Price Dynamics in a Vertical Sector: The Case of Butter

by

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and

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Abstract: We develop a reduced-form model of price transmission in a vertical sector, allowing for refined asymmetric, contemporaneous and lagged, own and cross price effects under time-varying volatility. The model is used to investigate wholesale-retail price dynamics in the US butter market. The analysis documents the nature of nonlinear price dynamics in a vertical sector, with implications for price transmission and the distribution of future prices. It finds strong evidence of asymmetric retail price responses, both in the short term and the longer term, but only weak evidence of asymmetric wholesale price responses. Asymmetric retail responses play a major role in generating a skewed distribution for butter price.

Key Words: price transmission, asymmetry, nonlinear dynamics, butter.

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1. Introduction

The issue of price transmission in a vertical sector has been the subject of much research. A common issue is that retail prices do not respond very quickly to changes in market conditions. Under fluctuating market conditions, this raises questions about the efficiency of vertical markets. Examples include situations where retail prices remain “sticky” in the face of large decreases in farm or wholesale prices (e.g., Borenstein et al.; Peltzman; Miller and Hayenga). Peltzman finds strong evidence that in many markets retail prices tend to rise faster than they fall, both in the short term and in the longer term.

This has stimulated research on the possible cause of asymmetric price adjustments. Potential explanations include imperfect competition and adjustment costs. A traditional explanation under oligopoly is a kinked-demand schedule that generates sticky prices. More generally, barriers to entry can create asymmetric economic adjustments (see Tirole for an overview). Many other sources of asymmetry have been explored. In general, in the presence of adjustment cost, firms and consumers may not respond to small or transitory price changes until the benefits of changing strategies outweigh the cost. Consider, for example, the unequal cost of maintaining high versus low inventory, where the high cost of experiencing a stockout can generate asymmetric price adjustments (e.g., Reagan and Weitzman). Also, consumers may not respond quickly to price changes in the presence of search costs. This can allow retailers to boost profits by increasing their prices fast as wholesale prices rise, and lowering them slowly when wholesale prices fall. In addition, menu costs can prevent firms from changing prices rapidly in response to small and transitory market changes (e.g., Blinder; Blinder et
Finally, sunk investment costs can create irreversibility in firms’ strategies (e.g., Dixit and Pindyck). Thus, there are many reasons why price transmission may be asymmetric in a vertical sector. Peltzman’s analysis suggests that current theories fail to explain the prevalence of price asymmetry. His empirical evidence covering many markets shows no correlation between price asymmetry and inventory cost, menu cost or imperfect competition. This raises significant challenges to our theory of markets. It also stresses the need for a better understanding of the empirical regularities found in price transmissions.

The objective of this paper is to investigate these empirical regularities. For this purpose, the paper develops a flexible dynamic reduced form model of asymmetric price transmission in a vertical sector. The analysis expands on previous models of dynamic price transmission by allowing asymmetry for both contemporaneous and lagged, own and cross price effects. It also allows for time varying volatility. The model is applied to wholesale-retail price dynamics in the US butter market. As illustrated in Figure 1, butter prices have exhibited large fluctuations over the last 10 years. This makes the butter market an interesting case study of dynamic price adjustments in a vertical sector. Following Peltzman, in the absence of a clear theory of asymmetric price adjustments, the analysis is unrepentantly descriptive. The empirical results provide evidence of asymmetric price transmissions in the US butter market. Although the evidence of asymmetry is weak for wholesale price adjustments, it is strong for retail price adjustments. For example, we find that retail prices respond strongly to wholesale price increases, but less to wholesale price decreases. The analysis shows that price volatility is much higher at the wholesale level than the retail level. Price volatility also varies with market conditions. For example, we find that wholesale price volatility increases with the
wholesale price level, a result that is consistent with theory linking storage behavior to asymmetric price adjustment (as discussed above). Finally, we evaluate the complex nature of nonlinear price dynamics in a vertical sector. We point out the effects of asymmetric responses on the skewness of the price distribution. This stresses the limitations of previous models of price dynamics that rely solely on autocovariance (or spectral density in the frequency domain). The analysis finds that the skewness in the price distribution is due in large part to the non-linear dynamics implied by asymmetric price transmission.

2. A Model of Price Dynamics

Consider a vertical sector involving $m$ markets in a vertical sector. Let $y_t = (y_{1t}, y_{2t}, \ldots, y_{mt})'$ be an $(m \times 1)$ vector of market prices at time $t$. Assume that the price vector $y_t$ has a dynamic reduced-form representation given by the vector autoregression (VAR) model

$$y_t = \alpha + \sum_{k=1}^{K} A_k y_{t-k} + e_t, \quad (1)$$

where $\alpha$ is an $(m \times 1)$ vector, $A_k$ is an $(m \times m)$ matrix, $k = 1, \ldots, K$, and $e_t$ is an $(m \times 1)$ error term independently and normally distributed with mean zero and variance $\Omega$. This can be alternatively written in terms of the error-correction model (ECM)

$$\Delta y_t = \alpha + B_0 y_{t-1} + \sum_{k=1}^{K-1} B_k \Delta y_{t-k} + e_t, \quad (2)$$

where $\Delta y_t = y_t - y_{t-1}$, $B_0 = -[I_K - A_1 - A_2 - \ldots - A_K]$, and $B_k = -[A_{k+1} + A_{k+2} + \ldots + A_K]$, $k = 1, 2, \ldots, K-1$.

