The Magnitude and Timing of Retail Beef and Bread Price Response to Changes in Input Costs

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1. Introduction

The rapid rise and fall of commodity prices from 2007 to 2009 created renewed interest in estimating the impact of large, and sometimes volatile, swings in commodity prices on retail food prices. In measuring price response behavior between production stages such observable shifts in price volatility necessitate that modeling be done in a way that is flexible. In this study we develop models for price pass-through behavior for farm to wholesale and wholesale to retail price changes using 36 years of monthly price data (1972-2008). The food price chains that we focus on are the wheat to wholesale wheat flour to retail (white) bread chain and the cattle to wholesale beef to retail beef chain, which present examples of production chains with significantly different degrees of processing between stages. This is done in order to estimate how much of the change in commodity costs is generally passed through to retail prices, how the rate of pass-through varies by food type, and, just as important, estimate the time lag between commodity price changes and retail price changes. A main feature of our study is to characterize price response behavior in a manner that is not overly influenced by any relative market conditions that can dominate samples of data that are limited to fewer years. In this manner we construct a framework that can describe price response behavior when prices are relatively stable or in periods of substantial input price growth. From this, we gain a more detailed and well rounded understanding of the dynamic relationships between prices at different production levels over time and, ideally, expectations for the effects felt by retailers and consumers of shocks to prices at the farm level will be improved.

At least since the early 1970s there have been periodic spikes in the prices of major field crops as well as interspersed periods of relatively stable farm prices. Although there are certainly differences in price cycles across time, there are also certain common factors that can jointly characterize past shocks. Commodity price surges such as those from 1971-1974, 1994-1996, and 2006-2008 have generally occurred as a result of a combination of demand, supply, and macroeconomic situations. Some of these factors would include growth in export demand, changes in government food policies, slowing agricultural production growth, unpredictable weather events, and depreciation of the U.S. dollar. Also, for commodity price spikes prior to 2006 (except for the expansion in the early 1970s), after prices peak they have typically fallen back to a level seen before the surge (Trostle, 2008).

However, there are also factors that set apart the most recent period of rapidly rising commodity prices from those in the past, and reasons to believe that there may be a more lasting effect on market volatility (Peters et al., 2009). One of these issues is the long term trend in economic growth in developing countries. This affects agriculture in a number of ways including increased demand for fuel supplies and diet diversification from rising incomes. In the U.S. and other developed countries there have also been large increases in the demand for biofuel production which affects commodities prices by taking a large share of feed crop stocks out of food markets. Both of these major features may lead to continued demand pressure beyond the particular combination of factors that led to the 2007-2008 commodity price spike.

The characterization of the pass-through relationship between a retail food product and its principal agricultural input can be direct but also complex. A downstream production price will generally follow its upstream production price but often there are factors that limit this responsiveness. The basic explanation for this generalization is that the downstream product is 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. Kinnucan and Forker (1987) also suggest that even if a retail price is to respond, delays may arise. 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 between production stages, and at times, a lack of measurable response in the downstream product's price.

Additionally, when viewed over longer periods of time this relationship between farm and retail prices is subject to noticeable shifts. Such changes can arise as the amount of processing and marketing costs grow over time and may differ between food categories. Looking at the farm share of the retail food dollar for the food-at-home categories of beef or cereals and bakery products gives a basic sense of this change. Between 1970 and 2008, the farm share for each of these categories dropped from $0.64 to $0.46 and $0.16 to $0.10, respectively[1].

In recent years, many empirical studies have investigated the complexity of commodity pass-through relationships using newly developed statistical tools. Goodwin and Harper (2000) combine an error correction model (ECM) with the possibility of a non-linear threshold type response. An ECM is a method that can account for both short term price responses and adjustments to a stable long term equilibrium. In studying weekly pork prices from 1987 to 1999, the authors find evidence that retail prices may 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 behavior in light of structural breaks in the long term relationships between production level prices. Both sets of

[1] Summary of USDA, ERS meat price spread data available at http://www.ers.usda.gov/Data/MeatPriceSpreads/ and field crops price spread data available at http://www.ers.usda.gov/Data/FarmToConsumer/pricespreads.htm.

authors generally find it beneficial to model the pass-through relationships as a combination of 1) a short term response to input price changes and adjustments to an expected long term equilibrium and 2) allowing for points of asymmetric price response.

Our research seeks to describe how commodity price changes affect retail food prices by continuing the work of some of these past studies, while also focusing more closely on areas that appear absent from the present literature. We build on the features of including a long time period and considering different possibilities of asymmetric price adjustment by extending our analysis to combine these aspects more thoroughly. Other additions of our work include allowing more freedom for the relationships between production stages to vary within a food group and the consideration of energy and labor variables as short term inputs. All of this is done, not just exclusively on the traditionally studied food categories of meat and dairy, but on two categories with markedly different degrees of processing – beef and white bread. These extensions to current research are included in the goal of helping to describe in better detail the differing nature of price response between production stages and across food categories.

The remainder of this paper proceeds as follows: Section 2 describes the data used, the procedural steps followed, and the results of the preliminary statistical tests. Section 3 presents the results of the pass-through estimation for the different production stages and food categories. Finally, we conclude and explore future extensions to our study in section 4[2].

2. Procedural Description

2.1 Data

Our analysis uses price information at different production stages for two products, (white) bread and beef. In order to stay abreast of general trends in these respective industries

[2] All figures and tables are presented following the complete text of this report. An appendix is also provided that presents the regression estimates for the different pass-through models.

and avoid issues with following production chains for very specific retail products, the price series data was gathered at the aggregate product level using Bureau of Labor Statistics (BLS) price indices[3]. Table 1 briefly describes the CPI and Producer Price Index (PPI) food and commodity data used for each product and production level.

In addition to the principal food and agricultural commodity prices in each production stage model we also use energy and labor prices, where possible. For all models the wholesale diesel PPI is used as a proxy for transport costs. The variables for labor or additional energy inputs are necessarily more specific to the individual products and production stages. For the wholesale to retail pass-through relationship for both beef and bread, this amounts to a variable for the average hourly grocery store wage. For the farm to wholesale relationship there is an additional variable for the aggregate hourly slaughtering wage[4] for beef and a variable for the electric power PPI for wheat flour.

We chose a time horizon in such a way as to attempt to include as much dynamic movement in the series as possible under the constraint of having consistently available data for all of the variables in the model. Our analysis therefore uses data from the beginning of 1972 (except in the case of the farm to wholesale beef model, which starts with 1976 due to data limitations) through December 2008. The time series data is monthly, not seasonally adjusted, and all price series were converted into their natural logarithms before analysis. The different price series for bread and beef illustrate broadly the changes in pass-through relationships over time and the degree of consistency of response between production levels (figures 1 and 2, respectively).

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[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.

[4] For both the slaughtering wage and grocery store wage, data from the BLS National Compensation Survey was used.

2.2 A Cointegrating Relationship

In order to investigate any underlying long term relationship between an upstream and a downstream price series as well as capture short term price responses, we construct a pass-through model that uses an error correction framework and incorporates any cointegrating relationships between series. A cointegrating relationship would imply that even if two price series themselves are non-stationary and subject to different short term fluctuations, a stable long term equilibrium relationship between them can still be expressed. To first establish the time series properties (integration order) of the individual price series we used the modified Dickey-Fuller test (DF-GLS) as described by Elliot et al. (1996) and included a trend term in the unit root test conditional on the presence of a clear linear trend in the time series data. The individual results of the unit root tests showed all of the series to be first difference stationary (table 2), and thus, each of the individual series are (possibly) suited for a cointegrating relationship for the time period in consideration.

Following the Engles and Granger (1987) approach the cointegrating or long term equation can be first estimated via OLS,

$$P_{O,t} = \beta_0 + \beta_1 P_{I,t} + u_t, \qquad (1)$$

where P_I represents the input price series of the production level at time t, P_O represents the output price series, and u represents the estimation residuals. The test for stationarity was then conducted on the residual series from each estimation, with a Phillips-Perron unit root test. For all cases the null hypothesis of a unit root in the residuals, u, was rejected (table 3). This information combined with the results of the price series being first difference stationary suggests that a cointegrating relationship likely exists between the production level price series. An ECM is then constructed to describe the changes to the output price based on a number of short term lagged first differenced variables and a lagged error correction term (in levels). The error correction term represents the cointegration equation (CE) residuals being used to describe the reliance (or error correction) of the changes in the output price to the expected long term relationship. This basic representation can be expressed as

$$\Delta P_{O,t} = \varphi_0 + \Sigma^{Q}_{i=1} (\varphi_{1,i}\, \Delta P_{O,t-i}) + \Sigma^{R}_{i=1} (\varphi_{2,i}\, \Delta P_{I,t-i}) + \Sigma^{S}_{i=1} (\varphi_{3,i}\, \Delta x_{1,t-i})$$

$$+ \Sigma^{T}_{i=1} (\varphi_{4,i}\, \Delta x_{2,t-i}) + \gamma\, u_{t-1} + \upsilon_t,$$

(2)[5].

where x_1 and x_2 are variables that are assumed to have an effect on P_O in the short term but without necessarily having a stable long term relationship with the variable, and υ is the residual from the ECM[6]. In this equation, the sign on γ will necessarily need to be negative for P_O to be converging towards the long term relationship.

