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Harvest-Time Protein Shocks and Price Adjustment in U.S. Wheat Markets

Barry K. Goodwin and Vincent H. Smith

Dynamic relationships among three classes of wheat are investigated using threshold VAR models that incorporate the effects of protein availability. Changes in the stock of protein are found to generate significant responses in the prices of hard red spring wheat and hard red winter wheat, but not soft red wheat. The responses to identical changes in protein stocks are larger when the magnitudes of deviations of protein stocks from normal levels are large. Shocks to the prices of individual classes of wheat result in complex responses in the prices of the other wheat classes. Notably, however, a shock to the price of hard red winter wheat appears to result in little or no response in the price of hard spring wheat, though importantly, the opposite is not true.

Key words: protein, thresholds, vector autoregressions, wheat prices

Introduction

Agricultural commodities like wheat are typically heterogeneous, with quality characteristics that differ across space, time, and variety. The extent to which market prices account for those quality differences has been an important issue for the overall efficiency and operation of markets for agricultural commodities. The benefits associated with accurate measurements of qualities by buyers and sellers in a market must be weighed against the potential costs associated with those measurements. Some characteristics (foreign matter, shrunken and broken kernels, etc.) are easy to measure, while others (valorimeter and farinograph measures) are much more difficult and expensive to identify.

Protein content is one of the most basic quality characteristics shaping the potential utility of a particular class of wheat for various uses. It plays such an important role in price interrelationships among different types and grades of wheat that it also forms the basis for U.S. standard variety grades. For example, higher protein wheat varieties such as hard red spring and hard red winter typically command a price premium over wheat varieties with lower protein contents (e.g., see Espinosa and Goodwin, 1991). In addition, this price premium varies over time almost surely in accord with shifts in aggregate supply and demand for protein (Parcell and Stiegert, 1998), as implied by the theoretical hedonic pricing framework developed by Rosen (1974).

Several earlier studies have examined the dynamics of domestic and international wheat price relationships (see, e.g., Goodwin and Schroeder, 1991; U.S. International Trade Commission, 1994; Mohanty, Meyers, and Smith, 1999). However, relatively little attention has been directed toward interrelationships among different types of wheat prices and quality

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shocks that may relate to the aggregate level of quality. Failure to account for these shocks is likely to distort estimates of these relationships and provide misleading assessments of the extent to which prices of different types of wheat are related to one another, including the extent to which different types of wheat are substitutes for one another.¹

In this paper, we are concerned primarily with the aggregate market for protein (wheat gluten) and its effects on price relationships among different classes of wheat. We consider multivariate time-series models for three classes of wheat—hard red spring, hard red winter, and soft red winter. We are interested in quantifying the relationships between the protein content associated with each year's harvest for each type of wheat and the differentials (reflecting protein supply and demand effects) between various classes of wheat. Monthly price data are used in conjunction with new data constructed by the authors that report the average (aggregate) protein content associated with each year's U.S. harvest. These data on protein content are then combined with quarterly data on wheat stocks to obtain quarterly measures of protein availability that are converted to monthly estimates using cubic spline interpolation.

The relationships between wheat prices and protein content may vary substantially from year to year, depending on overall wheat yields and other quality factors.² Further, protein content in any given year may be affected by the characteristics of the market for protein in preceding years, since grain stocks are held from year to year, and production practices and varietal choices may be important considerations in the realized protein content of a wheat crop. It is also possible that the adjustment paths to exogenous price and protein shocks may be of a nonlinear nature. In particular, millers and bakers are likely to face adjustment costs when shifting from one type of flour to another or from supplementing the protein content of a certain wheat product. The presence of adjustment costs suggests the response may differ when protein either is in short supply or is abundant.

We use nonstructural time-series models that allow for costly adjustment by incorporating threshold procedures to evaluate the effects of protein content shocks on the time paths of wheat prices. We account for protein availability effects on price interrelationships from year to year and quantify the extent to which shocks in the levels of protein availability affect the differentials in wheat prices among individual wheat classes. Our analysis uses dynamic impulse responses to track price responses to shocks in the protein market and other shocks to specific wheat class prices.

The analysis provides new insights about the substitutability of different classes of wheat among end uses, a critical issue in recent trade dispute cases. For example, if hard red spring wheat and hard red winter wheat are perfect or very close substitutes, as suggested by Canadian Wheat Board expert witnesses in testimony before the International Trade Commission on behalf of the Canadian Wheat Board in September 2003, then hard red winter prices are likely to respond rapidly in similar ways to a shock in hard red spring prices, and vice versa. Yet, this does not appear to be the case. Shocks to hard red spring wheat prices do generate substantial responses in hard red winter wheat prices. However, shocks to hard red winter prices generate relatively weak responses in hard red spring prices, suggesting hard red winter wheat is an imperfect substitute for hard red spring wheat.

¹ The issue of elasticities of substitution among wheat classes has been addressed in studies by Marsh (2005) and Barnes and Shields (1998) using structural models of derived demand estimated with annual data. Both studies, while providing different estimates, find that wheat is not just wheat, in the sense that elasticities of substitution among different classes of wheat are by no means as large as has been suggested by some researchers (e.g., Alston, Gray, and Sumner, 1994).

² Studies by Parcell and Stiegert (1998) and Stiegert and Blanc (1997) both report that the effect of a marginal increase in protein on protein premiums varies among different classes of wheat such as hard red spring, hard red winter, and soft red winter.

Data and Empirical Methods

The primary objective of the empirical analysis is to evaluate the extent to which dynamic relationships among prices for different classes of wheat are affected by shocks to the quality of the overall U.S. wheat harvest. In particular, we are interested in the role played by protein content—one of the major determinants of the quality and functionality of different classes and grades of wheat for different uses.

Certainly, a wide variety of wheat characteristics may be pertinent to the quality of any given quantity of wheat. These include factors such as valorimeter and other farinograph measures,³ foreign materials, falling numbers, ash content, and so forth.⁴ However, in terms of the aggregate wheat market and the price relationships between different types of wheat, the results of several hedonic studies (Espinosa and Goodwin, 1991; Parcell and Stiegert, 1998; Stiegert and Blanc, 1997) and current industry pricing practices indicate each wheat harvest's protein content is likely to be the most relevant factor influencing dynamic relationships among the prices of different types of wheat.

Further, other quality characteristics typically do not vary across years in the aggregate U.S. market to the same extent as protein content, which is driven by yields and growing conditions that vary considerably from one year to the next. For example, low moisture during the growing season leads to higher wheat protein content, while the opposite is true for high moisture growing conditions. Prices for specific wheat varieties are typically quoted on the basis of fixed protein content (e.g., prices per bushel for 14% hard red spring and 11% hard red winter wheat). Changes in the value of a unit of protein, which for the most part appear to result from largely exogenous changes in the supply of protein associated with growing conditions, are therefore likely to shock the relationships between the prices of those different wheat varieties in systematic ways. Consequently, failing to account for the effects of protein supply shocks on price relationships in time-series analyses using such prices may result in misspecified empirical models.⁵

The analysis uses data on monthly averages of daily cash prices for three alternative classes of wheat—HRS in Minneapolis, HRW in Kansas City, and SRW in Chicago⁶—and the aggregate protein content of wheat stocks. The data cover the 1989–2003 crop years and were obtained from the Bridge database.⁷ Monthly estimates of protein availability were constructed as follows. Data on the average protein content for all classes of U.S. wheat (HRW, HRS, SRW, durum, and white wheat) for each crop year were obtained from the annual *Grain Quality Reports* for 1990–2004 published by U.S. Wheat Associates. Quarterly wheat stocks data were obtained from unpublished data provided by the U.S. Department of Agriculture's National Agricultural Statistics Service.

