Volatility contagion and market integration across major coal markets: A diagonal BEKK GARCH approach

George Varghese[i]

IFMR Graduate School of Business

Dr. T. Bangar Raju[ii]

University of Petroleum and Energy Studies

Abstract

The present study attempts to meaningfully add to the existing strand of literature on coal market predictability by examining the level of market integration across three major coal export markets. Using a tri-variate diagonal BEKK GARCH framework, the study investigates the own-volatility persistence and cross-volatility contagion effects among European, Australian, and South African coal markets. The results validate the presence of strong volatility contagion among the three markets, indicating a high level of market integration. The contagion effect is observed to be heterogeneous across market pairs. Further, while the study finds convincing evidence for volatility clustering, the EGARCH results fail to affirm the presence of leverage effect among the returns series. In short, the study unveiled complex dynamics in the coal markets' price generation mechanism that necessitates active portfolio management. As such, besides having significant policy implications, the study's findings would be of pertinent interest to financial practitioners and investors who seek to diversify their portfolio through investments in global commodity markets.

Keywords: Coal market, Volatility contagion, Leverage effect, Diagonal BEKK GARCH, Volatility clustering, Spillover

JEL Classification: Q43, G15, F15, P34

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i) Corresponding Author. IFMR Graduate School of Business #5655, Central Expressway, Sri City, Andhra Pradesh, India (517646) E-mail: georgevarghese215@gmail.com

ii) University of Petroleum and Energy Studies Dehradun, India. E-mail: bangarraju@gmail.com

First received, August 14, 2019; Revision received, January 23, 2020; Accepted, February 25, 2020.

1 Introduction

Volatility is a concept that is of great interest to economists for the very reason that it is a measure of uncertainty. Over the last few decades, there has been an increasing number of studies that look into the transmission of volatility and its contagion effects, most of which pertain to international stock markets, global crude oil markets and foreign exchange markets. This growth in literature was primarily due to scholarly efforts aimed at understanding the integration of global capital markets in the light of liberalization of capital accounts, across the globe. Such liberalization offered a gateway for international investors towards portfolio diversification across currencies, commodities and national stock markets.

However, similar studies in the area of global coal markets have not received due attention despite coal being one of the most vital and influential commodities traded globally. Coal is an important source of power generation, and more than 35% of the power generated globally is dependent on this fuel. Countries like South Africa, Poland, China, and Australia have been relying on coal for about 70% of their power generation. Additionally, countries like Japan, India, South Korea, Germany, UK, and Russia heavily depend on coal imports to meet a significant percentage of their total power generation.

Moreover, with economies world over becoming more and more energy-hungry, the dependence on coal reserves has been constantly increasing as is the case with other energy generating sources. Though countries like China, France, United Kingdom, Denmark and New Zealand (among others) are making big strides towards diversifying their energy dependence through the deliberate phase-out of coal use and by building larger dependence on renewable sources, this effort has been counterbalanced by the simultaneous industrialization in other parts of the world.

From the report of the International Energy Agency (2016), the world steam coal production declined in the year 2015 at around 200 Mt and was recorded as one of the largest declines since 1971. The year 2015 also saw a decrease in Steam coal prices which had positively impacted the electricity generation prices. From the report (IEA Coal Industry Advisory Board, 2014), coal prices have an increasing impact on electricity prices in various countries across Europe, Australia, Japan, China, South Africa, and the USA to name a few. While the degree of variation in energy prices is heterogeneous across different countries, the volatility of wholesale electricity prices invariably depends on the volatility of international coal prices.

The exceptional fluxes and volatilities in international coal prices manifest itself in the form of unstable energy prices all around the globe. As such, understanding the nature and characteristics of coal prices and analyzing the magnitude and direction of volatility transmissions, particularly in the case of major coal export markets is of paramount importance. This is more so when such markets exert a disproportionally large influence over a larger pool of coal importing economies. The present study is a step in this direction.

The present study examines the presence and magnitude of volatility transmission across the three major coal export markets, namely Europe, Australia, and South Africa. The study employs an EGARCH framework to analyze the presence of leverage effect among the underlying variables. Following which, the authors investigate the time-varying conditional variance, own volatility persistence and the cross volatility contagion effects among the three global coal markets using a trivariate Diagonal BEKK GARCH model.

The findings of the study show no evidence for the presence of leverage effect across any of the underlying coal markets. However, the study showed that there exists a high level of market integration among the three markets. Additionally, while evidence supports volatility contagion across market pairs, the magnitude of volatility contagion is observed to be heterogeneous across each market pair. Further, the study found GARCH effects to be more dominant than ARCH effects, implying that co-variation in shocks are more dependent on its own lags rather than on past errors.

The study's findings may be of pertinent interest to investors who seek to diversify their portfolio through investments in global commodity markets. The findings show that investing in two or more global coal indices at a time do not help diversify or reduce portfolio risk. Rather, investors should look to diversify their portfolio through investments across commodity and equity markets. When it comes to financial practitioners and researchers, the study sheds light on the need to systematically observe the cross-correlations and volatility contagions across all markets in the process of portfolio creation, for markets tend to become more and more integrated as and when the economy becomes unstable (volatile). As such, a high level of financial integration weakens the portfolio against external shocks. Indicatively, the study's findings would be of pertinent interest to financial practitioners and investors who seek to diversify their portfolio through investments in global commodity markets.

