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OCEAN FREIGHT AND ASYMMETRIC NEWS IMPACT

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This paper applies the news impact curve for the specification of the conditional volatility. The standard GARCH model, which imposes symmetry on the conditional variances, is shown to produce biased estimates when freight movements are negative. The estimated news impact curve for the GARCH suggests that the conditional variance is underestimated for negative shocks and overestimated for positive shocks. This paper also shows that the AGARCH model is the best at capturing this asymmetric effect.

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I. INTRODUCTION

Forecasting the ocean freight generally means the prediction of the bulk cargo freight. It is because the tramper freight is determined by the demand and supply of the market, while liner's freight is the tariff rate announced by the shipping company. While many studies have been implemented to analyze the ocean freight, most of them have no interest in the effect of the risk (or uncertainty) on ocean freight. In particular, many empirical papers tend to ignore the responses of the freight to the shocks in the world output and exchange rate and the effects of the unanticipated changes of these variables (news) on the freight volatility. Misleading results may be produced without considering news effects.

There appears to be widespread agreement that the volatility of economic

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variables is, to a degree, forecastable. Recently, a great deal of attention has been focused on this volatility. Theory suggests that the price of a variable is a function of the volatility, or risk, of the variable. Consequently, an understanding of how volatility evolves over time is central to the decision making process. This is accomplished by estimating a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. Judging by the findings in voluminous recent literature, GARCH is ubiquitous. Its key characteristics-autocorrelated volatility and contiguous periods of volatility and quiescence-are exhibited by a wide variety of time series (Laux and Ng, 1993).

Moreover, optimal inference about the conditional mean of a variable requires that the conditional second moment be correctly specified. Misspecified models of volatility may lead to incorrect, or invalid, conclusions about freight dynamics.

The rest of the paper is organized as follows: In Section Ⅱ the integer differencing cointegration tests such as the Engle-Granger approach and multivariate Johansen procedure, and the fractional cointegration approach, GPH test, are presented. In Section Ⅲ we examine the persistence, size and dynamics of the response paths of freight to innovations in the exchange rate and industrial activity. We also discuss several models of predictable volatility and present the idea of a news impact curve which characterizes the impact of past shocks on the freight volatility. And we compare the GARCH(1, 1) model with the EGARCH (exponential GARCH), AGARCH (Asymmetric GARCH), and GJR (Glosten, Jaganathan and Runkle) models that allow for asymmetry in the impact of news on volatility. Finally, Section Ⅳ provides the concluding remarks.

Ⅱ. COINTEGRATION

The freight in this paper is modelled as a function of world output, world trade volume, and exchange rate. We assume a freight function of the following (log-linear) form:

$$mri = a_0 + a_1 wip + a_2 vol + a_3 rs \qquad (1)$$

where mri refers to the MRI general freight index, vol is the world trade volume, rs is the real effective exchange rate of US dollar published by the IMF and wip is the world output, which is proxied by the trade-weighted averages of industrial production indexes of the US and Japan[1]. All series are extracted from the International Monetary Fund's *International Fianancial Statistics* CD ROM and the Korea Maritime Institute's *KMI Maritime Review*. They span the period January 1980 to December 2000.

[1] The shipping industry is known to be greatly affected by the industrial activities of Japan and America(Lee, 1990; Yang, 1995).

We first examine the univariate time-series properties of the series by testing whether the series are stationary or not. Existence of unit root means that a series is not stationary. Two tests are conducted to determine the existence of unit roots in the series. The first, the augmented Dickey-Fuller (ADF) test for unit roots (Dickey and Fuller, 1979, 1981) indicates whether an individual series, X, is stationary by estimating the following regression using ordinary least squares:

$$\Delta X_t = c_0 + b_0(Time) + b_1 X_{t-1} + \sum_{i=1}^{p} c_i \Delta X_{t-i} + \varepsilon_t \tag{2}$$

where X_t is the individual time series, Δ is the first difference operator, ε_t is a serially uncorrelated random term, and p is the number of lags. A series is stationary if the coefficient of the lagged variable(b_1 in Equation 2) is negative and significantly different from zero. We test the null hypothesis of a unit root with a constant in the regression by $t\alpha^*$ and with a constant and a time trend in the regression by $\tilde{t\alpha}$ statistic. In addition, we provide Phillips-Perron[2] (Phillips and Perron, 1988) unit root test statistics which are more robust in the case of weakly autocorrelated and heteroscedastic regression residuals(Zhu, 1996).

