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The Impact of 9/11 on the Persistence of Financial Return Volatility of Marine Firms

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This paper analyzes the effects of the terror attacks of 9/11 on a set of listed marine operator equities. The paper uses GARCH models to compare volatility before 9/11 and after 9/11 to determine whether there was a systematic change in the persistence of volatility. The results of the paper indicate that the persistence of volatility increased following 9/11. The increased persistence implies that the negative effects from increased market risk die out more slowly. If, as expected, society prefers less risk persistence to more, the results suggest that policy actions that reduced these effects would be welfare enhancing. Having quantifiable measures of the secondary impacts of terrorism is valuable since it is challenging to measure primary effects of terror threat levels and changes to those levels from policy actions.
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INTRODUCTION

The attacks of September 11, 2001 had both political and economic effects. After 9/11, investors may have perceived that the physical assets of the transport system were not only targets but were a means to carry out terrorist attacks. Ships, goods, cargo, and facilities can all serve as weapons of destruction of terrorism. Additionally, the response to a significant terror attack has wider impacts on trade and transportation. For example, the US government response to 9/11 included shutting down the traffic system, which caused huge delays and disruptions to users of the port system [Bichou 2004]. Because of potential adverse impacts to future business operations, investor's perceptions of future profit and dividend streams would be less than before. In efficient market pricing theory, prices are a function of those streams and the market translates new information and perceptions on the threat of terror attacks into prices. Similarly, the market translates this information into changes to the assets' financial risk profile based on its underlying relationship with the market. In other words, if 9/11 exerted a relatively negative impact on the financial risk of marine operators, then these firms would face a higher relative financial risk than the market as a whole. If the market viewed these events as having a long-term impact on the operations of directly impacted firms such as marine operators (and airlines), then there could be long-term adverse market effects to these firms. Conversely, if the market viewed the terrorist attacks as a one-time fluke event, there would not be any expected long-term impacts on financial risk.

Preliminary results are that there have been long-term effects. Drakos [2004] found that there was an increase in systematic risk (beta) on a set of airline stocks following the terror attacks of September 11, 2001. His results had adverse implications for portfolio diversification and the cost (and ability) of airlines in raising capital. Drakos also found that idiosyncratic risk (return volatility) increased significantly as well; this result implies increased market risk for those firms. Both were real economic costs and were ancillary costs resulting from 9/11. Similar to Drakos, Homan [2006] also found that 9/11 resulted in a structural increase in systematic and idiosyncratic risk for a sample of marine operator firms listed on Nasdaq and the NYSE. Both of these papers investigated first and second moment effects on the return probability distribution.

This paper studies the effects of 9/11 on kurtosis and the persistence of idiosyncratic risk (volatility) on the same set of marine operator stocks studied by Homan. The analysis focuses on investigating structural changes in return volatility (idiosyncratic risk) following 9/11 and structural changes affecting the persistence of that return volatility. The paper builds on Homan and differs from it in that it investigates the persistence of second moment effects and investigates fourth moment effects. The paper is organized as follows: The next section provides a description of the data sources used and the firms in the sample. The third section provides a general background on the finance theory underpinning the discussion of total financial risk, and the section that follows discusses the impact of 9/11 on changes in return volatility and kurtosis. The fifth section discusses the impact of 9/11 on the persistence of return volatility using a generalized autoregressive conditional heteroskedasticity (GARCH) approach. The sixth section provides a sensitivity analysis. The section investigates results using higher order GARCH models, looks at results after controlling for significant firm-specific events, and investigates the results using asymmetric models. The section also compares the results to two samples of firms potentially affected by 9/11: one that is expected to be more affected (airlines) and one that would be somewhat less (more diversified marine firms). The final section concludes the paper.

