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THE BEHAVIOR OF STOCK RETURNS IN THE ASIA-PACIFIC MINING INDUSTRY FOLLOWING THE IRAQ WAR

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Abstract

In this article, we pursue to determine which mining firms have seen their stock returns become more sensitive to fluctuations in energy prices, over a time period predominated by the political turmoil caused by 9/11 and the subsequent invasion of Iraq. By resorting to wavelets and spatial statistics, we characterize the behavior of volatility and the degree of co-movement of the stock returns of ten leading mining firms operating in the Asia-Pacific region: Alcan Inc., Antofagasta, Barrick Gold Corp., BHP Billiton, International Nickel Ind., Peabody Energy, Phelps Dodge Corp, Rio Tinto plc., Teck Cominco Ltd., and Yanzhou Coal Mining Co.

Our findings can be summarized as follows. Firstly, most mining company returns became especially volatile around the time of the declaration of war on terror and the subsequent invasion of Iraq, and around the time of the sizeable hike in the oil price during 2005-2006. Interestingly, firms which belong to a particular industry did not necessarily display identical patterns of return volatility. Secondly, the metals and minerals analyzed exhibited different degrees of dependency on energy prices. The maximum correlation was observed for aluminum and the minimum for Nickel. Gold and copper tended to be more energy dependent at the upper scales of the data (i.e., trend component). As to spatial dependency, there is evidence of it over the first quarter of 2003, the first three quarters of 2004, and towards the second and third quarters of 2006.

JEL: C5, G1; Keywords: Iraq war, volatility shifts, wavelets, spatial correlation.

1 Introduction

Following the Asian crisis and 9/11, gauging permanent volatility shifts in worldwide financial markets has gained new interest in the finance field (e.g., Hammoudeh, and Li 2006; Fernandez 2006a; Covarrubias et al. 2006; Gravelle et al. 2006; Cheong 2007; Fernandez and Lucey 2007). Two techniques have been usually utilized in such studies, namely, the iterative cumulative sum of squares (ICSS) algorithm and wavelet analysis. The ICSS algorithm, which was developed by Inclan and Tiao, G. (1994) and made well-known in the finance field by Aggarwal, Inclan, and Leal (1999), makes it possible to

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detect multiple variance shifts in a time series. However, it is usually fairly sensitive to the presence of volatility clustering, which in turn leads to an overestimation of the number of variance breakpoints. In that aspect, wavelets arise as a more robust tool, which in addition allow for a decomposition of volatility at different time horizons (e.g., Fernandez 2007). Wavelets have been applied in several studies in the fields of economics and finance from the mid-1990's onwards, such as the permanent income hypothesis, the relation between futures and spot prices, the estimation of systematic risk of an asset in the context of the domestic and international version of the capital asset pricing model, heterogeneous trading in commodity markets, selection of an optimal hedge ratio for a commodities portfolio, structural breakpoints in volatility and wavelet-based computation of value at risk, among other themes (e.g., Ramsey, J., & Lampart, C. 1998; Ramsey 1999; Ramsey 2002; Lin and Stevenson 2001; Gençay, Whitcher, and Selçuk 2001, 2003, 2005; Lien and Shrestha 2007; Connor and Rossiter 2005; Fernandez 2005, 2006b; In and Kim 2006; and, Fernandez and Lucey 2007).

The focus of this study is to quantify to what extent the Iraq invasion has had an impact on the evolution of stock returns of mining firms through the volatility inflicted on energy prices by the current political instability in the Middle East. To that end, we concentrate on ten mining companies whose operations are primarily in the Asia-Pacific area: Alcan Inc., Antofagasta, Barrick Gold Corp., BHP Billiton, International Nickel Ind., Peabody Energy, Phelps Dodge Corp, Rio Tinto plc., Teck Cominco Ltd., and Yanzhou Coal Mining Co. Ltd. The production of these companies focus across a range of metals from aluminum, copper, gold, silver, zinc, to nickel, and of minerals, such as coal and carbon. In order to trace the evolution of the energy and utilities sectors, we resort to the Energy Select Sector and Utilities Select Sector SPDRs (spiders). Our sample period covers from January 2000 to October 2006. Related studies in this area are McMillan and Speight (2001)'s analysis of non-ferrous metals price volatility, and Fong and See (2002)'s and Yang et al. (2002)'s work on oil volatility of spot and futures prices, respectively.

By resorting to wavelets and spatial statistics, we analyze the behavior of volatility and the potential presence of structural breaks, the persistence of volatility, and the degree of co-movement of stock returns over the sample period under consideration. This article is organized as follows. Section 2 presents the mathematical and statistical tools utilized in our empirical analysis, namely, wavelets variance analysis, fractionally differenced processes, and spatial correlation. Section 3 describes the data and discusses our empirical results. Section 4 concludes.

2 Methodology

2.1 Wavelet variance analysis

Wavelets make it possible to decompose a time series or signal into high- and low-frequency components (see, for instance, Percival and Walden 2000). High-frequency components describe the short-term dynamics, whereas low-frequency components represent the long-term behavior of a series. Wavelets are classified into father and mother wavelets. Father wavelets capture the smooth and low-frequency parts of a signal, whereas mother wavelets describe its detailed and high-frequency parts.

Applications of wavelet analysis usually resort to a discrete wavelet transform (DWT). The DWT maps a vector of n observations to a vector of n smooth and detail wavelet coefficients[2], which make it possible to capture the underlying smooth behavior of the data and the deviations from it. By assuming J levels when the length of the data, n, is divisible by 2^J, we have n/2 wavelet coefficients at the finest scale 2^1, $n/2^2$ coefficients at the next finest scale 2^2, and etcetera.[3] The number of wavelet coefficients at a given scale is related to the width of the wavelet function. This implies that the lowest scales will mimic the short-term fluctuations of the original time series.

In particular, wavelet analysis enables us to decompose a time series into its fundamental components, where each of them contains information regarding the variability of the data at a particular scale. Such a decomposition is called a multi-resolution decomposition (MRD) of a time series y(t), which is the sum of the orthogonal components $S_J(t)$, $D_J(t)$, $D_{J-1}(t)$,.., $D_1(t)$ from scales 1 through J:

$$y(t) \approx S_J(t)+D_J(t)+D_{J-1}(t)+...+D_1(t), \quad (1)$$

where $S_J(t)$ and $D_J(t)$ are denominated the smooth and detail components, respectively. Wavelet scales are such that times are separated by multiples of 2^j, j=1,.., J. For instance,

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[2] $s_{J,k}$ and $d_{j,k}$, j=1,2,…, J, respectively, where J is the total number of levels. At level j=1, ..., J, the $n/2^j$-vector of the detail wavelet coefficients d_{jk} is associated with changes on a scale of length 2^{j-1}, whereas the $n/2^J$-vector of smooth wavelet coefficients s_{Jk} is associated with averages on a scale of length 2^J.

[3] These are denominated dyadic scales (see Percival and Walden 2000, chapter 1).

for daily data, scale 1 is associated with 2-4 day dynamics, scale 2 with 4-8 day dynamics, scale 3 with 8-16 day dynamics, etcetera.

An application of wavelets, which is of particular interest to this study, is the decomposition of the variance of a time series into its time-scale components. Specifically, wavelet variance analysis enables us to identify which scales are the most important contributors to the overall variability of the data (see Percival and Walden, op cit.). In particular, let x_1, x_2,..., x_n be a time series of interest, assumed to be a realization of a stationary process with variance σ_X^2. If $\upsilon_X^2(\tau_j)$ denotes the wavelet variance at scale $\tau_j \equiv 2^{j-1}$, then the following relationship holds:

$$\sigma_X^2 = \sum_{j=1}^{\infty} \upsilon_x^2(\tau_j) \tag{2}$$

where the square root of the wavelet variance is expressed in the same units as the original time series.

Let $n'_j = \lfloor n/2^j \rfloor$ be the number of DWT coefficients at level j, where n is the sample size, and let $L'_j \equiv \left\lceil (L-2)(1-\frac{1}{2^j}) \right\rceil$ be the number of DWT boundary coefficients[4] at level j (provided that $n'_j > L'_j$), where L is the width of the wavelet filter. An unbiased estimator of the wavelet variance based on the DWT is given by

$$\tilde{\upsilon}_X^2(\tau_j) \equiv \frac{1}{(n'_j - L'_j)2^j} \sum_{t=L'_j}^{n'_j-1} d_{j,t}^2 \ . \tag{3}$$

Given that the DWT de-correlates the data, the non-boundary wavelet coefficients at a given level ($\mathbf{d}_j$) are zero-mean Gaussian white-noise processes. Under the null hypothesis of variance homogeneity:

$$H_0:\ \mathrm{var}(d_{j,L'_j}) = \mathrm{var}(d_{j,L'_j+1}) = ... = \mathrm{var}(d_{j,n'_j-1})$$

whereas under the alternative

$$H_1:\ \mathrm{var}(d_{j,L'_j}) = .. = \mathrm{var}(d_{j,t'}) \neq \mathrm{var}(d_{j,t'+1}).... = \mathrm{var}(d_{j,n'_j-1})$$

where t′ is an unknown breakpoint.

[4] $\lfloor x \rfloor$ and $\lceil x \rceil$ represent the greatest integer ≤x and the smallest integer ≥x, respectively. The boundary coefficients are those obtained by putting together some values from the beginning and the end of the time series.

The D-test statistic quantifies the maximum deviation (positive or negative) of a normalized cumulative sum of squares, C_k, from a hypothetical linear cumulative energy[5] trend:

$$D=\max(D^{+},D^{-}) \qquad D^{+}=\max_k\left(\frac{k-L_j'+1}{n_j'-1}-C_k\right),\; D^{-}=\max_k\left(C_k-\frac{k-L_j'}{n_j'-1}\right) \qquad (4)$$

with $C_k=\dfrac{\sum_{t=L_j'}^{k} d_{j,t}^2}{\sum_{t=L_j'}^{n_j'-1} d_{j,t}^2}$, $k=L_j',\ldots, n_j'-2$.

Under the null hypothesis, the ratio of the expected value of the numerator of C_k and the expected value of its denominator is $(k+L_j'+1)/(n_j'-L_j')$, which is a linear function of k. Therefore, the null hypothesis will be rejected when D departures from this expected linear increase. Details on the computation of the critical values of the test are given in Percival and Walden, op cit., chapter 9.

