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Abstract: In recent decades, the momentum of global environmental protection has culminated in the Kyoto Agreement of 1998, placing the limelight on "green" issues. This paper argues that the protection of environmental systems involves a fragile balance between the costs of environment preservation and the profit motivations of industrialists. In particular, one of the issues that needs to be addressed is the risk pressures environmental industries face in financial markets, where the higher the risk, the more pressure industries are under to exploit natural resources. Therefore, in order to devise effective environmentally-friendly yet economically viable policies, it is crucial to analyse the risks encountered by environmental industries in financial markets. The success of the autoregressive conditional heteroskedasticity (ARCH) or generalised ARCH (GARCH) models in explaining the stylised facts of financial asset returns has led to its widespread use in the empirical finance literature. By modelling the time-variation in conditional variances or volatility, the univariate ARCH model by Engle (1982) and the GARCH model by Bollerslev (1986) are able to capture the stylized features of the persistence of volatility, volatility clusters and kurtosis, while extensions of the GARCH model such as the asymmetric GARCH (GJR) model by Glosten, Jagannathan and Runkle (1993) can accommodate the additional stylized fact that positive and negative shocks have asymmetric effects, whereby a negative shock has a greater impact on volatility than a positive shock. This paper models the time-varying conditional variances of the returns on a variety of environmental industry sectors using the univariate ARMA(1,1)-GARCH(1,1) and the ARMA(1,1)-GJR (1,1) models. Our dataset consists of daily returns on seven Australian environmental industry sectors including Gold Mining, Other Mining, Mining Finance, Oil & Gas, Farming & Fishing, Forestry and Paper over their respective time periods. The findings of this paper suggest that the risks faced by environmental industries in financial markets are generally well-explained by the ARMA(1,1)-GARCH(1,1); the ARMA(1,1)-GJR(1,1), on the other hand, received much less support due to the lack of asymmetric effects. The log-moment and second moment conditions were also satisfied empirically, implying that moments exist and the QMLE are both consistent and asymptotically normal. Therefore, inferences of the ARMA(1,1)-GARCH(1,1) estimates can be used to aid in formulating new "green" and economically viable environmental policies.

Keywords: Univariate GARCH; Asymmetric effects

1. INTRODUCTION

In recent decades, the momentum of global environmental protection has culminated in the Kyoto Agreement of 1998, placing the limelight on "green" issues. This paper argues that the protection of environmental systems involves a fragile balance between the costs of environment preservation and the profit motivations of industrialists. In particular, one of the issues that needs to be addressed is the risk pressures environmental industries face in financial markets, where the higher the risk, the more pressure industries are under to exploit natural resources. Therefore, in order to devise effective environmentally-friendly yet economically viable policies, it is crucial to analyse the risks encountered by environmental industries in financial markets.

The success of the autoregressive conditional heteroskedasticity (ARCH) or generalised ARCH (GARCH) models in explaining the stylised facts of financial asset returns has led to its widespread use in the empirical finance literature. By modelling the time-variation in conditional variances or volatility, the univariate ARCH model by Engle (1982) and the GARCH model by Bollerslev (1986) are able to capture the stylized features of the persistence of volatility, volatility clusters and kurtosis, while extensions of the GARCH model such as the GJR asymmetric GARCH model by Glosten, Jagannathan and Runkle (1993) can accommodate the additional stylized fact that positive and negative shocks have asymmetric effects, whereby a negative shock has a greater impact on volatility than a positive shock.

2. UNIVARIATE GARCH MODELS

The main objective of this paper is to model the time-varying conditional volatility of returns using univariate GARCH models. The outline and content of the following section on GARCH and GJR models is based on the theoretical presentation in McAleer, Chan and Marinova (2003).

To estimate time-varying conditional variance, Engle (1982) proposed the Autoregressive Conditional Heteroskedasticity (ARCH) model. The univariate ARCH (p) process is as follows:

$$\varepsilon_t = \eta_t \sqrt{h_t} \ ,$$

where ε_t is the unconditional shock, η_t is an independently and identically distributed standardised (or conditional) shock with zero mean and unit variance, and h_t is the conditional variance of ε_t, given by:

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

with $\omega > 0$, $\alpha_i \geq 0$ for $i = 1,..., p$ as sufficient conditions to guarantee that h_t is non-negative for all t. In practice, it is usually assumed that η_t is normally distributed such that maximizing the likelihood function yields the Maximum Likelihood Estimator (MLE). If η_t is non-normal, however, then maximizing the likelihood function will lead to the Quasi-MLE (QMLE).

