AGRICULTURAL ECONOMICS

Agricultural Economics 47 (2016) 193–203

Modeling price transmission between farm and retail prices: a soft switches approach

William Hahn[a,*], Hayden Stewart[a], Donald P. Blayney[b], Christopher G. Davis[a]

[a]*United States Department of Agriculture, Economic Research Service, Washington, DC, USA*
[b]*New Mexico State University Las Cruces, NM, USA*

Received 28 January 2015; received in revised form 2 September 2015; accepted 14 October 2015

Abstract

Vector error correction models (VECM) are used to model price transmission when farm and retail prices are cointegrated. To allow for nonlinearity in the cointegration process, researchers may specify thresholds to break the error correction process into regimes according to whether the retail price is above, below, or close to its equilibrium value given farm prices. However, because the coefficients in a VECM can change when there is movement from one regime to another, the model can be discontinuous. This implies sudden, "hard" regime changes. In this study, we extend the threshold VECM to include features of smooth transition autoregression (STAR) models. Our approach allows for gradual, soft regime changes. An empirical application to retail cheese and farm milk prices is presented.

JEL classifications: C3, C4, Q1

Keywords: Smooth transition autoregressive; Price transmission; Asymmetry; Cheddar cheese; Mozzarella cheese

1. Introduction

A perennial. issue in agricultural economics is the relationship between retail food prices and the prices farmers receive for their products. The U.S. Department of Agriculture (USDA) has published economic statistics on these relationships dating back to at least 1913 (USDA, 1945). For years, a question of particular interest to researchers, policymakers, and farm groups alike is whether farm product price shocks are transmitted "symmetrically" or "asymmetrically" to retail food prices. The American Farm Bureau Federation (AFBF) asserts that, when the farm price of milk increases, marketers quickly pass the increases on to consumers. By contrast, when the farm milk price declines, retail prices are adjusted downward slowly in order to increase marketers' profits (AFBF, 2003). In general, there is a suspicion that asymmetry of price transmission contributes to lower farm prices. In 2010, special hearings sponsored jointly the U.S. Department of Justice (USDOJ) and the USDA were held where price transmission and other related concerns were addressed (USDOJ and USDA, 2010).

In a 2004 survey article, Meyer and von Cramon-Taubadel note that vector error correction models (VECM) dominate the applied literature on asymmetric price transmission. VECMs capture the tendency of cointegrated variables to revert to their long-run relationships after a shock. The speed of adjustment may be allowed to differ according to whether the retail price is substantially above, below, or close to its equilibrium value given the farm price. To allow for this type of nonlinearity in the cointegration process, researchers may specify thresholds that break the error correction process into distinct regimes, each of which may have different speeds of adjustment. In the applied literature, threshold VECMs (TVECM) are generally estimated in two steps, require cointegrated data, allow for 2 or 3 different price-transmission regimes, and are used to model the relationship between a single retail price and a single farm price. However, researchers seek still more flexible and general models.

Hassouneh et al. (2012) propose extending the TVECM to include features of smooth-transition autoregressive (STAR) models. (The STAR approach also has been applied to

*Corresponding author. Tel: +(202) 694–5175; fax:+(202) 245–4779. *E-mail address*: whahn@ers.usda.gov (W. Hahn)

Any opinions, findings, recommendations, or conclusions are those of the authors and do not necessarily reflect the views of the Economic Research Service or New Mexico State University. The analysis, findings, and conclusions expressed in this paper also should not be attributed to either Nielsen or Information Resources, Inc. (IRI).

Data Appendix Available Online

A data appendix to replicate main results is available in the online version of this article.

DOI: 10.1111/agec.12222

vector systems [Djik et al., 2002]). We follow Hassouneh et al.'s suggestion (2012) and use STAR approaches to model price transmission. Based on the present literature, this study is perhaps the first to take advantage of STAR models in this manner.

The model is estimated in a single step and does not require cointegration. The empirical application presented includes asymmetric and threshold interactions among retail prices for two types of cheese and the farm value of milk. We build a 3-equation model for the retail prices of Cheddar and Mozzarella cheeses, and the farm price of milk used to make cheese. Marketers commonly transform individual farm products such as milk, cattle, hogs, and poultry, among others, into multiple retail food products. The STAR approach allows us to analyze more regimes than is practical in a TVECM. We have 3 regimes for each of our 3 prices, 9 in total.

2. Why study dairy prices? Data and descriptive statistics

Production of natural cheese is the major use of milk produced in the United States. The quantity of milk used in natural cheeses grew steadily from about 68 billion pounds in 2000 to just over 86 billion pounds in 2011. According to the USDA Economic Research Service (ERS), annual sales of fluid milk and cream products hovered between 59 and 62 billion pounds of milk during that time. Thus, in 2011, fluid milk, cream, and cheese together absorbed three quarters (75.2%) of total U.S. milk production. American (Cheddar) styles dominated cheese production until the mid 1980s. "Other than American" styles are now more important, especially Italian types like Mozzarella.

Data on the farm value of milk are available from USDA's Agricultural Marketing Service (AMS) which administers the Federal Milk Market Order (FMMO) system. Through its administration of this program, the AMS sets minimum prices according to the type (class) of product a milk processing plant produces. The "Class III" milk price represents the minimum price paid for milk used to make cheese.

How much Class III Milk is needed to make a pound of Cheddar and Mozzarella? Milk leaving the farm has two economically significant components—fat solids and skim solids—each with its own farm price. One hundred pounds of U.S.-produced farm milk typically contains, on average, approximately 3.7 pounds of fat solids and 8.6 pounds of skim solids. Cheddar and Mozzarella contain relatively more fat solids and less skim solids than fluid milk. Using the Van Slyke formula, the amount of Class III milk in a pound of each type of cheese is calculated, as well as the amount of skim solids left over.[1] Two farm prices were created originally, one for Cheddar and one for Mozzarella, based on the Class III price and the butterfat differential. However, the two were nearly perfectly correlated, >99.9%. The cost of farm milk in a pound of Mozzarella is approximately 9.8% higher than the cost of farm milk to make Cheddar, which is the same relationship used in the model.

Movements in farm-level prices are compared with movements in retail prices. Past studies for cheese have used retail price data from the U.S. Department of Labor's Bureau of Labor Statistics (BLS). The BLS reports retail price data for a wide selection of food items as a part of its Consumer Price Index (CPI) program. These retail prices include all-city average prices charged by supermarkets and other retail food outlets for one pound of Cheddar cheese.

