Agribusiness & Applied Economics Report No. 587 August 2006

Substitution between U.S. and Canadian Wheat by Class

Kranti Mulik
Won W. Koo

Center for Agricultural Policy and Trade Studies
Department of Agribusiness and Applied Economics
North Dakota State University
Fargo, North Dakota

ACKNOWLEDGMENTS

The authors extend appreciation to Mr. Richard D. Taylor and Mr. Andrew Swenson for their constructive comments and suggestions. Special thanks go to Ms. Beth Ambrosio, who helped to prepare the manuscript.

The research was conducted under the U.S. agricultural policy and trade research program funded by the U.S. Department of Homeland Security/U.S. Customs and Border Protection Service (Grant No. TC-03-003G, ND1301).

We would be happy to provide a single copy of this publication free of charge. You can address your inquiry to: Beth Ambrosio, Center for Agricultural Policy and Trade Studies, Department of Agribusiness & Applied Economics, North Dakota State University, P.O. Box 5636, Fargo, ND, 58105-5636, Ph. 701-231-7334, Fax 701-231-7400, e-mail beth.ambrosio@ndsu.nodak.edu. This publication is also available electronically at this web site: http://agecon.lib.umn.edu/.

Information on other titles in this series may be obtained from: Department of Agribusiness and Applied Economics, North Dakota State University, P.O. Box 5636, Fargo, ND 58105. Telephone: 701-231-7441, Fax: 701-231-7400, or e-mail: cjensen@ndsuext.nodak.edu.

Table of Contents

List of Tables

List of Figures

Abstract

The importation of hard red winter and durum wheat from Canada has been a source of contention among U.S. wheat growers, due to the likeness between domestic and imported Canadian wheat. It has also been investigated as a source of material injury to the U.S. market. We examine the relative substitution between U.S. and Canadian wheat, by class, by treating wheat as an input in flour production. We find that while U.S. hard red spring wheat and U.S. hard red winter wheat are economic substitutes, there is limited price substitution between U.S. and Canadian durum and U.S. and Canadian hard red spring wheat. Quality differences from the millers' perspective may be the reason driving the import demand for hard red spring and durum wheat from Canada.

Substitution Between U.S. and Canadian Wheat by Class

Kranti Mulik and Won W. Koo*

INTRODUCTION

Trade in grains, particularly wheat, forms one of the key components of U.S.-Canada agricultural trade. Due to the similarity in products, trade disputes are not uncommon in international trade. Wheat trade between the two countries has been one of the most disputed issues in international trade, often plagued by U.S. allegations of material injury to its domestic market. Recently, the United States International Trade Commission (USITC) investigated a petition filed by the North Dakota Wheat Commission and Durum Growers Trade Section Committee claiming that imports of durum and hard red spring (HRS) wheat from Canada were being subsidized and sold at less than fair value (LSFV).[1] The USITC later ruled that while imports of HRS wheat from Canada caused material injury to the United States, this did not hold true for imports of durum wheat.

In resolving the extent of material injury caused to the United States, likeness between the different classes of wheat was used as key determinant. While it is generally recognized that substitutability between like products is the key in resolving such disputes, product differentiation of wheat has largely been ignored in recent studies on wheat trade, with most studies treating wheat as a homogenous product.[2] Only recently, the importance of treating wheat as heterogenous product has begun to be fully appreciated. However, recent studies which addressed the issue of substitutability between different classes of wheat have either ignored the issue of including classes of Canadian wheat in their estimation or treated wheat as a direct consumption good. For instance, Marsh (2005) estimated a normalized profit function and calculated factor ratio elasticities of substitution between classes of U.S. wheat, treating wheat as an input in the production process, without considering the different classes of wheat imported from Canada.[3] Mohanty and Peterson (1999) estimated two separate demand systems: one for U.S. spring wheat, which included Canadian spring wheat and U.S. other wheat (aggregated), and another for U.S. and Canadian durum wheat as a good used for direct consumption. Our paper contributes to the existing literature by estimating a translog cost function by treating wheat as an input, similar to Koo (2001) and Marsh (2005). However, we go further by dividing U.S. domestic wheat into classes; we also include two major types of wheat (western red spring and durum) imported from Canada and estimate elasticity of substitution between the different classes of wheat.

Thus, the objectives of this paper are two-fold. First, we estimate a demand system by treating the different classes of wheat used by millers as inputs for flour production. Second, we estimate factor ratio elasticities of substitution between the different classes of U.S. and Canadian wheat.

---

* Research Assistant Professor, and Professor and Director, respectively, in the Center for Agricultural Policy and Trade Studies, North Dakota State University.
[1] See USITC publication 3639 for a list of previous disputes.
[2] See Marsh (2005) for an in-depth literature review of studies which focused on the wheat market.
[3] Koo et al (2001) also used a similar approach to estimate the Japanese import demand for different classes of wheat using a translog cost function.

The degree of substitution between the different wheat classes will help to resolve future trade disputes between the United States and Canada.

The remainder of the paper is organized as follows. The first section provides a brief background on the different types of wheat produced in the United States based on their end-use, as well as the imports of the different classes of Canadian wheat by the United States. We also include U.S. millers' perceptions regarding the relative substitutability between U.S. and Canadian wheat in flour production. Section two gives a brief description of the theoretical framework, while section three explains the empirical model and estimation procedures used in this paper. Section four describes the data sources used in this study. Finally, section five discusses the empirical results and their implications, followed by the conclusion in section six.

BACKGROUND

There are five major classes of wheat produced in the United States: hard red winter (HRW), hard red spring (HRS), soft red winter (SRW), soft white (SWW) and durum wheat. Figure 1 shows the production trends for the different classes of wheat for the period 1989/90 to 2003/04.