The remaining part of the paper is organized as follows. Section two explores select theoretical as well as empirical literature available in the area of international coal markets and identifies the research gap which the present study attempts to fill. The next section is devoted to the introduction of data used for the study. Section four gives a concise explanation of the econometric models used for our analysis along with the rationale for choosing them. The empirical findings and the interpretations thereof are discussed in section five. Section six summarizes the main findings and concludes.

2 Literature review

The emergence and evolution of the coal trade have been discussed extensively by Ekawan & Duchene (2006) and Ekawan et al. (2006). The papers discussed the birth of various coal indices like API 2 for steam coal prices CIF, ARA (Amsterdam, Rotterdam, and Antwerp) for European prices and API 4 for steam coal prices FOB Richards Bay Terminal, South African prices. The evolution of Australian index prices calculated FOB, Newcastle is marked due to the trading of Australian coal to Asian markets (Schernikau, 2010). API stands for the Argus/McCloskey's Coal Price Index service which creates key indices (API 2, API 4 and API 6 among others) used for international physical and derivatives coal business.

Zaklan et al. (2012) empirically analyzed the globalization of steam coal markets using comprehensive multivariate cointegration analysis in the three parts of the steam coal value chain – namely transport, export, and import prices. Warell (2005) also suggests that there has been a partial integration of coal markets to some extent until the early 1990s between Europe and Japan. Studies such as Papiez & Smiech (2015) and Smiech, et al., (2016) found strong evidence of the Pacific Ocean region trade dominating international coal prices. Further, by employing cointegration analysis in coal markets and using Granger causality tests, the study found the integration of steam coal markets to be stronger when the freight prices are relatively low.

By employing the Johansen cointegration procedure for the coal markets, Liu & Geman (2017) found the coal markets to be weakly integrated. Wilmot (2016) studied discontinuities in the steam coal market using GARCH analysis and found the presence of high volatilities which thereby forced the power plants to switch to alternative fuels. Humphreys & McClain (1998) in their study used the GARCH methodology in order to identify the optimum energy portfolio selection between coal, natural gas, and crude oil - keeping in view the various energy shocks and thereby reducing its impact on power generation costs. To understand the volatility in coal, electricity and CO2 markets in Germany, Kiesel & Metka (2013) used GARCH, GJR-GARCH and exponentially weighted moving average methods in their analysis and found evidence for high price volatility and suggested the need to set up risk management by power utilities.

An extensive study was done by Papiez & Smiech, (2013) to understand the integration of steam coal markets using ARMA GARCH and ARMA EGARCH methods. The results showed that the coal prices tend to exhibit a significant reaction to impulses if they had come from the same regions over and above, had the impulses been from coal prices of different regions. The analysis of causality-in-variance found volatility spillover to be a rare event signifying that the coal markets do not resemble the traditional financial markets, where volatility spillover is a frequent occurrence. However, papers such as Li et al. (2010), Smiech et al. (2016) and Papiez & Smiech (2015) show mixed results in regard to the degree of integration among the various coal markets.

BEKK GARCH and DCC GARCH models were used to study the time-varying correlation and dynamic volatility spillover among the European carbon futures prices and the energy prices of coal, Brent crude oil, and natural gas by Zhang & Sun (2016). BEKK GARCH results on volatility spillover between the four markets showed the coal market to have a high correlation with the carbon market as compared to that of Brent crude and natural gas markets. Further, as can be seen from the literature, several other methods have also been used to study the international coal prices, such as, multiple regression analysis (Ali & Rahman, 2013), Generalised Regression, Neural Network and AR(2) methods (Kezemien et al., 2015), and multi-layer perceptron network model (Fan et al., 2016) to name a few.

The transmission of volatility and its contagion effects have been studied extensively over the last decade using multivariate GARCH models and there is a growing body of literature in and around volatility contagion effects. However, most of such studies have been in the area of international stock markets, crude oil markets, and foreign exchanges (Varghese, 2018; Varghese and Madhavan, 2019). Similar studies in the area of international coal export markets are very few. Moreover, studies that explore the volatility spillover among the major coal indexes of coal API 2, API 4 and API 6 are further limited (Papiez & Smiech, 2013).

In this backdrop, the present study tries to bridge this gap in the literature by empirically examining the nature and magnitude of volatility contagion among the three major coal exporting markets, namely, the European, the Australian and the South African coal export markets. At the outset, the ARCH test is conducted to check for volatility clustering. An EGARCH model is then used to validate the presence/absence of the leverage effect. Finally, the study employs a trivariate Diagonal BEKK GARCH model to estimate the time-varying conditional variance and to examine the own volatility persistence as well as the cross volatility contagion effects among the three markets.

3 Data

The end of 2004 saw the creation of Coal Indexes following the emergence of coal derivatives. API 2 was created to understand the CIF ARA prices in Europe. API 4 was created to understand the FOB prices of South Africa at the Richards Bay coal terminal. These indices were started by Argus and were published on a weekly basis. Later, API 6 was created to understand the FOB prices of steam coal from Australia. Understandings from Papiez & Smiech, (2013) on – API 2 CIF ARA (Amsterdam Rotterdam and Antwerp) European prices, API 4 FOB Richards Bay terminal South African prices and API 6 CIF Newcastle Australian prices – were taken into consideration to study the volatility contagion effects in the coal market price indices. Weekly data from 3rd September 2010 till 23rd September 2016 were used for the study.