The National Consumer Panel (NCP) is another source of retail food prices. Information Resources, Inc. and Nielsen jointly maintain a panel of households that is demographically and geographically representative of the continental United States. Participating households keep a scanner in their home. After a shopping occasion, panelists use these scanners to record their purchases including the quantities bought and the amount of money paid. For this study, we used 2000–2012 NCP data. This allows us to examine prices for almost any dairy product, including Mozzarella cheese, as well as Cheddar.

Monthly average retail and farm values for Cheddar and Mozzarella cheese between 2000 and 2012 can be seen in Fig. 1. These values appear to move together over the long run, though not necessarily in the short run. It is also clear that retail values for the two cheeses move essentially in tandem.

3. Previous studies

Price transmission is *asymmetric* when the speed and/or completeness of adjustment depends on the direction of the adjustment. For example, retail food prices may adjust more quickly to farm price increases than to farm price decreases. Meyer and von Cramon-Taubadel (2004) identified two major approaches to modeling (potentially) asymmetric price transmission. The first, based on Wolffram (1971), was popular in the 1970s and 1980s. Kinnucan and Forker (1987) used a Wolffram-based approach in their seminal study of price transmission in dairy markets, finding that it is asymmetric for dairy products including cheese.

von Cramon-Taubadel (1998) criticized Wolffram-based approaches as being inconsistent with cointegration. The second approach, which has dominated the literature in recent years, is based on Engel and Granger's (1987) error correction model—or in the terminology of this paper, the vector error-correction model (VECM). The VECM is designed to deal with prices in related markets that often are cointegrated. Milk-price transmission studies using VECM frameworks include Capps and Sherwell (2007), Awokose and Wang (2009), and Stewart and Blayney (2011).

Engel and Granger developed a 2-step procedure for estimating a simple VECM that has since been expanded to accommodate thresholds. Here we outline the basic VECM[2]

[1] Formulae and worksheets deriving farm value of each product are available upon request.

[2] Unless otherwise noted, the 1987 work by Engel and Granger is the source for statements in the next several paragraphs.

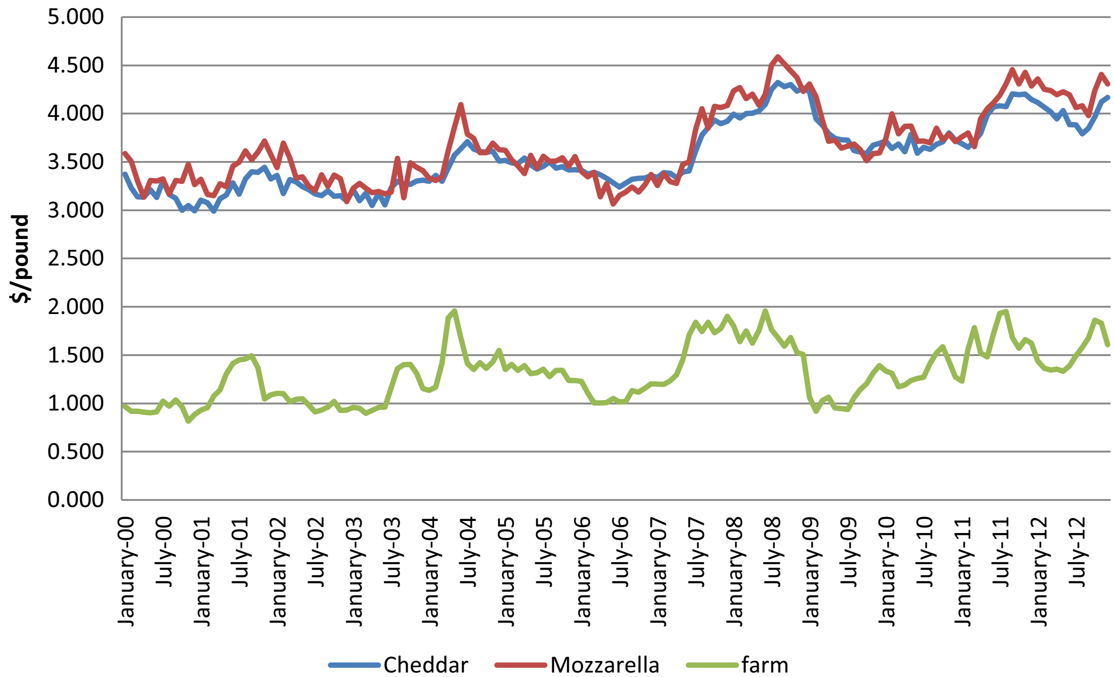

Fig. 1. Prices for retail cheeses and the farm cost of milk to make 1 pound of cheddar.

using a simple example with two endogenous variables. One implication of cointegration is that while the two endogenous variables each have a unit root, a linear combination of them exists that does not have a unit root. For example, consider the following equation:

$$y_{2,t} = \theta_2 y_{1,t} + u_{2,t}, \tag{1}$$

where θ_2 is a coefficient that determines the long-term relationship between $y_{2,t}$ and $y_{1,t}$, and $u_{2,t}$ is the first-stage error term. (Numerical subscripts are attached to θ and u_t because the implication also applies to more than 2 endogenous variables, provided that all the terms are cointegrated). The error term in Eq. (1) has a mean of 0 but will generally exhibit some autocorrelation. Error-correction comes into play when large errors in period t are followed by smaller errors (in absolute value) in the following time periods.

If the data are cointegrated, one can estimate the first-order regression in Eq. (1) and obtain a consistent estimate of θ_2. Testing for cointegration involves testing the individual endogenous variables for unit roots, and then estimating Eq. (1) and testing the error terms from that regression for unit roots. If the endogenous variables have unit roots, but not the estimated errors, the data are cointegrated.

