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END-USE PERFORMANCE UNCERTAINTY AND COMPETITION IN INTERNATIONAL WHEAT MARKETS* **

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In many commodity markets, differences in quality characteristics and prices have an important impact on competition among exporting countries. Ladd and Martin's (1976) input characteristics model (ICM) provides an appropriate foundation for analyzing demand for inputs with different characteristics. The ICM has not been used to analyze demand in agricultural trade even though a large proportion is comprised of raw commodities. Technical characteristics of imported inputs and quality requirements of buyers are demand features that can be incorporated only through the ICM. In addition, each import market has idiosyncrasies that can be traced to the microstructure of demand. The ICM is valuable for explaining some apparent anomalies in import demand and identifying sources of competitive advantage between sellers. This study incorporates the impact of uncertainty in commodities' end-use performance in the ICM. The model is used to analyze the impact of price, quality and characteristic uncertainty in a selected wheat import market--the United Kingdom.

The intent of many regulations and trading practices is to decrease uncertainty of commodities' end-use performance. Policy discussions about grain quality in international and domestic trade have focused on these issues. A 1989 U.S. Congress Office of Technology Assessment survey of foreign grain buyers indicated a growing concern about lack of consistency and uniformity in wheat imported from the United States. Analysis of the evolution of competition in the U.S. milling industry concluded that "performance consistency is a pressing concern..." (USDA 1991). Yet the focus of quality-related research in agriculture has primarily been on a characteristic's "level." In commercial practice, both the level and variance of a characteristic are important quality parameters. Lower variance (or greater consistency) means better quality from a buyer's perspective. Lack of consistency, that is, large deviations in quality characteristics, can interrupt production schedules, increase processing costs, require additional storage capacity, or reduce product quality.

Traditional trade models using aggregate data cannot provide insight into impacts of quality characteristics on demand and competition. Optimization models based on spatial equilibrium usually identify single supply sources for each importing country, despite that imports frequently come from more than one source. Models based on econometric methodologies use aggregate trade units and average prices, and results are generally limited to elasticities of substitution. The ICM is attractive because it can simultaneously account for the product's quality requirements, input characteristics, prices, and import market idiosyncracies.

THE INPUT CHARACTERISTICS MODEL AND UNCERTAINTY

Most ICM applications use regression models to estimate implicit or hedonic input characteristic values. Optimization models can also be used to calculate these values.[1] Typically, optimization models use an objective function representing total input (ingredient) cost, which is minimized subject to a set of constraints that control each characteristic's level. The input's value is calculated from optimal solution values in the following dual equation:[2]

$$(1) \qquad \sum_i A_{ij} Y_i = P_j \, ,$$

where A_{ij} is the marginal physical product of the i^{th} characteristic in the j^{th} input, Y_i is a dual price (the marginal product value of characteristic i), and P_j is the value of the j^{th} input. This equation states that input j's value is the summation of implicit characteristic values.

The effects of uncertain technical coefficients can be incorporated into the ICM, resulting in a probabilistic specification. Uncertainty affects the probability of a characteristic's actual level meeting the desired level. The probabilistic model is converted to an equivalent deterministic model and solved using nonlinear programming. Assuming each technical coefficient is characterized by a normal independent distribution, the constraint is converted to a "chance constraint" (Bracken and McCormick 1968), in the following general form:

$$(2) \qquad P\left[\sum_{j=1}^{n} \bar{A}_{ij} X_j \gtreqless b_i\right] \geq 1 - \alpha_i ,$$

where $\bar{A}_{ij}$ is the technical coefficient's expected value (mean marginal physical product of i^{th} characteristic in j^{th} input), X_j is the quantity of input j used in the blend, b_i is the desired constraint value, and $1 - \alpha_i$ is the prescribed probability of satisfying the bracketed constraint. The risk of violating the constraint is $1 - \alpha_i$. Manipulation results in the following nonlinear constraint for each characteristic containing random variables:

$$(3) \qquad \sum_{j=1}^{n} \bar{A}_{ij} X_j \pm \Omega(\alpha_i)\left[\sum_{j=1}^{n} \sigma^2(A_{ij})\, X_j^2\right]^{1/2} \lesseqgtr b_i ,$$

where $\Omega(\alpha_i)$ is the standard normal distribution coefficient for α_i level of significance, and $\sigma^2(A_{ij})$ is the technical coefficient variance for characteristic i in input j. In the complete model, each stochastic constraint is expanded separately following this general formulation.

