Retail Dairy Prices Fluctuate with the Farm Value of Milk

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Farm milk prices tend to be volatile. Dairy farmers, industry pundits, and policymakers further tend to react to price volatility with alarm. One point of concern is the response of retail prices. This study investigates farm-to-retail price transmission in the 2000s for whole milk and cheddar cheese. Results show that price shocks at the farm gate are transmitted with delay and asymmetry to retail. Differences in the nature of price transmission for whole milk and cheddar cheese prices are also identified.

Key Words: asymmetric price transmission, cointegration, dairy prices, error correction models

Price volatility in U.S. dairy markets is not "new" but, because it affects farm receipts and the ability of producers to maintain operations, it continues to generate questions about market structure and performance. The most recent incidence of volatility occurred in 2007-2009. Milk prices received by dairy farmers fluctuated between $18 and $22 per cwt (100 pounds) from May 2007 through September 2008 before falling below $12 per cwt in February 2009.[1] A similar pattern of farm price movements took place between May 2004 and May 2006.

Recent price volatility has been unique in some ways. Low farm milk prices in late 2008 throughout 2009 coincided with higher than previous feed prices. The annual average feed cost[2] was $4.69 per cwt between 2000 and 2006. It then rose to

$7.75 per cwt between 2007 and 2009, an increase of 65 percent. The cost-price squeeze in 2009 was devastating for dairy farmers. Milk producers in the Northeast, for example, responded to their cash flow and debt repayment situations by, among other things, drawing down liquidity gained in 2007 and 2008 (Putnam 2010). Total industry losses were estimated at over $6 billion (Elam 2010).

Questions about market structure and performance often generated by volatility include questions about the behavior of retail food prices. According to the American Farm Bureau Federation (AFBF), when the farm price of milk increases, marketers quickly pass higher prices on to consumers. By contrast, when farm prices decrease, marketers adjust retail prices slowly in order to increase their profits. The net effect, says the AFBF, is a wider farm-to-retail price spread (AFBF 2003). Debate over this matter grew more intense when retail prices appeared to change relatively little as farm prices dropped in late 2008 and early 2009. In February 2009, the *Cheese Reporter*, a trade publication, ran an editorial "Sometimes, Retail Dairy Prices Do the Strangest Things" (Groves 2009, p. 2). At various times during 2009, it was claimed that large fluid milk processors were engaging in anticompetitive practices, claims that prompted a decision to hold hearings/workshops the following year.

Over the course of 2010, the U.S. Department of Justice (USDOJ) and the U.S. Department of Agriculture (USDA) held a series of five workshops on competition and regulatory issues in agriculture (USDOJ and USDA 2010). One work-

[1] The "all milk" price published in *Agricultural Prices*, by the U.S. Department of Agriculture, National Agricultural Statistical Service (NASS) for product with a fat content of 3.7 percent.
[2] The cost of 16 percent commercial prepared dairy feed based on prices received for corn, soybeans, and alfalfa hay in *Agricultural Prices*. Shares of feed components are 51 percent, 8 percent, and 41 percent.

shop focused on the dairy industry and another focused on farm-to-retail price spreads for foods, including meat and dairy products.

Existing research corroborates the fears of dairy farmers, pundits, and policymakers. In a seminal study, Kinnucan and Forker (1987) find that price transmission is asymmetric for dairy products. Symmetry would require retail prices to adjust with equal speed and completeness, up when farm prices rise and down when they fall. The analysis finds instead asymmetry similar to that described by the AFBF. However, since data from 1971 through 1981 were used, Kinnucan and Forker's (1987) conclusions may not apply to recent events.

The question of farm-to-retail price transmission has been revisited often for U.S. fluid milk prices. Lass, Adanu, and Allen (2001) examined fluid milk prices in the Hartford, Connecticut, and Boston, Massachusetts markets between January 1982 and June 1998. Lass (2005) reported on an extension of that study using data through September 2001. Capps and Sherwell (2007) investigated fluid milk prices in seven cities between January 1994 and October 2002. Most recently, Awokuse and Wang (2009) examined national average fluid milk prices between January 1987 and December 2006. Differences in methodology across these studies complicate efforts to compare their findings. However, all studies find evidence of some type of asymmetry.

Much less research has been conducted on price transmission for U.S. cheese prices. Since Kinnucan and Forker (1987), we are aware of only Awokuse and Wang (2009) analyzing wholesale and retail prices for cheddar cheese. However, these prices represent only one part of the overall farm-to-retail price spread.

This study examines farm-to-retail price transmission for whole milk and cheddar cheese between January 2000 and September 2010. Results for these two products are compared. We also address the opinion expressed in the *Cheese Reporter* that retail dairy prices behaved strangely in 2009. A second contribution of the study is methodological. Models employed in early studies of price transmission are inconsistent with farm and retail price cointegration. If farm and retail prices are cointegrated, some specification of an error correction model (ECM) is more appropriate. Empirical research is now dominated by ECMs with linear and two-regime threshold cointegration, but other ECMs exist. Our results for cheddar cheese

prices underscore the importance of examining alternative model specifications.

Models Used to Study Price Transmission

In a review of modeling techniques used to analyze price transmission, Meyer and von Cramon-Taubadel (2004) examined 40 studies published between 1980 and 2002. Early researchers used a distributed lag model to describe how retail prices change in the days, weeks, or months after a shock to farm prices. To allow for asymmetry, these researchers further employed a variable-splitting technique developed by Wolffram (1971) and refined by Houck (1977). Bailey and Brorsen (1989), for one, proposed a model similar to the following:

$$(1) \qquad \Delta R_t = \alpha_0 + \sum_{k=0}^{M}(\alpha_{1k}^+ D_{t-k}^+ \Delta F_{t-k})$$

$$+ \sum_{k=0}^{N}(\alpha_{1k}^- D_{t-k}^- \Delta F_{t-k}) + u_t$$

where R_t is the retail price at time t, F_t is farm receipts per retail unit, α_0 is an intercept, and u_t is an error term. The variables D^+ and D^- split ΔF_t into rising and falling prices regimes. That is,

$$D_{t-k}^+ = 1 \text{ if } F_{t-k} \geq F_{t-k-1}$$

and 0 otherwise. Likewise,

$$D_{t-k}^- = 1 \text{ if } F_{t-k} < F_{t-k-1}$$

and 0 otherwise. Hypothesis tests can be conducted on the estimated coefficients,

$$\hat{\alpha}_{1k}^+ \text{ and } \hat{\alpha}_{1k}^-.$$

Price transmission is symmetric if the absolute size of the change in retail prices is equal in all periods after an increase or decrease in the farm price; i.e.,

$$\hat{\alpha}_{1k}^+ = \hat{\alpha}_{1k}^-,$$

and the same number of periods is required for the transmission process to finish (i.e., M = N).