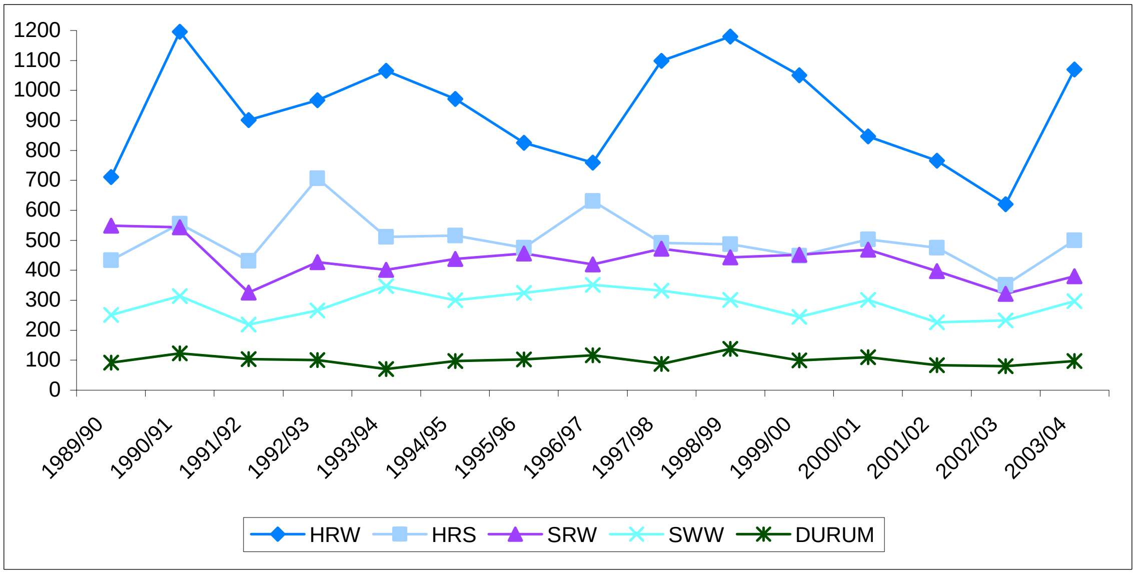

Figure 1. U.S. Wheat Production for the Period 1989/90-2003/04, by Class

Over the years, production of HRS and HRW shows substantial variation, while the production of SRW, SWW, and durum has been relatively stable. For the marketing year 2002/03, HRW wheat accounted for 38 percent of domestic production, HRS wheat 22 percent, SRW wheat 21 percent, white wheat (both hard and soft) 15 percent, and the production of durum wheat was five percent. Spring wheat is planted in spring and typically harvested in the late summer or early fall. Winter wheat is planted in late fall and harvested between mid and late summer. The five types of wheat can be differentiated by their end use and protein content. A hard wheat is usually high in protein content and gluten. Typically, HRS and HRW are ideally suited to producing flour that is later used for baking bread and rolls. Durum is another type of hard wheat which is used to produce semolina used for making pasta. A soft wheat, on the other hand, has a kernel with a lower protein content and is suitable for the production of crackers, cookies, and pastries; white wheat is ideally used to make breakfast cereals, crackers, donuts, layer cakes, and foam cakes.

The United States is the largest exporter of wheat in the world. About 95 percent of the wheat consumed in the United States is produced domestically. For the period 1999-2004, less than 5 percent of wheat was imported from Canada. However, U.S. millers prefer to import Canadian wheat because of its uniformity, consistency, and quality. The United States imports mostly Canadian western red spring wheat and durum wheat. Canadian western red spring wheat is typically used by U.S. millers as a blending wheat to enhance the quality and value of bread flour. Thus, it can serve as an effective complement to different classes of U.S. wheat.

Figure 2 shows the total U.S. domestic consumption of wheat by class for the period 1989/90-2003/04. U.S. domestic production of durum wheat has not been able to meet the domestic demand, in spite of the fact that production has increased over the years. This is because the United States exports almost 49 percent of its durum wheat production, resulting in a domestic shortage. The U.S. processing industry makes up for the domestic shortage by importing durum wheat from Canada. The United States tends to export lower-quality durum wheat to North Africa and import high-quality durum from Canada. In addition, the United States imports durum products such as pasta from Canada and other countries. U.S. pasta imports increased from $285 million in 1996 to $415 million in 2003, averaging a 5.8 percent increase each year. Italy was the major source for U.S. pasta imports (34 percent) followed by Canada (29 percent). Between 1999-2000 and 2003-2004, 48 percent of the total U.S. durum wheat imports consisted of pasta and other processed products. According to the USDA, imports of durum products in certain years exceed imports of durum wheat as grain. Imports of durum wheat from Canada averaged 364,000 tonnes in the period 1999-2003, while the imports of durum products amounted to 391,000 tonnes. In recent years, trade policies to limit durum wheat imports from Canada have shifted U.S. imports to durum wheat from other countries (Agri-Food Canada, 2004). Figure 3 shows U.S. imports of HRS and durum from Canada for the period 1989/90-2003/04. The wheat classes show similar trends, increasing steadily after 1989/90, but declining in 2003/04 as the United States tried to curb Canadian imports. This decrease in U.S. imports corresponds to the period of the USITC investigation.