2.2 Fractionally differenced processes

A time series x_t is said to have long-memory or to be a fractionally differenced process if its autocovariance sequence decays at a rate slower than that of an autoregressive moving average (ARMA) process. Mathematically, if $\lambda_s=\mathrm{cov}(x_t,x_{t+s})$, $s=-1,0,1$ and there exist constants C and β, such that $\lim_{s\to\infty}\frac{\lambda_s}{Cs^{\beta}}=1$, then x_t is a long-memory process. Furthermore, $\lim_{s\to\infty}\frac{\lambda_s}{Cs^{\beta}}=1$ if and only if $\lim_{f\to 0}\frac{S(f)}{K|f|^{\alpha}}=1$, where $\alpha+\beta=-1$, K is a constant, $|f|<1/2$, and S(f) is the spectral density function of the process, where $S(f)\propto |f|^{\alpha}$, for f small. [6]

The exponent $\alpha=-2d$ is called the spectral exponent, where d represents the long-memory parameter. If $0<d<1$, x_t is a long-memory process. In particular, if $0<d<0.5$, x_t is

[5] The energy-concentration function of a vector $\mathbf{x}=(x_1, x_2, \ldots, x_n)'$ is defined as $E_x(K)=\sum_{i=1}^{K}x_{(i)}^2 \Big/ \sum_{i=1}^{n}x_i^2$, where $x_{(i)}$ is the ith-largest absolute value in $\mathbf{x}$

[6] In general $S(f)=\frac{\sigma_\varepsilon^2}{|2\sin(\pi f)|^{\alpha}}$, $|f|<1/2$, where σ_ε^2 represents the innovation variance.

stationary but shocks decay at a hyperbolic rate, while if $0.5 \leq d < 1$, x_t is non-stationary. On the other hand, if $-0.5 < x_t < 0$ is stationary and it has short memory.

Percival and Walden, op cit., chapter 9, discuss how d can be estimated from a regression of the logarithm of the wavelet variance on the logarithm of the corresponding scale. Specifically, an approximation to the wavelet variance is given by

$$\upsilon_X^2(\tau_j) \approx 2 \int_{1/2^{j+1}}^{1/2^j} S(f)\, df = 2 \int_{1/2^{j+1}}^{1/2^j} \frac{\sigma_\varepsilon^2}{|\, 2\sin(\pi f)\,|^\alpha}\, df \qquad (5)$$

For $j \geq 3$, $\sin(\pi f) \approx \pi f$, from which

$$\upsilon_X^2(\tau_j) \approx \frac{\sigma_\varepsilon^2 \pi^\alpha (1 - 2^{1-\alpha})}{(1+\alpha)} \tau^{1-\alpha} \qquad (6)$$

Given that $\upsilon_X^2(\tau_j)$ is unknown, an estimator is called for. Specifically, if the maximal overlap DWT (MODWT) is considered[7], an unbiased MODWT estimator of the wavelet variance is given by

$$\hat{\upsilon}_X^2(\tau_j) \equiv \frac{1}{M_j} \sum_{t=L_j-1}^{n-1} \tilde{d}_{j,t}^2 \qquad (7)$$

where $\tilde{d}_{j,t}^2$ is the MODWT-wavelet coefficient at level j and time t, $M_j \equiv n - L_j + 1$, $L_j \equiv (2^j - 1)(L-1) + 1$ is the width of the MODWT filter for level j, and n is the number of observations in the original time series. While there are n MODWT-wavelet coefficients at each level j, the first (L_j–1)-boundary coefficients are discarded in order to obtain an unbiased estimate.

$\hat{\upsilon}_X^2(\tau_j)$ is known to be approximately distributed as the product of a chi-square random variable with η degrees of freedom and the constant $\upsilon_X^2(\tau_j)/\eta$. Percival and Walden, op cit. define the random variable

$$y(\tau_j) \equiv \ln(\hat{\upsilon}_X^2(\tau_j)) - \psi\left(\frac{\eta_j}{2}\right) + \ln\left(\frac{\eta_j}{2}\right) \qquad (8)$$

[7] The non-decimated DWT is a non-orthogonal variant of the DWT, which is time-invariant. That is to say, unlike the classical DWT, the output is not affected by the date at which a time series starts to be recorded. In addition, the number of coefficients at each scale equals the number of observations in the original time series. The scaling $(\tilde{l}_k)$ and wavelet $(\tilde{h}_k)$ filter coefficients for the MODWT are rescaled versions of those of the DWT, l_k and h_k. Specifically, $\tilde{l}_k \equiv l_k / \sqrt{2}$ and $\tilde{h}_k \equiv h_k / \sqrt{2}$.

where $\psi(.)$ is the digamma function. By properties of the chi-square distribution, $E(y(\tau_j)) = \ln(\upsilon_X^2(\tau_j))$ and $Var(y(\tau_j)) = \psi'\left(\frac{\eta_j}{2}\right)$, where $\psi'(.)$ is the trigamma function. Therefore, from (6) and (8), the following regression model can be stated

$$y(\tau_j) = \beta_1 + \beta_2 \ln(\tau_j) + \varepsilon_j \qquad (9)$$

where $\varepsilon_j \equiv \ln(\hat{\upsilon}_X^2 / \upsilon_X^2) - \psi(\eta_j/2) + \ln(\eta_j/2)$ is an error term with zero mean and variance equal to $\psi'(\eta_j/2)$.

A weighted-least square estimator (WLSE) of β_2 is given by

$$\hat{\beta}_{2,wlse} = \frac{\sum_j \omega_j \sum_j \omega_j \ln(\tau_j) y(\tau_j) - \sum_j \omega_j \ln(\tau_j) \sum_j \omega_j y(\tau_j)}{\sum_j \omega_j \sum_j \omega_j \ln^2(\tau_j) - \left(\sum_j \omega_j \ln(\tau_j)\right)^2} \qquad (10)$$

where $\omega_j = (\psi'(\eta_j/2))^{-1}$.

The WLSE of d is therefore given by $\hat{d} = \frac{\hat{\beta}_{2,wlse} + 1}{2}$.

2.3 Spatial autocorrelation

One way to quantify contemporaneous dependency in financial markets is through spatial autocorrelation, a concept developed in the field of spatial statistics (e.g., Haining 2003). Specifically, spatial autocorrelation aims at measuring whether an event at a specific point in space affects another. Spatial dependency is usually associated to geographic proximity or contiguity. Although spatial statistics has been widely applied in other fields, such as geography and urban economics, its use to tackle financial phenomena is fairly recent (e.g., Frexeda and Vaya 2005).

A well-known statistic to test for the presence of spatial autocorrelation is Moran's, which computed as

$$M = \frac{n}{S} \frac{\sum_i \sum_j \varpi_{ij} z_i z_j}{\sum_i z_i^2} \qquad (11)$$

where ϖ_{ij} is the (i, j)-element of the so-called spatial weights matrix, which measures the degree of dependency between regions i and j, n is the number of observations, S is the sum of the elements of the weights matrix, and z_i is the normalized value of the variable analyzed in region i. As already mentioned, dependency is associated with geographical proximity. However, the definition of the weights will depend on the object of study. The spatial weights matrix is an $n \times n$ matrix, although not necessarily symmetric, whose elements on the main diagonal are zeros. The distribution of M, under the null hypothesis of no spatial autocorrelation, can be derived by assuming that z_i and z_j are identically distributed and correspond with independent draws from a normal distribution.

3 Empirical analysis

3.1 The data

Our data set is comprised of the following 12 series (2 spiders and 10 stock price series), recorded at a daily frequency, and which are freely available at http://finance.yahoo.com: Alcan Inc., Antofagasta, Barrick Gold Corp., BHP Billiton, International Nickel Ind., Peabody Energy, Phelps Dodge Corp, Rio Tinto plc., Teck Cominco Ltd., and Yanzhou Coal Mining Co. Ltd. In order to trace the evolution of the energy and utilities sectors, we resort to the Energy Select Sector and Utilities Select Sector SPDRs (spiders).

Some descriptive statistics of the data are presented in Table 1. The sample period is January 2000-October 2006, except for those cases in which shorter time spans were available. As is empirically observed in most applications, the individual return series reject normality, according to Shapiro-Wilk’s test. On the other hand, the inter-quartile range suggests that the returns on Rio Tinto and Teck Cominco were the most volatile, followed by those on Barrick Gold and Peabody Energy. The production of the sampled companies focus across a range of metals from aluminum, copper, gold, silver, zinc, to nickel, and of minerals, such as coal and carbon. Detailed information on each company profile is provided in Table 2.

The analysis of the individual series was carried out by using their corresponding sample periods. In order to compute paired correlations and Moran’s statistic, we focused on the July 2001-October 2006 period, which covers 9/11, the declaration of the war on terror, and the subsequent invasion of Iraq.

3.2 Behavior of volatility

Based on the unbiased MODWT estimator of the wavelet variance given by equation (7), we constructed rolling estimates of volatility for the two returns series on the SPDRs and for the return series on the ten afore-mentioned mining companies at scales 1 and 3 (i.e., 2-8 and 8-16 day-dynamics, respectively). Our estimation results are depicted in Figure 1, (a) through (f). Although there is not a single pattern, in general volatility was high around 2003-2004, it tended to decrease between 2004 and 2005, and it increased again towards 2006. In other words, it appears that the returns on most mining firms became especially volatile around the time of the declaration of war on terror and the subsequent invasion of Iraq, and around the time of the sizeable hike in the oil price during 2005-2006.[8]

Some exceptions to such a stylized pattern are the utility SPDR and Barrick Gold, whose volatility reached its peak during 2003-2004 to decline thereafter (Panels (a) and (f), respectively); International Nickel Inc. (Inco), whose volatility exhibited a decreasing trend from 2002 onwards (Panel (b)); and, Teck Cominco, whose return series suggests that the time scale can be an important factor to take into consideration. For instance, at scale 1, the return volatility of Teck Cominco behaved similarly to that of Barrick Gold. However, at scale 3, which captures longer-term dynamics, its volatility exhibited an increasing trend from 2002 onwards.

