Price and Price Risk Dynamics in Barge and Ocean Freight Markets and the Effects on Commodity Trading

Michael S. Haigh

and

Henry L. Bryant*

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Assistant Professor (mshaigh@tamu.edu) and Graduate research assistant (hlb9686@pop.tamu.edu), Department of Agricultural Economics, Texas A&M University. This research was supported by the USDA AMS Transportation Division under cooperative agreement number 12–25–A–3859.

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The effects of volatility of barge and ocean freight prices on prices throughout the international grain-marketing channel are analyzed using a Multivariate GARCH-M model. The model is used to infer the extent to which transportation price risk affects the level of international grain prices. Results indicate that both barge and ocean price volatility influence grain prices, but barge price volatility tends to have a greater impact on grain prices than that arising from ocean price volatility. The lack of a futures contract for barge rates may be partially responsible for its significant influence on grain price levels.

Keywords: Barge and ocean freight prices: futures contracts: Multivariate GARCH-M models: price volatility

1. Introduction

The role of price risk has received a considerable amount of interest in recent years, and still continues to be an important and popular topic of applied research. This is particularly true in agricultural analysis where prices typically experience excess volatility especially when compared to other sectors of the economy. Because of its relative importance, research has to date focused on a wide variety of issues surrounding price risk, and in particular, investigating the inclusion of risk terms in commodity modeling using various econometric methods.

The Autoregressive Conditional Heteroskedasticitic (ARCH) class of models originally developed by Engle (1982), and expanded to the Generalized – ARCH (GARCH) framework by Bollerslev (1986) have, in particular, proven to be popular approaches to estimating time-varying risk terms in econometric models. The methodology was originally applied in the financial econometric literature in the search for the existence of time-varying risk premia with examples being provided by Bollerslev, Engle and Wooldridge (1988), Baillie and Bollerslev (1990) and Pagan and Schwert (1990) to name a few, but has since been adopted and used successfully in a wide variety of commodity econometric models. For instance, Aradhyula and Holt (1989) used the modeling technique to isolate the effect time-varying price variance on broiler supply, while Schroter and Azzam (1991) explored the connection between output price uncertainty and marketing margins. Closely related in terms of methodology was the research undertaken by Holt and Moschini (1992), and Holt (1993), who estimated the effect of price risk on hog supply, and the beef-marketing channel respectively. One other interesting application of the methodology was by Jayne and Myers (1994) who isolated the effects of time-varying commodity price risk on equilibrium price levels and marketing margins in international trade.

Applications of the GARCH modeling technique have been made to investigate the effect of foreign exchange rate uncertainty on agricultural trade (e.g., Pick (1990)), but there has thus far, surprisingly been no attempt to investigate the influence of time-varying price risk arising from transportation rates on prices throughout the international marketing channel.[1] This is of particular interest as grain shipments quite frequently involve long distances and may experience several changes in ownership along the various stages of the international marketing channel.

Moreover, freight prices can be a large percentage of the delivered price, especially for low valued commodities, and erratic fluctuations in the price of freight may eliminate expected profit or even induce loss.[2]

The purpose of this study is therefore to isolate the effect of volatility of transportation prices (barge and ocean freight) on the grain prices at the sources and destinations of the transportation. To undertake such analysis, a Multivariate GARCH-in-Mean (MGARCH-M) model will be estimated. Such a modeling procedure allows one to include potentially important variance-covariance terms in the specification of the mean price equations and to determine the extent of volatility spillovers between transportation (barge and ocean) and grain prices.

The focus on ocean and barge freight price risk is of particular interest not just because of its obvious role in international grain markets, but also because, since 1985, ocean freight futures trading has occurred at the London International Financial Futures Exchange (LIFFE) while no equivalent futures market for barge rates has existed. While the ocean futures market allows market intermediaries to spread price risks, thus insulating grain prices from ocean freight price volatility throughout the international grain marketing channel, no such option has been available to traders to spread the affect of barge freight rate volatility. Therefore, in this study, in addition to identifying the extent of volatility spillovers between transportation rates and international grain prices several stochastic simulations are undertaken to isolate the individual contribution of barge rate risk and ocean freight risk on the level of international grain prices.

While several studies have made important contributions toward understanding price dynamics in international grain markets, this study will illustrate the potentially important role played by transportation in international commodity price dynamics. The research will examine how volatility shocks in the transportation market influence prices, volatility and ultimately trade in other markets. Identifying interrelationships of this type is not only important for obtaining a deeper understanding of the effects that transportation volatility might have on trade, but also to analyze the degree of price risk facing merchandisers at various locations within the marketing channel. Moreover, the research will provide useful insights for the potential development of exchange traded barge rate derivative contracts.[3]

The remainder of the paper is as follows. First the econometric methodology will be briefly outlined that enables one to examine the effect of time-varying volatility on the level of prices. Next, data will be described, and then the exact model specification used in this paper will be presented. Estimation results, model diagnostics and dynamic simulations that isolate the effect of barge and ocean freight price uncertainty will then be presented and discussed followed lastly by some concluding comments.

2. Econometric Methodology

There have been several multivariate extensions to the original ARCH and GARCH class of models originally introduced by Engle (1982) and Bollerslev (1986). Of particular interest here is the multivariate extension of the ARCH-M (ARCH-in-mean) model originally presented by Engle, Lilien and Robins (1987) which permits the conditional variance of a series to directly affect the level of a price series. The univariate version of the GARCH – M has been extended to multivariate setting by several authors, including, Bollerslev, Engle, and Wooldridge (1988), Bollerslev (1986), Baillie and Bollerslev (1990), Holt (1993), Holt and Moschini (1992) and Holt and Aradhyula (1998).

Owing to the computational complexity of estimating MGARCH models several specifications have been proposed to make the resulting model more parsimonious. One such specification is the constant correlation parameterization. Such a setup is parsimonious in nature, reduces computational complexity, allows for time-varying conditional variances and covariances, but assumes constant conditional correlations.[4] This framework has been used by Cecheeti et al (1988), Bollerslev (1990), Baillie and Bollerslev (1990), Kroner and Sultan (1993) and Holt and Aradhyula (1998).