[Table 1] Tests for unit root

			mri	*vol*	*wip*	*rs*
Dickey-Fuller	$t\alpha^*$	Level	-2.17(8)	-1.35(9)	-0.48(7)	-1.19(1)
		First Difference	-5.35(7)*	-3.85(9)*	-4.33(6)*	-11.4*
	$\tilde{t\alpha}$	Level	-2.70(8)	-0.27(9)	-0.45(6)	-1.25(1)
		First Difference	-5.44(7)*	-4.21(9)*	-4.29(6)*	-10.2(1)*
Phillips-Perron	$Z(t\alpha^*)$	Level	-2.50	0.71^s	-0.37	-1.07
		First Difference	-8.01*	-15.2*	-26.2*	-9.07*
	$Z(\tilde{t\alpha})$	Level	-2.39	-2.78^s	-2.51	-1.12
		First Difference	-22.8*	-3.58*	-4.52*	-14.0*

Notes: Numbers in parentheses after these statistics indicate the lag length used in the autoregression to ensure residual whiteness. For both sets of statistics, the null hypothesis is that the series in question is $I(1)$. Approximate critical value at the 5 percent level for $t\alpha^*$ and $Z(t\alpha^*)$ is -2.89, with rejection region $\{\phi | \phi < -2.89\}$; the 5 percent rejection region for $\tilde{t\alpha}$ and $Z(\tilde{t\alpha})$ is $\{\phi | \phi < -3.43\}$(See Fuller, 1976). An asterisk denotes significance at the 5 percent level.

[2] The ADF test relies on a parametric approach to deal with serial correlation and heterogeneity. Since this solution reduces the power of the test, the testing procedure by Phillips and Perron (1988), which is based on a non-parametric correction for serial correlation, has been implemented.

Table 1 provides the unit root test results. The number of lags entering the estimated equation is determined on the performance of the Lagrange multiplier test for serial correlation. It is clear that we cannot reject the null hypothesis of a unit root in each of the level variables at the 5 percent significance level. All of the statistics indicate that the first differences of the variables are stationary. Therefore, we conclude that the variables are nonstationary in levels and stationary in differences. Based on this result, we test whether variables are cointegrated or whether there is an equilibrium relationship between them.

The next step in the test for cointegration is to estimate the cointegrating regressions and to conduct unit root tests upon the residuals from these regressions. The augmented Dickey-Fuller test procedure is used to test for the presence of a unit root for the residuals from the cointegrating regression. The ADF regression equation is

$$u_t - u_{t-1} = \Delta u_t = \gamma_0 u_{t-1} + \sum_{j=1}^{p} \Delta u_{t-j} + \varepsilon_t \tag{3}$$

The lag length (p=3) entering Equation 3 is chosen to be shortest for which, using the Box-Ljung Q-statistic, the hypothesis of white noise of the residuals cannot be rejected at the 5 percent significance level. The results from Table 2 show that the null hypothesis of a unit root for the residuals from the cointegration cannot be rejected at the 5 percent level.

[Table 2] Engle-Granger cointegration tests

DF	ADF
-2.25	-3.28(3)

However, the test, which relies on the Engle-Granger two step methodology, suffers from a number of deficiencies. The Johansen procedure poses several advantages over the popular residual-based Engle-Granger two-step approach in testing for cointegration.[3]

To test for cointegration we follow the procedure developed by Johansen (1988). The following explanation of this procedure borrows heavily from Johansen and Juselius (1990). Suppose that we have a pth order vector autoregressive process (VAR)

$$X_t = A_1 X_{t-1} + A_2 X_{t-2} + \cdot \cdot \cdot + A_p X_{t-p} + \varepsilon_t \tag{4}$$

where X_t is the 4×1 vector(mri, wip, vol, rs), A_i $(i=1,2,\cdots,p)$ is the

[3] Although applications of the Johansen procedure have been quite popular in a multivariate context, results from Johansen statistics in bivariate studies have also been shown to be more robust than those from adopting the Engle-Granger approach (Masih and Masih, 1995).

4×4 matrix of coefficients and ε_t is a four-dimensional Gaussian error process. We can rewrite Equation 4 as

$$\Delta X_t=\sum_{i=1}^{p-1}\Pi_i \Delta X_{t-i}+\Pi X_{t-p}+\varepsilon_t \tag{5}$$

where

$$\Pi=-(I-\sum_{i=1}^{p}A_i)$$

and

$$\Pi_i=-(I-\sum_{j=1}^{i}A_j)$$

The rank of the matrix Π is equal to the number of independent cointegrating vectors and the number of distinct cointegrating vectors can be obtained by checking the significance of the characteristic roots of Π. This test for the number of characteristic roots that are insignificantly from unit can be conducted using the following two test statistics:

$$trace(r)=-T\sum_{i=r+1}^{n}\ln(1-\hat{\lambda}_i) \tag{6}$$

$$\lambda_{\max}(r,\ r+1)=-T\ln(1-\hat{\lambda}_{r+1}) \tag{7}$$

where $\hat{\lambda}_i$ are the estimated values of the characteristic roots obtained from the estimated Π matrix and T is the number of usable observations. The first statistic tests the null hypothesis that the number of distinct cointegrating vectors is less than or equal to r against a general alternative. The second statistic tests the null hypothesis that the number of cointegrating vectors is r against the alternative of $r+1$ cointegrating vectors.