Interestingly, firms which belong to a particular industry did not necessarily share an identical pattern of return volatility. This is the case for the coal mining firms Peabody and Yanzhou (Panel (e)), and the copper mining firms Antofagasta and Phelps Dodge. Indeed, Peabody's return volatility exhibited a U-shaped pattern, while that of Yanzhou exhibited a U-shape between 2002 and 2005, which reversed towards 2005 to end up reaching a minimum towards the end of 2006. In turn, the greatest contrast between Antofagasta and Phelps Dodge is observed at scale 3, where the former showed a decreasing trend between 2002 and 2003, while the latter reached its peak around 2003 to decline thereafter. A possible explanation for this finding may lie in the degree of

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[8] The price of standard crude oil on NYMEX increased from $25/barrel in September 2003 to $78 per barrel in mid July 2006. Such a considerable increase was partially explained by the instability in the Middle East—the largest oil-producing region of the world. However, other forces behind it were 2005's Hurricane Katrina, strikes and political problems in Venezuela and West Africa, declining petroleum reserves in the United States, and the depreciation of the U.S. dollar against the Euro.

diversification of a firm. Indeed, according to Table 2, Phelps Dodge and Yanzhou are more diversified than their counterparts.

A further characterization of volatility can be carried out by computing a weighted-least square estimate of the long-memory parameter, d, of absolute returns (i.e., a proxy for volatility), as discussed in Section 2.2. Figure 2 (a)-(b) reports the rolling d-estimate, along with a 95-percent confidence band, for the two SPDRs, and two mining companies: Teck Cominco and Inco. The computed series exhibit some interesting patterns. The utilities SPDR presented volatility persistence in 2002-2003 (i.e., d>0), no persistence between 2004 and 2005, and again some persistence towards the end of the sample period. The absolute return on the energy SPDR in turn presented persistence only prior to 2004, whereas around the third quarter of 2004, it became anti-persistence (i.e., d<0). Thereafter, no persistence was observed in statistical terms.

The absolute return on Teck Cominco shares some similarities with that on the energy SPDR. Indeed, it was persistent for the most part between 2002 and 2005, but it eventually became anti-persistent (beginning of 2006 onwards). Interestingly, we see that Inco's returns series was not only relatively less volatile, but it also exhibited little evidence of persistence. (This was present only in 2002).

An empirical regularity, which has been documented in the finance literature, is the positive correlation between squared or absolute returns and trading volume. Such finding has received theoretical support from the mixture of distribution hypothesis (MDH) due to Clark (1973). The MDH states that the variance of returns and trading volume are driven by the same latent variable, which captures the arrival of information relevant to the price-formation process. A refinement of the MHD, due to Tauchen and Pitts (1983), is the bivariate mixture model (BMM), in which volatility and trading volume are jointly determined by the latent new information arrival. If the BMM model is correct, trading volume and volatility should exhibit the same time-dependence process. This issue is discussed in detail in a recent article by Ané and Ureche-Rangau (2006), who find that the relation between volatility and trading volume seems weaker than what the BMM would suggest.

In order to find out whether fluctuations in persistence may be linked to changes in trading volume, we constructed a rolling estimate of wavelet correlation between absolute returns and trading volume. Similarly to the unbiased MODWT-variance estimator, the MODWT covariance between the returns on X and Y at scale τ_j can be obtained as $\hat{\upsilon}^2_{XY}(\tau_j) \equiv \frac{1}{M_j}\sum_{t=L'_j}^{n-1}\tilde{d}^{(X)}_{j,t}\tilde{d}^{(Y)}_{j,t}$. An estimate of the wavelet-based correlation coefficient can be hence obtained as $\hat{\rho}(\tau_j) = \frac{\hat{\upsilon}^2_{XY}(\tau_j)}{\sqrt{\hat{\upsilon}^2_X(\tau_j)\hat{\upsilon}^2_Y(\tau_j)}}$.

Our computations are reported in Figure 3 for the two series that exhibited anti-persistence along the sample period, that is, the energy SPDR and Teck Cominco. For the raw data and scale 5 (32-64 day dynamics), we observe that the correlation between the absolute return on the Energy SPDR and its trading volume exhibited an increasing trend after the third quarter of 2004, period around which the correlation between the two series reached a minimum (Panel (a) of Figure 3). Interestingly, around that time period the absolute return was anti-persistent. However, the high correlation between the two series at scale 5 during 2006 (equal to 0.6) coincides with a period in which the absolute return displayed no persistence. As reported in previous research (e.g., Ané and Ureche-Rangau, op cit.), trading volume tends to be more persistent than absolute returns. Results not reported here show that the trading volume of the energy SPDR was persistent along most of the sample period, with a d parameter ranging between 0.1 and 0.3.

For the Teck Cominco series, there is a more distinct pattern between volatility persistence and the co-movement between the absolute return and trading volume. Indeed, the period of highest volatility persistence (Panel (b) of Figure 2) coincides with that of lowest correlation between the absolute return and trading volume (Panel (b) of Figure 3). On the other hand, the anti-persistence of the absolute return takes place around the period of highest correlation between the absolute return and trading volume in the raw data and at the first scale component (first and second quarters of 2006). Once again, computations of the persistence of trading volume show that this tended to be more persistent than the absolute return (d ranged between 0.1 and 0.25 during 2002-2006).

In sum, the above results for Teck Cominco suggest that it is possible that trading volume may have more incidence on the persistence of volatility than it has been reported in previous studies. The next question we address is whether the fluctuations in volatility level and persistence may be associated with permanent shifts in long-run volatility. In order to answer this question, we resort to the test of constancy of variance of Section 2.1 and compute a rolling series of the D-test statistic, along with its corresponding 95-percent significance level, at scales 2 and 3 for the two SPDRs and Teck Cominco and Alcan. We choose these four series because of the pattern of volatility shifts they display (Figure 4 (a)-(d)).

First of all, the energy SPDR exhibits several breakpoints at scales 2 and 3 (Panel (a)). In particular, at a 2-8 day horizon (i.e., scale 2), the years 2003 and 2005 look particularly unstable. At an 8-16 day horizon (i.e., scale 3), the number of breakpoints tends to disappear towards the beginning of 2006. However, as before, the period 2001-2004 suggests the presence of multiple variance shifts. This last pattern is also present in the utilities SPDR. However, in this series there is mostly no evidence of variance shifts from the first quarter of 2005 to the end of the sample.

The two depicted mining companies also display different variance shifts patterns, particularly at a longer-term horizon. Indeed, at scale 3, Alcan exhibited several variance constancy violations, particularly in 2003 and 2005, while Teck Cominco displayed virtually none. At scale 2, by contrast the two series presented only a few number of variance shifts. (Alcan looked more unstable towards the end of the sample period). In sum, at least at scale 3, the pattern of Alcan resembles to some extent that of the Energy SPDR. We conjecture that an explanation to this empirical finding is that Alcan co-moves more closely with the Energy SPDR than most of the other metals and minerals under analysis do, as we will analyze next.

3.3 Co-movement

We utilize two techniques to quantify the degree of co-movement in paired returns: a rolling-estimate of wavelet correlation and a rolling estimate of Moran statistic of spatial autocorrelation.

Figure 5, Panels (a) through (f), exhibits the rolling estimates of the paired correlation of raw returns and returns at scales 2 and 5 for six selected pairs: the Energy and Utilities SPDRs, and the corresponding pairs of the Energy SPDR with Alcan, Barrick Gold, Rio Tinto, Inco, and Teck Cominco. The motivation is look at the linkages between the returns on mining companies and on the Energy SPDR.

Panels (c), (d), and (f) show that the rolling pair-wise correlation coefficients between the Energy SPDR and Barrick, Rin Tinto, and Teck Cominco experienced a significant increase from 2003 onwards. For instance, for the Rio Tinto case, at scale 5 (i.e., 32-64 day dynamics), the correlation between the returns on the two series increased from –0.4 in 2003 to 0.4 in 2006. By contrast the correlation between Inco and the Energy SPDR in the raw data and at scale 2 was relatively small along the whole sample period (the peak in the raw data was 0.06 and 0.1 at scale 1). However, in the long-term component (scale 5), we found a much larger correlation, of around 0.6, towards the end of 2006.

The evolution of the rolling correlation between Alcan and the Energy SPDR deserves some attention. In general, we see that this was greater than for the other metals and minerals depicted in the raw data and at scale 2. Indeed, in the raw data, the correlation fluctuated between 0.35 and 0.55. The maximum correlation was observed in 2003, rather than by the end of the sample. At scale 2, a peak of 0.5 was also observed in 2003, afterwards the correlation tended to decline, to reach momentum again in 2005 and end up at a level of 0.5 towards the end of 2006. At scale 5, by contrast the pair-wise correlation reached a peak of 0.6 in 2003 and tended to decline thereafter.

These figures suggest that metals and minerals exhibit different degrees of dependency on energy prices. Indeed, as Table 3 shows, aluminum is much more energy-intensive in its production process than copper and primary nonferrous metals are (e.g., gold, nickel, and zinc). In our sample, the maximum correlation with the energy SPDR was observed for aluminum and the minimum, for Nickel. Gold and copper tended to be more energy-dependent at the upper scales of the data (i.e., trend component). This analysis stresses the importance of decomposing correlations across timescales in order to have a better understanding of the dynamics involved.

In order to rely on a global measure of co-movement of the sampled series, we computed Moran's statistic of spatial autocorrelation. Towards that end, we considered the 12 return series in the sample and their corresponding standardized cumulative returns over a 3-month rolling window. Cumulative returns are standardized in order that clusters in volatility do not bias Moran's statistic. The (i, j) element of the weights matrix is given by a measure of distance between the returns on i and j, d_{ij}, where $d_{ij} = \sqrt{2(1-\rho_{ij})}$ and ρ_{ij} is Spearman's correlation coefficient of trading volume. The definition of d_{ij} follows

Mantegna and Stanley (2000), chapter 13. For the sake of computational speed, we kept the weights matrix fixed across iterations (1,189 in total). We also allowed the weights matrix to vary across iterations, but, besides making the calculations much slower, the statistical significance of Moran's statistic exhibited an erratic pattern.

A 3-month rolling Moran's statistic, along with a 90-percent confidence band, is depicted in Figure 6. As we see, there is evidence of spatial correlation over the first quarter of 2003, that is, at the beginning of the Iraq invasion; the first three quarters of 2004, and towards the end of the sample period, that is, during the second and third quarters of 2006.