³ Wheat varieties differ with respect to dough stability, mixing time, flour water absorption, and breakdown characteristics, which are all measured by a farinograph. A dough's valorimeter value shows the amount of breakdown that occurs 12 minutes after it has reached its maximum consistency. Stronger dough, often made from hard wheat, has a higher valorimeter value and is more suited to bread-making. Soft red wheat flour is typically used for cakes, cookies, and crackers.

⁴ See Espinosa and Goodwin (1991) for a detailed discussion of how different quality factors are related to wheat prices.

⁵ Previous studies of the time-series properties of wheat prices in which all or some prices are for varieties of wheat with specific protein content include Mohanty, Meyers, and Smith (1999); Smith and Goodwin (1995); Smith, Goodwin, and Holt (1995); and Spriggs, Kaylen, and Bessler (1982). These studies focused on the question of whether Granger causality tests indicate the existence of price leadership-follower relationships among Canada, the United States, Australia, and Argentina in international wheat markets. They did not examine the interrelationships between prices of different classes of wheat within a country over time.

⁶ The other U.S. classes of wheat are for durum and white wheat. Durum wheat is used mainly to produce pasta and is not viewed by millers as a substitute for the other classes of wheat. White wheat has a small market share and consists of a wide array of varieties including both hard and soft white wheat. In addition, contracts for these two classes are not currently traded on the major grain exchanges. Further, even though a durum wheat contract was offered on the Minneapolis Grain Exchange for several years in the late 1990s and early 2000s, the modal and median number of durum contracts traded daily was zero. Hence, both durum and white wheat were excluded from this analysis.

⁷ The Bridge database is a comprehensive set of futures and cash prices published by the Commodity Research Bureau.

The aggregate weighted average protein content was calculated for the total U.S. wheat harvest in each crop year using USDA statistics on production for each class in each year to form weights. Next, the quarterly stocks data were multiplied by the protein content of the crop to obtain “protein stocks” for each quarter of the year. We then utilized cubic spline smoothing to interpolate the observed quarterly protein stock measures to derive monthly observations. Such interpolation is expected to adequately represent data at a higher frequency in cases where movements in the variable between observations are likely to be smooth and gradual. This is certainly the case for a highly aggregated variable such as the total protein stocks implied for the aggregate U.S. market.

In the spirit of the relatively extensive literature that has addressed these issues, we begin by considering a standard vector autoregression (VAR) model which includes prices of the three major wheats—hard red spring (HRS) in Minneapolis, hard red winter (HRW) in Kansas City, and soft red winter (SRW) in Chicago. HRS and HRW wheats typically have much higher protein contents than SRW and are directed toward end uses requiring stronger gluten content (e.g., breads). In contrast to previous studies, we also include our measure of the overall protein content implicit in stocks at any point in time.

To test for nonstationarity in the three price series (frequently a concern with price data expressed in level rather than log form because of the effects of inflation over time), we applied Phillips-Perron and seasonal Dickey-Fuller tests. The results generally supported the assumption that the series are stationary with p -values always less than 0.10, rejecting the null hypothesis of the presence of a unit root in each series.⁸

A standard VAR model can be written as $\mathbf{y}_t = \Gamma \mathbf{X}_t + \mathbf{e}_t$, where \mathbf{y}_t is a vector of endogenous variables, Γ a parameter matrix, \mathbf{e}_t a vector of random error terms, $\mathbf{X}_t = [1, y_{t-1}, \dots, y_{t-j}, \mathbf{Z}_t]$, and \mathbf{Z}_t is a matrix of observations on other exogenous variables such as protein content. In addition to estimating a simple VAR model, we are interested in considering the potential for nonlinearities in the underlying relationships represented by the VAR model. To this end, we appeal to recent developments in the time-series literature that consider nonlinearities in the relationships inherent in nonstructural VAR-type models and, in particular, nonlinear threshold models that allow for regime changes (see, e.g., Tong, 1978; Tsay, 1989; Balke and Fomby, 1997; and, in a setting where agricultural commodity price relationships are examined, Goodwin and Piggott, 2002). Adjustments to shocks in the inherent qualities of wheat by end-users (e.g., bakers, millers, and food processors) are hypothesized to be costly. In particular, most production processes are tightly calibrated and have specific quality requirements. End-users may be able to make adjustments in production processes even in the short run (from month to month), although these adjustments are likely to require significant technological modifications and to be costly.⁹

To account for these effects, we utilize a threshold modification to the standard VAR modeling framework. In particular, we allow the underlying structure of the model (represented by the nonstructural, reduced-form parameters of the VAR system of equations) to vary according to implied protein availability in the market. Specifically, we consider a threshold defined by deviations from normal levels of protein in the market.

⁸ Further, as Hamilton (1994, p. 579) notes, variables that are nonstationary but linked by a long-run equilibrium (i.e., the variables are cointegrated) can be evaluated using a VAR in levels, as is the case with our specification. In this setting, the VAR representation is less efficient than the equivalent error-correction representation, but remains a valid approach to estimation.

⁹ This is widely recognized by the milling industry. In the September 2003 International Trade Commission (ITC) antidumping hearings with respect to Canadian dumping of hard red spring wheat and durum wheat, U.S. milling industry executives stated in oral testimony that they tended to determine blends of different wheat at the beginning of each marketing year just after harvest once the quality characteristics of different wheat classes were known. Thereafter, they were generally reluctant to change those blends.

The “normal” level of protein is defined by using a regression of quarterly protein availability, p_t , on a second-order Fourier series expansion with respect to time, which is intended to capture the large degree of seasonality that accompanies the wheat harvests and subsequent adjustments to stocks. The implied monthly pattern of seasonality in protein is illustrated in figure 1. The monthly patterns are inferred from the quarterly observations, where each quarter corresponds to one quarter of a calendar year and each month is one-twelfth of a year. Note that a large increase in stocks occurs with the influx of the winter wheat harvest in the summer and a second smaller increase takes place with the influx of the spring wheat harvest in the late summer and early fall.

We define the “normal” level of protein [given by the function $f(t)$ which consists of a second-order Fourier series expansion] by $\hat{p}_t = f(t)$. Departures from normal levels are then defined as:

$$p_t - f(t) = v_t.$$

Deviations from normal protein levels in any period (quarter), therefore, are represented by the deviations from the seasonal patterns. These estimated deviations are presented in figure 2. The diamond shaped blocks in figure 2 represent estimated deviations based on observed quarterly data. The deviations from normal protein levels obtained using the interpolated monthly observations are reflected in the continuous line that passes through those diamond blocks.

We allow for three regimes, defined on the basis of the value of v_t . One is a normal protein regime, which obtains when the value of v_t lies between a lower bound (c_l) and an upper bound (c_u). The second regime occurs when v_t lies below the lower bound of the normal range, c_l , and protein is in relatively short supply. The third regime occurs when v_t exceeds the upper bound of the normal range, c_u , and protein is relatively plentiful. A switch between any pair of regimes from one period to the next is triggered by shifts in protein levels that cause large enough changes in v_t . For example, an increase in protein that results in v_t moving from within the normal protein range defined by c_l and c_u to exceed c_u causes a change in regime. The regime switching model is written as follows:

$$\mathbf{y}_t = \begin{cases} \mathbf{\Gamma}^{(1)}\mathbf{X}_t & \text{if } v_t < c_l, \\ \mathbf{\Gamma}^{(2)}\mathbf{X}_t & \text{if } c_l \leq v_t \leq c_u, \\ \mathbf{\Gamma}^{(3)}\mathbf{X}_t & \text{if } v_t > c_u, \end{cases}$$

where $\mathbf{\Gamma}^{(i)}$ represents parameter estimates associated with the i th regime. Equivalently,

$$\mathbf{y}_t = [\delta_1 \mathbf{\Gamma}^1 + \delta_2 \mathbf{\Gamma}^2 + (1 - \delta_1 - \delta_2) \mathbf{\Gamma}^3] \mathbf{X}_t,$$

where $\delta_1 = 1$ if $v_t < c_l$ and zero otherwise, and $\delta_2 = 1$ if $c_l \leq v_t \leq c_u$ and zero otherwise.