In order to implement the Johansen procedure, a lag length must be chosen for the VAR, and the orders of integration of the series entering the VAR must be determined. Our procedure for choosing the optimal lag length was to test down from a general 12-lag system until reducing the order of the VAR by 1 lag could be rejected using a likelihood ratio statistic. The residuals from the chosen VAR were then checked for whiteness. If the residuals in any question proved to be nonwhite, we sequentially chose a higher lag structure until they were whitened.

The maximum likelihood estimates of the cointegrating vectors appear in Table 3. The row headed VAR(i) displays the results of the Johansen test on a vector regression of lag length i. In all cases the hypothesis of no cointegrating vector($r=0$) can be rejected at the 5 percent level.

[Table 3] Results of the Johansen test

	trace				λ_{max}			
	$r=0$	$r\leq1$	$r\leq2$	$r\leq3$	$r=0$	$r\leq1$	$r\leq2$	$r\leq3$
VAR(1)	70.51*	28.94	10.75	0.417	41.56*	18.19	10.75	0.417
VAR(2)	57.25*	30.57	12.13	0.303	28.68*	18.44	10.12	0.303
VAR(3)	59.71*	32.47	14.21	0.722	29.24*	18.25	12.14	0.722

Notes: An asterisk denotes significance at the 5 percent level. Critical values are found in Osterwald-Lenum (1992).

The Johansen test results differ dramatically from those of the residual-based tests. This is because the above-mentioned cointegration analyses enable us to test for a long-run relationship, but ignores the short-run dynamics. Tests for cointegration often draw on unit root tests that presume the order of integration of the equilibrium error to be an integer. A system of economic variables, however, can be fractionally cointegrated such that its equilibrium errors follow a fractionally integrated process (Granger, 1986).

Fractionally differenced processes explored by, e.g., Granger and Joyeux (1980) and Hosking (1981) can be used to model parametrically long-memory dynamics. Under this approach, whether a series displays long memory depends on a fractional differencing parameter, which is amenable to estimation and hypothesis testing. A general class of long-memory process is described by

$$B(L)(1-L)^d x_t = C(L)u_t, \tag{8}$$

where $B(L)=1-b_1L-\cdots-b_pL^p$ and $C(L)=1+c_1L+\cdots+c_qL^q$ are polynomials in the lag operator L, all roots of $B(L)$ and $C(L)$ are stable, and u_t is a white-noise disturbance term. The fractional parameter, given by d, assumes any real values. This fractional model includes the usual autoregressive moving-average (ARMA) model as a special case in which $d=0$. The extension to have non-integer values of d raises the flexibility in modeling long-term dynamics by allowing for a rich class of spectral behavior at low frequencies. Granger and Joyeux (1980) and Hosking (1981) show that the spectral density function of x_t, denoted by $f_x(w)$, is proportional to w^{-2d} as w becomes small. The fractional parameter thus crucially determines the low-frequency dynamics of the process.

A spectral method suggested by Geweke and Porter-Hudak (1983) can be used to estimate the fractional parameter d. The Geweke-Porter-Hudak (GPH) method provides a semi-non-parametric test for fractional processes that requires no explicit parameterization of the unknown ARMA dynamics. The statistical procedure involves estimating d using a spectral regression:

$$\ln(I(w_j)) = \phi_0 - \phi_1 \ln(4\sin^2(w_j/2)) + \varepsilon_t, \quad j=1,2,\cdots,n, \tag{9}$$

where $I(w_j)$ is the periodogram at the harmonic frequency $w_j = 2\pi j/T$, ε_t is a random error term, and $n = T^{\mu}$ for $0<\mu<1$ is the number of low-frequency ordinates used in the regression. The periodogram $I(w_j)$ is computed as the product of $2/T$ and the square of the exact finite Fourier transform of the series $\{x_1, x_2, \cdots, x_T\}$ at the respective harmonic ordinate. Geweke and Porter-Hudak (1983) show that the least squares estimate of ϕ_1 provides a consistent estimate of d and hypothesis testing concerning the value of d can be based on the usual t-statistic. The theoretical error variance for ε_t is known to be equal to $\pi^2/6$, which is typically imposed in estimation to raise efficiency.

