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How Retail Beef and Bread Prices Respond to Changes in Ingredient and Input Costs

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Abstract

The extent to which cost changes pass through a vertically organized production process depends on the value added by each producer in the chain as well as a number of other organizational and marketing factors at each stage of production. Using 36 years of monthly Bureau of Labor Statistics price indices data (1972-2008), we model pass-through behavior for beef and bread, two retail food items with different levels of processing. Both the farm-to-wholesale and wholesale-to-retail price responses are modeled to allow for the presence of structural breaks in the underlying long-term relationships between price series. Broad differences in price behavior are found not only between food categories (retail beef prices respond more to farm-price changes than do retail bread prices) but also across stages in the supply chain. While farm-to-wholesale relationships generally appear to be symmetric, retail prices have a more complicated response behavior. For both bread and beef, the pass-through from wholesale to retail is weaker than that from farm to wholesale.

Keywords: pass through, wholesale, retail, farm prices, beef, bread, supply chain, price transmission, price response

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Contents

Summary

What Is the Issue?

Periodic spikes in the prices of major field crops and related commodities such as those from 1971 to 1974, 1994 to 1996, and 2006 to 2008 have stimulated questions about how these shocks affect wholesale and retail food prices. To what extent do wholesale food prices respond to changes in the underlying costs of inputs? How much of a change in input costs is passed through to retail prices and how long does it take for such cost changes to pass through?

Retail and wholesale prices will generally follow upstream commodity prices directionally, but there are often factors that limit this responsiveness. The extent to which price changes are passed through depends on the value added by each producer in the production process and a number of other organizational and marketing factors at each stage of production, leading to input price changes that are only partially reflected in later stages of the supply chain, and, at times, a lack of measurable response in the downstream product's price.

In this study, we develop price pass-through models for farm-to-wholesale and wholesale-to-retail price changes using 36 years of monthly Bureau of Labor Statistics price indices data (1972-2008). We focus on the wheat to retail bread and the cattle to retail beef chains because they represent examples of supply chains with significantly different degrees of processing between stages.

What Were the Major Findings?

Pass-through rates and timing can vary dynamically between prices at different stages in the supply chain, across food categories, and for a given relationship over time.

- A more processed item (bread/wheat flour) showed less response to upstream price changes than did a less processed item (retail/wholesale beef).
    - Retail beef prices typically incorporated between 19 to 29 percent of a change in the wholesale beef price after 6 months, while wholesale beef prices incorporated 52 to 54 percent of the change in cattle prices.
    - Retail bread prices typically incorporated 16 to 21 percent of wholesale wheat flour price changes, while wholesale prices of wheat flour incorporated 29 to 31 percent of changes in wheat commodity prices.
- Wholesale prices for beef and wheat flour both responded in a generally symmetric manner to changes in farm prices regardless of the size and direction of change, while retail prices for both beef and bread adjusted asymmetrically (especially in more recent years), with the adjustment dependent upon the characteristics of the wholesale price change.

- For both beef and bread, most of the change at the farm level was passed on to the wholesale stage within the first month, with some additional adjustments to the long-term equilibrium price after that.
- Retail prices had a more complicated response to wholesale price changes, and for both bread and beef, the pass-through from wholesale to retail was weaker than the pass-through from farm to wholesale. Retail price responses were strongest when wholesale prices were relatively high. When prices were more stable or in times of price declines, significant pass-through often did not appear for several months.

How Was the Study Conducted?

We analyze the farm-to-wholesale and wholesale-to-retail price relationships using a two-stage error correction model that allows for the possibility of asymmetric price response. We also test for structural breaks in the long-term (cointegrating) relationships. Variations in the response of the downstream prices that are dependent on the magnitude and/or sign of changes in the upstream prices are modeled by considering a threshold-type response based on the downstream price's position relative to the expected long-term relationship.

This research extends the work of recent empirical studies that have investigated the complexity of commodity pass-through relationships using newly developed statistical tools. We characterize price-response behavior in a manner that is not overly influenced by any short-term market conditions that can dominate samples of fewer years by including a long time period and considering different possible types of asymmetric price adjustment. Our models also allow more freedom for the relationships between points in the supply chain to vary for a given food group and include energy and labor variables as short-term inputs.

Introduction

What is the effect of changes in commodity prices on manufacturer and retail food prices? As commodity prices surged in late 2007 and most of 2008, much focus turned to estimating the impact of these increases on retail food prices. The drop in commodity prices from late 2008 to late 2009 led to the same concerns in the opposite direction. Commodity market swings can have significant, and often complicated, impacts on retail food prices. In order to investigate these effects, we estimate how much of a change in commodity costs is passed through to retail prices, how the rate of pass-through varies by food type, and, just as important, the time lag between commodity price changes and retail price changes. From this, we gain a more detailed understanding of the dynamic relationships between farm, wholesale, and retail prices over time and the tools to develop better expectations for the effects of farm-level price shocks on consumers. These tools will be used to refine the Economic Research Service's Consumer Price Index for Food forecasts[1] by incorporating additional farm and wholesale price changes into the forecasts.

[1]See the ERS web briefing room, Food CPI and Expenditures, for more information about the forecasts, at: http://www.ers.usda.gov/briefing/cpi-foodandexpenditures/.

The 2006 to 2009 upturn in agricultural price volatility was in sharp contrast to price behavior in preceding years. In measuring farm-to-retail price response behavior, such observable shifts in price volatility necessitate that flexible models be developed and utilized. To emphasize this flexibility, we focus on pricing relationships one stage at a time—the effect of farm price changes on wholesale prices, and then wholesale to retail prices—and include modeling variations that allow downstream prices to respond in a nonlinear manner. We develop a multistage model for pass-through behavior using 36 years of monthly data (1972-2008) and focus on two retail food items that have different levels of processing across their supply chains, beef and (white) bread.

Our research extends the work of some recent price transmission studies, while also focusing more closely on areas that appear absent from the current literature. We do this by looking at a time period that is longer than typical studies and we consider more flexibility in price response through the use of a model that allows for output prices to respond in a non-uniform manner to different input-price changes. In addition, we allow the relationships between points in the supply chain to vary within a food group and include energy and labor variables as short-term inputs, along with the standard food inputs. These extensions to the existing literature are included to better describe the differing nature of price response through the supply chain and across food categories.

The Price Series Data

Our analysis uses farm-level data on wheat and cattle prices, wholesale-level wheat flour and beef prices, and retail-level (white) bread and beef prices from 1972 through 2008.[2] In order to track general trends in these respective industries and avoid problems with following production and marketing chains for very specific retail products, we used Bureau of Labor Statistics (BLS) price indices at the aggregate product level.[3] Table 1 lists the CPI and Producer Price Index (PPI) food and commodity data series used for each product and price stage. The time-series data is monthly, not seasonally adjusted, and all price series were converted into their natural logarithms before analysis.[4] The different price series for bread and beef over this time period broadly illustrate the degree of consistency of response across price stages and changes in co-movement over time (figs. 1 and 2, respectively).

In addition to the principal food and agricultural commodity prices in each model, we also included energy and labor prices, where available. For all models we used the wholesale diesel PPI as a proxy for transport costs, while the variables for labor or additional energy inputs are more specific to the individual products and points in the supply chain. For the wholesale-to-retail pass-through relationship for both beef and bread, we controlled for variation in labor costs by using the monthly average hourly grocery store wage, while for the farm-to-wholesale relationship, we included an additional variable for the aggregate hourly slaughtering wage for beef and a variable for the electric power PPI for wheat flour.[5]

We focused specifically on white bread and beef supply chains in order to highlight differences in the degree of processing from farm to retail across these two food products. These differences can affect price-transmission relationships because as an input price represents a smaller share of the output price, it is expected that input price changes will have a smaller and/or more delayed effect on the output price. This expectation arises because in the (theoretical) example of complete price transmission, the downstream price response would be equal to the proportion of the total cost represented by the upstream price. This difference in the level of processing (or value added) to the original agricultural input can be seen in the farm share of the retail price, which in 2008 was 48 percent for beef and 10 percent for bread.

Beyond the general trends shown in figures 1 and 2, we can estimate the relative degree of price change passed through to the next stage in the supply chain by comparing price series volatility at each level in the chain. To summarize volatility, we looked at key values in the monthly price change

Table 1
Time series price variables

Supply chain level	Bread	Beef
Retail	White bread CPI	Beef and veal CPI
Wholesale	Wheat flour PPI	Beef and veal, fresh or frozen PPI
Farm	Wheat PPI	Cattle PPI

CPI = Consumer Price Index; PPI = Producer Price Index
Source: USDA, Economic Research Service.

[2]In the case of the farm-to-wholesale beef model, the sample starts with 1976 due to data limitations.

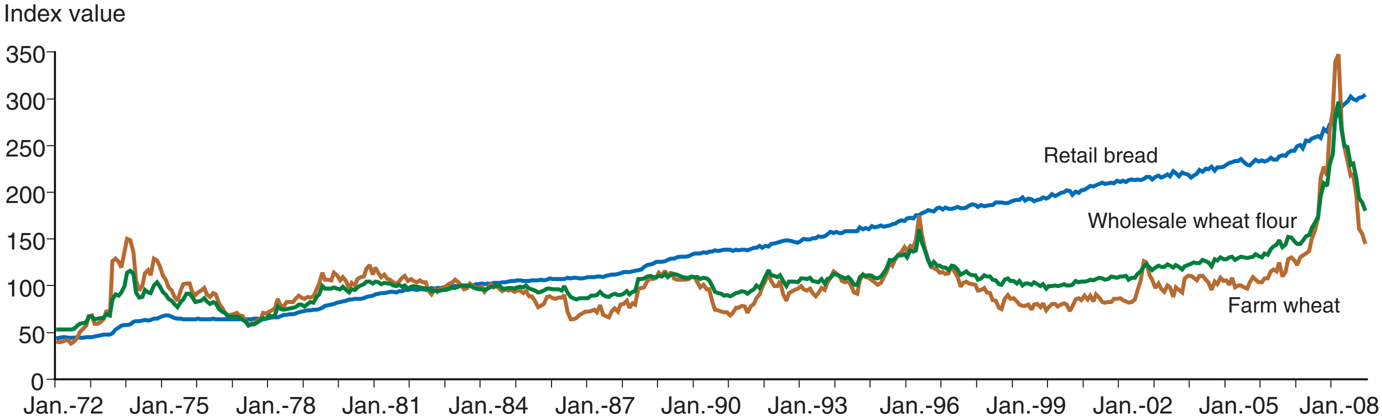
[3]For example, for retail beef, the overall Consumer Price Index (CPI) value for beef and veal is used instead of pricing information for a specific beef product. This avoids the problems associated with having to track back the production origins of a specific product that may not be representative of the larger category.