Equation (2) means that $\Delta y_t$ is stationary if and only if $[B_0 y_{t-1} + \sum_{k=1}^{K-1} B_k \Delta y_{t-k}]$ is stationary. Obviously, $y_t$ being stationary is sufficient for $\Delta y_t$ to be stationary. In addition,
if $y_t$ is not stationary (e.g., in the presence of units roots), then a stationary $\Delta y_t$ implies that $[B_0 y_{t-1}]$ must be stationary. Such a process is cointegrated, and $B_0$ identifies stationary linear combinations of the non-stationary variables $(y_{1t}, \ldots, y_{mt})'$. In this case, the matrix $B_0$ is singular and can be written as $B_0 \equiv \beta \gamma$, where $\beta$ is an $(m \times c)$ matrix, $\gamma$ is a $(c \times m)$ matrix of $c$ cointegration vectors, with $c = \text{rank}(B_0)$. In the error-correction model (2), the vector $z_t \equiv [\gamma y_{t-1}]$ is stationary, reflecting long-term relationships among prices, and $B_0 y_{t-1} \equiv \beta z_t$ (see Hamilton, p. 580). The general specification includes as a special case the situation where $B_0 \equiv -[I_K - A_1 - A_2 - \ldots - A_K] = 0$ and (2) implies that price dynamics can be properly analyzed using a VAR in differences. However, when $\text{rank}(B_0) \geq 1$, equation (2) shows that a VAR in differences is an inappropriate representation of price dynamics.

The linear specification (1) or (2) can be extended in a number of directions. First, the intercept $\alpha$ can change over time in at least two ways: 1/ it can have a time trend (reflecting inflation, technical progress, or other long term changes); and 2/ it can involve seasonal effects. This corresponds to $\alpha = a_0 + a_1 t + \sum_{s=1}^{S} \alpha_s D_{ts}$, where $D_{ts}$ is a dummy variable for the $s$-th season: $D_{ts}$ equals 1 if $t$ is in the $s$-th season and zero otherwise, $s = 1, \ldots, S$. Then, $(a_0 + a_1 t)$ is the intercept at time $t$ in the $S$-th season, and $a_1$ measures the change in intercept between two successive periods.

Second, we consider the case where the dynamics in (1) or (2) vary between regimes. For simplicity we focus on the case of binary regimes denoted by the dummy variables $R$. Let $R_{it} = 1$ if $y_{it}$ is in regime 1 at time $t$, and $R_{it} = 0$ if $y_{it}$ is in regime 0 at time $t$, $i = 1, \ldots, m$. In equation (2), let $B_k =$
means that the impact of $\Delta y_{jt-k}$ on $\Delta y_{it}$ varies across regimes as $\partial \Delta y_{it}/\partial \Delta y_{jt-k} = B_{kij}^1 R_{j,t-k} + B_{kij}^0 (1-R_{j,t-k})$, which equals $B_{kij}^1$ when $y_{jt-k}$ is in regime 1 but $B_{kij}^0$ when in regime 0. As a result, at time $t$, equation (2) becomes

$$\Delta y_{it} = a_{i0} + a_{i1} t + \sum_{s=1}^{S-1} s_{is} D_s + \sum_{j=1}^{m} B_{0ij} y_{jt-1} + \sum_{k=1}^{K-1} \sum_{j=1}^{m} [B_{kij}^1 R_{j,t-k} + B_{kij}^0 (1-R_{j,t-k}) B_k] \Delta y_{rk} + e_{it},$$

(3)
i = 1, \ldots, m. Equation (3) provides a framework to investigate whether price dynamics vary across regimes. Indeed, prices would exhibit the same dynamics under both regimes if $B_{kij}^1 = B_{kij}^0$ for all $(k, i, j)$. Alternatively, finding that $B_{kij}^1 \neq B_{kij}^0$ for some $(k, j, i)$ would be sufficient to conclude that price dynamics vary across regimes.3

Next, consider the Cholesky decomposition of the variance of $e_t$: $\Omega = S S'$, where

$$S = \begin{bmatrix}
s_{11} & 0 & \cdots & 0 \\
s_{21} & s_{22} & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
s_{m1} & s_{m2} & \cdots & s_{mm}
\end{bmatrix}$$
is a lower triangular matrix satisfying $s_{ij} > 0$, $i = 1, \ldots, m$. It means that equation (2) can be alternatively written as

$$S^{-1} \Delta y_t = S^{-1} \alpha + S^{-1} B_0 y_{t-1} + \sum_{k=1}^{K-1} S^{-1} B_k \Delta y_{t-k} + e_t,$$

(2')

where $e_t = S^{-1} e_t$ is normally distributed with mean zero and variance $I_m$. Note that the off-diagonal elements of $S$ capture the contemporaneous effects across dependent variables. For example, the covariance between $y_{1t}$ and $y_{2t}$ is $\text{Cov}(y_{1t}, y_{2t}) = s_{11} s_{21}$, and the contemporaneous impact of a shock in $y_{2t}$ on $y_{1t}$ is $\partial y_{1t}/\partial y_{2t} = s_{21}/s_{11}$. Also, the contemporaneous cross-price effects vanish if $s_{ij} = 0$ for all $i > j$. Thus, the presence of
contemporaneous cross-price effects can be confirmed by rejection of the null hypothesis: \( s_{ij} = 0 \) for all \( i > j \). In addition, if we are interested in exploring whether price volatility or contemporaneous cross-price effects are situation-specific, we can consider the more general specification: \( s_{ij} = \sigma_{ij0} + \sigma_{ij} z_t \), where \( z_t \) is a vector of predetermined variables at time \( t \), \( i \geq j \). In this context, constant variances implies \( \sigma_{ii} = 0 \) for \( i = 1, \ldots, m \). And constant contemporaneous effects across dependent variables implies that \( \sigma_{ij} = 0 \) for all \( i > j \). This means that finding \( \sigma_{ii} \neq 0 \) implies time-varying volatility for the \( i \)-th price. And finding \( \sigma_{ij} \neq 0 \) for some \( i > j \) would be sufficient to conclude that some contemporaneous cross-price effects vary over time. Econometrically, this corresponds to situations of heteroscedasticity where the covariance matrix \( \Omega_t \equiv S_t S_t' \) is time-varying. This provides a framework to analyze how price volatility and contemporaneous cross-price effects vary with market conditions.

In summary, the model exhibits three types of price transmission: contemporaneous cross price effects (captured by the specification for \( s_{ij} \)); lagged effects (captured by \( B_k \), \( k = 1, \ldots, K \)); and long term effects (captured by \( B_0 \)). The model is novel in the flexibility with which it captures these different dynamic price relationships.