A question of interest is: Can the farm-to-retail price spread grow over time because of volatility in farm prices? Suppose that fluid milk processors more fully pass down to retailers farm price increases than decreases, i.e.,

$$\sum_{k=0}^{M} \alpha_{1k}^{+} > \sum_{k=0}^{N} \alpha_{1k}^{-}.$$

Suppose further that farm prices rise this month and fall by an equal amount next month. The retail price increase associated with the initial farm price increase will exceed in absolute value the retail price decrease associated with the subsequent farm price decrease. Retail prices and the spread will likewise be larger and may grow further if such episodes continue.

However, as von Cramon-Taubadel (1998) demonstrated, most of the models traditionally employed to study price transmission are inconsistent with cointegration. A food's retail and farm price may share a long-run relationship that can be described as:

(2) $R_t = \beta_0 + \beta_1 F_t + \varepsilon_t$

where R_t and F_t are defined in equation (1) and ε_t is an error term with a constant mean and variance (i.e., ε_t is stationary). After a shock to R_t or F_t, if these prices are cointegrated, they will move back towards their long-run relationship. For example, if fluid milk processors do not pass down a decrease in farm prices, some retailers may search for better (lower price) supply deals. Competition may then reduce the extra margin that processors had been collecting.

One method for analyzing price transmission between cointegrated prices is to augment equation (1) with an error correction term (ECT) that captures the tendency of prices to revert toward their long-run relationship in equation (2). The resulting equation is known as an error correction model (ECM). As in Engle and Granger's (1987) original specification, many researchers posit a linear relationship between the change in the retail price and the ECT:

(3) $\Delta R_t = \alpha_0 + \sum_{k=0}^{M}(\alpha_{1k}^{+} D_{t-k}^{+} \Delta F_{t-k})$

$+ \sum_{k=0}^{N}(\alpha_{1k}^{-} D_{t-k}^{-} \Delta F_{t-k})$

$+ \gamma ECT_t + u_t$

where $ECT_t = \varepsilon_{t-1}$ is the lagged residual in equation (2) and γ is a negative-valued "speed of adjustment" parameter. Suppose, for example, that R_t exceeds its expected value in equation (2) so that the residual in this equation, ε_t, is positive. It follows that ECT_{t+1} is also positive in period t+1.

The negativity of γ in equation (3) then ensures that ΔR_{t+1} will be lower than otherwise.

Augmenting the traditional Wolffram-Houck model with an error correction process affects the interpretation of the model's other parameters. It is correct to omit the constant, α_0, from equation (3) since its inclusion suggests a time trend in equation (2). However, many empirical researchers retain α_0 in order to test whether labor, energy, or other input costs changed. It is also customary to interpret α_{1k}^{+} and α_{1k}^{-} as "short-run" parameters. These parameters still measure how much, say, fluid milk processors pass down changes in the farm price to retailers. However, even if

$$\sum_{k=0}^{M} \alpha_{1k}^{+} \neq \sum_{k=0}^{N} \alpha_{1k}^{-},$$

the error correction process prevents price volatility from growing the spread between R_t and F_t over the long run.

More general ECMs than Engle and Granger's (1987) linear specification have been developed to allow for asymmetry in both the short-run parameters, α_{1k}^{+} and α_{1k}^{-}, and the error correction process. To account for the range of ECMs now in the literature, we write

(4) $\Delta R_t = \alpha_0 + \sum_{k=0}^{M}(\alpha_{1k}^{+} D_{t-k}^{+} \Delta F_{t-k})$

$+ \sum_{k=0}^{N}(\alpha_{1k}^{-} D_{t-k}^{-} \Delta F_{t-k})$

$+ f(ECT) + u_t.$

where f(ECT) is an as yet unspecified function. Meyer and von Cramon-Taubadel (2004) provide an overview of some popular specifications.

Threshold Models

Threshold ECMs have been widely applied in the literature. Following the notation in Enders and Siklos (2001), a threshold ECM with two regimes is:

(5) $\Delta R_t = \alpha_0 + \sum_{k=0}^{M}(\alpha_{1k}^{+} D_{t-k}^{+} \Delta F_{t-k})$

$+ \sum_{k=0}^{N}(\alpha_{1k}^{-} D_{t-k}^{-} \Delta F_{t-k})$

$+ \gamma_1 I_t ECT_t + \gamma_2 (1 - I_t) ECT_t + u_t,$

where the coefficient on the ECT in equation (3) is split according to the binary variable, I_t. This

model therefore permits a different speed of adjustment depending on whether the value of the ECT falls into the first regime ($I_t=1$) or into the second regime ($I_t=0$).

Different models are defined according to the specification of the binary variable, I_t, that determines the regime. Popular specifications include the threshold autoregressive (TAR) and the momentum-TAR (M-TAR) models. Enders and Siklos (2001) discuss both. Use of the following Heaviside indicator produces the TAR model:

$$I_t = \begin{cases} 1 & \text{if } \varepsilon_{t-1} \geq \tau \\ 0 & \text{if } \varepsilon_{t-1} < \tau \end{cases}$$

where τ is the threshold. Suppose, for example, that $\tau = 0$ and $\gamma_2 < \gamma_1 < 0$. In this case, the speed of adjustment will be faster when R_t is below its expected value ($\varepsilon_{t-1} = ECT_t < 0$) than when R_t is above its expected value ($\varepsilon_{t-1} = ECT_t \geq 0$).

It is possible to allow for a third regime. Goodwin and Holt (1999), for one, estimated a three-regime threshold ECM that includes both a negative, C1, and a positive threshold, C2:

$$(6) \quad \Delta R_t = \alpha_0 + \sum_{k=0}^{M}(\alpha_{1k}^+ D_{t-k}^+ \Delta F_{t-k})$$

$$+ \sum_{k=0}^{N}(\alpha_{1k}^- D_{t-k}^- \Delta F_{t-k})$$

$$+ f(ECT) + u_t$$

where

$$f(ECT) = \begin{cases} \gamma_1 ECT_t & \text{if} & \varepsilon_{t-1} > C2 \\ \gamma_2 ECT_t & \text{if} & C1 \leq \varepsilon_{t-1} \leq C2 \\ \gamma_3 ECT_t & \text{if} & \varepsilon_{t-1} < C1 \end{cases}$$

which is based on a model first proposed by Balke and Fomby (1997). They hypothesized that market forces may not move farm and retail prices back towards their long-run relationship in equation (2) for small enough deviations from this relationship. For example, firms may not adjust production levels continuously if they face fixed costs for doing so. They may instead wait until input prices have changed enough to outweigh adjustment costs. In this case, downstream prices will also not adjust continuously with upstream prices, creating a middle regime of values for the ECT over which the speed of adjustment parameter is zero (i.e., $\gamma_1 < 0$, $\gamma_2 = 0$, $\gamma_3 < 0$).