The MGARCH-M model is designed to provide an assessment of the reduced form impact of risk (measured by volatility) on prices using a joint estimation technique in the context of a parameterized model of the conditional variances and covariances. Such an econometric model permits the joint estimation of the relationship between risk and prices and how past information is related to perceived risk. Importantly, as pointed out by Kroner and Lastrapes (1993), this approach does not require a two-step estimation procedure (the first to estimate the volatility measure and second to estimate the relationship), which may lead to inefficient estimators. Therefore, the MGARCH-M procedure restricts the volatility estimates that affect the price levels to be the same as that generated by the data series.

To illustrate the MGARCH-M with a constant conditional correlation framework for a general case, consider the following:

$$Y_t = \Gamma_0 + \sum_{i=1}^{k} \Gamma_i Y_{t-k} + \Pi X_t + \Psi vech(H_t) + e_t \text{, where} \tag{1}$$

$$e_t \mid \Omega_{t-1} \sim N(0, H_t) \quad \text{and} \quad \{H_t\}_{ij} = s_{ijt} \quad i,j = 1,....,R, \text{and} \tag{2}$$

$$s_{iit} = w_i + a_{i1} e^2_{it-1} + b_{i1} s_{iit-1}, \quad \text{and} \tag{3}$$

$$s_{ijt} = r_{ij} \sqrt{(s_{iit} s_{jjt}}, \; i \neq j. \tag{4}$$

Here, Y_t as the vector of (N x 1) endogenous variables, represented by a linear dynamic system of R equations where the means of the variables depend on lagged values of each of the series, a vector of exogenous variables observed at time t-1, X_t, and the variances and covariances of the endogenous variables captured within H_t. G , P and Y represent the fixed parameters to be estimated and vech (.) is a vectorization operator that stacks elements of H_t into a single column vector.[5] In this case, e_t denotes a (R x 1) vector of normally distributed forecast errors of Y_t conditional on W_{t-1} which denotes the sigma field generated by all available information up through time t –1. Here we define s_{ijt} as the ijth element of H_t which is almost surely (a.s) positive definite for all t. The conditional correlation between the ith and jth price series is then defined as $r_{ijt} = s_{ijt}\sqrt{(s_{iit}s_{jjt}}$, where $-1 \leq r_{ijt} \leq 1$ a.s for all time periods, t. Such a formulization thus provides a natural scale invariant measure of the coherence between the respective price series studied. Although r_{ijt} can, in general, be time - varying, it is often useful (for computational ease) to assume that $r_{ijt} = r_{ij}$ for all t. That is, to assume that the conditional correlations are constant. It then follows that that $s_{ijt} = r_{ij}\sqrt{(s_{iit}s_{jjt}}$, $i = 1,.., N$; $j = i + 1,.., N$.

An appealing feature of the constant conditional correlation parameterization relates directly to simplifications in the estimation and inference procedures. The full conditional covariance matrix, H_t, can be partitioned as:

$$H_t = D_t \Phi D_t\,, \tag{5}$$

where D_t is an N x N diagonal matrix including elements s_{1t}, ……… s_{Nt} and F is N x N time invariant, positive semi-definite matrix with typical element r_{ij}. Assuming conditional normality, the log likelihood function becomes (after ignoring the constant terms):

$$L(h) = -\frac{T}{2}\ln|\Phi| - \sum_{t=1}^{T}\ln|Dt| - \frac{1}{2}\sum_{t=1}^{T}\tilde{e}_t{}'\Phi^{-1}\tilde{e}_t \tag{6}$$

where $\tilde{e}_t = D_t^{-1}e_t$ is an (N x 1) vector of residuals (standardized) and η is the parameter vector. The important feature of this model, and its particular application in this instance is that (1) the conditional covariance matrix H_t is itself allowed to be time-varying; and (2) the unique elements of H_t, $\{H_t\}_{ij} = s_{ij,t}$, enter as inputs in the conditional mean price equations.

This inclusion of risk in the mean equations is consistent with the assumption that traders in the international grain markets do not know exactly the level of variability of prices that may affect the profitability of trading and that the traders are risk averse.

3. Data

Because the application here looks at price volatility spillovers between transportation rates along the international grain-marketing channel several data series were collected. First, weekly river terminal soybean bid and ask prices for south of Peoria, Illinois (*ILS*) were collected from the Illinois Department of Agriculture covering the period 4th January 1985 to the 15th January 1999, yielding a total of 733 observations. The mid-point between the bid-ask spread for these prices was then calculated. Grain barge rate data (*B*) covering the same period was also provided for the same period from the United States Department of Agriculture's (USDA's) Agricultural Marketing Service, Transportation and Marketing Division. The collected rate information is through privately negotiated spot and longer-term commitment rates. The barge rate information supplied by the USDA is a weekly quote that reflected the current rate as a percent of the historic benchmark tariff rate (southbound barge freight call session basis trading benchmark (July (1979)). From this figure the dollar per ton rate was obtained by multiplying the quoted rate (a percentage of the benchmark rate) by the historic benchmark rate associated with the particular stretch of river analyzed in this study (south of Peoria). Weekly Gulf soybean export prices (*GS*) were provided by the USDA, and ocean freight rates (*O*) from the U.S. Gulf to Rotterdam were collected from the Baltic Exchange in London, U.K. and Datastream International. Finally, weekly soybean import prices at Rotterdam (*RS*) were collected from the International Grains Council in London, U.K. These data also cover the period 4th January 1985 to the 15th January 1999. All price series are in dollars per ton, and are the Friday prices, but where Friday prices are not available, Thursday prices are used. Finally, with regard to the data there were several missing values (5.2% of the barge rates, 0.81% of south of Peoria soybean prices and 0.27% of the Rotterdam prices). These observations were replaced with predicted values from a cubic-spline interpolation.

