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The effect of barge and ocean freight price volatility in international grain markets

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Abstract

This paper looks at the potential role of time-varying volatility of Mississippi river barge and ocean freight prices on commodity prices in Illinois, at the US Gulf and in Rotterdam using a Vector Error Correction GARCH-in-Mean model. The model is used to infer the extent to which transportation price risk affects price dynamics in international grain markets. Results from a simulation exercise indicate that both barge and ocean price volatility influence grain prices, but barge price volatility tends to have a greater impact on grain prices and marketing margins than that arising from ocean price volatility. Consistent with most studies that evaluate the role of risk in marketing channels, results here suggest that a reduction in barge rate risk would reduce marketing margins between Illinois and the US Gulf, and between the US Gulf and Rotterdam. The existence of an ocean freight futures contract coupled with the lack of a futures contract for barge rates may be partially responsible for the finding that barge rates have a significant influence on grain prices and contribute most to wide marketing margins found throughout the international grain-marketing system.

JEL classification: C32; Q17; R4

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 be 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.

For instance, important theoretical and empirical analysis undertaken by Brorsen et al. (1985, 1987) considered the influence of risk on various market participants in the US wheat and rice marketing channel. These studies presented empirical evidence in support of the proposition that increases in wheat and rice price risks tended to cause the expected marketing margin for these commodities to widen. In order to infer the risk reactions within the marketing channel, both studies employed simple fixed-weight moving average methods. However, such methods have since been shown to provide inaccurate results (Pagan and Ullah, 1988). Since this work, various applications of the autoregressive conditional heteroskedasticitic

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(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 et al. (1988), Baillie and Bollerslev (1990) and Pagan and Schwert (1990) to name a few. The methodology has since been adopted and used successfully in a wide variety of econometric commodity models simply because the procedures have been shown to provide a clear improvement over extrapolative techniques. For instance, Aradhyula and Holt (1989) used the modeling technique to isolate the effect of time-varying price variance on broiler supply, while Schroeter 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.

A unique application of the GARCH methodology was undertaken by Jayne and Myers (1994), who isolated the effects of time-varying commodity price volatility (risk) on equilibrium price levels and marketing margins in international trade. Using a bivariate GARCH-in-Mean approach, the authors studied the role of price risk in a system of dynamic regression equations using Japanese and US wheat prices. A key finding was that an increase in price volatility had little effect on US export prices, but had some effect on Japanese import prices and the resulting international marketing margin. The study made an important contribution towards understanding how price volatility is transmitted throughout the international marketing channel, and acknowledged the fact that ocean freight prices have an important role in the determination of international commodity prices. As such, the authors included oil prices (proxying freight prices) in their system of dynamic equations. The authors did not, however, explore how changes in oil prices influence the international commodity price levels and the resulting international marketing margins.

Incorporating freight prices into the system of equations is especially important, as there is an intuitively appealing (and documented) linkage between freight rates and international commodity prices. For instance, in their empirical analysis of testing the law of one price (LOP), Goodwin et al. (1990) relax the assumption of constant transportation rates by employing actual freight rate prices between the US Gulf and the European continent. A significant linkage between commodity and freight prices was reported by the authors who found stronger support for the LOP after incorporating non-constant freight prices. There has thus far, however, 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 build on the work of Jayne and Myers (1994) by isolating the effect of price risk, measured by the volatility of transportation prices (barge and ocean freight), on the grain prices at Illinois, the US Gulf and Rotterdam. To undertake such analysis, a Vector Error Correction GARCH-in-Mean (VEC-GARCH-M) model is estimated. The model builds upon the multivariate GARCH-M (MGARCH-M) model used by Holt (1993) by including cointegration information into the systems of equations. The VEC-GARCH-M procedure allows one to include potentially important volatility terms in the specification of the mean price equations and to determine the extent of volatility

[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; 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 to 8.7% of the value of Rotterdam soybean prices between January 1985 and January 1999, and barge rates (between Illinois and the US Gulf) ranged from 1.3 to 7.7% of the value of the US Gulf soybean prices between January 1985 and January 1999.

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 effect 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/margins, several 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 a simulation that isolates 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 et al. (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 et al. (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-M 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 Cecchetti 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 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, an MGARCH-M procedure

[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).

restricts the volatility estimates that affect the prices to be the same as these generated by the data series.

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

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

where

$$\varepsilon_t | \Omega_{t-1} \sim N(0, H_t) \text{ and } \{H_t\}_{ij} = h_{ijt}, \quad i, j = 1, \dots, R, \tag{2}$$

$$h_{iit} = \omega_i + \alpha_{i1}\varepsilon_{it-1}^2 + \beta_{i1} h_{iit-1}, \tag{3}$$

$$h_{ijt} = \rho_{ij}\sqrt{h_{iit}h_{jjt}}, \quad i \neq j. \tag{4}$$

Here, Y_t as the vector of $(R \times 1)$ 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. Γ, Π and Ψ represent the fixed parameters to be estimated and vech $(\cdot)$ is a vectorization operator that stacks elements of H_t into a single column vector.[5] In this case, ε_t denotes a $(R \times 1)$ vector of normally distributed forecast errors of Y_t conditional on Ω_{t-1} which denotes the sigma field generated by all available information up through time $t-1$. Here we define h_{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 $\rho_{ijt} = h_{ijt}/\sqrt{h_{iit}h_{jjt}}$, where $-1 \leq \rho_{ijt} \leq 1$ 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 ρ_{ijt} can, in general, be time-varying, it is often useful (for computational ease) to assume that $\rho_{ijt} = \rho_{ij}$ for all t, i.e. to assume that the conditional correlations are constant. It then follows that that $h_{ijt} = \rho_{ij}\sqrt{h_{iit}h_{jjt}}$, $i = 1, \dots, N$, $j = i+1, \dots, N$.

[5] Elements (or the square root of elements — standard deviations) 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.

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 $N \times N$ diagonal matrix including the square roots of the ijth elements of the conditional covariance matrix (standard deviations): $\sigma_{1t}, \dots, \sigma_{Nt}$ and Φ is $N \times N$ time invariant, positive semi-definite matrix with typical element ρ_{ij} and ones across the main diagonal. Assuming conditional normality, the log-likelihood function becomes (after ignoring the constant terms):

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

where $\tilde{\varepsilon}_t = D_t^{-1}\varepsilon_t$ is an $(N \times 1)$ vector of residuals (standardized) and η 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 H_t (or the corresponding standard deviations, $\sigma_{ij,t}$) 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 international grain markets do not know exactly the level of variability of prices that may affect the profitability of trading and that grain 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 covering the period 4 January 1985–15 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 were also provided for the stretch of river beginning at south of Peoria. While other barge prices were available for the Upper Mississippi, the focus of the study was for the south of Peoria region as this area, unlike the other areas, is not frozen for several months of the year. It is however prone to drought conditions which might slow down, but not stop barge traffic.