Bollerslev (1986) extended ARCH (p) to the Generalised ARCH (GARCH) model, GARCH (p,q), which specifies the conditional variance as:

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

where $\omega > 0$, $\alpha_i \geq 0$ for $i = 1,..., p$ and $\beta_i \geq 0$ for $i = 1,..., p$ are sufficient conditions to ensure that h_t is non-negative for all t. The ARCH (or $\sum \alpha$) effects contribute to the short-run persistence of volatility shocks, while the GARCH (or $\sum \beta$) effects contribute to the long-run persistence of volatility shocks, $\sum \alpha + \sum \beta$.

Ling and McAleer (2002a) established the necessary and sufficient conditions for the existence of moments and the asymptotic theory for QMLE of the univariate GARCH(p,q). They showed that the QMLE of the GARCH(p,q) is consistent if the second moment is finite. For the existence of the second moment of ε_t for GARCH(1,1), the necessary and sufficient condition is $\alpha + \beta < 0$. Jeantheau (1998) showed that the weaker log-moment condition is sufficient for consistency of the QMLE for the GARCH(p,q) model. The sufficient condition for consistency and asymptotic normality of the QMLE of GARCH(1,1) is $E[(\log(\alpha\eta_t^2 + \beta)] < 0$.

The univariate ARCH and GARCH models are attractive in that they are able to explain stylised facts, or features, of financial asset returns such as the persistence of volatility, volatility clusters and excess kurtosis. Another striking feature of financial asset returns is that positive and negative shocks have asymmetric effects, whereby a negative shock has a greater impact on volatility than a positive shock. This feature has led to several extensions of univariate GARCH, one of which is the Glosten, Jagannathan and Runkle's (1993) asymmetric (or threshold) GARCH (GJR).

The univariate GJR (p,q) model of Glosen *et al*. (1992) incorporates asymmetric effects into the conditional volatility process, and is given as:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum \gamma_i I(\varepsilon_t) \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \ ,$$

where $\omega > 0$, $\alpha_i + \gamma_i \geq 0$ for $i = 1,..., p$ and $\beta_i \geq 0$ for $i = 1,..., p$ are sufficient conditions for h_t to be non-negative for all t, while $I(\varepsilon_t)$ is an indicator variable defined by:

$$I(\varepsilon_t) = \begin{cases} 1, & \varepsilon_t \leq 0 \\ 0, & \varepsilon_t > 0, \end{cases}$$

which allows the sign of the lagged unconditional shock affect the conditional variance.

The GJR (or $\sum \gamma$) effect measures the impact of asymmetric conditional volatility and contributes to both the short-run persistence of shocks, $\sum \alpha + \sum \gamma / 2$, and the long-run persistence of shocks, $\sum \alpha + \sum \beta + \sum \gamma / 2$.

Ling and McAleer (2002b) established the necessary and sufficient conditions for the existence of moments and the asymptotic theory for QMLE of the univariate GJR(p,q). For the existence of the second moment of GJR(1,1) under symmetry of η_t is $\sum \alpha + \sum \beta + \sum \gamma / 2 < 1$. The weaker sufficient log moment for GJR(1,1) to ensure consistency and asymptotic normality of the QMLE of GJR(1,1) is $E[(\log((\alpha + \gamma I(\eta_t))\eta_t^2 + \beta)] < 0$.

A comprehensive survey of recent theoretical (that is, structural and statistical) developments associated with univariate and multivariate GARCH models that are of interest to applied practitioners in financial economics and econometrics is provided in Li, Ling and McAleer (2002).

3. DATA

Our data sample contains daily (5-day weeks) share price indices on seven environmental industry sectors - Gold Mining (GOLDS), Other Mining (MINES), Mining Finance (MIFIN), Oil & Gas (OILEP), Farming & Fishing (FMFSH), Forestry (FORST) and Paper (PAPER) - in Australia. The sample time periods are as follows: Gold Mining, Other Mining, Mining Finance and Oil & Gas, 1/1/73 to 14/11/03; Farming & Fishing, 10/1/73 to 14/11/03; Forestry, 2/1/96 to 14/11/03; and Paper, 5/6/99 to 14/11/03. Daily returns are calculated for each environmental industry sector on a continuous-compounding basis, computed as the natural logarithm of the price differences. All data is obtained from Thompson Datastream Advance.