Several different threshold modeling procedures have been developed. Here we utilize grid search procedures to find the values for the thresholds, c_l and c_u , which minimize the log of the determinant of the residual covariance matrix. This procedure is equivalent to maximizing a normal likelihood function. We constrain the grid search procedures to require each regime to have at least 25 observations. The parameters describing the two alternative regimes are estimated conditional on the optimal threshold values for c_l and c_u . We chose the lag order of the VAR model using the minimum value of the Akaike information criterion (AIC) for a

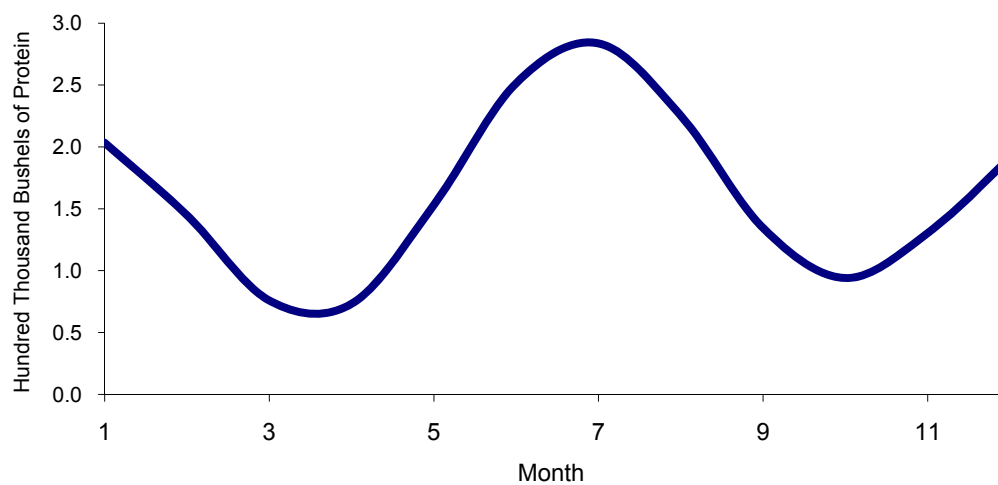


Figure 1. Estimated seasonality in protein stocks variable

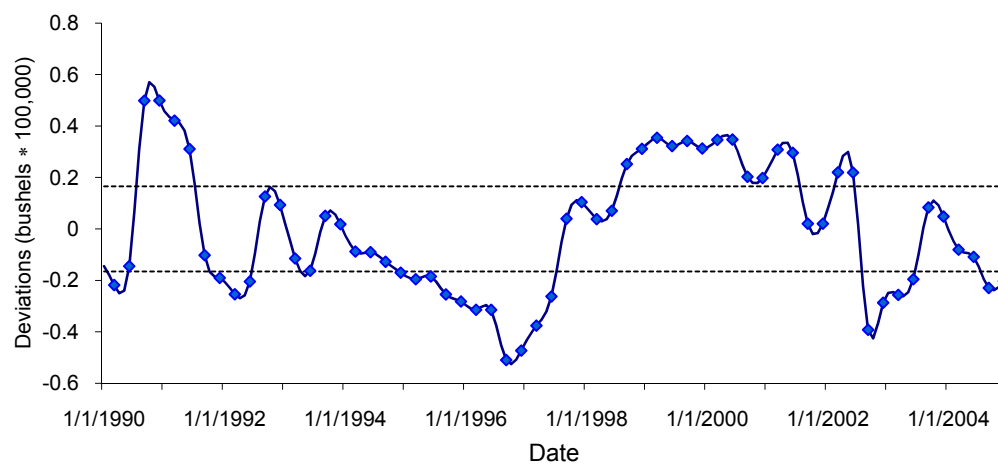


Figure 2. Estimated deviations from normal levels of protein stock

standard VAR model containing the relevant variables. We also considered alternative specifications of the protein variable, including various lags, which yielded very similar results to those presented below. Protein, which is largely determined by annual plantings and exogenous growing conditions, is assumed to be exogenous to monthly prices in order to conserve degrees of freedom in the multi-regime model.

Once the parameters of the standard and regime-switching VAR models have been estimated, standard methods of inference can be used to evaluate the relationships among the price and protein variables. Here we utilize standard impulse response functions to evaluate the dynamic relationships among wheat class prices implied by the alternative parameters. In threshold models, several versions of the impulse responses could be evaluated because, in these models, impulse responses may not be unique for alternative observations or sizes of shocks. Potter's (1995) nonlinear impulse response analysis procedures could be used to evaluate the responses at a particular observation and allow for switching among regimes over the period of the response. Alternatively, impulses could be calculated at every observation for randomly sampled observations. Mean responses or some other summary measure could then be reported (Koop, Pesaran, and Potter, 1996). Finally, impulse responses could be evaluated for each alternative regime with no shifting between regimes allowed during the response. Generally, we adopt the latter approach because it yields the clearest inferences regarding the differences in regimes. However, to evaluate whether or not impulse responses to protein shocks are significantly different from zero in the VAR threshold model, we use a method that is a combination of Potter's procedures, which allow for shifting between regimes, and a variant of approaches that calculate responses at different observations and report mean responses and other summary measures. In particular, we randomly choose observations of the prices and their respective lags and estimate responses to shocks of a given size.

Empirical Results from a Standard VAR Model

Parameter estimates for a standard VAR model of the prices for hard red spring, hard red winter, and soft red winter wheat are presented in table 1, while parameter estimates for a threshold VAR model are presented in table 2.¹⁰ Diagnostic statistics for both the standard and threshold models are given in table 3.

For the standard VAR model, a lag order of two was suggested by the minimum AIC value reported in table 3. Parameter estimates for nonstructural models of this form are usually of limited interest, and inferences are more efficiently extracted from impulse responses. However, the coefficients on the protein stocks variable in the three equations are of interest in their own right. These coefficients are negative in all three cases, suggesting above-normal stocks of protein are likely to depress prices for each class of wheat. The coefficient is largest in the Kansas City hard red winter price equation. The negative effect is also relatively large for the Minneapolis hard red spring price. The effect for soft wheat prices in Chicago is much smaller and not statistically significant.

These results are consistent with a priori expectations. They imply that positive shocks to the aggregate protein content of wheat in the U.S. market have negative effects on hard red winter and hard red spring wheat prices—classes of high protein wheat generally directed to uses requiring varieties of wheat with high gluten content. In contrast, the effect is not

¹⁰ Alternative standard and threshold VAR models were estimated in which various lagged values of the protein stocks variable were used as regressors instead of its current value. These models yielded similar results, suggesting the assumption that protein availability is weakly exogenous is not unreasonable.

Table 1. Standard VAR Model of Wheat Prices: Parameter Estimates

Dependent Variable	Explanatory Variable	Parameter Estimate	Standard Error	<i>t</i> -Ratio
<i>Chicago Price</i>	Constant	37.3687	17.1231	2.18
	<i>Protein Stocks (t)</i>	-20.7671	13.1919	-1.57
	<i>Chicago Price (t - 1)</i>	0.7734	0.1183	6.54
	<i>Kansas City Price (t - 1)</i>	0.2567	0.1234	2.08
	<i>Minneapolis Price (t - 1)</i>	-0.0638	0.0922	-0.69
	<i>Chicago Price (t - 2)</i>	0.0341	0.1184	0.29
	<i>Kansas City Price (t - 2)</i>	-0.1826	0.1220	-1.50
	<i>Minneapolis Price (t - 2)</i>	0.0585	0.0912	0.64
<i>Kansas City Price</i>	Constant	67.6815	17.8796	3.79
	<i>Protein Stocks (t)</i>	-41.1863	13.7747	-2.99
	<i>Chicago Price (t - 1)</i>	-0.0504	0.1235	-0.41
	<i>Kansas City Price (t - 1)</i>	1.0444	0.1288	8.11
	<i>Minneapolis Price (t - 1)</i>	0.0112	0.0962	0.12
	<i>Chicago Price (t - 2)</i>	0.0891	0.1237	0.72
	<i>Kansas City Price (t - 2)</i>	-0.2491	0.1274	-1.96
	<i>Minneapolis Price (t - 2)</i>	-0.0217	0.0952	-0.23
<i>Minneapolis Price</i>	Constant	65.5465	19.3841	3.38
	<i>Protein Stocks (t)</i>	-33.5678	14.9338	-2.25
	<i>Chicago Price (t - 1)</i>	-0.2288	0.1339	-1.71
	<i>Kansas City Price (t - 1)</i>	0.5022	0.1397	3.60
	<i>Minneapolis Price (t - 1)</i>	0.6614	0.1043	6.34
	<i>Chicago Price (t - 2)</i>	0.2000	0.1341	1.49
	<i>Kansas City Price (t - 2)</i>	-0.4948	0.1381	-3.58
	<i>Minneapolis Price (t - 2)</i>	0.1993	0.1032	1.93