Table 1. Description of data

Variable	Symbol	Stands for:
European coal export prices	ARA	API 2 Amsterdam Rotterdam and Antwerp
Australian coal export prices	NewCastle	API 6 Australian Coal index
South African coal export prices	RB1	API 4 Richards Bay terminal

Note: Table 1 indicates the symbol and the proxy used for each of the three coal markets. Henceforth, the respective symbols, as mentioned above, will be interchangeably used throughout the text.

Figure 1. Weekly coal market prices of ARA, NewCastle, and RB1

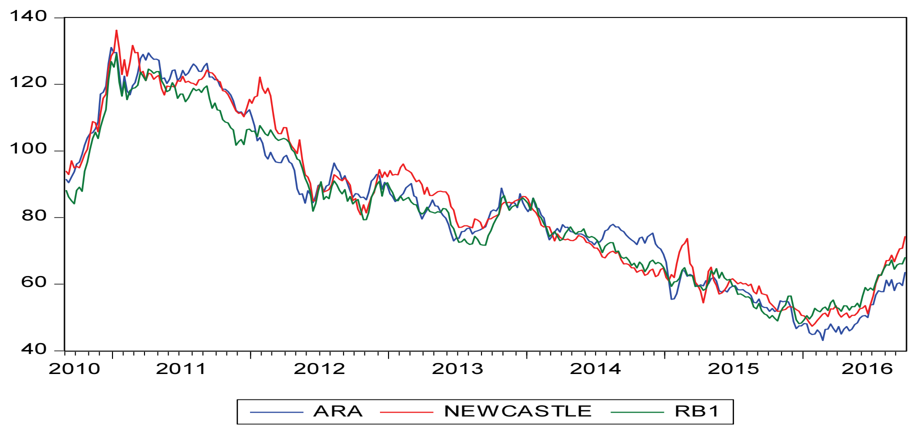


Figure 1 shows the weekly price series for ARA, NewCastle, and RB1 for the period 3rd September 2010 through 23rd September 2016. These graphs clearly display a decreasing trend for coal prices for the most part of the period of study with the prices starting to pick up around mid-2015. Interestingly, besides the decreasing trend, we could also observe that all the three markets move in tandem with each other except for the differences in their degree of fluctuations. Intrigued by these observations, the present study is aimed at examining the direction and magnitude of financial contagion across the three markets (if any) using the diagonally restricted BEKK GARCH approach.

4 Econometric methodology

4.1 Stationary test (Unit Root Test)

It is a stylized fact that a financial time series data more often than not exhibit non-stationarity at its level form. Consequently, the weekly returns of all the three time series under consideration were computed as log differences of successive observations viz. $Rt = (\ln Pt - \ln Pt\text{-}1) \times 100$. Then the Augmented Dickey-Fuller (ADF) test and Phillip Perron (PP) unit root test were performed with a lag of 4 and 8 respectively to test for the stationarity of model variables. The null hypothesis that the variable series under investigation has a unit root was rejected against the alternative that it does not for all the three variables. With that, the data was found to satisfy the condition of stationarity even at 1% level of significance.

4.2 ARCH test

Autoregressive conditional heteroscedasticity (ARCH) models are econometric models that are used to model the financial time series with time-varying volatility. The concept as developed by Robert F Engel is documented as "An uncorrelated time series can still be serially dependent due to a dynamic conditional variance process. A time series exhibiting conditional heteroskedasticity or autocorrelation in the squared series is said to have autoregressive conditional heteroscedasticity (ARCH) effects" (Engel, 1982). Engel's ARCH test is a Lagrange multiplier test to assess the significance of ARCH effects.

The ARCH effect or the otherwise serial correlation of heteroscedasticity can be modeled as follows:

$$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t$$

$$\varepsilon_t \sim N(0, \alpha_0 + \alpha_1 \epsilon_{t-1}^2)$$

Here, the innovation term is assumed to be normally distributed with zero mean and a conditional variance that is dependent on one time period lagged squared innovation term.

Precisely, the ARCH models assume that the volatility of the current innovation is related to the size of the previous periods' innovation. This leads to volatility clustering. Volatility clustering is a time series property observed in most financial markets, where, the periods of high returns tend to be followed by periods of higher returns and the periods of low returns tend to be followed by periods of a lower returns.

4.3 EGARCH model

The standard GARCH models assume that both negative and positive innovation terms have a symmetric effect on the volatility. However, this is an unrealistic assumption as, in reality; we see that there is generally a greater increase in volatility following bad news than after good news - what is commonly known as the leverage effect. Thus, we can say that the volatility reacts asymmetrically to the sign of the shock and hence a parameterized extension of GARCH model has to be employed when both negative and positive shocks contribute to volatility at unequal magnitudes. The most popular GARCH family model for estimating the leverage effects among the asset returns is the Exponential GARCH or the EGARCH model.