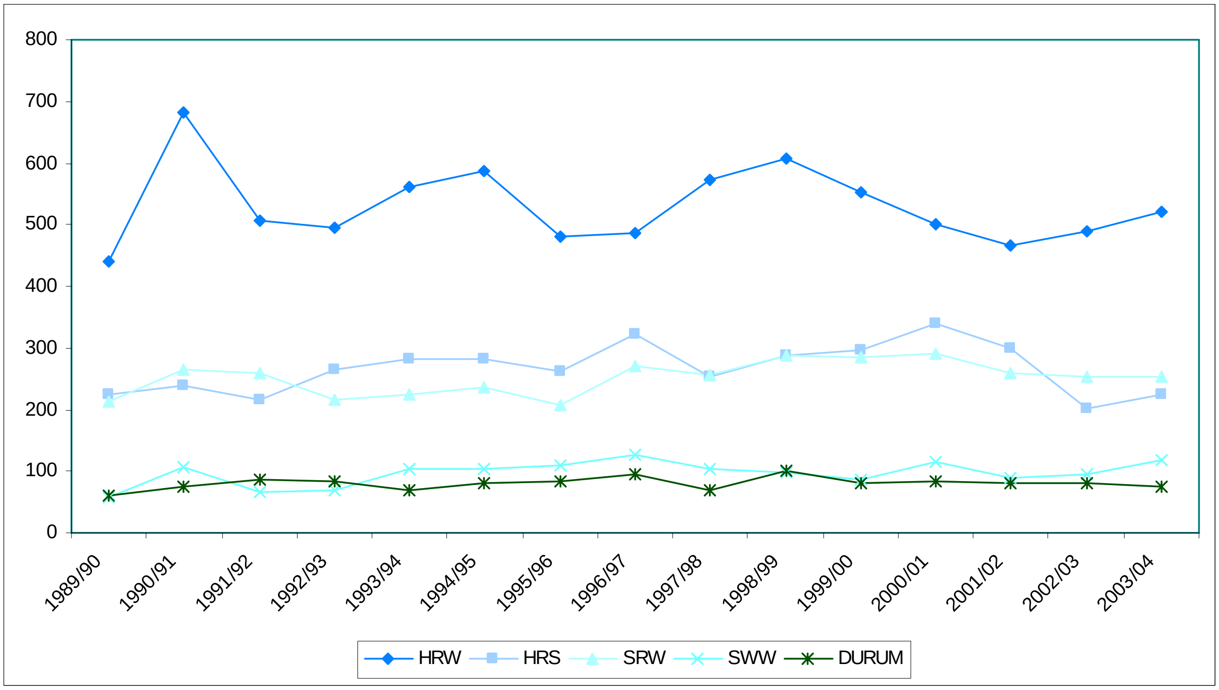

Figure 2. U.S. Wheat Consumption for the Period 1989/90-2003/04, by Class

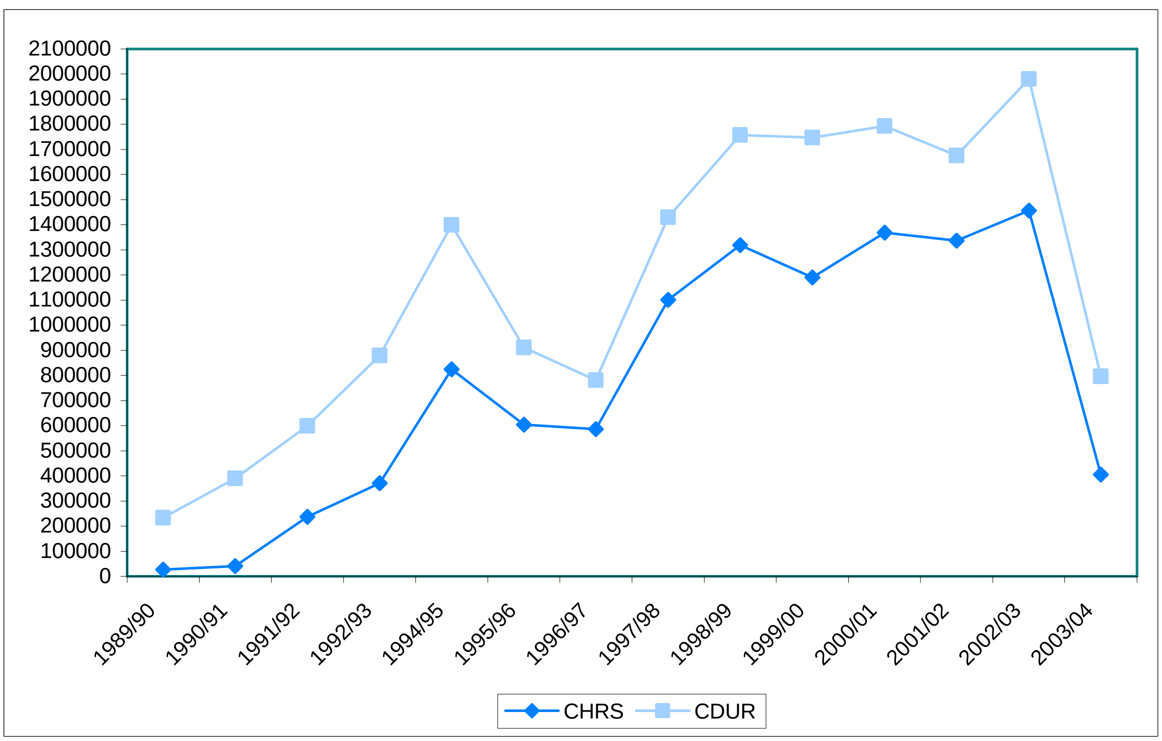

Figure 3. U.S. Imports of Canadian Durum Wheat and Canadian Hard Red Wheat for the Period 1989/90-2003/04, by Class

The USITC conducted a survey of U.S. millers to determine the relative substitutability of imported durum and HRS with U.S. durum and HRS. The commission found that relative prices, quality, and terms of sale were considered to be the most important factors in the millers' determination of substitutability. Millers indicated that Canadian HRS and durum are close though not perfectly substitutable with U.S. HRS and durum, respectively.[4] All of the millers surveyed indicated that both Canadian and U.S. wheat could be used in similar applications. Because U.S. millers use both domestic wheat and imported Canadian wheat in flour production, the results from this study will help determine the relative substitution between the different classes of wheat in the two countries. As pointed out by Mohanty and Peterson (1999), if U.S. and Canadian wheat are imperfect substitutes, a small price change in one type of wheat will not trigger a change in the purchasing behavior of the miller. However, if U.S. and Canadian wheat are highly substitutable, a small change in the price of one class of wheat will cause the miller to switch to another.

THEORETICAL FRAMEWORK

Assuming that a representative miller in the U.S. flour milling industry is a price taker, we can use the duality theory to represent their behavior, employing either a profit function or cost function approach. The Hotelling's Theorem or the Shepard's Lemma can then be used to obtain input demand and output supply compatible with the firm optimization problem. Thus, the derived input demand may be considered as the outcome of profit maximization or cost minimization.

