Volatility Transmissions and Dynamic Correlations between Energy Returns with Applications

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November 22, 2014

Preliminary Draft[1]
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Abstract

Population growth along with the increased development of emerging economies are expanding the production and consumption of energy resources. At the same time, national security issues and environmental concerns place constraints as to the source of energy generation. As a consequence, the dynamics governing energy markets are evolving greatly. The paper asks how news and volatility from one energy market spills over into another energy market's volatility. This question is addressed using daily data comprised of an alternative energy index, technology index, coal, oil, and natural gas futures from 2006 to 2014, using an asymmetric dynamic conditional correlation multivariate GARCH model with a VARMA second moment. First, it is found news "shocks" in one market have little impact, both in magnitude and statistical significance, between markets whereas own-news drives the respective market's volatility. Second, little statistical evidence is found of volatility spilling over between markets, own-volatility effects are strongly supported. On average, a $1 long position in oil can be hedged for 32 cents with a short position in the alternative energy index, 16 cents with a short position in the natural gas futures market, and 37 cents with a short position in the coal futures market.

Keywords: Renewable (Clean) Energy; Multivariate GARCH; Oil Prices; Natural Gas Prices; Coal Prices; Dynamic Conditional Correlation; Volatility Spillovers; Asymmetries; Hedging

JEL Classification: G11, G13, Q42

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[1] This is a preliminary draft of my job market paper and will be included as part of my doctoral dissertation in economics at the University of Illinois at Chicago. The paper was presented at the Illinois Economics Association's 44$^{\text{th}}$ Annual Meeting, 17–18 October 2014. Constructive comments are welcome, but please do not cite or distribute without the author's permission.

1 Introduction

The energy sector is experiencing unparalleled uncertainty and change, induced by an accelerating and growing complexity of energy determinants along with policy and investment signals. Meeting energy demand, fundamental for economic growth and human development, must be balanced with reliable and environmentally conscientious energy production. Oil is the world's leading fuel, currently accounting for approximately 33.1% of global energy consumption (BP, 2013), but is often found in geopolitical hot spots and significantly contributes to carbon dioxide emissions. Energy security concerns are driving oil importing regions to shift, in part, towards domestic sources of energy to meet demand; primarily taking the form of coal and natural gas. At the same time, environmental concerns are compelling economies to seek cleaner energy sources. As a consequence, energy generation from wind turbines and solar photovoltaics are increasingly utilized. However, natural gas also benefits since it is viewed as a relatively cleaner alternative to oil and coal while being more reliable than renewable energy; i.e., a transition or bridge fuel. From this perspective, policymakers, business leaders, and consumers face the daunting task of making critical decisions regarding the future of energy infrastructure.

Citing growth in population and emerging economies, the New Policies Scenario[2], the central scenario of the International Energy Agency (IEA)[3], global energy demand is expected to increase by one-third over the period 2011–2035. For context, this is comparable to adding a country with twice the energy usage as the United States at 2011 levels[4]. Additionally, global energy demand growth may be further exacerbated due to recovery from the Great Recession (CEA, 2013). From 2011 to 2035 demand for oil is predicted to grow by 13%, coal 17%, natural gas by 48%, and renewables by 77% (WEO, 2013, p. 55). Further, renewable energy's share of total power generation increases from 20% in 2011 to 31% by 2035 overtaking natural gas as the second-largest source of energy generation in the next few years (WEO, 2013).

Capturing and modeling energy market dynamics (i.e., volatility and correlations) is crucial for policymakers and investors. However, there are surprisingly few studies examining the impact of traditional energy returns (e.g., oil) on alternative energy firms' return volatility or the interplay of the fuels themselves; e.g., between oil and natural gas. Further, there is much to be learned about the volatility dynamics of alternative energy stock price returns and the correlations between alternative energy stock prices and traditional energy price returns. The present paper seeks to remedy this gap by significantly extending Sadorsky (2012)[5] and Ewing et al. (2002). The paper Sadorsky (2012) uses a multivariate DCC-GARCH to examine volatility spillovers and dynamic correlations between the price returns of oil, a clean energy index, and a technology index. He finds the alternative energy index correlates more with the technology index than the oil returns, arguing alternative energies are technology specific. The earlier paper, Ewing et al. (2002), uses a multivariate GARCH model to focus exclusively on how volatility spills over between the oil and natural gas markets. The authors find volatility is persistent in both markets.