The sign of Moran's statistic deserves some interpretation. As we know, the distance between firms is measured in terms of Spearman's correlation coefficient between their trading volumes. This implies that two firms whose trading volumes are positive and highly correlated will be close to one another, and, hence, their corresponding weight will be small. The weights in Moran's statistic will be largest for paired firms which exhibit highly heterogeneous transaction patterns. On the other hand, Moran's statistic will be negative when the numerator of expression (11) is negative. For paired firms, a negative sign will arise when one firm's return is below the sample average while the other's is above it. Overall, this implies that heterogeneity in trading volume will be amplified by heterogeneity in returns performance. If we look at Figure 5, we see that, except for the end of the sample, whenever statistically significant, spatial correlation is associated with negative values of Moran's statistic.

4 Conclusions

Based on the statistical techniques of wavelets and spatial statistics, we characterized the behavior of volatility (e.g., evolution over time, persistence, and presence of structural breaks) and the degree of co-movement of the stock returns of ten leading mining firms operating in the Asia-Pacific region—Alcan Inc., Antofagasta, Barrick Gold Corp., BHP Billiton, International Nickel Ind., Peabody Energy, Phelps Dodge Corp, Rio Tinto plc., Teck Cominco Ltd., and Yanzhou Coal Mining Co— over a time period predominated by the political turmoil caused by 9/11 and the subsequent invasion of Iraq.

We concluded that most mining company returns became especially volatile around the time of the declaration of war on terror and the subsequent invasion of Iraq, and around the time of the sizeable hike in the oil price during 2005-2006. Interestingly, firms which belong to a particular industry did not necessarily display identical patterns of return volatility. As to volatility persistence, we concluded that trading volume may have more incidence than it has been reported in previous studies.

In addition, we found that the metals and minerals analyzed exhibited different degrees of dependency on energy prices. The maximum correlation was observed for aluminum and the minimum for Nickel. These results are line with what is empirically observed about the manufacturing processes of these minerals. Gold and copper in turn tended to be more energy dependent at the upper scales of the data (i.e., long-term horizon), which stresses the importance of resorting to a timescale decomposition of correlation. As to spatial dependency, we found evidence for the first quarter of 2003; the first three quarters of 2004, and towards the second and third quarters of 2006.

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Table 1 Summary statistics of daily series

Statistic	Energy SPDR	Utilities SPDR	Alcan	Antofagasta	Barrick	BHP
Minimum	–0.063	–0.089	–0.123	–0.094	–0.117	–0.111
1st Qu.	–0.009	–0.006	–0.012	–0.008	–0.014	–0.011
Median	0.001	0.001	0.000	0.000	0.000	0.000
Mean	0.000	0.000	0.000	0.001	0.000	0.001
3rd. Qu.	0.010	0.007	0.012	0.010	0.014	0.013
IQ range	0.019	0.013	0.024	0.018	0.028	0.024
Maximum	0.067	0.085	0.105	0.092	0.104	0.123
Kurtosis–3	0.92	6.43	2.44	2.82	1.37	2.58
Skewness	–0.19	–0.20	–0.05	0.11	–0.02	0.02
Pr. SW stat	0.000	0.000	0.000	0.000	0.000	0.000
Observations	1,717	1,677	1,717	1,780	1,711	1,683
Sample period	Jan 00-Oct 06	Jan 00-Oct 06	Jan00-Oct06	Jan 00-Oct 06	Jan 00-Oct 06	May 00-Oct 06
Statistic	Inco	Peabody	Phelps	Rio Tinto	Teck Cominco	Yanzhou
Minimum	–0.407	–0.155	–0.071	–0.099	–0.200	–0.204
1st Qu.	–0.012	–0.013	–0.010	–0.014	–0.014	–0.013
Median	0.000	0.001	0.000	0.001	0.000	0.000
Mean	0.001	0.001	0.000	0.001	0.001	0.000
3rd. Qu.	0.014	0.015	0.010	0.016	0.017	0.014
IQ range	0.026	0.028	0.020	0.030	0.030	0.027
Maximum	0.424	0.12	0.072	0.133	0.210	0.213
Kurtosis–3	52.58	2.75	0.80	1.19	5.56	6.05
Skewness	0.62	–0.12	0.00	0.03	–0.10	0.13
Pr. SW stat	0.000	0.00	0.000	0.000	0.000	0.000
Observations	1,778	1,366	1,782	1,717	1,715	1,695
Sample period	Jan 00-Oct 06	May 01-Oct 06	Jan 00-Oct 06	Jan 00-Oct 06	Jan 00-Oct 06	Jan 00-Oct 06

Notes: (1) The sampled series are Energy Select Sector SPDR (Energy SPDR), Utilities Select Sector SPDR (Utilities SPDR); Alcan Inc. (Alcan), Antofagasta (Antofagasta), Barrick Gold Corp. (Barrick), BHP Billiton (BHP), International Nickel Ind. (Inco), Peabody Energy (Peabody), Phelps Dodge Corp (Phelps), Rio Tinto plc. (Rio Tinto), Teck Cominco Ltd. (Teck Cominco), and Yanzhou Coal Mining Co. Ltd. (Yanzhou). (2) The inter-quartile range (IQ range) is computed as the difference between the third and the first quartile of the empirical distribution. (3) 'Pr. SW stat' denotes the probability value of the Shapiro-Wilk's statistic. Under the null hypothesis, individual return series are normally distributed.

Table 2 SPDR description and firm profiles

Series	Description
Energy SPDR	Companies involved in developing and producing crude oil and natural gas, and provide drilling and other energy-related services (e.g., ExxonMobil Corp., ChevronTexaco Corp, and ConocoPhillips)
Utilities SPDR	Companies involved in water and electrical power and natural gas distribution industries (e.g., Duke Energy Corp., Excelon Corp., and Dominion Resources Inc.)
Alcan	Primary aluminum, light gage sheet, foil and packaging materials. Headquartered in Montreal, Canada.
Antofagasta	Copper and cathodes .Its production is mainly concentrated in South American where it operates two quarries in Chile. Headquartered in London,. U.K.
Barrick	Gold, copper, silver, and zinc. It holds interests in various gold mineral resources located in North and South America, Australia Pacific, and in Africa. Headquartered in Toronto, Canada.
BHP Billiton	Petroleum, Aluminum, Base Metals (copper, silver, zinc, lead, uranium, and copper by-products, including gold), Carbon Steel Materials, Diamonds and Specialty Products, Energy Coal, and Stainless Steel Materials. It operates primarily in Australia, South America, Africa, and Canada. Headquartered in Melbourne, Australia
Inco	Nickel, copper, precious metals and cobalt. It operates in two segments: finished products and intermediates. Finished products segment comprises the mining and processing operations in Canada, and refining operations in the United Kingdom and interests in refining operations in Japan and other Asian countries. Intermediates segment comprises the mining and processing operations in Indonesia where nickel-in-matte is produced and sold primarily into the Japanese market. Headquartered in Manitoba and Toronto, Canada.
Peabody	Coal. It owns interests in 40 coal operations located in the United States and Australia, as well as owns joint venture interests in a Venezuelan mine. It also develops mine-mouth coal-fueled generating plants; produces coalbed methane; and develops Btu Conversion technologies. Based in St. Louis, Missouri, U.S.
Phelps Dodge	Copper and molybdenum, with mines and processing facilities in North and South America, Europe and China. It also processes other minerals as byproducts, such as gold, silver and rhenium. Headquartered in Arizona, U.S.
Rio Tinto	Aluminum; copper; diamonds; energy products (e.g., coal and uranium; gold); industrial minerals (e.g., borax, titanium dioxide, salt, and talc; and iron ore). It operates primarily in North America, Europe, Asia, Australia, and New Zealand. Headquartered in London, U.K.
Teck Cominco	Zinc, copper, and metallurgical coal, as well as precious metals, lead, molybdenum, electrical power, fertilizers, and various specialty metals. It operates in Canada, the United States, Latin America, Asia, Europe, and Australia. Headquartered in Vancouver, Canada.
Yanzhou	Coal, methanol; investments in heat and electricity. It has interests in China and New South Wales, Australia. Heardquartered in Zoucheng, the People's Republic of China.

Notes: (1) Information collected from finance.yahoo.com and companies websites; (2) Sector SPDRs are unique ETFs (Exchange Traded Funds) that divide the S&P 500 into nine sector index funds: consumer discretionary, consumer staples, energy, financial sector, health care, industrial sector, materials, technology, and utilities. (http://www.sectorspdr.com).

Table 3 Manufacturing primary energy consumption by type of fuel and major industry group (Trillions of Btu)

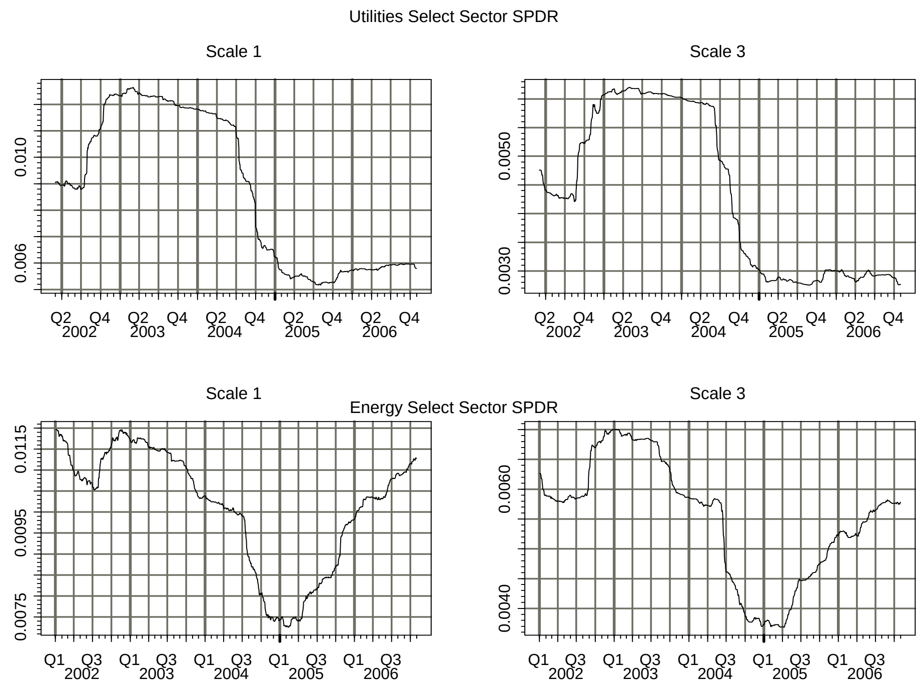
Industry	Total	Net electricity	Natural gas	LPG	Coal	Coke & breeze	Other
All Industries	21,663	2,656	6,835	1,631	2,105	449	7,926
Petroleum and coal products	6,339	121	811	47	(D)	(D)	5,344
Petroleum refining	6,263	114	756	(D)	(D)	0	5,271
Primary metal industries	2,462	493	811	5	922	424	85
Electrometallurgical products	38	16	3	(Z)	13	(S)	5
Gray and ductile iron foundries	94	30	33	1	1	29	1
Primary copper	32	5	22	(D)	(D)	0	(D)
Primary aluminum	241	183	17	(D)	(D)	(D)	40
Primary nonferrous metals (except copper & aluminum)	45	14	12	(Z)	10	(D)	2
Fabricated metal products	367	115	220	5	(D)	(D)	(S)