Returns and their volatilities for the seven environmental industry sectors over their respective sample periods are plotted in Figure 1 and Figure 2 respectively. Volatility is defined as the squared deviation of each industry sector return observation from its respective mean return. Visual observation of Figure 1 shows that environmental industry returns, in general, fluctuated around a zero mean with no apparent trends or seasonalities over the sample period. In Gold Mining, there is a dramatic change in the magnitude of its returns, where returns soared in the 1970s before stabilising. In Other Mining, there is a distinct negative spike signifying the October 1987 stock market crash outlier, while for Mining Finance and Oil & Gas, both the second oil price shock of 1979 and the October 1987 outliers are noticeable. There are also obvious negative spikes in 1998 and 1999 for the Forestry industry. For Farming & Fishing, a high degree of variation is present from year 2000 onwards compared to the rest of the sample period, while for Paper, the converse was true, where a higher degree of variation was present prior to year 2000.

There is discernible volatility clusterings for the environmental industry sectors of Farming & Fishing and Paper. High volatility clusters were apparent in the early 2000s for Farming & Fishing, while high volatilities were bunched up in 1999 for Paper. The conditional volatilities of the Other Mining, Mining Finance, Oil & Gas and Forestry industry returns are typical of financial time-series data, where volatility clustering is not as noticeable, except for presence of outliers.

As the return time-series of the environmental industry sectors show a considerable degree of persistence (see Figure 1), we choose to model the returns using the Autoregressive Moving Average (ARMA) processes of Box and Jenkins (1976), which assume that a time series is a linear combination of its own past values as well as current and past values of a random error term For simplicity, we employ an ARMA(1,1) process, given by:

$$R_{it} = \phi_{i1} R_{it-1} + \delta + \varepsilon_{it} - \theta_{i1} \varepsilon_{it-1} .$$

Table 1 reports the results of the OLS regression of the ARMA(1,1) for each of the seven environmental industry sectors under the assumption that the error term is independently, identically distributed (iid) with zero mean and unit variance. The Newey-West (1987) method is employed to correct for the potential unspecified departures from homoskedasticity and no serial correlation. There is some support for the ARMA(1,1) model. The AR(1) and MA(1) terms are statistically significant for Other Mining, Mining Finance, Farming & Fishing and Paper. The test for conditional heteroskedasticity is the Lagrange multiplier test (LM) for autoregressive conditional heteroskedasticity (ARCH) by Engle (1982). The LM (ARCH) test statistic is asymptotically distributed as $\chi^2_{(p)}$, where we choose $p = 1$ to test for ARCH(1). The LM (ARCH) p-values indicate that there is considerable conditional heteroskedasticity in the return residuals, where the null hypothesis of homoskedasticity is rejected in all seven of the environmental industry sectors

Table 1. OLS Estimation of the ARIMA(1,1) Model and the ARCH(LM) of the ARIMA model residuals

	δ	*AR(1)*	*MA(1)*	*ARCH(LM)*
GOLDS	**0.090**	**-0.118**	**-0.020**	**16.252**
	1.387	-0.935	-0.180	0.000
MINES	**0.029**	**-0.334**	**0.449**	**26.168**
	1.573	-3.147	4.349	0.000
MIFIN	**0.024**	**-0.533**	**0.581**	**101.171**
	0.960	-3.087	3.560	0.000
OILEP	**0.023**	**-0.205**	**0.260**	**227.031**
	1.004	-0.634	0.813	0.000
FMFSH	**0.055**	**-0.484**	**0.507**	**45.44**
	2.45	-3.65	3.95	0.00
FORST	**0.070**	**0.049**	**-0.137**	**64.69**
	1.696	0.18	-0.495	0.00
PAPER	**-0.008**	**0.288**	**-0.215**	**15.95**
	-0.13	6.10	-3.71	0.00

Notes: The entries corresponding to the estimates (in bold) for the constant, AR(1) and MA(1) are the Newey-West(1987) corrected t-ratios , while the entries corresponding to the estimate (in bold) for the ARCH(LM) are p-values.

In brief, a preliminary investigation of our dataset has revealed that the environmental industry returns display considerable ARCH/GARCH effects. Accordingly, we model the conditional volatilities using univariate GARCH models. In addition, we also investigate univariate GJR models, which incorporate asymmetric effects such that a negative shock has a greater impact on volatility than a positive shock.