In applying the GPH spectral procedure, the number of low-frequency ordinates, n, used in the spectral regression is a choice variable. The choice necessarily involves judgment. While too large a value of n will cause contamination of the d estimate due to medium- or high-frequency components, too small a value of n will lead to imprecise estimates due to limited degree of freedom in estimation. To balance these two consideration factors, we experiment with a range of μ values used for the sample size function, $n = T^{\mu}$. The results are for μ=0.500, 0.525, 0.550, 0.575, and 0.600.

Table 4 contains the estimates for the fractional parameter d from the GPH spectral regression. The d estimates are reported together with their t-statistics. Table 4 shows that all of the estimates of d lie between 0 and 1, suggesting possible fractional integration behavior. Moreover, in all cases, the estimates of d are significantly greater than 0 and less than 1. The results indicate the presence of cointegration and fractional cointegration.

[Table 4] Results of the GPH test for cointegration

	μ				
	0.500	0.525	0.550	0.575	0.600
$d(d=0)$	0.441*(2.535)	0.468*(2.804)	0.453*(2.634)	0.277*(3.548)	0.328*(3.748)
$d=1$	0.0054*	0.0041*	0.0012*	0.0000*	0.0000*

Notes: The sample size for the GPH is given by $n = T^{\mu}$. An asterisk denotes significance at the 5 percent level. The hypothesis H_0: $d=1$ is tested against the one-sided alternative of $d<1$. The hypothesis H_0: $d=0$ is tested against the two-sided alternative of $d\neq 0$. The figures in parentheses are the t-statistics for the corresponding fractional parameter d estimates.

Ⅲ. NEWS AND FREIGHT VOLATILITY

In this section we use a GARCH model to test whether the uncertainty has any effect on the freight. The most popular approaches to forecasting volatility are the ARCH model, introduced by Engle (1982) and expanded by Engle et al. (1987), and GARCH model, proposed by Bollerslev (1986).

According to the ARCH model the conditional error distribution is normal, but with conditional variance equal to a linear function of past squared errors. Thus, there is a tendency for extreme values to be followed by other extreme values, but of unpredictable sign. Mandelbrot (1963) notes that large changes tend to be followed by large changes-of either sign-and small changes tend to be followed by small changes. These aspects, periods of quiescence followed by periods of turbulence, are captured by the ARCH model (Domowitz and Hakkio, 1985).

Engle (1982) suggests that the conditional variance h_t can be modeled as a function of the lagged ε's. That is, the predictable volatility is dependent on past news. The most detailed model he develops is the pth order autoregressive conditional heteroskedasticity model, the ARCH(p):

$$\Delta rs_t = b_0 + b_1 \Delta rs_{t-1} + \varepsilon_{t+1} \tag{10}$$

$$\Delta wip_t = b_0 + b_1 \Delta wip_{t-1} + \varepsilon_{t+1} \tag{11}$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \tag{12}$$

where $\alpha_1, \cdots, \alpha_p$, and ω are constant parameters. The effect of a return shock i periods ago ($i \le p$) on current volatility is governed by the parameter α_i. Normally, we would expect that $\alpha_i < \alpha_j$ for $i > j$. That is, the older the news, the less effect it has on current volatility. In an ARCH(p) model, old news which arrived at the market more than p periods ago has no effect at all on current volatility.

Bollerslev (1986) generalizes the ARCH(p) model to the GARCH(p, q) model, such that

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} \tag{13}$$

where $\alpha_1, \cdots, \alpha_p$, $\beta_1, \cdots, \beta_p$, and ω are constant parameters. The GARCH model corresponds to an infinite order ARCH model. A common parameterization for the GARCH model that has been adopted is the GARCH (1, 1) specification under which the effect of a shock to volatility declines geometrically over time.

[Table 5] Maximum-likelihood estimates of GARCH model

	exchange rate volatility	world output volatility
b_0	-0.0013*(-6.387)	0.0028(1.205)
b_1	0.326*(54.64)	0.103*(5.518)
ω	0.0003*(26.04)	0.0001(1.527)
α_1	0.120*(10.11)	0.677*(5.005)
β_1	0.131*(2.181)	0.222*(2.206)

Notes: An asterisk denotes significance at the 5 percent level.

Empirically, the family of GARCH (1, 1) is preferred in most cases (Bollerslev et al., 1992). Table 5 contains estimation results for the exchange rate volatility and world output volatility. The parameters(α_1 and β_1) are less than unity and statistically significant.