Engle and Granger wrote the VECM as:

$$\Delta y_{j,t} = \sum_i \sum_l \Delta y_{i,t-l}\beta_{j,i,l} + \pi_j u_{2,t-1} + \varepsilon_{j,t},$$
$$\text{where } j = 1, 2, i = 1, 2, l = 1, \ldots, L., \tag{2}$$

The model has "L" lags of endogenous variables and the $\beta_{i,j,l}$ are the coefficients of the ECM. The term π_j multiplies the lagged, estimated first-stage error term and $\varepsilon_{j,t}$ is a random error term with mean 0. For most applications analysts assume that the $\varepsilon_{j,t}$ are independently and identically distributed over time—an assumption that we make as well. Additional assumptions about the error distribution are not needed for estimating VECM or TVECM. When the lagged error is negative, $y_{1,t\text{-}1}$ is large relative to $y_{2,t\text{-}1}$. To get the prices closer to their long-run relationship, π_1 has to be positive and π_2 has to be negative.

The 2-step procedure of Engel and Granger involves estimating Eq. (1) or its equivalent and then using the lagged error from that step to estimate Eq. (2). Shortly after the Engel and Granger article was published, Johansen (1988) demonstrated that the ECM can be estimated in one step. He wrote the ECM as:

$$\Delta y_{j,t} = \sum_i \sum_l \Delta y_{i,t-1}\beta j, i, l + \sum_i y_{i,t-1}\beta_{j,i,0} + \varepsilon_{j,t}. \tag{3}$$

Johansen demonstrated that unit roots implied nonlinear restrictions on the lagged-level terms' coefficients, $\beta_{j,i,0}$. One could test for unit roots by comparing the likelihood of the estimates with the unit-root restrictions on the $\beta_{j,i,0}$, to those of an unconstrained mode l. Johansen also derived the asymptotic distributions for these unit root tests.

The "classic" TVECM continues to be estimated in two steps (e.g., Balke and Fomby, 1997; Stewart and Blayney, 2011).

In TVECM specifications, the coefficients of the VECM shift depending on the value of the lagged error terms. A typical, 3-regime TVECM can be written:

$$\Delta y_{j,t} = \sum_i \sum_l \Delta y_{i,t-1}\beta_{j,i,l,B} + \pi_{j,B}u_{2,t-1} + \varepsilon_{j,t}\ , \quad \text{when}\, u_{2},_{t-1} < \alpha_B\ ,$$

$$\Delta y_{j,t} = \sum_i \sum_l \Delta y_{i,t-1}\beta_{j,i,l,W} + \pi_{j,W}u_{2,t-1} + \varepsilon_{j,t}, \quad \text{when}\, \alpha_B \le u_{2,t-1} \le \alpha_A,$$

$$\Delta y_{j,t} = \sum_i \sum_l \Delta y_{i,t-1}\beta_{j,i,l,A} + \pi_{j,A}u_{2,t-1} + \varepsilon_{j,t}, \quad \text{when}\, \alpha_A < \upsilon_{2,\tau-1}. \tag{4}$$

In this 3-regime model, the number of coefficients has basically been tripled and another set of subscripts: *B*, for Below, *W* for betWeen, and *A* for Above have been added. We also identified two threshold terms, α_B and α_A.

Greb et al. (2012) provide more detail on how the TVECM is estimated and discuss some problems in its estimation. While their basic model has intercepts and exogenous variables, this study uses a more parsimonious specification for the purpose of simplifying the equations.

The "between" case is of particular interest. Balke and Fomby (1997) originally proposed that the error correction process may contain a middle zone they called the "zone of inaction" in which the cointegrating relationship is inactive, possibly because fixed costs prevent economic agents from altering their behavior. In this zone, the two endogenous variables are close enough to their equilibrium relationship that we would expect minimal (or even zero) amounts of error correction; π_{jW} will be 0 for both *j*. The cointegrating relationship again becomes effective when the system is far enough from equilibrium (i.e., in the Above and Below zones).

Because all the coefficients in Eq. (3) change when there is movement from one regime to another, the general TVECM can be discontinuous at its threshold levels. Some analysts find these discontinuities implausible. Mainardi (2001), who investigated international wheat prices over the period 1973–1999, argued that United States and Australian prices tend to follow very similar movements and long-run trends though price gaps are not unusual because transportation and other transactions costs may limit arbitrage opportunities. That is, when price differences do not exceed transaction costs, arbitrage is not profitable and a zone of inaction may exist.

Moreover, if traders and investors respond heterogeneously to changes in transaction costs, especially to changes occurring in the proximity of the thresholds, then the threshold points become "blurred." Mainardi (2001) concludes that gradual regime changes would make more sense than sudden regime switches. The estimation of smooth transition, nonlinear error-correction models would also be preferred to a TVECM. One approach he suggested is the use of polynomial adjustments:

$$\Delta y_{j,t} = \sum_i \sum_l \Delta y_{i,t-1}\beta_{j,i,l} + \pi_{1,j}u_{2,t-1} + \pi_{2,j}u_{2,t-1}^2 + \pi_{3,j}u_{2,t-1}^3 + \varepsilon_{j,t} \tag{5}$$

developed by von Cramon-Taubadel (1996) and Escribano (2004).

In their study of fluid milk and cheese prices, Stewart and Blayney (2011) compared results for various ECMs. They found that both a three-regime TVECM and a cubic polynomial VECM better explained movements in cheese prices than either a two-regime threshold or a single-regime (linear) model. However, they preferred the cubic polynomial VECM on theoretical grounds.

Milk used to make cheese may pass from the farm gate to a first manufacturer who may deliver barrels or blocks to a second manufacturer for further processing. One of these firms may then negotiate prices with a firm still further downstream. The prices downstream firms negotiate may bear no relationship to either the current farm price of milk or the price paid for the milk now in the cheese. Those costs are sunk. 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. Total supply of cheese would then start to decrease, and firms would subsequently be able to negotiate higher prices from their customers.

Moreover, if different firms at different stages of the marketing chain respond differently to input price changes because, for example, they have different costs for adjusting their production levels, then, following Balke and Fomby's (1997) theory, this process would not be a continuous one.