Figure 2

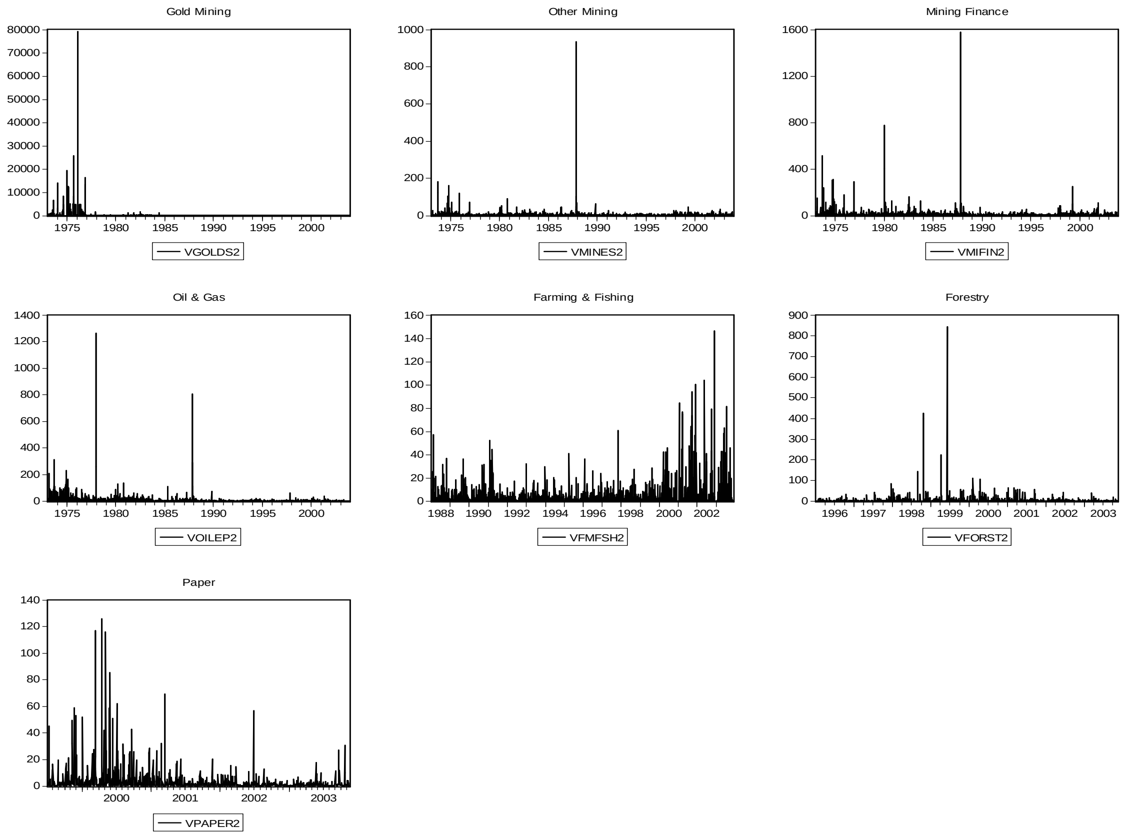
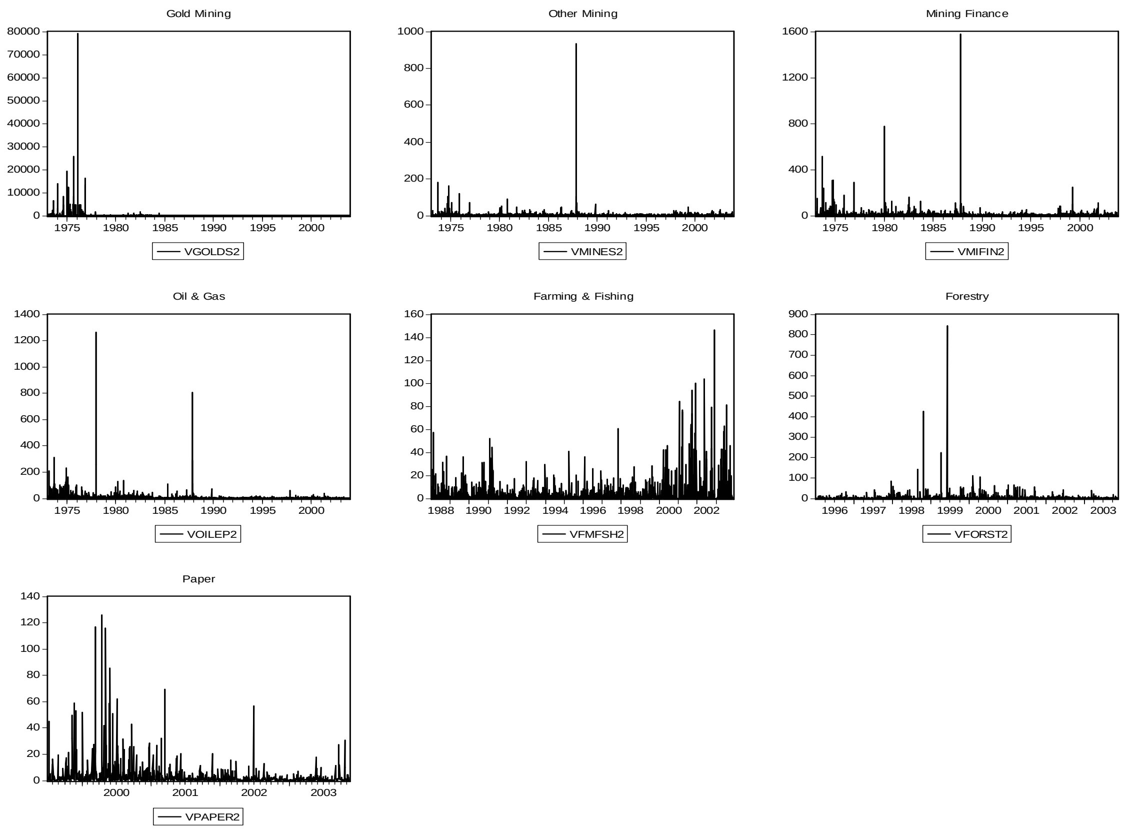