DATA AND SAMPLE

The paper uses the exact same sample that Homan [2006] used to estimate the impact of 9/11 on systematic risk, returns, and volatility. In this way, any inferences about the persistence of volatility are applicable to the earlier results. The data set for the analysis consists of daily stock market returns for the 19 marine operators found in the August 2005 *Workboat* Composite Index who are listed on Nasdaq or the NYSE. These operators' primary business, or a significant portion of their business, relates to marine transportation services. At the same time, they are diversified businesses. There is not a sample of publicly traded US businesses whose sole line of business is marine transportation services during the sample period. As such, there is not an exact "pure play" for studying the impact of 9/11 as there is with airlines. However, these firms represent the closest proxy to a "pure play" for studying the effects of terrorism on marine operators trading on US markets. The Workboat index also contains sub-groups for suppliers like Raytheon and shipyards such as Northrop Grumman. However, many of the firms in these two sub-groups are more diversified and some are likely to have been beneficiaries of 9/11 due to increased defense spending. The additional diversification might mitigate somewhat any effects from 9/11. Consequently, these firms are less of a "pure play" than the sub-group for marine operators and we do not include them in the sample. However,

Table 1 Marine operators in sample

Firm	*Stock symbol*	*Exchange*	*Description*
TECO energy Inc.	TE	NYSE	TECO provides waterborne transportation, storage, and transfer services of coal and other dry bulk commodities.
Tidewater Inc.	TDW	NYSE	Tidewater provides offshore supply vessels and marine support services to the offshore energy industry.
Kirby Corp.	KEX	NYSE	Kirby engages in inland transportation of chemicals and oil products by tank barges and offshore transportation of dry-bulk cargoes by barge.
Ensco International	ESV	NYSE	Ensco provides offshore drilling services and maintains and operates a fleet of offshore equipment.
Maritrans Inc.	TUG	NYSE	Maritrans engages in the ownership and operation of ocean-going tank barges, tugboats, and tankers used in the transportation of oil in the United States.
Superior Energy Services	SPN	NYSE	Superior provides oilfield services and equipment and operates lifeboats for production service activities.
Seacor Holdings Inc.	CKH	NYSE	Seacor engages in the ownership, operation, and marketing of offshore supply vessels and a fleet of inland dry cargo barges.
Global Industries	GLBL	Nasdaq	Global provides marine construction services and operates a fleet of offshore construction vessels.
Gulfmark Offshore	GMRK	Nasdaq	Gulfmark operates vessels and provides marine support and transportation services to offshore energy industry.
Global Santa Fe Corp.	GSF	NYSE	The company operates as an offshore oil and gas drilling company and operates a fleet of offshore equipment.
Cal Dive Int'l	CDIS	Nasdaq	Cal Dive operates a fleet of vessels offering marine construction and diving services to the energy services industry.

the sensitivity analysis section will compare the results of this sample to the results for the marine operators.[1] That section will also compare the results to a sample of domestic (i.e., US) airlines; this includes US airlines in Drakos' sample as well as important additions.[2]

Only marine operators traded over the full period of analysis from 9/01/00 through 10/31/02 that had a statistically significant relationship with the market are in the final sample.[3] The period of analysis covers a year before 9/11 and a period of just over a year following the attacks. This "full sample" constraint excludes eight firms from the sample. The S&P 500 is the proxy for the market portfolio. All returns data are from the Center for Research in Security Prices. All returns are daily returns based on closing prices. Throughout the study, the paper will report results for the market, an equally weighted portfolio of the 11 companies in the sample, as well for the individual firms in the sample. Table 1 shows the remaining 11 marine operators in the sample and a brief description of each firm.

FINANCIAL ECONOMICS AND RISK

As previously noted, if the market viewed the threat of terror attacks as having a permanent impact on the operations of directly impacted firms such as marine operators, then there could be permanent adverse market effects to these firms. Kavussanos et al. [2003] and Kavussanos and Marcoulis [2001] have previously investigated shipping-related stock returns using monthly returns data. Homan [2006] investigated stock returns, systematic risk, and return volatility using daily data. Like Homan, this paper uses daily returns data. It is the first paper to directly investigate how 9/11 affected the persistence of return volatility to the US-regulated community affected by it. It differs from Homan in that it investigates the persistence of volatility (as opposed to the actual level of volatility) and investigates kurtosis.