2.3 Structural Breaks

As discussed above, certain factors may cause divergence in the relationship between P_O and P_I over time. Over a long enough time horizon this separation between price series can significantly affect the upstream/downstream relationship because an increasing difference between the prices implies that upstream price changes will have less impact. One way to account for such changes is to introduce parameters into equation 1 that are specific to certain time periods. Including these terms would alter equation 1 as follows,

$$P_{O,t} = \beta_0 + \beta_1\, P_{I,t} + \beta_2\, \varphi_1 + \beta_3\, \varphi_2 + \beta_4\, \varphi_{3}. \qquad (1a)$$

[5] The constant term, φ_0, may be omitted in cases in which the output price series does not appear to have a clear trend over time.
[6] The energy and labor inputs are modeled as short term variables, in that they are present in the error correction model but not in the cointegrating equation.

The φ terms all represent variables that are present in equation 1a only for certain periods of time. In this way, these newly added terms are meant to stand in for the long term change to the farm or wholesale share of the final price that is considered. The dates that these added value variables (the φ terms) correspond to are chosen endogenously (that is they are a product of data) so that patterns within the data are explored rather than imposing assumptions onto the data. These dates can also be considered as structural break dates, in the sense that they are estimates of points in time that signify a change in the relationship between P_O and P_I[7].

In order to estimate the number and timing of any structural changes in the cointegrated system, the procedure developed by Kejriwal and Perron (2008) can be employed. Here the procedures are followed in which only the intercept is allowed to change. Boetel and Liu (2008) follow a similar approach when investigating the long run price linkage between farm, wholesale, and retail beef and pork prices over a comparable 38 year time span. The tests were conducted for each of the different production stage relationships following the setup of equation 1 and with a 15% trimming rate that specified that a break would not be searched for in the beginning or ending 15% of the data. This particular trimming rate is in following with critical values calculated and presented by Kejriwal and Perron in their 2008 work. A test is first considered to confirm that some positive number of breaks may be appropriate. The test statistic here is constructed around the sum of squared residuals from the model with the included breaks and then compared against critical values derived by the authors. The second set of tests used from the authors' procedure revolves around the sequential method of comparing a model with k breaks against a model with $k+1$ breaks. If the sum of squared residuals from the model with the higher number of breaks exceeds that of the model with k breaks by a certain specified amount,

[7] While these structural break dates are specific points, they are chosen to represent shifts that may take place over longer periods of time.

then the model with *k+1* breaks is favored. In each type of test a maximum of three breaks is specified for this analysis. The specific results of both tests can be seen in table 4.

The results of the structural break tests pointed towards 3 breaks in each of the wholesale to retail price relationships and 2 breaks in each of the farm to wholesale relationships. Plots of the price indices with markers for the estimated break dates can be seen in Figures 3 and 4, and the estimates of the cointegrating equations with structural breaks can be found in Table 5. Within the choice of structural breaks, several trends come forward. First, as expected, the breaks for different production stage relationships within a product occur at similar times. The generally closer co-movement of farm and wholesale prices leads to the consistent finding of fewer structural breaks in the farm to wholesale relationships. The coefficient estimates of the structural break variables also indicate an increasing margin over time between the downstream component and the associated upstream component.

The timing of the chosen structural breaks in the long term equations roughly correspond to periods concurrent with significant supply and demand changes within the respective industries in the time horizon considered. In looking at beef, the earliest chosen break date of 1980 may serve as a marker for the conclusion of production shifts in the 1960s and 70s towards commercial cattle feeding businesses. Also, around 1980 there began a period of increasing concentration among processors with the share of purchases made by the 4 largest processors doubling between 1980 and 1990. The middle beef breaks of 1991 and 1995 correspond with a time of significant increases in operation sizes (measured between 1992 and 1997) where the production locus[8] went from 23,891 head to 38,000 head for fed cattle. This increase in production locus was more than 3 times the increase in size from 1987 to 1992. For the later

[8] The production locus, as described here, is meant to represent the measure where 50 percent of the cattle operations were smaller than this number and 50 percent were larger.

chosen breaks for beef of 2000 and 2001, both of these are approximate in time to the Congressional Livestock Mandatory Reporting Act of 1999 (and its implementation by USDA in 2001), and are in the middle of a period (1997 to 2002) characterized by a leveling off of the past trend of industry consolidation and rapid growth in operation size. (MacDonald and McBride, 2009)

Significant supply and demand changes may also underlie the reasoning in the dates chosen for the wheat, wheat flour, and bread structural breaks. In both long term price relationships a break was chosen in the early 1980s (1980 and 1983); this roughly matches up with the timing of highs in the acreage planted for wheat in the U.S. (peaking in 1981) with acreages since then dropping off considerably (Ali, 2002). The middle break date of 1989 marks a period of sharp volatility in the price of wheat and wheat flour. The later breaks for both production stage relationships, 1997 and 1998, are very close to a major turning point in U.S. consumer demand for wheat. Since the early 1970s per capita wheat flour consumption had been consistently rising but changes in consumer preferences proved 1997 to be an end to this trend of rising usage (Vocke et al., 2008).

2.4 Asymmetric Response

Beyond the issue of structural changes across time, we also consider how different strategies of price setting behavior can affect pass-through among production levels. In our analysis the formal price setting behavior is not sought, but what is of interest is the representation in the data of such behavior, which is to say, how variations in the response of P_O may differ depending on the magnitude and/or sign of changes in P_I. These variations can be viewed as asymmetric adjustments in the short-term price response or the corrections to the long-term relationship.

A direct way to explore if these asymmetries are present is to simply break up the variables in the ECM that are thought to possibly exhibit such behavior. For the short term response, the lags of ΔP_I can be divided up into increasing or decreasing values. A similar approach can also be taken with the adjustment to the long term equilibrium (the term $\gamma\, u_{t-1}$ in equation 2). To account for both of these types of asymmetric behavior, we alter equation 2 to be:

$$\Delta P_{O,t} = \varphi_0 + \Sigma^{Q}_{i=1} (\varphi_{1,i}\, \Delta P_{O,t-i}) + \Sigma^{R}_{i=1} (\varphi_{2,i}\, \Delta P^{+}_{I,t-i}) + \Sigma^{W}_{i=1} (\varphi_{2,i}\, \Delta P^{--}_{I,t-i})$$

$$+ \Sigma^{S}_{i=1} (\varphi_{3,i}\, \Delta x_{1,t-i}) + \Sigma^{T}_{i=1} (\varphi_{4,i}\, \Delta x_{2,t-i}) + \gamma^{+}\, u_{t-1} + \gamma^{--}\, u_{t-1} + \upsilon_t. \quad (3)$$

Similar examples of this type of asymmetric model framework are reviewed in Frey and Manera (2007). However, while equation 3 does provide more detail into pass-through behavior, more flexibility to considerations of how changes to P_I of different magnitudes will affect P_O may be useful.

2.5 Threshold Behavior

Another way to describe asymmetry in the pass-through relationship is to consider the current state of the levels of P_O and P_I relative to the long term equilibrium relationship. In this manner, asymmetries in the response of P_O to different sign and magnitude changes of P_I are indirectly accounted for through how they affect the error correction term, u_{t-1}. This structure is described as estimating equation 2 conditional on the magnitude and sign of the residuals from the CE (equation 1). This particular estimation strategy is consistent with several other studies considering similar questions[9] and leads us to the following transformation of equation 2:

$$\Delta P_{O,t} = \{ f^{(1)} (\varphi_0, \Delta P_{O,t-i}, \Delta P_{I,t-i}, \Delta x_{1,t-i}, \Delta x_{2,t-i}, u_{t-1}) \quad \text{if} \quad u_{t-1} \leq c_1,$$

[9] See, for example, Goodwin and Harper (2000), Martens et al. (1998), and Balke and Fomby (1997).

$$\{f^{(2)}(\varphi_0, \Delta P_{O,t-i}, \Delta P_{I,t-i}, \Delta x_{1,t-i}, \Delta x_{2,t-i}, u_{t-1}) \qquad c_1 < u_{t-1} \leq c_2,$$

$$\{f^{(3)}(\varphi_0, \Delta P_{O,t-i}, \Delta P_{I,t-i}, \Delta x_{1,t-i}, \Delta x_{2,t-i}, u_{t-1}) \qquad u_{t-1} > c_2$$

(4)

where $f^{(1)}$, $f^{(2)}$, and $f^{(3)}$ all have the same general form, essentially equation 2 (with the possibility of different lag lengths). The first group (or regime) in equation 4 are points in time in which the output price is relatively low when compared to what is expected from the estimated long term relationship, the second group is for observations in which the output price is relatively in line with the long term expectation (or small deviations from this), and the third group is when the output price is relatively high. By breaking up the estimation of equation 2 for each of these different regimes, pass-through rates are allowed to differ depending on the recent movements of the output and input prices.

With this threshold model steps are taken to first identify the appropriate threshold values, c_1 and c_2. As proposed by Balke and Fomby (1997) a grid search was conducted for threshold values that will minimize the total sum of squared errors across the conditional regression models. The search for the optimal threshold values, c_1 and c_2, was done over the values of u with the restrictions that c_1 be greater than the lowest 15% of values, c_2 be less than the highest 15%, and a 15% band around 0 also excluded. This optimization, thus, provides the best grouping of negative and positive value CE error terms, and allows the observations to be divided into three regimes. The chosen threshold values and regime compositions of the CE residuals are plotted together in figures 5 through 8.