4. Exact Model Specification

In order to implement the MGARCH – M constant correlation model, it is necessary to jointly model the first two moments of the price series relevant to the international marketing channel. The primary data described above were first tested for stationarity properties. Each series was tested for the existence of a unit root by using the augmented Dickey-Fuller (1981) (ADF) tests. ADF test results (presented in Table 1) indicated that all series, with the exception of the barge rate (*B*) are indeed nonstationary. Such results suggest that the price series should be first differenced.[6] When the tests are applied to the differenced series, however , test statistics clearly reject the null hypothesis of unit root. In the event that a pair (or any number) of I(1) variables being cointegrated, so that a linear combination of them is I(0) (stationary), then a system of equations (Vector Autoregressive Model (VAR)) should include an error correction term (*ECT*). Therefore, Johansen's (1988) procedure was used to test for cointegration between the sets of prices. The results, presented in Table 2, indicate that there appear to be two stable cointegrating vectors linking the price series together. The *ECT* was formed by standardizing the first cointegrating vector on price series *RS*.[7]

Finally, the conditional variance dynamics of each individual series is investigated. Preliminary time-series analysis on each differenced series was undertaken to determine the possible need for an ARMA process, then the conditional variance dynamics were modeled by using Bollerslev's (1986) GARCH(1,1) process. Table 3 illustrates the respective AR structures applied to each of the series. In each case, the GARCH(1,1) specification indicates substantial GARCH behavior for the price series. In two instances $\hat{a} + \hat{b}$ exceeds unity, so that the unconditional variance does not exist. As pointed out by Bollerslev (1990), however, the conditional moments are still well defined. Tests for residual autocorrelation in the standardized and squared standardized residuals fail to detect any misspecifications of the univariate GARCH models. Because no substantial deviations from normality are detected (as shown by the m_3 (skewness) and m_4 (kurtosis) statistics), the multivariate systems were estimated under the assumption of normality.

Therefore based on these test results and preliminary time series diagnostics, the following econometric specification (in first difference form) was estimated:

$$\begin{aligned}\Delta ILS_t &= d_0 + d_1\Delta O_{t-1} + d_2\Delta B_{t-1} + d_3\Delta GS_{t-1} + d_4\Delta RS_{t-1} + d_5\Delta ILS_{t-1} + d_6 COS_{t-1} + d_7 SIN_{t-1} \\ &+ t_1 ECT_{t-1} + n_{11}\Delta s_{44t} + n_{12}\Delta s_{22t} + n_{13} s_{44t-1} + n_{14} s_{22t-1} + e_{ILSt},\end{aligned} \tag{7}$$

$$\Delta B_t = f_0 + f_1 \Delta O_{t-1} + f_2 \Delta B_{t-1} + f_3 \Delta GS_{t-1} + f_4 \Delta RS_{t-1} + f_5 \Delta ILS_{t-1} + f_6 COS_{t-1} + f_7 SIN_{t-1} + t_2 ECT_{t-1} + e_{Bt}, \tag{8}$$

$$\Delta GS_t = j_0 + j_1 \Delta O_{t-1} + j_2 \Delta B_{t-1} + j_3 \Delta GS_{t-1} + j_4 \Delta RS_{t-1} + j_5 \Delta ILS_{t-1} + j_6 COS_{t-1} + j_7 SIN_{t-1} + t_3 ECT_{t-1} + n_{31} \Delta s_{44t} + n_{32} \Delta s_{22t} + n_{33} s_{44t-1} + n_{34} s_{22t-1} + e_{GSt}, \tag{9}$$

$$\Delta O_t = l_0 + l_1 \Delta O_{t-1} + l_2 \Delta B_{t-1} + l_3 \Delta GS_{t-1} + l_4 \Delta RS_{t-1} + l_5 \Delta ILS_{t-1} + l_6 COS_{t-1} + l_7 SIN_{t-1} + t_4 ECT_{t-1} + e_{Ot}, \tag{10}$$

$$\Delta RS_t = q_0 + q_1 \Delta O_{t-1} + q_2 \Delta B_{t-1} + q_3 \Delta GS_{t-1} + q_4 \Delta RS_{t-1} + q_5 \Delta ILS_{t-1} + q_6 COS_{t-1} + q_7 SIN_{t-1} + t_5 ECT_{t-1} + n_{51} \Delta s_{44t} + n_{52} \Delta s_{22t} + n_{53} s_{44t-1} + n_{54} s_{22t-1} + e_{RSt}, \tag{11}$$

$$e_t = [e_{ILSt}, e_{Bt}, e_{GSt}, e_{Ot}, e_{RSt}] \,|\, \Omega_{t-1} \sim N(0, H_t), \qquad \{\mathrm{Ht}\}_{ij} = s_{ijt}, \quad i,j = 1,....,5, \tag{12}$$

$$s_{iit} = w_i + a_{i1} e^2_{it-1} + b_{i1} s_{iit-1}, \text{ and} \tag{13}$$

$$s_{ijt} = r_{ij} / \sqrt{(s_{iit} s_{jjt}}, \; i \neq j. \tag{14}$$

All price series are as defined previously and all mean equations were estimated as an AR(1) process – designed to account for short-run conditional mean dynamics. These terms are included to pick up any remaining serial correlation in the reduced form systems errors which may exist, for instance to lagged adjustment to changes in the exogenous variables. Such as structure was found to be suitable to render the residuals white noise. The existence of seasonality was also accounted for by including harmonic variables set at monthly cycles represented by *COS* and *SIN* respectively.[8] All equations also include the error correction term, ECT_{t-1} to capture the cointegrating relationship between the price series. The variables s_{22t} , s_{44t} represent the square root of the *ij*th elements from the conditional covariance matrix H_t representing the conditional standard deviations of the barge rate and ocean freight rate price series respectively. Other functional forms, for instance, including the conditional variance terms were applied to the model. However, the model including the conditional standard deviations seemed to provide the best fit of the data.

As the effect of transportation risk on the price levels of the grain throughout the international marketing channel is the main focus of this paper their inclusion is confined to the grain equations (equations (7), (9) and (11)). Following Kroner and Lastrapes (1993) both the first differences of the risk variables, Ds_{22t} and Ds_{44t} and lagged levels of the risk variables, s_{22t-1} and s_{44t-1} are included in the mean equations to represent the risk associated the transportation in the international marketing channel.

The MGARCH-M model depicted above can be interpreted as a reduced form of a structural model that might explain price movements throughout the international grain-marketing channel. In this paper no attempt was made to identify structural (e.g., using supply and demand analysis) coefficients from a reduced form system, but rather to concentrate on the determinants of prices within the marketing channel in equilibrium.