4. Our "soft-switched" approach

As noted previously, this study follows the approach suggested in Hassouneh et al. (2012) to use a STAR-type modeling approach for analyzing asymmetric price transmission and the effects of threshold behavior. STAR models are written with switches. What do we mean by switches? The model uses switches to determine which sets of coefficients are used in which time periods. The TVECM in Eq. (4) is a switching regression; however it is not written with switches. We could have written Eq. (4) using a set of 0–1 switches defined as follows:

$$s_{t,B} = \begin{cases} 1 & u_{2,t-1} < \alpha_B \\ 0 & \text{otherwise} \end{cases}, \quad \text{define the "below" switch,}$$

$$s_{t,W} = \begin{cases} 1 & \alpha_B \le u_{2,t-1} \le \alpha_A \\ 0 & \text{otherwise} \end{cases}, \quad \text{the " between" switch,}$$

and,

$$s_{t,A} = \begin{cases} 1 & \alpha_A < u_{2,t-1} \\ 0 & \text{otherwise} \end{cases} \quad \text{the "above" switch.} \tag{6}$$

Note that each time period will have 2 of the 3 switches set to 0 and 1 of the 3 set to 1. The switched version of Eq. (4) is Eq. (4s) below:

$$\Delta y_{j,t} = \sum_K s_{t,K} \left(\sum_i \sum_l \Delta y_{i,t-l} \beta_{j,i,l,K} + \pi_{j,K} u_{2,t-1} \right) + \varepsilon_{j,t}$$
$$\text{where } K = \{B, W, A\}, \tag{4s}$$

The switches defined in Eq. (6) are either 0 or 1. We will call these 0,1 switches "hard switches." The STAR-based switches are continuous variables on the closed interval [0,1], which we refer to as "soft switches." Soft switches will give us a continuous model; however, we are going to specify our model to be continuous even if it were hard-switched.

TVEC and STAR models are often specified as pure time series models; the only exogenous variables in many specifications are intercepts and/or seasonal variables. Our basic model incorporates a more complete set of explanatory variables. The vector of exogenous variables is denoted as X_t, where "t" is a numbered index for a month. As before, the endogenous variables are written in scalar form as $y_{t,i}$. Here the index "i" is defined over three prices: farm, Cheddar, and Mozzarella. Although the basic model has exogenous variables, it does have a limited lag structure and rests on specification of a vector, partial adjustment model. We refer to the model as the "Cheese Price Model" or CPM.

The initial assumption is that a set of exogenous variables determines the full-adjustment or "target" value of the prices. In our model, as in a TVECM, there may be only partial adjustment in the short run, with prices moving closer to their target values-relationships over time. Our basic, partial–adjustment relationship without switches is:

$$\Delta y_{i,t} = \sum_j \beta_{i,j} (X_t C_j - y_{j,t-1}) + e_{i,t}, \ or$$

$$\Delta y_{i,t} = D_i X_t - \sum_j \beta_{i,j} y_{j,t-1} + e_{i,t}, \ where \ D_i = \sum_j B_{i,j} C_j. \tag{7}$$

Compared with the VECM in Eq. (4), the partial–adjustment relationship in Eq. (7) has exogenous variables not included in Eq. (4) but has only a single lag. In Eq. (7), C_j is a vector of coefficients that determine the target value for price j. The online Appendix outlines our exogenous variables and discusses how we imposed "markup" relationships between the farm price and the two retail cheese prices.

One reason we begin with Eq. (7) is that the form resembles the VECM; it has changes in the endogenous variables on the left-hand side and lagged endogenous variable levels on the right. Also, note Eq. (4) has lagged price changes but no exogenous variables. Some of our "experimental" versions of the model in Eq. (7) do have lagged price changes; however, we found much better fit by specifying the error term as a second-order VAR.

The basic relationship in Eq. (7) is linear in its coefficients, albeit with nonlinear coefficient restrictions. Note that the current price changes are negatively related to the lagged dependent variable coefficients. It is expected that all the own-price terms, β_{ii}, are positive. Large lagged endogenous prices are likely to be larger than their target values—implying that the price needs to decrease. If the cross-price terms, β_{ij}, $i{\neq}j$ are positive, when price j is above its target and needs to decrease, price i also decreases. A negative β_{ij} implies that high lagged prices for j tend to lead to higher current prices for i. One could impose and test unit roots on Eq. (7) using Johansen's approaches and restricting the matrix made of the β coefficients.

Although this type of model is called a partial adjustment model, it may exhibit "complete" or even "over adjustment" depending on the magnitude of β. If β_{ii} is 1 and the two β_{ij} are 0, complete adjustment is achieved. $\beta_{ii} < 1$ implies partial adjustment, and $\beta_{ii} > 1$ implies over adjustment. The cross-price effects can lead to complex[3] patterns.

All prices are deflated using the U.S. Department of Commerce, Bureau of Economic Analysis (BEA) personal consumption deflator. Variables that measure marketing costs are simple functions of time: the intercept, trend and long harmonics. Deflating the prices and using simple functions of time as cost shifters makes the markup from farm to retail prices a function of the general price level.

4.1. Adding switches to the model

The CPM is specified to nest the partial adjustment model defined in Eq. (7). The switches in the model are driven by the predictable, nonerror component of Eq. (7). To make the switched model equations shorter, the term $f_{i,t}$ is defined as:

$$f_{i,t} = D_i X_t - \sum_j \beta_{i,j} y_{j,t-1} \tag{8}$$

which is the right-hand side of Eq. (7) without the error term. Instead of 3 regimes for the whole system, we have 3 regimes for each equation, and each equation has its own set of thresholds.

We specified our example TVECM with three sets of coefficients defined over {below, between, above}, {b,w,a} for short. A 3-regime STAR is generally specified using 2 switches; our coefficient set is defined as {linear, below, above} or {l, b, a}. The subset {below, above} or {b,a} will be called the "outside"

[3] This includes both complicated and complex numbers, i.e., c+/−di. Complex roots imply a cyclical type of adjustment.

subset—meaning outside the thresholds. Our switching model can now be written as:

$$\Delta y_{i,t} = \lambda_{i,l} f_{i,t} + s_{t,i,b}\lambda_{i,b}(f_{i,t} - \alpha_{i.,b}) + s_{t,i,a}\lambda_{i,a}(f_{i,t} - \alpha_{i.a}) + e_{i,t}. \tag{9}$$

In Eq. (9), the λs are adjustment parameters and now the switches are triple-subscripted. The αs are double-subscripted now as they vary by their position and the equation. For each equation $\alpha_{i,b} \leq \alpha_{i,a}$.