Notes: (1) D: withheld to avoid disclosing data for individual establishments; S: Withheld because relative standard error is greater than 50 percent; Z: Less than 0.5 trillion Btu. (2) Net electricity is obtained by aggregating purchases, transfers in, and generation from noncombustible renewable resources minus quantities sold and transferred out. It excludes electricity inputs from onsite cogeneration or generation from combustible fuels because that energy has already been included as generating fuel (for example, coal). (3) Natural gas is obtained from utilities, transmission pipelines, and any other supplier such as brokers and producers. (4) "Other" includes net steam, and other energy that respondents indicated was used to produce heat and power or as feedstock/raw material inputs. (5) Primary nonferrous include, among others, gold, lead, nickel, platinum, silver, tin, titanium, and zinc.

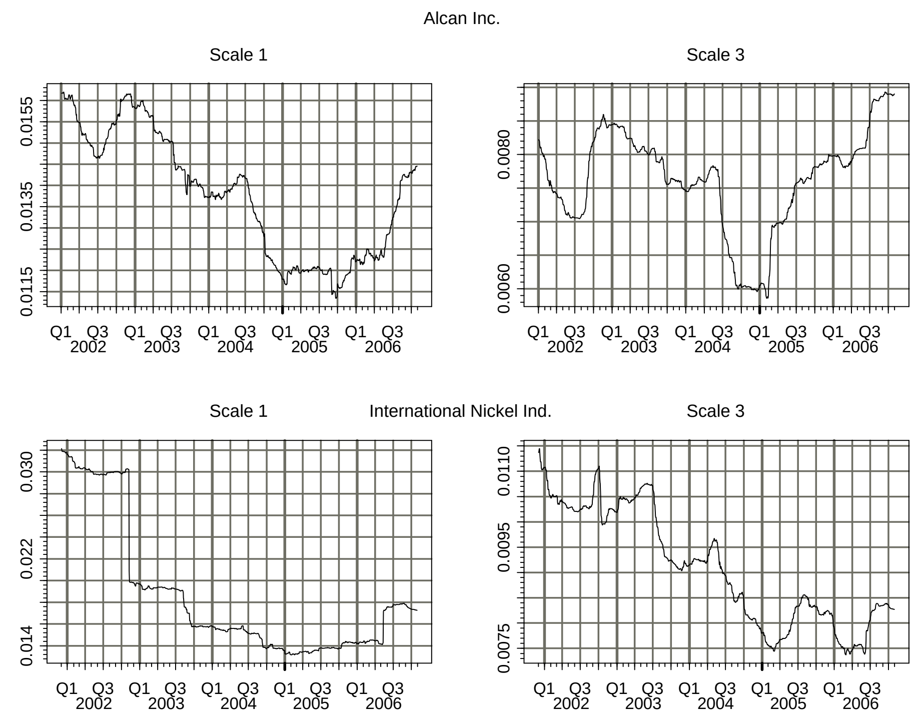
Source: http://allcountries.org/uscensus/951_manufacturing_primary_energy_consumption_for_all.html. The information here reported is based on the 1994 U.S. Manufacturing Energy Consumption Survey.

Figure 1 Wavelet-based rolling estimate of volatility

(a) Spiders

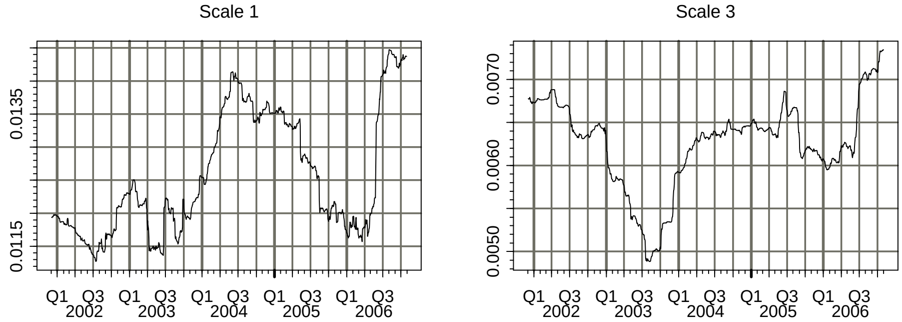


(b) Aluminum (Alcan) and Nickel (Inco)

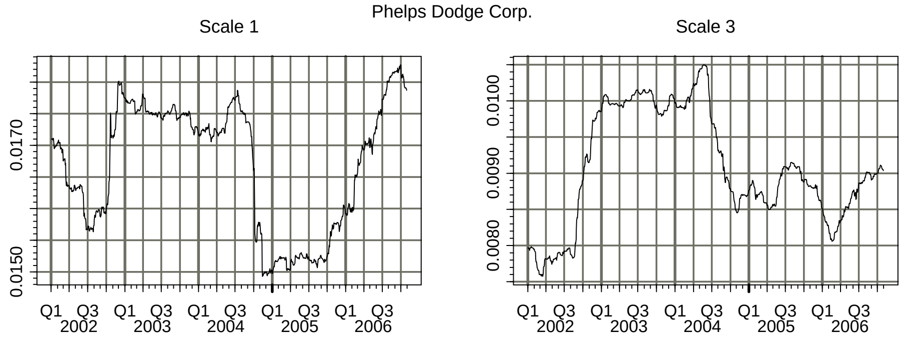


(c) Copper

Antofagasta

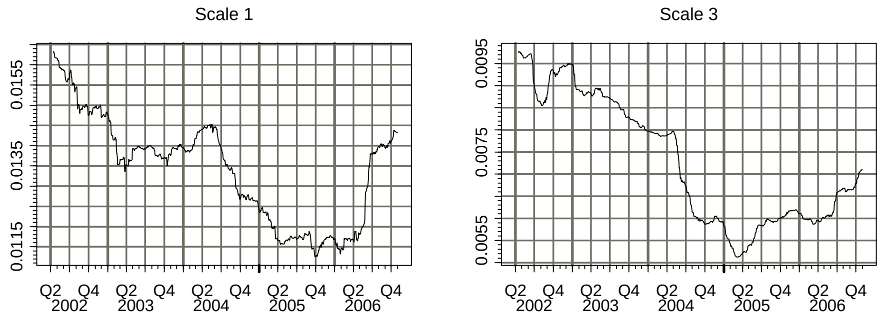


Phelps Dodge Corp.

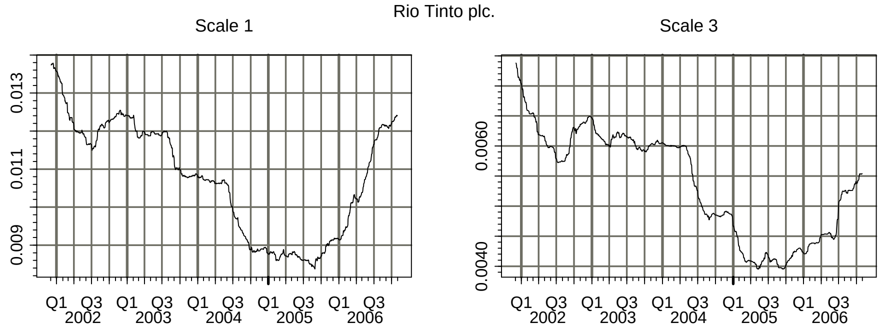


(d) Aluminum and Base metals (BHP) &Aluminum; copper; energy products, gold (Rio Tinto)