In comparing the time series residual patterns based on whether it is a farm to wholesale or wholesale to retail relationship, there appears to be some particular distinction. For both beef and bread, the residuals for the wholesale to retail production relationship seem to follow more of a linear path between structural breaks. This may be indicative of the general upward divergence of retail prices over time. Meanwhile, the farm to wholesale residuals appear to have a slight tendency to appear cyclical within the periods defined by the structural breaks implying that there has been tighter co-movement over time.

Between beef and bread, the values of the thresholds themselves can also be descriptive. The bounds for beef are more symmetric around zero, which implies that the positive and negative deviations from the long term equilibrium are able to be grouped together more uniformly. The bounds for both of the bread relationships, however, are more asymmetric, and this relatively smaller upper bound may imply that the upstream production price shocks are larger and more differentiable from the smaller input price shocks.

As previously mentioned, a threshold model is an example of a model with asymmetric responses. Thus, this model will describe pass-through relationships more accurately and fit to 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 production stages this may well be the case as under certain conditions, marketing inertia causes downstream prices to be inflexible or unresponsive, but for others this may be less typical.

To assess the statistical significance of the threshold effects the procedure of Hansen (1997) is employed. In this test a standard Chow type 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 results of this test for each production stage relationship of beef and bread are provided in table 6. For the wholesale to retail price relationships, the test confirms that the threshold setting may prove beneficial over a linear model, however, with farm to wholesale considerable doubt is placed on this hypothesis.

3. Pass-through Estimation Results

3.1 Regression Estimation Results

Each of the pass-through ECMs - symmetric (equation 2), asymmetric (equation 3), and threshold (equation 4) – were estimated for each production stage relationship for beef and bread by maximum likelihood estimation with constant terms included in the ECM as appropriate (the coefficients and their standard errors for all models can be found in the appendix). The number of lags to include for each variable in the model was determined by using the Hannan-Quinn information criterion, and the lag order was allowed to be flexible across models[10].

Broadly, several patterns within the regression results emerge that lead to comparisons across products and production stages. For both beef and bread the farm to wholesale asymmetric ECM and threshold ECM pass-through coefficients look to follow a fairly symmetrical pattern of response (in both short term and long term adjustment) to rising or falling input prices, which is consistent with what was previously implied in the Hansen test for threshold significance. This also supports the expectation that the prices at this point in the marketing chain are more closely linked. Among food products, the strength of the pass-through rate appears to be inversely correlated with the level of processing on the input commodity, thus beef generally has larger and quicker pass-through than bread/wheat flour.

Retail prices in particular have a somewhat more complicated response behavior, but for both food products the pass-through at this stage is weaker than the upstream stage. The retail

[10] Contemporaneous impacts on the dependent variable from the exogenous variables were not considered in this analysis. Also, across the different regimes within the threshold ECM the lag order was allowed to be flexible.

bread models seem to have the most variation among the different types. The asymmetric ECM shows a strong short term response to wheat flour price increases, but otherwise in this model bread prices have a tendency to diverge. The retail bread threshold ECM estimates show a similar pattern but with a little more detail. The pass-through is strongest (and fastest) for large wheat flour price spikes, and for other input price movements, retail prices do seem to follow but the effect is spread out and delayed with little or no tracking to the long term relationship.

Beef retail prices seem to follow a similar story. The asymmetric ECM shows faster and stronger pass-through when wholesale beef prices are rising, and the error correction finds some evidence of diverging long run behavior when retail prices are relatively high but the estimates may not be statistically significant in this specification. The threshold ECM finds retail prices the strongest when wholesale price are surging, and in times of modest changes or dropping wholesale prices, there is still a fairly high level of responsiveness. In this model, retail beef prices only have serious tracking to the long term relationship after large wholesale price increases (with some possible adjustment also in the third regime, when retail prices are relatively high), but in the second regime retail prices seem to have a long term trend of pulling away from wholesale prices.

Turning to the non-agricultural price inputs, there were also some similarities in estimation results across production stages[11]. For both farm to wholesale relationships the response to diesel price changes looked to be small in magnitude but significant and fairly quick. The other input variables (slaughtering wage and electricity) were both significant in their respective models for this price relationship and had effects occurring with a much greater lag as compared to diesel prices. In the wholesale to retail models, only beef had a significant short

[11] Between the symmetric and asymmetric ECMs, the coefficients for these variables were almost the same, and in the threshold ECMs the sample splitting makes the interpretation of the estimates of these variables more difficult.

term response to labor or energy price fluctuations with changes to the grocery store wage appearing to have a modest effect after two months.

3.2 Summary of Pass-Through and Non-Linear Impulse Response Functions

Interpreting the full results of a non-linear 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. A tool that can be helpful in exploring the results of this type of model is a non-linear impulse response function (NLIRF) [12]. The NLIRF uses a simulation approach to gauge the impact of a specific change at a specific point in time and 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, 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 7). The NLRIF results (described as “6 Month Total”) represent the cumulative pass-through for a positive or negative change of one standard deviation of change in the input price at 6 months after the initial input price change has taken place[13]. These NLIRF results presented here are average results for January 2000 through January 2008 because the threshold models (and consequently the NLIRF) are sensitive to time period considerations.

When interpreting the results of table 7 it is important to consider that the pass-through rates from the threshold models are sensitive to the relative standing of the output price to the expected long term relationship. This relative standing is important for these threshold models

[12] This method is described in further detail in Potter (1995).
[13] It should be noted that that the response functions are based on impulses where 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.

because it determines which regime a time period falls into *and* the amount of change necessary to switch regimes. As the regression results emphasized, for estimating the amount of pass-through at the wholesale to retail stage, significant differences exist among regimes, and for the beef and bread wholesale to retail threshold models the first regime has the highest expected pass-through rates. Between beef and bread retail prices in the time period 2000 through 2008 there was a noticeable difference in the input price changes necessary for the threshold models to switch between regimes. While for both retail prices the tendency was to be in the second regime during this period (61 percent of the observations for beef and 82 percent for bread), the bread prices were much more clustered around the boundary for switching to the third regime. This is evidenced by the observation that for beef, on average, a 6.7 percent wholesale price increase would move the model into the first regime and a 4.1 percent wholesale price decrease for the third regime. The same sets of numbers for bread are 25.2 percent and 6.3 percent. Thus, for this time period, the models predict that retail beef prices will generally have a stronger response to price increases than retail bread prices will for similar wholesale price increases.

Although in table 7 the NLIRF was used to generate characteristic response numbers over period of time, we were also interested in considering how the retail threshold models perform at specific points in time when markets are stressed and pass-through rates may be higher. Figures 10 and 11 present NLIRF examples for retail beef and bread pass-through responses on a month-by-month basis for +/-1 and +/- 3 standard deviations of change in the input price at points in time when input prices were greatly climbing. This shows specific cases in which rapid input price increases cause the retail threshold models to be represented by the higher (and not as often observed) price response behavior in the first regime, and also emphasizes that with this type of model, pass-through rates can be highly variable.

4. Conclusion and Future Extensions

Pricing events of the last few years have again raised questions as to the nature of price response between retail prices and their upstream components. Although commodity prices have largely retreated from their 2008 peaks, market volatility and increasing levels of processing between production stages continue to change the complexity of pass-through relationships. We examined 36 years of monthly data and several different pass-through models in order to provide more detail as to how price changes are transmitted between different production stages and among different food categories. Through the use of a two-stage error correction approach with the possibilities of asymmetric and threshold type behavior, we analyzed the relationships between production levels allowing for underlying long term relationships and non-linear responses.

Our results indicate that farm to wholesale relationships follow a more symmetric pattern with the majority of price response occurring within one month and some additional pass-through from adjustments to the long term equilibrium after that. Single period pass-through response estimates were also generally higher for the farm to wholesale stage than the respective wholesale to retail stages. The pass-through of wholesale price changes to retail prices appears to be characterized by more complex behavior with statistically significant threshold effects and short term responses taking up to five months to occur. We also find differences in response across food categories, with more processed items (bread and wheat flour) showing less response to upstream price changes than less processed items (beef). Even though each price series has its own singular pattern of movement and responses to input price changes in certain cases depend on the setting, some type of pass-through relationship was always identified.

Although the results of our study are robust to a number of different model specifications, several underlying assumptions should be noted. We assumed that the BLS price indices data provide a reasonable representation of aggregate prices at the farm, wholesale, and retail levels despite any issues introduced by using this type of data over a long time horizon. There is an implicit assumption present in the setup of the production stage models that downstream prices have negligible or inconsistent feedback on their upstream prices. This setting 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 of a number of authors of retail prices changes having little impact back through the production chain to commodity prices changes[14]. Finally, in accounting for change within a pass-through relationship over time, we assumed that the presence of structural break dummy variables in the cointegrating equation and the ECM (when constants are present) performed this task satisfactorily. While it is difficult to assess how successful this was, other possible methods (for example, considering changing slope coefficients across time) do exist and may have certain advantages.