We analyze the representative miller's optimization problem using a cost-minimization approach. Flour production is considered as a single output of the miller's production process, using different classes of wheat as inputs. The miller minimizes cost based on the prices and substitutability of the different inputs. Thus, we can analyze the impact of substitutability between the different classes of wheat on the miller's production decisions. The cost function of a firm is defined by:

$$TC(P,Y) = \left\{ \min_{X} \sum_{j=1}^{J} P_j X_j \right\} \tag{1}$$

subject to the constraint $F(X_i; \gamma)$, which is the production function associated with a given level of output Y. TC_i is the total cost of production incurred by the representative miller. X is the vector $(J \times 1)$ of inputs with prices P, and γ is the vector of parameters to be estimated for the

[4] Specifically, millers were asked to compare U.S. durum and HRS wheat with Canadian durum and HRS, based on 19 factors. Millers indicated that U.S. durum was better than the Canadian variety in terms of discounts offered, lowest spot price, and moisture-adjusted protein content. They rated U.S. durum inferior to Canadian Durum in terms of dockage, product consistency, reliability of supply, and availability of forward contracts. For HRS wheat, millers rated U.S. HRS as superior to Canadian HRS for most of the 19 factors. Canadian HRS was rated superior to U.S. HRS in terms of dockage and consistency.

inputs. The following output-conditional input demand functions can be obtained by solving the first order conditions of the cost minimization problem stated above[5].

$$X\big|Y = X\big|Y\left(P, Y; \delta\right) \tag{2}$$

where P is a vector of input prices and δ is a vector of parameters to be estimated. Substituting (2) into (1), we can obtain the indirect cost function as follows:

$$C = c\left(P, Y; \lambda\right) \tag{3}$$

where λ is a vector of parameters to be estimated in the cost function. This cost function has standard properties, in that it is homogenous of degree one, non-decreasing, and satisfies concavity in prices. In addition, we assume weak separability of inputs such that[6]

$$c\left(p, Y\right) = C^*\left(Y, c^1\left(Y, p^1\right), c^2\left(Y, p^2\right)\right) \tag{4}$$

where P^1 is a vector of input prices for the different classes of wheat and P^2 is a vector of other input prices besides the wheat class, such as labor and capital used in flour production.
Using Shepherd's Lemma, we can differentiate the cost function in Equation (3) with respect to the input prices in order to obtain a cost-minimizing system of input demand equations for the different classes of wheat. Thus, the input demand for the j^{th} input (X_j) is:

$$\partial C \big/ \partial P_j = X_j = f\left(P, Y; \sigma\right) \tag{5}$$

where σ is the vector of parameters to be estimated.

EMPIRICAL MODEL

We make the assumption that the cost function specified in Equation (3) can be estimated using a flexible functional form. We use a translog functional form to represent the miller's cost function. The translog cost function is flexible, parsimonious, and allows us to impose restrictions on the parameters to be estimated. By normalizing the variables by their means, the translog cost function becomes a second order approximation of the cost function. The general form of the translog cost function with *n* inputs (w) and *m* outputs (y) is defined as follows:

---

[5] For a detailed derivation of the cost function and the input demand system, see Chambers (1988).
[6] Ideally, we should estimate a system of equations for the different classes of wheat and labor and capital. However, due to lack of data on labor and capital, we consider only the different classes of wheat. Marsh (2005) made a similar assumption. Weak separability in the case of a cost function implies that $\frac{\partial x_i\left(p, y\right)/\partial p_n}{x_i\left(p, y\right)} = \frac{\partial x_j\left(p, y\right)/\partial p_n}{x_j\left(p, y\right)}$. This is a logical assumption, as pointed out by Marsh (2005), given that for the period 1994-1998, cost of wheat as an input in flour production contributed to 91 percent of the wholesale price of wheat.

$$\ln c(w,y) = a_0 + \sum_{i=1}^{n} a_i \ln w_i + \sum_{i=1}^{m} a_y \ln y_i + 1/2 \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} \ln w_i \ln w_j + \sum_{i-1}^{n}\sum_{j=1}^{m} a_{iy} \ln w_i \ln y_j \qquad (6)$$

$$+ 1/2 \sum_{i=1}^{m}\sum_{j=1}^{m} a_{ij} \ln y_i \ln y_j$$

where $a_{ij} = a_{ji}$ for all i,j

$$\sum_{i=1}^{n} a_i = 1$$

$$\sum_{j=1}^{n} a_{ij} = 0, i = 1,...,n$$

$\sum_{j=1}^{n} a_{ij} = 0$ ensures that homogeneity of degree one in factor prices is imposed in the translog cost function. Symmetry is imposed by setting $a_{ij}=a_{ji}$ for all *i,j*. The parameters of the translog cost function are estimated as a system of equations which includes the log cost function and *n*-1 share equations. By applying Shepherds lemma, the cost minimizing input demand functions can be derived by differentiating the cost function as follows:

$$\frac{\partial \ln C}{\partial \ln w_i} = \frac{\partial C}{\partial w_i}\frac{w_i}{C}, \quad i = 1...,n. \qquad (7)$$

Since $\partial C / \partial w_i = x_i$, for *i=1,…,n,* we can specify the input demand function in share form as:

$$S_i\,(w,y) = \frac{w_i x_i}{C} = a_i + \sum_{j=1}^{n} a_{ij} \ln w_j + a_{iy} \ln y \,, \qquad i = 1,..., n\,. \qquad (8)$$

where S_i represents the cost share of input i and x_i is the quantity of input i used in the production of flour. Thus, we can estimate the cost function and the six share equations for seven different classes of wheat (HRS, HRW, SRW, SWW, DUR, CHRS and CDUR). The 7th share equation (CDUR) and the resulting parameters are recovered by homogeneity[7]**.**

Monotonicity in input prices for the translog cost function requires non-negative shares. Concavity restrictions on the input side can be checked by ensuring that the Hessian matrix is negative semi-definite[8].

Finally, we calculate own price elasticities as:

---

[7] As the cost share equations sum to one, we must estimate only j-1share equations to avoid singularity of the variance-covaraince matrix.

[8] Alternatively, the Allen partial matrix can be used to check whether curvature restrictions hold, as defined as Z_{ij} / s_j, where Z_{ij} is the elasticity and s_j is the share equation. Concavity of the Allen Partial matrix implies that the Hessian matrix is also concave.

$$E_{ii} = a_{ii} / S_i + S_i - 1, \qquad i=j \tag{9}$$

where E_{ii} is the own price elasticity and S_i is the share of the i^{th} input .

Cross price elasticities are calculated as:

$$E_{ij} = a_{ij} / S_i + S_j, \qquad i \neq j \tag{10}$$

where E_{ij} is the cross price elasticity and S_i and S_j are the shares associated with the i^{th} and j^{th} inputs, respectively. Generalized factor ratio elasticities of substitution are defined as

$$\sigma_{ij} = \frac{\partial \ln\left(x_j / x_i \right)}{\partial \ln\left(p_i / p_j \right)} = \varepsilon_{ji} - \varepsilon_{ii} \quad for\, i, j = 1, \ldots.. n \tag{11}$$

where σ_{ij} is the factor ratio elasticity of substitution, which measures the effect of varying the factor price ratio p_i / p_j in the i^{th} direction on the factor quantity ratio x_j / x_i (Davis and Shumway,1996)[9].