5. Estimation Results, Model Diagnostics and Dynamic Simulations

Maximum likelihood estimates of the model represented by equations (6 – 13) obtained by employing the Berndt et al. (1974) algorithm are presented in Table 4. In many cases lagged prices are significant in explaining movements in each of the price series studied. Also, the *ECT* term and seasonal variables appear to be significant in explaining short run movements in the price levels. Point estimates of a_i and b_i , i = 1,….,5 are positive and individually significant, indicating the presence of conditional heteroskedasticity in the error terms of the price equations. Results of several diagnostic tests are reported in Table 5. Skewness and kurtosis estimates that the assumption of normality appears to be well justified. Tests for remaining residual autocorrelation in the standardized residuals, and their crossproducts, show that the MGARCH-M framework does an adequate job of estimating the conditional mean and variance dynamics in the estimated model.

Figure 1 and 2 plots the historical path of standardized conditional variances for each of the price series studied.[9] It is evident from the plots that price series have experienced periods of excessive volatility. Moreover, as can be seen from the plots there is a tendency for the conditional variances to move fairly closely over time. Estimates of the conditional correlation parameters, r_{ij}, reported in Table 4 are statistically significant in several instances illustrating the presence of significant cross-equation influences.

Of particular interest here, however, are the estimates of the risk parameters associated with barge and ocean freight price uncertainty. Parameter estimates for the first difference of the risk variables associated with Ds_{22t} and $Ds_{44t},$ (namely n_{i1} and n_{i2}) are highly significant and positive in the *GS* and *RS* equations, while the level of risk appears to have little role on the Illinois grain prices (*ILS*). This implies that there is evidence of a positive short-run price risk on the price levels in the Gulf and Rotterdam regions. A similar result, (in terms of the statistical significance) seems to hold for the lagged levels of the risk variables in the equations.

As can be seen on the left hand side of Table 6, the average fitted price with risk (representing the predicted values from the MGARCH – M model), appears to do a good job at predicting the actual average price level that occurred between 1985 – 1999, as the two price series are very close to one another. Such a finding lends support to the econometric specification outlined by equations (7 – 14).

As noted previously there appears to be significant volatility in barge and ocean freight rates, and the influence of the risk (measured by time - varying volatility) appears to affect the level of prices throughout the international marketing channel. This says nothing however of how transportation risk has affected market performance in the international grain-marketing channel. Fortunately, the MGARCH-M model can be used to see how risk, arising from volatile transportation rates (either barge or ocean freight, or both), has affected market performance and to trace out the effects of risk on short-run equilibrium prices period by period. To this end, the estimated model is first evaluated stochastically by setting all risk parameters associated with ocean freight price volatility equal to zero. Specifically, $n_{i1} = n_{i3} = 0$. The average fitted price by excluding the influence of ocean freight price volatility is then calculated.

The corresponding results are presented in the 4th column of Table 6, with Rotterdam, the Gulf and Illinois prices presented in the upper, middle and lower panels respectively. As can be seen the effects on all price series is relatively small, with the average decrease in prices that can be attributed by illuminating ocean freight price volatility for Rotterdam, Gulf and Illinois prices being 0.142%, 0.170% and 0.09% respectively. However, these are average figures, and as can be seen from Figure 3, the simulated percentage decreases in soybean prices by eliminating ocean freight price risk is quite volatile over the time-period. This phenomenon is verified by observing the reported maximum and minimum values of percentage decreases for each year in Table 6. Interestingly, periods of excess volatility in ocean freight rates tend to affect all locations grain prices, but by different amounts, with the least impact occurring at the hinterland location in Illinois.

Setting all risk parameters associated with the freight markets equal to zero, implying no ocean and barge rate risk ($n_{i1} = n_{i2} = n_{i3} = n_{i4} = 0$), and comparing this price (Av. fitted price: no ocean or barge price risk) with the other average prices (Actual av. price, and Av. fitted price: no ocean price risk) enables us to isolate the contribution of barge price volatility on the international grain price levels. As can be seen by the summary statistics presented in Table 6, the elimination of barge rate uncertainty over the period 1985 – 1999 would have <u>reduced</u> the price of grain at all locations. The barge risk's effect on the grain price level is, on average much greater than the ocean freight risk, and as such, eliminating the barge and ocean risk would have over the time period in question, reduced Rotterdam, Gulf and Illinois prices by approximately 0.807%, 0.632% and 0.131% <u>on average</u>. However, as was the case with the ocean freight price levels, the average figures reported hide the true extent of the impact of the risk. For instance, as shown in Figure 4 and the maximum and minimum percentage reduction values reported in Table 6, the percentage reductions are much more volatile. To highlight just one example, on November 11th 1994 (week 513) the maximum reduction in price levels was 11.820% for the Rotterdam price series. In that particular week, reported prices would have been estimated to have fallen just 0.07% if only ocean freight rate uncertainty was removed from the international marketing channel, implying that the majority of risk comes from barge rate uncertainty. The relative importance of barge rate risk over the ocean freight risk holds true over the vast majority of the weeks studied in this analysis. Importantly, as can be seen from the right hand side of Table 6, the effect of barge rate uncertainty does not just affect the level of prices in Illinois and the Gulf, but also 'spills' over into the price of grain in Rotterdam.

One possible explanation for the fact that ocean freight rates have tended to have little 'spillover' effects onto the price level of grain throughout the marketing channel, even though, as pointed out previously, grain prices can be a substantial portion of the price of grain, is that a freight futures contract has traded at the LIFFE since 1985. Such a contract, designed to remove price uncertainty related to ocean price uncertainty for international grain traders, may have contributed to the relative insulation of grain prices from ocean price risk. Although, the contract has experienced relatively low levels of trading activity since its inception, it has been shown in several studies (Haigh and Holt, 1999a, 1999b) to be a relatively effective hedging mechanism for grain traders. Its hedging effectiveness has presumably enabled international grain traders to offset any gains/losses associated with the cash price of ocean freight with corresponding gains/losses from the freight futures market. As such, the finding that ocean freight price volatility does not get fully transmitted through to the price of grain is not particularly surprising.