[4]The conversion to natural logs allows for the interpretation of the estimated pass-through coefficients to be in terms of proportional price movements.

[5]For both the slaughtering wage and grocery-store wage, we use data from the Bureau of Labor Statistics National Compensation Survey.

Figure 1

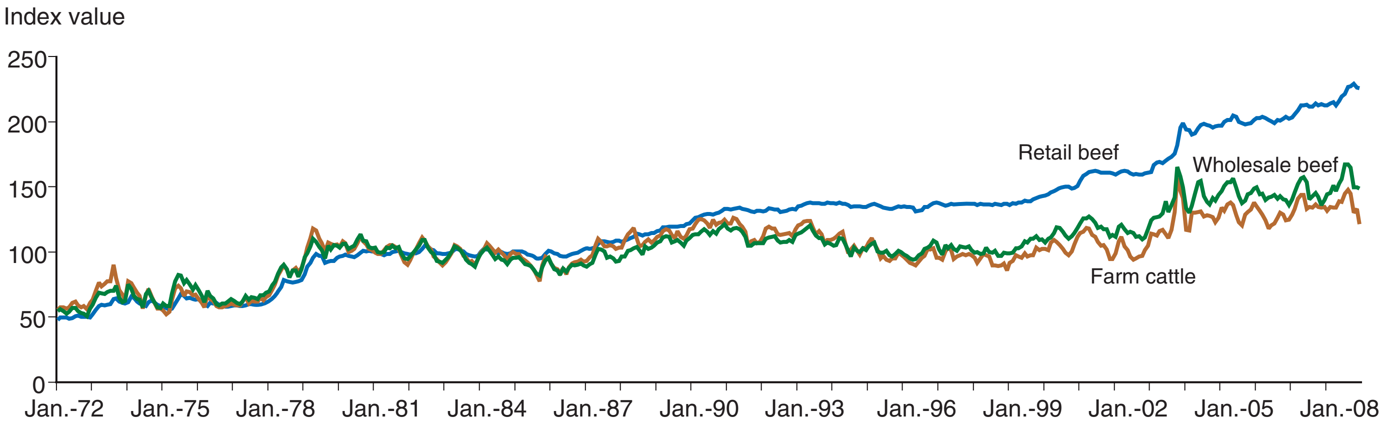
Bread price indices at different production stages



Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

Figure 2

Beef price indices at different production stages



Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

distribution of each of the series. Table 2 presents the minimum, maximum, standard deviation, and 10th and 90th percentile values of monthly changes in each series, for the entire time period, and some selected subintervals. Within each food category (over the entire period), volatility (as estimated by the bounds of the 10th and 90th percentiles) decreased when moving from farm-to-retail prices, showing that downstream prices are more stable and price response is decreasing through the distribution chain. Between food categories, bread and wheat flour prices are less volatile than beef prices at the retail and wholesale stages. The differences among food categories' price volatility probably results from the higher degree of processing (which implies less use and reliance on the agricultural input commodity) for wheat flour and bread that has led to fewer price swings and less pass-through of the wheat price volatility.

Table 2 also shows that within shorter time periods, the amount of price variation can vary dramatically from the overall time-period average. This range of price variations has implications for studies that try to quantify pass-through rates from a limited time horizon, since these studies may find results that are due to a particular pricing environment and may not be representative of other situations or time periods. For example, if considering the co-movement between wholesale wheat flour and retail bread prices in the plot of the price series from the late 1990s through the early 2000s, it might seem that there is very little price response from wholesale to retail (see fig. 1). With this focus, the more-than-15-percent increase in the retail bread CPI over the short period from mid-2007 to mid-2008 would look unprecedented.[6] The years included in our analysis were chosen with the goal of including as much dynamic movement in the price series as possible under the constraint of having consistently available data for all of the variables in the model. There is, however, a tradeoff with using a sample covering a large number of years in that the possibility of structural change in relationships over time becomes more prevalent. As will be described later, steps are taken in our analysis to address this issue.

[6]In comparison, the rise in the retail bread CPI from the beginning of 1997 to the end of 2002 was slightly less than 18 percent.

Table 2

Price series volatility measures for different products in different time periods

Variable	Time period	10th and 90th percentiles		Standard deviation	Largest decrease	Largest increase
				Percent		
	1972-2008	-0.66	1.44	0.97	-2.11	8.18
Δ White bread CPI	1990-2008	-0.92	1.49	0.96	-2.11	3.52
	2000-2006	-1.03	1.40	0.96	-2.11	2.64
	1972-2008	-3.70	3.88	3.67	-19.12	22.87
Δ Wheat flour PPI	1990-2008	-3.78	4.36	3.53	-11.39	15.67
	2000-2006	-1.99	3.03	2.04	-4.76	6.01
	1972-2008	-7.33	7.27	6.96	-25.51	63.85
Δ Wheat PPI	1990-2008	-7.77	7.78	6.53	-25.51	22.02
	2000-2006	-6.12	8.93	5.87	-12.61	17.43
	1972-2008	-1.10	1.82	1.59	-5.62	7.36
Δ Beef CPI	1990-2008	-0.66	1.27	0.94	-2.39	7.15
	2000-2006	-0.66	1.51	1.24	-2.39	7.15
	1972-2008	-4.23	4.47	3.90	-13.70	18.10
Δ Beef PPI	1990-2008	-3.64	3.51	3.16	-11.24	15.14
	2000-2006	-3.88	4.10	3.73	-11.24	15.14
	1972-2008	-4.79	5.34	4.53	-19.25	19.64
Δ Cattle PPI	1990-2008	-4.06	4.44	3.97	-19.25	18.55
	2000-2006	-3.98	5.53	4.82	-19.25	18.55

Note: The 10th and 90th percentiles represent the range of numbers that are the bounds that 80 percent of the monthly changes fall between.
CPI = Consumer Price Index; PPI = Producer Price Index

Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

Long-Term Price Relationships and Structural Breaks

A basic pass-through relationship between price series in a supply chain relates an output price to an input price by viewing the downstream product as essentially a value-added version of the upstream product. However, the amount of "value" that is added and the inclusion of other inputs can have substantial effects on the price response of the retail food product to changes in its principal agricultural input's price. Over a long enough time horizon, changes to this difference between downstream and upstream price series can significantly affect the price response.

The farm share of the retail food dollar for beef as well as cereals and bakery products has been declining over time due to the increased demand for and supply of value-added convenience items in both of these categories. This trend is not limited to beef and bread. Additional processing and food preparation beyond the farmgate has increased the number of ready-to-eat products available to consumers and decreased the farm share for all food products from 32 percent in 1970 to 19 percent in 2006. For beef and cereals and bakery categories, specifically, the farm share dropped from 64 to 46 percent and 16 to 10 percent, respectively, during that time period.[7] As these numbers show, retail bread prices have typically had a lower share of input commodity prices than beef, but there has been a significant decline in the farm share of retail beef prices over the last 38 years. Such changes have certainly affected price pass-through rates between points in the supply chain.

Given that changes in pass-through may occur over time, we begin with a model that allows for the relationship between input and output prices to vary in different sub-intervals of time. We therefore express the long-term relationship between two prices as:

$$P_{O,t} = \beta_0 + \beta_1 P_{I,t} + \beta_2 \varphi_1 + \beta_3 \varphi_2 + \beta_4 \varphi_3 + u_t. \qquad (1)$$

where $P_{O,t}$ and $P_{I,t}$ represent the output and input price series at time t, respectively, $\beta_0 - \beta_4$ are parameters to be estimated, φ terms represent time-period specific dummy variables, and u is an error term. The φ terms represent structural-break variables and provide time-sensitive measures of differences in the long-term relationship between P_O and P_I, which are points in time at which the relationship between P_O and P_I is diverging (assuming $\beta_2, \beta_3, \beta_4 > 0$).

In order to let the data drive the specification of these time-period specific dummy variables, we follow an approach similar to Boetel and Liu (2008) in their investigation of the longrun price linkage between farm, wholesale, and retail beef and pork prices. Rather than imposing assumptions on the data regarding when structural breaks occur, we explore patterns within the data in order to identify potential structural breaks endogenously. We find three structural break dates during the 36 years in each of the wholesale-to-retail price relationships and two in each of the farm- to-wholesale relationships (table 3).[8] Plots of the price indices with markers for the estimated break

[7]A summary of USDA, ERS meat price-spread data are available at http://www.ers.usda.gov/data/meatpricespreads/. Field crops price-spread data are available at http://www.ers.usda.gov/data/farmtoconsumer/pricespreads.htm/.

[8]While structural break dates were identified at specific points, they may represent shifts that take place over longer periods of time, as well. More detail on the tests to determine the number and placement of the structural break dates is given in the appendix.

Table 3
Estimated structural breaks in long-term relationships

	Supply chain relationship	Estimated break dates
Beef		
	Wholesale to retail	Oct. 1980, June 1991, June 2001
	Farm to wholesale	April 1995, April 2000
Bread		
	Wholesale to retail	March 1980, July 1989, May 1997
	Farm to wholesale	May 1983, March 1998

Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

dates are given in figures 3 and 4, and the estimates of the long-term equations with structural breaks are presented in table 4.