This paper extends the previous studies by using daily data, modeling five series simultaneously, comprised of an alternative energy index, technology index, coal, oil, and natural gas futures from 2006 to 2014 while allowing for asymmetrical effects. An asymmetric dynamic conditional correlation multivariate GARCH (DCC-MGARCH) model with a VARMA second moment is utilized, thus allowing for volatility spillover effects. As a preview of the results, it is found news "shocks" in one market have little to no impact, both in economic and statistical significance, between markets whereas own-news drives the respective market's volatility in the alternative energy and technology series. Little statistical evidence is found of volatility spilling over between markets with own-volatility effects strongly supported and by far the largest driver of volatility. Similar to the previous literature examining renewable energy, the alternative energy index and technology index are highly correlated

[2]The New Policies Scenario takes account of existing policies and the anticipated impact of the cautious implementation of declared policy intentions. See (WEO, 2013, p. 36) for key assumptions.

[3]The IEA is an autonomous body within the OECD with the purpose of ensuring reliable, affordable, and clean energy to its 28 member countries. For more information see `http://www.iea.org/`.

[4]This is based on the author's calculation; see (WEO, 2013, p. 69).

[5]To the best of the author's knowledge only five peer-reviewed papers have looked at oil's impact on alternative energy; only one examining volatility spillover effects, and none have included natural gas, coal, or allowed for asymmetrical effects. See Table 1 for a summary with an extended discussion in the theory section below.

through time. Not discussed in the previous literature is the fact that approximately 40% of the companies listed in the alternative energy index used are cross-listed as technology firms, making the result unsurprising. In way of an application, the conditional variances from the multivariate GARCH model are used to construct portfolio weights and hedging ratios.

2 Theory

2.1 Stock Market Returns, Volatility, and Lags

Negative oil price shocks have an adverse affect on the macroeconomy by reducing gross domestic product (GDP)[6] and increasing inflationary pressure[7]. As discussed by Narayan and Sharma (2011), a reduction in GDP will lead to lower earnings for corporations through increased operating costs. Lower earnings are subsequently reflected by a lower stock price and a fall in returns. Chen et al. (1986) contend stock returns are affected by two factors: expected future cash flows and/or the discount rate on expected future cash flows. Formally, stock prices (p) are functions of expected future cash flows ($\mathbb{E}(c)$) appropriately discounted by the discount rate on future cash flows k,

$$p = \frac{\mathbb{E}(c)}{k}, \tag{1}$$

implying actual stock returns are given by

$$\frac{dp}{p} = \frac{d[\mathbb{E}(c)]}{\mathbb{E}(c)} - \frac{dk}{k}. \tag{2}$$

Chen et al. (1986) find inflation affects both expected future cash flows and the discount rate. This results in rising oil prices having a negative affect on stock market price returns[8]. Unless the stock market is efficient the impact on stock market returns will occur with a lag (Narayan and Sharma, 2011).

Changes in levels are not the only driver of stock market returns. Sauter and Awerbuch (2003) argue oil price volatility strongly impacts economic output. According to Hampton (1995), although energy options are available, the energy sector is still highly susceptible to energy price uncertainty. Consequently, an energy firm's discounted expected future cash flow is potentially influenced by volatility from energy markets; a possible channel being increased hedging costs for energy firms. Additionally, Pindyck (2004) argues volatility negatively impacts non-renewable resources by increasing total marginal cost, thereby inducing a decrease in production. Using a similar line of reasoning, Oberndorfer (2009), concludes volatility in energy markets will negatively impact expected future cash flows with oil, natural gas, and coal firms particularly affected.