statistically significant in the case of soft red winter wheat in Chicago. Soft wheat varieties typically have much lower protein content and are directed toward uses calling for lower gluten wheat (e.g., cakes and crackers rather than bread).

Impulse responses for the standard VAR model are presented in figures 3A, 4A, 5A, and 6A. Figure 3A illustrates the dynamic paths of adjustment in prices to a positive one-unit shock to the protein stocks variable. The largest impact is on the Kansas City price—a result consistent with a simple consideration of the VAR model protein coefficients reported in table 1. The impulse results indicate a one-unit increase in protein generates a 42¢ per bushel decrease in the Kansas City price and a 34¢ per bushel decrease in the Minneapolis price. In contrast, the soft wheat price in Chicago has a small negative response to the same protein shock. In every case, the largest price response occurs two months after the shock, and responses take 10 or more months to die out. This suggests end users are likely to be somewhat slow to adjust to protein shocks and the market effects of these shocks persist for several months.

Table 2. Threshold Switching Regime Model Parameter Estimates

Depend. Variable	Explan. Variable	Low Protein Regime				Normal Protein Regime				High Protein Regime			
		Param. Est.	Std. Error	t-Ratio		Param. Est.	Std. Error	t-Ratio		Param. Est.	Std. Error	t-Ratio	
<i>Chicago Price</i>	Constant	91.2455	80.2143	1.14		38.3200	20.1305	1.90		85.9199	35.7230	2.41	
	<i>Chicago Price (t-1)</i>	0.3020	0.2585	1.17		0.3803	0.1779	2.14		1.3042	0.2033	6.41	
	<i>Chicago Price (t-2)</i>	0.2674	0.2741	0.98		0.0725	0.1761	0.41		-0.2871	0.1871	-1.53	
	<i>Kansas City Price (t-1)</i>	0.3088	0.2961	1.04		0.8063	0.2027	3.98		-0.3652	0.2121	-1.72	
	<i>Kansas City Price (t-2)</i>	-0.0627	0.3028	-0.21		-0.6208	0.2067	-3.00		0.1911	0.1850	1.03	
<i>Kansas City Price</i>	<i>Minneapolis Price (t-1)</i>	0.0775	0.2376	0.33		-0.2506	0.1742	-1.44		-0.0265	0.1178	-0.23	
	<i>Minneapolis Price (t-2)</i>	-0.2767	0.2339	-1.18		0.4807	0.1636	2.94		-0.0358	0.1194	-0.30	
	<i>Stocks (t)</i>	37.3341	48.3475	0.77		62.6459	44.9082	1.39		-13.1946	36.0585	-0.37	
	Constant	201.2043	84.1474	2.39		59.1220	21.1176	2.80		144.7974	37.4746	3.86	
	<i>Chicago Price (t-1)</i>	-0.5543	0.2712	-2.04		-0.2682	0.1866	-1.44		0.6244	0.2133	2.93	
<i>Minneapolis Price</i>	<i>Chicago Price (t-2)</i>	0.2000	0.2875	0.70		0.2741	0.1847	1.48		-0.0868	0.1963	-0.44	
	<i>Kansas City Price (t-1)</i>	0.8569	0.3106	2.76		1.4332	0.2126	6.74		0.1662	0.2225	0.75	
	<i>Kansas City Price (t-2)</i>	0.1494	0.3177	0.47		-0.7680	0.2169	-3.54		-0.0640	0.1941	-0.33	
	<i>Minneapolis Price (t-1)</i>	0.1027	0.2492	0.41		-0.0835	0.1827	-0.46		0.0378	0.1236	0.31	
	<i>Minneapolis Price (t-2)</i>	-0.3899	0.2454	-1.59		0.2628	0.1716	1.53		-0.0371	0.1253	-0.30	
<i>Stocks (t)</i>	Constant	-41.7298	50.7181	-0.82		-18.9708	47.1102	-0.40		-20.1873	37.8266	-0.53	
	<i>Chicago Price (t-1)</i>	213.1673	93.6090	2.28		63.0232	23.4920	2.68		106.6062	41.6883	2.56	
	<i>Chicago Price (t-2)</i>	-0.3615	0.3017	-1.20		-0.5606	0.2076	-2.70		0.2421	0.2373	1.02	
	<i>Kansas City Price (t-1)</i>	-0.1042	0.3198	-0.33		0.4409	0.2055	2.15		0.0131	0.2184	0.06	
	<i>Kansas City Price (t-2)</i>	0.3098	0.3456	0.90		1.0251	0.2365	4.33		-0.1928	0.2475	-0.78	
Threshold Parameters	<i>Kansas City Price (t-1)</i>	-0.1675	0.3534	-0.47		-0.7498	0.2412	-3.11		-0.2158	0.2159	-1.00	
	<i>Minneapolis Price (t-1)</i>	0.6789	0.2772	2.45		0.5615	0.2033	2.76		0.5412	0.1375	3.94	
	<i>Minneapolis Price (t-2)</i>	-0.0554	0.2730	-0.20		0.1855	0.1909	0.97		0.3566	0.1394	2.56	
	<i>Stocks (t)</i>	-24.6478	56.4209	-0.44		67.1056	52.4073	1.28		-22.7985	42.0798	-0.54	
	Proportion of Observations	< -0.5702 0.2889				0.3389				> 0.5702 0.3722			
Hansen's Test of Thresholds		67.4800											
Hansen's Test p -Value		0.0001											

Table 3. Standard and Threshold Model Diagnostics

Standard VAR		Threshold VAR		
Lag Order	AIC	Test	Value	<i>p</i> -Value
1	18.4684	Shapiro-Wilk normality for Chicago price	0.99	0.8186
2	18.4622	Shapiro-Wilk normality for Kansas City price	0.96	0.0005
3	18.4864	Shapiro-Wilk normality for Minneapolis price	0.98	0.2697
4	18.5365	Henze-Zirkler multivariate normality test for system	1.10	0.2702
5	18.5592	Autocorrelation test for Chicago price residual (lag = 6)	11.37	0.0777
6	18.6576	Autocorrelation test for Kansas City price residual (lag = 6)	4.47	0.6135
		Autocorrelation test for Minneapolis price residual (lag = 6)	1.72	0.9435
		Autocorrelation test for Chicago price residual (lag = 12)	17.46	0.1331
		Autocorrelation test for Kansas City price residual (lag = 12)	13.71	0.3196
		Autocorrelation test for Minneapolis price residual (lag = 12)	13.68	0.3217

This finding seems to be consistent with statements by U.S. millers at the 2003 International Trade Commission hearings on dumping by the Canadian Wheat Board. The millers stated they tend to determine blends of different varieties of wheat for milling on an annual marketing year basis after harvest and are relatively unresponsive to price changes within the marketing year.