DATA SOURCES AND ESTIMATION PROCEDURE

Quarterly data on the quantities of different classes of wheat used in U.S. food production were obtained from the Wheat Yearbook (USDA) for the period 1989/90 to 2003/04. These data are available only annually. The USDA provides quarterly information on wheat supply and disappearance in the Wheat Yearbook, but this information is not available by class. Thus, to obtain the quantity of each class of wheat used in food production, the overall percentage of wheat used for food was calculated for each quarter. This quarterly percentage was then applied to the annual data on the use of wheat for food by class to obtain the quantity of wheat used for flour production by class.[10] Quarterly data on the quantity of flour production were available from the U.S. Bureau of Census, but the period did not correspond with the typical marketing year for wheat (June-May). However, annual data on the quantity of flour production were available from the U.S. Bureau of Census and the Economic Research Service (ERS) of the USDA. Thus, using the quarterly data and the annual data, the percentage of flour produced in each quarter was calculated. This percentage was later applied to the annual data on flour production to obtain the quarterly flour production.[11] As pointed out earlier, the protein content

[9] The generalized factor ratio elasticities are also asymmetric like the Morishima elasticities of substitution (Blackorby and Russell 1989). See Davis and Shumway (1996) for a detailed discussion.

[10] Due to data limitations, we make the assumption from the total domestic production that the percentage of wheat as inputs used for food is identical for all classes. This assumption is not unrealistic since the five classes of wheat produced in the United States are used predominantly for food.

[11] Due to data limitations, we assume that only one type of flour is produced.

of wheat is extremely important when determining substitutability between different classes. Thus, the price of HRW wheat is represented by Kansas City No.1 (13 percent protein), HRS by Minneapolis dark No.1 spring (14 percent protein), the price of SRW by Chicago No.2, SWW by Portland No.1, and durum wheat by Minneapolis No.1 hard amber durum.[12] All prices used in the model are cash prices from major markets. All quantities were converted to metric tons and the prices are expressed as price/MT. The main U.S. imports from Canada include Canadian western red spring wheat and Canadian durum wheat. Data on the quantity and value of these two wheat varieties were obtained from the Foreign Agricultural Trade of the United States (FATUS). The prices of Canadian HRS and durum were calculated by dividing value by quantity. Data on the U.S. CPI for food were obtained from the International Labor Statistics, published by the International Labor Organization (ILO).[13] All prices were deflated by the food CPI.

The empirical model specified in Equation (6) was estimated using the Bayesian inference framework (full details in Appendix). The Bayesian approach has the advantage of maintaining flexibility of the functional form by imposing general demand restrictions, i.e., monotonicity and curvature and drawing finite sample inferences related to nonlinear functions of parameters.[14] This method also allows us to construct Monte Carlo confidence intervals for price and substitution elasticities.

RESULTS

Parameter estimates from the Bayesian approach are presented in Table 1. Of the estimated coefficients, only 16 were statistically significant at the 10 percent level. The price elasticties and the bootstrapped confidence intervals for the elasticity estimates from the Bayesian approach are presented in Table 2.

The confidence intervals were constructed after the burn-in period.[15] After imposing curvature, all own-price elasticities are negative. This implies that as the own-price of the different classes of wheat increases, the quantity demanded by the millers decreases. The own-price elasticities of HRW and HRS are both elastic, with HRS being the most price elastic. Thus, a one percent increase in the price of HRW and HRS results in a 1.54 percent and 2.46 percent decrease in the

---

[12] Marsh (2005) used similar prices based on protein content. The data are monthly data on cash price. The quarterly averages are taken based on the marketing year for wheat, which runs from June-May.

[13] The data on food CPI are monthly data. The quarterly averages are taken based on the marketing year for wheat, which runs from June-May.

[14] This approach can be extremely useful in obtaining reliable elasticity estimates for studies that require the use of flexible functional forms. It is further useful to test the robustness of the estimates within the observed data range as well as outside the data range.

[15] Bootstrap estimates were obtained by re-sampling the residuals from the estimated model, predicting cost and quantities of wheat with the model, re-estimating the system of equations with predicted values and then recalculating the elasticities. This process was repeated 1,000 times to obtain price elasticities. We construct the 90 percent confidence interval based on the percentile method. Following Mittelhammer et al. (2000), we first order the estimated elasticities and then select outcome 50(0.05*1000) for the lower critical value and outcome 950(0.95*1000) for the upper critical value. For hypothesis testing, if the bootstrapped confidence intervals contained zero, then the elasticity was considered not significantly different from zero at the 10 percent level.

quantity demanded of HRS and HRW, respectively. The own-price elasticities of other classes of wheat are inelastic, with durum being the most inelastic, followed by SRW, SWW, and Canadian HRS and durum. Except for the elastic cross price effects between HRW and HRS, all other cross effects were inelastic.

Table 1. Parameter Estimates from the Translog Cost System Bayesian Approach

Coefficient	Coefficient Estimate	Lower Critical Value+	Upper Critical Value+
α 0	-1534.316052*	-2585.290160	-787.058152
α 1	0.269276	-1.813672	2.350873
α 2	0.724822	-1.952795	3.308358
α 3	0.823130*	0.183584	1.494002
α 4	0.176681	-0.990179	1.549377
α 5	0.740289	-0.063822	1.578918
α 6	-1.464018*	-2.324658	-0.685711
α 8	366.526067*	187.591120	620.142549
β 11	-0.070442	-0.210314	0.053689
β 12	0.207868*	0.078252	0.360621
β 13	-0.082653*	-0.115934	-0.051407
β 14	-0.013955	-0.044942	0.015840
β 15	-0.039725*	-0.065475	-0.011133
β 16	0.005126	-0.030970	0.041307
β 22	-0.228718*	-0.426797	-0.067980
β 23	0.029556	-0.006671	0.072291
β 24	-0.014188	-0.039722	0.012826
β 25	-0.009151	-0.036284	0.017886
β 26	-0.001695	-0.048630	0.045900
β 33	0.081734*	0.066842	0.094484
β 34	-0.007554	-0.017910	0.002871
β 35	-0.013213	-0.021567	-0.005479
β 36	-0.009092	-0.020604	0.002838
β 44	0.049036*	0.034474	0.063254
β 45	-0.008084	-0.017133	0.000385
β 46	-0.008168	-0.017318	0.000892
β 55	0.093541*	0.081505	0.104520
β 56	-0.010684	-0.021274	-0.000014
β 66	0.026782*	0.004388	0.047325
γ 11	-0.006002	-0.251681	0.237136
γ 12	-0.077476	-0.383803	0.241243
γ 13	-0.078444*	-0.158062	-0.002306
γ 14	0.004892	-0.154212	0.141304
γ 15	-0.064966	-0.164436	0.029063
γ 16	0.186477*	0.093425	0.290431
γ17	0.067146*	0.013394	0.125135
δ11	-43.463585*	-74.081327	-22.045642