To estimate market impacts of 9/11 on marine operators, the paper starts by calculating and analyzing returns for these companies. Financial economics focuses primarily on returns since returns have more attractive statistical properties.[4] In particular, returns are stationary (do not have a unit root) while prices are non-stationary. This implies, among other things, that after a significant decline in price due to a negative news event, future prices are less than before. Throughout the paper, the analysis relies on log returns (continuously compounded returns). The log return of any asset R_i is as follows:

(1) $$R_i = lnP_t - lnP_{t-1}$$

Financial Economics relies on the market model to estimate the impact on systematic risk. The market model is a statistical model that models the return on any given security according to its relationship with the market. The market model decomposes each asset's total financial risk into two components of risk: systematic and idiosyncratic risk [Sharpe 1964]. Investors can costlessly diversify away idiosyncratic risk, which, as a result, means that the market does not reward investors for bearing that risk. Conversely, investors cannot diversify away systematic risk. Consequently, the only risk that rational economic agents price in efficient markets is systematic risk since the market must reward investors for bearing that risk.

In the market model, systematic risk is the asset's return covariance with the market return. This is the beta regression coefficient from the market model regression equation [Campbell et al. 1997].

(2) $$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

In the model, R_{it} and R_{mt} are the period-t returns on security i and the market portfolio, respectively, and ε_{it} is the zero mean disturbance term. The parameters of the market model are α_i and β_i. The β_i parameter, or the quantity of systematic risk, is simply the resulting beta coefficient from the ordinary least squares (OLS) regression shown below.

(3) $$\beta_i = cov(R_{it}, R_{mt})/var(R_{mt})$$

This is the beta that both Drakos and Homan estimate to determine whether 9/11 had an adverse impact on systematic risk following 9/11. When using the market model in an event study, the correct procedure is to apply parameter estimates from an estimation period to actual market returns in an event period. The estimation period does not include the event period in question, and usually ends at least several trading days before the start of the event period. The event period usually covers the period where the release of news or a catastrophic event would have an impact on prices. This can be a trading day or for a somewhat longer period when even more cumulative effects are of interest. With the market model, expected returns are a function of the equation parameters from the estimation period and actual market returns in the event period. In the model, *abnormal returns* are expected returns subtracted from actual returns in the event period. Without any new information, the expected value of an abnormal return should not be (statistically) significantly different from zero. For example, if the significance level is a 95 percent level of confidence, statistically significant abnormal returns could happen by chance five times out of 100 or less; otherwise, they are likely to be a function of new and *material* information. In other words, the event is exogenous with respect to the change in the market value of the security. Equation 4 shows the abnormal return ($ARET$), where α_e and β_e are the estimated coefficients from the estimation period.

(4) $$ARET = R_{it} - \alpha_e - \beta_e R_{mt}$$

SAR is the significance level of $ARET$. The calculation of SAR is the following standard t-test, where σ_e is the standard error of the regression in the estimation period.

(5) $$SAR = ARET/\sigma_e$$

The paper uses the event study approach in the sensitivity analysis section to capture firm-specific significant news events. This is also the approach Homan used to determine whether 9/11 had an adverse effect on returns of marine operators.

This paper will also use the market model in the section on the persistence of volatility; that section will look at the persistence of both individual return volatility and the persistence taking the market (through the market model) into account. The paper uses the sample variance of returns (σ_i^2) as the measure of return volatility (idiosyncratic risk).

Although investors should not price this risk in equilibrium since they can costlessly avoid it, idiosyncratic risk (return volatility) does have some secondary economic impacts. Increased volatility can increase market risk [Duffie and Singleton 2003]. This can result in increased prices for option-embedded securities (affects the mount of arbitrage) and in the probability of a portfolio loss of a given amount (holding other factors constant). Increased volatility can also lead to wider bid-ask spreads (due to dealers' adverse selection risk) that can reduce trading levels and result in a less than optimal amount of trading activity [O'Hara 1995]. These are real economic costs. Additionally, increased volatility can increase investment uncertainty (not to be confused with financial risk), which results in firms postponing "irreversible" investment decisions. Firms do so because the future is less certain since the predictability that demand will be either very high or very low is greater. As such, firms "wait and see" and postpone investment plans until variability returns to its old level [Bernanke 1983]. In addition to increased volatility, 9/11 may have also increased the persistence of that volatility. This would imply that future news events would swing prices more than they would have in the past. This would also have real economic costs.

CHANGES TO VOLATILITY (IDIOSYNCRATIC RISK) AND KURTOSIS

This paper seeks to determine whether 9/11 increased the persistence of return volatility and to model that volatility for both the periods prior to and after 9/11. The whole sample is for 9/1/00 through 10/31/02. The breakpoint between the two periods is 9/11/01. In this way, the paper analyzes results from 9/1/00 through 9/10/01 and the results from 9/17/01 through 10/31/02; 9/17/01 was the first trading day following the terror attacks of 9/11.