Adjustments to price shocks, shown in figures 4A, 5A, and 6A, are modest once protein shocks are taken into account. Minneapolis HRS and Kansas City HRW prices appear to be more closely linked with one another than with Chicago SRW prices. The results also appear to imply a price leadership role for the Minneapolis market in the Kansas City-Minneapolis relationships. An innovation in the Kansas City price generates almost no impulse response in the Minneapolis price. However, an innovation of a given size in the Minneapolis price results in a smaller adjustment in the same direction in the Kansas City price that wanes after about six months.

Empirical Results from a Threshold Model

Price adjustment patterns, as discussed above, may reflect adjustment costs associated with changes in production technologies which may be needed to respond to substantial changes in wheat protein availability. Table 2 reports estimates from a threshold VAR model that allows shifting between regimes according to the absolute value of the size of shocks to the overall protein stocks available in the market. Note, we use the same lag order as was suggested by the AIC for the standard VAR model. The optimal threshold model has threshold values for the lower and upper bounds of the normal regime (c_l and c_u) of -0.5702 and $+0.5702$, respectively.¹¹ Hansen's test statistic for the comparison of the threshold and standard VAR models (Hansen, 1997) is 67.48 and has a *p*-value of 0.0001, implying rejection of the null hypothesis that there is no difference in the explanatory power of the standard VAR model and the threshold model, and indicating the threshold model provides a better fit than the standard VAR model reported in table 1.

¹¹ Note that the estimation procedure did not constrain the upper and lower values for the normal regime band for v_t to have the same absolute values (i.e., to be symmetric around an expected value for v_t of zero), and there were small differences in the estimated absolute values of c_l and c_u beyond the fourth decimal point.

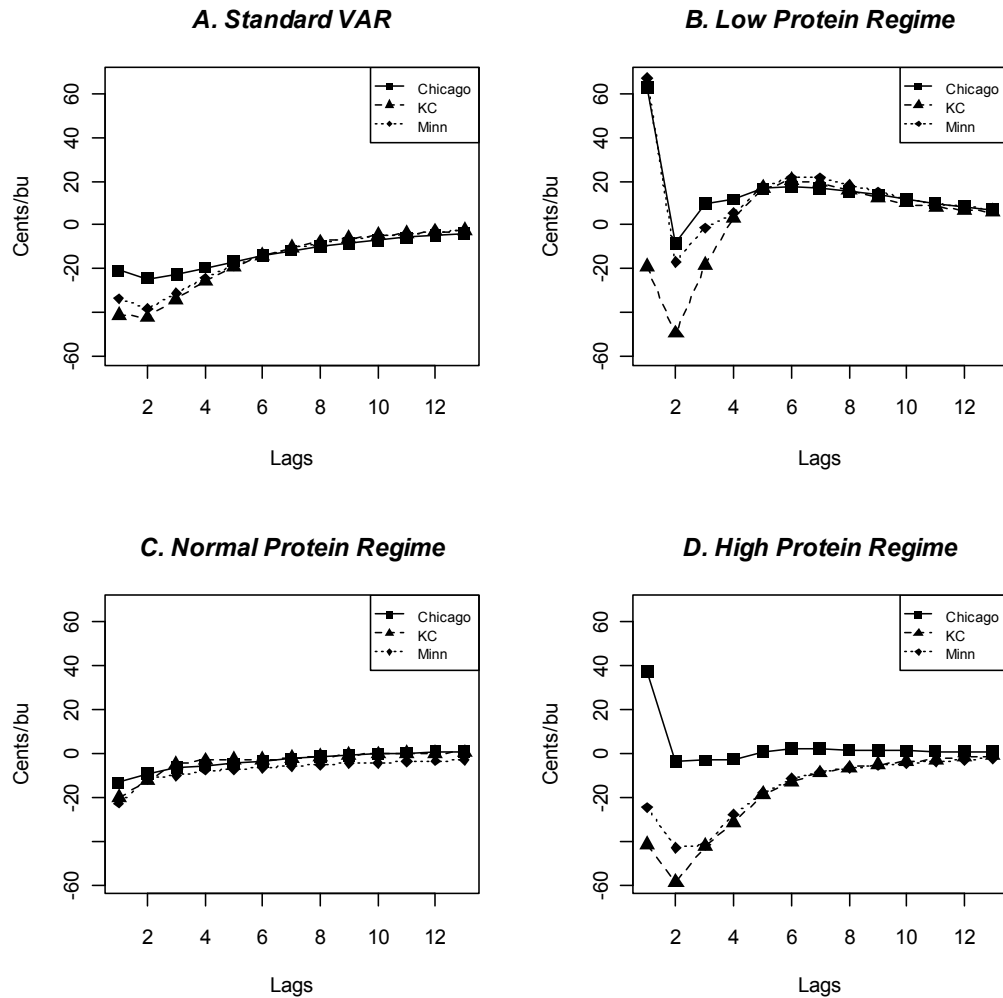


Figure 3. Responses to positive protein stock shock

A series of model diagnostic tests is presented in table 3. Univariate and multivariate tests generally support normality of the residual terms from the threshold model. An exception exists for the residuals for the Kansas City prices, although a joint test of normality for the entire system is not rejected. Further, little evidence of residual autocorrelation is implied by residual white noise tests at lag orders of 6 and 12 months. In all, these diagnostic tests support the threshold specification.

The estimates of the upper and lower threshold values that define the three alternative regimes—low protein, normal protein, and high protein—are identified by the two dotted horizontal lines in figure 2. Switching among regimes is relatively infrequent, reflecting the fact that the overall availability of protein in the market adjusts slowly, at least between harvests. This implies the market tends to remain in a regime for an extended period of time rather than jumping back and forth between alternative regimes on a month-to-month basis.