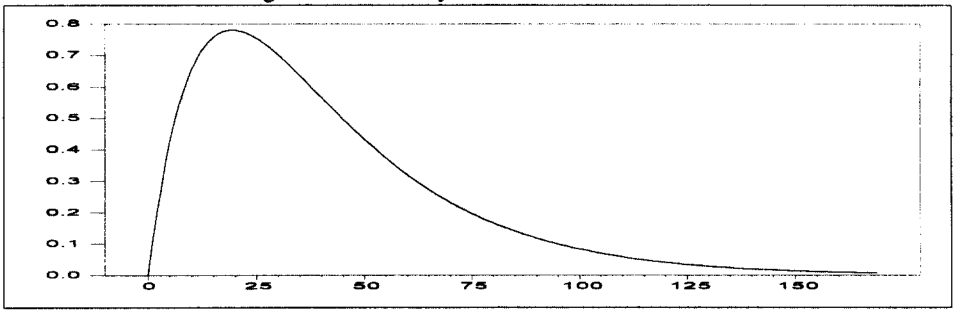
We also employ the impulse response functions to get additional information regarding the responses of the variables to the shocks in the other variable. These impulse response functions show the effect of a one standard deviation shock applied to one of the equations, on both the short and long-run responses of all variables in the system.[4]

Consider a pth order vector autoregressive process

$$X_t = \sum_{i=1}^{p} A_i X_{t-i} + \varepsilon_t \tag{14}$$

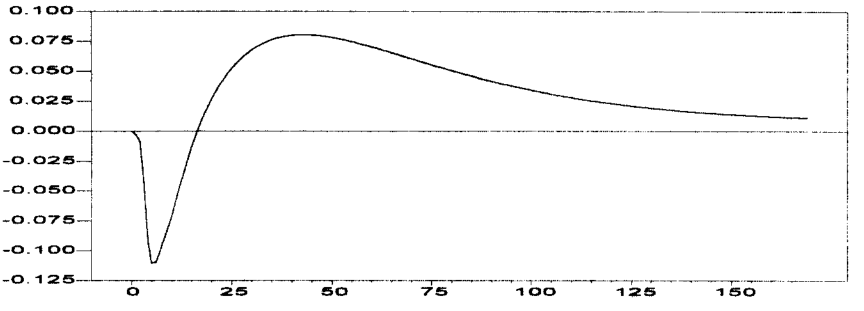
where X_t is the 5×1 vector(*mri, vol, wip, rs, volatility*), and A_i's are estimable parameters. The responses of freight to a shock in the uncertainty of exchange rate and industrial activity are presented in Figure 1 and 2. Figure 1 indicates that freight increases sharply before peaking twenty months after the shocks to exchange rate and declines slowly to its pre-shock level.

[Figure 1] Impulse responses of freight from a one standard deviation shock to the exchange rate volatility



[4] The results are presented assuming no contemporaneous feedback, although any ordering of these variables does not qualitatively affect the results.

[Figure 2] Impulse responses of freight from a one standard deviation shock to the industrial activity volatility



Compared to the response pattern in exchange rate shock, Figure 2 shows that a positive industrial activity uncertainty shock causes freight to increase after a six-month lag, peaking after forty months but to decline more slowly to its pre-shock level. These results show that the ocean freight contain a risk premium, representing the extra freight the shipping companies require to compensate for the risk.

Despite the apparent success of these simple parameterizations, the ARCH and GARCH models cannot capture some important features of the data. The most interesting feature not addressed by these models is the leverage or asymmetric effect discovered by Black (1976), and confirmed by the findings of French, Schwert, and Stambaugh (1987), Nelson (1990), and Schwert (1990), among others.[5] Statistically, this effect occurs when an unexpected drop in price(bad news) increases predictable volatility more than an unexpected increase in price(good news) of similar magnitude. This effect suggests that a symmetry constraint on the conditional variance function in past ε's is inappropriate. One method proposed to capture such asymmetric effects is Nelson's (1990) exponential GARCH or EGARCH model.

The ARCH(p) and GARCH(p, q) models impose symmetry on the conditional variance structure which may not be appropriate for modelling and forecasting stock return volatility. Nelson (1991) proposes the exponential GARCH or EGARCH model as a way to deal with this problem. Under the EGARCH (1, 1) the conditional variance is given by

$$\log(h_t) = \omega + \alpha\left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{2/\pi}\right] + \beta\log(h_{t-1}) + \delta\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \tag{15}$$

[5] It is not yet clear in the finance literature that the asymmetric properties of variances are due to changing leverage. The name "leverage effect" is used simply because it is popular among researchers when referring to such a phenomenon.

where w, α, β, and δ are constant parameters. The EGARCH model has two distinct advantages over the GARCH model. First, the logarithmic construction of Equation 15 ensures that the estimated conditional variance is strictly positive, thus the non-negativity constraints used in the estimation of the ARCH and GARCH models are not necessary. Secondly, since the parameter δ typically enters Equation 15 with a negative sign, bad news, $\varepsilon_t<0$, generates more volatility than good news.