Notably, λ, β, and α are not identified for either the hard-switched or our soft-switched model. For instance, it is possible to double β and α in any equation, halve its λ, and get the exact same behavior for the $\Delta y_{i,t}$. The following arbitrary restriction will identify each equation:

$$\lambda_{i,l} + (\lambda_{i,b} + \lambda_{i,a})\frac{1}{2} = 1. \tag{10}$$

In addition to the restriction imposed by Eq. (10), all the λs are required to be positive. This assists us in 2 ways. First, if all λs in an equation are positive, then the change in the endogenous variable is monotonic in *f*. Second, it is still possible to have monotonic adjustment with a negative λ. However, a stronger adjustment is expected the farther a price is from its target value. Requiring all λs to be positive insures that adjustment outside the thresholds is at least as strong as adjustment between the thresholds. Recall that we require that the lower threshold cannot be above the upper threshold for any of the products: $\alpha_{i,b} \leq \alpha_{i,a}$. In our estimation program, the "below" threshold is restricted to be nonpositive and the "above" to be nonnegative. Both could be 0 at the same time.

4.2. Hard and soft switches

The switching terms have not been defined in Eq. (10). Our STAR-based approach is used to define these switches as "soft" switching. To make Eq. (10) into a hard-switched model, like a TVECM, the two switches are defined as:

$$s_{i,t,b} = \begin{matrix} 1 & \text{if } f_{i,t} < \alpha_{i,b}, \\ 0 & \text{otherwise;} \end{matrix} \quad \text{and}$$

$$s_{i,t,a} = \begin{matrix} 1 & \text{if } f_{i,t} > \alpha_{i,a}, \\ 0 & \text{otherwise.} \end{matrix} \tag{11}$$

In (11) the "below" switch turns on when the *f* is below its lower threshold, the "above" switch turns on when the *f* is above the higher threshold. Both the switches are off when the *f* is between the thresholds.

Our model has 3 regimes per equation. For each equation, the "outside" cases are modeled using a logit type function and the between-the-thresholds case is modeled using an exponent with a quadratic function. Our general approach to building these soft switches is to start with 3 functions of f_t whose values are always positive, $g_{b,i}(f_{t,i})$, $g_{w,i}(f_{t,i})$, and $g_a(f_{t,i})$. The "*w*" subscript here stands for function for when $f_{t,i}$ is bet**W**een the thresholds. The three functions we use for our estimates are:

$$\begin{aligned} gb, i\,(fi,\, t) \; &= e^{-\Gamma\left(f_{i,t}-\alpha_{i,b}\right)}, \\ gw, i\,(fi,\, t) \; &= e^{-\Gamma\left(f_{i,t}-\alpha_{i,b}\right)*\left(f_{i,t}-\alpha_{i,a}\right)}, \\ ga, i\,(fi,\, t) \; &= e^{\Gamma\left(f_{i,t}-\alpha_{i,a}\right)}. \end{aligned} \tag{12}$$

The first and third functions above are for outside cases, and are the same functions used in a typical logit analysis. The between function is inspired by the normal distribution in so far as it involves a squared term. It will achieve its maximum at the mid-point of the thresholds. At either threshold, the exponent of g_w is 0, so its value is 1. The outside functions are also 1 at their thresholds. The switches are defined as:

$$s_{i,t,k} = \frac{g_{k,i}(f_{i,t})}{g_{b,i}(f_{i,t}) + g_{w,i}(f_{i,t}) + g_{a,i}(f_{i,t})}, \text{for } k = (b,\, a)\,. \tag{13}$$

The larger the value of Γ, the more the soft switch resembles the hard switch. In most STAR applications, Γ is an estimated coefficient. Djik et al. (2002) note that it is possible to specify STAR-type models so that they closely approximate abrupt-hard switched cases. In this case, the larger the value of Γ the more closely the soft-switch model resembles the hard-switched approach. We fixed Γ to 100 so that the soft switches would closely resemble hard switches.[4]

4.3. Model specification through hypothesis testing

The approach taken in developing our cheese price model (CPM) has been to develop the most general and flexible model possible. Thus, to begin, our model is defined as Eq. (9) with the switches as defined in Eq. (13). A more parsimonious specification can be achieved by testing restrictions on the λs and αs. The estimation routine we used is maximum likelihood for normally distributed error terms. It is often the case that the coefficient estimates are asymptotically normal even if the errors are not. Our tests are likelihood ratio tests. We impose a restriction on the model and use twice the change in the likelihood as our test statistic.

[4] We experimented with different values of Γ to see how they performed. When Γ is too large, the software generates calculation errors. We found that making Γ = 100 gave us relatively hard regime breaks with few other issues. (Poor starting values for the other coefficients could still cause problems). Generally, what constitutes a "large" Γ depends on how the data is scaled. For our data a change of 0.10 (10 cents) is large. The greater the dispersion in the data, the smaller a "large" Γ is. Also, after the fact, we tried out a range of Γ values on our final model. Once Γ was larger than 9, the model likelihood changed little for different values between 9 and 120.

However, there are two issues with our model that prevent some of the hypothesis tests from being (asymptotically) normal or chi-square. The first is the sign constraints and bounds we have put on the λ and α estimates. The second is the "nuisance parameter" problem first identified by Davies (1977). Most STAR specifications suffer from the nuisance parameter problem (Djik et al., 2002). To evaluate the "problem tests," a Monte Carlo or parametric bootstrapping procedure is used. More details on the testing procedures are available in the online technical Appendix. The authors will post-computer code on the web as well.

4.3.1. Imposing linear adjustment and the nuisance-parameter problem

We specified the CPM as generally as possible in order to nest the relatively simple partial adjustment model in Eq. (7). Equation (9) can be turned into Eq. (7) for any equation in the CPM by making both outside λs equal 0: $\lambda_{i,a} = \lambda_{i,b} = 0$. Equation (10) implies that if both outside λs are 0, then $\lambda_{i,l}$ is 1. However, eliminating either or both of the "outside" λs, leaves the matching α unidentified. This is the "nuisance parameter" problem noted by Davies (1977).

4.3.2. Imposing a two-regime equation model

A general equation in our CPM has 3 regimes. However, any or all of the equations in the CPM can be constrained to create a linear partial-adjustment equation. The constrained equation(s) will have only 1 regime. Similarly, if the two αs in an equation are both 0, then the hard-switched model has effectively two regimes, similar to a threshold autoregressive (TAR) model (e.g., Enders and Siklos, 2001). In this case, Eq. (10) is no longer sufficient to identify the equation's λ. Our solution for the hard-switched case would be to pick one of the 3 λs and force it to be 0. Even though a soft-switched equation's λs are *technically* identified when both αs are 0, we continue to use the "set-1-λ-to-0-constraint" when both αs in the equation are 0. The restricted 2-regime model has both α set to 0. The least-restricted model has freely estimated α.