Figure 2



4. EMPIRICAL RESULTS

This paper models the time-varying conditional means and conditional variances of the daily returns of the seven environmental industry sectors over their respective sample time periods using the ARMA (1,1)–GARCH(1,1) and the ARMA (1,1)–GJR (1,1). Both the ARMA (1,1)–GARCH(1,1) and the ARMA (1,1)–GJR (1,1) models are estimated using Eviews Version 4.1. The Brendt-Hall-Hall-Hausman (Berndt *et al*, 1974) algorithm is used to maximise the likelihood function, with the quasi-maximum likelihood (QMLE) estimates converging in all cases.

Tables 2 and 3 present the QMLE coefficient estimates for ARMA (1,1)–GARCH(1,1) and the ARMA (1,1)–GJR (1,1) for all seven environmental industry sectors respectively. The AR(1) estimates for GARCH(1,1) and GJR(1,1) are highly significant for Other Mining, Farming & Fishing, Forestry and Paper, suggesting a considerable degree of persistence in the returns of these industries. The MA(1) estimates, on the other hand, are highly significant for Other Mining, Mining Finance, Farming & Fishing, Forestry and Paper, which indicate that the unconditional shock on the previous day affects returns today. It should be also noted that the coefficients of the AR(1) term are negative for Other Mining and Farming & Fishing, while the coefficients of the MA(1) term are negative for Forestry and Paper.

The estimates of the conditional volatility for the GARCH(1,1) and the GJR(1,1) are highly satisfactory. The sufficient conditions $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$ to ensure that the conditional variance is non-negative for all time periods are met for all seven environmental industry sectors, except for Gold Mining. The log-moment conditions and the second moment conditions are also satisfied for all seven environmental sectors, except for Gold Mining. This result establishes the existence of moments and ensures that the QMLE for GARCH(1,1) and GJR(1,1) are consistent and asymptotically normal. Hence, inferences on these estimates can be used in the formation of new environmental policies. The estimates of the asymmetric effect in GJR(1,1), however, are insignificant for all environmental industries except for Paper, based on the Bollerslev-Wooldridge (1992) robust-t-ratios, suggesting that the GARCH(1,1) is preferred to GJR(1,1).

4. CONCLUDING REMARKS

The findings of this paper suggest that the risks faced by environmental industries in financial markets are generally well-explained by the ARMA(1,1)-GARCH(1,1); the ARMA(1,1)-GJR(1,1), on the other hand, received much less support due to the lack of asymmetric effects. The log-moment and second moment conditions were also satisfied empirically, implying that moments exist and the QMLE are both consistent and asymptotically normal. Therefore, inferences of the ARMA(1,1)-GARCH(1,1) estimates can be used to aid in formulating new "green" and economically viable environmental policies.