Weekly Gulf soybean export prices (GS), ocean freight rates (O) from the US Gulf to Rotterdam and weekly soybean import prices at Rotterdam (RS) were also collected. The barge rate data links the south of Peoria market with the US Gulf export market and the ocean price data links the US Gulf export market with the Rotterdam import market. These data also cover the period 4 January 1985–15 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. Further details on all data can be found in Appendix A.

4. Exact model specification

In order to implement what we term the VEC-GARCH-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 and 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 non-stationary. 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 of a pair (or any number) of $I(1)$ variables being cointegrated, so that a linear combination of them is $I(0)$ (stationary), 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 three stable cointegrating vectors linking the price series together. The ECT was formed by standardizing the first cointegrating vector on price series RS. [7]

Table 1
Augmented Dickey–Fuller (ADF) tests for order of integration on cash prices (test is on the estimated coefficient θ_1 from the following prototype model: $\Delta X_t = \theta_0+\theta_1 X_{t-1}+\sum_{k=1}^{K}\beta_k \Delta X_{t-k})^{a}$

Price series	K	HO:$I(1)$ vs. HA:$I(0)$ ADF	HO:$I(2)$ vs. HA:$I(1)$ ADF
Illinois soy (ILS)	10	−2.892	−8.177
Barge (B)	3	−6.230	−11.471
Gulf soy (GS)	5	−2.376	−11.379
Ocean (O)	8	−2.869	−9.984
Rott soy (RS)	8	−2.085	−10.827

[a] Critical values are taken from Fuller (1976). They are −2.57 (10%), −2.88* (5%) and −3.46 (1%). Therefore, based on these results the series are $I(1)$, except barge (B). The optimal lag length (K) was based on the Akaike Information Criterion (Akaike, 1973).

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

[6] The barge rate data was found to be stationary at conventional levels of significance but the data was differenced so that all the price series would be in similar magnitudes thus ensuring stability of the non-linear estimation of the VEC-GARCH-M model. Residual diagnostics presented in Tables 3 and 5 indicate that no serious misspecifications occurred as a result of potentially over-differencing the barge rate price series (no moving average term was introduced). In particular Ljung-Box Q and Q^2 statistics indicate that the time series structures applied to all the differenced data are quite 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 statistically insignificant and so its value was set to zero in the cointegrating vector. The corresponding ECT was therefore composed entirely of the non-stationary variables. As suggested by an anonymous reviewer, in the mean equation for B, a lagged term (B_{t-2}) was included on the right-hand side of the equation. While the sign of the lagged term was significantly negative (as expected), its inclusion introduced serial correlation into the model. Therefore, the multivariate system was estimated by excluding B_{t-2}.

Table 2
Johansen cointegration tests[a]

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	$r\leq 1$	55.43	72.45	$r=1$	32.14
60.65	$r\leq 2$	37.22	39.93	$r=2$	25.75
20.72	$r\leq 3$	23.52	14.79	$r=3$	19.19
5.93	$r\leq 4$	11.65	5.93	$r=4$	11.65

Standardized cointegrating vector (ECT): RS $-$ 0.924$O$$-$1.301GS + 0.307ILS $-$ 1.261

[a] Tests are on eigenvalues with the Π matrix, where Π represents the matrix of estimated parameters from an error correction representation (see Johansen, 1988, for further details). The λ_{trace} statistic is $N\sum_{i=r+1}^{2}\ln(1-\lambda_i)$ where λ_i are ordered (largest to smallest) eigenvalues on Π, and the λ_{max} statistic is $N(1-\lambda_{r+1})$. Critical values for the λ_{max} and λ_{trace} statistics are from Osterwald-Lenum (1992). The optimal lag length (6) was based on the Akaike Information Criterion (Akaike, 1973).

GARCH behavior for the price series. 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:

$$\begin{aligned}\Delta \mathrm{ILS}_t = {} & \delta_0 + \delta_1\Delta O_{t-1} + \delta_2\Delta B_{t-1} + \delta_3\Delta \mathrm{GS}_{t-1} \\ & +\delta_4\Delta \mathrm{RS}_{t-1} + \delta_5\Delta \mathrm{ILS}_{t-1} + \delta_6\,\mathrm{COS}_{t-1} \\ & +\delta_7\,\mathrm{SIN}_{t-1} + \tau_1\mathrm{ECT}_{t-1} + \nu_{11}\Delta\sigma_{44t} \\ & +\nu_{12}\Delta\sigma_{22t} + \nu_{13}\sigma_{44t-1} + \nu_{14}\sigma_{22t-1} \\ & +\varepsilon_{\mathrm{ILS}t}, \end{aligned} \tag{7}$$

$$\begin{aligned}\Delta B_t = {} & \phi_0 + \phi_1\Delta O_{t-1} + \phi_2\Delta B_{t-1} + \phi_3\Delta \mathrm{GS}_{t-1} \\ & +\phi_4\Delta \mathrm{RS}_{t-1} + \phi_5\Delta \mathrm{ILS}_{t-1} + \phi_6\,\mathrm{COS}_{t-1} \\ & +\phi_7\,\mathrm{SIN}_{t-1} + \tau_2\mathrm{ECT}_{t-1} + \varepsilon_{Bt}, \end{aligned} \tag{8}$$

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

Parameter	Illinois soy (ILS)	Barge (B)	Gulf soy (GS)	Ocean (O)	Rotterdam soy (RS)
ϕ_0	0.189 (0.216)	0.480 (0.000)	0.066 (0.710)	−0.001 (0.946)	0.025 (0.889)
ϕ_1	0.153 (0.000)	1.122 (0.000)	−0.038 (0.383)	0.475 (0.000)	−0.062 (0.174)
ϕ_2	–	−0.269 (0.000)	–	−0.005 (0.917)	0.054 (0.187)
ϕ_3	–	0.065 (0.304)	–	−0.023 (0.607)	–
ϕ_4	–	−0.014 (0.695)	–	−0.104 (0.010)	–
ϕ_5	–	–	–	0.095 (0.020)	–
ϕ_6	–	–	–	−0.117 (0.002)	–
ω	1.287 (0.000)	0.041 (0.000)	1.587 (0.000)	0.069 (0.000)	1.705 (0.000)
α	0.196 (0.000)	0.677 (0.000)	0.217 (0.000)	0.123 (0.000)	0.329 (0.000)
β	0.777 (0.000)	0.520 (0.000)	0.768 (0.000)	0.601 (0.000)	0.699 (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 (0.310)	4.052 (0.908)	7.072 (0.629)	5.490 (0.789)	12.710 (0.176)
$Q^2(12)$	8.723 (0.463)	11.590 (0.237)	7.988 (0.535)	2.423 (0.983)	10.113 (0.341)
Log-likelihood	−1520.51	−242.93	−1634.53	161.365	−1718.05