The sign constraints imposed on both of the αs raise an additional econometric issue when estimating a two-regime model. The "below" α has an upper bound of 0, while the "above" α has a lower bound of 0. If the true value of a specific α is 0, it is possible, perhaps even likely, that the optimal estimate of that α will actually be 0. (A freely estimated value might come out on the wrong side of 0). In this case, the constrained and freely estimated models could converge to the same estimates and the likelihood-ratio test would be 0. The likelihood ratio test for a two-regime model will have a mixed continuous-discrete distribution and if the estimated test statistic is 0, we will accept the null hypothesis of a two-regime model.

4.3.3. Imposing asymmetric price adjustment

Price adjustment is going to be *asymmetric* if the speed of adjustment depends on the direction of adjustment. That is, if the speeds of adjustments associated with the above and below λs are different, i.e., $\lambda_{i,a} \neq \lambda_{i,b}$, then the process is asymmetric. Symmetric adjustment is achieved if $\lambda_{i,a} = \lambda_{i,b}$. Note that when the linear model Eq. (7) has both its outside λ equal to zero and it is symmetric. Our requirement that the all λ are positive may complicate tests for symmetry.

4.3.4. The zone of inaction

Like Balke and Fomby (1997) and Greb et al. (2013), we get a zone of inaction in our hard-switched case for price i, if the linear adjustment coefficient, $\lambda_{i,l}$, is 0 and if either or both of the α are not 0. Technically, the soft-switched model will have no true zone of inaction. With our large-Γ case there is some minor amount of adjustment between the thresholds when $\lambda_{i,l}$, is 0. Imposing a zone of inaction on an equation requires us to set its $\lambda_{i,l}$, to 0.

The test statistics for $\lambda_{i,l} = 0$ are mixed continuous-discrete random variables just like the test statistics for $\alpha = 0$. Making a $\lambda_{i,l} = 0$ gives us another flavor of the nuisance-parameter problem. When $\lambda_{i,l} = 0$ the equation's intercept and thresholds are not identified. The same small number can be added or subtracted to the intercept and both αs without changing the prediction for $\Delta y_{i,t}$ when $\lambda_{i,l} = 0$. "Zone of inaction" cases are identified by making the equations' thresholds symmetric around 0, i.e., by requiring that $\alpha_{i,b}+\alpha_{i,a} = 0$.

5. Empirical analysis

Our CPM was estimated with the monthly data on retail and farm prices for 2000 through 2012 previously described. Below, the results of our hypothesis tests conducted to specify a parsimonious model are summarized followed by estimation results and model interpretation. As previously noted above, our model tests and procedures are outlined in the online Appendix. The computer code will also be available online.

5.1. Model specification

The process of identifying a parsimonious CPM model involved estimating and testing our model in a series of steps. The first set of hypothesis tests were carried out to see whether our CPM could be written as a standard partial-adjustment model without soft switching. This hypothesis was rejected by our tests.

Next, the constraints on α and λ are examined. These coefficients all have sign or bound constraints, and there are three cases where parameter estimates consistently reached their bounds. Both retail cheese prices consistently converged to estimates when their "linear" λ coefficients were 0. Making the "linear" λ equal to 0 for either or both retail prices gives a test statistic of 0—and we accept that the two retail prices have a zone of inaction. Each retail price equation's thresholds are identified by making the two thresholds symmetric, i.e., $\alpha_{i,b}+\alpha_{i,a} = 0$.

Table 1
Testing the cross-price Beta coefficients against zero

Equation	Lagged dependent	Test	Degrees of freedom	Chi-square alpha	Insignificant
Retail cheddar	Farm milk cheese	18.09	1	0.00%	
Retail cheddar	Retail mozzarella	0.43	1	51.20%	yes
Farm milk cheese	Retail cheddar cheese	13.73	1	0.02%	
Farm milk cheese	Retail mozzarella	22.18	1	0.00%	
Retail mozzarella	Retail cheddar	0.33	1	56.64%	yes
Retail mozzarella	Farm milk cheese	39.24	1	0.00%	
Imposing two insignificant terms together		0.89	2	64.15%	yes

Note: The test statistic is the difference between the free model likelihood and constrained model likelihood.

Table 2
Beta coefficient estimates

	95% confidence interval[1]			
Equation	Lagged dependent	Estimate	Lower	Upper
Cheddar	Cheddar	0.1929	0.1056	0.3915
	Farm	0.1840	0.1128	0.3404
Mozzarella	Mozzarella	0.4642	0.3789	0.6463
	Farm	−0.7654	−1.0887	−0.6278
	Cheddar	−1.2656	−1.7074	−0.8230
Farm	Mozzarella	0.7071	0.4508	1.0160
	Farm	1.0888	0.9345	1.3285

[a]The confidence intervals are based on the 97.5 and 2.5 percentiles from 5,000 Monte Carlo iterations.

The farm milk price thresholds collapsed on one another. That is, the upper and lower thresholds were both 0. Additionally, the "above" λ consistently equaled 0. For our subsequent analysis, we therefore forced $\alpha_{i,b}=\alpha_{i,a}=0$ and further set $\lambda_{i,a}$ (the above case) to be 0 for the farm price. These restrictions allow us to specify the farm-price equation using only one switch, the "below" switch. This simplifies the program mathematically and speeds up convergence.

Our estimates establish zones of inaction for the two retail prices while a two-regime model is used for the farm price. Tests for any or all of these restrictions are 0—we accepted these hypotheses. Notably, α estimates for the retail prices are remarkably similar—identical to two or three significant digits. A hypothesis test was added for whether both retail prices have the same thresholds. The resulting test statistic is 0–5 places; this is considered insignificant. Price adjustment for both retail prices is subject to the same zone of inaction.

It is also interesting to test for asymmetry of price adjustment. As discussed above, we allow for two-regimes in our farm price equation. If the speed of adjustment is the same in each of these two regimes, the error correction process would further simplify to a linear one. In our tests, we rejected the 1-regime model and likewise concluded that adjustment for farm price is asymmetric. For retail prices, since we have accepted above that the linear part of λ is 0, adjustment will be symmetric adjustment if the "above" and "below" λs are the same (i.e., both equal 1). Our Monte Carlo evaluations of these tests show that each retail price's test is insignificant as is the joint test of retail price symmetry.