As discussed in the introduction, much recent research has focused on whether price dynamics respond symmetrically to price increases versus price decreases. The first area of flexibility, then, corresponds to \( R_{it} = 1 \) if \( \Delta y_{it} > 0 \) and \( R_{it} = 0 \) if \( \Delta y_{it} \leq 0 \). In this context, equation (3) extends previous specifications of asymmetric price response found in the literature. The \( B_k^0 \)'s and \( B_k^1 \)'s capture asymmetric response to price shocks after \( k \) lags, \( k = 1, \ldots, K \). This extends Wolffram’s specification, which restricts the \( B_k^i \)'s to be the same for all \( k \). By allowing the \( B_k^i \)'s to vary, equation (3) allows for dynamic
asymmetry to vary between the short run and the intermediate run (e.g., as investigated by Peltzman). Second, under cointegration, $[B_0 y_{t-1}]$ is the “error correction term” which captures deviations from long-term relationships among prices. While equation (3) reduces to the Miller-Hayenga specification when $B_0 = 0$, the Miller-Hayenga specification of asymmetric price response becomes inappropriate when $B_0 \neq 0$.5 Third, the specification $s_{ij} = \sigma_{ij0} + \sigma_{ij} z_t$ expands on both the Miller-Hayenga and the Peltzman specifications. It allows for price volatility as well as contemporaneous cross-price effects to be time-varying. The Miller-Hayenga specification implicitly assumes constant $s_{ij}$’s, thus restricting variances and contemporaneous cross-price effects to be constant. The Peltzman specification (Peltzman’s equation (2) on p. 476) corresponds to equation (2’) above with $y_1 = “output price”$ and $y_2 = “input price”$. It allows for asymmetric contemporaneous effects from “input price” to “output price”, but implicitly assumes symmetric and constant contemporaneous effects from “output price” to “input price”. The specification $s_{ij} = \sigma_{ij0} + \sigma_{ij} z_t$ is more flexible and allows for more complex contemporaneous cross-price effects (see below).

Finally, as suggested by equations (1) and (2), one must choose between estimating the model “in levels” (equation (1)) or “in differences” (equation (2)). Both approaches can generate consistent parameter estimates. Below, we focus on the specification “in differences” for two reasons. First, the estimation of models “in differences” can perform better in small samples (Hamilton, p. 652). Second, hypothesis testing is easier “in differences” as test statistics exhibit more standard distributions (e.g., see Hamilton, p. 528-529; Toda and Phillips). Thus, the analysis presented below focuses on the estimation of equation (3). Equation (3) can be estimated by maximum likelihood,
which under a correct specification generates consistent and asymptotically efficient parameter estimates.

3. Application to the US Butter Sector

We apply model (3) to price dynamics in the vertical sector for US butter. The analysis focuses on the dynamics of two prices \( m = 2 \): the wholesale and retail prices of butter. The analysis uses monthly data from the period January 1980 to August 2001. The wholesale price is the Chicago Mercantile Exchange AA butter cash price, and the retail price for butter is from the Bureau of Labor Statistics. They are presented in Figure 1.

We evaluated two basic properties of butter prices. First, we investigated possible skewness\(^6\) in the distribution of seasonally adjusted and trended butter prices over the sample period. The skewness coefficient was estimated to be 0.810 for wholesale prices and 0.259 for retail butter prices. The null hypothesis of zero skewness under normality was tested and strongly rejected (at the 1 percent significance level) for each price. This provides evidence that the probability distribution of butter prices is asymmetric and has a “long tail” associated with high prices. Below, we will investigate possible sources of this asymmetry.

Second, the augmented Dickey-Fuller (ADF) test for a unit root was implemented for each butter price. ADF testing of the null of a unit root yielded t-values of -1.38 for retail prices and -2.58 for wholesale prices. At the 5 percent significance level, the ADF critical value is -3.43. Thus, we fail to reject the null hypotheses of unit roots. This suggests that both prices are non-stationary.

Next, we investigated the nature of price dynamics in the butter market. For this purpose, we relied on the specification given in equation (3). For the i-th price at time t-k,
we defined two market regimes: $R_{i,t-k} = 0$ (regime 0) when $\Delta y_{i,t-k} \leq 0$, and $R_{i,t-k} = 1$ (regime 1) when $\Delta y_{i,t-k} > 0$. This provides a framework to investigate whether price dynamics differ for price increases versus price decreases, including both own price and cross price effects. In addition, we wanted to analyze whether contemporaneous price relationships change with market conditions. With $m = 2$, let $y_1 \equiv y_r$ represent the retail price, and $y_2 \equiv y_w$ represent the wholesale price. We allow the covariance between $y_{rt}$ and $y_{wt}$ to vary with market conditions and consider the specification

$$s_{wr} = \sigma_{wr,0} + \sigma_{wr,\Delta w} \Delta y_{w,t-1} + \sigma_{wr,\Delta r} \Delta y_{r,t-1},$$

where $s_{wr}$ is the off-diagonal element in the Cholesky decomposition of the variance of $e_t$. When $\sigma_{wr,\Delta w} \neq 0$ and/or $\sigma_{wr,\Delta r} \neq 0$, this specification allows market conditions to affect the contemporaneous cross price effects between $y_r$ and $y_w$. For example, finding that $\sigma_{wr,\Delta r} > 0$ ($\sigma_{wr,\Delta w} > 0$) would mean that a rise in retail price (wholesale price) would increase the contemporaneous covariance between retail and wholesale prices. Note that, unlike the Peltzman specification, this allows retail market conditions to affect the contemporaneous relationships between retail and wholesale prices. In addition, we allow the variance of prices to vary with market conditions. We let

$$s_{ii} = \sigma_{ii,0} + \sigma_{ii,w} y_{w,t-1} + \sigma_{ii,r} y_{r,t-1}, \quad i = (w, r),$$

where the $\sigma_{ii}$’s correspond to the diagonal elements in the Cholesky decomposition of the variance of $e_t$. This can be motivated from the theory of competitive storage. Indeed, when stocks are positive, competitive stockholding can help stabilize prices. But such stabilizing effects disappear when stocks vanish, which is often associated with high market prices (see Williams and Wright; Deaton and Laroque, 1992, 1996). This means that high price volatility is expected to be associated with high prices. Our variance
specification can capture such effects. It will help shed some light on the dynamics of price volatility.