Estimating a threshold ECM starts with selecting appropriate threshold values. Capps and Sherwell (2007) estimated two-regime TAR models under the assumption of a zero threshold (i.e., $\tau = 0$). Awokuse and Wang (2009) used a search procedure described in Enders and Siklos (2001), to identify the threshold values for their M-TAR models. Goodwin and Holt (1999) used a grid search to estimate C1 and C2 in a three-regime model.

STAR Models

In smooth transition autoregressive (STAR) models, the change in the retail price is a continuous, nonlinear function of the ECT. For example, using an exponential function for f(ECT) produces the ESTAR and using a logistic function produces the LSTAR.

When the form of f(ECT) is a priori unknown, some analysts include higher-order polynomials as a local approximation to a continuous, nonlinear function. Applying this approach, we obtain the following:

$$(7) \quad \Delta R_t = \alpha_0 + \sum_{k=0}^{M}(\alpha_{1k}^+ D_{t-k}^+ \Delta F_{t-k})$$

$$+ \sum_{k=0}^{N}(\alpha_{1k}^- D_{t-k}^- \Delta F_{t-k})$$

$$+ \gamma_1 ECT_t + \gamma_2 ECT_t^2 + \gamma_3 ECT_t^3 + u_t$$

where the ECT is again the lagged residual in equation (2). Von Cramon-Taubadel (1996) and Escribano (2004) respectively call this the "quadratic" and "cubic polynomial" ECM.

Models with a cubic polynomial adjustment are an extension of threshold models without the assumption of "knife-edged regime switches" (Mainardi 2001, p. 341). Firms may have different cost structures and respond differently to market forces. In turn, firm heterogeneity may cause the points of regime change to become "blurred" (Mainardi 2001, p. 336). Then gradual regime changes instead of sudden regime switches occur.

Cubic polynomial ECMs are widely used to study horizontal price relationships. For example, Mainardi (2001) examined price relationships between American, Australian, and other countries' wheat. However, to our knowledge, this approach has not been used to examine the vertical transmission of price shocks from the farm gate to retail stores for individual foods.

Model Selection and Inference

A first step in modeling price transmission is deciding whether to include an error correction process in the model. Error correction processes should not be included unless the price series under analysis are integrated of the same order. A variable is integrated of order zero, I(0), if it is stationary in levels. If it is instead the variable's first difference that is stationary, then the variable is integrated of order one, I(1). Variables that require differencing a second time to be stationary are I(2). The Augmented Dickey-Fuller (ADF) procedure is one test for stationarity (see, for example, Said and Dickey 1984). This procedure can be applied to a variable and then to its differences until a stationary series is identified. However, many researchers also apply Kwiatkowski et al.'s (1992) KPSS test. The two procedures are confirmatory. Non-stationarity is the null hypothesis in the ADF test, whereas stationarity is the null hypothesis in the KPSS test.

Formal tests for cointegration between farm and retail prices can be conducted if both price series are integrated of order one or a higher order. Johansen's (1995) procedure has been widely applied when variables are I(1), as price series often are.[3] For the long-run relationship between retail and farm prices specified in equation (2), this method identifies the number of unique vectors

$$\beta = [\beta_0 \; \beta_1]$$

that produce a stationary error term, ε_t. Each of these 2x1 vectors is a "cointegrating vector." Two test statistics, λ_{trace} and λ_{max}, exist. According to Enders (2004), the λ_{max} test has a "sharper alternative hypothesis" and is preferred (p. 354).

Having determined whether to include an error correction process in the model, it is next necessary to decide on a single-equation or a multiple-equation approach. Many studies report estimates for a single-equation model in which farm prices are treated as exogenous. However, this approach is correct only if farm prices have been

unaffected by shocks to retail prices during the time period under study. Whether this is "true" can be determined by a test for Granger causality. Enders (2004) proposed regressing the change in the farm price on its own lags, lagged changes in the retail price, and, if the two prices are cointegrated, the ECT. Further recognizing that increases and decreases in farm prices may affect markets differently, the regression model used to test for Granger causality becomes:

$$(8) \qquad \Delta F_t = \sum_{k=1}^{K} (\alpha_{1k}^+ D_{t-k}^+ \Delta F_{t-k})$$
$$+ \sum_{k=1}^{K} (\alpha_{1k}^- D_{t-k}^- \Delta F_{t-k})$$
$$+ \sum_{k=1}^{K} \alpha_{2k} \Delta R_{t-k} + \gamma_F ECT_t$$

where one can conduct an F-test for the joint significance of the α_{2k} parameters and a t-test for the significance of γ_F. Finding that either set of variables is significant would suggest that a multiple-equation approach, such as a vector error correction model, is best.

A next step in modeling price transmission is to incorporate institutional features of the market into the analysis. One of these features may be the length of time required to transform an agricultural commodity into a final product. In a study of price transmission in beef and pork markets, Boetel and Liu (2010) accounted for the time required for animals to reach the consumer. Instead of assuming a long-run relationship between contemporaneous retail and farm prices, as is done in equation (2), they hypothesized that current retail prices share a long-run relationship with farm prices in a previous month.

Finally, after estimating the price transmission model, one can conduct hypotheses tests on the parameter coefficients. It can also be informative to conduct simulations and graphically examine these results in an impulse response function.

Farm and Retail Dairy Prices

Milk supplied by dairy farmers is transformed into a variety of foods. According to the USDA National Agricultural Statistical Service (NASS), cheese and fluid products are the primary uses. In 2009, U.S. dairy farmers produced 189.3 billion pounds of milk. On average, this milk contained 3.67 percent fat and 8.78 percent skim solids, such as whey protein and casein. Manufacturers

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[3] Johansen's (1995) procedure tests the null hypothesis that the prices series are not cointegrated against the alternative of cointegration with linear adjustment. Further analysis is needed to substantiate a nonlinear error correcting process over a linear one. Capps and Sherwell (2007) and von Cramon-Taubadel (1998), among others, followed this approach. Enders and Siklos (2001) proposed a cointegration test that may be more powerful if the prices are cointegrated with threshold-type adjustment. That approach is not pursued here.

of cheese used 41 percent of the fat and 14 percent of the nonfat solids available. Processors of fluid products used 22 percent of the fat and 31 percent of the nonfat solids (NASS 2010a).

Obtaining farm-level "prices" (or values) that "match up" with retail prices is a complex proposition. One source of data is the USDA Agricultural Marketing Service (AMS). The AMS administers the Federal Milk Order (FMO) program. This program sets minimum prices for fluid-grade milk used in fluid products, semi-hard products (like ice cream), cheese, and butter. We can refer to each of these four minimums as a "plant price" because they represent what regulated processing and manufacturing plants must pay.[4] Farmers do not receive any one of these four minimums, instead receiving a weighted average blend price (also a minimum) that depends on the mix of dairy products sold where they sell milk. In addition, farmers may negotiate with buyers for "over-order payments." Through its administration of the FMO program, the AMS generates data on milk supplies, utilization, sales, plant prices, over-order payments, and retail prices for packaged milk. However, these data only cover parts of the nation that participate in the FMO program. California, for example, has its own, state-run dairy program. Details on the FMO program are readily available at the AMS Dairy Programs Website (AMS 2010).