Ferderer (1996) finds increasing oil prices and volatility adversely impact output growth. Using a VAR, Sadorsky (1999) finds both oil prices and oil price volatility are important drivers that influence stock market returns. Focusing on the Eurozone, Oberndorfer (2009) uses several alternative specifications to measure oil volatility finding a robust negative effect on stock returns; including oil and gas stocks, consistent with the Pindyck (2004) reduced production story. Chang et al. (2013) examine volatility spillover effects from oil to stock index returns. Using VARMA-GARCH and VARMA-AGARCH models scant evidence of volatility spillovers between the series is found. The authors conjecture a general stock market index is composed of both producers and consumers of oil and oil-related firms whereby an adverse oil shock may "balance out" on net. Dhaoui and Khraief (2014) find oil return volatility has a significant impact in six of the eight markets examined.

[6] The following papers analyze the impact and transmission mechanism: Hamilton (2003), Hamilton (2009), Kilian (2008a), Kilian (2008b).

[7] Fama (1981), Darby (1982), and Cunado and Perez de Gracia (2005)

[8] See, for example, Hamilton (1983), Cong et al. (2008), Huang and Masulis (1996), Jones and Kaul (1996), Park and Ratti (2008), Sadorsky (1999), (2001), Kilian and Park (2009), Driesprong et al. (2008).

2.2 Asymmetrical Effects

There are two types of asymmetric effects regarding energy markets, particularly related to oil shocks. First, rising oil prices are shown, in general, to weaken the overall economy, but lower oil prices do not help the economy[9]. Asymmetrical effects help explain the Sauter and Awerbuch (2003) claim that volatility is more important than the change in price levels[10]. Second, oil price shocks do not affect all sectors in the same manner; e.g., increasing oil prices hurt the banking sector, but are a boon for the oil companies themselves.

The previous discussion highlighted increasing oil prices' negative impact on aggregate stock market returns, but specific sectors are affected differently both in sign and magnitude. Narayan and Sharma (2011) find firms in the energy sector experience positive returns with increased oil prices. This is consistent with Chen et al. (1986) since rising oil, natural gas, and coal prices will benefit firms related to these industries subsequently increasing expected future cash flows. The opposite will hold true as well. Persistently rising and volatile oil prices provide an incentive to search for other viable energy sources. These alternative energy sources take the form of natural gas, coal, and, increasingly, clean or renewable energy. Although none of the above are perfect substitutes for oil, increasing oil prices may be beneficial to the stock returns of the imperfect substitutes.

In economic terms, asymmetric volatility is typically justified by two mechanisms: the leverage effect and volatility feedback effect (time-varying risk premia). The leverage effect[11] gets its name due to falling stock prices causing increased leverage and financial risk for the respective firm. Specifically, as a firm's stock price decreases its debt-to-equity ratio increases resulting in greater risk of holding the stock followed by increased stock return volatility. The volatility feedback effect[12] states whenever there is an expected increase in market-level volatility investors demand higher returns leading to lower stock prices. The effects are not mutually exclusive with Bekaert and Wu (2000) modeling both simultaneously finding the leverage effect by itself is insufficient to explain variation in volatility following a stock price decline. It may be important to point out asymmetric volatility is most pronounced during bear markets. An alternative explanation for asymmetric volatility is given by Hibbert et al. (2008) where it is found neither the leverage or volatility feedback hypotheses are the main reasons for asymmetric volatility. Instead the authors posit a behavioral approach connected with representativeness, affect, and extrapolation bias.

2.3 Linking Oil, Natural Gas, and the Stock Market

Ewing et al. (2002) investigate the transmission of volatility between oil and natural gas markets. Using daily data the authors find volatility spillover effects between the series with oil return volatility depending on past natural gas return volatility. Further, it is found that past oil volatility drives current oil volatility more so than economic news or shocks, while the opposite is found for current natural gas volatility.