Model specification (3) requires choosing the number of lags K. The Schwartz criterion suggested choosing K = 2. We evaluated the implications of this choice for the serial correlation of the standardized error terms $\epsilon_t = S_t^{-1} e_t$. The null hypothesis that $\epsilon_t$ is white noise was tested using the Ljung-Box test for serial correlation up to p lags, $p = 1, \ldots, 6$. Under the null hypothesis, the Ljung-Box test statistic has a chi-square distribution with p degrees of freedom. The results are presented in Table 1. We fail to reject the null hypothesis at the 5 percent significance level. This shows that the standardized error terms in (3) appear serially uncorrelated up to 6 lags. This suggests that the dynamic specification gives an appropriate representation of price movements.

Given K = 2, the model was estimated using the maximum likelihood method. The resulting econometric estimates are presented in Table 2. Many of the estimates are found to be significant. In general, the coefficients ($\alpha_{it}$) of the monthly seasonal dummies $D_{it}$ show more evidence of seasonality in wholesale prices than in retail prices. Also, the time trend effects differ: the trend coefficient $a_{i1}$ is negative but insignificant for wholesale price, while it is positive and significant for retail price. This reflects that the marketing margin ($y_r - y_w$) has increased over time during the sample period. Finally, a number of the coefficients on lagged prices are significant, indicating the presence of significant dynamic adjustments in the US butter market.

The nature of the dynamic relationships between $y_r$ and $y_w$ was investigated. First, we implemented a Johansen cointegration test for model (3). The null hypothesis of a cointegration relation between $y_r$ and $y_w$ was investigated using a likelihood ratio test of the rank of the $B_0$ matrix. Testing the null hypothesis that rank($B_0$) = 0 versus the
alternative rank($B_0$) = 1, the Johansen test statistic was 44.94, which is significant at the 5 percent level. This provides evidence that a VAR in differences would be misspecified. Testing the hypothesis that rank($B_0$) = 1 versus the alternative rank($B_0$) = 2, the Johansen test statistic was 2.11, which is not significant at either the 5 or 10 percent level. Thus, there is statistical evidence that the $B_0$ matrix has rank 1. In conjunction with the results to the Augmented Dickey Fuller test, this suggests that wholesale and retail butter prices are cointegrated, i.e. that they exhibit long-term relationships. Using Johansen’s approach, the cointegration vector is estimated to be (0.801, -1). This shows that, after taking into consideration trend and seasonality effects, the wholesale price tends to be about 80 percent of the retail price in the long run.

Second, we tested for lagged effects among prices. In particular, we investigated whether lagged price changes $\Delta y_{j,t-1}$ affect current prices $\Delta y_{it}$ using likelihood ratio tests. The corresponding null hypotheses involve $B_{ij}^1 = 0$ and $B_{ij}^0 = 0$ with $i, j = (r, w)$. The associated test statistics have a chi-square distribution under the null hypothesis (Hamilton, p. p. 529). For lagged cross price effects (with $i \neq j$), the test statistic is 245.65 for the effects of lagged wholesale on retail price, and 1.21 for the effects of lagged retail on wholesale price. At the 5 percent significance level and with 2 degrees of freedom, the critical value is 5.99. Thus, we find strong evidence that lagged wholesale prices affect retail prices. However, we fail to reject the null hypothesis that lagged retail prices have no impact on wholesale prices. Thus, butter price transmission is such that lagged cross effects are strong from wholesale to retail, but weak from retail to wholesale. Such effects will be further evaluated below. For lagged own price effects (with $i = j$), the test statistic is 59.53 for retail price and 14.16 for wholesale price. With 2 degrees of freedom, we strongly reject the null hypothesis of zero own lagged effects for
each price. This provides evidence of significant dynamic adjustments in both wholesale and retail prices.

Third, we evaluated the symmetry of lagged price effects. In the context of equation (3), the symmetry of dynamic effects of price $j$ on price $i$ corresponds to the null hypothesis $B_{1ij}^1 = B_{1ij}^0$. Using a likelihood ratio test, the associated test statistics are 23.00 for $(i, j) = (r, r)$, 0.04 for $(i, j) = (w, w)$, 15.81 for $(i, j) = (r, w)$, and 0.001 for $(i, j) = (w, r)$. Based on a chi square distribution with 1 degree of freedom, the critical value is 3.84 at the 5 percent significance level. Thus, we strongly reject the symmetry of dynamic adjustments for retail prices (corresponding to $(i, j) = (r, r)$ and $(r, w)$). For example, the estimates in Table 2 show that retail prices respond much more strongly to a lagged wholesale price increase than to an equivalent price decrease. This asymmetry implies non-linear dynamics. The implications of non-linear dynamics for both retail and wholesale prices are evaluated below. In contrast, we fail to reject the null hypothesis of symmetry for wholesale prices (corresponding to $(i, j) = (w, w)$ and $(w, r)$). This result can be sensitive to model specification in interesting ways. In particular, the evidence against symmetry in wholesale price adjustments was found to become stronger when time-varying volatility is neglected (i.e., under homoscedasticity). This stresses the importance of considering heteroscedastic error structures in the analysis of asymmetric price transmission. Finally, we should keep in mind that these test results only concern lagged price effects (e.g., they do not reflect contemporaneous cross price effects).

Fourth, we investigated the presence of contemporaneous cross price effects. This is captured by the Cholesky term $s_{wr} = \sigma_{wr,0} + \sigma_{wr,\Delta w} \Delta y_{w,t-1} + \sigma_{wr,\Delta r} \Delta y_{r,t-1}$. The null hypothesis that $\sigma_{wr,0} = \sigma_{wr,\Delta w} = \sigma_{wr,\Delta r} = 0$ implies a zero correlation between $y_r$ and $y_w$ and thus zero contemporaneous effects between retail and wholesale prices. A likelihood ratio
test of this hypothesis yielded a test statistic of 36.57. Based on a chi-square distribution with 3 degrees of freedom, we strongly reject the null hypothesis. This provides evidence of significant contemporaneous cross price effects between the two butter prices.