The EGARCH or the Exponential GARCH model is a member of the extended GARCH family of models, first proposed by Nelson (1991). The EGARCH model is used in our study for its two innovative properties. Firstly, it ensures a non-negative conditional variance without having to impose complicated restrictions on parameters. Secondly, in the return generating process, the model allows for an asymmetrical response of conditional variance in assets to positive as well as negative shocks. The model can be specified as follows:

$$log\ \sigma_t^2 = \omega + \sum_{k=1}^{q} \alpha_k g(Z_{t-k}) + \sum_{k=1}^{p} \beta_k log\ \sigma_{t-k}^2$$

and

$$g(Z_t) = \theta Z_t + \gamma[|Z_t| - E|Z_t|]$$

where, σ_t^2 is the conditional variance, $\omega, \alpha, \beta, \theta$ and γ, are deterministic coefficients and Z_t comes from a generalised error distribution. The function $g(Z_t)$ is linear in Z_t containing two parameters that define the size and sign effect of volatility shocks. The term, $\gamma[|Z_t| - E|Z_t|]$ is typically an ARCH term that determine the size effect and the term θZ_t is asymmetric and determines the sign (leverage) effect. Thus the sign and magnitude of Z_t is allowed to have separate effects on the volatility by the specific formulation of $g(Z_t)$. The function $g(Z_t)$ has a slope coefficient $\theta + \gamma$ if Z_t is positive and will have a slope coefficient $\theta - \gamma$ if Z_t is negative.

4.4 Modeling volatility through trivariate diagonal BEKK GARCH model

Within the GARCH family of models, the first multivariate variance model was the VECH model, introduced by Bollerslev, Engle, and Wooldridge in the year 1988. However, this model has a few drawbacks. Firstly, the results tend to have some numerical issues since the parameterization in this model does not enforce positive-definiteness. Secondly, this model does not provide for interactions among the underlying variables such as returns/volatility spillovers across variables. As such, in an attempt to allow of a greater range of interactions as well as to enforce positive definiteness Baba, Engle, Kraft, and Kroner introduced what is known as the BEKK model. Put simply, BEKK is a multivariate GARCH model that allows for the explicit and dynamic parameterization of conditional covariance (Engle and Kroner, 1995). Further, in order to overcome the difficulties associated with a large number of parameters in an unrestricted Full-BEKK model, they introduced a restricted model called diagonal BEKK model wherein the number of free parameters to be estimated is significantly reduced.

In this backdrop, the present study employs a trivariate Diagonal

BEKK-GARCH model to estimate the time-varying conditional variance and covariance (volatility contagion effects) of the three major coal markets. We obtain the betas associated with each of the variable series from the estimates of the conditional second moments. The Diagonal BEKK model is specified as follows:

$$H_t = \Omega'\Omega + A'(u_{t-1}u'_{t-1})A \ \ + B'H_{t-1}B$$

Where, H_t is an N x N conditional variance-covariance matrix, Ω is an upper triangular matrix of parameters, u_{t-1} is an N x 1 innovation vector, and, A and B are N x N diagonal parameter matrices. For a step by step derivation of Diagonal BEKK GARCH equations, the readers may refer to Varghese (2018). The resultant conditional and covariance equations can be represented as follows.

$$h_{11,t} = \omega^2{}_{11} + \alpha^2{}_{11}u^2{}_{1,t-1} + \beta^2{}_{11}h_{11,t-1}$$

$$h_{12,t} = \omega_{11}\omega_{12} + \alpha_{11}\alpha_{22}u_{1,t-1}u_{2,t-1} + \beta_{11}\beta_{22}h_{12,t-1}$$

$$h_{13,t} = \omega_{11}\omega_{13} + \alpha_{11}\alpha_{33}u_{1,t-1}u_{3,t-1} + \beta_{11}\beta_{33}h_{13,t-1}$$

$$h_{22,t} = \omega_{12}^2\omega_{22}^2 + \alpha^2{}_{22}u^2{}_{2,t-1} + \beta^2{}_{22}h_{22,t-1}$$

$$h_{23,t} = \omega_{12}\omega_{13} + \omega_{22}\omega_{23} + \alpha_{22}\alpha_{33}u_{2,t-1}u_{3,t-1} + \beta_{22}\beta_{33}h_{23,t-1}$$

$$h_{33,t} = \omega_{13}^2\omega_{23}^2\omega_{33}^2 + \alpha^2{}_{33}u^2{}_{3,t-1} + \beta^2{}_{33}h_{33,t-1}$$

Assuming that the standardized residuals of the proposed Trivariate BEKK GARCH model are conditionally normally distributed, the parameters of the model can be estimated by maximizing the conditional log-likelihood function:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(log|H_t| + \varepsilon'_t H_t^{-1}\varepsilon_t)$$

5 Empirical discussion

5.1 Descriptive statistics

First, the descriptive statistics for each of the three major coal market returns for the period 3rd September 2010 through 23rd September 2016 are computed. The results are reported in Table 2.