+ 90 percent confidence interval
*90 percent confidence interval does not contain zero.

Table 2. Price Elasticity Estimates for the Translog Model at the Sample Mean with Bootstrapped 90% Percentile Confidence Intervals by Bayesian Method

	Price Elasticities						
Price	HRW	HRS	SRW	SWW	DUR	CHRS	CDUR
HRW	-1.54317*	1.58030*	-0.37199*	0.21508*	0.022497	0.187851	-0.090570
HRS	1.48864*	-2.46342*	0.39285*	0.104646	0.124382	0.116659	0.236240
SRW	-0.33708*	0.37790*	-0.34560*	0.16906*	0.06541*	0.029003	0.041301
SWW	0.13140*	0.067868	0.11398*	-0.56659*	0.14242*	0.05057*	0.060338
DUR	0.017725	0.104034	0.05687*	0.18368*	-0.32308*	-0.022866	-0.016372
CHRS	0.345217	0.227587	0.058820	0.15213*	-0.053334	-0.66974*	-0.060675
CDUR	-0.298639	0.826925	0.150286	0.325656	-0.068516	-0.108867	-0.82684*

90 PERCENT CONFIDENCE INTERVAL UPPER CRITICAL VALUE

	HRW	HRS	SRW	SWW	DUR	CHRS	CDUR
HRW	-0.533144	2.040361	-0.058970	0.323391	0.142740	0.290839	0.124347
HRS	6.182458	-1.778116	1.276731	0.403450	0.484358	0.802285	0.805109
SRW	-0.082324	0.548837	-0.263026	0.242710	0.171238	0.122446	0.089396
SWW	0.285702	0.145372	0.178478	-0.487238	0.205953	0.110408	0.090141
DUR	0.153184	0.175634	0.138737	0.220559	-0.252212	0.101938	0.004930
CHRS	0.642074	0.553448	0.192012	0.233384	0.198115	-0.439575	0.110859
CDUR	1.012320	2.427984	0.673303	0.913800	0.034332	0.504003	-0.596258

90 PERCENT CONFIDENCE INTERVAL LOWER CRITICAL VALUE

	HRW	HRS	SRW	SWW	DUR	CHRS	CDUR
HRW	-1.952343	0.392477	-0.445033	0.009148	-0.104999	-0.057344	-0.128309
HRS	1.212838	-7.359090	0.067134	-0.570246	-0.436413	-0.733482	-0.162590
SRW	-0.527993	0.025043	-0.423407	0.100056	0.052487	-0.027051	-0.012787
SWW	0.010292	-0.118939	0.078140	-0.622348	0.107607	0.017020	-0.001402
DUR	-0.116635	-0.114615	0.047022	0.126142	-0.394935	-0.008605	-0.075939
CHRS	-0.115316	-0.402794	-0.045258	0.036639	-0.016476	-0.854758	-0.105872
CDUR	-1.386056	-0.414356	-0.094979	-0.015592	-0.810252	-0.485548	-1.704767

*90 percent confidence interval does not contain zero.
HRW, hard red winter; HRS, hard red spring; SRW, soft red winter; SWW, soft winter white; DUR, Durum; CHRS, Canadian Hard Red Spring; CDUR, Canadian Durum.

Table 3 reports the generalized factor ratio elasticities of substititution. The factor ratio elasticity measures the percentage change in the ratio of quantity demanded of factor x_j to factor x_i for a change in price of factor p_i. Thus, a one percent increase in the price of HRW results in 3.123, 1.171, 1.758, 1.565, 1.731 and 1.452 percent increases in the factor ratios of HRS, SRW, SWW, durum, and Canadian HRS and durum, relative to HRW, respectively. For example, a one percent increase in the price of HRW results in a 2.856 percent increase in the quantity of HRS relative to HRW demanded by millers. Similarly, a one percent increase in the price of HRS yields 3.952, 2.856, 2.568, 2.587, 2.580, and 2.699 percent increases in the factor ratios of HRW, SRW, SWW, durum, and Canadian HRS and durum, relative to HRS, respectively.[16] In contrast, price changes in SRW, SWW, and durum results in inelastic substitution effects in terms of factor ratio elasticity of substitution. A price change in Canadian HRS yields inelastic substitution effects for all other wheat classes except HRW. For example, an increase in the price of Canadian HRS results in a 0.89 percent increase in the quantity of domestic HRS demanded by millers relative to Canadian HRS. Similarly, a price change in Canadian durum yields elastic substitution effects with respect to HRS and SWW and inelastic effects with all other wheat classes.