This constraint's purpose is to create a confidence interval for the characteristic being satisfied. The first term in equation (3) measures the characteristic's mean level. The second term is an adjustment factor related to the standard deviation's value. To ensure that $(1-\alpha)$ percent of the observations are below (above) the right-hand side value, the mean is decreased (increased) relative to the characteristic level in a certainty model.[3] Confidence level $(1-\alpha)$ can be changed iteratively to evaluate the impacts of uncertainty on the solution.

The ICM with characteristic uncertainty illustrates several important effects. Marginal cost increases as uncertainty increases. Specifically, ingredient costs increase as variance or required confidence levels increase. Either impact forces end users to specify purchase contracts for an average quality higher than necessary since characteristics are uncertain. An important component of competition is also reflected in these results. Since buyers cannot observe all relevant quality characteristics before a purchase, they must rely on past performance. Because sellers' reputations depend on past performance, their decision to sell high-quality products increases repeat purchases, with benefits accruing in future periods. This practice reflects concepts embedded in the economics of quality and reputation (Shapiro 1983).

END-USE CHARACTERISTICS AND COMPETITION IN THE U.K. WHEAT MARKET

Wheat demand should be viewed as derived since it is ultimately used as an input. Buyer's desired end-product requirements and wheat quality characteristics affect demands for wheat imported from different origins. Imported wheat can be used alone or blended with other imported or domestically produced wheats.

The United Kingdom principally imports Canadian western red spring (CWRS). Only a minor amount of U.S. hard red spring (HRS) is imported. Wheat produced in the United Kingdom is weak (low protein) and generally contains a greater proportion of sprout-damaged kernels. North American higher protein wheats are primarily blended because they have greater gluten strength. Although the U. K. market is of declining importance, it is used here for three reasons 1) U.S. HRS and CWRS competition has always been intense, even though that competition's peculiar features are not well understood, 2) increases in domestically produced wheat with disparate quality characteristics potentially has the impact of changing the distribution of import market shares, and 3) the United Kingdom is typical of numerous markets in which higher-protein U.S. and Canadian wheats compete for use in blends with lower-quality indigenous wheats.

Each country has its own grain standards that are used in commercial transactions. However, grade and non-grade determining factors only measure physical characteristics, such as test weight and damaged kernels. Other easily measured characteristics are used as proxies for end-use performance. For example, protein quantity, a common term in purchase contracts, is a proxy for end-use performance characteristics such as farinograph absorption and loaf volume that cannot be measured directly. Thus, the model's technical coefficients should be viewed as expected values. Most wheat-producing countries, in order to reduce variance in end-use performance, have quality control procedures, such as classification, variety licensing and release mechanisms, and regulations in grain handling and ship loading. Depending on the import market, end-use performance variance is potentially an important source of competitive advantage or disadvantage.

Measures of end-use performance were derived from samples of individual shipments of HRS and CWRS wheat classes exported from the United States and Canada through the Great Lakes.[4] The protein level used in purchase contract specifications is a proxy for desired end-use characteristics. To evaluate these relationships, regression models were estimated for each end-use performance characteristic. The dependent variable was characteristic A_{ij}, and wheat protein (S_j) was the independent variable. To allow for potential nonlinear relationships, S_j^2 was also included and retained in those models where significant. One class of wheat with different protein levels was assumed available to the importer from each country: HRS 15 and HRS 14 from the United States and CWRS 14.5 and CWRS 13.5 from Canada. Numerical values refer to each class's protein quantity and are used for contract specification.

Each characteristic's expected value was derived along with the variance of the error (table 1). Conditional expected values were used for those characteristics having a significant relationship with wheat protein. For example, from regression estimates we derived $E(A_{ij} \mid S_j = m)$, where m is the purchase contract's protein level. We assume buyers formulate expectations about end-use performance that can be controlled through contractual specification; other characteristics have unconditional expectations. For characteristics that did not have a significant relationship with wheat protein, the technical coefficients were unconditional expected values, $E(A_{ij}) = \mu$.