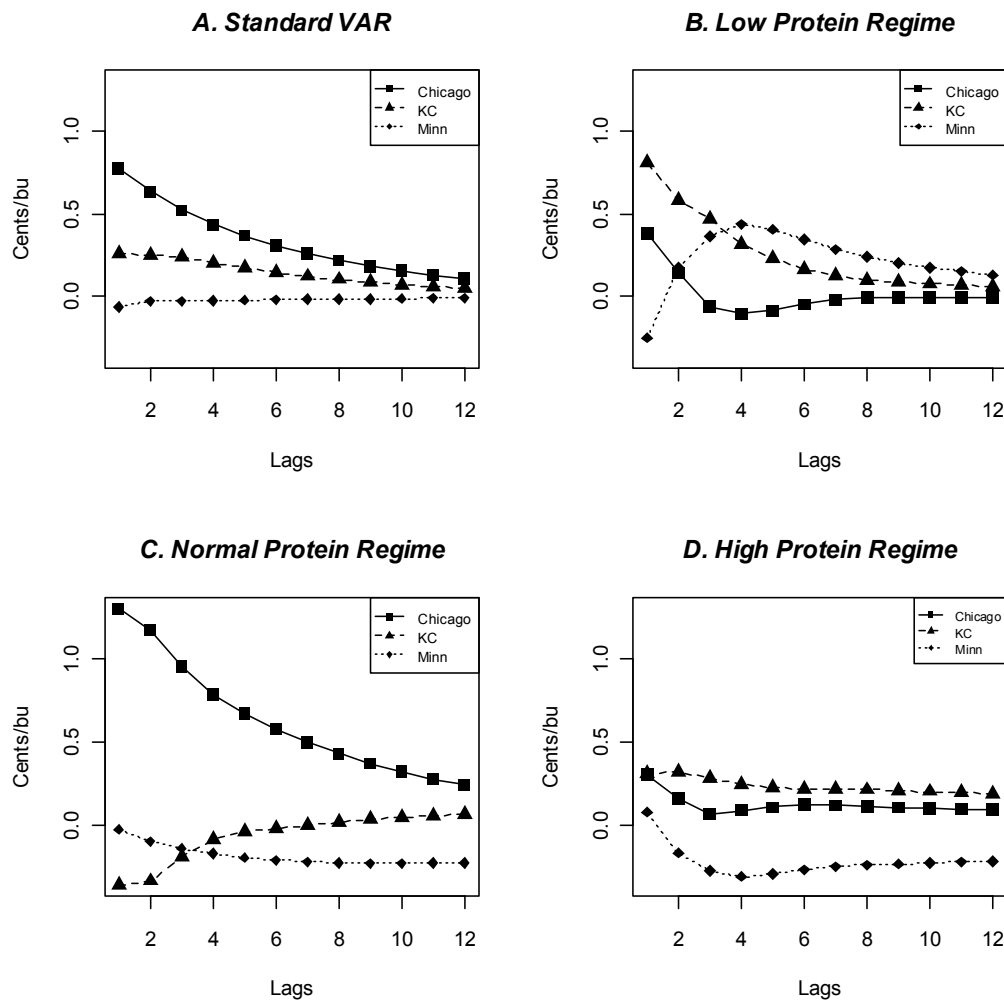


Figure 4. Responses to positive Chicago price shock

In the threshold model, as in the standard VAR model, protein stocks have different effects on the prices of each type of wheat. The coefficients for protein stocks are not significantly different from zero for the Chicago soft red wheat price in all three regimes, with absolute t -values ranging from 0.37 to 1.39. A similar result was obtained in the standard VAR model, in which the protein stock coefficient had no statistically significant effect on the Chicago SRW price. Perhaps surprisingly, the protein stock coefficients are also not statistically significant in the Kansas City hard red winter and Minneapolis hard red spring price equations, although inferences about coefficients in a threshold model are complicated by the fact that nuisance parameters are unidentified when the thresholds are zero, thus making standard inferences invalid. This is known as Davies' (1977) problem, which implies it is impossible to solve directly for the correct distribution of any test statistic. However, the results from hedonic studies consistently conclude that protein premiums are important for hard wheat prices (Espinosa and Goodwin, 1991; Stiegert and Blanc, 1997). An examination of the

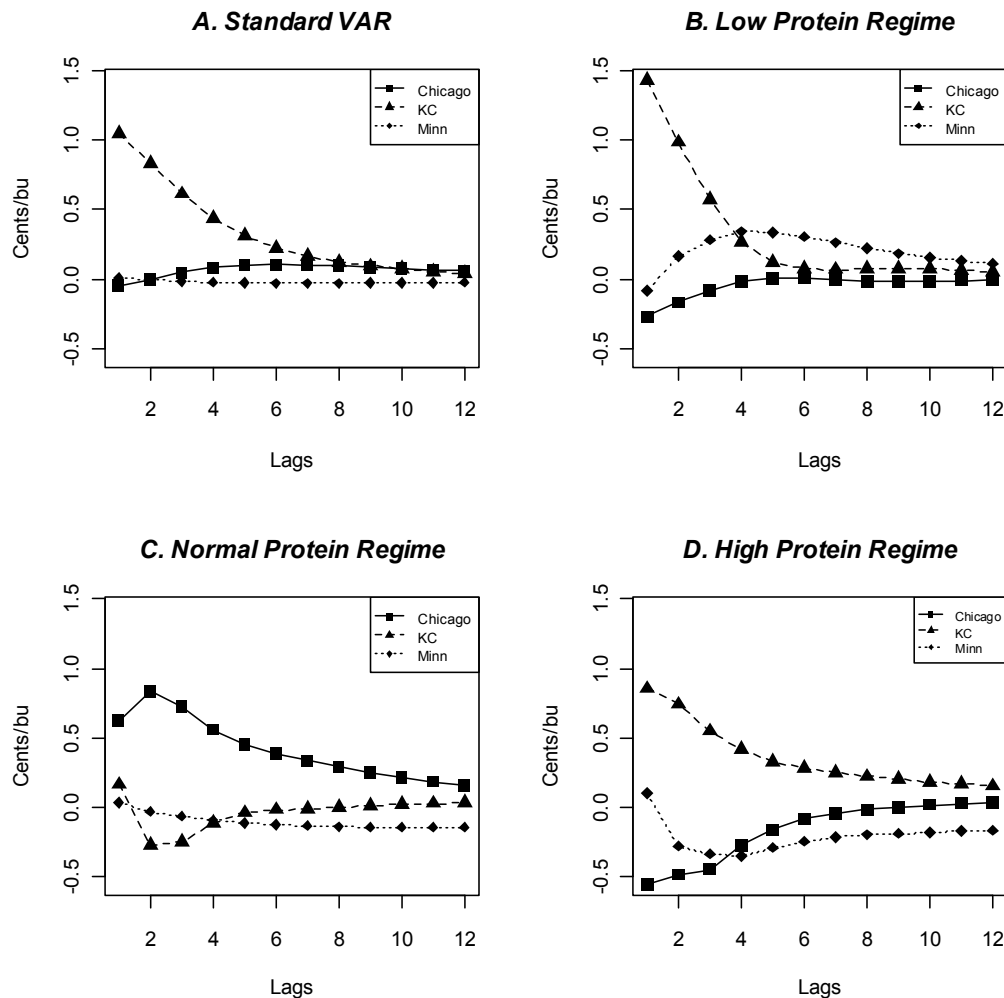


Figure 5. Responses to positive Kansas City price shock

impulse response functions of the three prices for a one-unit positive shock to protein levels in the three regimes also provides evidence supporting this view. These impulse responses are illustrated in figures 3B–3D.

In the low protein regime (figure 3B), an increase in protein initially lowers the Kansas City price but increases both the Minneapolis and Chicago prices. Thereafter, prices for all three types of wheat fall below their pre-shock levels and then, by period 3, recover somewhat and adjust to their long-run equilibrium values. In the normal protein regime (figure 3C), as expected, all three prices initially decline as a result of a protein shock and then also gradually adjust to their long-run equilibrium values.

In the high protein regime (figure 3D), the initial effect of the protein shock is to substantially reduce the Minneapolis and Kansas City hard red wheat prices, but the impact on the Kansas City hard red winter wheat price is approximately twice as large as the impact on the Minneapolis hard red spring wheat price (about a 40¢ per bushel decrease as compared to a