There are two channels by which natural gas may affect stock market returns: (1) energy is an important expenditure for firms with rising energy costs having the ability to lower profit margins; (2) natural gas price shocks may influence macroeconomic variables (Acaravci et al., 2012). Few studies study how natural gas impacts the stock market, either in general or specific sectors. Acaravci et al. (2012) examine the effect of natural gas using quarterly data from 1990–2008 on fifteen European Union stock markets. The results from Johansen and Juselius cointegration tests and error-correction based Granger causality models is mixed. Boyer and Filion (2007) investigate what sources influence Canadian oil and natural gas stock market returns finding both oil and natural gas prices are significant. Ergun and Ibrahim (2013) find both oil and natural gas affect the stock prices of energy companies as well.

[9] The following articles find oil price shocks asymmetrically affect the economy: Hamilton (1983), Hamilton (1996); Mork (1989); Mork et al. (1994); Ferderer (1996); Lee et al. (1995). Sadorsky (1999) finds no evidence of oil price volatility having asymmetric effects on the economy

[10] Mork (1989), Lougani (1986); Sauteer and Awerbuch (2002) discuss other studies relating to this topic.

[11] Black (1976) and Christie (1982)

[12] Campbell and Hentschel (1992), Pindyck (1984), Poterba and Summers (1986), French, Schwert, and Stambaugh (1987), Wu (2001)

2.4 Alternative Energy Studies

Henriques and Sadorsky (2008) use weekly data[13] and a vector autoregressive (VAR) approach finding a positive effect between stock prices of alternative energy companies and shocks to technology stock prices, but no effect between shocks to oil prices and alternative energy companies. Henriques and Sadorsky (2008) make the case that investors may view alternative energy companies as comparable to high-technology firms in terms of returns relative to risk and other deciding factors. The authors provide anecdotal correlative evidence for the late 1990s. Consequently, the aforementioned paper and Sadorsky (2012) include an index of technology firms. More to the point, neglected by the previous published studies, is the fact that approximately 40% of the firms listed in the WilderHill Clean Energy Fund are cross-listed as technology firms. Intuitively rising oil prices should prove beneficial (e.g. higher stock prices) for any industry viewed as a substitute for petroleum. In contrast, however, Henriques and Sadorsky (2008) and Sadorsky (2012) find that shocks to technology firms are more important drivers of clean energy companies. As noted by Sadorsky (2012), at first glance this is a surprising result, however, in a broader context the success or failure of alternative energy companies often depends upon the success or failure of fairly specific technologies. As a result, alternative energy companies often share more in common with technology companies than they do with fossil fuel based energy companies. Oberndorfer (2014) posits that the finding of little statistical significance of oil on alternative energy may be explained by the observation that the majority of alternative energy sources are simply not competitive in energy markets relying on subsidies and public support. Kumar et al. (2012) extend Henriques and Sadorsky (2008) using data from 22 April 2005 to 26 November 2008 finding a small positive effect between oil prices and the stock prices of alternative energy companies, but noting technology firms' returns are a larger driver of clean energy firms. Sadorsky (2012), the closest to the present paper, uses a multivariate GARCH approach finding stock prices of clean energy companies correlate more highly with technology stock prices than with oil prices. Finally, Managi and Okimoto (2013) use weekly data from January 3, 2001 to February 24, 2010 with 478 observations and a Markov-switching VAR. Managi and Okimoto (2013) find a positive effect between oil prices and the stock prices of alternative energy companies along with a structural break occurring in late 2007.

2.5 Stylized Facts of Financial Time Series

According to Engle and Patton (2001), any good volatility model should incorporate the typical stylized facts associated with the volatility of financial asset prices. Fat tails (leptokurtosis) are a common feature of financial assets prices whereby the distribution has thicker (more weight in the) tails and is more peaked around the mean compared with a Normal distribution. This results from asset prices possessing a larger number of extreme values relative to Normal distributions. Kurtosis estimates are often (well) above four, as is the case in this paper.

Another empirical observation with financial asset series is volatility clustering. There is often a pattern of large (small) fluctuations in returns during a period being followed by large (small) changes in following periods, thus establishing that volatility evolves over time. This phenomenon is linked to the frequency of the data whereby daily observations exhibit more pronounced volatility clustering compared with weekly, monthly, etc. Engle et al. (1990) posit volatility clustering occurs through new information being serially correlated. The last common feature of financial time series, asymmetrical effects, has already been discussed in section 2.2 above.