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

$$\begin{aligned}\Delta \mathrm{GS}_t = {} & \varphi_0 + \varphi_1 \Delta O_{t-1} + \varphi_2 \Delta B_{t-1} + \varphi_3 \Delta \mathrm{GS}_{t-1} \\ & + \varphi_4 \Delta \mathrm{RS}_{t-1} + \varphi_5 \Delta \mathrm{ILS}_{t-1} + \varphi_6 \mathrm{COS}_{t-1} \\ & + \varphi_7 \mathrm{SIN}_{t-1} + \tau_3 \mathrm{ECT}_{t-1} + \nu_{31} \Delta \sigma_{44t} \\ & + \nu_{32} \Delta \sigma_{22t} + \nu_{33} \sigma_{44t-1} + \nu_{34} \sigma_{22t-1} \\ & + \varepsilon_{\mathrm{GS}t}, \end{aligned} \tag{9}$$

$$\begin{aligned}\Delta O_t = {} & \lambda_0 + \lambda_1 \Delta O_{t-1} + \lambda_2 \Delta B_{t-1} + \lambda_3 \Delta \mathrm{GS}_{t-1} \\ & + \lambda_4 \Delta \mathrm{RS}_{t-1} + \lambda_5 \Delta \mathrm{ILS}_{t-1} + \lambda_6 \mathrm{COS}_{t-1} \\ & + \lambda_7 \mathrm{SIN}_{t-1} + \tau_4 \mathrm{ECT}_{t-1} + \varepsilon_{Ot}, \end{aligned} \tag{10}$$

$$\begin{aligned}\Delta \mathrm{RS}_t = {} & \theta_0 + \theta_1 \Delta O_{t-1} + \theta_2 \Delta B_{t-1} + \theta_3 \Delta \mathrm{GS}_{t-1} \\ & + \theta_4 \Delta \mathrm{RS}_{t-1} + \theta_5 \Delta \mathrm{ILS}_{t-1} + \theta_6 \mathrm{COS}_{t-1} \\ & + \theta_7 \mathrm{SIN}_{t-1} + \tau_5 \mathrm{ECT}_{t-1} + \nu_{51} \Delta \sigma_{44t} \\ & + \nu_{52} \Delta \sigma_{22t} + \nu_{53} \sigma_{44t-1} + \nu_{54} \sigma_{22t-1} \\ & + \varepsilon_{\mathrm{RS}t}, \end{aligned} \tag{11}$$

$$\begin{aligned} & \varepsilon_t = [\varepsilon_{\mathrm{ILS}t}, \varepsilon_{Bt}, \varepsilon_{\mathrm{GS}t}, \varepsilon_{Ot}, \varepsilon_{\mathrm{RS}t}] | \Omega_{t-1} \sim N(0, H_t), \\ & \{H_t\}_{ij} = h_{ijt}, \quad i, j = 1, \dots, 5, \end{aligned} \tag{12}$$

$$h_{iit} = \omega_i + \alpha_{i1} \varepsilon_{it-1}^2 + \beta_{i1} h_{iit-1}, \tag{13}$$

$$h_{ijt} = \rho_{ij} \sqrt{h_{iit} h_{jjt}}, \quad i \neq j. \tag{14}$$

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. Such a parsimonious structure was chosen because even though price reactions in the spot market to changes in transportation rates occur almost immediately it takes longer than 1 week to transport grains either from Illinois to the Gulf, or from the Gulf to Rotterdam, and so these terms are included to pick up any remaining serial correlation in the system's errors which may exist due to potential lagged adjustments to changes in any of the variables.

Due to any seasonality in commodity flows (prices) or freight prices we include harmonic variables set at monthly cycles represented by COS and SIN, respectively.[8] All equations also include the ECT, ECT_{t-1} to capture the cointegrating relationship between the price series. Other exogenous variables including grain flows, exchange rates and oil prices were also included and tested for statistical significance in the mean equations. However, as was also found by Miljkovic et al. (2000) and Jayne and Myers (1994) the exogenous variables were found to be insignificant in explaining transportation and grain prices and so were excluded from the final analysis in order to keep the model more parsimonious.[9]

The variables σ_{22t}, σ_{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 risk term functional forms, for instance, including the conditional variance terms, rather than the standard deviations were included in the mean specification 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 prices of the grain throughout the international marketing channel is the main focus of this paper, their inclusion is confined to the grain equations (Eqs. (7), (9) and (11)). Both the first differences of the risk variables, $\Delta\sigma_{22t}$ and $\Delta\sigma_{44t}$ and lagged levels of the risk variables, σ_{22t-1} and σ_{44t-1} are included in the mean equations to represent the risk associated with the transportation in the international marketing channel (Kroner and Lastrapes, 1993).

The VEC-GARCH-M model therefore attempts to study the dynamic relationships in observed data in the international marketing channel. However, following Bessler and Fuller (2000) we do not attempt 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, i.e. we attempt to

[8] The harmonic variables are defined as: $\mathrm{COS} = \cos(2\pi t/4)$ and $\mathrm{SIN} = \sin(2\pi t/4)$, $t = 1, \dots, T$. Miljkovic et al. (2000) also accounted for seasonality in their paper but included seasonal dummy variables. They discover that seasonality played a significant role in the model.

[9] In particular, we follow Miljkovic et al. (2000) by including weekly data on the volume of grains transported to the US Gulf by barge for export (V). Also, because foreign exchange rates have been shown to influence both transportation and grain prices (Haigh and Holt, 1999) we include an indicator of exchange rates (EX) represented by the US dollar index. Oil prices, denoted OIL, were also included as this is generally considered to be the most significant variable cost in freight transportation (Thuong and Visscher, 1990). Results on the insignificance of these variables are excluded for brevity but are available upon request. A full description of these data can be found in Appendix A.

study the relationships between these components of the marketing channel using observed prices rather than the unobservable parameters of demand and supply.