The asymmetric GARCH(1, 1) model (AGARCH(1, 1)) of Sentena (1992) takes the form

$$h_t=\omega+\alpha(\varepsilon_{t-1}+\delta)^2+\beta h_{t-1} \tag{16}$$

where $w>0$, $\alpha\geq 0$, $\beta\geq 0$ are constant parameters. The estimated value of the parameter δ is usually negative, thus Equation 16 responds asymmetrically to positive and negative shocks of equal magnitude. Glosten et al. (1993), hereafter GJR, propose an alternative model

$$h_t=\omega+\alpha\varepsilon_{t-1}^2+\beta h_{t-1}+\delta N_{t-1}\varepsilon_{t-1}^2 \tag{17}$$

where N_{t-1} is a dummy variable that takes the value of unity if $\varepsilon_{t-1}<0$ and zero otherwise. The GJR model is closely related to the threshold ARCH, or TARCH model of Rabemananjara and Zakoian (1993) and Zakoian (1994). Provided that $\delta>0$, the GJR model generates higher values for h_t, given $\varepsilon_{t-1}<0$, than for a positive shock of equal magnitude. As with the ARCH and GARCH models the parameters of the conditional variance, Equation 17, are subject to non-negativity constraints.

[Table 6] News impact curves

Model	News impact curve
GARCH(1, 1)	$h_t=A+\alpha\varepsilon_{t-1}^2$ where $A=\omega+\beta\sigma^2$
EGARCH(1, 1)	$h_t=A\cdot\exp\left[\frac{(\delta+\alpha)}{\sigma}\cdot\varepsilon_{t-1}\right]$, for $\varepsilon_{t-1}>0$ $h_t=A\cdot\exp\left[\frac{(\delta-\alpha)}{\sigma}\cdot\varepsilon_{t-1}\right]$, for $\varepsilon_{t-1}<0$ where $A\equiv\sigma^2\beta\cdot\exp\left[\omega-\alpha\sqrt{\frac{2}{\pi}}\right]$
AGARCH	$h_t=A+\alpha(\varepsilon_{t-1}+\delta)^2$ where $A=\omega+\beta\sigma^2$
GJR	$h_t=A+\alpha\varepsilon_{t-1}^2$, for $\varepsilon_{t-1}>0$ $h_t=A+(\alpha+\delta)\varepsilon_{t-1}^2$, for $\varepsilon_{t-1}<0$ where $A=\omega+\beta\sigma^2$

Supposing that information is held constant at time $t-2$ and before, Engel and Ng (1993) describe the relationship between ε_{t-1} and h_t as the news impact curve. It is the purpose of this study to illustrate the difficulties in deciding upon the shape and location of the relationship between ε_{t-1} and h_t.

The news impact curves of the GARCH(1, 1) and AGARCH models are symmetric and centered at $\varepsilon_{t-1}=0$ and $\varepsilon_{t-1}=-\delta$, respectively. The news impact curves of the EGARCH(1, 1) and GJR models are centered at $\varepsilon_{t-1}=0$. The EGARCH(1, 1) has a steeper slope for $\varepsilon_{t-1}<0$, provided that $\delta<0$ in Equation 15, while the GJR has different slopes for its positive and negative sides. Table 6 and Figure 3 present the relevant news impact curves, evaluating the lagged conditional variance h_t, at its unconditional level σ^2.