3 Econometric Models

The econometric specification in this paper models both the mean (first-moment) and variance (second-moment) equations. The conditional mean equation is a vector autoregession of order one [VAR(1)]. The lag order is selected by the Hannan-Quinn (HQ) information criterion.[14] A multivariate conditional volatility model is used

[13] 3 January 2001 to 30 May 2007; 335 weekly observations

[14] The Akaike information criterion (AIC) chose a lag order of three while the Schwarz information criterion (SIC) chose a lag order of zero.

to examine the conditional correlations and volatility spillovers between crude oil returns, natural gas returns, coal returns, alternative energy firm returns, and technology firm returns. The empirical methods implemented in this paper to model the variance equation, presented in this section, are modifications of the DCC model of Engle (2002), VARMA-GARCH model of Ling and McAleer (2003), and VARMA-AGARCH model from McAleer et al. (2009).

$$r_{i,t} = \varphi_{i0} + \sum_{j=1}^{n} \varphi_{ij} r_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

$$\varepsilon_{i,t} | \mathscr{F}_{i,t-1} \sim N(0, h_{i,t})$$

$$i, j = 1, \ldots, 5$$

$$\varepsilon_{i,t} = \eta_{i,t} h_{i,t}^{\frac{1}{2}} \tag{4}$$

$$\eta_{i,t} \sim N(0,1)$$

$$h_{i,t} = \omega_{ii} + \sum_{j=1}^{n} \alpha_{ij} \varepsilon_{j,t-1}^{2} + \sum_{j=1}^{n} \gamma_i I(\eta_{i,t-1}) \varepsilon_{j,t-1}^{2} + \sum_{j=1}^{n} \beta_{ij} h_{j,t-1} \tag{5}$$

In equation (3) $r_{i,t}$ is the return for series i and $\varepsilon_{i,t}$ is random error term with conditional variance $h_{i,t}$, where i represents the returns series oil, gas, clean, tech, and coal, respectively. The market information available at time $t-1$ is denoted as $\mathscr{F}_{i,t-1}$. Equation (4) specifies the relation between the error term $\varepsilon_{i,t}$ and the conditional variance $h_{i,t}$. Equation (5) specifies a GARCH(1,1) process with VARMA terms (Ling and McAleer, 2003). The Ling and McAleer (2003) approach to modeling the conditional variances allows large shocks to one variable to affect the variances of the other variables. This is a convenient specification which allows for volatility spillovers.

$I(\cdot)$ is an indicator variable such that

$$I(\eta_{i,t}) = \begin{cases} 0, \ \varepsilon_{i,t} > 0 \\ 1, \ \varepsilon_{i,t} \leq 0. \end{cases} \tag{6}$$

One expects γ_i to be positive so that prior negative returns have higher impact on the volatility.

The Engle (2002) dynamic conditional correlation (DCC) model is estimated in two steps. In the first step, the GARCH parameters are estimated. In the second step, the correlations are estimated.

$$H_t = D_t \Gamma_t D_t \tag{7}$$

$$\begin{bmatrix} h_{11,t} & h_{12,t} & \cdots & h_{15,t} \\ h_{21,t} & h_{22,t} & \cdots & h_{25,t} \\ \vdots & \vdots & \ddots & \vdots \\ h_{51,t} & h_{52,t} & \cdots & h_{55,t} \end{bmatrix} = \begin{bmatrix} h_{11,t}^{\frac{1}{2}} & 0 & \cdots & 0 \\ 0 & h_{22,t}^{\frac{1}{2}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & h_{55,t}^{\frac{1}{2}} \end{bmatrix} \begin{bmatrix} 1 & \rho_{12,t} & \cdots & \rho_{15,t} \\ \rho_{21,t} & 1 & \cdots & \rho_{25,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{51,t} & \rho_{52,t} & \cdots & 1 \end{bmatrix} \begin{bmatrix} h_{11,t}^{\frac{1}{2}} & 0 & \cdots & 0 \\ 0 & h_{22,t}^{\frac{1}{2}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & h_{55,t}^{\frac{1}{2}} \end{bmatrix} \tag{8}$$