A second source of data is *Agricultural Prices*, a monthly publication by NASS. Data in this publication include nationwide average prices received by dairy farmers for all milk, manufacturing-grade milk, and fluid-grade milk. Fluid-grade milk accounted for 98 percent of the milk marketed by U.S. producers in 2009 (NASS 2010b).

The U.S. Department of Commerce Bureau of Labor Statistics (BLS) is a source of data on retail prices. It publishes the nationwide average prices charged by supermarkets and other retail food outlets for one gallon of whole milk and one pound of cheddar cheese.

Different measures of the value of a dairy product at the farm gate and the retail store can be generated from USDA and BLS data. We report results for one pair of retail and farm prices for each product selected based on discussions with industry experts. However, we also checked whether our results were robust to how we measured retail and farm values by considering at least one alternative combination for both whole milk and cheddar cheese.

Whole Milk

Fluid milk markets are likely the simplest of the milk and dairy product markets. Milk typically moves from the farm gate to a fluid milk processor who pasteurizes, homogenizes, adjusts for fat content, and packages the products for delivery directly to retail outlets.

The farm value of whole milk can be estimated using the announced cooperative Class I price reported by AMS. This price includes the minimum that AMS requires processors to pay for milk used in fluid products and many of the over-order payments that dairy farmers may negotiate with buyers. The data are collected by AMS through a nonstatistical survey that has only incomplete coverage of the parts of the nation that participate in the FMO program.
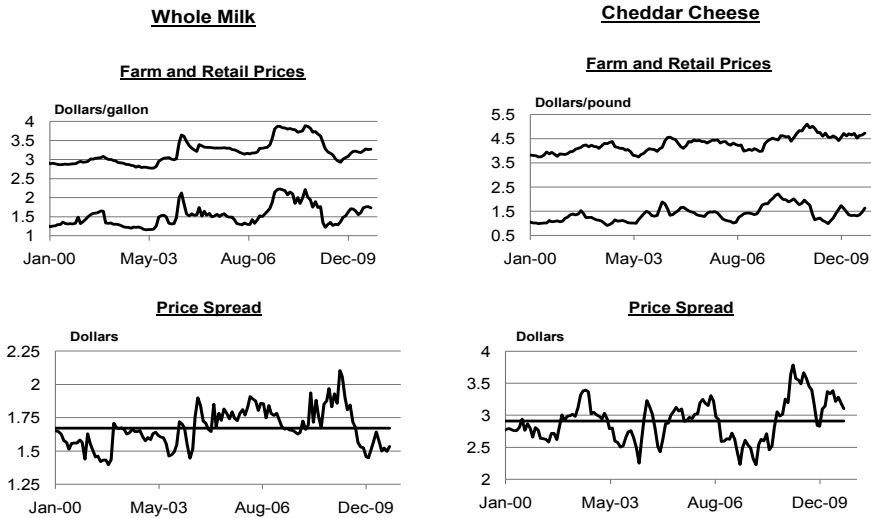
Adjustments must be made to the announced cooperative Class I price to be consistent with the composition of whole milk sold at retail. AMS reports prices for farm milk with a 3.5 percent fat content. By contrast, "whole" milk has a fat content of roughly 3.3 percent.[5] The value of the difference in fat content is subtracted from the plant price. There is also the complication that the Class I price is reported in dollars per cwt, whereas retail prices are reported in gallons. After adjusting for fat content, the conversion is 1:1—that is, a pound of milk at the farm is assumed to equal a pound of whole milk at retail. One gallon of whole milk weighs about 8.6 pounds.

Retail prices for whole milk reported by AMS cover the same areas of the country as does the announced cooperative Class I price. AMS does a very simple, nonstatistical survey of prices at several retail stores in selected cities covered by the FMO program. A city-average price can be calculated from these data.

Given questions about the rigorousness of the sampling methodology underlying retail price data collected by AMS, we also checked for robustness by considering an alternative measure of

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[4] We thank an anonymous reviewer for suggesting this terminology.

[5] Federal standards of identity require "whole milk" to be at least 3.25 percent fat. We assume that whole milk is 3.3 percent fat, as marketers may leave a little extra fat to ensure remaining above the required minimum.

Whole Milk

Farm and Retail Prices

Cheddar Cheese

Farm and Retail Prices

Dollars/gallon

Dollars/pound

Jan-00   May-03   Aug-06   Dec-09

Price Spread

Dollars

Price Spread

Dollars

Note: Horizontal lines in the farm-to-retail price spread graphs indicate average values over the sample period.

Figure 1. Prices and Price Spreads for Whole Milk and Cheddar Cheese, January 2000 to September 2010, Nominal Prices

the retail price of whole milk based on the BLS-reported, nationwide price.

Cheddar Cheese

Cheese markets are more complex than fluid milk markets. Manufacturers may produce barrels or blocks for delivery to firms that age cheese. The length of time depends on the condition of the milk used. If unpasteurized milk is used, the cheese must be aged 60 or more days. These same firms may also cut, shred, wrap, or do some further processing. These intermediaries add value and their costs contribute to the spread between farm and retail prices.

The BLS average price is an appropriate measure of the value of cheddar cheese at retail stores. Unlike fluid milk markets, the market for cheddar cheese is inherently national. Consumers in the Northeast, for example, may purchase cheese manufactured regionally or at a plant in California or Idaho, among other places.

The NASS average price of manufacturing-grade milk can be used to measure the farm value of cheddar cheese. This price represents what farmers received for milk that went into all manufactured dairy products, including cheese. It is not restricted to parts of the nation that participate in the FMO program but represents the value of manufacturing-grade milk in all parts of the nation where this milk is produced. Still, manufacturing-grade milk accounts for only a very small share of all the milk used to produce cheese.

The NASS farm price for manufacturing-grade milk must be adjusted for the composition of cheddar cheese. The Van Slyke formula is widely used for this purpose. This formula estimates the amount of cheese that can be produced from milk given the composition of the milk, the recovery of milk fat in the cheese, and the whey content of the cheese. In this study, we use a specification of the Van Slyke formula provided by the American Jersey Cattle Association (AJCA) on its Website (AJCA 2010). For example, producing one pound

of cheddar cheese requires about 10 pounds of milk that is 3.76 percent milk fat.[6] Because cheese manufacturers may also sell dry whey to recoup some of their costs for this milk, we follow the procedure used by the USDA Economic Research Service (ERS) to further adjust the farm value of the milk for the value of any dry whey that may be produced as a coproduct (USDA ERS 2010).

Since manufacturing-grade milk accounts for only a small portion of the total supply of milk in the United States, we reestimated our model using a farm value measure based on the minimum plant price for fluid-grade milk sold for cheese production in parts of the country in the FMO program. However, unlike the announced cooperative Class I price for fluid milk, this price is only a minimum that does not include any over-order payments. It also excludes some parts of the country that are significant producers of cheddar cheese, such as South Central Idaho.