Table 2 presents descriptive statistics for each period. As noted earlier, results are for log changes (log returns). Table 2 shows that volatility increased for nine of the 11 firms in the sample and for the portfolio. Homan [2006] found that the increase in volatility was significant for much of the sample. However, the increase in volatility occurred during a time when the underlying market volatility also increased. Therefore, it is uncertain how much of the increase in volatility was due to increased uncertainty concerning marine operators' business operations and how much was due to underlying market conditions. Most of the sample exhibits excess kurtosis (fat tails). Kurtosis is the normalized fourth moment of a random variable. Normal distributions have a kurtosis equal to three. Distributions with excess kurtosis have extra probability mass in the tail areas of the distribution. This is an indication of a higher frequency of larger, more extreme return days than with a normal distribution. Kurtosis increased for seven firms and for the portfolio following 9/11. What is of interest is that kurtosis did not increase for the underlying market.[5] This might indicate that the probability of larger, more extreme return days increased for marine operators while it remained stable for the underlying market. The increased kurtosis may also be more indicative of the increased investment uncertainty stemming from the increased probability of larger (and potentially adverse) return days. If so, these results indicate that the increased investment uncertainty is not likely due to changes in the underlying market (as may have been the case with volatility). It might also indicate an increased persistence of "old bad news" events in the reaction of investors to current news events. This could imply increased persistence of volatility over time.

Table 2 Descriptive statistics

Symbol	*Mean* $r_{i\ pre\ 9/11}$	*Mean* $r_{i\ post\ 9/11}$	$\sigma^2_{i\ pre\ 9/11\ (\times 100)}$	$\sigma^2_{i\ post\ 9/11\ (\times 100)}$	*Kurtosis* $_{pre\ 9/11}$	*Kurtosis* $_{post\ 9/11}$
Portfolio	−0.000038	0.0002	0.0342	0.0416	2.976	4.162
TE	0.00073	−0.0020	0.0246	0.0740	6.512	14.490
TDW	−0.00105	−0.0002	0.0676	0.0801	4.009	3.061
KEX	0.00011	−0.0001	0.0396	0.0524	5.781	3.773
ESV	−0.00295	0.0013	0.1267	0.1282	3.747	3.760
TUG	0.00195	0.00091	0.0361	0.0404	5.747	33.939
SPN	−0.00130	0.00014	0.1253	0.1347	3.757	4.171
CKH	−0.00001	−0.00036	0.0416	0.0581	3.397	3.820
GLBL	−0.00216	−0.00204	0.1683	0.1998	4.234	9.36
GMRK	0.00086	0.00007	0.1232	0.1673	5.286	7.428
GSF	−0.00188	−0.00001	0.1253	0.1089	4.109	4.053
CDIS	−0.00185	0.00072	0.1640	0.0986	5.055	4.050
S&P 500	−0.00128	−0.00074	0.0185	0.0259	4.050	3.878

PERSISTENCE OF VOLATILITY

GARCH models are a way to model and forecast return volatility. Bollerslev [1986] originally introduced the GARCH concept and researchers frequently use these models in financial settings, as well as in other settings such as to model unemployment rates [Ewing et al. 2005]. Given the excess kurtosis shown in Table 2, GARCH models are well suited [Harvey 1994] for this sample. The approach can assist in investigating whether there are any systematic changes in the underlying components that affect volatility. These changes can affect the persistence of volatility over time.

The GARCH specification incorporates the familiar phenomenon of volatility clustering often seen in financial returns. Large returns, instead of small returns, more likely follow large returns of either sign. The most widely used model is a GARCH (1,1) model. In essence, the model has one autoregressive conditional heteroskedasticity (ARCH) term and one GARCH term. The model specifies that the variance depends on past values of the dependent variable. Older shocks to volatility have less of an effect on current volatility than more recent shocks. Equations 6 and 7 show the equations for the conditional variance and for the conventional mean.