Fifth, we explored the nature of contemporaneous cross price effects. The estimates reported in Table 2 give $s_{w,r} = \sigma_{w,r,0} + \sigma_{w,r,\Delta w} \Delta y_{w,t-1} + \sigma_{w,r,\Delta r} \Delta y_{r,t-1}$. The estimates $\sigma_{w,r,\Delta w} = -0.0645$ and $\sigma_{w,r,\Delta r} = 0.0778$ are each significant at the 5 percent level. It means that an increase in wholesale price has a negative effect on the covariance between $y_{rt}$ and $y_{wt}$. And a rise in retail price has a positive effect on the covariance between $y_{rt}$ and $y_{wt}$. This provides statistical evidence that the contemporaneous effects of one price on the other are sensitive to market pressure. It suggests that the contemporaneous linkages between retail and wholesale prices become weaker (stronger) when the wholesale (retail) price increases. This is another form of asymmetry between retail and wholesale butter prices. Note that such patterns are not consistent with competitive pricing. We interpret them to reflect short-term market imperfections. For example, as argued by Chevalier et al., such price behavior may be due to interactions between retail pricing rules and advertising effects. This would stress the importance of retailers’ behavior in short-term price determination.

Sixth, we investigated the time-varying nature of price volatility. This is captured by the Cholesky terms $s_{i,t} = \sigma_{i,0} + \sigma_{i,w} y_{w,t-1} + \sigma_{i,r} y_{r,t-1}$, $i = (w, r)$. The null hypothesis that the $s_{i,t}$’s are constant over time was tested using a likelihood ratio test. The test statistic is 269.07, with 4 degrees of freedom. Thus, we strongly reject the null hypothesis. This provides strong evidence that price variances vary over time, i.e. that butter price volatility changes with market conditions. Evaluated at sample means, the estimated standard deviation of $e_t$ is 0.078 for wholesale prices and 0.043 for retail prices, with a
correlation coefficient of 0.095. This shows that, on average, volatility is much higher for
wholesale butter prices than for retail prices. From the estimates reported in Table 2, the
retail price $y_{r,t-1}$ has a positive effect on price volatility (although only the effect on retail
price volatility is significant). The wholesale price $y_{w,t-1}$ has statistically significant
effects on the contemporaneous volatility of both prices. The effect on wholesale price
volatility is positive: a rise in wholesale price tends to increase wholesale price volatility.
As discussed above, this can be attributed to storage behavior. Indeed, competitive
stockholding can help stabilize prices but only when stocks are positive, which is likely
to happen when prices are relatively low. To the extent that storage services are mainly
performed at the wholesale level, this suggests that wholesale price volatility would rise
with the wholesale price level. Our estimated positive effect of wholesale butter price on
wholesale price volatility is thus consistent with stockholding behavior. Somewhat
surprisingly, opposite results are obtained for retail price volatility: a rise in wholesale
price tends to lower retail price volatility (see Table 2). Why would retail prices become
more stable under higher wholesale price? At this point, this seems difficult to explain.10
Again, this stresses the need to understand better retailers’ behavior and its impact on
short-term price determination.

Finally, to evaluate explanatory power, predicted prices were obtained from the
estimated model and compared with actual prices during the sample period. The results
are presented in Figure 1. The model has high explanatory power and provides a good fit
to the butter price data. Figures 2a and 2b presents the estimated standard deviations and
correlation coefficients of $e_t$ for retail and wholesale prices. Figure 2a illustrates the time-
varying nature of butter price volatility. It shows a large increase in price volatility since
1990. It also shows that the wholesale price is consistently more volatile than the retail
price. The correlation coefficient presented in Figure 2b indicates how the covariance between retail and wholesale prices varied during the sample period. As noted above, our parameter estimates imply that the contemporaneous linkages between retail and wholesale prices become weaker (stronger) when the wholesale (retail) price increases. Evaluated under June 1991 conditions, the marginal contemporaneous effect of a change in retail (wholesale) price on the wholesale (retail) price is estimated to be 0.149 (0.050). This shows contemporaneous cross price effects are stronger from wholesale price to retail price than vice versa.

4. Price Dynamics

The empirical results show strong evidence of asymmetry in price effects and dynamics in the US butter market. This asymmetry means that price dynamics are nonlinear in two ways: 1/ contemporaneous cross-price effects vary with market conditions; and 2/ price dynamics vary across regimes between situations of price increases and price decreases. These nonlinearities mean that, in general, the forward path of prices depends on initial conditions (Potter). As a result, the dynamic price response to exogenous shocks is typically situation specific. To evaluate the nature of dynamic adjustments in the US butter market, dynamic stochastic simulations of the estimated model were performed. The nonlinear dynamics imply that there is no simple way of summarizing price effects (since the results always depend on initial conditions). Below, we report selected simulation results that illustrate the dynamic implications of the estimated model.

The stochastic simulations were performed as follows. A random number generator was used to generate pseudo-random draws for the standardized error terms $\varepsilon_t = \ldots$
(\varepsilon_{rs}, \varepsilon_{wr})' distributed N(0, I_2). For given initial conditions (say at time \tau), these error terms were used to simulate forward the estimated model (3) with \varepsilon_{\tau+i} = S_{\tau+i} \varepsilon_{\tau+i}, i = 0, 1, 2, \ldots \), where \Omega_t \equiv S_t S_t'. Repeated dynamic simulation generated a distribution of prices \( y_{\tau+i} \) at time \tau+i, i = 0, 1, 2, \ldots This simulates the distribution of predicted prices at time \tau+i, based on the information available at time \tau. In addition, for given pseudo-random draws for the \varepsilon_i's, the dynamic simulation can be repeated after shocking the system at time \tau. Comparison of the paths of the simulated series with and without the shock provides a basis for measuring numerically the effects of the shock on the dynamics and distribution of prices. It measures the dynamic impulse response to the initial shock, which can shed light on the nature of price dynamics. We consider two kinds of shock: a shock in retail price at time \tau, and a shock in wholesale price at time \tau. The former is represented by an exogenous change in \varepsilon_{\tau}, and the latter by an exogenous change in \varepsilon_{wr}.