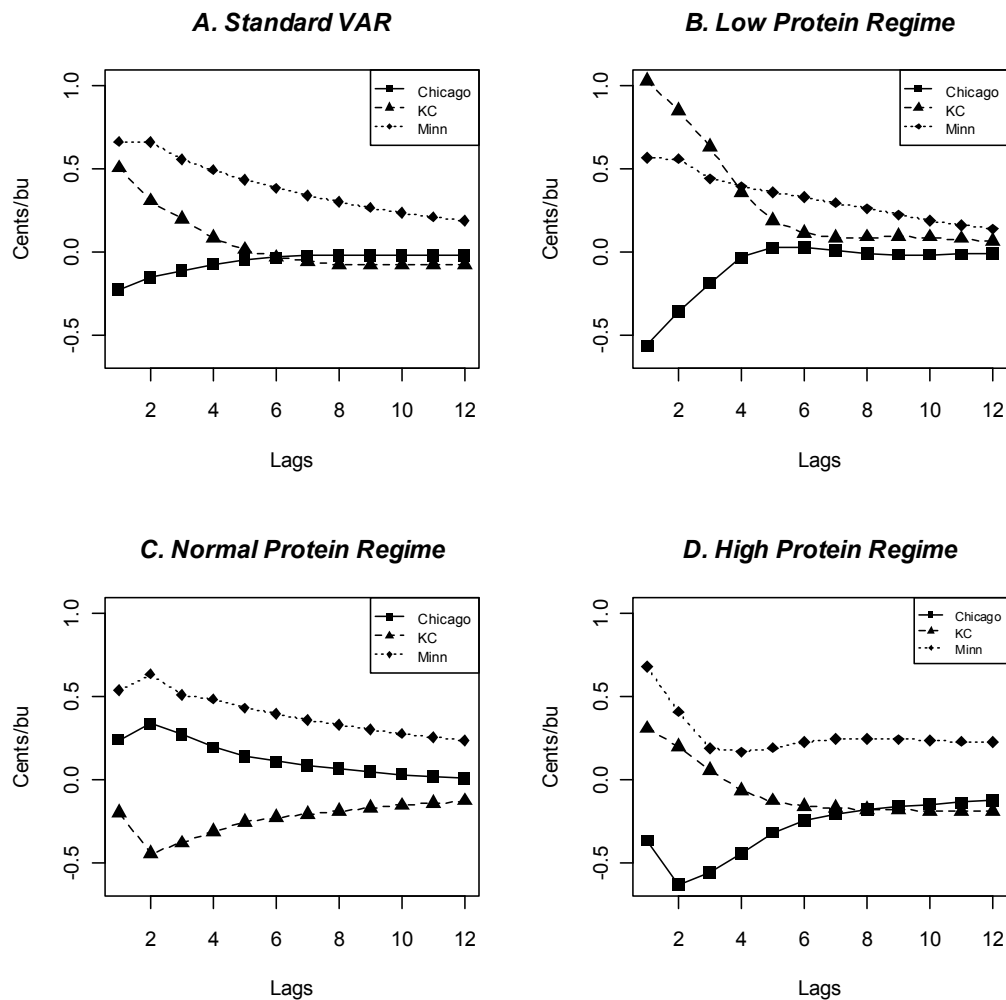


Figure 6. Responses to positive Minneapolis price shock

20¢ per bushel decrease). In this regime, the Chicago soft wheat price initially increases as a result of the protein shock. Subsequently, in period 2 (two months after the shock), the prices of all three classes of wheat decline before gradually converging to their long-run equilibrium values.

A comparison of the three price impulse responses to a one-unit shock in protein stocks provides useful insights. First, as expected, an increase in protein reduces the prices of the two hard wheat varieties immediately or within two periods. Impacts on the price of soft red wheat are different and generally smaller in magnitude, a finding consistent with the fact that low protein soft wheat has end uses which do not require high protein content. Second, the effects of protein shocks on Minneapolis hard red spring prices and Kansas City hard red winter prices differ in magnitude (and are larger for Kansas City hard red winter), while generally resulting in similar patterns in the impulse responses for the two types of wheat. Third, the threshold model implies the impulse responses to a one-unit shock to protein are

larger when initial protein levels are either above or below the normal range. When initial protein levels are in the normal range, prices react but, especially in the case of hard red winter wheat, the adjustments are considerably smaller than when initial protein levels deviate substantially from normal protein levels. This result is consistent with the hypothesis that changes in protein levels may have larger effects on prices when protein stocks are substantially different than their long-run average values.¹²

To test whether protein shocks result in significant impulse response effects in the VAR threshold model, we utilize Potter's (1995) procedures, which allow for impulse responses to switch between regimes, in combination with the following approach. We draw 100 random observations from the sample and apply an identical protein shock to each of those observations. Next, we calculate the average or mean impulse response for each period over those 100 observations. This experiment is then repeated 1,000 times to obtain the average and the standard deviation of the mean impulse response at each period (month) subsequent to the shock. The entire process is repeated for two protein shocks, one positive and one negative, where the absolute value of each shock equals one standard deviation of the deviations from the average level of available protein. The resulting average impulse responses to these protein shocks are reported in figures 7A–7C, where estimates for a given period are denoted by dots if they are statistically significantly different from zero at the 10% level. In each figure, the continuous line represents the impulse responses for a positive shock (an increase in protein availability) and the dotted line represents the impulse responses for a negative shock (a reduction in protein availability).

When averaged among all three regimes, an increase in protein availability consistently results in statistically significant decreases in the prices of all three wheat classes when the shock occurs, and further decreases one period after the shock. However, the average effects of the positive protein shock on the Kansas City price for HRW (an immediate per bushel decrease of 30¢ and, relative to the pre-shock price, a decrease of 31¢ in period 1) are larger than on the Minneapolis HRS price (an immediate decrease of 25¢ and, relative to the pre-shock price, a decrease of 27¢ in period 1). The effects of the protein decrease on the Chicago price for SRW are much smaller (an immediate per bushel decrease of 10¢ and, relative to the pre-shock price, a decrease of about 18¢ in period 1). After period 1, the effects of the positive protein shock on the price of each class of wheat moderates, but those effects remain statistically significantly different from period zero through period 12.

The effects of a negative protein shock differ among the three classes of wheat when averaged among all three regimes. The impulse function results reveal that the negative shock has no statistically significant effect on the price of Chicago SRW in any subsequent period. However, the reduction in protein causes an immediate, statistically significant positive effect on the price of Kansas City HRW (an increase of 10¢ per bushel) and this effect, while moderating, remains statistically significant for five periods subsequent to the shock. The impact of the negative protein shock on the Minneapolis HRS price is generally statistically significant but, although small, negative.

In the threshold VAR models, when protein levels are either high or low (i.e., deviations from predicted levels lie outside of the normal range defined by c_l and c_u), the price adjustments resulting from one-unit shocks in the Chicago, Kansas City, and Minnesota prices in

¹² The terminology may be somewhat confusing here. Impulse response diagrams illustrate responses to equivalent one-unit shocks. However, the regimes are defined by the size of the protein shock. We could have presented shocks that differed in terms of the size of the shocks in alternative regimes. In such a case, the differences in impulse responses would be exaggerated. Comparing the impulses at a common level of shock allows a clearer view of how the underlying structures of the models differ across regimes.