Interestingly, a barge freight call session at the Merchants Exchange of St. Louis was developed in 1978, prompting the development of a cash/forward market for southbound grain freight on the Mississippi River system. However this market is used largely for spot transactions, so the benefits of a liquid forward market that could help spread barge freight rate uncertainty does not exist (see Hauser and Buck(1989)). We might expect therefore that barge rate volatility to perhaps have a greater effect on international grain prices simply because there is a lack of an effective hedging instrument for barge rates.

6. Conclusions

This paper has sought to determine the role that barge and ocean freight price risk plays in the international grain marketing channel. Although previous research has found significant risk effects in price linkage equations for other commodities using time-series econometrics, to date the investigation of the role of transportation risk on price levels using time-series econometrics (MGARCH-M models) has not yet been undertaken.

The estimated MGARCH-M model applied to weekly soybean price and ocean and barge rate price data and various stages within the international grain marketing channel provides a good fit; and the estimated time-varying conditional structure indicates substantial GARCH effects which seem to represent freight risks quite well. That is, barge and ocean price risk, as measured by the time-varying standard deviation of barge and ocean freight risk is significant in the system of equations representing the marketing channel.

The impact of risk on the international grain market was further evaluated using stochastic simulations by setting barge and ocean risk terms to zero. Results suggest that barge price volatility in particular tends to have a greater impact on grain prices than that arising from ocean price volatility. The existence of an ocean freight futures contract coupled with the lack of a futures contract for barge rates may help explain the results presented in this study. It would therefore be interesting to see if barge rate futures were developed whether the transmission of barge rate volatility through to international grain prices might be reduced.

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Table 1 Augmented Dickey-Fuller (ADF) tests for order of integration on cash prices

Test is on the estimated coefficient $\theta_1$from the following prototype model:

$$\Delta X_t = q_0 + q_1 X_{t-1} + \sum_{k=1}^{K} b_k \Delta X_{t-k}$$

Price Series	K	<u>HO: *I*(1) vs. HA: *I*(0)</u> ADF
Illinois Soy (*ILS*)	2	-2.842
Barge (*B*)	2	-5.216
Gulf Soy (*GS*)	2	-2.625
Ocean (*O*)	2	-2.616
Rott Soy (*RS*)	9	-2.830

Critical values are taken from Fuller (1976). They are –2.57 (10%), -2.88* (5%) and –3.46 (1%). Therefore, based on these results are series are I(1). The optimal lag length (K) was based on the Akaike Information Criterion.

Table 2 Johansen cointegration tests

λ_{trace}			λ_{max}		
test statistic	*hypothesis*	*99% critical value*	*test statistic*	*hypothesis*	*99% critical value*
226.84	r = 0	78.87	93.74	r = 0	38.78
133.10	r ≤ 1	55.43	72.45	r = 1	32.14
60.65	r ≤ 2	37.22	39.93	r = 2	25.75
20.72	r ≤ 3	23.52	14.79	r = 3	19.19
5.93	r ≤ 4	11.65	5.93	r = 4	11.65
Standardized Cointegrating Vector (*ECT*): *RS* – 0.924*O*-1.301*GS*+0.307*ILS*-1.261					

Tests are on eigenvalues with the Π matrix. The λ_{trace} statistic is $N(\sum_{i=r+1}^{2} \ln(1 - l_i)),$ where λ_i are ordered (largest to smallest) eigenvalues on Π, and the λ_{max} statistic is $N(1 - l_{r+1})$. Critical values for the λ_{max} and λ_{trace} statistics are from Osterwald-Lenum. The optimal lag length (k) is based on the Akaike Information Criterion.

Table 3 Univariate GARCH(1,1) models and residual diagnostics

Parameter	Illinois Soy (*ILS*)	Barge (*B*)	Gulf Soy (*GS*)	Ocean (*O*)	Rotterdam Soy (*RS*)
f_0	0.189	0.480	0.066	-0.001	0.025
	(0.216)	(0.000)	(0.710)	(0.946)	(0.889)
f_1	0.153	1.122	-0.038	0.475	-0.062
	(0.000)	(0.000)	(0.383)	(0.000)	(0.174)
f_2	-	-0.269	-	-0.005	0.054
		(0.000)		(0.917)	(0.187)
f_3	-	0.065	-	-0.023	-
		(0.304)		(0.607)	
f_4	-	-0.014	-	-0.104	-
		(0.695)		(0.010)	
f_5	-	-	-	0.095	-
				(0.020)	
f_6	-	-	-	-0.117	-
				(0.002)	
w	1.287	0.041	1.587	0.069	1.705
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
a	0.196	0.677	0.217	0.123	0.329
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b	0.777	0.520	0.768	0.601	0.699
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
m_3	0.103	0.767	-0.230	0.129	-0.099
m_4	1.763	2.518	2.114	3.818	1.590
Q(12)	10.570	4.052	7.072	5.490	12.710
	(0.310)	(0.908)	(0.629)	(0.789)	(0.176)
$Q^2(12)$	8.723	11.590	7.988	2.423	10.113
	(0.463)	(0.237)	(0.535)	(0.983)	(0.341)
Log-Likelihood	-1520.51	-242.93	-1634.53	161.365	-1718.05

Asymptotic *p* -values are in parenthesis; m_3 is sample skewness and m_4 is sample kurtosis; Q(12) and $Q^2(12)$ denote Box-Pierce test statistics for 12th order autocorrelation in standardized and squared standardized residuals, respectively.