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \Phi\sigma_{t-1}^2 \tag{6}$$

$$y_t = x_t\pi + \varepsilon_t \tag{7}$$

The sum $(\alpha + \Phi)$ in equation 6 provides information as to the degree of variance persistence. Higher sums imply that volatility shocks (impacts from economic news) die out very slowly. When the mean equation is only a constant, the actual and the residual values for ε are the same; in this case the value is theoretically the return. This paper will first estimate equation 7 with the mean as only a constant. The paper then estimates the equation using a generally accepted specification for the mean; this framework is that of the market model shown in equation 2. Consequently, the latter approach incorporates both a constant and the market return to equation 7.[6]

As a further suitability check, we run an ARCH LM test [Engle 1982] across the whole sample period on the OLS residuals of the two conventional mean equations discussed above. The procedure determines whether the size of lagged residuals influences the size of current residuals. If so, then there is likely to be ARCH and GARCH models may then be appropriate. The test is a regression of squared residuals on lagged squared residuals. For the suitability test, the paper looks at 1–3 lags.

In the conventional mean equation with only a constant, the test significantly indicates the presence of ARCH for the portfolio, the market, and for nine of the 11 individual firms in the sample. For the conventional mean equation based on the market model, the finding of ARCH in the portfolio is nearly significant (11 percent significance level) and is significant for seven of the individual firms in the sample (two more were nearly significant). These findings also suggest that the use of GARCH framework is an acceptable method of investigating the persistence of volatility in this sample.

As a check to determine whether the GARCH (1, 1) variance equation is the correct specification, we run the GARCH (1, 1) model across the whole sample period and analyze the correlograms of the squared standardized residuals. If the variance equation is correctly specified, the Ljung–Box (LB) Q-statistics should not be significant. The correlograms indicate that the variance equations were correctly specified. This was true using both mean equations.

With respect to the specification of the mean equation, we analyze the correlograms of the standardized residuals from the GARCH (1,1) models across the whole sample period. If the mean equation is correctly specified, the Q-statistics should not be significant. Q-statistics generally suggested that the mean equation with only a constant was free from serial correlation. Running the models using the conventional mean equation based on the market model improved upon the Q-statistics and suggested that the mean equation was free from serial correlation.

As noted earlier, increased volatility implies increased idiosyncratic risk. This risk carries with it the economic costs noted in the second section. If the persistence of volatility shocks is greater after 9/11, then the negative effects from the increased market risk linger longer. This paper tests whether the persistence of return volatility is higher for marine operators following 9/11. The testable hypothesis is as follows:

H1 9/11 did not affect (increase) volatility persistence for marine operators. Persistence of $\sigma^2_{i\ pre\ 9/11}$ = Persistence of $\sigma^2_{i\ post\ 9/11}$

The paper uses the GARCH framework noted above to test H1.[7] Essentially, it is a test to see whether the sum ($\alpha + \Phi$) increased following 9/11. As before, the whole sample is for 9/1/00 through 10/31/02. The breakpoint between the two periods is 9/11/01. Tables 3 and 4 show the GARCH estimation results.

As can be seen in Table 3, the GARCH term (Φ) was significant for the portfolio and for nearly all the individual firms in the sample both before and after 9/11. This was less so for the ARCH term (α). For the primary variable of interest, the portfolio, the sum ($\alpha + \Phi$) increased substantially following 9/11. This sum also increased for seven of the 11 individual firms.[8] However, during this period the sum for the market also increased, albeit by a small amount.

As can be seen in Table 4, the GARCH term was again significant for nearly all the individual firms in the sample both before and after 9/11. For the primary

Table 3 GARCH estimation results — mean equation is a constant

Symbol	*α pre-9/11*	*Φ pre-9/11*	*α post-9/11*	*Φ post-9/11*	*(α+Φ) ↑ post-9/11*
Portfolio	0.0890	0.6292**	0.0923	0.8430***	√
TE	0.1815*	0.6973***	0.0930***	0.9219***	√
TDW	0.0261	0.8402**	0.0225	0.8571***	√
KEX	0.0474	0.8977***	0.1034	0.7115***	
ESV	0.0680**	−0.8257***	0.0179	0.9434***	√
TUG	−0.0200***	1.006***	−0.0130	0.5473	
SPN	0.2303**	−0.4265	0.0732**	0.9121***	√
CKH	0.1410	0.1292	0.0133	0.9562***	√
GLBL	0.2022*	−0.0518	0.2369**	0.6207***	√
GMRK	−0.0711***	1.0138***	0.1562*	0.8039***	√
GSF	0.0463	0.8852***	0.1035	0.6980***	
CDIS	0.0747*	0.8543***	0.1062**	0.8173***	
S&P 500	0.0880*	0.8578***	0.1256***	0.8207***	√

* Denotes significance at the 10 percent significance level.
** Denotes significance at the 5 percent significance level.
*** Denotes significance at the 1 percent significance level.