Table 2. Descriptive statistics for returns in ARA, NewCastle, and RB1

	ARA	NEWCASTLE	RB1
Mean	-0.0012	-0.0007	-0.0008
Median	-0.0004	-0.0007	-0.0019
Maximum	0.0742	0.0935	0.0759
Minimum	-0.0999	-0.1072	-0.0703
Std. Dev.	0.0254	0.0252	0.0245
Skewness	-0.0935	-0.0361	0.1018
Kurtosis	4.2671	4.4289	3.2535
Jarque-Bera	21.599	26.9502	1.3921
Probability	0.0000	0.0000	0.4986
Observations	316	316	316

From Table 2, it is evident that the market returns for both ARA and NewCastle are negatively skewed while that of RB1 is positively skewed. The skewness of the statistics suggests a lack of normality in the distribution of the return series. The statistic of skewness of lesser than zero implies a left-skewed distribution where most values are concentrated on the right of the mean value, with extreme values on the left and vice versa. As can be observed in the table above, ARA and NewCastle exhibit kurtosis of 4.27 and 4.48 respectively, demonstrating a leptokurtic distribution. A leptokurtic curve is sharper than a normal distribution with the values concentrated around the mean and having thicker tails indicating a higher probability for extreme values. RB1, however, follows a mesokurtic distribution with a kurtosis value of 3.25. Consistent with the above observations, using Jarque-Bera statistic we can reject the null hypothesis that both ARA and NewCastle returns series follow normal distribution while we fail to reject the same for RB1. The

P-value for Jarque-Bera statistic is significant for ARA and NewCastle even at 1% level of significance while it is not significant for RB1 even at 10% level of significance. This shows non-normality in the distribution of the first two return series indicating randomness and inefficiency of the market.

5.2 Volatility clustering

A random walk series tends to have no memory of past events. In other words, future returns are completely independent of past returns. This randomness in the prices is a natural outcome of the multitude of external and internal factors that affect the variable market. However, in most cases, it is observed that periods of high fluctuations in prices tend to be followed by periods of high fluctuations, while periods of low fluctuations in prices tend to be followed by periods of low fluctuations indicating a phenomenon commonly known as volatility clustering (persistence of volatility shocks). Put simply, "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes" (Mandelbrot, 1997). Thus, even if the price changes tend to follow a random walk, one can make predictions about the magnitude of future price changes based on the magnitude of price changes corresponding to the previous periods. As such, the plot of time-varying volatility of an asset can act as an electrocardiogram, reflecting the pulse of the underlying market.

Figure 2. Weekly coal market returns of ARA, NewCastle, and RB1

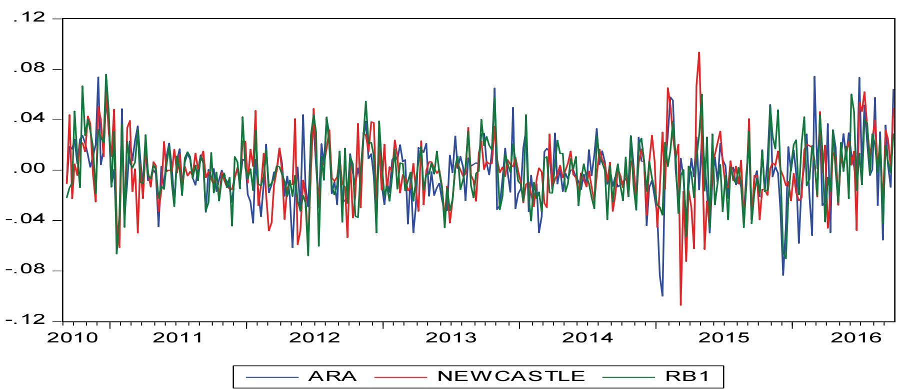


Figure 2 exhibits the weekly returns series corresponding to ARA, NewCastle, and RB1. Though an almost coinciding pattern was observed among the three coal markets with respect to their price movements (figure 1), the returns series, as shown in figure 2 expose the differences in their volatility. It is interesting to note that, among the three coal markets, while volatility clustering is directly observable in the case of NewCastle and ARA, it is relatively difficult for an untrained eye to observe the same in the case of RB1. As such, to uncover the presence (absence thereof) of volatility clustering in all the three markets statistically; we adopt the ARCH test approach. The test results pertaining to the parsimonious ARCH (1) analysis is reported in Table 3.

Table 3. ARCH test results for ARA, NewCastle, and RB1

Variable	F-statistic	Prob. F(1,313)	Obs*R-squared	Probability
ARA	13.3874	0.0003	12.9203	0.0003
NewCastle	12.5577	0.0005	12.1504	0.0005
RB1	5.1313	0.0242	5.0809*	0.0242

In table 3, the column of interest is 'Obs*R-squared', where 'Obs' represents the number of observations in the model. It follows a chi-squared distribution with p degrees of freedom, with p being the number of lags allowed. In our study, we use only a single lag on the squared innovation and hence we have an ARCH (1) model. The null hypothesis is that there is no ARCH effect and we test it against the alternative that there is an ARCH effect. In our study, as can be observed from the above table, the probability value is less than 5 percent for all the three variables - ARA, NewCastle, and RB1. Hence, we reject the null hypothesis and go with the alternative hypothesis that there is an ARCH effect for each of the underlying markets. However, it is also to be noted that we fail to reject the null for RB1 at 1 percent level of significance. This is consistent with our earlier observation that RB1 returns plot exhibit weakly observable volatility clustering.