Table 3: Generalised Factor Ratio Elasticities of Substitution at the Sample Mean

	HRW	HRS	SRW	SWW	DUR	CHRS	CDUR
HRW	-	3.123476	1.171185	1.758262	1.565672	1.731026	1.452605
HRS	3.952072	-	2.856286	2.568075	2.587811	2.580088	2.699669
SRW	0.008528	0.723515	-	0.514671	0.411022	0.374611	0.386909
SWW	0.697998	0.634463	0.680578	-	0.709024	0.617169	0.626933
DUR	0.340809	0.427118	0.379961	0.50677	-	0.300218	0.306712
CHRS	1.014962	0.897332	0.728565	0.821875	0.616411	-	0.60907
CDUR	0.528207	1.653771	0.977132	1.152502	0.75833	0.717979	-

HRW, hard red winter; HRS, hard red spring; SRW, soft red winter; SWW, soft winter white; DUR, Durum; CHRS, Canadian Hard Red Spring; CDUR, Canadian Durum

Thus, based on our results, there is maximum potential for substitution between HRS and HRW. As previously stated, in a survey of U.S. millers conducted by the USITC, respondents rated Canadian HRS as inferior to U.S. HRS for most of the 19 factors queried in the survey, with the exception of factors related to dockage and consistency. This could be the reason for the relatively small price responsiveness of Canadian HRS wheat. Further, U.S. millers blend Canadian HRS with U.S. wheat to achieve desired characteristics in baking. Specifically, U.S. millers indicate that blending Canadian HRS with U.S. wheat adds value to their milling operations by softening the variations in U.S. wheat and enhancing flour performance. The limited substitutability between Canadian and U.S. durum could be due to the fact that U.S. millers prefer the Canadian durum wheat because of its higher quality and are willing to pay a price premium for the level of quality, as indicated in the survey conducted by the USITC. Also, in recent years, the production of mill-quality durum in the United States has been well below the domestic requirements of the processing industry. In particular, the declining U.S.

[16] The higher substitution effects between HRS and the other wheat classes are similar to Marsh (2005), who states that changes in the prices of wheat with higher protein content result in larger substitution effects across all other wheat classes.

production of #1 and #2 grade durum, the grades required by the U.S. pasta industry, has resulted in increased durum imports from Canada. There has been a consistent shortage of milling-quality durum in the United States for each crop year since 1990-91 (Canadian Embassy, 2000).

In summary, an important point to note is that while HRS and durum wheat produced in the United States and Canada can be used in similar milling applications, there is a quality differential between U.S. and Canadian wheat, which may be the cause for limited substitution between the two countries' products.[17]

While we cannot directly compare our results with other studies since they did not include Canadian wheat varieties in their analysis,[18] in general, the magnitude of our own-price elasticities for the different classes of wheat are larger than those in other studies.[19] Our results are also consistent with the evidence from these studies that, in general, the demand for hard wheat varieties is more price responsive than the demand for soft wheat varieties.[20]

IMPLICATIONS AND CONCLUSIONS

Substitutability is extremely important in resolving trade disputes that arise when countries trade in similar products. In light of the recent investigation conducted by the USITC to determine whether there was material injury to the United States as a result of HRS and durum wheat imports from Canada, we estimated a demand function to determine the relative substitution between U.S. and Canadian wheat varieties. We find that while HRS and HRW are highly substitutable, there is limited substitution between U.S. and Canadian durum and between U.S. and Canadian spring wheat. Thus, U.S. millers import Canadian wheat for achieving desired quality and consistency in flour production, and they are relatively less price responsive to changes in prices of Canadian HRS and durum wheat. For example, the United States imports durum wheat from Canada to cover the shortage of domestic durum wheat production, particularly the #1 and #2 grade durum required for making high quality pasta for domestic consumption. Thus, a change in the price of Canadian durum does not trigger a large response in the quantity demanded by U.S. millers. This is demonstrated by the inelastic own-price elasticity of Canadian durum wheat and the low substitution elasticity between U.S. and Canadian durum.

[17] In the case of HRS wheat, respondents of the USITC survey indicated that price was the most important factor affecting their purchase decisions. However, HRS wheat is traded in the futures and spot market and also through forward contracting. Therefore, millers are able to buy wheat futures and evade unexpected price changes. This may be the cause for limited price substitution between U.S. and Canadian HRS.

[18] While Mohanty and Peterson (1999) include Canadian spring and durum wheat in their estimation, they estimate a different system of equations for each class of wheat. Further, they combine the different classes of U.S. wheat, with the exception of durum and spring, as other wheat.

[19] For example, see Chai (1972), Barnes and Shields (1998), and Marsh 2005. Though slightly larger, our results are closer in magnitude to those reported by Marsh (2005) than other studies. Our larger elasticities could be the result of using quarterly data and also a result of the inclusion of two Canadian wheat varieties in our estimation. Mohanty and Peterson (1999) report larger own-price elasticities for Canadian durum and HRS wheat, but smaller elasticies for U.S. durum and spring wheat.

[20] Also, as pointed out by Koo et al (2001), higher quality wheats (such as HRS and HRW) are more price responsive than lower quality wheats.

In the case of Canadian HRS, as indicated in a survey conducted by the USITC, U.S. millers prefer U.S. to Canadian varieties on most factors**.** Therefore, there is a quality differential between U.S. and Canadian HRS from the millers' view-point. The greater the quality difference between two similar classes of wheat, the less responsive millers will be to changes in the price of one class of wheat over the other, and they will be less likely substitute one class of wheat for the other.

U.S. millers prefer to use Canadian HRS to achieve the desired consistency in flour production. This may explain the inelastic own-price elasticity of Canadian HRS and the relatively low substitution elasticity between U.S. and Canadian HRS. Thus, in the event of a price change in Canadian HRS and durum, U.S. millers are less likely to shift to other wheat classes, and the impact of Canadian wheat imports on the U.S. domestic market may be limited.

References

Agri-Food Canda. 2004. The Canada-United States Wheat Trade: A Mutually Beneficial Partnership. Available at: http://www.agr.gc.ca/itpd-dpci/english/country/Wheat_brochure-2004_e.htm

Barnes, J.N. and D.A. Shields. 1998. The growth in U.S. wheat food demand. In Wheat Yearbook, 21-29. Washington D.C:U.S. Department of Agriculture, Economic Research Service.

Blackorby,C. and R.B.Russell. 1989. Will the real elasticity of substitution please stand up? (A Comparison of Allen/Uzawa and Morishima elasticities. *American Economic Review* 79:882-888.

Bureau of Census. Avaialble at: http://www.census.gov/

Canadian Embassy. 2000. Some Factors in Canada-United States Wheat Trade. Available at: www.canadianembassy.org

Chai, J.C. 1972. The U.S. Food Demand for Wheat by Class. Staff Paper. Madison: University of Minnesota, Department of Agricultural and Applied Economics.

Chambers, R.G. 1988. *Applied Production Analysis: A Dual Approach*. New York: Cambridge University Press.

Chib, S., and E. Greenberg. 1996. Markov Chain Monte Carlo Methods in Econometrics. *Econometric Theory* 12:409-31.