5. Estimation results, model diagnostics and dynamic simulations

Maximum likelihood estimates of the model represented by Eqs. (7)–(14) 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 prices. Point estimates of α_i and β_i, $i = 1, \dots, 5$ are positive and individually significant, indicating the presence of conditional heteroskedasticity in the error terms of the price equations. In two instances $\hat{\alpha} + \hat{\beta}$ exceeds unity, so that the unconditional variance does not exist.[10] As pointed out by Bollerslev (1990), however, the conditional moments are still well defined. Results of several diagnostic tests are reported in Table 5. Skewness and kurtosis estimates reported in Table 5 reveal that the assumption of normality is apparently justified. Tests for remaining residual autocorrelation in the standardized residuals, and their cross-products, show that nearly all residual autocorrelation is accounted for in the model. One exception is for the autoregressive representation of ΔILS, where there appears evidence of remaining autocorrelation in the normalized residuals. However, despite this one statistic, the VEC-GARCH-M model appears to represent the mean and variance dynamics associated with the international grain-marketing channel.[11]

Figs. 1 and 2 plot the historical path of standardized conditional variances for each of the price series studied.[12] 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, ρ_{ij}, reported in Table 4 are statistically significant in several instances illustrating the presence of significant cross-equation influences. For instance, the correlation parameters associated with barge rates and grain prices at Illinois (ρ_{12}) and the Gulf (ρ_{23}) are statistically significant with p-values of 0.018 and 0.077, respectively.

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 $\Delta\sigma_{22t}$ and $\Delta\sigma_{44t}$ (namely ν_{i1} and ν_{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 prices 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. In order to test for the statistical significance of all risk parameters a likelihood ratio (LR) test was performed by setting all risk parameters equal to zero. The LR value obtained was 83.49, a value with an asymptotic χ^2 (12) distribution under the null hypothesis. The 'risk-free' model is thus rejected under the null hypothesis at all conventional levels of significance.

The fitted series of prices (representing the predicted values from the VEC-GARCH-M model converted back to levels), are simply the one-step-ahead forecast of prices in period t that are computed taking everything in period $t-1$, including the price itself, as given. These forecasts can then be compared to the actual price series observed. As can be seen on the left-hand side of Table 6, the average fitted price with risk, appears to do a good job in predicting the actual average price level that occurred between 1985 and 1999, as the two price series are very close to one

[10] As suggested by an anonymous reviewer, for each of the two equations, the restriction was imposed that $\hat{\alpha}+\hat{\beta} = 1$. This reduced the total number of parameters to be estimated by two. The resulting likelihood ratio (LR) test statistic comparing the unrestricted model (where $\hat{\alpha} + \hat{\beta}$ exceeded unity in the two instances) to the restricted model where $\hat{\alpha} + \hat{\beta} = 1$, strongly rejected the restriction and so the unrestricted model was used throughout the analysis.

[11] Minor evidence of remaining autocorrelation is not uncommon in multivariate GARCH models such as the one estimated here. For instance, Holt and Aradhyula (1998) also reported evidence of residual autocorrelation in their system of equations. In the current paper, other econometric specifications were attempted so as to clear up remaining autocorrelation. The current specification seemed to provide the best description of the price dynamics.

[12] Each price series conditional variance was divided by the mean value of the conditional variance in order to put each series in comparable magnitudes.

Table 4
Maximum likelihood estimates of the VEC-GARCH-M model

Variable	Illinois soy (ILS)			Barge (B)			Gulf soy (GS)			Ocean (O)			Rotterdam soy (RS)		
	Parameter	Coefficient	p-value	Parameter	Coefficient	p-value	Parameter	Coefficient	p-value	Parameter	Coefficient	p-value	Parameter	Coefficient	p-value
Constant	δ_0	−0.226	0.607	ϕ_0	−0.043	0.091	φ_0	−1.361	0.052	λ_0	−0.000	0.986	θ_0	−1.788	0.002
ΔO_t	δ_1	−0.393	0.055	ϕ_1	−0.078	0.382	φ_1	−0.348	0.211	λ_1	0.466	0.000	θ_1	−0.397	0.127
ΔB_t	δ_2	−0.499	0.000	ϕ_2	0.154	0.049	φ_2	0.223	0.167	λ_2	−0.012	0.509	θ_2	0.314	0.011
$\Delta \mathrm{GS}_t$	δ_3	0.399	0.000	ϕ_3	−0.006	0.000	φ_3	−0.137	0.004	λ_3	−0.004	0.315	θ_3	0.144	0.000
$\Delta \mathrm{RS}_t$	δ_4	0.078	0.000	ϕ_4	90.876	0.041	φ_4	−0.028	0.394	λ_4	0.001	0.849	θ_4	−0.206	0.000
$\Delta \mathrm{ILS}_t$	δ_5	−0.058	0.033	ϕ_5	−90.873	0.000	φ_5	0.237	0.000	λ_5	−0.004	0.231	θ_5	0.300	0.000
COS_t	δ_6	0.352	0.002	ϕ_6	0.057	0.000	φ_6	0.763	0.000	λ_6	0.031	0.262	θ_6	0.475	0.005
SIN_t	δ_7	−0.130	0.304	ϕ_7	0.073	0.101	φ_7	−0.081	0.724	λ_7	0.042	0.131	θ_7	0.016	0.930
ECT_t	τ_1	−0.139	0.000	τ_2	−0.004	0.382	τ_3	0.074	0.021	τ_4	0.002	0.488	τ_5	−0.279	0.000
$\Delta\sigma_{\mathrm{ocean}\,t} = \Delta\sigma_{44t}$	ν_{11}	1.844	0.208	–	–	–	ν_{31}	4.548	0.010	–	–	–	ν_{51}	4.026	0.028
$\Delta\sigma_{\mathrm{barge}\,t} = \Delta\sigma_{22t}$	ν_{12}	−0.459	0.211	–	–	–	ν_{32}	1.287	0.012	–	–	–	ν_{52}	1.356	0.000
$\sigma_{\mathrm{ocean}\,t-1} = \sigma_{44t-1}$	ν_{13}	0.752	0.357	–	–	–	ν_{33}	1.500	0.206	–	–	–	ν_{53}	1.326	0.238
$\sigma_{\mathrm{barge}t-1} = \sigma_{22t-1}$	ν_{14}	0.071	0.654	–	–	–	ν_{34}	0.813	0.004	–	–	–	ν_{54}	1.255	0.000
Variance parameters															
	ω_1	0.336	0.002	ω_2	0.049	0.000	ω_3	1.592	0.000	ω_4	0.061	0.000	ω_5	4.794	0.000
	α_1	0.314	0.000	α_2	0.614	0.000	α_3	0.219	0.000	α_4	0.218	0.000	α_5	0.347	0.000
	β_1	0.723	0.000	β_2	0.427	0.000	β_3	0.757	0.000	β_4	0.573	0.000	β_5	0.516	0.000

Covariance parameters

Parameter[a]	Series	Coefficient	p-value
ρ_{12}	(ILS, B)	−0.114	0.018
ρ_{13}	(ILS, GS)	0.549	0.000
ρ_{14}	(ILS, O)	0.059	0.166
ρ_{15}	(ILS, RS)	0.459	0.000
ρ_{23}	(B, GS)	0.069	0.077
ρ_{24}	(B, O)	0.011	0.807
ρ_{25}	(B, RS)	0.052	0.182
ρ_{34}	(GS, O)	0.020	0.648
ρ_{35}	(GS, RS)	0.660	0.000
ρ_{45}	(O, RS)	0.023	0.593

[a] The estimated correlation parameters between series i and j.