In the last phase of model testing, the off-diagonal elements of the β_{ij} coefficients were examined. We tested whether $\beta_{ij}=0$, for all the $i\neq j$. Analysts often look for lead-lag relationships in vector price-transmission models. Price i leads price j when the lagged value of i is in *j's* equation, $\beta_{ji}\neq 0$, but *j's* lag is not in *i's* equation, $\beta_{ij}=0$. Table 1 shows the results of our tests for the individual β coefficients. Those associated with the cross effects between the two retail cheese prices are insignificant. Shown in the bottom row of Table 1 are the results of our test forcing both of these insignificant cross-price terms to be 0 simultaneously. This joint restriction is also insignificant. Both lagged retail prices have a significant effect on the current farm price and lagged farm prices significantly influence current retail prices. The two retail prices can have only indirect influence on one another through their interactions with the farm price. Our estimates imply that there are no leaders or followers in these prices.

5.2. Model estimates

The price adjustment implied by our model estimates is a function of its β, λ, and α parameters. The two retail prices have a zone of inaction. Outside that zone, their adjustment is symmetric and driven by their β coefficients. The farm price exhibits asymmetric adjustment with no zone of inaction. Farm price's adjustment will vary depending on whether it is likely to increase or decrease and is a function of its β and its λ.

Table 2 shows the β estimates. The Mozzarella effect on current Cheddar and the Cheddar effect on current Mozzarella

Table 3
Lambda estimates for the farm price of milk[a]

	Linear	Below	"Net" below effect
Estimates	0.9184	0.1632	1.0816
Lower bound,95% confidence interval[b]	0.8336	0.0	1.0
Upper bound	1.0	0.3328	1.1664
Percentage of estimates at the bound	3.02%		

[a]The two retail prices have symmetric "outside" lambda whose values were fixed to 1. The upper bound for farm price's linear lambda is 1, the lower bound for the "below" lambda is 0.
[b]The confidence intervals are based on the 97.5 and 2.5 percentiles from 5,000 Monte Carlo iterations.

are set to 0; these 0's are not shown in the table. As expected, each price's β_{ii}, the coefficient for the difference between its own target and lag, is positive and less than 1, implying partial adjustment. Cheddar's lagged farm price coefficient is also positive implying that Cheddar prices tend to increase with the current farm price.

Like Cheddar, the price of Mozzarella exhibits partial adjustment to its target value. Mozzarella also has a large negative coefficient for its farm-price effect. This negative coefficient implies that Mozzarella is reacting to lagged farm prices: high farm prices last month mean high Mozzarella prices this month.

Price adjustment for the farm price is a product of its β and λ coefficients. The farm price has a β_{ii} that is close to 1. The Cheddar effect is large and negative, implying that the current farm price is reacting to the lagged Cheddar price; the Mozzarella effect is also positive implying that the current farm price tends to increase or decrease along with current Mozzarella prices. Note that the retail price βs in the farm price equation have the opposite signs of the farm-price βs in the retail price equations.

Table 3 shows the λ estimates for the farm price. In those cases where farm prices would tend to increase, the β effects are multiplied by the linear λ. When the farm price would tend to decrease, the β are multiplied by the sum of the linear and below λ. Table 5 also shows the sum of the two farm-price λ. Farm prices tend to show partial adjustment to their own target when increasing and over-adjustment when decreasing.

No formal test of symmetry was conducted for farm price. To make the farm-price adjustment symmetric, we would make its "below" $\lambda = 0$, which would make its linear $\lambda = 1$. Our Monte Carlo simulations are based on an asymmetric farm-price adjustment. Table 3 shows that in slightly over 3% of our Monte Carlo iterations, the linear λ estimate hit its upper bound of 1 simultaneously forcing the "below" λ to 0, its lower bound. This result can be used as supporting evidence that the farm-price adjustment is significantly asymmetric; however, the number of times we get symmetric estimates implies that the power of the asymmetry test is low.

Table 4 shows estimates and confidence intervals for the retail prices' common threshold parameters, the αs. Because these two prices have no linear λ, the thresholds are identified by making them symmetric around 0. Table 4 shows only the upper threshold; the lower one is the negative of the upper.

Table 4
The threshold-bound parameter α[a]

Estimate		0.0537
Lower bound	*95% confidence interval*[b]	0.0424
Upper bound		0.0840

[a]This table shows the "above" threshold for the two retail prices. The below threshold is the negative of the above.
[b]The confidence intervals are based on 5,000 Monte Carlo iterations. The lower bound is the 2.5% percentile value of those 5,000 iterated coefficients, the upper the 97.5% value.

5.3. The effects of asymmetry and thresholds on prices

Farm prices are subject to asymmetric price transmission. They tend to adjust more rapidly when decreasing than when increasing. Considering an observation made in the introduction, one may ask the question: Does this asymmetry depress farm milk prices? Our model's estimates are used to simulate the effects of asymmetric price transmission on farm prices.

Our first set of simulations were made with the linear $\lambda = 1$ and the below $\lambda = 0$ for farm prices but kept the rest of the model parameters as estimated. The actual prices have error terms associated with them so we added in the estimated errors to our model simulations. A drawback of this simulation procedure is that it does not allow for real supply and demand responses. One of our exogenous variables is lagged milk production suggesting changes in the prices farmers receive will change the amount of milk they are willing to supply. Thus, it is expected that higher farm prices would lead to greater supply, which would in turn lead to lower prices.

For our second set of simulations, the farm-price adjustment is made symmetric and the thresholds for the retail prices are eliminated. This makes the model the linear, partial adjustment model specified in Eq. (7). Error terms are also used in these simulations. Just as with the first set of simulations, this model simulation will not correct for supply or demand responses resulting from the price changes.