In general, under nonlinear dynamics, the impulse response depends not just on the initial conditions, but also on the nature and magnitude of the shock (Potter). To evaluate the effects of asymmetric price adjustments, we distinguish between positive and negative shocks to prices.

The distribution of impulse-responses to 10\% shocks (both positive and negative) in wholesale price in June 1991 is presented in Figure 3. Figure 3 shows the evolution of the 10\textsuperscript{th}, 25\textsuperscript{th}, 50\textsuperscript{th}, 75\textsuperscript{th}, and 90\textsuperscript{th} percentiles of the distribution over the 11-month period following the shock. Figures 3A and 3C show the own price response to a wholesale price shock. Following the initial shock, the wholesale price overreacts in the following 2 months, with a longer-term effect that slowly declines over time. From Figures 3B and 3D, a positive (negative) shock in wholesale price has a positive (negative) impact on
retail price. The impact is small in the short run, increases and is largest after 3 months, and then decays slowly over time.

Figure 3 illustrates the effects generated by a positive shock versus a negative shock. It shows how the distribution of the impulse response can vary. From Figures 3A and 3C, compared to a negative shock, a positive wholesale shock generates lower short-term variability in wholesale price. Figures 3A and 3C also suggest that the distribution of wholesale price response is approximately symmetric around its mean. However, nonlinear dynamics generate a skewed distribution of retail price responses to a wholesale price shock. For example, Figure 3B shows that a positive wholesale shock yields a retail price distribution with a long tail for high prices.

Similarly, Figure 4 presents the distribution of impulse response to 5% shocks (both positive and negative) in retail price in June 1991. From Figures 4A and 4C, a positive (negative) shock in retail price tends to have a positive (negative) impact on wholesale price. Note that this impact is small in the short run and that it does not decay quickly in the longer term. Figures 4B and 4D show the own price response to a retail price shock. The effect of the initial shock on the retail price slowly declines over time, but it persists for many months. The differences between a positive and a negative shock are quite apparent comparing Figure 4A with 4C, or Figure 4B with 4D. The effect on retail price persists longer for a positive shock (Figure 4B) than for a negative shock (Figure 4D). And the variability of both wholesale and retail price responses is larger for a retail price increase than for a retail price decrease. Figures 4B and 4D also indicates the presence of skewness in the distribution of the retail price response. For example, a positive retail shock yields a retail price distribution with long tail for high prices.
To show that the results presented in Figures 3 and 4 can be sensitive to initial conditions, we evaluate the impulse responses to price shocks for other selected periods. These are presented in Figure 5. Contrasting Figures 3 and 4 with Figure 5 illustrates the important effects of initial conditions on dynamics. Dynamic conditions are always “local” in nonlinear models, making price forecasts much more complex. In all cases, in response to a retail shock, price variability tends to be larger for wholesale prices than retail prices. This reflects the fact that the variance of $e_w$ is always larger than the variance of $e_r$. The contemporaneous impacts on wholesale price of retail shocks in December 1995 (Figure 5A) are much larger than in June 1991 (Figures 4A). The comparison between Figure 4A and 5A shows that initial conditions affect not only the scale but also the shape of the median and distribution of the impulse response of wholesale price. Also, Figures 4B and 5B illustrate how retail response to retail shocks can vary greatly across scenarios. Compared to June 1991 (Figure 4B), December 1995 (Figure 5B) shows lower short-term variability, an initial overshooting after 2 months, and a slower decay in longer run effects. It illustrates how regime switching can affect price dynamics and the distribution of forecasted prices.

Figures 5C and 5D present impulse response for November 1987, when the covariance between $e_r$ and $e_w$ is negative. This negative covariance means that contemporaneous cross-price effects are negative. As shown in Figure 2b, while such situations are not very common, they do occur within the sample period. Figure 5C shows the wholesale response to a 5% positive retail shock. In contrast with Figure 4A (which corresponds to a positive covariance), Figure 5C shows negative cross-price effects that peaks after 2 months, but then decay faster. Figure 5D shows the impact of a 10% positive wholesale shock on the retail price. It illustrates that, despite an initial negative
impact, the retail price response climbs rapidly out of the negative range after a few months. In the longer term, most of the initial wholesale shock ($0.15) is transferred to the retail sector. Figures 5C and 5D illustrate well the asymmetry of price response between retail and wholesale markets, with wholesale prices exhibiting much larger longer term adjustments. It also stresses the importance of dynamics in the study of price transmission.

The implications of nonlinear dynamics for the asymmetry of impulse response to positive versus negative shocks are investigated further. Table 3 reports the testing of the hypothesis of symmetry. Formally, the null hypothesis is $H_0$: the distribution of impulse responses at a point in time is symmetric for a price increase versus an equivalent price decrease. This is done using a chi-square Pearson test. The results in Table 3 are presented for different initial conditions, different shock sizes and at different time intervals (1, 5 and 11 months of simulation after the shock date). First, Table 3 makes it clear that the magnitude of the shock has a large impact on the presence of asymmetry. The evidence of asymmetry is very weak in the case of a small shock (e.g., 1% shock), but becomes strong with increases in the size of the shock. This reflects in large part the piece-wise linearity in model (3): it may take large changes to switch from one regime to another. As a result, the model can still exhibit “linear properties” locally, i.e. in the neighborhood of some path. The non-linearities become apparent only globally, when path changes are large enough to induce regime switching.