Table 5
Residual diagnostics tests for the VEC-GARCH-M model (asymptotic p-values are in parenthesis; m_3 is sample skewness and m_4 is sample kurtosis; $Q(12)$ and $Q^2(12)$ denote Ljung-Box test statistics for 12th order autocorrelation in standardized and squared standardized residuals, respectively)

	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 (0.001)	7.399 (0.687)	14.788 (0.140)	25.189 (0.050)	6.055 (0.811)
$Q^2(12)$					
Illinois soy (ILS)	5.685 (0.841)				
Barge (B)	6.557 (0.766)	3.466 (0.968)			
Gulf soy (GS)	6.336 (0.786)	14.017 (0.172)	5.130 (0.882)		
Ocean (O)	14.024 (0.172)	11.070 (0.352)	7.855 (0.643)	4.872 (0.899)	
Rotterdam soy (RS)	16.070 (0.100)	18.859 (0.042)	17.993 (0.055)	14.760 (0.141)	22.941 (0.011)

another. Such a finding lends support to the econometric specification outlined by Eqs. (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 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 VEC-GARCH-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

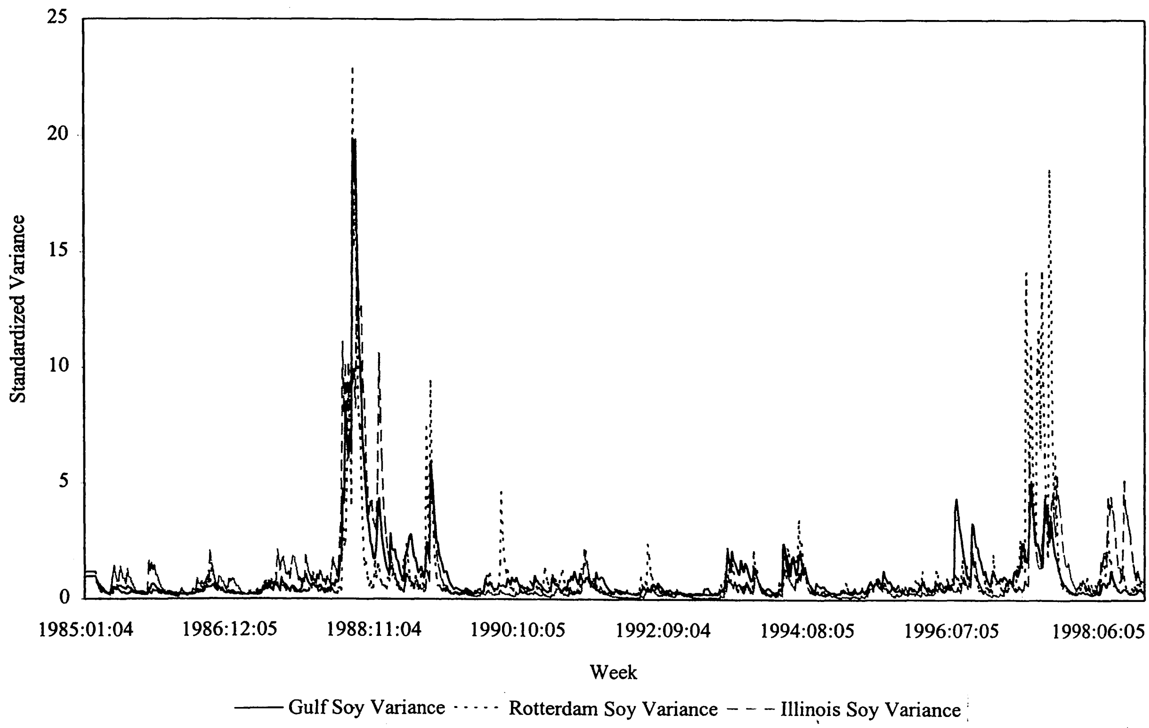

Fig. 1. Illinois (I), Gulf (GS) and Rotterdam (RS) time-varying standardized variance.

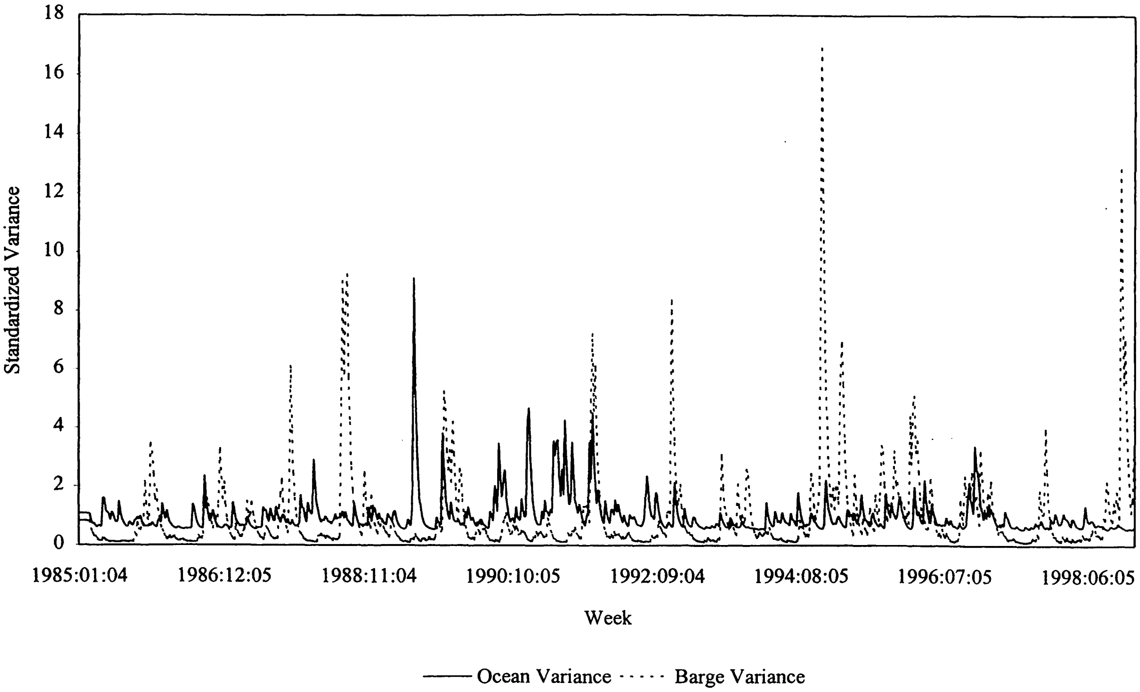

Fig. 2. Ocean (O) and barge (B) freight time-varying variance.