Table 4 GARCH estimation results — mean equation is a constant and market return

Symbol	*α pre-9/11*	*Φ pre-9/11*	*α post-9/11*	*Φ post-9/11*	*(α+Φ) ↑ post-9/11*
Portfolio	0.0692	0.3031	0.0912	0.8518***	√
TE	0.1890*	0.6833***	0.1119***	0.9070***	√
TDW	0.0203	0.8683**	0.0772	0 .7838***	
KEX	0.0267	0.8237*	0.0779	0.6858	
ESV	0.0700***	−0.9815***	−0.0321*	1.0062***	√
TUG	−0.0247***	1.0154***	−0.0094	0.9598***	
SPN	0.2461**	−0.3952	0.1153**	0.8692***	√
CKH	0.1056	0.2084	−0.0245	1.0078***	√
GLBL	0.2354*	−0.0415	0.0713	0.7530***	√
GMRK	−0.0761***	1.0163***	0.1806	0.7753***	√
GSF	0.0405	0.8890***	0.0876	0.7068***	
CDIS	0.2210*	0.4225*	0.1036*	0.8149***	√
S&P 500	n/a	n/a	n/a	n/a	n/a

* Denotes significance at the 10 percent significance level.
** Denotes significance at the 5 percent significance level.
*** Denotes significance at the 1 percent significance level.

variable of interest, the portfolio, the sum $(\alpha + \Phi)$ again increased substantially following 9/11; however, the GARCH term was not significant prior to 9/11. The sum increased for seven of the 11 individual firms. Since the conventional mean equation already incorporates market effects, there is less uncertainty to the results with respect to the market as a whole.

The GARCH results under both conventional mean equations show that the persistence of volatility increased for the portfolio and for many of the individual firms in the sample. It is somewhat uncertain how much of this was due to the underlying market and how much may be due to 9/11 (or other factors). However, the increase in the sum $(\alpha + \Phi)$ was quite substantial for the portfolio while it was relatively small for the market (first mean equation). Additionally, the second mean equation does incorporate some market effects already since it analyzes residuals of returns adjusted for their statistical relationship with the market. These results would indicate a rejection of the null hypothesis and might indicate that the persistence of volatility increased after 9/11 for the sample of marine operators.

SENSITIVITY ANALYSIS

This section considers different approaches to determine how robust the results are with respect to those changes. In order to determine to what extent the post 9/11 results are due to events unrelated to 9/11, the paper controls for significant firm-specific events in the period following 9/11. We do so using the event study methodology with the market model noted earlier in the paper. First, we determine whether any trading day had a statistically significant abnormal return. Equation 4 shows the estimation of the abnormal return and equation 5 shows the estimation of the significance level of that abnormal return. As noted earlier, the model uses estimation parameters from an estimation period to calculate the abnormal return and the *SAR* in the event period. The estimation period is from 9/1/00 through 9/10/01 and the event period is from 9/17/01 through 10/31/02. The next step is to match any firm-specific news to any trading day with a statistically significant *SAR* (10 percent significance or better). Marketwatch.com is the source for news.

To recalculate kurtosis, we exclude any significant day with a corresponding firm-specific news event from the estimation period. For the portfolio, we exclude any day where any one firm had such an event. Based on this approach, there was little change in the results for the portfolio or for most of the individual firms. Only one firm had a noticeable decline in kurtosis from the earlier results (but kurtosis still increased in the post 9/11 period). As a whole, eight of the 11 firms now had an increase in kurtosis following 9/11 (an increase of one firm).