Chib, S., and E. Greenberg. 1995. Understanding the Metropolis-Hastings Algorithm. *American Statistician* 49:327-35

Davis, G.C. and C.R. Shumway. 1996. To tell the truth about interpreting the Morishima elasticity of substitution. *Canadian Journal of Agricultural Economics* 44:173-182.

Dong F. 2006. State Trading Enterprises in a Differentiated Product Environment: The Case of Global Malting Barley Markets. *American Journal of Agricultural Economics* 88(1):90-103.

FATUS, ERS, USDA. Available at: http://www.ers.usda.gov/data/FATUS/

Griffiths, W., C. O'Donnell and A.Cruz. 2000. Imposing Regularity Conditions on a System of Cost and Factor Share Equations. *Australian Journal of Agricultural and Resource Economics* 44:107-27

Judge,G.G., W.E Griffiths, R.C.Hill, H. Lutkepohl and T.C Lee. 1995. *The Theory and Practice of Econometrics*. New York: John Wiley 2nd edn.

Koo, W.W., W. Mao and T. Sakuarai. 2001. Wheat Demand in Japanese flour milling industry: A production theory approach. *Agricultural Economics* 24:167-178.

International Labor Organization. Available at: www.ilo.org.

Marsh, T.L. 2005. Economic Substitution for U.S. wheat food use by class. *The Australian Journal of Agricultural and Resource Economics* 49:283-301.

Mohanty, S. and E.W.F. Peterson. 1999. Estimation of demand for wheat by classes in the United States and the European Union. *Agricultural and Resource Economics Review* 28:158-168.

Mittlehammer, R.C., G. Judge and D. Miller. 2000. *Econometric Foundations*. New York: Cambridge University Press

USDA. Wheat Yearbook. Available at: http://usda.mannlib.cornell.edu/reports/erssor/field/whs-bby/

USITC. 2003. Durum and Hard Red Spring Wheat from Canda. Investigations Nos. 701-TA-430A and 430B and 731-TA1019A and 1019B (Final). Publication 3639. Washington, DC.

Appendix: Bayesian Estimation

The Bayesian framework is based on Bayes Theorem which states that

$$f(\beta,\Sigma|Y,X) \propto L(Y,X|\beta,\Sigma)p(\beta,\Sigma) \tag{12}$$

where β is a vector of parameters to be estimated, Σ denotes the covariance matrix, and Y and X denote data observations. Under the Bayesian approach, the posterior density function $f(\beta,\Sigma|Y,X)$ is proportional ($\propto$) to the product of likelihood function $L(Y,X|\beta,\Sigma)$ and the prior density function $p(\beta,\Sigma)$ for β and Σ. We use non-informative prior on β and Σ to permit better comparison of maximum likelihood results with Bayesian results irrespective of availability of information on monotonicity and concavity (Griffiths et al. 2000). Further, using a non-informative prior allows for a consistent algebraic form of the prior density function which does not alter according to availability of information on monotonicity and concavity despite the fact that the region over which the prior density function is defined varies (Judge et al, 1998). A Markov Chain Monte Carlo Method (MCMC) is used to solve problematic issues related to integrating and analytically evaluating the moments of the posterior density in Bayesian estimation. This method has the advantage of drawing finite samples from the posterior density without derivation of the density itself.

Using a Metropolis-Hastings algorithm (M-H), the MCMC simulation method is used to perform the Bayesian estimation. This M-H algorithm permits us to impose monotonicity, curvature, and other restrictions at a given set of prices during the Monte Carlo simulation by truncating the sample. Curvature restrictions are imposed locally.

The procedure for the Metropolis-Hastings algorithm proposed by Chib and Greenburg (1995, 1996) and Griffiths et al (2000) is described below:

Step 1: Specify an arbitrary starting value (β^0) which satisfies the constraints of the translog cost function, and set the iteration level at i=0.

Step 2: Use the current value of β^i and a symmetric transition density to generate the next candidate value in the sequence (β^c).

Step 3: Use the candidate value generated (β^c) to test the monotonicity and curvature restrictions imposed. If any of the restrictions are violated, then set $u(\beta^i, \beta^c) = 0$ and go to step five.

Step 4: Estimate $u(\beta^i, \beta^c)=\min(g(\beta^c)/g(\beta^i)),1)$, where $g(\beta)$ is the kernel of $f(\beta|Y,X)$.

Step 5: Generate an independent uniform random variable U from the interval [0,1].

Step 6: Set $\beta^{i+1}= \{ \beta^c$ if $U < U(\beta^i, \beta^c)$, or $\beta^{i+1}= \beta^i$ otherwise.

Step 7: Set $i = i+1$ and go back to step 2.

To complete the MCMC approach, the burn-in period for the sample was set at 375,000 iterations in order to reduce the influence of starting values and ascertain that the MCMC chain converged to a stationary distribution. The post-burn-in sample size was set to 375,000 iterations. This iteration results in a chain β^1, β^2,…,which has a property that for a large i, β^i+1 is a effective sample point from f(β |Y,X), the posterior density. Thus, f(β |Y,X) can be regarded as the posterior density for β given Y and X, which gives us all required information about β after Y and X have been observed from the sample. Essentially, the sequence β^{i+1},…., β^{k+m} can be regarded as a sample for f(β |Y,X) which satisfies monotonicity and curvature constraints. Curvature restrictions are checked in step 3 by using the maximum eigen value of the Hessian matrix. We chose starting values of a_i = 0.125 (i= 1,….,6) and a_{ij} = 0 for all $i \neq j$. The starting values were chosen such that they satisfied monotonicity and curvature restrictions. The transition density we use (q (β^i, β^c)) is arbitrary. The usual procedure is to assume multivariate normal distribution for the transition density, which has mean β^i and a covariance matrix equal to the estimated covariance matrix of the unrestricted, nonlinear, seemingly unrelated regression estimator.

In order to determine the rate at which the initial candidate value β^c is accepted as the next value in the sequence, the covariance matrix is multiplied by a tuning constant (h). This tuning constant was set at h=0.001. The value of h was chosen by trial and error. We found that a smaller tuning generally raises the acceptance rate. With the tuning constant set at h= 0.01, and post-burn-in period set at 375000, we obtained an acceptance rate of approximately 50 percent.