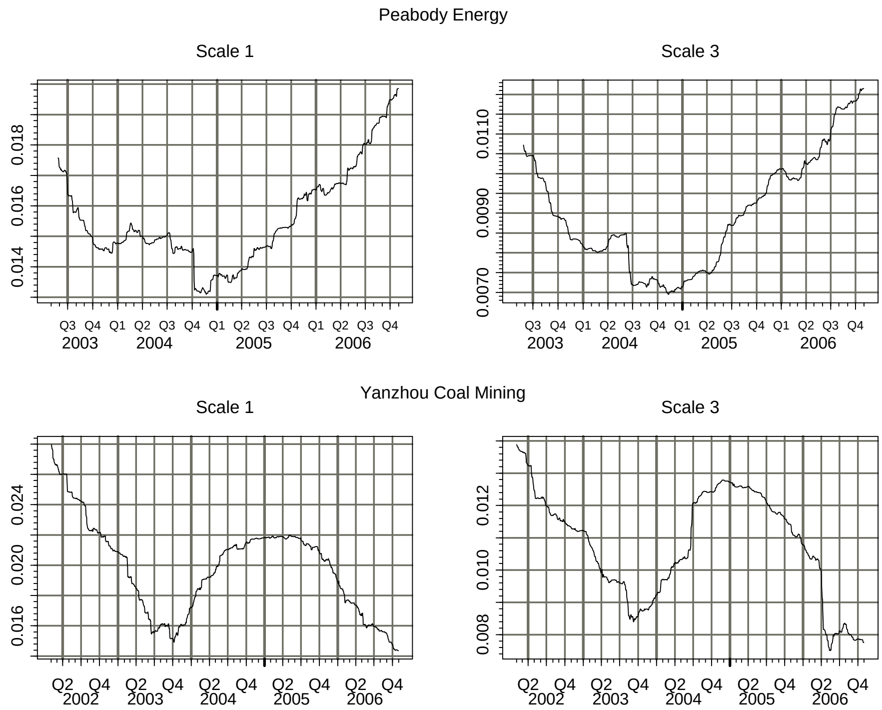
BHP Billiton



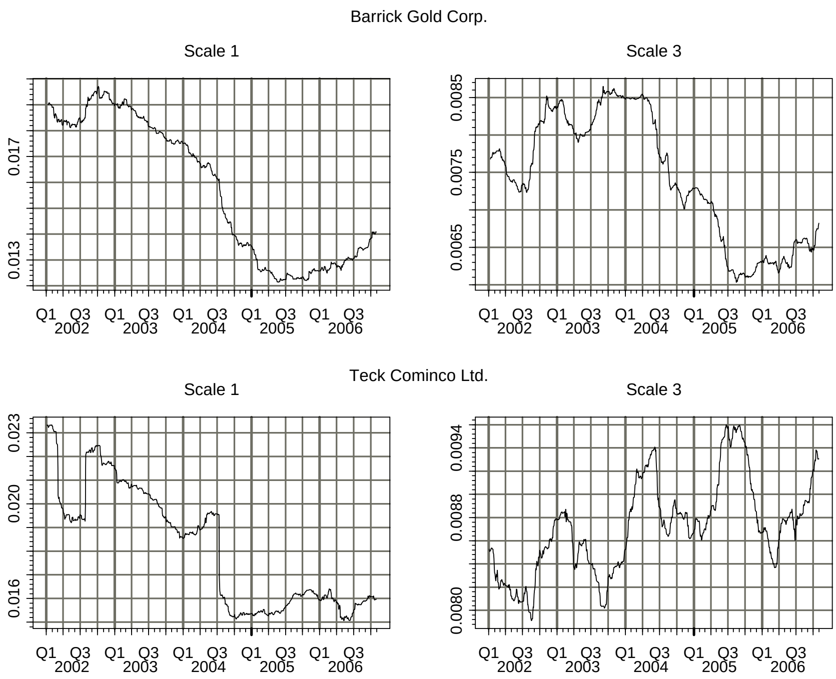
Rio Tinto plc.



(e) Coal



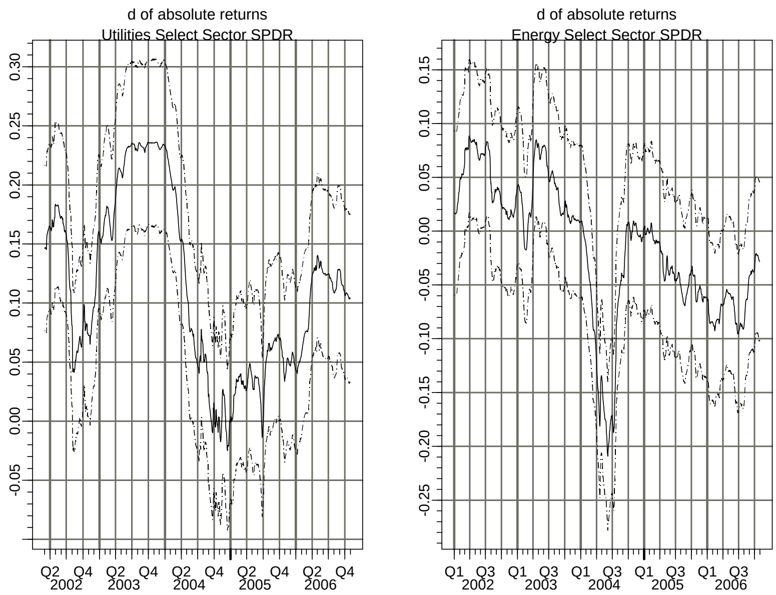
(f) Gold (Barrick) & Zinc, copper, and metallurgical coal (Teck Cominco)



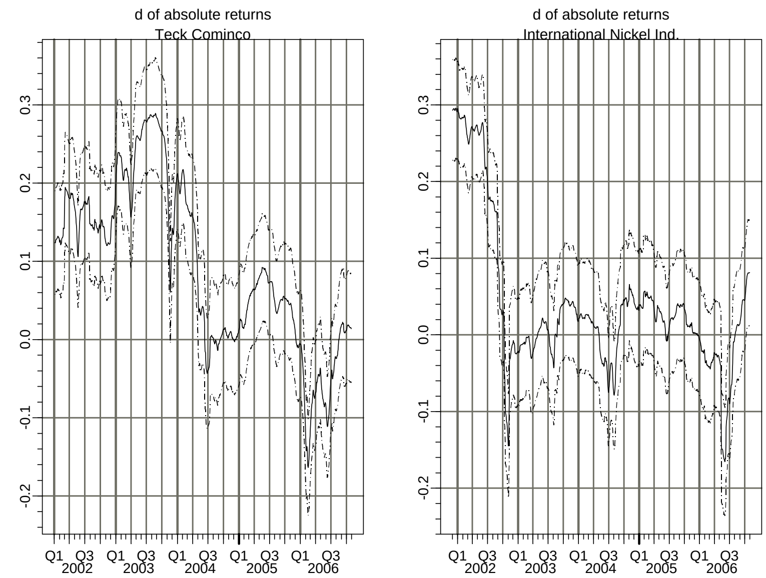
<u>Note</u>: A rolling-window of 500 observations is utilized in Panels (a) through (f).

Figure 2 Rolling estimate of the long-memory parameter for a selected group of series

(a)



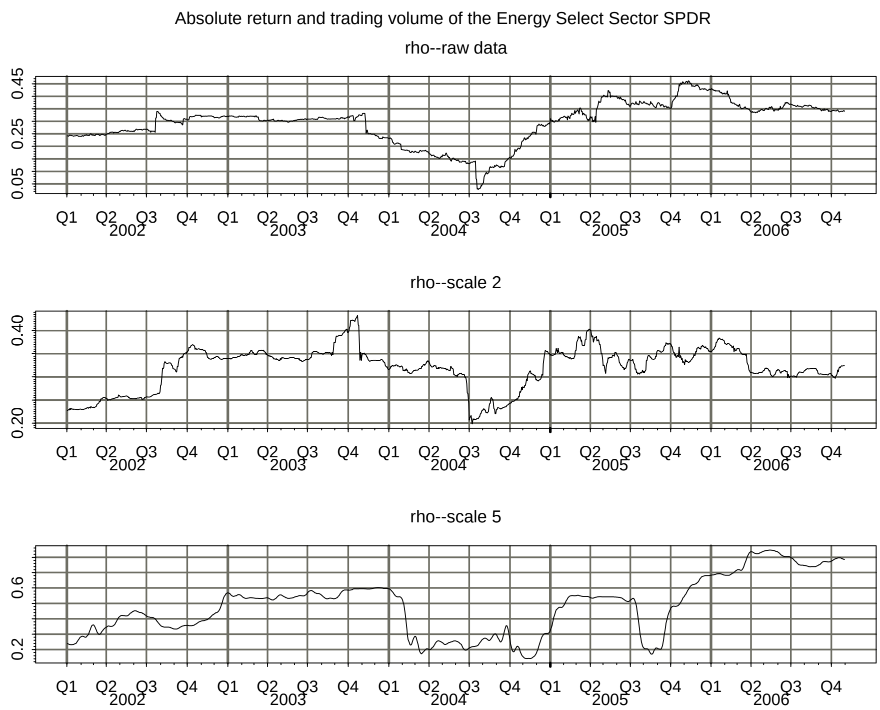
(b)



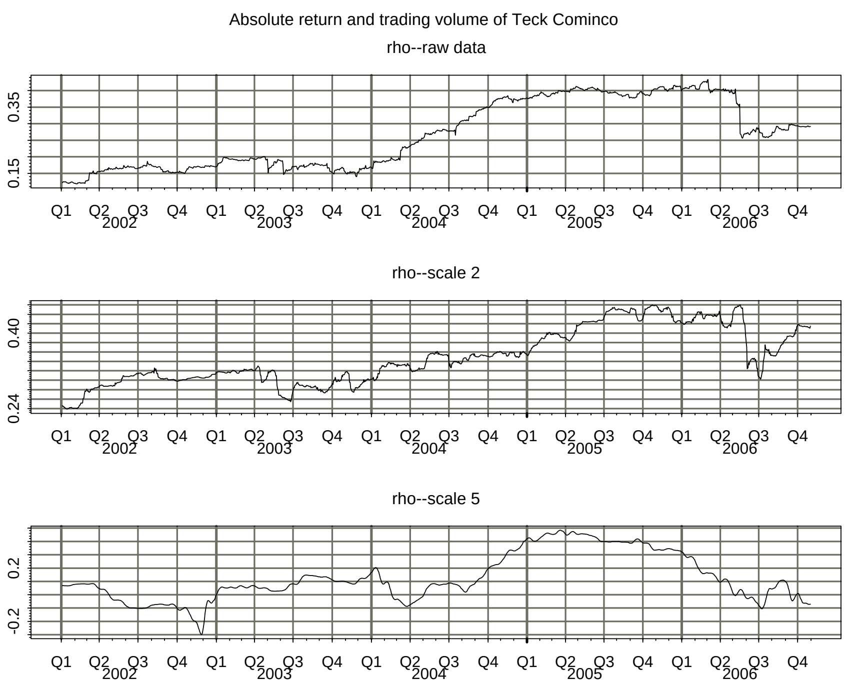
Note: A rolling-window of 500 observations is utilized in Panels (a) and (b).

