond disproportionately to high-price news. Of the total sample, there are significant price surprise effects in the first two columns of Table 3 for only a quarter of the items. Of these 16 items, high-price news is destabilizing for about half. For the remaining items, either there are no price news effects or there is no effect on variance.

Inferences based on GARCH-type models can be fragile as discussed by Jones *et al.* (1998) and an additional test on asymmetry is the regression

$$s_t^2 = \delta_0 + \delta_1 s_{t-1} + \delta_2 s_{t-2} + \delta_3 s_{t-3} + v_t \qquad (7)$$

where $s_t = (\varepsilon_t / h_t^{1/2})'$, the predicted standardized residual from (4). A statistically significant value of F for the null hypothesis $\delta_1 = \delta_2 = \delta_3 = 0$ indicates remaining asymmetry effects as developed by Enders (2004). In that case, the model is misspecified in that sources of asymmetry are omitted. To make the test as complete as possible (7) is estimated for all items in Table 1 that have a significant γ. Results suggest the EGARCH model is well-specified in the sense that asymmetric effects are fully accounted for 22 of the 23 cases in Table 4. The exception is potatoes with the null hypothesis rejected at the 1% probability level. For the other commodities computed F-statistics are very small providing confidence that (7) has no explanatory power and the noted asymmetry effects are legitimate.

IV. Conclusion

Price volatility is welfare decreasing and may reduce competition by increasing consumer search costs. There is time varying variance for all but 5 of the 45 food prices from the US Consumer Price Index over the past 25 years. Price news affects variance for only 16 of the items and there is asymmetric volatility with larger effects for high-price news for 10 of

Table 3. 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
*Apples	*Carrots	Cabbage	Bananas	Cola
*Bacon	*Chicken	Celery	Broccoli	Eggs
Bread	Grapefruit	Cucumbers	Butter	Ground beef
*Coffee	*Lettuce	Flour	American cheese	Peanut butter
Cookies	*Onions	Turkey	Cheddar cheese	
Ice cream	*Potatoes		Chuck roast	Steak, sirloin
Potato chips	*Tomatoes		Ham	
Steak, T-bone			Lemons	
*Wine			Milk	
			Orange juice	
			Rice	
			Round roast	
			Sausage	
			Spaghetti	
			Steak, round	
			Sugar	
			Tuna	
			Yogurt	

Note: *Disproportionate responses to high-price news.

Table 4. Diagnostic regression

Item	F-statistic for H_N: $\delta_1 = \delta_2 = \delta_3 = 0$	Probability
Apples	1.62	0.18
Bacon	0.02	0.99
Bread	0.86	0.46
Cabbage	0.15	0.93
Carrots	1.01	0.39
Celery	0.32	0.81
Chicken	0.22	0.88
Coffee	0.03	0.99
Cookies	0.09	0.97
Cucumbers	1.73	0.16
Flour	0.99	0.40
Ground beef	0.33	0.80
Grapefruit	1.81	0.15
Ice cream	1.57	0.20
Lettuce	0.40	0.76
Onions	0.36	0.78
Pork	0.62	0.60
Potatoes	6.26	0.0004
Potato chips	2.23	0.08
Steak T-bone	0.77	0.51
Tomatoes	2.15	0.09
Turkey	1.45	0.28
Wine	1.45	0.23

those items. Low-price news stabilizes price in 7 of the markets.

The present results have implications for food markets in light of recent highly publicized instances of food safety. A food scare that lowers price might amplify price volatility, a neglected issue in the food contamination literature exemplified by Richards and Patterson (2005). Present results indicate the amplifying impact of news is an issue for about a third of the food markets.

It is worth noting that food price volatility has been declining over the period. The coefficient of variation in monthly food prices for these 45 items declined from 11% during the 1980s to 9% during the 1990s to 7% during 2000–2004. There is increased concentration in distribution and retailing and larger firms are able to absorb price changes pricing to market. The declining farmer share of final consumer spending suggests farm price volatility is not passed along to consumers. Unexpected high-prices, however, have an asymmetric effect on volatility in a number of markets. For the third of the food markets that have constant variance, the suggestion is that the markets are mature.

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