As expected, within a food category, the break dates for different price stages occur at similar times. The estimated coefficients corresponding to the φ terms provide some information as to how the long-term relationships between these upstream and downstream prices have changed since the 1970s. That is, the magnitudes consistently grow larger with the later structural breaks (i.e., $\beta_2 < \beta_3 < \beta_4$), confirming that output prices have been diverging from input prices over time. This trend is much more pronounced for retail prices and is especially strong for retail bread prices.

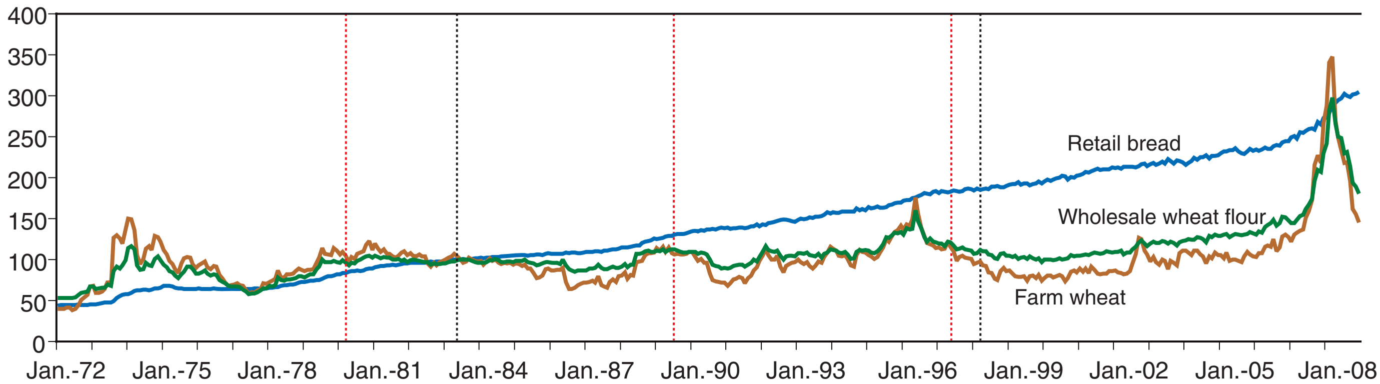
While shifts in the relationship among farm, wholesale, and retail prices over the last 36 years may not seem surprising, it is helpful to consider the background of these shifts in more depth. As previously mentioned, the farm shares for both beef and bread fell considerably over the period, implying that other factors have gained in significance over time. Hahn (2004) explores several reasons behind increasing (nominal) farm-to-wholesale and wholesale-to-retail price spreads. He finds that increasing productivity in the meatpacking and livestock industries have lowered real farm and wholesale prices (and the inflation-adjusted price spread) from 1970 to 2003, while an expanding service component in grocery stores has increased gross real margins between wholesale and retail meat values. Assuming similar trends in the bread supply chain (agricultural and processing productivity increases while overall grocery-store productivity falls) helps explain why we find more breaks in the wholesale-to-retail relationships than in the farm-to-wholesale relationships, as well as larger coefficients (implying faster growing margins) on the wholesale-to-retail break variables.

Significant specific supply-and-demand changes also have occurred across these industries through the 1972-to-2008 sample time period. In the bread supply chain, a long-term trend in increasing acreages of wheat planted in the United States ended in 1981 with acreages since then dropping off considerably (Ali, 2002). Trends in consumption also changed. In 1997, per capita wheat-flour consumption began to decline after steadily increasing since the 1970s. For beef, production shifts occurred over the sample period leading to increased grower-operation packer sizes and increased industry concentration. For example, the share of purchases made by the four largest beef processors doubled between 1980 and 1990, and significant increases in operation sizes also occurred between 1992 and 1997. The production locus[9]

[9]The production locus represents the number at which 50 percent of the cattle operations were smaller than this number and 50 percent were larger.

Figure 3

Bread price indices at different production stages

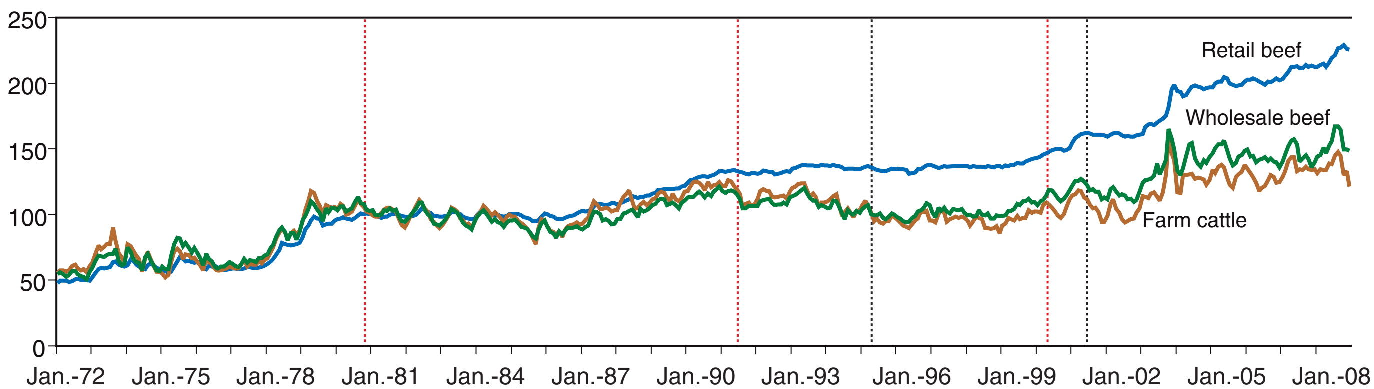


Note: Red dotted lines represent estimated structural breaks in the wholesale-to-retail relationship.
Black dotted lines represent estimated structural breaks in the farm-to-wholesale relationship.

Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

Figure 4

Beef price indices at different production stages



Note: Red dotted lines represent estimated structural breaks in the wholesale-to-retail relationship.
Black dotted lines represent estimated structural breaks in the farm-to-wholesale relationship.

Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

Table 4

Long-term relationship estimates with structural breaks

	Supply chain relationship	Estimated equation
Bread		
	Wholesale to retail	$P_{O,t} = 1.983 + 0.492\ P_{I,t} + 0.404\varphi_1 + 0.733\varphi_2 + 1.024\varphi_3$, R^2=0.96
	Farm to wholesale	$P_{O,t} = 1.385 + 0.676\ P_{I,t} + 0.176\varphi_1 + 0.305\varphi_2$, R^2=0.96
Beef		
	Wholesale to retail	$P_{O,t} = 0.413 + 0.882\ P_{I,t} + 0.198\varphi_1 + 0.399\varphi_2 + 0.496\varphi_3$, R^2=0.98
	Farm to wholesale	$P_{O,t} = 0.627 + 0.859\ P_{I,t} + 0.074\varphi_1 + 0.158\varphi_2$, R^2=0.98

Notes:

1. All estimated coefficients were statistically significant at an error rate of < 0.01 percent.
2. The variable $\varphi_1 = 1$ for Break Date 1 $\leq t <$ Break Date 2, otherwise $\varphi_1 = 0$.
3. The variable $\varphi_2 = 1$ for Break Date 2 $\leq t <$ Break Date 3, otherwise $\varphi_2 = 0$.
4. The variable $\varphi_3 = 1$ for t > Break Date 3, otherwise $\varphi_3 = 0$
5. Refer to table 3 for the estimated break dates for each model.

Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

for cattle-raising operations increased from 23,891 head to 38,000 head for fed cattle from 1992 to 1997 (MacDonald and McBride, 2009). This increase in production locus was more than twice the increase in size from 1987 to 1992. Toward the end of the 1972-to-2008 sample period, the Congressional Livestock Mandatory Reporting Act of 1999 was implemented by USDA in 2001. From 1997 to 2002, the trend of consolidation and rapid growth in beef-cattle operation size leveled off.

A More Detailed Model for Price Transmission

Equation 1 accounts for the long-term relationship between a downstream and upstream price series, but in describing pass-through, we are interested in the short-term dynamics as well, in order to more completely explain how a change in one price will be reflected in the change of another price series. Equation 1 should not be disregarded—to the contrary, the equation can be useful as an estimation of how the actual P_O compares to its expected value as predicted by the long-term relationship. To better capture the full pass-through relationship, we use an error correction model (ECM) that includes measures of short-term changes as well as adjustments to the expected long-term relationship, and is expressed as:

$$\Delta P_{O,t} = \alpha_0 + \Sigma^{Q}{}_{i=1} (\alpha_{1,i}\, \Delta P_{O,t-i}) + \Sigma^{R}{}_{i=1} (\alpha_{2,i}\, \Delta P_{I,t-i}) + \Sigma^{S}{}_{i=1} (\alpha_{3,i}\, \Delta x_{1,t-i}) + \Sigma^{T}{}_{i=1} (\alpha_{4,i}\, \Delta x_{2,t-i}) + \gamma\, u_{t-1} + \upsilon_t, \quad (2)$$

[10]

where x_1 and x_2 are variables that are assumed to have an effect on P_O in the short-term without necessarily having a stable long-term relationship with it, and υ is the residual from the ECM. In our analysis, the ECMs are constructed following Engle and Granger (1987). The constant term, α_0, and dummy variables corresponding to the identified structural break dates may be included conditional on the output price series appearing to have a clear trend over time; energy and labor inputs are modeled as short- term variables, in that they are present in the error correction model but not in the long- term equation. This is an ECM because of the $\gamma\, u_{t-1}$ term that represents changes in P_O due to the previous period's value of u (which is the part of P_O that is unexplained by the other terms in equation 1). This particular model is a symmetric ECM because the response of $\Delta P_{O,t}$ is the same regardless of the magnitude and sign of the $\Delta P_{I,t-i}$ and u_{t-1} terms. That is, input price increases are passed on to output prices as completely and quickly as input price decreases.