By looking at two food categories and two production stage relationships our study has provided an introduction to pass-through analysis, and there are many extensions to our work that could be done to further gain a more complete understanding of pricing behavior in the food marketing system. One direction to take things would be to look at more precise price measures and those available with greater frequency. This may provide a useful comparison to our analysis, but such data is unlikely to be available for an extended time horizon. Another future path would be to consider a greater number of production stage relationships 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

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

prices, and thus possibly gain more insight in 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 probably be quite useful because while similarities among groups are likely to exist, pass-through behavior itself is unique to each input and output price.

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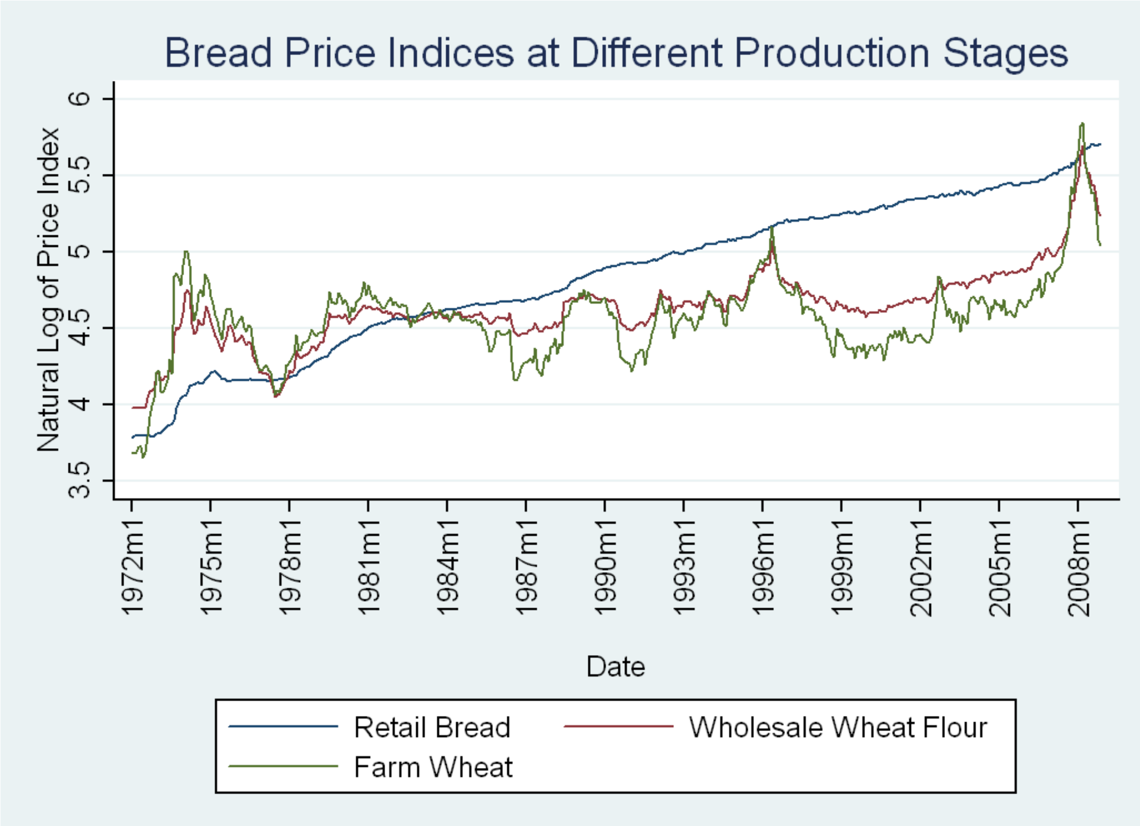
Figure 1.



Source: Bureau of Labor Statistics data

Figure 2.