[Figure 3] News impact curves

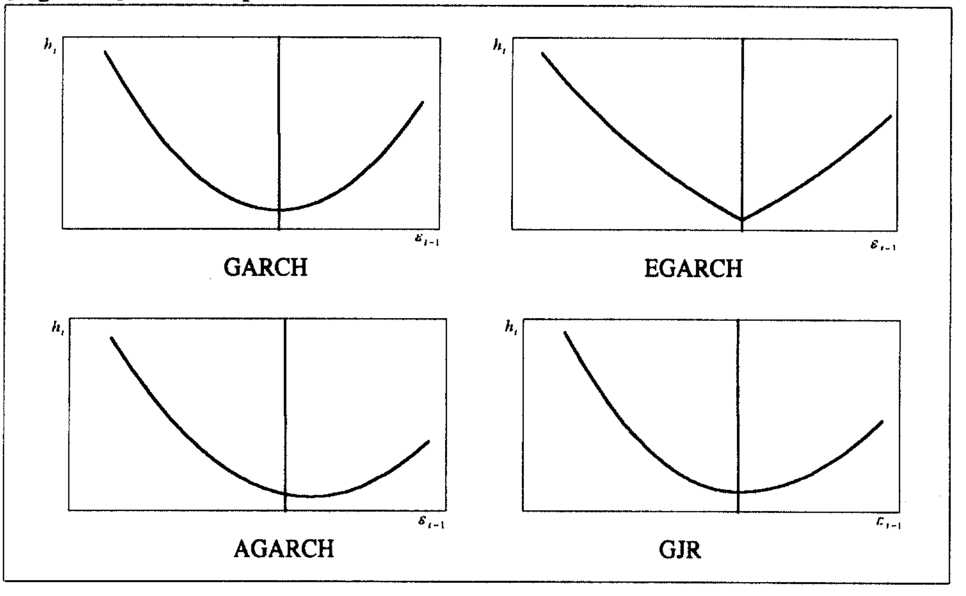


Table 7 reports the estimation results of various predictable volatility models. The estimation is performed by the method of quasi maximum likelihood using the BHHH (Berndt, Hall, Hall and Hausman) numerical optimization algorithm. The sample period is from January 1980 to December 2000. In the estimation results part of the table, the numbers of parentheses are the t-statistics. The estimation results in Table 7 indicate that the parameters corresponding to the $\varepsilon_{t-1}/\sqrt{h_{t-1}}$ term in the EGARCH, and the constant in the quadratic form in the AGARCH are all significant and negative. The parameter corresponding to the $\varepsilon_t^2 k_t$ term in the GJR is significant and positive. All these results are consistent with the hypothesis that negative shocks cause higher volatility than positive shocks. The clustering phenomenon can also be confirmed by showing the volatility of the variance models in Figure 4.

[Table 7] Estimation of the volatility models

GARCH(1, 1)

$$\begin{array}{llll} h_{t+1} = 0.006 & + \ 0.223 \cdot \varepsilon_t^2 & + \ 0.515 \cdot h_t \\ \quad\ (2.53) & \quad (2.39) & \quad (7.75) \end{array}$$

EGARCH(1, 1)

$$\begin{array}{lllll} \log(h_{t+1}) = & -1.408 & +\,0.342 \cdot \left[\left|\dfrac{\varepsilon_t}{\sqrt{h_t}}\right| - \sqrt{2/\pi}\right] & +\,0.414 \cdot \log(h_t) & -\,0.444 \cdot \dfrac{\varepsilon_t}{\sqrt{h_t}} \\ & (-12.6) & (17.5) & (10.6) & (-3.88) \end{array}$$

AGARCH(1, 1)

$$\begin{array}{llll} h_{t+1} = 0.003 & + \ 0.270 \cdot h_t & + \,0.426 \cdot & (\varepsilon_t - 0.347)^2 \\ \quad\ (1.01) & \quad (7.32) & \quad (7.57) & (-3.49) \end{array}$$

GJR

$$\begin{array}{lllll} h_{t+1} = & 0.001 & + \,0.295 \cdot h_t & + \,0.457 \cdot \varepsilon_t^2 & + \,0.238 \cdot \varepsilon_t^2 k_t \\ & (2.79) & (7.28) & (3.58) & (2.32) \end{array}$$