In recent years, many empirical studies have investigated the complexity of commodity pass-through relationships using this relatively new methodology that incorporates both short- and long-term relationships through ECMs. Goodwin and Harper (2000), for example, combine an ECM with the possibility of a nonlinear threshold setting in studying weekly pork prices from 1987 to 1999.[11] They find evidence that retail prices respond to upstream price changes differently depending on behavior characterized by regimes that are defined by different threshold values. Boetel and Liu (2008) also consider an ECM with a focus on livestock pricing. Looking at a longer time period (1970 to 2008), they investigate price response in light of structural breaks in the long-term relationships between prices across the supply chain. Both of these studies find it beneficial to model the pass-through relationship as a combination of (1) a short-term response to input price changes and adjustments to an expected long-term equilibrium and (2) asymmetric price responses that allow output prices to respond differently depending on the direction of input price changes.

[10]Contemporaneous impacts on the dependent variable from the exogenous variables were not considered in this analysis. The number of lags we include for each variable in the model was determined by using the Hannan-Quinn information criterion.

[11]As discussed in more detail in the next section, a threshold model allows for the response to changes in input prices to differ depending on the magnitude and sign of the input price change.

Asymmetric Pass-Through Behavior

Inspection of the graphs of the different bread and beef price levels (figs. 1 and 2) shows that while the downstream price (in most cases) does seem to have a tendency to follow changes in the upstream price, this behavior is not always consistent across all changes. Wholesale prices generally follow farm price changes fairly close, but for retail bread prices in particular, large responses to upstream price changes seem to occur only infrequently (especially in the last 30 years). With retail bread prices, only very substantial changes in wheat flour prices seem to elicit a response.

An asymmetric price response is defined as a relationship in which the output price does not necessarily respond proportionally to all input price changes, but instead varies depending on either the magnitude or the sign of the change in input prices. Why might price transmission be dependent upon the magnitude and sign of the input price change? Awokuse and Wang (2009) cite some possible theories that may result in asymmetric price transmission, including noncompetitive market structures, price rigidity due to transaction costs, and commodity storage characteristics. A review of a number of works focused on the underlying theories behind asymmetric price transmission by Meyer and von Cramon-Taubadel (2004) finds that, for the direction of asymmetry, there are arguments for either increases or decreases to cause greater downstream responses depending on the specific circumstances of the industry in question. The authors also point out (page 582) that, "Existing tests describe the nature of price adjustment but most are not discerning in the sense that they make it possible to differentiate between competing underlying causes on the basis of empirical results." Kinnucan and Forker (1987) also suggest that, even if a retail price responds symmetrically in the long run, delays may arise that increase the response time. They cite issues such as normal marketing inertia, repricing costs, and differences in information collection and transmission as all working to slow down or mitigate price transmission. Taken together, such factors can lead to incomplete pass-through across the supply chain and, at times, a lack of measurable response in the downstream product's price.

In this study, we allow output prices to respond asymmetrically to both adjustments in the short-term price response or corrections to the long-term relationship by using a threshold model. This allows for price responses to vary depending on certain threshold values that act as bounds to different pass-through behaviors. Using this model leads to the following transformation of equation 2:

$$\Delta P_{O,t} = \begin{cases} \{f^{(1)}(\Delta P_{O,t-i}, \Delta P_{I,t-i}, \Delta x_{1,t-i}, \Delta x_{2,t-i}, u_{t-1})\} & \text{if} \quad u_{t-1} \leq c_1, \\ \{f^{(2)}(\Delta P_{O,t-i}, \Delta P_{I,t-i}, \Delta x_{1,t-i}, \Delta x_{2,t-i}, u_{t-1})\} & c_1 < u_{t-1} \leq c_2, \\ \{f^{(3)}(\Delta P_{O,t-i}, \Delta P_{I,t-i}, \Delta x_{1,t-i}, \Delta x_{2,t-i}, u_{t-1})\} & u_{t-1} > c_2 \end{cases} \tag{3}$$

in which $f^{(1)}$, $f^{(2)}$, and $f^{(3)}$ all have the same general form, essentially equation 2 (with the possibility of different lag lengths).[12] The terms c_1 and c_2 refer to the lower and upper threshold bounds, respectively[13] and are in terms of values of the variable u_{t-1} (the difference between the actual P_O and its

[12]Again, these lag lengths were chosen using the Hannan-Quinn information criterion.

[13]See appendix for details on how c_1 and c_2 are determined.

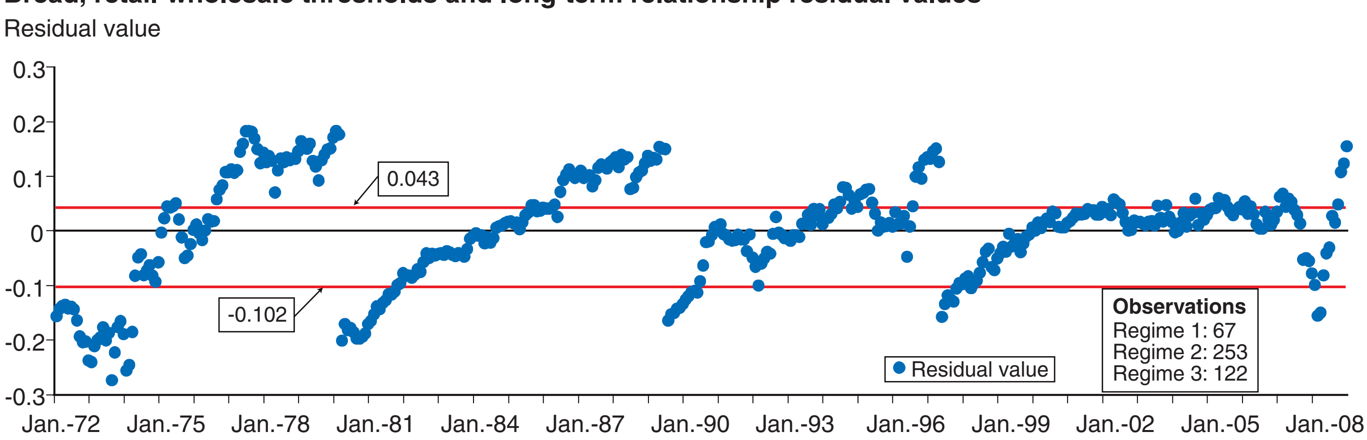
expected value from equation 1). This variable is used because it represents a comparison of the downstream price relative to its long-term expectation, and the threshold bounds are constrained such that $c_1 < 0$ and $c_2 > 0$. The first grouping of observations by the thresholds, or regime, are points in time in which the output price is relatively low compared with what is expected from the estimated long-term relationship ($u_{t-1} \leq c_1$), the second regime is for observations in which the output price is relatively consistent with the long-term expectation ($c_1 < u_{t-1} \leq c_2$), and the third regime is when the output price is relatively high ($u_{t-1} > c_2$). By breaking up the estimation of equation 2 for each of these different regimes, pass-through rates are allowed to differ depending on the deviations in the current relationship of P_O and P_I from the expected long-term relationship between these input and output prices. The sign *and* magnitude of input price changes may lead to different output price responses in this threshold model because, for example, if P_O is relatively close to its expected value, then (holding P_O constant) a large increase (decrease) in P_I will result in a large negative (positive) u value and categorization to the first (third) regime, while a small change in P_I will result in a u value that is small in magnitude and categorization in regime 2.

Figures 5-8 show the threshold values, the number of observations in each regime, and the patterns of u values (deviations from the expected long-term relationships) over time. For both the beef and bread categories, the values of the thresholds themselves can also be descriptive. The bounds for the beef threshold models are more symmetric around zero, which implies that for the threshold wholesale-to-retail beef model, the regimes are more clearly defined as large positive and negative deviations from the long-term relationship (regimes 1 and 3, respectively) or generally small deviations (regime 2). The bounds for both the wheat flour and bread threshold models, however, are not as symmetric around zero and the relatively smaller upper bound implies that, in these cases, the middle regime will be more balanced toward observations in which the expected downstream price is relatively low.

As an example of the mechanics of a threshold model, consider how a threshold ECM fits the price data for retail beef prices over a 12-month period and how the different pass-through estimates from each regime can provide a better fit at different points in time (fig. 9). When retail prices are

Figure 5

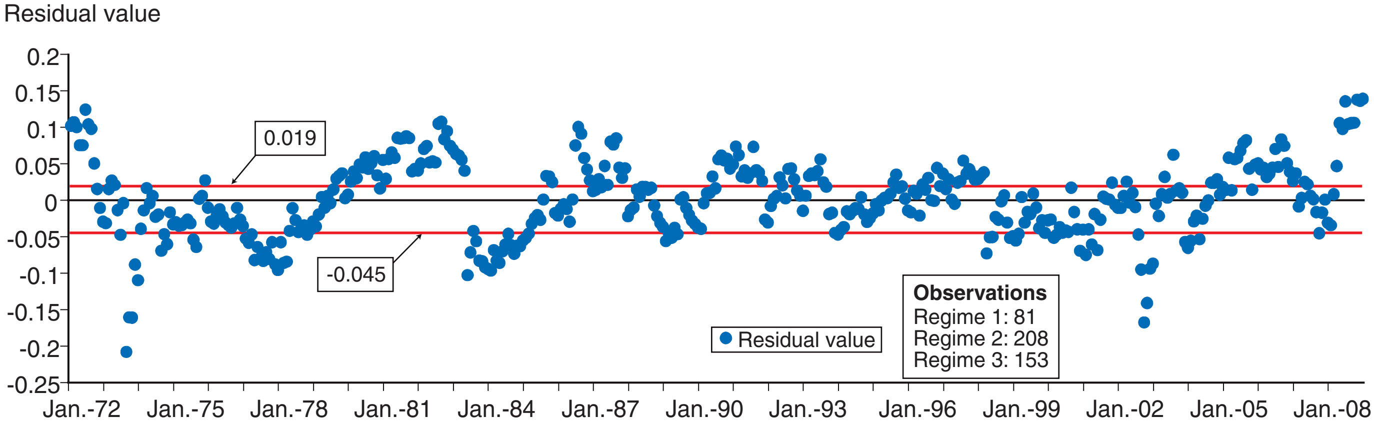
Bread, retail-wholesale thresholds and long-term relationship residual values



Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

Figure 6

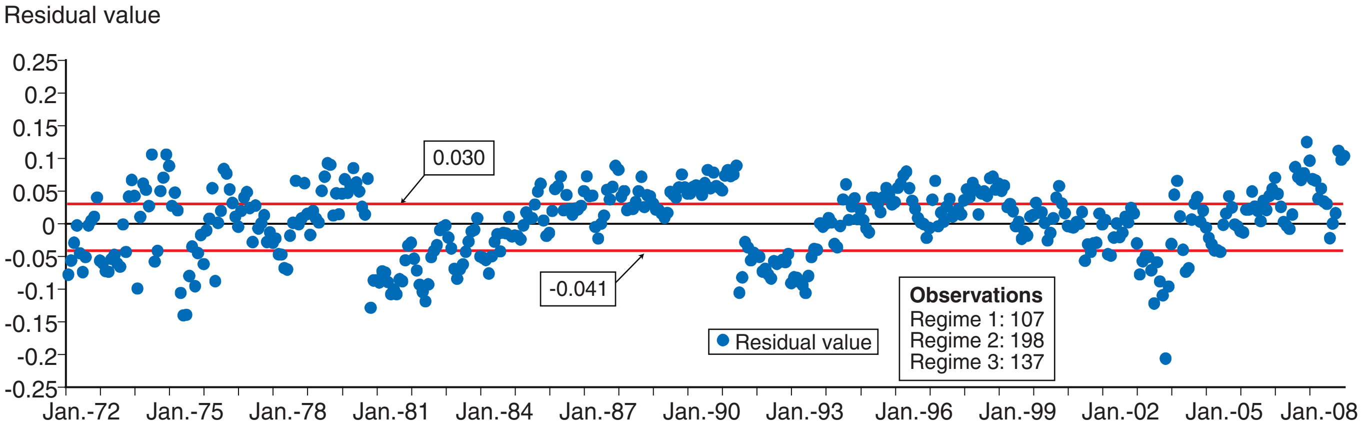
Bread, wholesale-farm thresholds and long-term relationship residual values



Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

Figure 7

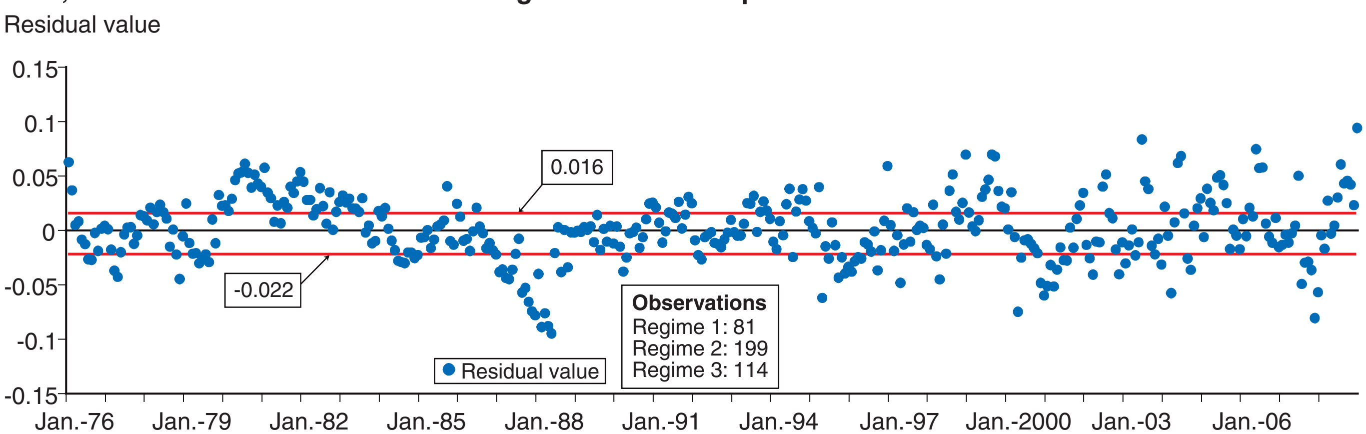
Beef, retail-wholesale thresholds and long-term relationship residual values



Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

Figure 8

Beef, wholesale-farm thresholds and long-term relationship residual values

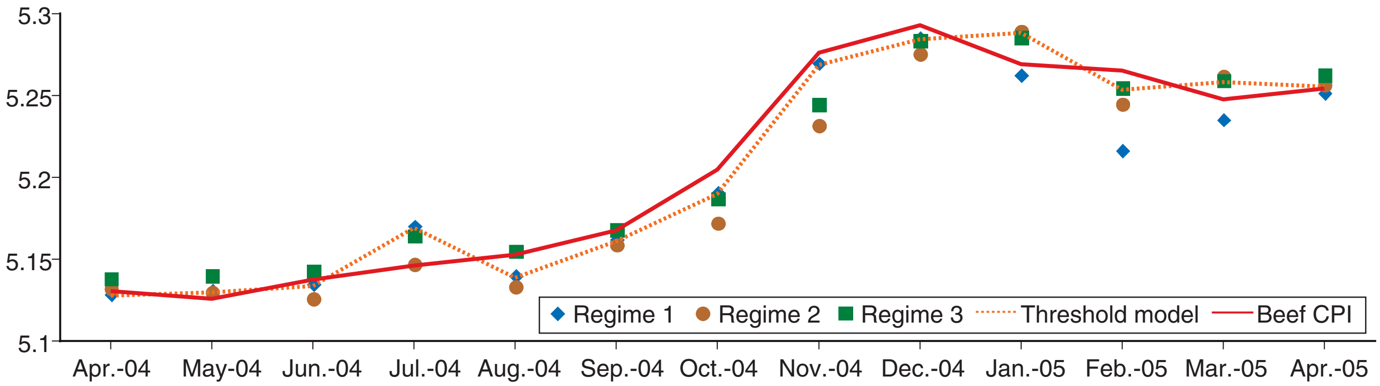


Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

Figure 9

Comparison of actual observations and threshold model by regimes

Natural log of price index



CPI= Consumer Price Index.

Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

more responsive (which our threshold ECM finds to be generally when retail prices are relatively low compared with the long-term relationship), the first regime estimates, which have higher pass-through rates and stronger error correction, mimic the actual response better. Conversely, there are also settings in which actual retail beef prices are less responsive and the pass-through estimates of the first regime would overpredict volatility in retail prices. In most of these cases, the threshold ECM applies the lower pass-through estimates of the second or third regimes (in which retail prices are about in line with long-term expectations or they are high compared with wholesale prices), and the predicted responses from the threshold ECM more closely follow the actual retail beef responses.

As noted earlier, a threshold model allows for price responses to differ based on the magnitude and/or sign of the input price change. Thus, this model will describe pass-through relationships more accurately and fit the data more closely when the downstream price does have a tendency to respond to input price changes in an inconsistent manner. For some food categories and stages in the supply chain, under certain conditions, marketing inertia causes downstream prices to be inflexible or unresponsive. Other categories and stages are less likely to experience such marketing inertia.

In our analysis, two different measures point toward a threshold setting as a good fit for the wholesale-to-retail price relationships but not for the farm-to-wholesale price relationships. The first measure is a statistical test that seeks to confirm the significance of threshold effects with the chosen threshold values.[14] The second measure compares predictions made for the change in a downstream price using a basic ECM (as in equation 2) and a threshold ECM and then builds on this prediction for a total of six consecutive monthly predictions. Table 5 highlights the findings of this application for a sequential series of 6-months-ahead predictions with starting points in each month from 2002 through 2008, showing the average prediction error by model (averaged across each 6-months-prediction horizon and then across the entire series of these predictions). The ranking of the results for each model indicates that the threshold models do not perform better than the symmetric ECMs in the

[14]This test is described in Hansen (1997); more details on the procedure that we used are given in this report's appendix.

farm-to-wholesale stages but are preferred in the wholesale-to-retail models. Thus, our findings indicate that for both wholesale beef and wholesale wheat flour, pass-through of farm level price changes appears to occur in a fairly uniform manner regardless of the size and direction of the change. For retail beef and bread prices, the response to an input price change may differ significantly depending on the magnitude and sign of the change.

Table 5

Six-month prediction comparison for 2002-08[1]

	Supply chain relationship	Average forecast error[2]
Beef		
Wholesale to retail	Threshold ECM	1.6689
	Symmetric ECM	2.0470
Farm to wholesale	Threshold ECM	4.3210
	Symmetric ECM	4.2752
Bread		
Wholesale to retail	Threshold ECM	2.1001
	Symmetric ECM	2.3680
Farm to wholesale	Threshold ECM	7.2701
	Symmetric ECM	7.2350

[1]Across the period 2002 to 2008, the different models were used to make 6-months-ahead predictions using each month as a different starting date.

[2]This can be described as the mean forecast error for each 6-months-ahead prediction horizon, averaged across the entire series of these predictions.

ECM = Error correction model.

Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

Pass-Through Model Estimates

We estimate each of the pass-through ECMs—symmetric (equation 2) and threshold (equation 3)—for each supply-chain relationship for beef and bread with a flexible lag order across models and regimes (appendix tables A1-A4).[15] Although estimates are given for both threshold and symmetric models in all cases, our discussion focuses on the symmetric ECMs for farm-to-wholesale movement and the threshold (asymmetric) ECMs for wholesale-to-retail movement, following our earlier discussion of model fit.