To recalculate the GARCH results, we cannot exclude trading days since the GARCH approach requires a continuous sample. Therefore, instead of excluding the day we impose a zero return on the trading day. Using this approach, there was no change in the GARCH results (i.e., whether $\alpha+\Phi$ increased) under both conventional mean models. This method also provided similar results for changes to kurtosis as those noted above.

In order to determine how robust the results are to the exact GARCH specification, the paper also compares results using different specifications. Although the LB Q-statistics noted earlier indicated that the variance equations were correctly specified, we also estimate and compare higher order models from the GARCH (p, q) family. We do so by examining autocorrelation functions and Akaike/Schwartz information criterion within GARCH (p, q) models with p and q ranging from 1 to 3. As before, we run the models over the whole sample period. Where there was an equivalent goodness of fit, we reran the models for both the pre and post 9/11 periods under the alternate specification (e.g., GARCH (3,1)). Using this approach, there was also no change in the GARCH results (i.e., whether $\alpha+\Phi$ increased) under both conventional mean models.

It is possible for shocks to have asymmetric effects such that the effect from a positive shock is different from a negative one. To determine how robust the results are to asymmetric effects, the paper also compares the results to asymmetric models. To determine whether there is asymmetry that would require such models, we examine the skew (cross) correlations from the cross-correlograms between the level of the standardized residual and the square of the series. A successful model (i.e., not asymmetric) should not have a significant LB Q-statistic for the skew correlations. As before, we ran the GARCH (1,1) models across the whole sample period to conduct the tests. In nearly all cases (under both mean specifications), the Q-statistic was significant at zero lags/leads (i.e., $i=0$) but not at any other. Therefore, there is some limited indication of potential asymmetries. While the purpose of this paper is not to determine whether an asymmetric model is a better structural form to model volatility, given these results, it is of interest to see whether using an asymmetric model framework changes the previous results.

Threshold ARCH (TARCH) models and Exponential GARCH (EGARCH) models are ways of describing these asymmetries. TARCH models [Zakoian 1994] model this leverage effect by treating good news' effect in equation 6 as α and bad news as $\alpha+\gamma$. The sum $(\alpha+\Phi+\gamma/2)$ now provides information as to the degree of variance persistence. With a TARCH (1, 1) model and only the mean in equation 7, the sum $(\alpha+\Phi+\gamma/2)$ increased for eight of the 11 firms in the sample and for the portfolio. It did not increase for the market. Using the market model in the mean equation, the sum increased for six of the 11 firms and the portfolio. These results also tend to confirm those from the GARCH models.

Nelson [1991] first proposed the EGARCH model. In the EGARCH model, the leverage effect is exponential. In the maritime industry, Chen and Wang [2004] investigated leverage effects in the international bulk shipping market using an

EGARCH model. Using an EGARCH model, the persistence parameter increased for nine of the 11 firms and the portfolio in the model with only the mean in equation 7. It did not increase for the market. Using the market model in the mean equation, it increased for seven of the 11 firms and for the portfolio. The EGARCH approach also tends to confirm the GARCH results.

The final robustness check involves comparing the results to two alternate samples of firms potentially affected by 9/11: one that is expected to be more affected (airlines) and one that would be somewhat less affected (more diversified marine firms). For the sample of marine suppliers/shipyards, kurtosis increased for 13 of the 16 firms and for the portfolio. The increase in the portfolio was similar to that of the marine operators. For the GARCH models, we adopt the same approach as before to check for the specification of the variance equations and find the GARCH (1,1) specification satisfactory. Post 9/11, the persistence of volatility increased for nine of the 16 firms in the sample using the mean equation without the market model. However, the portfolio did not change. Using the mean model with the market model, persistence increased for the portfolio and for 10 of the 16 firms. The increase in persistence for the portfolio was substantially lower than the increase for the portfolio of marine operators. Under both mean models, the increases were generally less than for the sample of marine operators. As the expectation is that 9/11 would affect these firms somewhat less, these results tend to support the results for the sample of marine operators.

The airline sample contains all the US airlines that Drakos investigated in 2004, as well as additional carriers. Drakos' results had shown that volatility and systematic risk increased significantly following 9/11; however, Drakos did not investigate kurtosis or volatility persistence. The results from this sample show that kurtosis increased substantially following 9/11 for all the airlines in the sample and for the portfolio of airlines. The increases were more pronounced than with the marine operators. For example, kurtosis for the portfolio increased from 3.6 to 28.4 following 9/11. These results tend to confirm that 9/11 affected kurtosis more for firms likelier to be affected by it than for the market in general. As such, they support the results for the sample of marine operators.