period by period. To this end, the estimated and fitted model is re-evaluated by setting all risk parameters associated with ocean freight price volatility equal to zero. Specifically, $\nu_{i1} = \nu_{i3} = 0$. The average fitted price by excluding the influence of ocean freight price volatility is then calculated by once again conducting the one-step-ahead forecasts of price in period t taking everything in $t-1$ as given, but this time excluding the influence of ocean freight price risk.

The corresponding results are presented in the fourth 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 are 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 0.139, 0.167 and 0.088%, respectively. However, these are average figures, and as can be seen from Fig. 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 ($\nu_{i1} = \nu_{i2} = \nu_{i3} = \nu_{i4} = 0$), and then re-forecasting the model, and converting back to levels, and comparing this price (average fitted price: no ocean or barge price risk) with the other average prices (actual average price, and average 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 *reduced* the price of grain at all locations. The barge risk's effect on the grain price level is, on an 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

Table 6

Average weekly simulated price impacts of freight price risk on Rotterdam (RS), Gulf (GS), and Illinois (ILS) markets by year, 1985–1999 (note: three observations are available for 1999)

Year	Actual average price	Average fitted price with risk	Average fitted price with no ocean price risk	Average % reduction	Minimum % reduction	Maximum % reduction	Average fitted price with no ocean or barge price risk	Average % reduction	Minimum % reduction	Maximum % reduction
RS										
1985	223.85	224.04	223.74	0.137	0.037	0.537	222.77	0.569	0.135	2.992
1986	208.44	208.45	208.16	0.139	0.048	1.061	206.96	0.716	0.139	2.921
1987	215.62	214.93	214.61	0.146	0.045	0.580	213.14	0.832	0.242	4.957
1988	303.37	302.44	302.09	0.116	0.031	0.964	299.67	0.913	0.104	4.033
1989	274.94	275.97	275.51	0.167	−0.185	3.019	274.04	0.701	0.045	3.879
1990	246.79	245.59	245.10	0.198	−0.091	1.547	244.16	0.582	0.018	1.967
1991	236.37	237.39	236.78	0.257	−0.051	1.387	235.07	0.977	0.067	6.400
1992	235.62	234.83	234.47	0.151	0.019	0.794	233.17	0.708	0.125	6.450
1993	255.64	254.60	254.35	0.097	0.046	0.391	253.17	0.562	0.157	1.972
1994	252.16	254.15	253.84	0.124	0.044	0.752	251.33	1.111	0.131	11.820
1995	259.38	260.04	259.69	0.132	0.035	0.567	256.69	1.223	0.294	4.890
1996	305.12	306.15	305.75	0.129	0.012	0.973	303.43	0.886	0.135	3.275
1997	306.20	306.41	306.14	0.089	0.043	0.242	304.89	0.496	0.123	2.514
1998	243.73	245.97	245.72	0.104	0.040	0.352	243.49	1.010	0.164	9.520
1999	221.45	225.83	225.61	0.095	0.080	0.114	222.29	1.568	0.896	2.456
Average	252.58	253.12	252.77	0.139	0.010	0.885	250.95	0.857	0.185	4.670
GS										
1985	214.14	214.05	213.71	0.162	0.045	0.637	213.06	0.464	0.115	2.871
1986	199.69	199.79	199.47	0.164	0.056	1.200	198.71	0.544	0.121	2.562
1987	204.07	203.23	202.88	0.175	0.056	0.690	201.93	0.643	0.199	4.687
1988	287.12	286.63	286.24	0.138	0.037	1.159	284.67	0.685	0.086	3.368
1989	259.35	260.68	260.17	0.200	−0.219	3.592	259.20	0.572	−0.027	3.890
1990	228.37	228.74	228.18	0.241	−0.109	1.876	227.59	0.499	−0.040	1.961
1991	220.98	221.23	220.54	0.312	−0.061	1.659	219.42	0.814	0.040	5.824
1992	220.00	219.99	219.59	0.183	0.024	0.972	218.72	0.576	0.103	6.301

1993	239.94	238.89	238.61	0.117	0.056	0.474	237.86	0.431	0.147	1.905
1994	238.73	240.04	239.68	0.149	0.052	0.943	238.05	0.831	0.109	11.798
1995	238.96	238.59	238.20	0.162	0.043	0.686	236.37	0.932	0.204	4.176
1996	289.70	290.63	290.18	0.154	0.015	1.669	288.65	0.679	0.116	2.575
1997	292.16	291.99	291.68	0.106	0.052	0.283	290.90	0.372	0.115	2.384
1998	234.27	235.31	235.02	0.122	0.048	0.415	233.56	0.743	0.141	9.386
1999	211.99	214.75	214.51	0.114	0.097	0.135	212.12	1.227	0.485	2.098
Average	238.63	238.97	238.58	0.167	0.013	1.093	237.39	0.667	0.128	4.386
ILS										
1985	203.84	204.28	204.10	0.085	0.006	0.370	204.07	0.102	−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	0.139	−1.145	1.031
1988	277.62	276.54	276.34	0.072	−0.013	0.677	276.21	0.119	−0.611	0.891
1989	246.44	247.77	247.51	0.105	−0.230	2.152	247.44	0.133	−1.223	2.165
1990	218.46	217.98	217.70	0.128	−0.127	1.107	217.63	0.163	−0.363	1.140
1991	210.57	211.02	210.68	0.163	−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	0.122	−1.839	1.324
1993	228.65	228.10	227.96	0.061	0.017	0.274	227.87	0.100	−1.615	0.389
1994	228.91	229.75	229.57	0.078	0.013	0.567	229.44	0.135	−3.831	2.092
1995	222.62	222.09	221.90	0.087	0.006	0.416	221.73	0.162	−1.027	0.791
1996	277.75	277.98	277.75	0.081	−0.012	0.697	277.65	0.119	−0.651	0.773
1997	279.84	280.09	279.94	0.055	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	0.113	−2.990	1.621
1999	198.54	200.75	200.63	0.061	0.050	0.076	200.70	0.022	−0.230	0.301
Average	227.20	227.43	227.23	0.088	−0.032	0.630	227.15	0.124	−1.195	1.024