We first look at the beef farm-to-wholesale symmetric ECM results as an example of how to interpret the estimated coefficients. A coefficient of 0.34 on $\Delta\,(\mathit{ln\ cattle\ PPI})_{t-1}$ implies a direct pass-through rate of 34 percent of a price change in the cattle price index to wholesale beef prices after 1 month. Also, the estimated coefficient of the error correction term (ECT) of -0.14 implies that there is some adjustment based on the difference between the last month's actual wholesale beef price and its expected value (as predicted by the long-term relationship from equation 1). For the ECT estimates, the magnitude of the number corresponds to the speed of adjustment to the long-term relationship, while a negative (positive) sign implies convergence (divergence) to the long-term relationship. The ECT estimates are most easily interpreted in a relative rather than direct manner. For example, the estimated ECTs for wholesale beef of -0.14 and wholesale wheat flour of -0.07 both imply that there is pressure on the respective prices to converge to the long-term relationship, but the larger magnitude of the estimate for beef suggests that the effect is stronger there (and thus adjustment to the long-term relationship is faster).

Several patterns emerge between products and between price stages from these regression results. Between food products, the strength of the pass-through rate is inversely correlated with the level of processing of the input commodity, thus beef generally has larger and quicker pass-through than bread/wheat flour. This can be seen in the direct pass-through responses (the $\Delta P_{I,t-i}$ terms, where I is the agricultural input price) which, in the first instance of direct response, for retail and wholesale beef models are 0.13 to 0.27 and 0.34, respectively.[16] This is in contrast to 0.05 to 0.10 and 0.12 for retail bread and wholesale wheat flour, respectively. When looking at these numbers across the supply chain instead of across food categories, the farm-to-wholesale price relationships also show more direct pass-through than that of wholesale-to-retail prices.

Looking now at farm-to-wholesale (symmetric ECM) results in more detail, we find that wholesale beef prices have a strong and immediate response to cattle price changes with pass-through comprised of a direct response after 1 month and strong error correction to the long-term relationship. Both of the coefficients for these responses, 0.34 and -0.14, respectively, are the largest coefficients estimated in any of the models in this study. These coefficients highlight the close co-movement of the two series, even in recent years. For the effect of wheat price changes on wheat flour, the symmetric ECM describes the response as quick yet relatively modest. One reason for this seemingly low short-term response rate of 11.5 percent after 1 month (with statistically significant but relatively modest error correction of -0.07, as well) is that wheat prices are generally prone to relatively large temporal swings,

[15]Estimates of the autoregressive terms in the models are not included in the regression output tables, though these terms were included when estimating the models.

[16]The retail beef result given here is a range of numbers since the threshold model results have three different sets of coefficients (one for each regime). The wholesale beef result is only one coefficient since the symmetric ECM has one set of results for each product and price relationship.

while wheat flour prices are generally more stable, implying less of these input changes are passed through.

Retail prices have a more complicated response behavior than wholesale prices, but for both food products the pass-through at this stage is weaker than the upstream stage. The retail bread threshold ECM estimates show pass-through to be strongest and fastest (10 percent directly after 1 month and -0.12 for the ECT) for the first regime, which characterizes times when retail prices are much below what would be predicted by the long-term relationship. When prices are approximately in line with long- term expectations or input prices are slightly increasing (regime 2), there is an estimated response of about 11 percent after a delay of 3 to 4 months and some slight response from the ECT (-0.03). When wheat flour prices are rapidly falling or when retail prices are relatively high (regime 3), wheat flour price changes still have an effect (about 15 percent pass-through delayed between 2 and 4 months), but the retail prices have no significant tracking to the long-term relationship between the series.

Beef retail prices seem to follow a similar pattern. Retail price response is strongest when wholesale prices are surging (first regime) with 38 percent direct pass-through within 2 months and -0.12 for the ECT. In times of modest changes or when retail prices are relatively high (regimes 2 and 3), there is still a fairly high level of responsiveness (about 22 and 31 percent, respectively) within a couple of months. Also, in this model, retail beef prices have significant adjustment back to the long-term relationship only after large wholesale price increases (while, in the second regime, the positive value of the ECT actually has a somewhat divergent effect between the series).

There were also some similarities in results across stages in the supply chain for the nonagricultural input prices.[17] For both food categories, the wholesale price response to diesel price changes is small in magnitude but significant and fairly quick. The other input variables (slaughtering wage and electricity) were both significant in their respective models and had effects occurring with a much greater lag as compared with diesel prices. In the wholesale-to-retail models, only retail beef prices had a significant response to labor or energy price fluctuations with changes to the grocery store wage appearing to have a modest effect after 2 months.

[17]In the threshold ECMs, the sample splitting makes the interpretation of the estimates of these variables more difficult.

Summarizing the Expected Pass-Through Rates

Interpreting the full results of a nonlinear model such as the threshold ECM can be difficult since the pass-through rate depends upon the sign and magnitude of the input price change as well as the time period in question.[18] A tool that can be helpful in exploring the results of these types of models is a nonlinear impulse response function (NLIRF).[19] The NLIRF is a simulation approach that can be used to gauge the impact of a specific change at a specific point in time. Beyond being able to focus on a particular point in time, this method combines the total expected pass-through from both the short- term response and error correction to the long-term relationship.

To summarize the pass-through results for the different models and provide some measure for response that is inclusive of the different pass-through factors, we calculated the cumulative short-term pass-through coefficients, timing for these coefficients, and estimates for pass-through based on NLIRF results for a 6-month time span (table 6). The first two rows of each section of the table summarize the information contained in the appendix tables. The other results in this table (NLIRF results, described as "6 Month Total") are presented to give a more complete sense of the pass-through that combines the different effects of the ECMs—the direct pass-through, adjustment to the long-term relationship, and any regime switching in the threshold models. We used a one-standard-deviation input price change (positive or negative) in our simulation in order to present a characteristic response.[20] The results presented here are a summarized average of the percent of the input price change that was passed through after 6 months, using each month from January 2000 through January 2008 as starting points.[21] The values for the NLIRF results lead to conclusions similar to those discussed in the previous section. On average from 2000 through 2008, retail and wholesale beef prices are more responsive to input price changes (19.2 to 28.6 percent and 52.6 percent, respectively) than are retail bread and wholesale wheat flour prices (16.3 to 21.4 percent and 30.3 percent, respectively). Comparing the same numbers across the supply chain, wholesale price responses are generally stronger than retail price responses.

As the threshold regression results for the wholesale to retail relationships showed, estimated pass-through rates are significantly different among regimes, with Regime 1 (relatively low retail prices) having the highest pass-through rates for both beef and bread. When interpreting the NLIRF results of table 6, it is important to consider that the pass-through rates from the threshold models are sensitive not just to the value of u (deviations from the expected long-term relationship), but also to how close the u value is to the threshold bounds. The relative position of u is important for these threshold models because it determines which regime a time period falls into and the amount of change necessary to switch regimes. This movement among regimes describes how the overall pass-through behavior of the output price changes with respect to the value of u because the estimated amount of pass-through and the timing differ between regimes.

From 2000 through 2008, retail bread prices typically appeared to be relatively high (in terms of the u variable) and close to the Regime 3 boundary,

[18]The threshold model is sensitive to the time period in question because the threshold bounds are in terms of a variable that is sensitive to the deviations in the current relationship from the expected long-term relationship of P_O and P_I.

[19]This method is described in further detail in Potter (1995).

[20]The response functions are based on impulses in which all input price changes (in percent terms) are the same as the actual input price changes after the date of the impulse, so that our estimates isolate the impact of a one-time change.

[21]The NLIRF analysis was sequentially repeated over this time period because the threshold models (and consequently the NLIRF) are sensitive to time-period considerations and our goal was to present an average response.

Table 6
Pass-through summary

	Threshold ECM			Symmetric ECM
	Regime 1	Regime 2	Regime 3	
Beef				
Wholesale to retail				
Total direct response[1]	38.0	31.0	19.6	31.2
Timing[2]	1 - 2	1	1 - 2	1 - 2
6-month total[3], $\Delta P_I > 0$		28.63		
6-month total, $\Delta P_I < 0$		19.22		35.1
Farm to wholesale				
Total direct response	28.7	41.1	22.3	34.0
Timing	1	1	1	1
6-month total, $\Delta P_I > 0$		48.03		
6-month total, $\Delta P_I < 0$		47.66		52.6
Bread				
Wholesale to retail				
Total direct response	10	10.8	15.5	18.5
Timing	1	3 - 4	2 - 4	1 - 4
6-month total, $\Delta P_I > 0$		16.32		
6-month total, $\Delta P_I < 0$		21.38		18.7
Farm to wholesale				
Total direct response	11.2	26.3	19.3	11.5
Timing	5	1 - 2	1	1
6-month total, $\Delta P_I > 0$		30.22		
6-month total, $\Delta P_I < 0$		39.68		30.27

[1]Total direct response refers to the cumulative direct pass-through (percentage) without considering the effect of the long-term relationship between price series.

[2]This is the range of months (after the input price change) that the direct pass-through is present.

[3]This is the cumulative pass-through (percent) (with error correction) after 6 months for an impulse of 1 standard deviation of change, and the average of using each month in the period January 2000 to January 2008 as a different starting date.

ECM = Error correction model.

Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

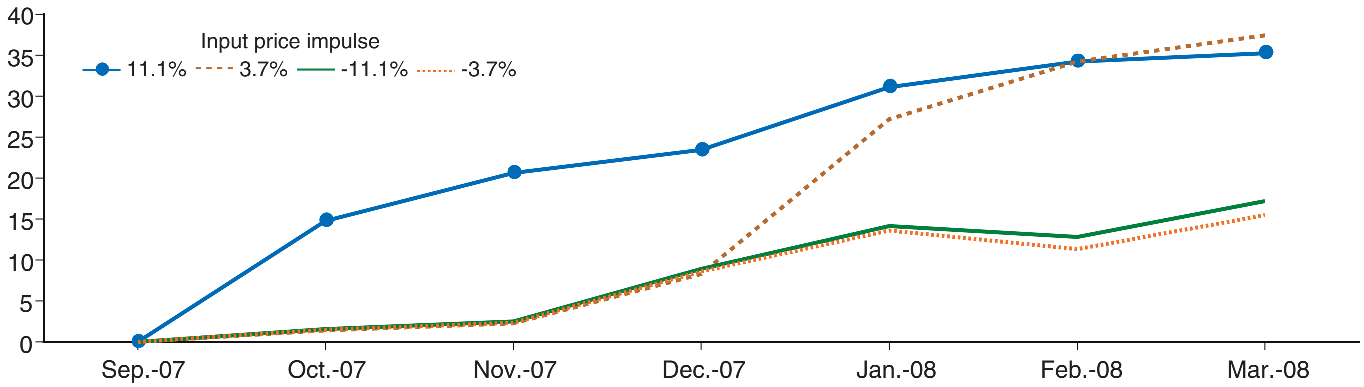
while retail beef prices typically were also in Regime 2 but in a less concentrated pattern. This difference likely explains why the models predict that retail bread prices, on average, will respond more to an input price decrease than to an input price increase of similar magnitude. Retail bread prices were much more clustered around the boundary for switching to Regime 3 (retail prices being relatively high) than were retail beef prices. This is evidenced by the finding that, for beef, a 6.7-percent wholesale price increase would generally move an observation from Regime 2 into Regime 1 (in which pass-through rates are estimated to be higher and retail prices are relatively low) or a 4.1-percent wholesale price decrease for moving from Regime 2 to Regime 3. The same sets of numbers for bread are 25.2 percent and 6.3 percent, respectively. This implies that a very large input price increase was generally needed to have higher pass-through rates (Regime 1) in retail bread prices while a relatively modest wheat flour price decrease would lead to the slightly higher pass-through rates estimated for Regime 3.

Although the results in table 6 provide characteristic responses for a given period of time, we were also interested in considering how the threshold models for retail prices perform at specific points in time when markets are stressed and pass-through rates may be higher. Figures 10 and 11, therefore, show NLIRF examples for retail beef and bread price responses on a month-by-month basis for 1 and 3 standard deviation changes in the downstream price, when downstream prices were accelerating at an above-normal rate. For an input price increase (decrease) of one standard deviation, total pass-through is estimated to be 63.0 percent (36.1 percent) for retail beef and 37.4 percent (15.5 percent) for retail bread. This is in contrast to the lower pass-through rates in table 6 because at these times rapid input price increases trigger price-response behavior in the first regime as the slower adjusting retail prices are especially low compared with the expected long-term relationship. Thus, pass-through rates can be highly variable and dependent upon the relative relationship between price series.

Figure 10

Pass-through in the nonlinear impulse response function bread wholesale-retail, threshold ECM

Percent of impulse passed through



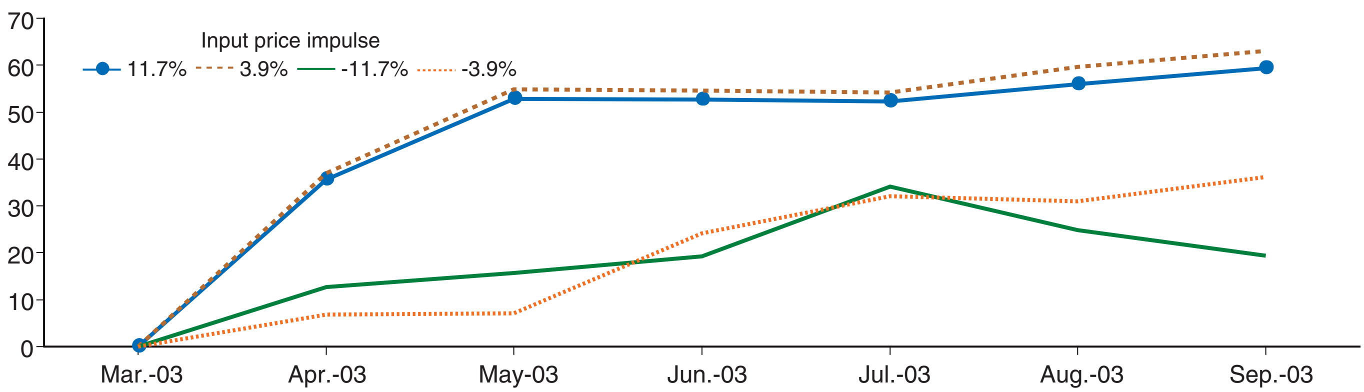
ECM = Error correction model.

Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

Figure 11

Pass-through in the nonlinear impulse response function beef wholesale-retail, threshold ECM

Percent of impulse passed through



ECM = Error correction model.

Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

Conclusion and Future Extensions

Our results indicate that wholesale prices respond to changes in farm-level prices in a generally symmetric manner, with the largest price response occurring within 1 month and some additional pass-through from adjustments to the long-term relationship after that. Single-period pass-through response estimates also were generally higher for farm to wholesale than wholesale to retail. Retail price responses to wholesale price changes are characterized by more complex behavior with threshold effects that are statistically significant and direct pass-through of changes at times occurring quickly (within 1 month) and under other conditions more slowly (taking between 2 to 4 months). Differences between food categories also exist, with more processed items (bread and wheat flour) showing less response to upstream price changes than less processed items (retail and wholesale beef).

Although the results of our study are robust to a number of different model specifications, there is an implicit assumption in our models that the direction of response between prices in the supply chain follows a single, natural path from farm to wholesale to retail and that downstream prices have negligible or inconsistent feedback on their upstream prices. This assumption stems from both the more direct and (the assumed) stronger effect of an input price on its output price (than vice versa) and the common finding that retail-price changes having little impact back through the supply chain to commodity-price changes.[22]

[22]See, for example, Abdulai (2002) and Goodwin and Holt (1999).

By modeling two food categories and two pricing relationships within each supply chain, our study provides examples of pass-through analyses, but there are a number of extensions to our work that would enhance understanding of pricing behavior in the food marketing system. One would be to conduct an analysis using price measures that are available with greater frequency. This may provide a useful comparison to our results, but such data are unlikely to include more than a few years of observations. Another path of inquiry would be to consider more points in the supply chain for some food categories in order to trace price change linkages even further back in the production chain. An example of this would be to trace back the effect of corn and soybean price changes on cattle prices, and thus gain further insight to how basic commodity prices affect retail markets.

Aside from these avenues, the most basic continuation of this work would be the application of these types of models to other food categories. This endeavor would be quite useful because, while similarities among groups are likely to exist, pass-through behavior itself is unique to each input and output relationship. Once these additional food categories are modeled, an update to ERS's forecasting of the Food Consumer Price Index and its subcomponents could be implemented and should improve our ability to predict changing trends in retail food-price inflation.

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Appendix: Statistical Test Descriptions

Time-Series Properties of the Data

We began the investigation of the time series properties of the price data with unit root tests to establish the integration order of the individual series. This is necessary because in order for a cointegrating relationship to be possible, the series considered must be integrated of order 1—the series in levels is nonstationary but the first difference of the series is stationary. Cointegration implies that a stable, long-term relationship exists between time series variables that are themselves nonstationary. We used the modified Dickey-Fuller unit root test (DF-GLS) as described by Elliot et al., (1996) and included a trend term in the unit root test (if the time series data appeared to be following a linear trend over time). The results of the unit root tests, in all cases, failed to reject the presence of a unit root in the series itself, but rejected a unit root in the first difference of the series. Thus, the series were concluded to be first difference stationary.

The test for cointegration proceeds by looking at the stability of the long-term relationship between series by considering the stationarity of the residuals of the cointegrating relation. To begin, the cointegrating relation of equation 1 was estimated (by OLS) for each input series and its direct output series within a product group. The test for stationarity was then conducted on the residuals from the estimation with a Phillips-Perron unit root test, and this was done before any consideration of structural breaks. For all cases the null hypothesis of a unit root in the residuals, u, was rejected. This information combined with the result that the price series is integrated of order 1 suggests that a cointegrating relationship likely exists between the supply chain level price series.

Structural Breaks in the Longrun Equations

In order to estimate the number and timing of any structural changes in the cointegrated system, we used the procedure developed by Kejriwal and Perron (2008). Their 2008 work builds on an extensive literature that has systematically developed testing methods to determine the presence and placement of unknown change points within time series relationships (a detailed discussion of this progression can be found in this report's Introduction). Kejriwal and Perron look at several techniques for allowing different parts of the cointegrating equation to change over time (e.g. intercepts or all coefficients, although the statistical properties of the breaks become more difficult to determine if the parameter considered is nonstationary), and in our analysis the procedures are followed in which only the intercept is allowed to change.

We first consider the general test used by Kejriwal and Perron to confirm that some positive number of breaks may be appropriate. This is followed by using a sequential procedure that compares a model with k breaks against a model with $k+1$ breaks. The tests were conducted for each of the different price stage relationships following the form of equation 1 and with a 15-percent trimming rate (specifying that an area the size of 15 percent of the total observations would not be searched around a break), consistent with critical values calculated and presented by Kejriwal and Perron (2008). In each test, a maximum of three breaks is specified for this analysis to ensure that necessary sample sizes are maintained within each period. Details of the test statistics can be found in Roeger and Leibtag (2010).

In this analysis, we chose to include intercept shifts as the only time-varying parameters for a number of reasons, but this should not imply that future research should be limited to only this method. In our analysis we also considered allowing the coefficient on P_I to shift over time which would imply that, aside from the other input costs changing over time, the response to the main agricultural input is also time variant. In testing this alternative specification, where β_I also shifts with the identified break dates, we found that this added little to the long-term models. This changed the residual values, u_t, in only minor ways and in comparing R^2 values, our initial adding of structural break dummy variable increased the amount of variance explained by the model by about 20 percent, while letting β_I change across time as well, explained less than 1 percent of additional variance.