The variances about these expected values are shown in the lower portion of table 1. For those characteristics that had a significant relationship with protein, forecast errors were used. For the other characteristics, unconditional variances were used. Variances for U.S. wheat end-use performance (except for flour ash) exceed Canada's, supporting some allegations that U.S. wheat is less uniform than Canada's. Variety controls, breeding programs, grading systems, marketing practices, and inter-crop-year storage may explain differences in variances between U.S. and Canadian wheat.

Distributions for all relevant quality characteristics could not be derived because testing procedures were incompatible, data were incomplete, and comparable time series of U.K. wheat quality data were not available. In these cases, samples were collected and technical analyses conducted to derive values for these characteristics (Germani and D'Appolonia 1986). Technical analyses were conducted on each type of wheat for loaf volume and falling numbers and for all U.K. wheat characteristics. These results are shown in table 1. Variances for these characteristics were assumed to be nil.[5]

Product quality requirements were obtained from personal interviews with U.K. millers and brokers. Prices were averages of weekly prices brokers offered from August 1986 to February 1987 (table 2). These prices were comprised of FOB export values for specific wheat classes, transport costs, and the variable import levy (VIL).

ANALYTICAL MODEL AND RESULTS

The objective is to minimize the total ingredient cost of a straight-grade flour blend, using up to five different wheats: two from the United States, two from Canada, and one from the United Kingdom. The following notation is used in the model's mathematical specification:

Z is the dollar value of the objective function, C_j is the cost of wheat to produce the j^{th} flour in U.S. dollars/mt, F_j is the quantity of straight-grade flour blended in the final output, b_i is the quality constraint for output produced by the i^{th} characteristic, A_{ij} is the quantity of the i^{th} quality characteristic of the j^{th} straight-grade flour, W_j is the quantity of wheat j milled to produce flour j, subscript $j = 1 \ldots 5$ is the straight-grade flour produced from the j^{th} wheat, and subscript $i = 1 \ldots 7$ identifies the quality characteristic.

To account for differences in the variance in extraction rates, the objective function was stated in terms of wheat (instead of flour) prices, and the following separate equation was added for each wheat:

$$E_j W_j - \Omega(\alpha_i)(\sigma^2_{E_j} W_j^2)^{1/2} = 100\, F_j ,$$

where E_j is extraction rate, $\Omega(\alpha_i)$ is the standard normal distribution coefficient, and $\sigma^2_{E_j}$ is the extraction rate variance for wheat j. The objective function is defined as

$$\text{Minimize } Z = \sum_{j=1}^{5} C_j W_j .$$

For those characteristics with a non-zero variance, the restrictions were chance constraints. Flour protein quantity has both upper and lower constraints and is specified as

$$\sum_{j=1}^{n} \bar{A}_{1_j} X_j - \Omega(\alpha_1) \left[\sum_{j=1}^{n} \sigma^2(A_{1_j}) X_j^2 \right]^{1/2} \geq 12.25 \text{ Protein Min (percent), and}$$

$$\sum_{j=1}^{n} \bar{A}_{2_j} X_j + \Omega(\alpha_2) \left[\sum_{j=1}^{n} \sigma^2(A_{2_j}) X_j^2 \right]^{1/2} \leq 12.75 \text{ Protein Max (percent).}$$

The other quality characteristic constraints are

$$\sum_{j=1}^{n} \bar{A}_{3_j} X_j + \Omega(\alpha_3) \left[\sum_{j=1}^{n} \sigma^2(A_{3_j}) X_j^2 \right]^{1/2} \leq 0.48 \quad \text{Flour ash (percent),}$$

$$\sum_{j=1}^{n} \bar{A}_{4_j} X_j - \Omega(\alpha_4) \left[\sum_{j=1}^{n} \sigma^2(A_{4_j}) X_j^2 \right]^{1/2} \geq 60.5 \quad \text{Farinograph absorption (percent),}$$

$$\sum_{j=1}^{n} \bar{A}_{5_j} X_j - \Omega(\alpha_5) \left[\sum_{j=1}^{n} \sigma^2(A_{5_j}) X_j^2 \right]^{1/2} \geq 5.25 \quad \text{Farinograph peak time (minutes),}$$