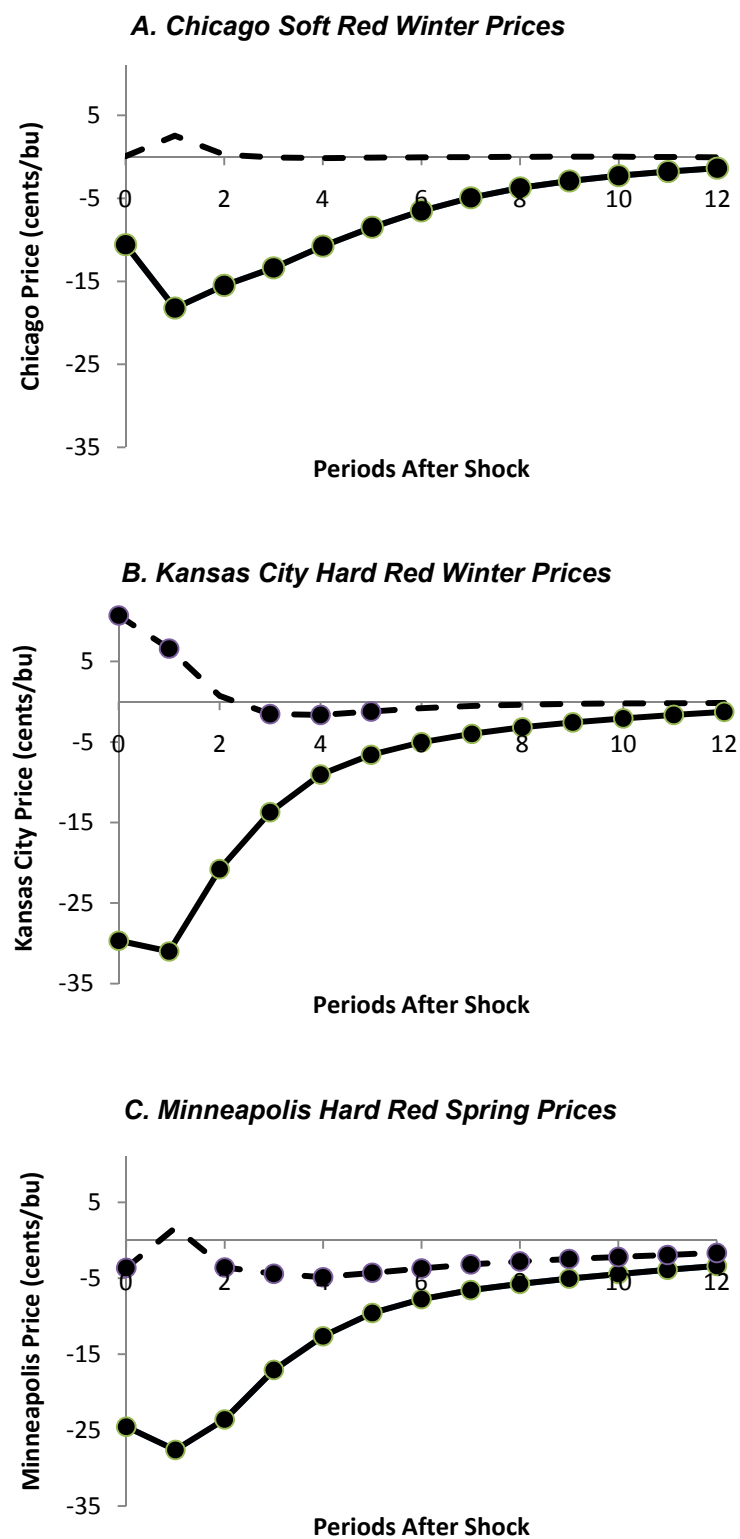


Figure 7. Average price impulse responses to protein shocks

the threshold model are generally similar to those obtained using the standard VAR model. As shown by figures 4B and 4D, in the regimes in which protein levels are either low or high, a positive shock to the Chicago soft red winter wheat price results in a similar initial increase in the Kansas City hard red winter price, but has almost no effect on the Minneapolis hard red spring price. Subsequently, although the Chicago and Kansas City impulse responses diverge to some degree in periods 2 and 3, their subsequent convergence paths are very similar. However, the Minneapolis price responses are negative after the first period and remain negative over the entire 12-month (one-year) adjustment period. In contrast, in the normal protein regime (figure 4C), a shock to the Chicago price generates almost no initial response in the Minneapolis price and an initial negative response in the Kansas City price. Hence, the impulse responses in figure 4C suggest that a shock to the Chicago price does not have similar effects on either the Minneapolis price or the Kansas City price when protein levels are normal. Taken together, the impulse responses presented in figures 4B–4D show that when protein levels are either relatively low or relatively high, shocks to soft red winter wheat prices affect hard red winter wheat prices but have little or no effect on hard red spring prices, regardless of the protein regime.

The effects of a one-unit positive shock to the Kansas City HRW price on all three wheat prices are presented in figures 5B–5D for each of the three protein regimes. A shock to the Kansas City price has very little effect on the Minneapolis price in any regime. In the low and high protein regimes, a shock to the Kansas City price causes an initial 58¢ decrease in the Chicago price, which then converges to its long-run equilibrium level. In the normal protein regime, a shock to the Kansas City price causes a substantial increase in the Chicago price, which, after the second period, converges to its long-run equilibrium. Thus, the impulse responses presented in figures 5B–5D suggest that shocks to hard red winter prices affect soft red winter prices in a qualitatively similar way when protein levels are relatively normal, but have little effect on hard red spring prices.

Impulse responses for a one-unit shock to the Minneapolis price are presented in figures 6B–6D. As shown by these responses, when protein levels are either relatively low or relatively high, a positive shock to the Minneapolis price causes a similar positive response in the Kansas City price, but results in a lower Chicago price. When protein stocks are in the normal range, a positive shock to the Minneapolis price causes a similar shock to the Chicago price but not to the Kansas City price.

An important implication of the impulse responses presented in figures 4–6 is that when protein levels are relatively high or low, hard red winter wheat prices respond to shocks in hard red spring prices, but the opposite does not hold true. A second result is that when protein levels are relatively high or low, shocks to soft red winter prices affect hard red winter prices. These findings suggest wheat is not just wheat, and soft red winter is by no means a perfect substitute for hard red winter or hard red spring. Similarly, the threshold model results also reveal that cross-market linkages between hard red spring wheat and hard red winter wheat are complex and not consistent with the proposition that millers and bakers behave as if hard red spring wheat and hard red winter wheat are very close substitutes.

Conclusions

This study has utilized new data and innovative econometric techniques to address a long-standing issue in discussions about wheat markets—the dynamic relationships between the prices of different classes of wheat. The data-related innovation consists of the development

of a measure of the aggregate stock of protein in the U.S. wheat crop that is then utilized in the time-series analysis to account for the potential effects of changes in protein availability on the structure of wheat prices among important classes of wheat. Data on average protein content by class of wheat were combined with USDA statistics on production by class and quarterly data on wheat stocks to obtain a measure of aggregate protein stocks for each quarter of the year. A second-order Fourier expansion was then utilized to obtain estimates of normal protein levels that accounted for quarterly seasonal effects. The quarterly data were then interpolated using cubic splines to derive monthly estimates of protein stocks.

The econometric and modeling innovation with respect to wheat price dynamics is the utilization of a threshold modification of a VAR model to account for potential adjustment costs associated with changing use patterns of different classes of wheat. The results from the estimated threshold variant of the VAR model were also compared with those from a standard VAR model in which adjustment costs were ignored.

The major findings of the research are as follows. In the standard VAR model, a positive one-unit shock to protein stocks has the largest negative effect on the Kansas City hard red winter price and a smaller but still substantial effect on the Minneapolis hard red spring price, as measured by impulse responses. The impulse response of the Chicago soft red price to the protein shocks was small.

Generally similar effects were found in the threshold model in which three regimes were identified: a “low” protein regime, a “normal” protein regime, and a “high” protein regime. In the normal protein regime, absolute deviations of protein levels from long-run expected or normal seasonal levels in aggregate wheat stocks are relatively small and fall within a range defined by lower and upper bounds. In the low protein regime, deviations in seasonal protein levels fall below the lower bound of the normal band, while in the high protein regime they exceed the upper bound of the normal band. The range within which protein levels are deemed to be normal was computed in the econometric estimation procedure.

In the threshold models, the impulse response effects of a unit change in the protein stock level are generally similar to those reported for the standard VAR model in the low protein and high protein regimes. Price impulse responses are relatively small when protein levels are close to their seasonal averages (the normal regime), but nevertheless are consistent with the hypothesis that hard red winter and hard red spring prices are inversely related to the availability of protein. In the low protein and high protein regimes, the impulse responses are much larger for hard red spring wheat and hard red winter wheat, and the initial impulse response of the Kansas City hard red winter price is considerably larger than the initial impulse response of the Minneapolis hard red spring price. These results are consistent with the hypothesis that buyers of different classes of wheat (millers, etc.) face relatively large adjustment costs when they change their patterns of use.

The effects of price shocks for a specific class of wheat also depend on the protein regime in the threshold models. However, one interesting finding is that shocks to the Kansas City hard red winter price result in very modest impulse responses on the part of Minneapolis hard red spring prices. In contrast, when protein levels are either relatively low or relatively high, shocks to the Minneapolis price generate qualitatively similar but quantitatively smaller impulse responses on the part of the Kansas City price. In addition, an exogenous shock to the Chicago soft red price generates very weak impulse responses in the Minneapolis price, although somewhat stronger impulse responses in the Kansas City price when protein availability is either relatively low or relatively high.

These results also provide some further insights relevant to a long-standing argument between the Canadian Wheat Board and U.S. wheat producers. Fairly consistently, in a variety of wheat trade cases brought before the U.S. International Trade Commission between 1992 and 2004, the Canadian Wheat Board and its expert witnesses have claimed that wheat is just wheat and, in particular, hard red winter and hard red spring are almost perfect substitutes for each other. The evidence from this study tends to suggest that such is not the case. The markets may be related, but exogenous shocks in the price of hard red winter wheat simply do not generally result in similar impulse responses in the price of hard red spring wheat.

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