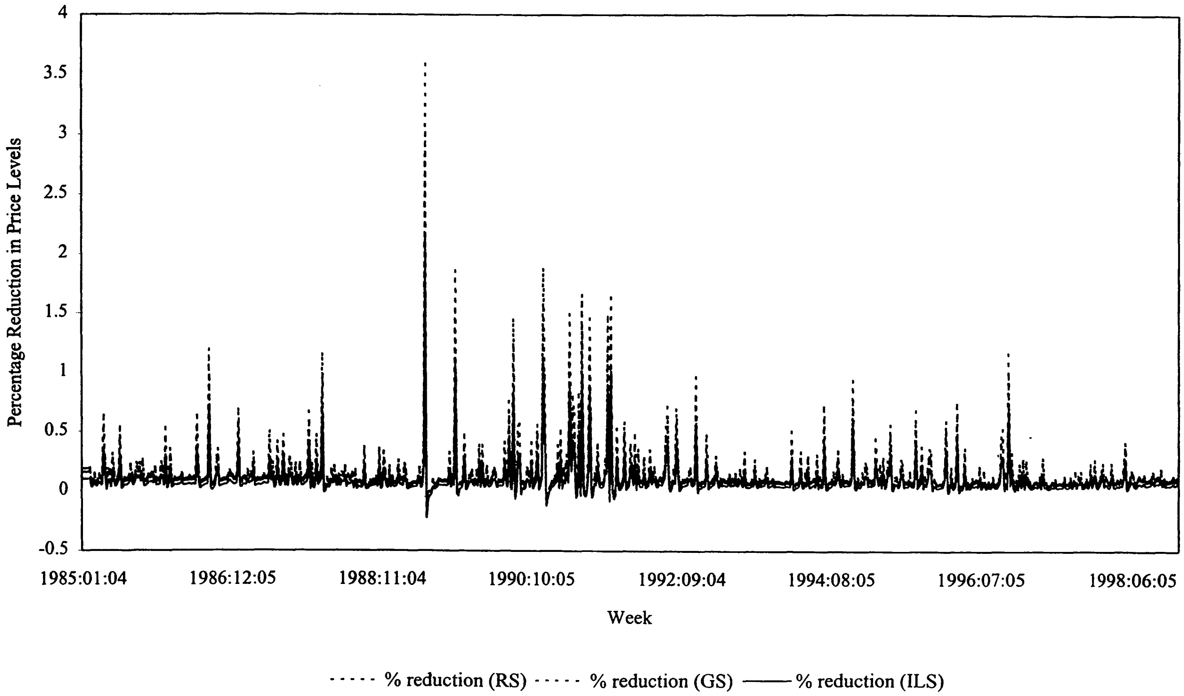

Fig. 3. Simulated percentage decreases in soybean prices (RS, GS, ILS) by eliminating ocean (O) freight price risk.

0.857, 0.667 and 0.124% *on an average*. 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 Fig. 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 11 November 1994 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% only if 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.

While the simulations thus far have shed light upon the reaction of prices to risk arising from ocean freight and barge rate volatility, perhaps a more interesting question is what happens to price spreads throughout the international marketing channel. Indeed this question appears to have been the focus of many studies that have studied the effect of risk throughout the marketing system (Brorsen et al., 1985, 1987; Holt, 1993; Jayne and Myers, 1994). A general finding in these studies is that increased price risk generally increases marketing margins, and as such might provide evidence supporting the development of either price stabilization programs (Brorsen et al., 1985) or a futures/options market (Holt, 1993).

Results in Table 7 support the results previously discussed on the effect of transportation price risk on grain prices. In particular, barge rate volatility rather than ocean price volatility seems to have a much more pronounced effect on international grain prices. Eliminating ocean price uncertainty from Rotterdam and the Gulf slightly increases the price spread. For instance, the average reduction is −0.329% on an average over the time period, suggesting that the spread actually increases (albeit by a tiny amount). Interestingly, this is the only portion of the marketing channel

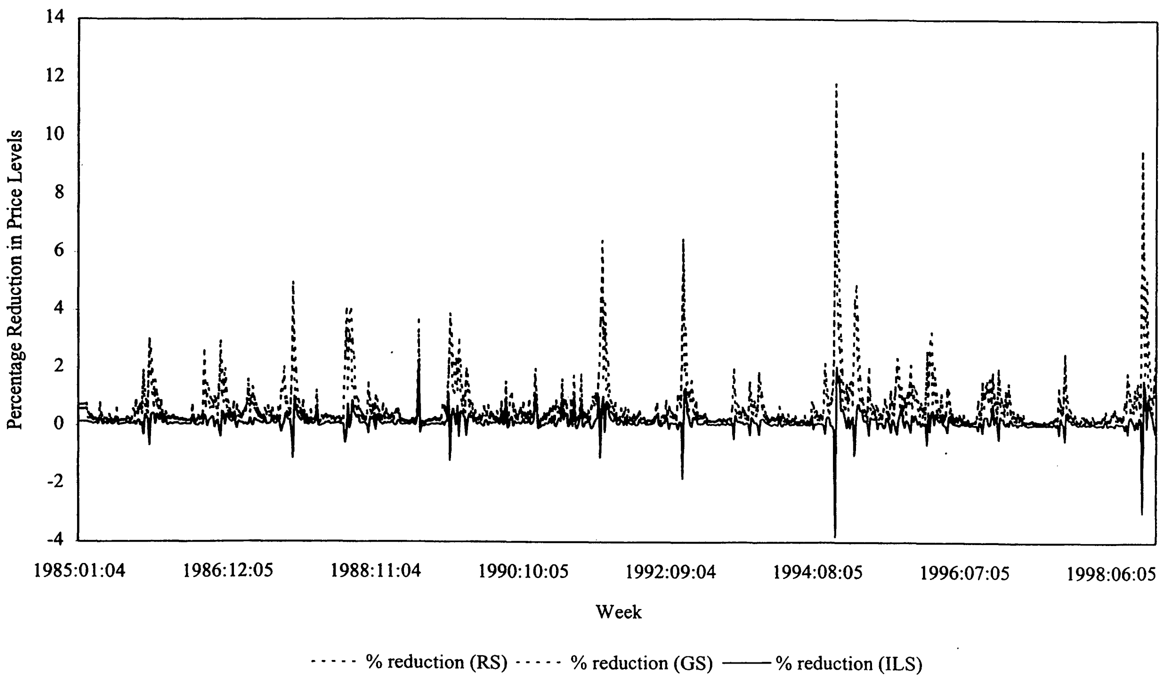

Fig. 4. Simulated percentage decreases in soybean prices (RS, GS, ILS) by eliminating total price risk (ocean (O) and barge (B) freight price risk).