Farm and Retail Prices in the 2000s

In this study, we examine monthly whole milk and cheddar cheese prices from January 2000 to September 2010. As shown in Figure 1, several cycles of rising and falling prices are evident over this time period. We begin our analysis in 2000 partly because significant changes were made to the FMO program in that year and because we are interested in whether retail prices behaved differently in the latest cycle as compared with the previous few cycles.

Also evident in Figure 1 is an inverse association between the farm-to-retail spread and farm prices. For whole milk, the spread between the plant and retail values averaged $1.67 per gallon between January 2000 and September 2010. The spread reached $2.10 in February 2009 when plant prices, adjusted for the composition of whole milk, were at a low of $1.35.

Retail and farm prices also appear to track more closely for whole milk than for cheddar cheese. Indeed, cheddar cheese retail and farm milk prices often move in opposite directions. For example, as the farm value of one pound of cheddar cheese fell from $1.52 in September 2001 to $1.23 in November 2001, the retail price rose from $4.14 to $4.24.

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[6] In addition to reporting the average farm value of manufactured-grade milk, the NASS also reports that milk grade's average fat content.

Empirical Results on Farm-to-Retail Price Transmission

A preliminary analysis of our data supports the estimation of single-equation ECMs. All price variables are I(1), and one cointegrating vector exists between each pair of retail and farm prices (see Table 1). We also estimated equation (8) to check for Granger causality and tested the null hypothesis that $\sum_{k=1}^{3} \alpha_{2k}\Delta R_{t-k}$ were jointly insignificant (critical value: $F_{(3,100,0.05)} = 2.7$). We failed to reject this hypothesis for both whole milk (F=1.03) and cheddar cheese (F=2.02). Because there is evidence of cointegration, we also tested the null hypothesis that farm prices are unaffected by the ECT (critical value: $t_{0.05} = \pm1.96$). We failed to reject this hypothesis for both whole milk (t= -0.63) and cheddar cheese (t = -0.87). It appears that farm prices were not significantly affected by any shocks to retail prices during the time period under study.

Linear, threshold, and cubic polynomial ECMs were estimated. Each model was initially evaluated with up to five lagged changes in the farm price (i.e., M=N=5). We ultimately chose the number of lags that minimized Akaike's Information Criterion (AIC). Asymmetry in the short-run parameters, α_{1k}^{+} and α_{1k}^{-}, was permitted via the Wolffram-Houck procedure.

Each ECM further included an intercept to allow for changes in marketing costs over time. We also considered proxies for input costs, including changes in the Consumer Price Index for energy (U.S. city average). Also considered were changes in average hourly earnings in manufacturing as a proxy for changes in labor costs in food manufacturing, wholesaling, and retailing. The BLS publishes both data series. However, neither proxy was significant in the models we estimated nor did the inclusion of these proxies significantly affect our results on other variables in the model.

Finally, to account for the amount of time required to transform farm milk into cheddar cheese, we adopt Boetel and Liu's (2010) approach. The long-run price relationship was otherwise specified as in equation (2) with a constant and a slope coefficient.

Each ECM was estimated using Engle and Granger's (1987) two-step method. In the first step, we used ordinary least squares (OLS) to estimate equation (2). In the second step, we used

Table 1. Time Series Properties of Dairy Price Series

Augmented Dickey-Fuller (ADF) Test for Stationarity

	Statistic		Critical Value	
	Whole Milk	Cheddar Cheese	5%	1%
Levels				
Farm Price	-2.43	-2.51	-2.89	-3.49
Retail Price	-2.27	-1.73	-2.89	-3.49
First Differences				
Farm Price	-10.29**	-7.84**	-2.89	-3.49
Retail Price	-6.75**	-10.88**	-2.89	-3.49
Johansen's Cointegration Rank Test, λ_{max} Test Statistic				
H_o: r = 0, H_1: r = 1	18.46*	15.77*	15.67	20.2

Notes: * = 0.05 level (5%) ** = 0.01 level (1%).

All models for the ADF test were estimated in first difference form including a constant term, but not a trend. AIC was used to determine appropriate lag lengths. The null hypothesis of the ADF test is that a variable is not stationary. By contrast, the null hypothesis in Kwiatkowski et al.'s (1992) KPSS test is that a variable is stationary. Both the ADF and KPSS procedures suggested all price series are I(1). Results of the KPSS tests are available upon request.

The cointegrating vector in Johansen's (1995) test included a constant term, but not a trend. The VAR included neither. AIC was used to determine appropriate lag lengths. The null hypothesis is that the number of cointegrating vectors is zero (r=0) against the alternative of one cointegrating vector (r=1). There can exist at most one cointegrating vector between two variables. Both the λ_{max} and λ_{trace} test statistics indicate the presence of one cointegrating vector between each series of farm and retail prices. Values of the λ_{trace} test statistic are available on request.

the lagged residuals from equation (2) for the values of the ECT. OLS was again used to estimate the linear ECM in equation (3) and the nonlinear ECMs in equations (5), (6), and (7). Stock (1987) shows that this method is super-consistent.[7] However, estimates of β in equation (2) have nonnormal, unusual limiting distributions so that inference tests cannot be conducted on these coefficients. Despite this drawback, Engle and Granger's (1987) procedure continues to be widely applied.

Competing ECMs were compared based on measures of model fit, including R^2 and AIC. This is the conventional method for comparing non-nested models. In Tables 2 and 3, we report our results for the ECMs that "best" fit the data.

Whole Milk

Shown in Table 2 are models for whole milk prices with linear and TAR cointegration. These

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[7] Stock (1987) also shows that nonlinear least squares (NLS) may produce better results. However, among the ECMs we estimate for this study, NLS can only be used to estimate the linear and cubic polynomial models. It cannot be used to estimate a threshold ECM. For the sake of consistency, we report results using only Engle and Granger's (1987) two-step method.