5.3 Leverage effect

The ARCH model along with its variants filled in towards the need for a dynamic volatility modeling tool as most financial markets tend to exhibit the property of time-varying volatility. In fact, the family of ARCH/GARCH models has been frequently used in volatility studies as it provides a more real-world context than most of the other forms. As such, in our attempt to test for the presence of leverage effect among the three coal market returns, we employ an Exponential GARCH model. In other words, an EGARCH model is used to examine whether the negative shocks and positive shocks of equal magnitude have a differential impact on the volatility (conditional variance) of coal returns. The leverage effect thus captures the presence of a negative correlation between the past return and the future volatility of returns (i.e., an increase in volatility in response to a decrease in asset return).

Table 4. Estimated coefficients of conditional variance equations for EGARCH (1, 2) model

Variable	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.	Coefficient	Std. Error	Prob.
	ARA (1)			NewCastle (2)			RB1 (2)		
Constant (ω)	-1.18	0.475	0.013	-0.55	0.236	0.019	-1.89	1.19	0.113
ARCH term (α)	0.434	0.094	0	0.232	0.084	0.006	0.345	0.137	0.012
Asymmetry term (θ)	0.006	0.048	0.896	0.004	0.029	0.903	0.041	0.08	0.605
GARCH term ($\beta 1$)	0.25	0.109	0.022	1.401	0.196	0	0.161	0.18	0.37
GARCH term ($\beta 2$)	0.636	0.122	0	-0.45	0.184	0.015	0.624	0.182	0.00

Note: The asymmetry term (θ) is not significant even at 10% level of significance for all the three variables

We found EGARCH (1, 2) to be the best fit model for all of the three series based on the Akaike Information Criterion (AIC). Table 4 reports the results for the EGARCH (1, 2) model, wherein the residuals derived from the parsimonious mean equation has been used to formulate the variance equation. The five coefficients in the EGARCH analysis represent the constant, ARCH term, volatility asymmetry term and the two GARCH terms in the sequence. This corresponds to $\omega, \alpha, \theta, \beta 1$ and $\beta 2$ from the EGARCH (1,2) equation as discussed in the methodology section. We can validate the presence of leverage effect in our EGARCH model if the asymmetry term is strictly negative and significant. The results however show the coefficients to be positive and not significant for the leverage (asymmetry) term in all the three cases as seen in table 4. As such, we can infer that there is no leverage effect across all the three coal markets under study. Put simply, both positive and negative news tend to impact the conditional variance of coal market returns in similar magnitudes.

5.4 Volatility contagion effect

In our attempt to examine the magnitude of volatility contagion across the three coal markets, we employ a diagonally restricted BEKK GARCH model. The estimation of the model involves the joint estimation of both its mean as well as variance equations. We specify the model as stated below:

Mean Equation:

$$y = \mu + \lambda * H + res$$

λ values are found to be significant at 1% level of significance for both ARA and NewCastle while it is found significant for RB1 at 5% level of significance. This shows that the mean value of returns for each of the three variables is influenced by their own volatilities. The residual values for the conditional variance equation are generated from the mean equation.

Variance Equation:

$$H = \omega' * \omega + \alpha' * res(-1) * res(-1)' * \alpha + \beta' * H(-1) * \beta$$

Here, we examine whether the lagged variance of the variables as well as their lagged squared residuals from the mean equation exert any positive and significant influence on the current volatility in order to substantiate the presence of volatility spillover.

The conditional variance-covariance equations as defined by the

Diagonal BEKK GARCH specification were computed to be as follows:

$$h_{11,t} = 0.00007 + 0.1492u^2{}_{1,t-1} + 0.7708h_{11,t-1}$$

$$h_{12,t} = 0.00002 + 0.1565u_{1,t-1}u_{2,t-1} + 0.7689h_{12,t-1}$$

$$h_{13,t} = 0.00007 + 0.1691u_{1,t-1}u_{3,t-1} + 0.6955h_{13,t-1}$$

$$h_{22,t} = 0.00003 + 0.16426u^2{}_{2,t-1} + 0.7671h_{22,t-1}$$

$$h_{23,t} = 0.00005 + 0.1774u_{2,t-1}u_{3,t-1} + 0.6938h_{23,t-1}$$

$$h_{33,t} = 0.00007 + 0.1917u^2{}_{3,t-1} + 0.6276h_{33,t-1}$$

The equations effectively capture the own volatility and cross volatility spillover among the three coal markets, arranged serially in the order ARA, NewCastle, and RB1. We find all the alphas (ARCH coefficients) and betas (GARCH coefficients) to be statistically significant at the 1% level of significance implying the presence of both ARCH and GARCH effects. While the results stand evidence for strong GARCH effects, we find the presence of ARCH effects to be relatively weak. As such, it can be deduced from the equations that there exists a statistically significant co-variation in shocks that are dependent more on its lags rather than on past errors. We explain this in greater detail in the subsequent discussions.

5.4.1 ARCH effect

As can be observed from the equations above, a GARCH model models the present value of conditional variance as a function of a) past error terms and b) past variance. This is effectively captured by the ARCH term and GARCH term respectively. As such, the coefficients corresponding to the ARCH term captures the own, as well as, cross volatility spillover effects that can be explained by the value of past innovations.