Second, the evidence of asymmetry is stronger for retail price response compared to wholesale price response (see Table 3). This is true irrespective of whether the shock is at the wholesale or retail level. Also, retail responses to retail shocks are the most asymmetric, followed by retail responses to wholesale shocks. The evidence of
asymmetry is weakest for the wholesale price response to retail price shocks, especially in the short run (after 1 month). The reason is two-fold: 1/ wholesale price dynamics do not exhibit strong evidence of asymmetry; and 2/ the retail price does not have a strong effect on wholesale price. However, dynamic asymmetric adjustments in retail prices eventually affect the dynamics of wholesale prices: Table 3 reports evidence of asymmetry for wholesale prices in the longer-term. To the extent that asymmetry is motivated by adjustment costs, finding that asymmetry is much stronger for retail price responses (compared to wholesale price responses) indicates the presence of significant short-term adjustment costs in the butter retail sector. This includes adjustment costs for consumers (e.g., search cost) as well as retailers (e.g., menu cost).

We evaluate the skewness of the distribution of impulse response. Table 4 presents the relative skewness obtained from the simulated effects of shocks in June 1991. It also reports tests of the null hypothesis of zero skewness (corresponding to a symmetric distribution of an impulse response around its mean). This is done using the Bera-Jarque test. The evidence against the null hypothesis is weak when considering the longer-term effect of a wholesale shock on the wholesale price. However, some statistical evidence of skewness is present in all other cases, and is found to be particularly strong in the effect of a retail shock on the retail price, both in the short run and the longer run. The importance of skewness indicates that mean-variance representations cannot provide sufficient statistics for the distribution of future prices. This shows the limitations of previous analyses of price dynamics based solely on autocovariance (or spectral density in the frequency domain, as used by Miller and Hayenga). Table 4 also shows that, when significant, positive (negative) shocks tend to generate positive (negative) skewness in the long run. This is true for wholesale price response as well as retail price response.
This indicates the nonlinear dynamics under regime switching can help explain the skewed distribution of butter prices (which as seen earlier exhibit a “long tail” for high prices).

Finally, we investigate whether nonlinear dynamics are in fact the main source of price skewness. To answer this question, we tested for skewness of the standardized regression residuals $\varepsilon_t = S_t^{-1} e_t$. The relative skewness was 0.0001 and 0.0012 for $\varepsilon_r$ and $\varepsilon_w$, respectively. The Bera-Jarque test of the null hypothesis of zero skewness has a p-value of 0.958 and 0.819 for retail price and wholesale price, respectively. Thus, we find no strong evidence that the standardized residuals have a skewed distribution. If the standardized residuals are symmetrically distributed, this means that nonlinear dynamics are indeed the main source of the skewness in the distribution of butter prices reported in section 3. In other words, the nonlinear dynamics in our model of asymmetric price response effectively capture the skewed distribution of observed butter prices at both the retail and wholesale level.

5. Concluding remarks

This paper developed a model of asymmetric price transmission in a vertical sector, allowing for refined asymmetry for both contemporaneous and lagged own and cross price effects. Applied to wholesale-retail price dynamics in the US butter market, the model provides strong evidence of asymmetric price transmissions. The asymmetry generates nonlinear dynamics in price adjustments in a vertical sector. We document the complex nature of price dynamics in the butter market. The effects of market shocks depend on initial conditions. For example, the impact of a change in retail price on wholesale price is found to vary significantly with market conditions (see Figures 3 and
Despite this sensitivity to initial conditions, the following regularities appear. First, the evidence of asymmetry grows with the size of the shock. Second, we show how asymmetric price responses affect the distribution of prices. We find strong evidence of skewness in the response to large price shocks. This highlights the limitations of previous analyses of price dynamics that relied only on the autocovariance (or spectral density in the frequency domain). Third, the asymmetric response is particularly strong for retail prices, both in the short run and the longer run. It is found that retail prices respond more strongly to a wholesale price increase than to a wholesale price decrease. This is consistent with the presence of consumer search costs and/or menu costs facing retailers. Fourth, the evidence of asymmetry in wholesale price response is weaker. However, some evidence of asymmetric adjustments remains for wholesale prices, due in part to linkages with asymmetric retail price adjustments. This illustrates how non-linear dynamics can affect price behavior in different stages of a marketing channel. Finally, we find that the non-linear dynamics are in fact the main source of skewness in the distribution of prices. This indicates how non-linear price transmission across markets can help better anticipate the distribution of price forecasts.

The analysis has focused on vertical price adjustments in the butter sector. It can be extended in several directions. First, it would useful to investigate whether our empirical findings hold for other sectors. Second, there may be more complex forms of nonlinear dynamics that are relevant in vertical price adjustments. Finally, following Peltzman, our empirical findings suggest significant challenges for improving our conceptual understanding of dynamic market adjustments. These are good topics for further research.
### Table 1: Ljung-Box test of white noise for standardized errors

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### Table 2: Maximum likelihood estimate of the parameters

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<th>Parameter</th>
<th>Estimate</th>
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Log Likelihood = 796.85. Number of Observations = 258.

Double asterisks (**) means significantly different from zero at the 5 percent level; single asterisk (*) means significantly different from zero at the 10 percent level.
Table 3: Testing the symmetry of impulse price response to price increase versus a price decrease.

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P-Values for the Null Hypothesis that Wholesale Shocks Produce Symmetric Wholesale Price Responses.

P-Values for the Null Hypothesis that Retail Shocks Produce Symmetric Wholesale Price Responses.

P-Values for the Null Hypothesis that Wholesale Shocks Produce Symmetric Retail Price Responses.