Figure 3 Co-movement of absolute returns and trading volume

(a)



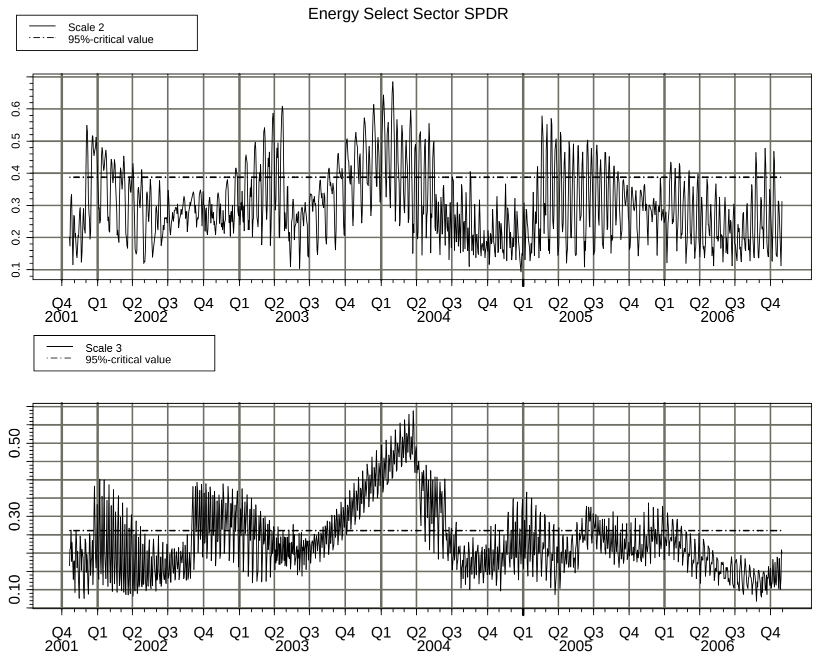
(b)



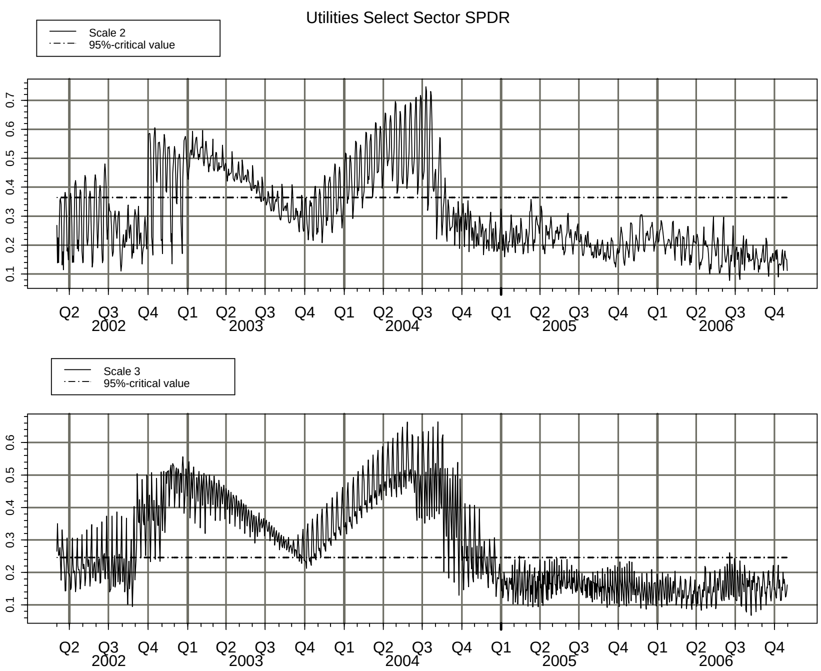
Note: A rolling-window of 500 observations is utilized in Panels (a) and (b).

Figure 4 Rolling-D test: some selected return series

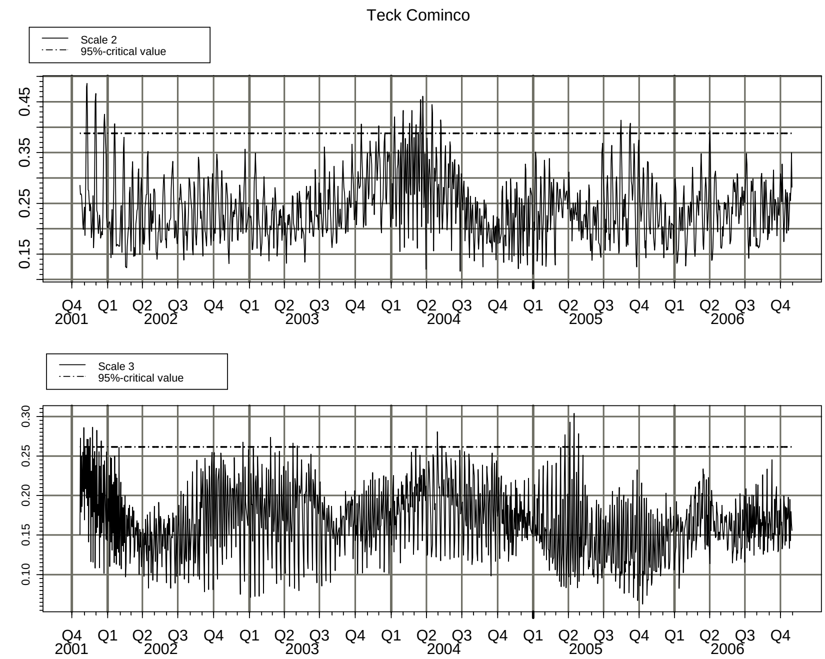
(a)



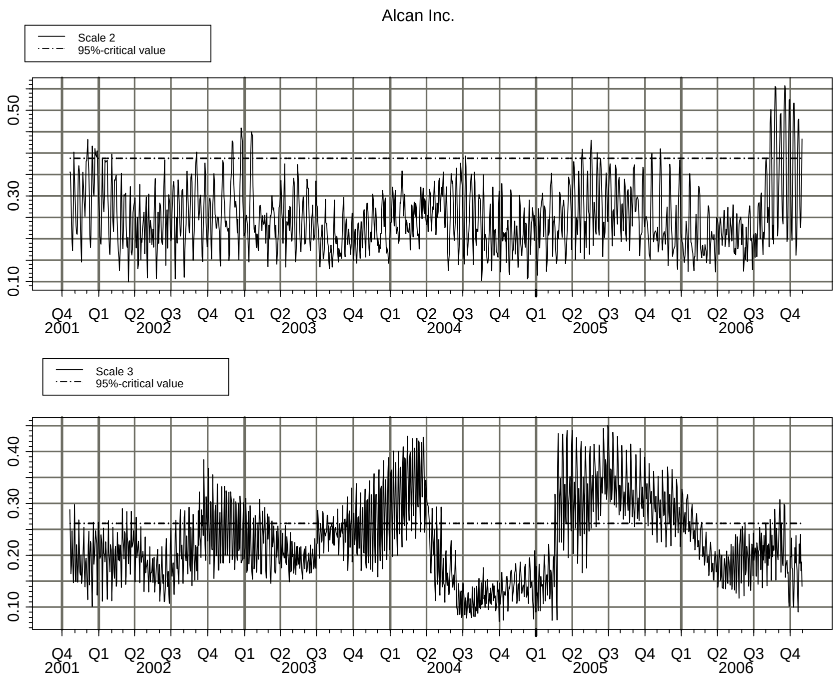
(b)



(c)



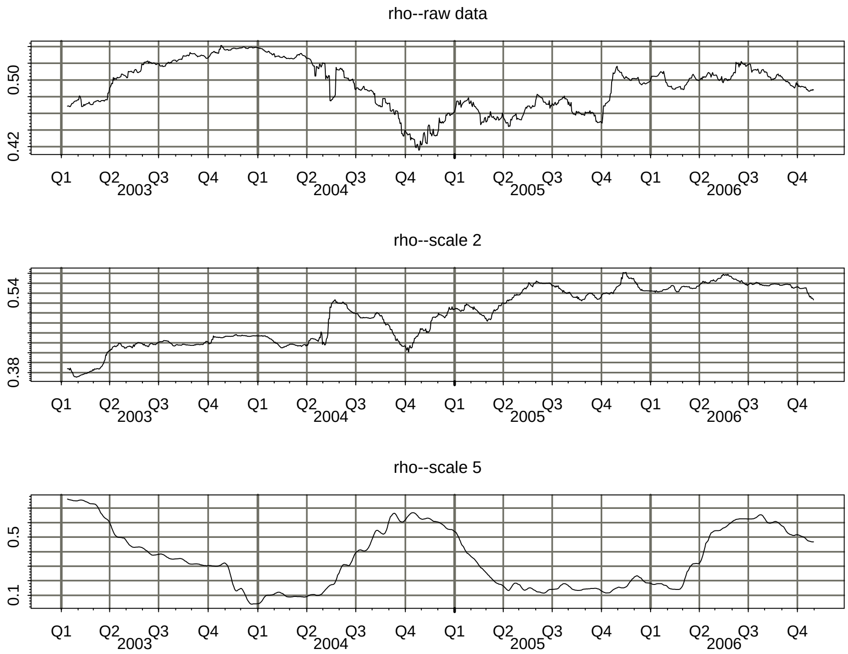
(d)



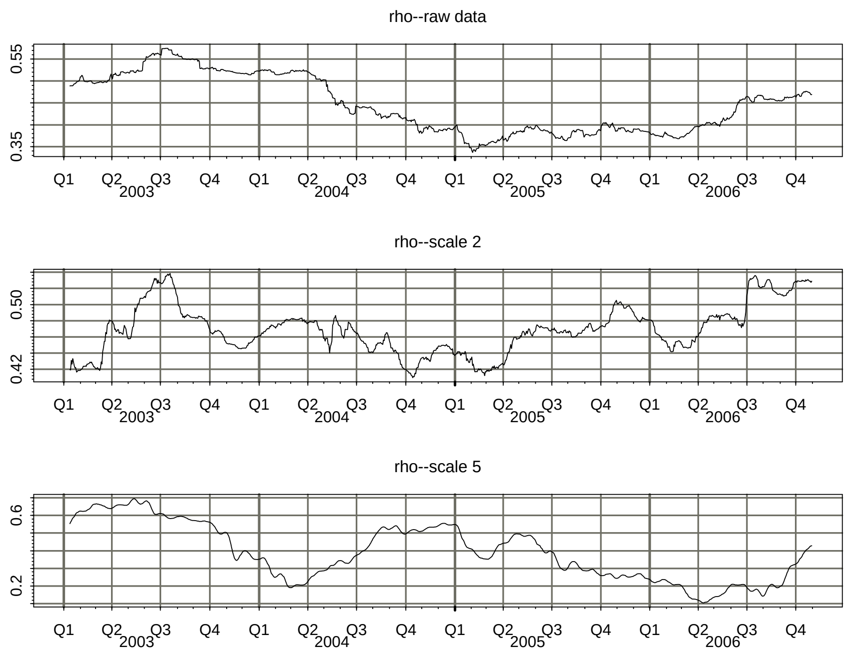
Note: A rolling-window of 450 observations is utilized in Panels (a) through (d).