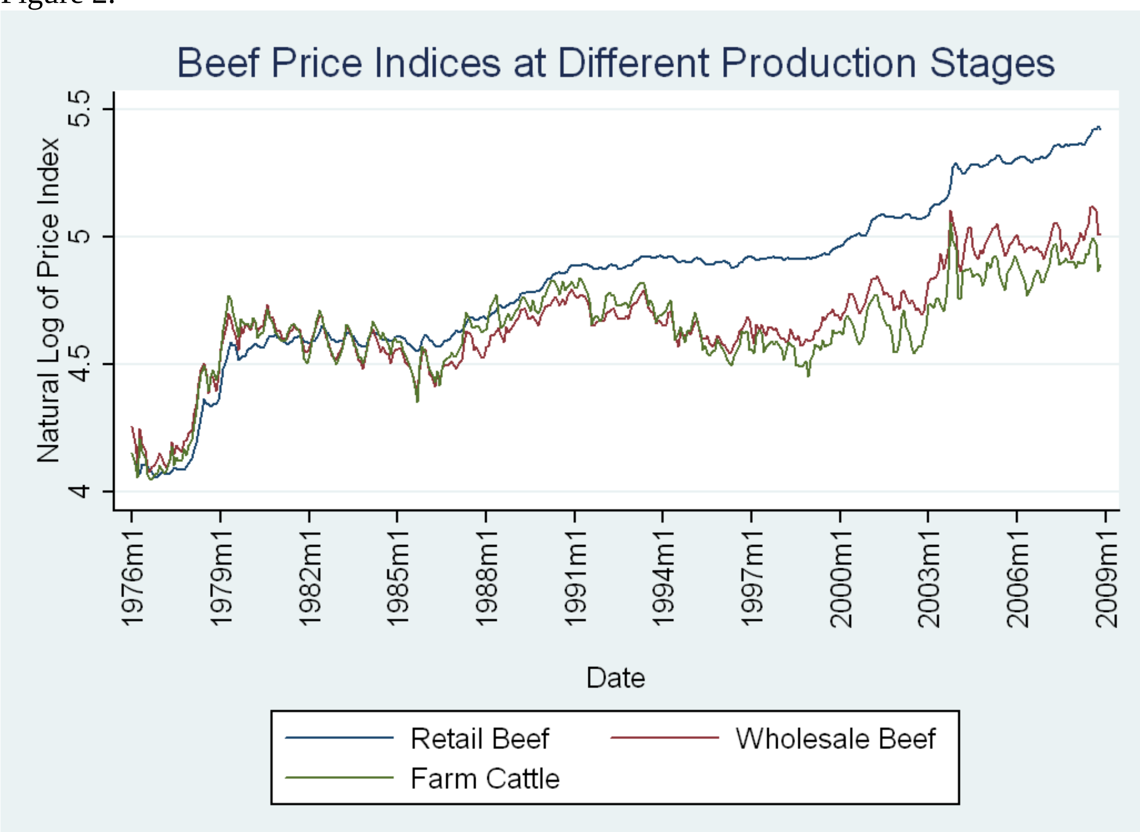


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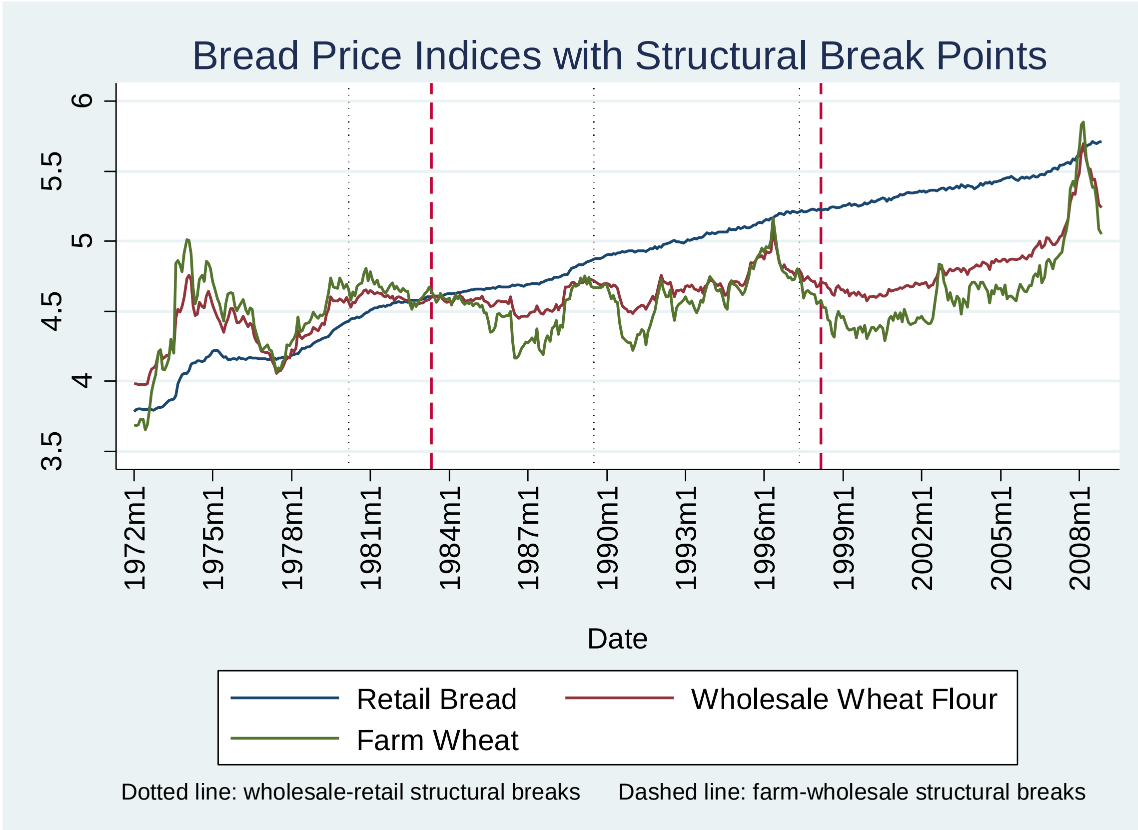
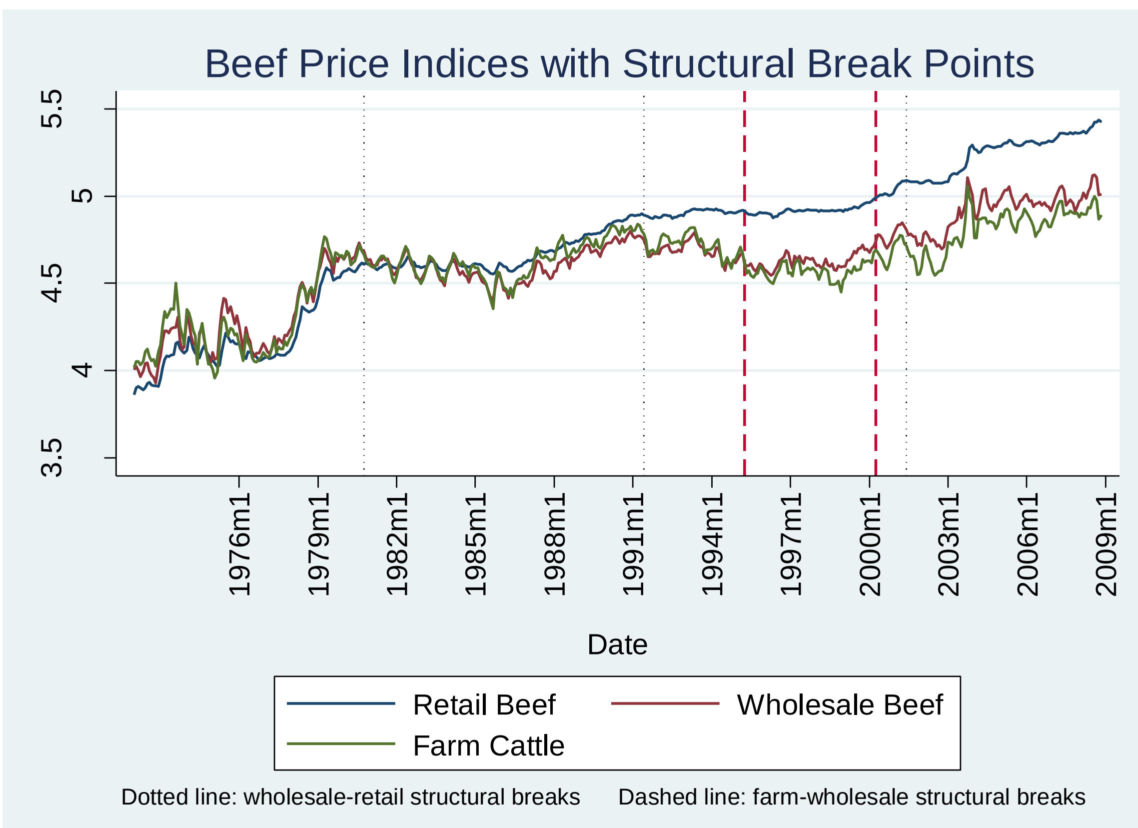
Figure 3.



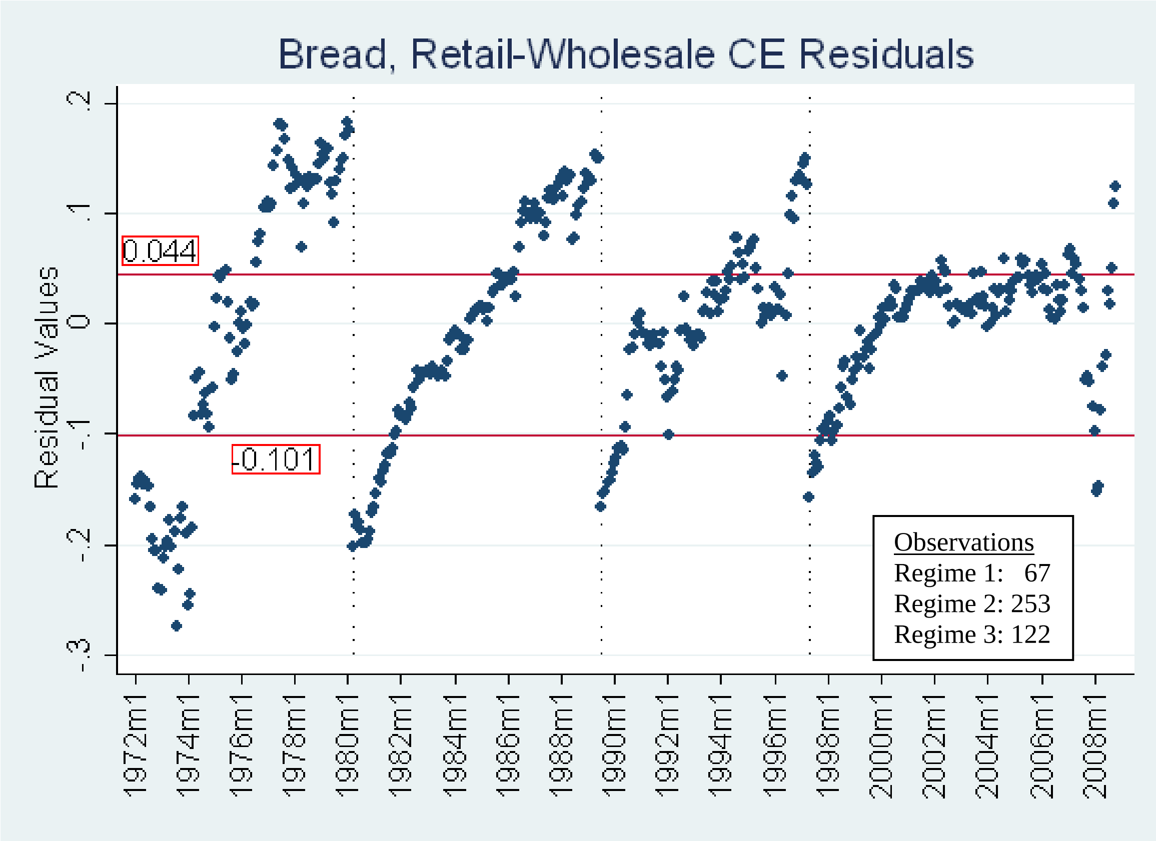
Source: Authors' calculations based on Bureau of Labor Statistics data

Figure 4.



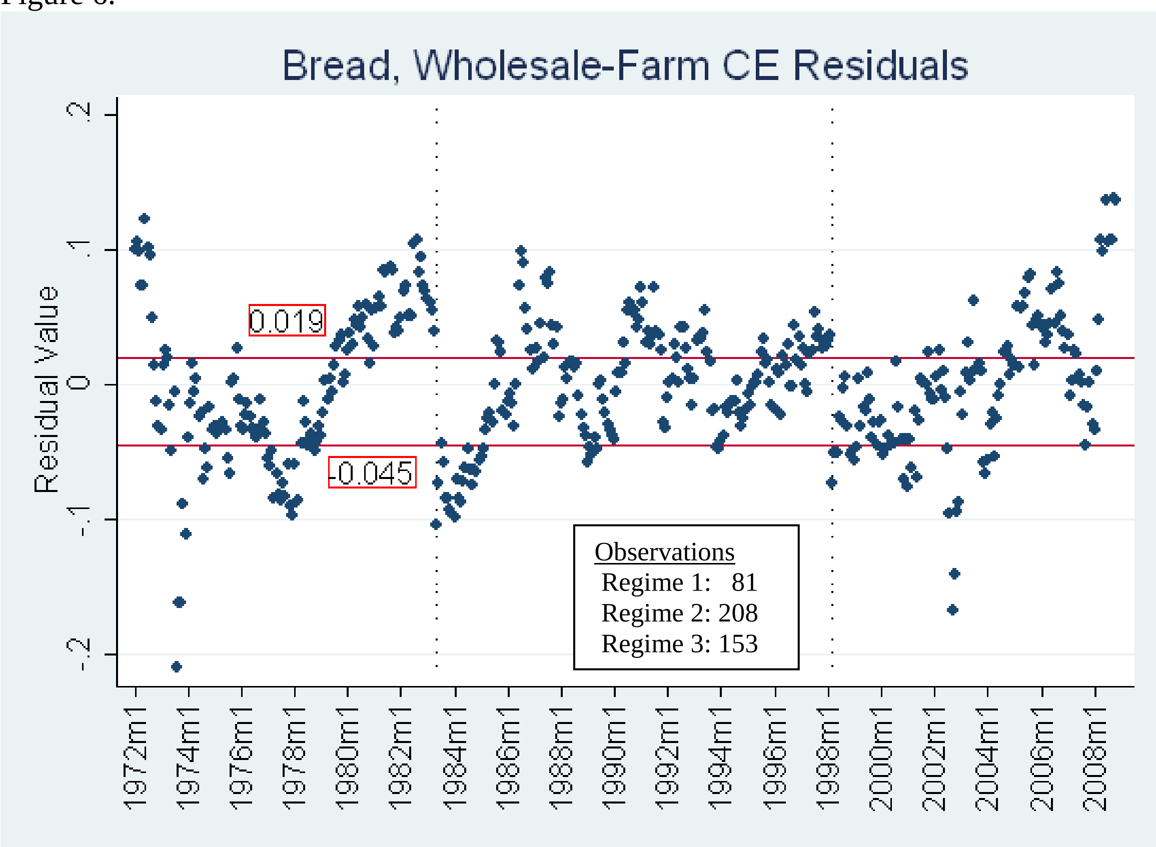
Source: Authors' calculations based on Bureau of Labor Statistics data

Figure 5.