Table 2. Estimation Results for Whole Milk

	January 2000 through September 2010 Prices		January 2000 through December 2008 Prices	
	Linear	TAR[a]	Linear	TAR[b]
Intercept	-0.015** (0.004)	-0.016** (0.0039)	-0.012** (0.004)	-0.014** (0.004)
ECT	-0.096** (0.024)		-0.068* (0.026)	
Regime 1 (ECT $\geq \tau$)		-0.222** (0.035)		-0.149** (0.044)
Regime 2 (ECT $< \tau$)		-0.063* (0.026)		-0.058* (0.029)
$\Delta F_t \times D_t^+$	0.645** (0.041)	0.661** (0.04)	0.667** (0.041)	0.681** (0.041)
$\Delta F_t \times D_t^-$	0.147** (0.039)	0.153** (0.037)	0.109* (0.044)	0.122** (0.043)
$\Delta F_{t-1} \times D_{t-1}^+$	0.215** (0.044)	0.205** (0.040)	0.193** (0.044)	0.171** (0.042)
$\Delta F_{t-1} \times D_{t-1}^-$	0.185** (0.045)	0.12** (0.044)	0.217** (0.049)	0.194** (0.049)
$\Delta F_{t-2} \times D_{t-2}^+$	-0.022 (0.042)		-0.029 (0.042)	
$\Delta F_{t-2} \times D_{t-2}^-$	0.1* (0.041)		0.093* (0.045)	
Cointegrating Vector				
Constant	1.684	1.684	1.602	1.602
Farm Price	0.991	0.991	1.047	1.047
Model Fit and Diagnostics				
AIC[c]	-525.414	-539.602	-451.618	-445.742
R^2	0.836	0.844	0.849	0.846
AR(3)[d]	1.365	0.675	1.053	0.115

Note: Standard errors in parentheses, * = 0.05 level (5%); ** = 0.01 level (1%).
[a] Search method described in Enders and Siklos (2001) used to identify threshold value of $\tau = 0.16$.
[b] Search method described in Enders and Siklos (2001) used to identify threshold value of $\tau = 0.14$
[c] Akaike's information criterion (AIC) with a second order correction for sample size. Calculated as AIC = 2p + t[ln(2πSSE/t) + 1 + 2p(p+2)/(n-p-1)
where p = number of unknown parameters and t= number of observations used.
[d] Breusch-Godfrey test with null hypothesis that the first three residual autocorrelations are jointly zero. Critical value of F   = 2.70 is used.
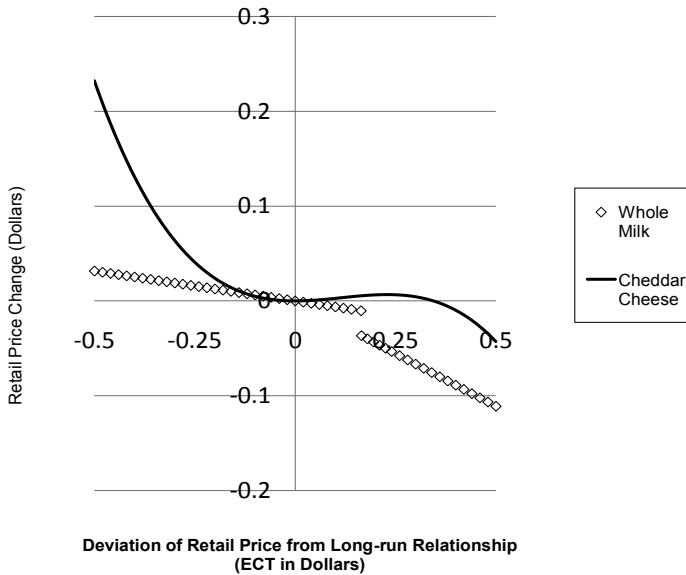
Table 3. Estimation Results for Cheddar Cheese

| | January 2000 through September 2010 Prices | | | January 2000 through December 2008 Prices |
	Linear	Three-regime TAR[a]	Cubic Polynomial	Cubic Polynomial
Intercept	-0.013 (0.012)	-0.012 (0.012)	-0.028 (0.015)	-0.037* (0.015)
ECT	-0.108** (0.031)			
ECT^2			0.379** (0.156)	0.977** (0.283)
ECT^3			-1.101** (0.253)	-2.53** (0.559)
Regime 1 (ECT > C2)		-0.207** (0.057)		
Regime 2 (C1 ≤ ECT ≤ C2)		-0.042 (0.037)		
Regime 3 (ECT < C1)		-0.338** (0.119)		
$\Delta F_{t-1} \times D_{t-1}^+$	0.471** (0.141)	0.48** (0.137)	0.423** (0.139)	0.411** (0.149)
$\Delta F_{t-1} \times D_{t-1}^-$	-0.027 (0.147)	-0.06 (0.143)	-0.066 (0.143)	-0.091 (0.179)
Cointegrating Vector				
Constant	3.499	3.499	3.499	3.332
Farm Price	0.575	0.575	0.575	0.639
Model Fit and Diagnostics				
AIC[b]	-252.471	-258.613	-258.81	-225.963
R^2	0.188	0.253	0.241	0.273
AR(3)[c]	0.192	1.653	0.452	2.29

Note: Standard errors in parentheses, * = 0.05 level (5%); ** = 0.01 level (1%).
[a] Threshold values of C1 = -0.334 and C2 = 0.455 were identified using the grid search described in Goodwin and Holt (1999).
[b] Akaike's information criterion (AIC) with a second order correction for sample size. Calculated as AIC = 2p + t[ln(2πSSE/t) + 1 + 2p(p+2)/(n-p-1)
where p = number of unknown parameters and t = number of observations used.
[c] Breusch-Godfrey test with null hypothesis that the first three residual autocorrelations are jointly zero. Critical value of $F_{0.05,3,100}$ = 2.70 is used.

Note: Illustration for whole milk price is based on the results in Table 2 for a TAR model using data from January 2000 through September 2010. Illustration for cheddar cheese price is based on the results in Table 3 for a cubic polynomial ECM using data from January 2000 through September 2010.

Figure 2. Error Correction Process for Whole Milk and Cheddar Cheese

two specifications best explained retail price changes among the ECMs we estimated.[8] The TAR had a slightly higher R^2 and a lower AIC than the linear ECM. However, as discussed below, these two models are very similar in how retail prices are predicted to respond to plant price shocks. Results for the linear ECM were also more robust.

Both the TAR and the linear ECMs suggest that marketers more fully pass down plant price increases than decreases. When we use a two-regime TAR model, for example, we estimate that the short-run parameter $\hat{\alpha}_{10}^+$ equals 0.661 with a standard error of 0.04. Thus, for a \$0.20 increase in the plant price, we expect retail prices to rise \$0.13 (0.661 x \$0.20) the same month. By
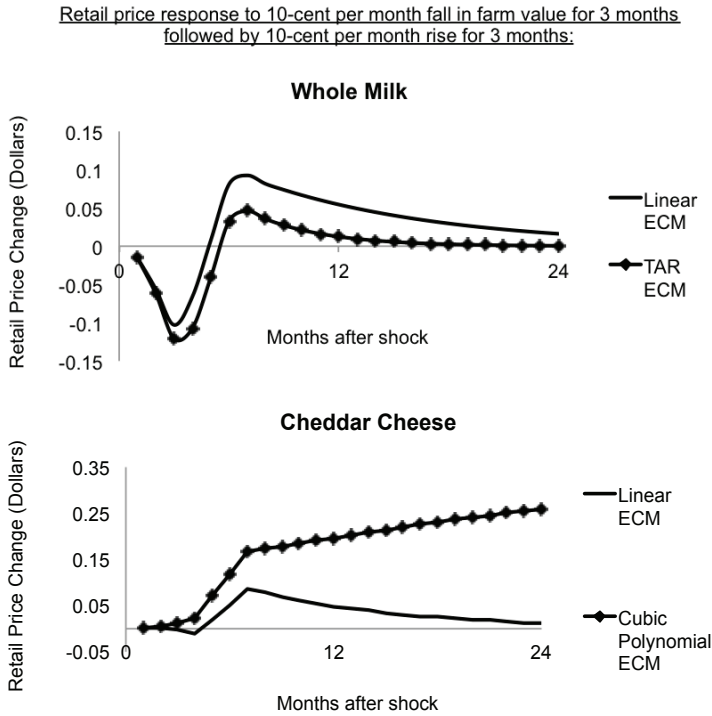
contrast, if the plant price falls \$0.20, we expect retail prices to fall \$0.03 (0.153 x \$0.20) that month. Both shocks are passed down only incompletely ($\alpha_{10}^- < \alpha_{10}^+ < 1$ at the 5 percent level).