P-Values for the Null Hypothesis that Retail Shocks Produce Symmetric Retail Price Responses.
Table 4: The Relative Skewness of distributions of Price Responses to Shocks in June 1991.

| Responding Price: | A Positive Wholesale Shock | | A Positive Retail Shock | | | | | |
|-------------------|----------------------------|----------------|-----------------------|----------------|----------------|----------------|----------------|----------------|----------------|
|                   | Wholesale | Retail | Wholesale | Retail | Wholesale | Retail | Wholesale | Retail | Wholesale | Retail |
| Month             | Relative Skewness | P-Value | Relative Skewness | P-Value | Relative Skewness | P-Value | Relative Skewness | P-Value | Relative Skewness | P-Value |
| 0                 | 1.0107    | 0.0000 | 1.3431    | 0.0000 | 1.2150    | 0.0000 | 1.0039    | 0.0000 | |
| 1                 | 0.1900    | 0.0142 | -0.3473   | 0.0000 | 0.0365    | 0.6376 | -0.3046   | 0.0001 | |
| 2                 | 0.2822    | 0.0003 | -0.4726   | 0.0000 | -0.0989   | 0.2018 | -0.0598   | 0.4402 | |
| 3                 | 0.4234    | 0.0000 | -0.1884   | 0.0150 | -0.3469   | 0.0000 | 0.3719    | 0.0000 | |
| 4                 | 0.5649    | 0.0000 | 0.0115    | 0.8815 | -0.2137   | 0.0058 | 0.4607    | 0.0000 | |
| 5                 | 0.3841    | 0.0000 | 0.1493    | 0.0539 | -0.1347   | 0.0820 | 0.5924    | 0.0000 | |
| 6                 | 0.1262    | 0.1031 | 0.3158    | 0.0000 | -0.1314   | 0.0899 | 0.6223    | 0.0000 | |
| 7                 | 0.1258    | 0.1044 | 0.4861    | 0.0000 | -0.0638   | 0.4103 | 0.6289    | 0.0000 | |
| 8                 | 0.0845    | 0.2754 | 0.6115    | 0.0000 | -0.0303   | 0.6958 | 0.6219    | 0.0000 | |
| 9                 | 0.1343    | 0.0829 | 0.8168    | 0.0000 | 0.0760    | 0.3268 | 0.6053    | 0.0000 | |
| 10                | 0.0467    | 0.5469 | 1.0566    | 0.0000 | 0.2124    | 0.0001 | 0.6092    | 0.0000 | |
| 11                | -0.0141   | 0.8554 | 1.0787    | 0.0000 | 0.2946    | 0.0001 | 0.6032    | 0.0000 | |

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Figure 1: Actual and predicted butter prices: January 1980-August 2001.
**Figure 2a:** Estimated standard deviations of error terms for butter prices: January 1980-August 2001.
Figure 2b: Estimated contemporaneous correlation between wholesale and retail butter prices: January 1980-August 2001.
Figure 3: Impulse Responses to 10% Wholesale Price Shocks in June 1991: 10th, 25th, 50th, 75th and 90th Percentiles

A: Wholesale Response to a Positive Wholesale Shock

B: Retail Response to a Positive Wholesale Shock

C: Wholesale Response to a Negative Wholesale Shock

D: Retail Response to a Negative Wholesale Shock
Figure 4: Impulse Responses to 5% Retail Shocks in June 1991: 10th, 25th, 50th, 75th and 90th Percentiles

A: Wholesale Response to a Positive Retail Shock

B: Retail Response to a Positive Retail Shock

C: Wholesale Response to a Negative Retail Shock

D: Retail Response to a Negative Retail Shock
Figure 5: Impulse Responses to Price Shocks for selected periods: 10th, 25th, 50th, 75th and 90th Percentiles
References


1 See Zellner and Palm for a discussion of the linkages between a structural model of price determination and the time series representation (1).

2 Note that equation (3) can be equivalently expressed in “levels” as

\[ y_{it} = a_{i0} + a_{i1} t + \sum_{s=1}^{S-1} \alpha_{is} D_{ts} + \sum_{k=1}^{K} \sum_{j=1}^{m} [A_{kij}^1 R_{j,t-k} + A_{kij}^0 (1-R_{j,t-k})B_k] y_{t-k} + e_{it}, \]

i, = 1, ..., m, where the A’s satisfy \( \sum_{k=1}^{K} A_{kij}^1 = \sum_{k=1}^{K} A_{kij}^0 \), for i, j = 1, ..., m.

3 Equation (3) restricts the B_{0ij}’s to be the same across regimes. It assumes that cointegration relationships among the dependent variables are not regime specific. This will prove convenient in the implementation of the Johansen test for cointegration (see below).

4 More general forms of asymmetry can treat the regime switching as endogenous. This includes threshold autoregression (TAR; see Hansen, and Koop and Potter), or Markov chains with regime switching (e.g., Hamilton, chapter 22).

5 There are two scenarios where B_{0} \neq 0: when y_{t} is stationary; or when y_{t} has a unit root and is cointegrated.

6 The skewness coefficient for a random variable y is \( \{E[y - E(y)]^3\}/\{E[y - E(y)]^2\}^{3/2} \) where E is the expectation operator. It provides a standard measure of the asymmetry of a probability distribution around its mean. The skewness coefficient is equal to zero for a symmetric distribution. And it is positive (negative) for an asymmetric probability distribution with a “long tail” above (below) the mean.

7 Allowing the s_{ij}’s to become time-varying means that the model specification changes with the ordering of the prices. To evaluate this issue, we also estimated the same model with y_{1} = y_{w} and y_{2} = y_{r}. This resulted in a lower log-likelihood value of the sample.
The Schwartz criterion selects the specification that maximizes \[\ln(\text{likelihood function}) - \frac{1}{2} k \ln(T)\], where \(k\) is the number of parameters and \(T\) the number of observations.

However, under cointegration, hypothesis testing involving the \(B_{bi}\)'s generates test statistics that can have non-standard distributions. This includes testing for Granger causality (Toda and Phillips).

This seems inconsistent with competitive pricing. Also, it is inconsistent with “sticky” retail pricing rules that are modified only when the wholesale price is high. Note that Peltzman also found some linkages between price volatility and price dynamics. He argues that reconciling such empirical results with current theories remains a significant challenge.

The Bera-Jarque test was also used to test for kurtosis, i.e. whether the fourth moment of \(\varepsilon_t\) is consistent with a normal distribution. The test results found evidence of excess kurtosis, indicating the presence of thick tails in the distribution of \(\varepsilon_t\). This suggests that our model may underestimate the likelihood of rare events (when prices are either very high or very low). Yet, it still provides consistent estimate of the parameters underlying price dynamics. And compared to a homoscedastic structure, our heteroscedastic specification provides efficiency gains in the parameter estimates.