Table 4 Maximum likelihood estimates of the MGARCH – M model

	Illinois Soy (*ILS*)			Barge (*B*)			Gulf Soy (*GS*)			Ocean (*O*)			Rotterdam Soy (*RS*)		
Variable	Parm.	Coeff	*t* - stat	Parm.	Coeff	*t* - stat	Parm.	Coeff	*t* - stat	Parm.	Coeff	*t* - stat	Parm.	Coeff	*t* - stat
Constant	d_0	-0.226	-0.514	f_0	-0.043	-1.688	j_0	-1.361	-1.943	l_0	-0.000	0.986	q_0	-1.788	-3.166
DO_t	d_1	-0.393	-1.916	f_1	-0.078	-1.969	j_1	-0.348	-1.252	l_1	0.466	10.641	q_1	-0.397	-1.528
DB_t	d_2	-0.499	-4.839	f_2	0.154	4.165	j_2	0.223	1.383	l_2	-0.012	-0.660	q_2	0.314	0.124
DGS_t	d_3	0.399	22.544	f_3	-0.006	-2.042	j_3	-0.137	-2.903	l_3	-0.004	-1.004	q_3	0.144	4.287
DRS_t	d_4	0.078	5.092	f_4	90.876	5.414	j_4	-0.028	-0.853	l_4	0.001	0.190	q_4	-0.206	-7.552
$DILS_t$	d_5	-0.058	-2.134	f_5	-90.873	-5.414	j_5	0.237	4.976	l_5	-0.004	-1.198	q_5	0.300	0.031
COS_t	d_6	0.352	3.106	f_6	0.057	1.639	j_6	0.763	3.519	l_6	0.031	1.121	q_6	0.475	2.822
SIN_t	d_7	-0.130	-1.029	f_7	0.073	2.300	j_7	-0.081	-0.353	l_7	0.042	1.510	q_7	0.016	0.088
ECT_t	t_1	-0.139	-9.227	t_2	-0.004	-0.873	t_3	0.074	2.316	t_4	0.002	0.693	t_5	-0.279	-11.782
$Ds_{Ocean\ t} = Ds_{44t}$	n_{11}	1.844	1.259	-	-	-	n_{31}	4.548	2.593	-	-	-	n_{51}	4.026	2.198
$Ds_{Barge\ t} = Ds_{22t}$	n_{12}	-0.459	-0.251	-	-	-	n_{32}	1.287	2.501	-	-	-	n_{52}	1.356	3.300
$s_{Ocean\ t-1} = s_{44\ t-1}$	n_{13}	0.752	0.920	-	-	-	n_{33}	1.500	1.266	-	-	-	n_{53}	1.326	1.179
$s_{Barge\ t-1} = s_{22\ t-1}$	n_{14}	0.071	0.448	-	-	-	n_{34}	0.813	2.916	-	-	-	n_{54}	1.255	10.712
							Variance Parameters								
	w_1	0.336	3.112	w_2	0.049	5.078	w_3	1.592	3.814	w_4	0.061	5.327	w_5	4.794	9.844
	a_1	0.314	8.980	a_2	0.614	29.954	a_3	0.219	8.010	a_4	0.218	12.840	a_5	0.347	11.460
	b_1	0.723	30.484	b_2	0.427	10.839	b_3	0.757	34.115	b_4	0.573	10.971	b_5	0.516	32.442

Covariance Parameters

Parm[a]	Series	Coeff	*t* - stat
r_{12}	*(ILS,B)*	-0.114	-2.364
r_{13}	*(ILS,GS)*	0.549	7.221
r_{14}	*(ILS,O)*	0.059	1.385
r_{15}	*(ILS,RS)*	0.459	6.985
r_{23}	*(B,GS)*	0.069	1.770
r_{24}	*(B,O)*	0.011	0.244
r_{25}	*(B,RS)*	0.052	1.336
r_{34}	*(GS,O)*	0.020	0.456
r_{35}	*(GS,RS)*	0.660	19.037
r_{45}	*(O,RS)*	0.023	0.534

[a]Parm represents the estimated correlation parameters between series *i* and *j*.

Table 5 Residual diagnostics tests for the MGARCH – M model

	Illinois Soy (*ILS*)	Barge (*B*)	Gulf Soy (*GS*)	Ocean (*O*)	Rotterdam Soy (*RS*)
m_3	-0.205	0.187	-0.150	0.145	0.001
m_4	2.095	4.257	1.649	3.281	2.618
Q(12)	30.062	7.399	14.788	25.189	6.055
	(0.001)	(0.687)	(0.140)	(0.050)	(0.811)
$Q^2(12)$					
Illinois Soy (*ILS*)	5.685				
	(0.841)				
Barge (*B*)	6.557	3.466			
	(0.766)	(0.968)			
Gulf Soy (*GS*)	6.336	14.017	5.130		
	(0.786)	(0.172)	(0.882)		
Ocean (*O*)	14.024	11.070	7.855	4.872	
	(0.172)	(0.352)	(0.643)	(0.899)	
Rotterdam Soy (*RS*)	16.070	18.859	31.674	14.760	22.941
	(0.100)	(0.042)	(0.083)	(0.141)	(0.011)

Asymptotic *p* -values are in parenthesis; m_3 is sample skewness and m_4 is sample kurtosis; Q(12) and $Q^2(12)$ denote Box-Pierce test statistics for 12th order autocorrelation in standardized and squared standardized residuals, respectively.

Table 6 Average weekly simulated price impacts of freight price risk on Rotterdam (*RS*), Gulf (*GS*), and Illinois (*ILS*) markets by year, 1985 - 1999