$$\sum_{j=1}^{5} A_{6j} F_j \geq 8 \qquad \text{Farinograph mix time (minutes),}$$

$$\sum_{j=1}^{5} A_{7j} F_j \geq 2900 \qquad \text{Loaf volume (cubic centimeters),}$$

$$\sum_{j=1}^{5} A_{8j} F_j \geq 250 \qquad \text{Flour falling number (seconds),}$$

$$\sum_{j=1}^{5} F_j = 1, \qquad \text{Material balance, and}$$

$$F_5 \geq .25 \qquad \text{Minimum U.K. flour.}$$

The material balance constraint allows optimum flour quantities to be interpreted as percentages. Several firms' internal policies require at least 25 percent U.K. flour be used in the final flour blend, which is reflected in the last constraint.

The model was solved using different values of α (all $\alpha_i = \alpha$), and those presented first are from $1-\alpha = 0.78$[6] (tables 3 and 4). The optimal solution requires a flour blend comprised of 32, 27, 7, and 34 percent, respectively, of CWRS 14.5, HRS 15, HRS 14, and U.K. Table 4 presents slack amount and dual prices for each constraint. For those constraints that are equal to zero,[7] a nonzero dual price is given.

Marginal values of the characteristics can be used to calculate the flour lot's value. The effect of a particular flour's variance depends on the variance of other flours in the blend. Thus, the effect of one flour's variance cannot be isolated. However, the value of individual lots can be inferred from reduced cost coefficients shown in table 3. In this analysis, CWRS 13.5 is overpriced by $1.43, whereas the rest have values equal to their prices.

Impacts of characteristic uncertainty can be evaluated in two ways. First, shadow prices of the variance for each characteristic were derived using the envelope theorem. Specifically, $\partial Z/\partial \sigma^2_{ij}$ was derived, where Z is the objective function value and σ^2_{ij} is the characteristic's variance (table 5). If HRS 15's variance for farinograph absorption decreases by 1 unit, for example, from 10.24 to 9.24, the objective function's value would decrease by $0.64. In all cases, these values are positive, indicating a positive relationship between variance and ingredient costs.[8] The results in table 5 show the benefit of reducing variance. If everything else remains the same, reducing the characteristic's variance reduces ingredient cost because a greater proportion of cheaper wheats can be used.

A second way to evaluate effects of characteristic uncertainty is through the confidence level. The model was solved, using several values of $(1-\alpha)$, and evaluated in terms of market shares and objective function values (table 6). The solution values for $\alpha = 0.50$ are equivalent to an LP solution under certainty and can be treated as the base model. As the confidence level $(1-\alpha)$ increases, ingredient costs increase from $393/mt to $411/mt for $(1-\alpha) = 0.75$, and a portion of HRS 15 imports shifts to CWRS 14.5 because the latter varies substantially less on key quality parameters. As the confidence level increases, a higher characteristic mean level (or lower, depending on the constraint's sign) is required. This results in a shift from a cheaper wheat (which may have a larger variance) to more expensive wheat with greater consistency.

CONCLUSIONS

Even though raw agricultural commodities comprise a large proportion of international trade, the input characteristics model (ICM) has had limited application. We expanded the ICM to account for uncertainties in technical coefficients. It was used to analyze effects of price and quality in exporter country competition for U.K. wheat imports. Lack of uniformity in end-use performance, which adversely impacts buyers, can be interpreted as uncertainty in technical coefficients in the ICM. A probabilistic specification of the ICM, which can be solved using deterministic nonlinear programming, captures the effects of uncertainty. Technical coefficients can be interpreted as either conditional or unconditional expected values.

The model and results can address issues related to inputs' end-use performance, an area of increasing concern as international competition intensifies for many agricultural commodities. Application of this model to the U.K. wheat import market reveals a number of important features of the international competitive environment in wheat. For most characteristics, the expected values of end-use performance for U.S. wheats have variances which exceed those of Canadian wheats. The United Kingdom is a market that is sensitive to quality characteristics. However, the impacts of quality cannot be assessed independently of price. Thus, both quality characteristics and price impact the distribution of market shares and are strategic variables for exporter countries.