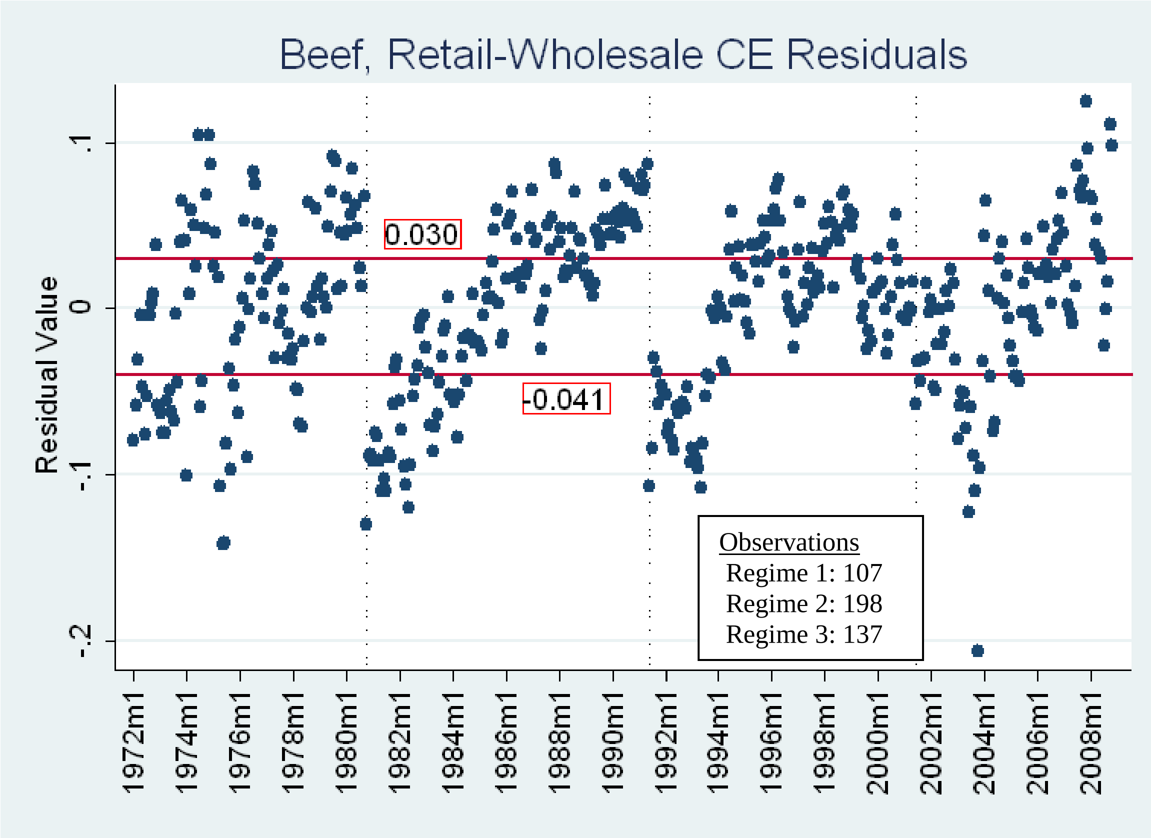
Source: Authors' calculations based on Bureau of Labor Statistics data

Figure 6.



Source: Authors' calculations based on Bureau of Labor Statistics data

Figure 7.



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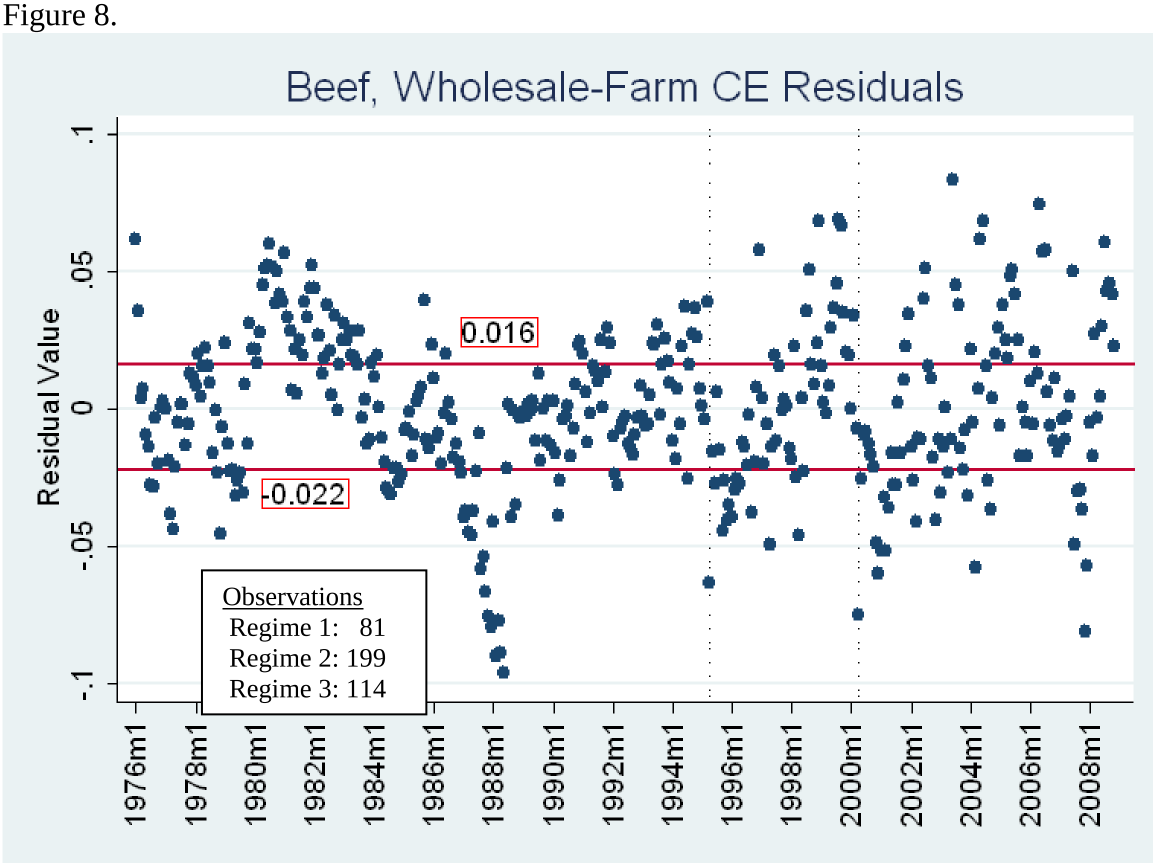
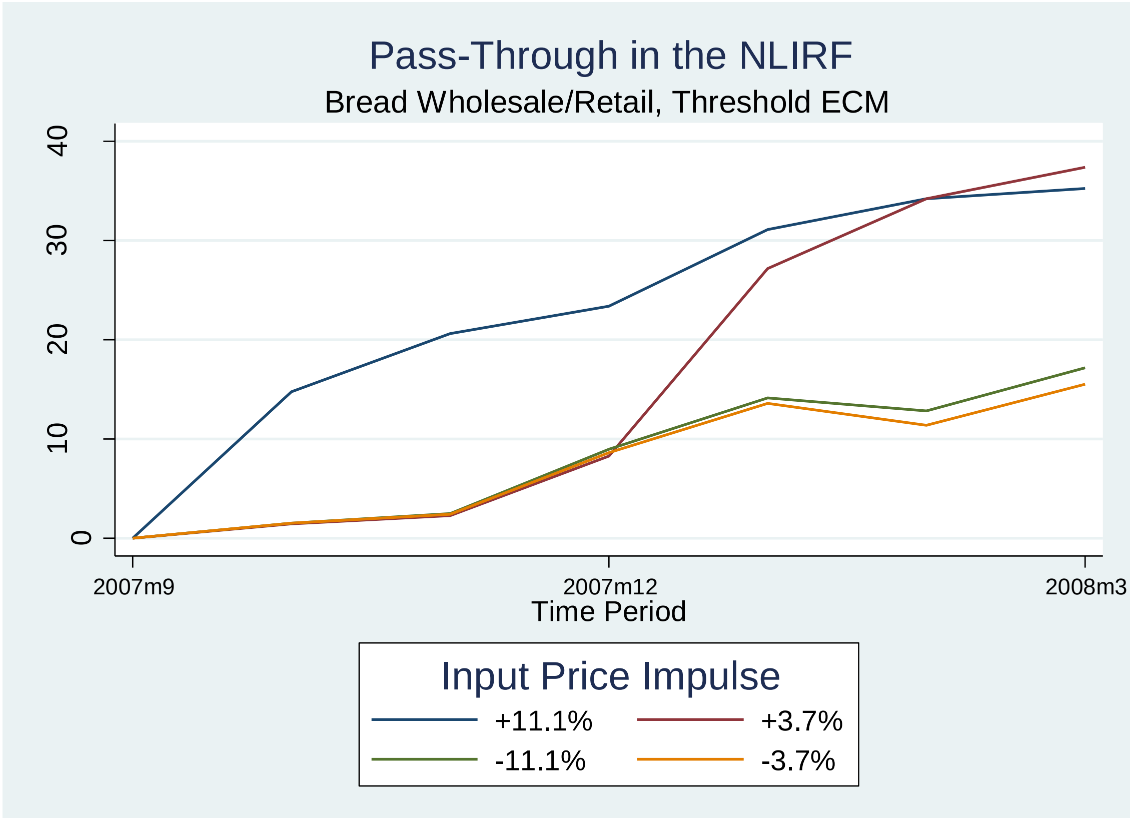