Year	Actual av. price	Av. fitted price with risk	Av. fitted price: no ocean price risk	Av. % reduction	Min % reduction	Max % reduction	Av. fitted price: no ocean or barge price risk	Av. % reduction	Min % reduction	Max % reduction
					RS					
1985	223.85	224.04	223.74	0.137	0.037	0.537	222.77	0.574	0.135	2.992
1986	208.44	208.45	208.16	0.139	0.048	1.061	206.96	0.722	0.139	2.921
1987	215.62	214.93	214.61	0.146	0.045	0.580	213.14	0.826	0.242	4.957
1988	303.37	302.44	302.09	0.120	0.031	0.964	299.67	0.814	0.104	4.033
1989	274.94	275.97	275.51	0.167	-0.185	3.019	274.04	0.736	0.045	3.879
1990	246.79	245.59	245.10	0.197	-0.091	1.547	244.16	0.581	0.018	1.967
1991	236.37	237.39	236.78	0.254	-0.051	1.387	235.07	0.963	0.067	6.400
1992	235.62	234.83	234.47	0.151	0.019	0.794	233.17	0.710	0.125	6.450
1993	255.64	254.60	254.35	0.098	0.046	0.391	253.17	0.548	0.157	1.972
1994	252.16	254.15	253.84	0.125	0.044	0.752	251.33	1.122	0.131	11.820
1995	259.38	260.04	259.69	0.132	0.035	0.567	256.69	1.230	0.294	4.890
1996	305.12	306.15	305.75	0.131	0.012	0.973	303.43	0.895	0.135	3.275
1997	306.20	306.41	306.14	0.090	0.043	0.242	304.89	0.503	0.123	2.514
1998	243.73	245.97	245.72	0.103	0.040	0.352	243.49	1.029	0.164	9.520
1999	221.45	225.83	225.61	0.095	0.080	0.114	222.29	1.559	0.896	2.456
Av.	254.74	255.10	254.74	0.142	0.010	0.885	253.03	0.807	0.185	4.670
					GS					
1985	214.14	214.05	213.71	0.161	0.045	0.637	213.06	0.469	0.115	2.871
1986	199.69	199.79	199.47	0.163	0.056	1.200	198.71	0.548	0.121	2.562
1987	204.07	203.23	202.88	0.174	0.056	0.690	201.93	0.641	0.199	4.687
1988	287.12	286.63	286.24	0.143	0.037	1.159	284.67	0.613	0.086	3.368
1989	259.35	260.68	260.17	0.200	-0.219	3.592	259.20	0.605	-0.027	3.890
1990	228.37	228.74	228.18	0.239	-0.109	1.876	227.59	0.497	-0.040	1.961
1991	220.98	221.23	220.54	0.309	-0.061	1.659	219.42	0.808	0.040	5.824
1992	220.00	219.99	219.59	0.182	0.024	0.972	218.72	0.576	0.103	6.301
1993	239.94	238.89	238.61	0.118	0.056	0.474	237.86	0.420	0.147	1.905
1994	238.73	240.04	239.68	0.150	0.052	0.943	238.05	0.860	0.109	11.798
1995	238.96	238.59	238.20	0.163	0.043	0.686	236.37	0.937	0.204	4.176
1996	289.70	290.63	290.18	0.157	0.015	1.669	288.65	0.690	0.116	2.575
1997	292.16	291.99	291.68	0.107	0.052	0.283	290.90	0.383	0.115	2.384
1998	234.27	235.31	235.02	0.122	0.048	0.415	233.56	0.765	0.141	9.386
1999	211.99	214.75	214.51	0.113	0.097	0.135	212.12	1.217	0.485	2.098
Av.	240.51	240.73	240.32	0.170	-0.032	0.630	239.21	0.632	0.128	4.386
					ILS					
1985	203.84	204.28	204.10	0.084	0.006	0.370	204.07	0.101	-0.701	0.413
1986	190.23	190.37	190.21	0.086	0.007	0.720	190.12	0.134	-0.040	0.907
1987	192.53	192.12	191.94	0.093	0.010	0.397	191.85	0.136	-1.145	1.031
1988	277.62	276.54	276.34	0.075	-0.013	0.677	276.21	0.119	-0.611	0.891
1989	246.44	247.77	247.51	0.106	-0.230	2.152	247.44	0.135	-1.223	2.165
1990	218.46	217.98	217.70	0.127	-0.127	1.107	217.63	0.162	-0.363	1.140
1991	210.57	211.02	210.68	0.162	-0.087	1.020	210.59	0.207	-1.128	1.033
1992	210.03	209.70	209.50	0.095	-0.15	0.585	209.45	0.120	-1.839	1.324
1993	228.65	228.10	227.96	0.062	0.017	0.274	227.87	0.100	-1.615	0.389
1994	228.91	229.75	229.57	0.079	0.013	0.567	229.44	0.135	-3.831	2.092
1995	222.62	222.09	221.90	0.088	0.006	0.416	221.73	0.162	-1.027	0.791
1996	277.75	277.98	277.75	0.083	-0.012	0.697	277.65	0.121	-0.651	0.773
1997	279.84	280.09	279.94	0.056	0.018	0.159	279.83	0.093	-0.527	0.485
1998	221.90	222.86	222.71	0.064	0.012	0.239	222.60	0.114	-2.990	1.621
1999	198.54	200.75	200.63	0.061	0.050	0.076	200.70	0.021	-0.230	0.301
Av.	229.35	229.35	229.15	0.090	-0.034	0.672	229.05	0.131	-1.195	1.024

Note: Four observations are available for 1999.

Footnotes

1. While a few papers have addressed the role of transportation costs on commodity markets, they have been developed within a 'static' framework, where risk is restricted not to vary over time (e.g., Binkley (1983), and Roehner(1996)). Despite this restriction, both these authors report evidence that ocean freight prices do influence international grain prices and that transportation costs seem to play an important role in the economics of international commodity markets.
2. For example, ocean freight prices ranged from 2.1% - 8.7% of the value of Rotterdam soybean prices between Jan 1985 – Jan 1999, and barge rates (between Illinois and the U.S. Gulf) ranged from 1.3% - 7.7% of the value of the U.S. Gulf soybean prices between Jan 1985 – Jan 1999.
3. Such a question is of interest because the development of a barge rate futures contract has been proposed in the past (Hauser and Buck(1989)).
4. Other specifications include the linear diagonal model used by Baillie and Myers (1991), and the positive semi-definite formulization introduced by Engle and Kroner (1995).
5. Elements of the H_t matrix can be restricted to enter some or all of the R equations. For instance, Holt and Moschini (1992), restrict elements of H_t to enter into just one of their conditional mean equations.
6. Although the barge rate was found to be I(0) first differencing was performed the series in put all prices in similar magnitudes in order to add stability to the non-linear estimation of the MGARCH – M models. Importantly, residual diagnostics presented in Tables 3 and 5 and indicate that no serious misspecifications occurred as a result of potentially over-differencing the price series. In particular Ljung-Box Q and Q^2 statistics indicate that the time series structures applied to the differenced data are adequate in explaining the data series.
7. As the barge rate was found to be I(0) the parameter associated with the barge rate in the cointegrating vector was tested for its statistical significance. The value was found to be not statistically significant and so its value was restricted to zero in the *ECT*.
8. The harmonic variables are defined as: COS = $\cos(2\pi t/4)$ and SIN = $\sin(2\pi t/4)$, t = 1, ….,T.
9. Each price series conditional variance was divided by the mean value of the conditional variance in order to put each series in comparable magnitudes.