The shadow prices associated with variances of characteristics were positive, indicating that an importer's uncertainty about end-use performance leads to higher ingredient costs. Reducing variance lowers costs because a greater proportion of cheaper wheats can be used in the blend. Ingredient costs also increase as the confidence level imposed on the model increases. This results in a shift away from U.S. wheat to CWRS, which is higher in price but varies less in key parameters. Thus, technical levels of end-use characteristics and their variances are important determinants of import market shares.

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TABLE 1. DISTRIBUTIONS OF END-USE PERFORMANCE CHARACTERISTICS

Characteristic	Grade and Protein				
	CWRS		HRS		UK[b]
	14.5	13.5	15	14	
	Expected value				
Flour protein	13.3[a]	12.9[a]	13.6[a]	12.8[a]	10.8
Farinograph absorption	64.0	64.0	62.5[a]	61.3[a]	57.5
Farinograph peak time	4.7[a]	4.6[a]	10.0[a]	8.11[a]	2.7
Flour ash	0.5	0.5	0.4	0.4	4.3
Extraction rate	73.3[a]	73.2[a]	75.8	76.1	81.3
Loaf volume[b]	3150	3025	3200	3000	2400
Falling number[b]	308	550	375	332	388
	Variance				
Flour protein	0.03[a]	0.02[a]	0.03[a]	0.03[a]	
Farinograph absorption	1.15	1.15	10.24[a]	10.18[a]	
Farinograph peak time	0.23[a]	0.23[a]	4.26[a]	4.24[a]	
Flour ash	0.01	0.01	0.01	0.01	
Extraction rate	0.55[a]	0.55	7.29	7.29	

[a] Expected values for these characteristics were derived from the conditional expectation equation, and the variance is that of the forecast error evaluated at the expected value. All other expected values and variances are unconditional.

[b] Derived from technical analysis of selected samples.

TABLE 2. WHEAT AND FLOUR PRICES USED IN THE ANALYSIS

		Grade and Protein			
		CWRS		HRS	
	U.K.	14.5	13.5	15	14
			($/mt)		
Wheat lots	212	365	353	357	342
Flour lots	261	499	483	472	449

TABLE 3. SOLUTION VALUES UNDER QUALITY UNCERTAINTY ($1-\alpha = 0.78$)

Item	Optimal blend	Reduced cost
Flour lots		
CWRS 14.5	0.32	0
CWRS 13.5	0	0
HRS 15	0.27	0
HRS 14	0.07	0
UK	0.34	0
Wheat lots		
CWRS 14.5	0.44	0
CWRS 13.5	0	1.43
HRS 15	0.36	0
HRS 14	0.10	0
UK	0.41	0
Objective function value $413.76		

TABLE 4. RIGHT-HAND SIDE PARAMETER VALUES OF THE U.K. FLOUR-BLENDING PROBLEM

Characteristic	Slack	Dual Price
Protein		
Maximum	0.21	0
Minimum	0.19	0
Flour ash	0.02	0
Farinograph absorption	-0.000087	-21.98
Farinograph peak time	-0.000058	-13.48
Loaf volume	0	-0.10
Falling number	144.04	0
U.K. blend	0.09	0
Percent	0	1,291.50
Extraction 1		-5.03
2		-4.84
3		-4.85
4		-4.62
5		-2.61

TABLE 5. SENSITIVITY OF OBJECTIVE FUNCTION WITH RESPECT TO VARIANCE OF CHARACTERISTICS ($\partial ZF/\partial \sigma_{ij}^2$)

	Grade and Protein			
	CWRS		HRS	
Characteristic	14.5	13.5	15	14
	------------------------$ per unit of variance------------------------			
Farinograph absorption	0.94	0	0.64	0.05
Farinograph peak time	0.93	0	0.63	0.05
Extraction rate	1.18	0	0.34	0.05

TABLE 6. OPTIMAL FLOUR BLENDS UNDER DIFFERENT CONFIDENCE LEVELS (1-α)

	$1-\alpha = 0.50$	$1-\alpha = 0.70$	$1-\alpha = 0.75$
CWRS 14.5	0	0.27	0.32
CWRS 13.5	0	0	0
HRS 15	0.62	0.37	0.32
HRS 14	0	0	0
UK	0.38	0.36	0.36
Objective function value	$393	$408	$411