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Table 2: GARCH (1,1) Estimates for the Daily Environmental Industry Sectors

INDUSTRY SECTOR	*AR(1)*	*MA(1)*	ω	α	β	*LOG-MOMENT*	*SECOND MOMENT*
GOLDS	**-0.029**	**0.050**	**-0.001**	**0.015**	**0.986**	**0.000**	**1.001**
	-0.058	0.098	-1.678	45.697	5297.669		
	-0.044	0.074	-0.203	5.714	320.733		
MINES	**-0.218**	**0.389**	**0.104**	**0.138**	**0.825**	**-0.064**	**0.963**
	-3.549	6.947	13.585	36.689	173.721		
	-2.719	4.191	3.172	2.593	15.858		
MIFIN	**-0.220**	**0.316**	**0.205**	**0.117**	**0.850**	**-0.057**	**0.966**
	-1.832	2.717	16.402	36.491	189.772		
	-1.895	2.844	4.030	4.070	30.552		
OILEP	**-0.095**	**0.191**	**0.029**	**0.080**	**0.917**	**-0.015**	**0.997**
	-0.791	1.620	13.706	38.402	366.247		
	-0.717	1.466	3.674	5.209	83.086		
FMFSH	**-0.527**	**0.564**	**0.051**	**0.031**	**0.948**	**-0.024**	**0.979**
	-3.510	3.857	10.761	18.740	330.503		
	-4.675	5.132	2.155	2.963	51.960		
FORST	**0.897**	**-0.913**	**4.002**	**0.214**	**0.054**	**-2.230**	**0.268**
	85.276	-1657.268	34.217	18.925	2.497		
	7.689	-8.865	6.381	1.576	0.533		
PAPER	**0.276**	**-0.242**	**0.014**	**0.033**	**0.963**	**-0.006**	**0.996**
	2.346	-2.001	2.838	5.820	152.967		
	3.725	-2.868	1.213	3.674	98.406		

Notes: The three entries correspond to the estimate (in bold), the asymptotic t-ratio and the Bollerslev- Wooldridge (1992) robust-t-ratio respectively.

Table 3: GJR (1,1) Estimates for the Daily Environmental Industry Sectors

INDUSTRY SECTOR	*AR(1)*	*MA(1)*	ω	α	γ	β	$\alpha+\gamma/2$	*LOG-MOMENT*	*SECOND MOMENT*
GOLDS	**0.286**	**-0.265**	**-0.001**	**0.014**	**0.002**	**0.986**	**0.015**	**-0.0002**	**1.001**
	0.629	-0.580	-1.644	32.192	3.820	5282.092			
	0.511	-0.470	-0.202	3.476	0.253	313.132			
MINES	**-0.220**	**0.383**	**0.092**	**0.082**	**0.094**	**0.840**	**0.129**	**-0.058**	**0.969**
	-3.412	6.370	13.440	13.939	13.998	175.182			
	-2.642	4.163	3.503	5.270	1.359	20.663			
MIFIN	**-0.230**	**0.322**	**0.191**	**0.092**	**0.042**	**0.856**	**0.113**	**-0.053**	**0.970**
	-1.847	2.665	15.453	21.115	6.016	185.388			
	-1.958	2.830	4.474	4.436	1.490	36.148			
OILEP	**-0.100**	**0.197**	**0.029**	**0.066**	**0.031**	**0.916**	**0.081**	**-0.015**	**0.997**
	-0.846	1.673	13.445	24.641	12.500	360.618			
	-0.741	1.477	3.726	4.989	0.804	79.280			
FMFSH	**-0.519**	**0.556**	**0.044**	**0.025**	**0.010**	**0.952**	**0.030**	**-0.021**	**0.982**
	-3.305	3.640	10.063	12.358	2.893	362.192			
	-4.639	5.095	2.153	1.957	0.642	57.395			
FORST	**0.706**	**-0.738**	**1.896**	**0.272**	**-0.158**	**0.356**	**0.193**	**-0.782**	**0.549**
	3.043	-3.432	15.559	16.839	-6.626	8.988			
	2.235	-2.471	3.002	1.682	-1.031	2.366			
PAPER	**0.274**	**-0.237**	**0.004**	**0.033**	**-0.032**	**0.982**	**0.017**	**-0.002**	**0.999**
	2.569	-2.161	2.002	6.486	-5.426	331.963			
	3.370	-2.600	0.900	2.974	-2.051	147.407			

Notes: The three entries correspond to the estimate (in bold), the asymptotic t-ratio and the Bollerslev- Wooldridge (1992) robust-t-ratio respectivel