that is covered by a futures market. A reduction in ocean price risk reduces the spread between Gulf and Illinois (1.748% on an average). However, as can be seen from the right-hand side of Table 7, a reduction in barge rate volatility significantly reduces marketing margins in all regions. Between Rotterdam and the Gulf the margin is reduced by 4.196% on an average over the time frame analyzed, but by far the greatest rewards to eliminating barge rate uncertainty would be found between Illinois and the Gulf where marketing margins would be reduced by 11.163% on an average. This finding in particular is consistent with the findings of previous research that suggest that reducing price risks does indeed reduce marketing margins.

One possible explanation for the finding that ocean freight rates have tended to have less significant effects on both prices of grain and the international marketing margins, even though, freight 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 freight price uncertainty for international grain traders, may have contributed to the relative insulation of grain prices from ocean freight price risk. Although the contract has experienced relatively low levels of trading activity since its inception, it has been shown to be a relatively effective hedging mechanism for grain traders (Haigh and Holt, 2000). Its hedging effectiveness has presumably enabled international grain traders to offset any gains/losses associated with the cash price of ocean freight between the US Gulf and Rotterdam with corresponding gains/losses from the freight futures market. As such, the finding that ocean freight price volatility does not get fully transmitted to the price of grain is not particularly surprising. Indeed, as suggested by Jayne and Myers (1994) if futures and options markets lead to substantial reductions in risk, then one might not expect to find a significant risk response in a market that has the underlying derivative contract. Thus, if the freight futures market is helpful in reducing uncertainty, it is not particularly surprising than we find little evidence of volatility spillovers into the international commodity marketing channel

Table 7
Average weekly simulated price impacts of freight price risk on Rotterdam (RS)–Gulf (GS) price spread, and Gulf (GS)–Illinois (ILS) price spread by year, 1985–1999

Year	Average fitted price spread	Average fitted price with no ocean price risk	Average % reduction	Average fitted price spread with no ocean or barge price risk	Average % reduction
RS–GS					
1985	9.991	10.03	−0.404	9.708	2.831
1986	8.655	8.694	−0.439	8.250	4.681
1987	11.693	11.734	−0.354	11.212	4.113
1988	15.808	15.850	−0.292	15.001	5.051
1989	15.284	15.345	−0.397	14.840	2.910
1990	16.855	16.919	−0.379	16.568	1.704
1991	16.166	16.247	−0.496	15.658	3.207
1992	14.842	14.888	−0.315	14.446	2.667
1993	15.713	15.746	−0.208	15.310	2.565
1994	14.109	14.151	−0.294	13.279	5.883
1995	21.447	21.492	−0.210	20.489	4.468
1996	15.518	15.570	−0.335	14.779	4.765
1997	14.423	14.459	−0.249	13.988	3.012
1998	10.662	10.695	−0.314	9.927	6.900
1999	11.078	11.107	−0.256	10.172	8.181
Average	14.150	14.195	−0.329	13.575	4.196
GS–ILS					
1985	9.775	9.601	1.779	8.991	8.017
1986	9.423	9.260	1.730	8.589	8.844
1987	11.116	10.940	1.587	10.076	9.360
1988	10.091	9.893	1.964	8.459	16.179
1989	12.916	12.656	2.014	11.755	8.988
1990	10.754	10.483	2.519	9.967	7.324
1991	10.203	9.857	3.394	8.839	13.368
1992	10.287	10.085	1.961	9.275	9.830
1993	10.784	10.644	1.299	9.984	7.416
1994	10.288	10.110	1.728	8.603	16.380
1995	16.494	16.301	1.173	14.631	11.292
1996	12.647	12.425	1.757	11.003	12.994
1997	11.891	11.737	1.296	11.065	6.950
1998	12.453	12.308	1.161	10.956	12.012
1999	14.003	13.882	0.864	11.413	18.497
Average	11.542	11.345	1.748	10.240	11.163

compared to that arising from the barge market which does not have an equivalent derivative contract.

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 play 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 prices and margins using time-series econometrics (a VEC-GARCH-M model) has not yet been undertaken.

The estimated VEC-GARCH-M model applied to weekly soybean price and ocean and barge rate price data at 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 evaluated using several simulations by isolating the marginal contribution of the barge rate and ocean rate risk on commodity prices. Results suggest that barge price volatility in particular tends to have a greater impact on grain prices and margins 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 to explain the results presented in this study. The empirical focus of this paper seems to suggest that the transmission of barge rate volatility might be indeed be reduced with the introduction of a barge rate contract (historically considered an important criterion in evaluating whether to introduce a new futures market). While results suggest that the development of a barge rate futures contract might indeed reduce volatility in the underlying spot market, issues surrounding the specification of the contract such as settlement procedures, or which segments of the river might be covered, due to freezing or drought conditions as well as issues relating to the concentration of the barge industry certainly deserve further study and consideration. These and other issues remain, however, as important topics for future research.

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Appendix A

Notation, definition and sources for all weekly commodity and transportation data (4 January 1985–15 January 1999) that were (a) employed in the empirical application or (b) tested for statistical significance are reported. All data cover the period 4 January 1985–15 January 1999 and are available upon request.

ILS river terminal soybean price (south of Peoria), Illinois Department of Agriculture

B grain barge rate (south of Peoria, US Gulf), USDA, 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)

GS soybean export price (US Gulf), USDA, Agricultural Marketing Service, Livestock and grain market news branch

O dry-bulk ocean freight rate (US Gulf, Rotterdam), Baltic Exchange, London, UK and Datastream

RS soybean import price (Rotterdam), International Grains Council, London, UK

V volume of grain exports from the US Gulf originating by barge from the Mississippi, Export Grain Information System, Federal Grain Inspection Service

OIL west Texas intermediate crude oil cash prices, Bridge CRB
EX US dollar index (trade weighted geometric average of six currencies), New York Board of Trade

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