For the GARCH models, we again adopt the same approach as before to check for the specification of the variance equations and find the GARCH (1,1) specification satisfactory. The persistence of volatility ($\alpha + \Phi$) did not increase for the portfolio or for most of the airlines; this was true using both mean equations. These results indicate that volatility shocks were not more prolonged than before. This is so even though there are more extreme return days (as measured by kurtosis) and that there was more variation in returns. The results for persistence may be because of a higher frequency of news events for airlines, and for that matter events unrelated to 9/11 or to security. The results may also be due to other structural factors such as market responses to actions by the Transportation Security Administration. To the extent it is not, the results for this sample do not necessarily support the prior for the sample of marine operators.

CONCLUSION

This paper investigated whether 9/11 resulted in increased persistence of financial return volatility for marine operators. Earlier work by found that volatility may have increased following 9/11; however, it was uncertain how much was due to the underlying market and how much was due to 9/11. To the extent that it was due to 9/11, it would have been an ancillary cost of the attack to these firms. Increased volatility increases market risk and has several economic costs such as reduced trading activity and market arbitrage. Consequently, financial markets are less efficient for these firms. Increased volatility is also an indication of increased investment uncertainty where firms are likely to postpone investment decisions. Increased kurtosis might be more indicative of increased investment uncertainty because of the increased probability of more extreme return days. The results of the paper indicate that kurtosis increased following 9/11 and that these results were not due to changes in the underlying market.

The results of the paper also indicate that the persistence of volatility increased following 9/11. The increased persistence implies that the negative effects from increased market risk die out more slowly. The paper provides several robustness checks that tend to support these results; however, the results from an alternate sample of airlines do not. The latter introduces some level of uncertainty with respect to the results on persistence.

Because the conditional volatility is a one-period-ahead forecast of volatility, we can consider it a measure of risk. To the extent the persistence of conditional volatility increased, and if (as expected) society prefers less risk and hence less risk persistence to more, the results suggest that policy actions that reduced these effects would be welfare enhancing. Investigating fourth moment effects and the persistence of second moment effects is particularly valuable since it is challenging to measure primary effects on terror threat levels from 9/11 and changes to those risk levels from policy actions. This research, along with earlier work by Homan on financial risk, provides identifiable metrics to look at secondary impacts from terror acts and efforts to mitigate them. This not only provides additional justification for policy actions but also provides metrics to measure the effectiveness of those actions. By doing so, it provides decision makers with improved tools to make better policy decisions.

Notes

1. Marine suppliers/shipyards include Caterpillar, Deere, Textron, Northrop Grumman, Raytheon, Todd Shipyards, Cummins Engine, Manitowoc, Trinity Industries, Twin Disc, Stewart & Stevenson Services, Trimble Navigation, KVH Industries, Gulf Island Fabrication, DaimlerChrysler AG, and Volvo AB.
2. Airlines include United, American, Delta, Alaska Air, Southwest, Continental, Air Tran, and America West.
3. Previous work [Homan 2006] investigated the impact of 9/11 on the exact same sample. This also covered a full period of analysis from September 2000 through October 2002. Forthcoming work is investigating the impact of the Maritime Transportation Security Act. This will cover a full period of analysis from October 2002 through December 2004.
4. See p. 9 of Campbell et al. [1997] for more details. Additionally, because of these attractive statistical properties, most widely used asset pricing models involve asset returns.
5. However, there is no good test to determine whether the change in kurtosis was statistically significant.
6. We also considered economic models for the mean, such as arbitrage price theory models. However, the use of the APT model has little practical advantage over the unrestricted market model and there did not appear to be a good reason to substitute an economic model for it. See p. 157 of Campbell et al. [1997] for more details.
7. All models use a Bollerslev–Woolridge heteroskedasticity consistent covariance; this produces robust standard errors and z statistics but does not change the parameter estimates.
8. Unfortunately, there is no breakpoint test for GARCH coefficients to determine whether changes are statistically significant. Consequently, the interpretation of the results is more subjective than with changes to standard regression coefficients.

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