Threshold Bounds Search

The optimal bounds for the threshold ECMs, c_1 and c_2 (unique for each model), were found by conducting a grid search of the values of u. We use the method proposed by Balke and Fomby (1997) in which a grid search is conducted for threshold values that minimize the total sum of squared errors (SSE) across the conditional regression models. The restrictions on this search were that c_1 be greater than the lowest 15 percent of values, c_2 be less than the highest 15 percent, and a 15-percent band around 0 also be excluded. These 15-percent restrictions are utilized so that each regime has a sizeable enough number of observations to have its own separate regression model. The search proceeded by grouping together the u values using the c_1 and c_2 values as bounds on each group and estimating an autoregressive model for each group.

Following the restrictions above, different u values were sequentially used as bounds with the goal of the search to find the combination of c_1 and c_2 values that would produce the lowest total SSE from the estimation of the conditional autoregression models. The u values found for bounds c_1 and c_2 leading to the lowest total SSE, thus, provide the best grouping of negative and positive value cointegrating equation error terms, and allow the observations to be divided into three regimes based on where the particular u value falls for that observation.

Threshold Significance Test

In order to evaluate the statistical significance of threshold effects, we used the testing procedure introduced by Hansen (1997). In this test, a standard Chow test is performed and then repeated through a series of simulations using the same model but replacing the dependent variable values with a random draw in order to approximate the p-value for threshold significance. The test was performed for each threshold ECM with 350 repetitions. The null hypothesis of nonsignificance of the thresholds was rejected with an error rate of less than 0.001 percent for both wholesale to retail models, but at 19.4 percent for farm to wholesale beef and 17.7 percent for farm to wholesale wheat flour. These results imply that for the retail models, the identified optimal threshold from the data are nearly always a better fit than groupings in random data, but for the wholesale models this is not the case 19.4 percent and 17.7 percent of the time (for beef and wheat flour, respectively).

Table A-1

Beef wholesale to retail pass-through regression estimation results

Model type	Variable		Coefficient	
Threshold ECM: Regime 1	Δ(ln beef PPI)$_{t-1}$	**	0.271	(0.043)
	Δ(ln beef PPI)$_{t-2}$	**	0.110	(0.055)
	Δ(ln grocery store wage)$_{t-2}$		0.035	(0.143)
	Δ(ln diesel)$_{t-6}$		0.002	(0.019)
	ECT$_{t-1}$	**	-0.120	(0.056)
Regime 2	Δ (ln beef PPI)$_{t-1}$	**	0.218	(0.021)
	Δ(ln grocery store wage)$_{t-2}$		0.092	(0.080)
	Δ(ln diesel)$_{t-6}$		0.002	(0.009)
	ECT$_{t-1}$	**	0.071	(0.035)
Regime 3	Δ(ln beef PPI)$_{t-1}$	**	0.131	(0.029)
	Δ(ln beef PPI)$_{t-2}$	**	0.065	(0.027)
	Δ(ln grocery store wage)$_{t-2}$	*	0.133	(0.075)
	Δ(ln diesel)$_{t-6}$		0.008	(0.009)
	ECT$_{t-1}$		-0.074	(0.047)
Symmetric	Δ(ln beef PPI)$_{t-1}$	**	0.247	(0.016)
	Δ(ln beef PPI)$_{t-2}$	**	0.065	(0.019)
	Δ(ln grocery store wage)$_{t-2}$	*	0.103	(0.057)
	Δ(ln diesel)$_{t-6}$		0.005	(0.007)
	ECT$_{t-1}$		-0.011	(0.011)

(*) denotes significance at least at the 10-percent level.

(**) denotes significance at least at the 5-percent level.

Coefficients for constant and autoregressive terms are not listed.

The dependent variable in this regression model is the change in the downstream price: Δ(ln beef CPI)$_t$.

ECM = Error correction model; ECT = error correction term; PPI = Producer Price Index

Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

Table A-2

Beef farm to wholesale pass-through regression estimation results

Model type	Variable		Coefficient	
Threshold ECM: Regime 1	Δ(ln cattle PPI)$_{t-1}$	*	0.287	(0.150)
	Δ(ln slaugtering wage)$_{t-8}$		0.435	(0.507)
	Δ(ln diesel)$_{t-2}$		0.000	(0.054)
	ECT_{t-1}	*	-0.161	(0.096)
Regime 2	Δ(ln cattle PPI)$_{t-1}$	**	0.412	(0.085)
	Δ(ln slaugtering wage)$_{t-8}$	**	0.793	(0.262)
	Δ(ln diesel)$_{t-2}$		0.017	(0.022)
	ECT_{t-1}	**	-0.534	(0.183)
Regime 3	Δ(ln cattle PPI)$_{t-1}$	*	0.224	(0.119)
	Δ(ln slaugtering wage)$_{t-8}$		0.258	(0.315)
	Δ(ln diesel)$_{t-2}$	**	0.125	(0.044)
	ECT_{t-1}		-0.134	(0.090)
Symmetric ECM	Δ(ln cattle PPI)$_{t-1}$	**	0.340	(0.063)
	Δ(ln slaugtering wage)$_{t-8}$	**	0.600	(0.185)
	Δ(ln diesel)$_{t-2}$	**	0.038	(0.019)
	ECT_{t-1}	**	-0.136	(0.054)

(*) denotes significance at least at the 10-percent level.

(**) denotes significance at least at the 5-percent level.

Coefficients for constant and autoregressive terms are not listed.

The dependent variable in this regression model is the change in the downstream price: Δ(ln beef PPI)$_t$.

ECM = Error correction model; ECT = error correction term; PPI = Producer Price Index

Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

Table A-3

Bread wholesale to retail pass-through regression estimation results

Model type	Variable		Coefficient	
Threshold ECM: Regime 1	Δ(ln wheat flour PPI)$_{t-1}$	**	0.100	(0.033)
	Δ(ln grocery store wage)$_{t-7}$		-0.060	(0.177)
	Δ(ln diesel)$_{t-6}$		0.044	(0.037)
	ECT$_{t-1}$	**	-0.124	(0.054)
Regime 2	Δ(ln wheat flour PPI)$_{t-3}$	**	0.052	(0.016)
	Δ(ln wheat flour PPI)$_{t-4}$	**	0.056	(0.016)
	Δ(ln grocery store wage)$_{t-7}$		0.078	(0.055)
	Δ(ln diesel)$_{t-6}$		0.002	(0.006)
	ECT$_{t-1}$	**	-0.033	(0.013)
Regime 3	Δ(ln wheat flour PPI)$_{t-2}$	**	0.062	(0.018)
	Δ(ln wheat flour PPI)$_{t-3}$	**	0.046	(0.018)
	Δ(ln wheat flour PPI)$_{t-4}$	**	0.047	(0.019)
	Δ(ln grocery store wage)$_{t-7}$		0.052	(0.059)
	Δ(ln diesel)$_{t-6}$		-0.004	(0.008)
	ECT$_{t-1}$		0.005	(0.022)
Symmetric	Δ(ln wheat flour PPI)$_{t-1}$	**	0.051	(0.011)
	Δ(ln wheat flour PPI)$_{t-2}$	**	0.037	(0.012)
	Δ(ln wheat flour PPI)$_{t-3}$	**	0.058	(0.012)
	Δ(ln wheat flour PPI)$_{t-4}$	**	0.039	(0.012)
	Δ(ln grocery store wage)$_{t-7}$		0.038	(0.043)
	Δ(ln diesel)$_{t-6}$		-0.002	(0.005)
	ECT$_{t-1}$	**	-0.009	(0.004)

(*) denotes significance at least at the 10-percent level.

(**) denotes significance at least at the 5-percent level.

Coefficients for constant and autoregressive terms are not listed.

The dependent variable in this regression model is the change in the downstream price: Δ(ln white bread CPI)$_t$.

ECM = Error correction model; ECT = error correction term; PPI = Producer Price Index

Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.

Table A-4

Bread farm to wholesale pass-through regression estimation results

Model type	Variable		Coefficient	
Threshold ECM: Regime 1	$\Delta(\ln \text{wheat PPI})_{t-1}$	**	0.112	(0.034)
	$\Delta(\ln \text{electricity price})_{t-9}$	**	0.421	(0.210)
	$\Delta(\ln \text{diesel})_{t-1}$		0.056	(0.058)
	ECT_{t-1}		-0.030	(0.047)
Regime 2	$\Delta(\ln \text{wheat PPI})_{t-1}$	**	0.159	(0.085)
	$\Delta(\ln \text{wheat PPI})_{t-2}$	**	0.104	(0.047)
	$\Delta(\ln \text{electricity price})_{t-9}$		0.003	(0.136)
	$\Delta(\ln \text{diesel})_{t-1}$	**	0.085	(0.036)
	ECT_{t-1}		-0.064	(0.132)
Regime 3	$\Delta(\ln \text{wheat PPI})_{t-1}$	**	0.193	(0.074)
	$\Delta(\ln \text{electricity price})_{t-9}$	**	0.395	(0.128)
	$\Delta(\ln \text{diesel})_{t-1}$		-0.012	(0.028)
	ECT_{t-1}	**	-0.090	(0.045)
Symmetric	$\Delta(\ln \text{wheat PPI})_{t-1}$	**	0.115	(0.047)
	$\Delta(\ln \text{electricity price})_{t-9}$	*	0.162	(0.088)
	$\Delta(\ln \text{diesel})_{t-1}$	*	0.042	(0.022)
	ECT_{t-1}	*	-0.069	(0.036)

(*) denotes significance at least at the 10-percent level.

(**) denotes significance at least at the 5-percent level.

Coefficients for constant and autoregressive terms are not listed.

The dependent variable in this regression model is the change in the downstream price: $\Delta(\ln \text{wheat flour PPI})_t$.

ECM = Error correction model; ECT = error correction term; PPI = Producer Price Index

Source: USDA, Economic Research Service calculations based on U.S. Department of Labor, Bureau of Labor Statistics data.