The alpha coefficients corresponding to $h_{11,t}$ $h_{22,t}$ and $h_{33,t}$ quantifies the own volatility spillover effects as explained by past error terms. Accordingly, we can infer that the own volatility spillover effect (in error terms) is highest for RB1 (0.1917) followed by NewCastle (0.1642) and ARA (0.1492). Indicatively, these positive and significant ARCH coefficients confirm the presence of volatility persistence for each return series that can be explained by its own past innovations.

The alpha coefficients corresponding to $h_{12,t}$ $h_{13,t}$ and $h_{23,t}$ quantifies the cross volatility spillover effects between the market pairs, ARA-NewCastle, ARA-RB1 and NewCastle-RB1 respectively, as explained by the value of its past error terms. By comparing the three coefficients, one could infer that the one period lagged error terms corresponding to RB1 exert the largest influence on both ARA (0.1691) and NewCastle (0.1774). That is to say, the one period lagged error terms in the South African coal returns series have a greater effect on the current volatility of both European and Australian coal returns as compared to their own lagged error terms. On a similar note, the current volatility in the South African coal returns series is explained by its own past error values as compared to that of the other two market returns. Fundamentally, as indicated by the ARCH terms corresponding to the diagonally restricted BEKK GARCH equations, we could infer that there exists volatility contagion from the South African market to the other two markets.

5.4.2 GARCH effect

The simplest form of GARCH specification asserts that variance realized in the current period is the best predictor for variance in the subsequent period. The magnitude by which the current volatility influences the future volatility is captured by the GARCH term (beta coefficients) in the BEKK GARCH equations. As can be observed from the equations computed above, the beta coefficients are much larger compared to the alpha coefficients, implying that the GARCH effects are much stronger as compared to the ARCH effects. Put simply, we evidence strong dependence of current volatility on their one-period lagged volatility as compared to the lagged error terms.

The beta coefficients corresponding to $h_{11,t}$ $h_{22,t}$ and $h_{33,t}$ quantifies the own volatility spillover effects as explained by past volatility. On comparison, we find own-volatility persistence (spillover) to be highest in the case of ARA (0.7708) followed by NewCastle (0.7670) and RB1 (0.6276). As such, more than 75 percent of the current volatility can be explained by its own past volatility for both European and Australian coal market returns while it is 63 percent in the case of South African coal market returns.

To ascertain the extent to which the current volatility in one market explains the future volatility of the other two markets (cross-volatility spillover), we examine the beta coefficients associated with $h_{12,t}$ $h_{13,t}$ and

$h_{23,t}$. Here, we see that, the cross volatility GARCH effect is highest between ARA and New Castle (0.7689), and least between NewCastle and RB1 (0.6939). It is also observed that for ARA, the own-volatility persistence is higher than the cross-volatility spillover from the other two markets. Reading these together, we could infer ARA to be the lead volatility transmitter across the other two markets (as it exhibits the strongest GARCH effect).

Conversely, for RB1, the cross-volatility spillover from ARA and NewCastle are more when compared to its own-volatility persistence. This indicates that the current volatility in the South African markets is better explained by the past volatility in the European and Australian coal markets as compared to its own one-period lagged variance. That is to say, there exists strong volatility spillover from the other two markets to the South African coal market. In the case of NewCastle, the cross volatility spillover between ARA and NewCastle slightly exceeds its own-volatility persistence from within the domestic market. This reaffirms our earlier observation of ARA being the lead volatility transmitter. These findings would be of pertinent importance to investors investing in major coal markets. In short, the study's findings indicate that investors investing in both the Australian and the South African coal markets can make reasonably good approximations about the future volatility of these markets based on the current volatility in the European coal market.

Figure 3. Combined conditional variance estimated by diagonal BEKK

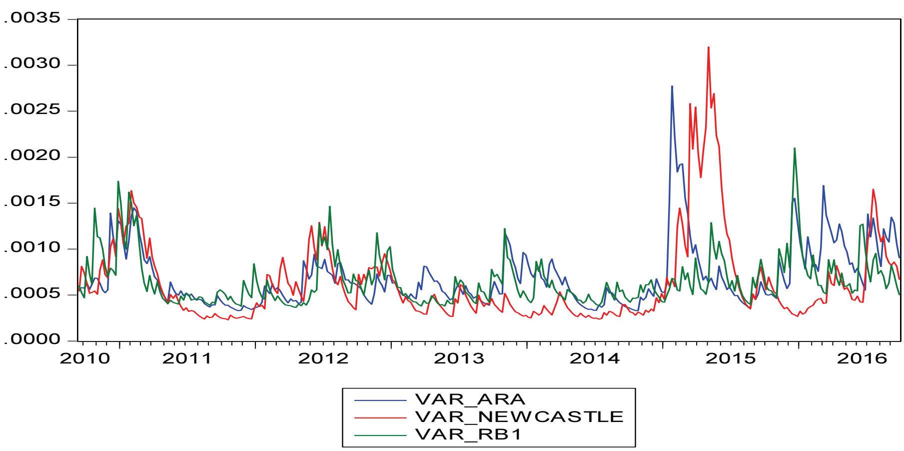
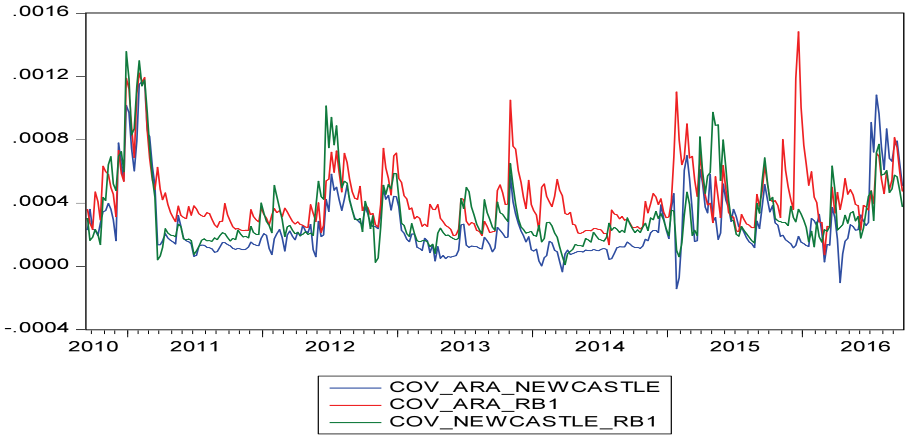