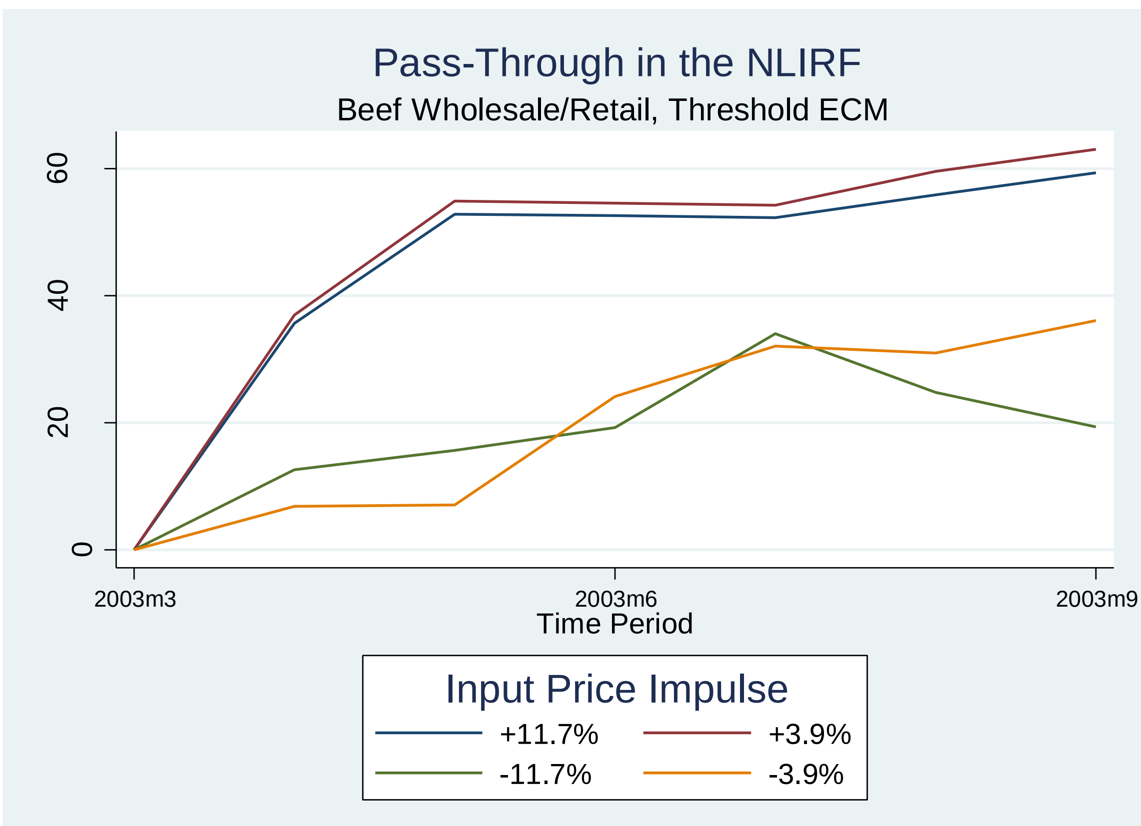
Source: Authors' calculations based on Bureau of Labor Statistics data

Figure 9.



Source: Authors' calculations based on Bureau of Labor Statistics data

Figure 10.



Source: Authors' calculations based on Bureau of Labor Statistics data

Table 1.

Time Series Price Variables		
Production 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

Source: Authors' calculations based on Bureau of Labor Statistics data

Table 2.

Time Series Properties of Individual Price Series				
	Variable	Null Hypothesis	Lags	p - Value
Beef				
	ln (beef cpi)	Unit Root	4	> 10%
	Δ ln (beef cpi)	Unit Root	4	< 0.01%
	ln (beef ppi)	Unit Root	4	> 10%
	Δ ln (beef ppi)	Unit Root	4	< 0.01%
	ln (cattle ppi)	Unit Root	5	> 10%
	Δ ln (cattle ppi)	Unit Root	5	< 0.01%
Bread				
	ln (bread cpi)	Unit Root	7	> 10%
	Δ ln (bread cpi)	Unit Root	7	< 0.01%
	ln (wheat flour ppi)	Unit Root	2	> 10%
	Δ ln (wheat flour ppi)	Unit Root	2	< 0.01%
	ln (wheat ppi)	Unit Root	2	> 10%
	Δ ln (wheat ppi)	Unit Root	2	< 0.01%

Source: Authors' calculations based on Bureau of Labor Statistics data

Table 3.

Cointegration Tests for Stationarity Of Residuals

	Production Relationship	Null Hypothesis	Lags	p - Value
Beef				
	Wholesale/Retail	Unit Root	6	< 0.01%
	Farm/Wholesale	Unit Root	5	< 0.01%
Bread				
	Wholesale/Retail	Unit Root	2	< 0.01%
	Farm/Wholesale	Unit Root	2	< 0.01%

Source: Authors' calculations based on Bureau of Labor Statistics data

Notes:

1. The model in the unit root test was run here without a trend or constant term because the series in question is composed of residuals which are expected to be mean zero.

Table 4.

Tests for Structural Breaks in the Cointegrating Relation

	Production Stage	Test	Breaks	Test Statistic	p Value
Beef					
	Wholesale/Retail				
		Sup F	(1/0)	34.97	< 0.01%
		Sup F	(2/0)	124.75	< 0.01%
		Sup F	(3/0)	53.70	< 0.01%
		Sequential	(2/1)	49.52	< 0.01%
		Sequential	(3/2)	12.10	< 0.5%
	Break Dates:		1980m10	1991m6	2001m6
	Farm/Wholesale				
		Sup F	(1/0)	105.88	< 0.01%
		Sup F	(2/0)	155.87	< 0.01%
		Sup F	(3/0)	129.09	< 0.01%
		Sequential	(2/1)	19.48	< 0.01%
		Sequential	(3/2)	6.01	> 10%
	Break Dates:		1995m4	2000m4	
Bread					
	Wholesale/Retail				
		Sup F	(1/0)	9.2041	< 0.01%
		Sup F	(2/0)	26.34	< 0.01%
		Sup F	(3/0)	172.90	< 0.01%
		Sequential	(2/1)	23.76	< 0.01%
		Sequential	(3/2)	53.64	< 0.01%
	Break Dates:		1980m3	1989m7	1997m5
	Farm/Wholesale				
		Sup F	(1/0)	38.02	< 0.01%
		Sup F	(2/0)	62.47	< 0.01%
		Sup F	(3/0)	217.55	< 0.01%
		Sequential	(2/1)	61.605	< 0.01%
		Sequential	(3/2)	9.00	> 10%
	Break Dates:		1983m5	1998m3	

Source: Authors' calculations based on Bureau of Labor Statistics data

Table 5.

Cointegration Equation Estimates with Structural Breaks

	Production Stage	Estimated Equation
Bread		
	Wholesale/Retail	$P_{O,t} = 1.983 + 0.492\ P_{I,t} + 0.404\varphi_1 + 0.733\varphi_2 + 1.024\varphi_3$
	Farm/Wholesale	$P_{O,t} = 1.385 + 0.676\ P_{I,t} + 0.176\varphi_1 + 0.305\varphi_2$
Beef		
	Wholesale/Retail	$P_{O,t} = 0.413 + 0.882\ P_{I,t} + 0.198\varphi_1 + 0.399\varphi_2 + 0.496\varphi_3$
	Farm/Wholesale	$P_{O,t} = 0.627 + 0.859\ P_{I,t} + 0.074\varphi_1 + 0.158\varphi_2$

Source: Authors' calculations based on Bureau of Labor Statistics data

Notes:
1. The variable $\varphi_1 = 1$ for Break Date 1 $\leq t <$ Break Date 2, otherwise $\varphi_1 = 0$.
2. The variable $\varphi_2 = 1$ for Break Date 2 $\leq t <$ Break Date 3, otherwise $\varphi_2 = 0$.
3. The variable $\varphi_3 = 1$ for $t >$ Break Date 3, otherwise $\varphi_3 = 0$
4. Refer to table 4 for the estimated break dates for each model.

Table 6.

Hansen Test for Significance of Threshold Effects

	Production Level	Null Hypothesis	p - Value
Beef	Wholesale/Retail	Threshold effects are insignificant	0.000
	Farm/Wholesale	Threshold effects are insignificant	0.194
Bread	Wholesale/Retail	Threshold effects are insignificant	0.000
	Farm/Wholesale	Threshold effects are insignificant	0.177

Source: Authors' calculations based on Bureau of Labor Statistics data

Table 7.