Table 5 summarizes the results of these two simulations. It shows the maximum, median and minimum percentage t difference between the simulated and actual prices for all 3 products. Of the three prices, the farm price shows the largest percentage changes between the actual and simulated price results. Requiring farm-price transmission to be symmetric would seem to have little effect on the price pattern over time. More

Table 5
summary statistics comparing the simulated with the actual prices

		Cheddar	Mozzarella	Farm
	Maximum change	0.33%	1.83%	4.66%
Assuming symmetric	Median change	−0.17%	0.14%	0.26%
Farm adjustment	Minimum change	−0.67%	−1.03%	−4.96%
Symmetric farm and	Maximum change	5.75%	7.33%	16.43%
The elimination of	Median change	−2.53%	−1.35%	−1.62%
Retail thresholds	Minimum change	−5.85%	−7.40%	−13.47%

Note: Calculated by the authors.

extreme effects are generated when the thresholds are also eliminated. Eliminating thresholds would make all three prices generally, albeit inconsistently, lower.

A number of different simulations are done using the estimated coefficients from our models. It is usually the case that when one retail price is at its upper threshold, the other tends to be above its full-adjustment target as well. This in turn makes the farm price above its full-adjustment target. The opposite is true when a retail price is at its lower threshold. The thresholds tend to make prices stick at either high or low levels. Over the course of our sample it appears that the "stuck at low levels" scenarios are somewhat more common.

6. Conclusions

Recent applied price-transmission literature has been dominated by error correction-type models. This includes research on price transmission for dairy U.S. dairy prices. Awokuse and Wang (2009) estimated several two-regime ECMs and reached mixed results as to whether shocks to the farm-gate value of milk are transmitted symmetrically to the retail price of Cheddar cheese. Stewart and Blayney (2011) later compared results for two-regime and three-regime ECMs. They found evidence of a "zone of inaction," and conclude that a three-regime specification better explains price movements than a two-regime model. Moreover, shocks to the farm price of milk are transmitted asymmetrically to the retail price of Cheddar cheese. The retail price rises faster when the farm value of milk increases than it falls when the farm value of milk decreases.

While existing models allow for nonlinearity in price transmission, researchers have sought still more flexible and general approaches. In this study, we extend the TVECM (threshold vector error correction model) to include features of STAR (smooth transition auto regressive) models. Our CPM (cheese price model) model is estimated in a single step and does not require data cointegration. Unlike most applications of TVECMs, we use our model to investigate asymmetric and threshold interactions among 3 prices: retail prices for two types of cheese and the Class III farm milk price.

Moreover, in order to increase flexibility, we allow for 9 regimes in total: 3 regimes for each of the 3 prices. Similar to Awokuse and Wang (2009) as well as Stewart and Blayney (2011), we find that farm price shocks are transmitted asymmetrically to retail cheese prices and identify a "zone of inaction" in which little error correction occurs. However, estimation results also confirm that our model captures nuances of price transmission for dairy prices beyond what these studies and a TVECM in general could have captured.

Finally, on the perennial question of whether price transmission is symmetric in the dairy industry, we find that it is asymmetric. But at the same time, our results suggest that this asymmetry is not economically significant to dairy farmers as there is no evidence that it reduces the price they receive for their milk.

References

American Farm Bureau Federation, 2003. Retail milk prices don't reflect farm-level prices, Farm Bureau News. 82, 7.

Awokuse, T., Wang, X., 2009. Threshold effects and asymmetric price adjustments in U.S. dairy markets, Can J. Agric. Econ. 57(2): 269–286.

Balke, N., Fomby, T., 1997. Threshold cointegration, Int. Econ. Rev. 38(3): 627–645.

Capps, O., Jr., Sherwell, P., 2007. Alternative approaches in detecting asymmetry in farm-retail price transmission of fluid milk, Agribusiness. 23(3): 313–331.

von Cramon-Taubadel, S., 1996. An investigation of non-linearity in error correction representations of agricultural price transmission, Paper presented at the VIII Congress of the European Association of Agricultural Economists, Edinburgh, Scotland.

von Cramon-Taubadel, S., 1998. Estimating asymmetric price transmission with the error correction representation: An application to the German pork market, Eur. Rev. Agric. Econ. 25(1): 1–18.

Davies, R.B., 1977. Hypothesis testing when a nuisance parameter is present only under the alternative, Biometrika. 64(2): 247–254.

Dijk, D.V., Teräsvirta, T., Franses, P.H., 2002. Smooth transition autoregressive models—A survey of recent developments, Econom. Rev. 21(1): 1–47.

Engle, R.F., Granger, C.W.J., 1987. Co-integration and error correction: representation, estimation, and testing, Econometrica. 55(2): 251–276.

Enders, W., Siklos, P., 2001. Cointegration and threshold adjustment, J. Bus. Econ Stats. 19(2): 166–67.

Escribano, A., 2004. Nonlinear error correction: the case of money demand in the United Kingdom, Macroecon. Dyn. 8(1): 76–116.

Greb, F., von Cramon-Taubadel, S., Krivobokova, T., Munk, A., 2012. The estimation of threshold models in price transmission analysis, Am. J. Agric. Econ. 95(4): 900–916.

Hassouneh, I., von Cramon-Taubadel, S., Serra, T., Gil, J.M., 2012. Recent developments in the econometric analysis of price transmission, Working Paper Number 2 Transparency of Food Pricing TRANSFOP.

Johansen, S., 1988. Statistical analysis of cointegration vectors, J. Econ. Dyn. Control. 12(2-3): 231–254.

Kinnucan, H.W., Forker, O.D., 1987. Asymmetry in farm-to-retail price transmission for major dairy products, Am. J. Agric. Econ. 69(2): 307–328.

Mainardi, S., 2001. Limited arbitrage in international wheat markets: threshold and smooth transition cointegration, Aust. J. Agric. Res. Econ. 45(3): 335–360.

Meyer, J., von Cramon-Taubadel, S., 2004. Asymmetric price transmission: a survey, J. Agric. Econ. 55(3): 581–611.

Stewart, H., Blayney, D.P., 2011. Retail dairy prices fluctuate with the farm value of milk, Agric. Res. Econ. Rev. 40(1): 201–217.

USDA Bureau of Agricultural Economics, 1945. Price Spreads Between Farmers and Consumers of Food Products 1913-44, Miscellaneous Publication No. 576, Washington, DC September 1945.

U.S. Department of Justice and U.S. Department of Agriculture, Public Workshops, Information. Accessed February 11, 2016, available at http://www.justice.gov/atr/public/workshops/ag2010/index.html

Wolffram, R., 1971. Positivistic measures of aggregate supply elasticities—Some new approaches—Some critical notes, Am. J. Agric. Econ. 52(2): 356–359.