Figure 4. Combined conditional covariance estimated by diagonal BEKK



The combined plot of conditional variance as estimated by the Diagonal BEKK GARCH model is illustrated in Figure 3. The conditional variance of the South African coal market returns (RB1) is observed to lie within a narrower range as compared to the other markets even at periods of high volatility. The Australian coal returns (NewCastle) however, exhibit the lowest volatility during most part of the study period except for a small duration (mid 2014-mid 2015) wherein it underwent huge fluctuations as compared to the other markets. A similar trend was observed for the European coal returns (ARA) with the surge in volatility occurring a few periods prior to that of the NewCastle. Consistent with our earlier findings, it can be deduced that the cross volatility spillover from the European market reinforces the magnitude of volatility in the Australian market, which is then sustained through its own-volatility persistence (GARCH effect) and volatility clustering (ARCH effect).

The combined pairwise co-variance among the three coal markets is depicted in figure 4. The co-movements are observed to be the highest between ARA and RB1 followed by NewCastle and RB1. This is consistent with our earlier observation that the South African coal market derives more of its volatility persistence from outside the domestic market than from within the domestic market. We can further infer from figure 4 that there exists a higher degree of market integration among the three coal markets even when the cross-volatility spillover is observed to be heterogeneous across the market pairs.

This volatility contagion among the coal markets and the degree of integration can be understood at least in two ways. Firstly, the volatility in all the three markets can be influenced by common international factors giving rise to an apparent causal relationship amongst the markets. Secondly, since the trading hours of the three markets are not common, it could induce a causal relationship among the markets wherein the volatility in one market gets transmitted to the other through a lead-lag relationship. This can be further explored and we leave it as scope for future research.

6 Summary

Over the past few decades, studies on volatility and its contagion effects continue to garner increasing attention among the academic and practitioner communities mostly because of the crucial ramifications that fluctuations in prices of financial assets have on the general economy. Historically, we have seen plenty of instances where exceptional volatilities or even unprecedented shocks in a major financial variable lead to an economic downturn which eventually evolves into a crisis. Associated with this phenomenon, we witness a rapid decline in investments, sense of insecurity, increasing inequality in income distribution, monetary and financial instability, among others. Undisputedly, coal is an important fossil fuel that has powered our lives for centuries and with more than 35% of the global energy still derived from coal, any radical change or exceptional volatility in the international coal prices will have far-reaching consequences across the globe. As a decisive determinant of economic growth for many countries across the globe, fluctuations in the international coal export prices deserve to be examined closely. The present study is a step in this direction.

Using weekly time series data over a period of six years, (September 2010 through September 2016), the study observed all the three coal indices to move in tandem. A general downward trend was observed until mid-2015, after which the prices started to pick up. The study employed a parsimonious ARCH (1) model to test for volatility clustering and found evidence for the same at 5% level of significance across all three markets. Appropriate EGARCH models were used to test for the presence of a negative correlation between the past return and the future volatility of returns (leverage effect). Surprisingly, the study failed to find any convincing evidence for the same.

A Diagonal BEKK GARCH model was then employed in order to assess the integration of global coal markets by way of volatility transmissions and contagion effects among the three underlying coal markets. A strong GARCH effect was observed while the ARCH effect was found to be relatively weak. It can thus be deduced that there exists a statistically significant co-variation in shocks that are dependent more on its lags rather than on past errors. The study observed all the three coal export prices (ARA, NewCastle, and RB1) to be interdependent evidencing a high level of market integration in the coal export sector.

With the increasing need to understand the nature and characteristics of international coal prices, the study was aimed at investigating the presence, magnitude, and direction of volatility transmission across three major coal export markets, namely, Europe, Australia, and South Africa. These markets exert excessive influence over a larger pool of coal importing economies that rely on this fossil fuel for a significant proportion of their overall power generation. Thus, any substantial variance in these global coal prices and their contagion thereof would induce uncertainty in the coal importing economies, often leading to unfavorable consequences. This validates the significance of this paper. Understanding the level of integration among the global coal markets would also be of pertinent interest to both policymakers and investors as it aids in the decision making processes while making policies of national importance as well as in optimal portfolio management.

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