Pass-Through Summary

	Threshold ECM Regime 1	Threshold ECM Regime 2	Threshold ECM Regime 3	Asymmetric ECM $\Delta P_I > 0$	Asymmetric ECM $\Delta P_I < 0$	Symmetric ECM
Beef						
Wholesale/Retail						
Total Direct[1]	38.0	31.0	19.6	45.0	38.7	31.2
Timing[2]	1 - 2	1	1 - 2	1 - 2	1 - 5	1 - 2
6 Month Total[3], $\Delta P_I > 0$		28.63		39.71		
6 Month Total, $\Delta P_I < 0$		19.22		34.18		35.1
Farm/Wholesale						
Total Direct PT	28.7	41.1	22.3	38.6	28.2	34.0
Timing	1	1	1	1	1	1
6 Month Total, $\Delta P_I > 0$		48.03		53.28		
6 Month Total, $\Delta P_I < 0$		47.66		54.09		52.6
Bread						
Wholesale/Retail						
Total Direct PT	10	10.8	15.5	24.6	9.2	18.5
Timing	1	3 - 4	2 - 4	1 - 3	4	1 - 4
6 Month Total, $\Delta P_I > 0$		16.32		17.57		
6 Month Total, $\Delta P_I < 0$		21.38		8.56		18.7
Farm/Wholesale						
Total Direct PT	11.2	26.3	19.3	11.5	11.4	11.5
Timing	5	1 - 2	1	1	1	1
6 Month Total, $\Delta P_I > 0$		30.22		29.23		
6 Month Total, $\Delta P_I < 0$		39.68		31.58		30.27

Source: Authors' calculations based on Bureau of Labor Statistics data

Notes:
1. This is the cumulative pass-through (%) without error correction.
2. This is a range of months.
3. This is the cumulative pass-through (%) with error correction after 6 months for an impulse of one standard deviation of change (plus and minus) average for all starting points between 2000m1 and 2008m1.

Appendix: Pass-Through Regression Estimates

Note: (**) denotes significance at the 10% level, (*) denotes significance at the 5% level

Beef Wholesale/Retail Pass-Through Regression Estimation Results

Model Type	Variable		Coefficient	
Threshold ECM: Regime 1	$\Delta(\ln \text{beef ppi})_{t-1}$	**	0.271	(0.043)
	$\Delta(\ln \text{beef ppi})_{t-2}$	**	0.110	(0.055)
	$\Delta(\ln \text{grocery store wage})_{t-2}$		0.035	(0.143)
	$\Delta(\ln \text{diesel})_{t-6}$		0.002	(0.019)
	ECT_{t-1}	**	-0.120	(0.056)
Regime 2	$\Delta(\ln \text{beef ppi})_{t-1}$	**	0.218	(0.021)
	$\Delta(\ln \text{grocery store wage})_{t-2}$		0.092	(0.080)
	$\Delta(\ln \text{diesel})_{t-6}$		0.002	(0.009)
	ECT_{t-1}	**	0.071	(0.035)
Regime 3	$\Delta(\ln \text{beef ppi})_{t-1}$	**	0.131	(0.029)
	$\Delta(\ln \text{beef ppi})_{t-2}$	**	0.065	(0.027)
	$\Delta(\ln \text{grocery store wage})_{t-2}$	*	0.133	(0.075)
	$\Delta(\ln \text{diesel})_{t-6}$		0.008	(0.009)
	ECT_{t-1}		-0.074	(0.047)
Asymmetric	$\Delta^{+}(\ln \text{beef ppi})_{t-1}$	**	0.336	(0.025)
	$\Delta^{+}(\ln \text{beef ppi})_{t-2}$	**	0.114	(0.030)
	$\Delta^{-}(\ln \text{beef ppi})_{t-1}$	**	0.153	(0.030)
	$\Delta^{-}(\ln \text{beef ppi})_{t-2}$	*	0.054	(0.030)
	$\Delta^{-}(\ln \text{beef ppi})_{t-3}$	**	0.071	(0.030)
	$\Delta^{-}(\ln \text{beef ppi})_{t-4}$		0.044	(0.029)
	$\Delta^{-}(\ln \text{beef ppi})_{t-5}$	**	0.065	(0.026)
	$\Delta(\ln \text{grocery store wage})_{t-2}$	*	0.095	(0.055)
	$\Delta(\ln \text{diesel})_{t-6}$		0.002	(0.007)
	ECT^{+}_{t-1}		0.038	(0.023)
	ECT^{-}_{t-1}		-0.027	(0.018)
Symmetric	$\Delta(\ln \text{beef ppi})_{t-1}$	**	0.247	(0.016)
	$\Delta(\ln \text{beef ppi})_{t-2}$	**	0.065	(0.019)
	$\Delta(\ln \text{grocery store wage})_{t-2}$	*	0.103	(0.057)
	$\Delta(\ln \text{diesel})_{t-6}$		0.005	(0.007)
	ECT_{t-1}		-0.011	(0.011)

Source: Authors' calculations based on Bureau of Labor Statistics data

Beef Farm/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)
Asymmetric ECM	Δ+(ln cattle ppi)t-1	**	0.386	(0.078)
	Δ-(ln cattle ppi)t-1	**	0.292	(0.082)
	Δ(ln slaugtering wage)t-8	**	0.548	(0.191)
	Δ(ln diesel)$_{t-2}$	**	0.038	(0.019)
	ECT^{+}_{t-1}		-0.139	(0.087)
	ECT^{-}_{t-1}	*	-0.138	(0.081)
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)

Source: Authors' calculations based on Bureau of Labor Statistics data

Bread Wholesale/Retail Pass-Through Regression Estimation Results

Model Type	Variable	Coefficient	
Threshold ECM: Regime 1	$\Delta(\ln \text{wheat flour ppi})_{t-1}$ **	0.100	(0.033)
	$\Delta(\ln \text{grocery store wage})_{t-7}$	-0.060	(0.177)
	$\Delta(\ln \text{diesel})_{t-6}$	0.044	(0.037)
	ECT_{t-1} **	-0.124	(0.054)
Regime 2	$\Delta(\ln \text{wheat flour ppi})_{t-3}$ **	0.052	(0.016)
	$\Delta(\ln \text{wheat flour ppi})_{t-4}$ **	0.056	(0.016)
	$\Delta(\ln \text{grocery store wage})_{t-7}$	0.078	(0.055)
	$\Delta(\ln \text{diesel})_{t-6}$	0.002	(0.006)
	ECT_{t-1} **	-0.033	(0.013)
Regime 3	$\Delta(\ln \text{wheat flour ppi})_{t-2}$ **	0.062	(0.018)
	$\Delta(\ln \text{wheat flour ppi})_{t-3}$ **	0.046	(0.018)
	$\Delta(\ln \text{wheat flour ppi})_{t-4}$ **	0.047	(0.019)
	$\Delta(\ln \text{grocery store wage})_{t-7}$	0.052	(0.059)
	$\Delta(\ln \text{diesel})_{t-6}$	-0.004	(0.008)
	ECT_{t-1}	0.005	(0.022)
Asymmetric	$\Delta^{+}(\ln \text{wheat flour ppi})_{t-1}$ **	0.088	(0.016)
	$\Delta^{+}(\ln \text{wheat flour ppi})_{t-2}$ **	0.075	(0.016)
	$\Delta^{+}(\ln \text{wheat flour ppi})_{t-3}$ **	0.082	(0.017)
	$\Delta^{-}(\ln \text{wheat flour ppi})_{t-1}$ **	0.092	(0.021)
	$\Delta(\ln \text{grocery store wage})_{t-7}$	0.030	(0.042)
	$\Delta(\ln \text{diesel})_{t-6}$	-0.002	(0.005)
	ECT^{+}_{t-1} *	0.019	(0.010)
	ECT^{-}_{t-1} **	-0.029	(0.008)
Symmetric	$\Delta(\ln \text{wheat flour ppi})_{t-1}$ **	0.051	(0.011)
	$\Delta(\ln \text{wheat flour ppi})_{t-2}$ **	0.037	(0.012)
	$\Delta(\ln \text{wheat flour ppi})_{t-3}$ **	0.058	(0.012)
	$\Delta(\ln \text{wheat flour ppi})_{t-4}$ **	0.039	(0.012)
	$\Delta(\ln \text{grocery store wage})_{t-7}$	0.038	(0.043)
	$\Delta(\ln \text{diesel})_{t-6}$	-0.002	(0.005)
	ECT_{t-1} **	-0.009	(0.004)

Source: Authors’ calculations based on Bureau of Labor Statistics data

Bread Farm/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)
Asymmetric	$\Delta^{+}(\ln \text{wheat ppi})_{t-1}$	**	0.115	(0.054)
	$\Delta^{-}(\ln \text{wheat ppi})_{t-1}$	*	0.114	(0.060)
	$\Delta(\ln \text{electricity price})_{t-9}$	*	0.161	(0.090)
	$\Delta(\ln \text{diesel})_{t-1}$	*	0.042	(0.022)
	ECT^{+}_{t-1}		-0.067	(0.062)
	ECT^{-}_{t-1}		-0.071	(0.055)
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)

Source: Authors' calculations based on Bureau of Labor Statistics data