Figure 5 Rolling estimates of pair-wise correlation coefficients

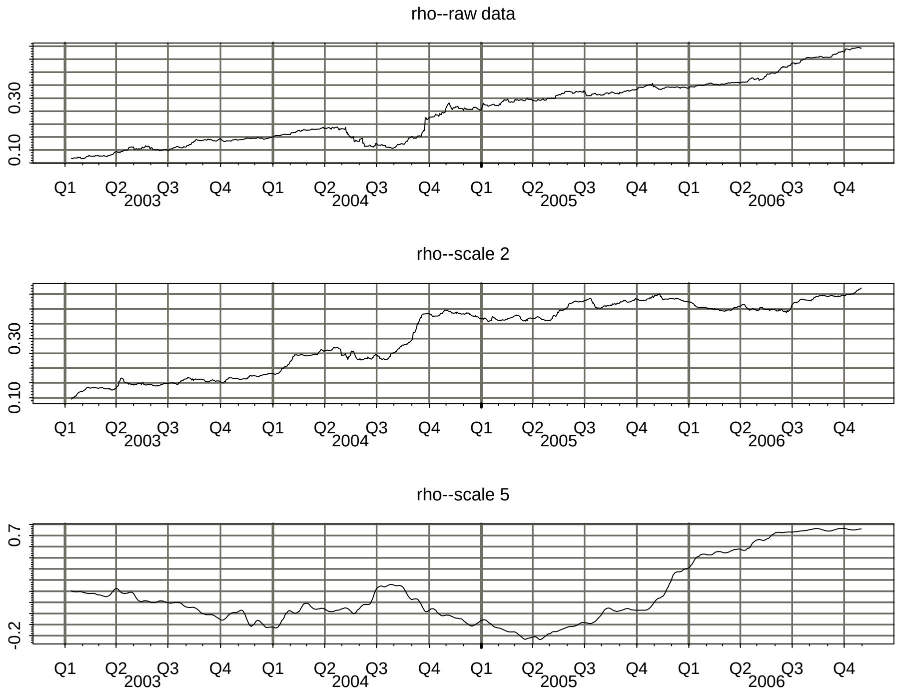
(a) Energy and Utilities Select Sector SPDRs



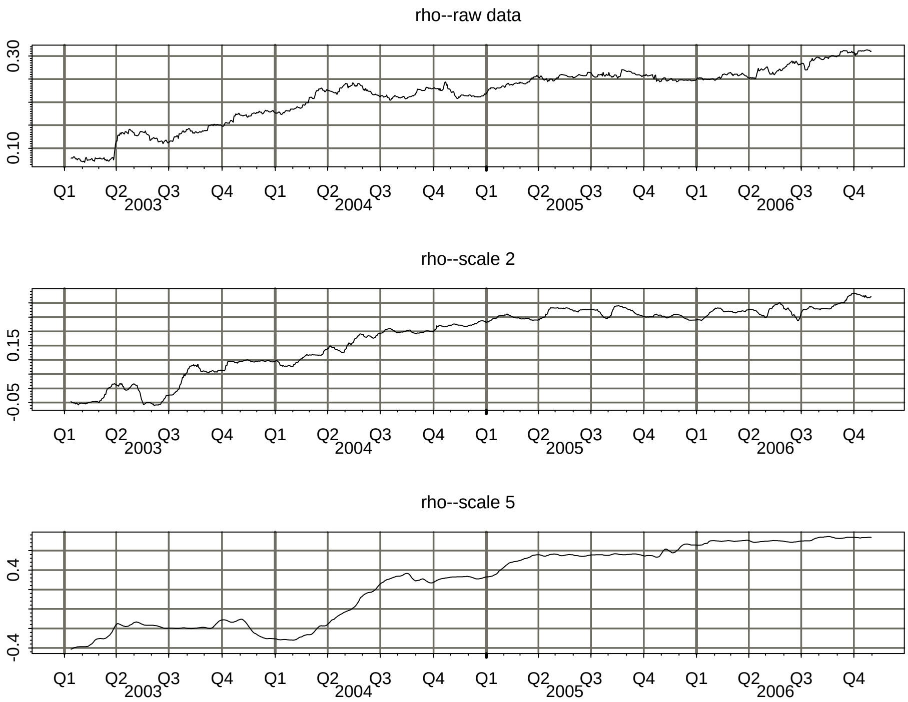
(b) Alcan Inc. and Energy Select Sector SPDR



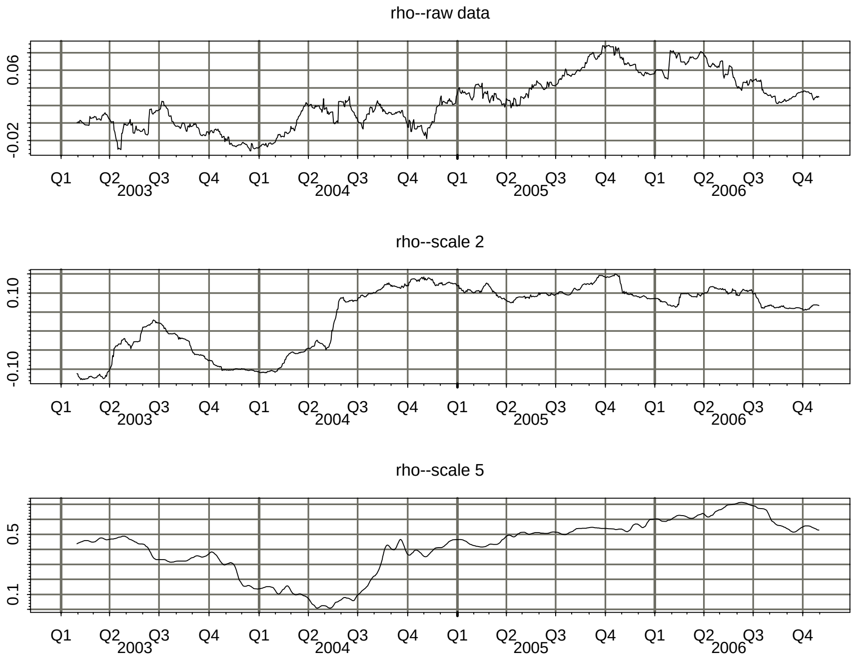
(c) Barrick Gold and Energy Select Sector SPDR



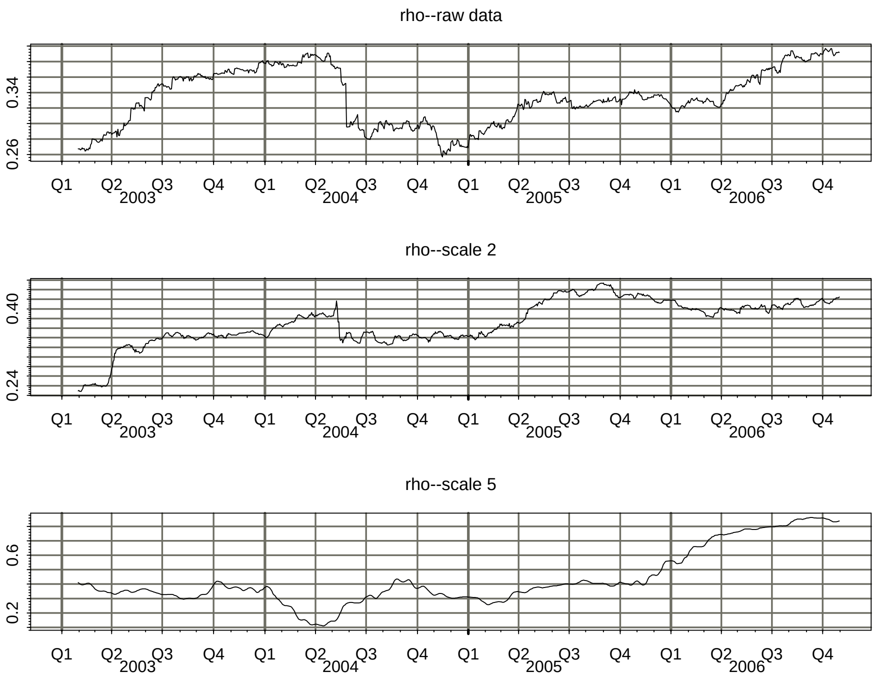
(d) Rio Tinto and Energy Select Sector SPDR



(e) International Nickel Ind. Energy Select Sector SPDR

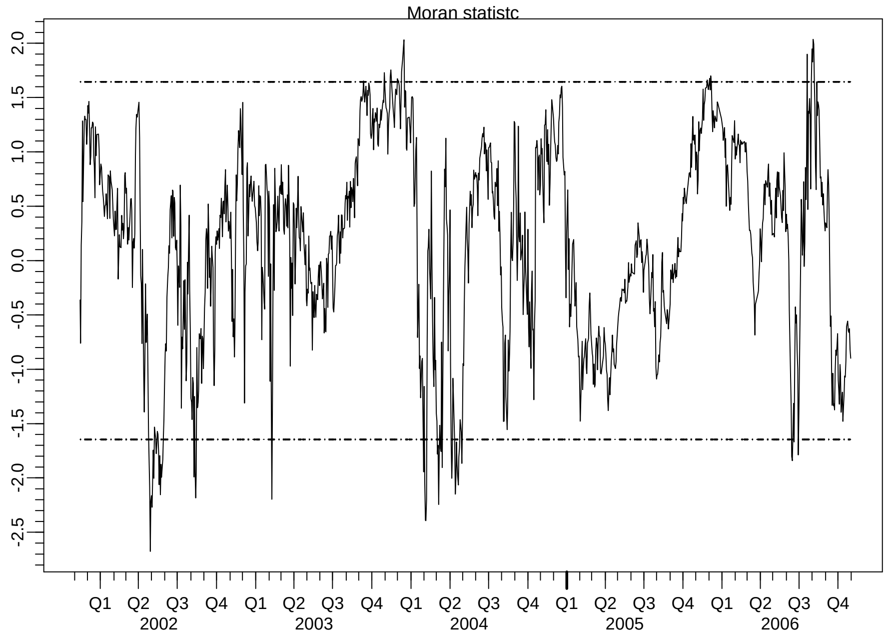


(f) Teck Cominco and Energy Select Sector SPDR



Note: A rolling-window of 500 observations is utilized in Panels (a) through (f).

Figure 6 Spatial autocorrelation



<u>Notes:</u> (1) Dashed lines represent a 90-percent confidence band. (2) A 3-month rolling window was used.

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