[Figure 4] Volatility of the variance models

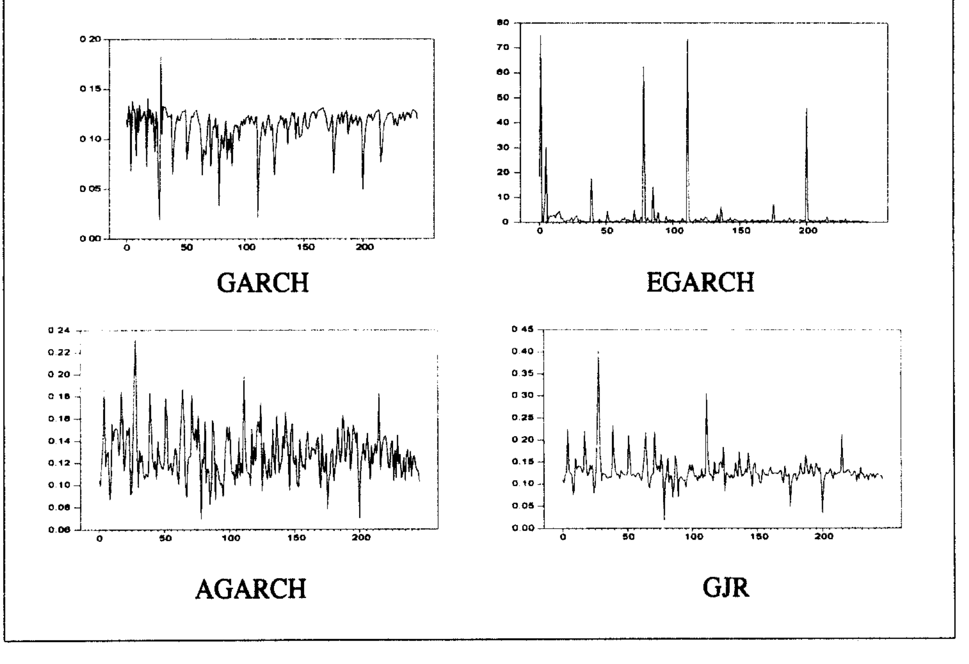


Table 8 reports news impact curves calculated for the various models for a range of values for ε_{t-1}. Relative to the asymmetric models, the symmetric GARCH(1, 1) model tends to overstate the variance for $\varepsilon_{t-1}>0$ and to understate the variance for $\varepsilon_{t-1}<0$. However, for large negative values of ε_{t-1} the EGARCH model returns unreasonably large estimates of h_t. For a value of -5.0 for ε_{t-1} the estimated conditional variance from the EGARCH news impact curve is 430.67.

[Table 8] Estimated News Impact Curves

ε_{t-1}	GARCH	EGARCH	AGARCH	GJR
5.0	5.576	309.24	8.871	11.42
4.5	4.517	112.89	7.037	9.255
4.0	3.569	41.21	5.409	7.313
3.5	2.733	15.04	3.998	5.599
3.0	2.008	5.492	2.799	4.114
2.5	1.395	2.005	1.814	2.857
2.0	0.893	0.732	1.042	1.829
1.5	0.503	0.267	0.482	1.029
1.0	0.224	0.097	0.136	0.458
0.5	0.057	0.035	0.082	0.115
0.0	0.001	0.013	0.003	0.001
-0.5	0.057	0.037	0.375	0.175
-1.0	0.224	0.104	0.881	0.696
-1.5	0.503	0.295	1.599	1.565
-2.0	0.893	0.835	2.531	2.781
-2.5	1.395	2.366	3.676	4.345
-3.0	2.008	6.699	5.033	6.256
-3.5	2.733	18.97	6.604	8.515
-4.0	3.569	53.71	8.388	11.12
-4.5	4.517	152.10	10.38	14.07
-5.0	5.576	430.67	12.59	17.37

Additionally, for large positive values of ε_{t-1} the estimated conditional variance increases for the EGARCH, which is unattractive. The news impact curve estimates suggest that the EGARCH model is too extreme in the tails, and thus is an inadequate characterization of the conditional variance of the freight. The AGARCH appears to be more reasonable model to use.

Ⅳ. CONCLUDING REMARKS

The main purpose of this paper is to show the relationship between freight and uncertainties of exchange rate and industrial output over the monthly period 1980-2000. First, we tested for a unit root; in no case could the null hypothesis of an $I(1)$ series be rejected. We then used the Engle-Granger cointegration procedure and Johansen technique to test for long-run stability. Two tests, however, showed the contradicting results. The GPH test was therefore applied, indicating the model introduced here is stationary.

We also employed the impulse response function to get an information regarding the responses of freight to the shocks in the volatility of exchange rate and industrial activity. The freight responded positively to the shock in the exchange rate volatility, whereas the response of the freight declined initially and then increased upon the shock to the industrial output.

This paper applied the news impact curve as a standard measure of how news is incorporated into volatility estimates. In order to better estimate and match news impact curves to the data, several candidates for modeling time-varying volatility were adopted and contrasted.

Empirically, the family of GARCH models has been successful. The GARCH models, however, cannot capture some important features of the data. The most interesting feature not addressed by these models is the leverage or asymmetric effect. Hence, we introduced the models capturing such asymmetric effect, which included the EGARCH, AGARCH, and GJR models.

These models were fitted to monthly freight volatility from 1980 to 2000. All the models found that negative shocks introduced more volatility than positive shocks, with this effect particularly apparent for the largest shocks. Overall, the AGARCH was the best at capturing this asymmetric effect. Furthermore, the AGARCH model successfully revealed the shape of the news impact curve and was a useful approach to modeling conditional heteroscedasticity.

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