Shocks to plant prices are not fully passed down to retail prices even two months after they occur. For our two-regime TAR model, both $\sum_{k=0}^{1} \hat{\alpha}_{1k}^+ = 0.866$ with a standard error of 0.055 and $\sum_{k=0}^{1} \hat{\alpha}_{1k}^- = 0.273$ with a standard error of 0.06 are less than one at the 5 percent level.[9]

The error correction process prevents volatility from growing the spread between retail and plant prices over the long run. This process is depicted graphically for our two-regime TAR model in Figure 2, which we base on a similar figure in Meyer and von Cramon-Taubadel (2004). The

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[8] Results for the cubic polynomial ECM were essentially identical to those for the linear ECM since both ECT^2 and ECT^3 were statistically insignificant. These results and those for an M-TAR model are available upon request.

[9] Variance of $\sum_{k=0}^{1} \hat{\alpha}_{1k}^-$, for example, calculated as the sum of the variances of $\hat{\alpha}_{10}^-$ and $\hat{\alpha}_{11}^-$ plus twice the covariance of these parameter estimates.

Retail price response to 10-cent per month fall in farm value for 3 months
followed by 10-cent per month rise for 3 months:

Whole Milk

Cheddar Cheese

Note: Simulations results based on estimated models in Tables 2 and 3.

Figure 3. Impulse Response Functions

existing deviation from the long-run relationship, ECT_t, is plotted against the expected change in retail price in the next period, ΔR_{t+1}, all else constant. For whole milk prices, the speed of adjustment ($\hat{\gamma}_2 = -0.063$) is constant for values of the ECT below $0.1643, which is the threshold identified using the search procedure in Enders and Siklos (2001). For example, when R_t exceeds its expected value by $0.15, we expect ΔR_{t+1} to be $0.01 (-0.063 x 0.15) less than otherwise. The speed of adjustment ($\hat{\gamma}_1 = -0.222$) is faster when retail prices exceed their expected value by $0.1643 or more. If the value of the ECT were $0.40, then we would expect ΔR_{t+1} to fall $0.09.

Simulations are useful to illustrate the response of retail prices to a plant price shock, including changes that occur through both our model's short-run parameters and its error correction process. We simulated the change in the retail price if the plant price fell 10 cents per month for three

months and then rose 10 cents per month for the next three months. Because we focus on the behavior of retail prices in 2009 after plant prices retreated from highs reached in 2007/2008, we adopt each variable's history up to a month during that high period (April 2008). Notably, when using a nonlinear model, Koop et al. (1996) warn that the choice of history can affect simulation results. For our TAR model, the ECT will fall into either the first or second regime depending on whether R_t was already below or above its expected value in the month prior to the shock. However, when we conducted our simulation using alternative histories, our impulse response function (IRF) for whole milk changed little.

Simulations using both our TAR and linear ECM show that a decrease in plant prices leads to a less-than-proportional decrease in retail prices (Figure 3). The retail price of whole milk falls only about 10 cents to 12 cents after plant prices

have fallen 30 cents over three months. The spread is being stretched. Next, as plant prices start to rise at the rate of 10 cents per month, retail prices reach above their starting level. They then fall and, ultimately, this episode of volatility has no long-run impact on the retail price or the spread.

Not only are predictions based on the TAR and linear ECMs very similar, but also our results on the linear model are more robust. We reestimated our model using BLS-reported retail prices and also using a specification that excludes the intercept term. In both cases, the TAR specification no longer outperformed the linear ECM.[10] Our estimation results for the linear ECM were little affected. Thus, for the case of whole milk prices, we did not gain additional insight on the nature of price transmission by considering more general forms of the error correction process, f(ECT), than a simple linear specification.

Controlling for volatility in plant prices, we also find no evidence of growth in the spread between retail and plant prices between January 2000 and September 2010. When included in the model, the intercept term in our ECM was negative. While some input costs may have gone up, Hausman and Leibtag (2007) demonstrate that downward pressure is also being put on retail food prices as Walmart expands its share of the retail grocery market.

Finally, using only data from 2000 through 2008, we reestimated our TAR and linear ECMs. These results appear in the final two columns of Table 2. Although a Chow test reveals a change in parameter values between January 2000 and September 2010, we again find that plant price decreases are incompletely and asymmetrically passed down:

$$\sum_{k=0}^{N} \widehat{\alpha}_{1k}^{-} < \sum_{k=0}^{M} \widehat{\alpha}_{1k}^{+} < 1.^{[11]}$$

A linear ECM still performs well as measured by R^2 and AIC.

Cheddar Cheese

Estimated price transmission models for cheddar cheese prices are presented in Table 3. In the case of this dairy product, we found that the three-regime threshold and cubic polynomial ECMs have the highest R^2 and the lowest AIC among the models we estimated.[12] As discussed below, these two models predict retail prices to respond to farm price shocks very differently than a simple linear ECM predicts. Results were also robust.

Because we allow for production lags using Boetel and Liu's (2010) approach, changes in the farm price require at least one month to affect prices farther down the marketing chain. Consider the cubic polynomial ECM. We find that $\widehat{\alpha}_{11}^{+} = 0.423$ with a standard error of 0.139 and that $\widehat{\alpha}_{11}^{-}$ is not different from zero (third column of results in Table 3). Following a \$0.20 increase in this month's farm price, we would therefore expect next month's retail price to be \$0.08 (0.423 x \$0.20) higher. If the farm price falls \$0.20, we would expect no impact at retail.

The error correction process limits growth in the spread over time due to volatility. However, based on results for both the three-regime threshold and cubic polynomial ECMs, we also find that retail prices can deviate somewhat from their long-run relationship with farm prices without being driven back towards that relationship. Shown in Figure 2 is the error correction process for our cubic polynomial ECM. There is a middle range over which ΔR_{t+1} is not decreasing in the ECT.[13] As discussed above, if firms incur fixed costs for adjusting their levels of output, then there can exist a range of values for the ECT over which the speed of adjustment parameter is zero. The error correction process is significant for values of the ECT outside this middle range. Here, in our study of cheddar cheese prices, if the retail price were \$0.40 below its expected value, all else constant, we would expect the retail price to increase next month by \$0.13 (0.379 x (-0.40)^2 – 1.101 x (-0.40)^3).