Figure 1. Illinois (*ILS*), Gulf (*GS*) and Rotterdam (*RS*) Soybean Price Time-Varying Volatility

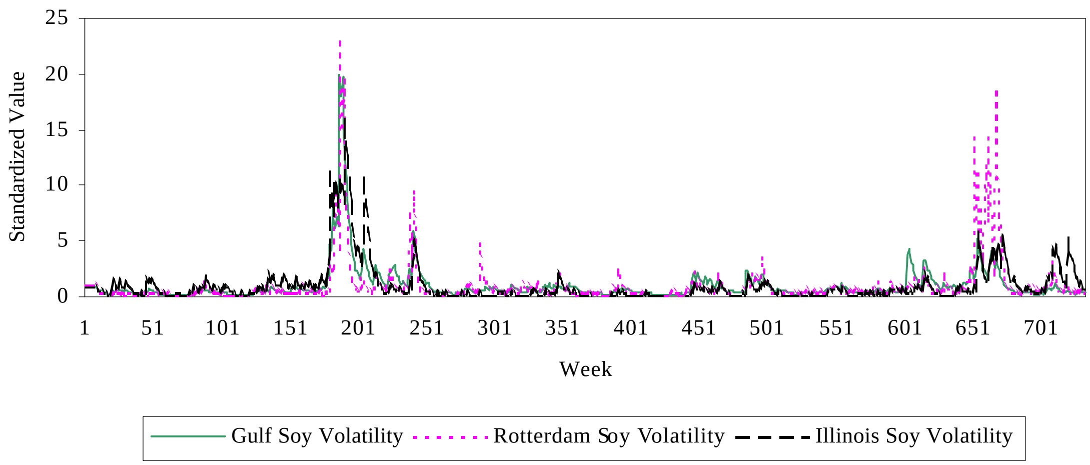

Figure 2. Ocean (*O*) and Barge (*B*) Freight Time-Varying Volatility

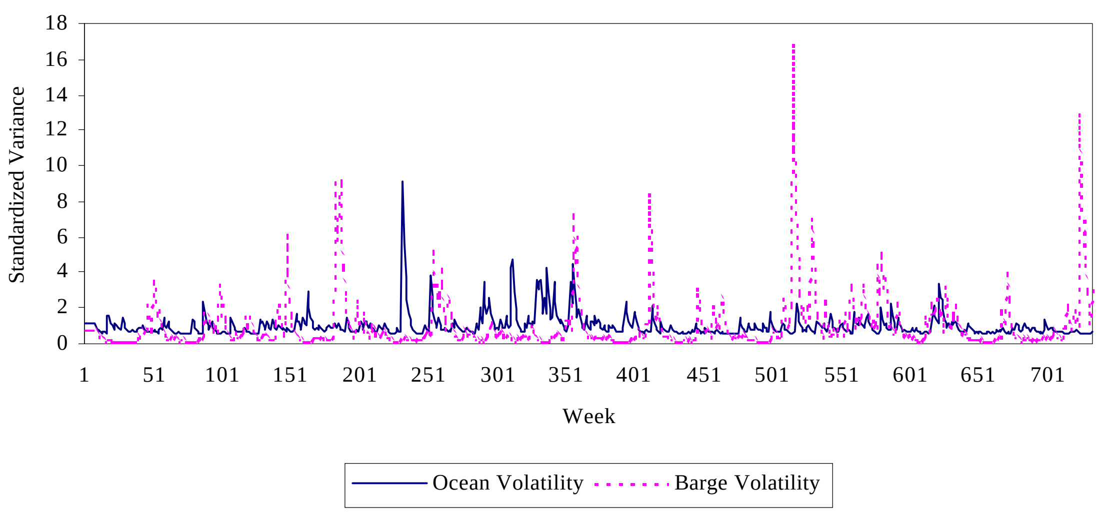

Figure 3. Simulated Percentage Decreases in Soybean Prices (*RS*, *GS*, *ILS*) by Eliminating Ocean (*O*) Freight Price Risk

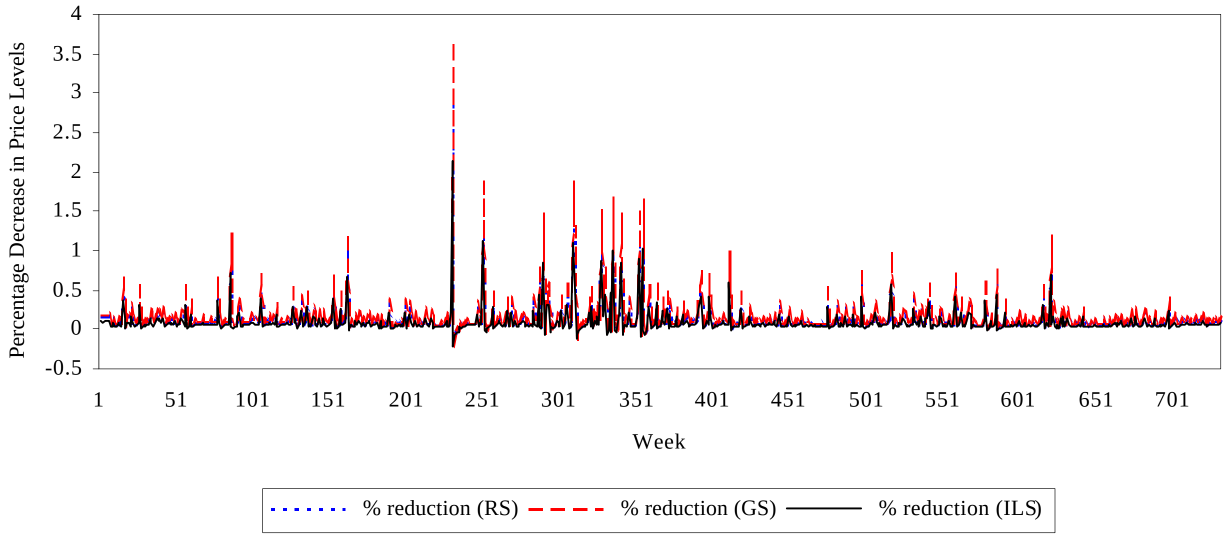

Figure 4. Simulated Percentage Decreases in Soybean Prices (*RS*, *GS*, *ILS*) by Eliminating Total Price Risk (Ocean (*O*) and Barge (*B*) Freight Price Risk)