As we did for whole milk prices, we conducted simulations using our results for the linear ECM and a more general ECM. For the case of cheddar cheese prices, we also selected our cubic polynomial model for simulation. We then examined how the retail price would behave if farm prices fell 10 cents per month for three months and then rose 10 cents per month for the next three months.

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[10] Results are available on request.

[11] Chow test results are available upon request.

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[12] Results for a two-regime TAR and M-TAR model are available on request.

[13] For our three-regime threshold model, this middle range of values is defined by C1 and C2 that, using the grid search described in Goodwin and Holt (1999), are C1 = -0.334 and C2 = 0.455.

We again begin our simulation with each variable's history up to April 2008. Importantly, this choice of history meant that the starting value for the error correction term ($ECT_t = -0.04$) fell into the middle range of values for which our cubic polynomial ECM imposes no significant error correction process.

Simulation results for cheddar cheese prices depend on the specification of the ECM. Results are shown in the bottom of Figure 3. It is clear that farm price decreases over the first three months are not passed down to retail store prices. Retail prices do increase as farm prices recover over the next three months. Whether retail prices thereafter return to their previous level depends on the model used for simulation purposes. The linear ECM predicts that retail prices will shortly begin the process of reverting back towards their previous level. However, when using the cubic polynomial ECM, we find that retail prices remain about $0.25 higher as a result of farm price volatility. Only if still further volatility were to drive retail prices farther enough away from their long-run relationship with farm prices would the error correction process become significant. Consistent with this result and Koop et al.'s (1996) critique of the IRF, when we conducted our simulation beginning with a history in which the value of the ECT was far enough from zero, we found that retail prices did return to their previous level.

Our results in Figure 3 using the cubic polynomial ECM are also consistent with the tendency shown in Figure 1 for retail and farm prices to track more closely for whole milk than for cheddar cheese. However, if we only had considered a linear ECM in this study, we would have instead predicted retail prices for whole milk and cheddar cheese to respond much more similarly to price volatility. This underscores the importance of considering alternative specifications of the error correction process when studying price transmission.

For a manufactured product, we prefer the cubic polynomial ECM to the three-regime threshold ECM. As discussed earlier, the former's interpretation allows for firm heterogeneity. Milk used to make cheddar cheese may pass from the farm gate to a first manufacturer and maybe even to a second manufacturer before arriving at a retail store. Firms at each of these stages of the marketing chain may respond differently to input price changes because, for example, they have different costs for adjusting their production levels.

Results for estimated price transmission models were also robust. We reestimated our cubic polynomial ECM using a measure of farm value based on the minimum plant price for fluid-grade milk sold for cheese production in parts of the country in the FMO program. We also reestimated our model without the intercept term. In both cases, similar results on the short-run parameters and on the error correction process were obtained.[14]

Were movements in retail prices in 2009 consistent with how farm price shocks affected retail prices earlier in the decade? We reestimated our ECM with cubic polynomial adjustment using only data from 2000 through 2008. Results are presented in the fourth column of Table 3. Parameter estimates appear similar and, in fact, a Chow test fails to find that results for the abridged and full data sets are different.[15]

Discussion

Dramatic shocks to farm prices, such as those witnessed in the 2000s, can cause farm groups, industry pundits, and policymakers to become upset about retail price movements, or the lack of them. Farm and retail prices represent the endpoints of a supply chain moving milk from producers to consumers, and price transmission describes how changes in prices at one end of the supply chain are "seen" at the other. When farm milk prices decrease with little evidence of a corresponding change in retail prices, it is widely heard that dairy farmers are at a disadvantage.

Was the behavior of retail prices in late 2008 and 2009 unusual? There is no doubt that dairy farmers faced a unique cost-price squeeze during these years of low farm prices and high feed costs. Retail prices were also a source of frustration. We find that farm and retail prices move together in a long-run relationship for both whole milk and cheddar cheese. There is likewise no evidence that farm price volatility increases the farm-to-retail price spread for either dairy product over the long run. However, milk price shocks are transmitted asymmetrically to retail store prices so that profits may be gained or lost in the short run.

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[14] Results are available on request.

[15] Chow test results are available upon request.

Frustration over asymmetry in price transmission may persist as long as price volatility remains a recurrent feature of U.S. dairy markets. With econometric results being susceptible to a researcher's choice of model, it is important to consider alternative model specifications. In this study, considering only a linear or a two-regime threshold ECM would have been sufficient for our analysis of whole milk prices, but not for cheddar cheese prices.

Upstream price shocks affect retail prices for whole milk and cheddar cheese differently. The sum of the short-run parameters associated with an increase in the plant price is greater for whole milk, $\sum_{k=0}^{1} \widehat{\alpha}_{1k}^{+} = 0.866$, than it is for the farm value of cheddar cheese, $\widehat{\alpha}_{11}^{+} = 0.423$. Similarly, the sum of the short-run parameters for a decrease in the plant price is greater for whole milk, $\sum_{k=0}^{1} \widehat{\alpha}_{1k}^{-} = 0.273$, than it is for the farm value of cheddar cheese, $\widehat{\alpha}_{11}^{-} \approx 0$. Overall, firms pass down a greater proportion of input price increases and decreases for whole milk.

Another key difference is in the nature of the error correction process. For whole milk, we find that this process is significant over all values of the ECT. For cheddar cheese, by contrast, retail prices can deviate somewhat from their long-run relationship with farm prices without being driven back towards that relationship.

Product characteristics may contribute to the differences we identify. Fluid milk moves relatively quickly from the farm gate to a retailer. Plant prices may still be a variable cost when the milk is sold to a retailer. And, of course, processors will not make products unless they receive prices that are sufficient to cover variable costs. If farm prices rise (fall), processors can reduce (expand) production, which may soon lead to higher (lower) retail prices.

Cheddar cheese manufacturers may instead deliver barrels or blocks to firms for further processing. One of these firms may then negotiate prices with a firm still further downstream without regard to either the current farm price of milk or the price paid for the milk now in the cheese. Those costs are sunk. The milk was bought, possibly, more than one month ago, made into cheese, and aged. Instead, if farm prices were to increase, manufacturers may reduce production. The total supply of cheddar cheese would then start to decrease, and firms would subsequently be able to negotiate higher prices from their customers.

However, if some firms along this supply chain face costs for adjusting their production levels then, following Balke and Fomby's (1997) theory, this process would not be a continuous one. Firms would instead wait until input prices had changed enough to outweigh adjustment costs.

Further research is needed to better understand the link between price transmission and marketing practices at each stage of milk and dairy foods production and marketing chains. In particular, public data are available on wholesale cheddar cheese prices and inventories. These data might be used to understand where in this chain the asymmetries identified in this study exist and what role, if any, inventory management on the part of firms plays.

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