In equation (7), H_t is the 5×5 conditional variance-covariance matrix, Γ_t is the conditional correlation matrix, and D_t is a diagonal matrix with time varying standard deviations on the diagonal.

$$D_t = diag\left(h_{11}^{\frac{1}{2}}, \ldots, h_{55}^{\frac{1}{2}}\right) \tag{9}$$

$$\Gamma_t = diag\left(q_{11}^{-\frac{1}{2}}, \ldots, q_{55}^{-\frac{1}{2}}\right) Q_t diag\left(q_{11}^{-\frac{1}{2}}, \ldots, q_{55}^{-\frac{1}{2}}\right) \tag{10}$$

Q_t is a symmetric positive definite matrix.

$$Q_t = (1 - \lambda_1 - \lambda_2)\, \overline{Q} + \lambda_1 \xi_{t-1} \xi_{t-1}' + \lambda_2 Q_{t-1} \tag{11}$$

$\overline{Q}$ is the 5×5 unconditional correlation matrix of the standardized residuals $\xi_{i,t}$. The parameters λ_1 and λ_2 are non-negative with a sum of less than unity. The correlation estimator is,

$$\rho_{ij,t} = \frac{h_{ij,t}}{\sqrt{h_{ii,t}h_{jj,t}}} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}$$
$$\rho_{ij} = \rho_{ji}$$

Assuming conditional normality, the log-likelihood function for the general heteroskedastic model is

$$\mathscr{L}(\theta) = -\frac{Tn}{2}\ln 2\pi - \frac{1}{2}\sum_{t=1}^{T}\left(\ln|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t\right) \tag{12}$$

where θ denotes all the unknown parameters in ε_t and H_t.

4 Preliminary Analysis

4.1 Data

This paper uses daily data ranging from 3 January 2006 to 1 August 2014. The data include the following series: an alternative energy stock index (CLEAN), technology stock index (TECH), crude oil price (OIL), natural gas price (GAS), and coal price (COAL). Any data not overlapping in all five markets simultaneously are deleted, in line with both Hamao et al. (1990) and Haixia and Shiping (2013). At the potential cost of noisier observations, daily data is used to avoid the sample size phenomenon identified by McClain et al. (1996) whereby ARCH effects are diminished in data containing too few data points. Using Monte Carlo analysis the aforementioned paper suggests at least 700 observations in order to identify the correct model.

The alternative energy stock index is represented by the WilderHill® Clean Energy Index (ECO)[15]. The WilderHill® Index is a modified equal-dollar weighted index[16] composed of 57 firms, at present, where a shift to cleaner energy and conservation would be favorable. Companies comprising the index are represented by the following areas: renewable energy supplies – harvesting (e.g., producer of photovoltaic (PV) panels); energy storage (e.g., makers of advanced batteries), cleaner fuels (e.g., biofuel manufacturer), energy conversion (e.g., electric vehicle company), power delivery and conversion (e.g., makers of power management systems), and green utilities (e.g., utilities using wind, hydro, solar, tidal, and geothermal; nuclear power is not included)[17]. Investing in the WilderHill® Index requires the purchasing of PowerShares WilderHill Clean Energy Portfolio (PBW)[18], an exchange trade fund (ETF) investing at least ninety-percent of its total assets in firms comprising the WilderHill® Clean Energy Index.

The technology stock index comes from the NYSE Arca Tech 100 Index (PSE)[19], a price-weighted index[20] composed of common stocks and American Depositary Receipts (ADR)[21] of U.S. exchange listed technology

[15] The same series is used by Henriques and Sadorsky (2008), Kumar et al. (2012), Sadorsky (2012), and Managi and Okimoto (2013).

[16] An "equal dollar-weighted" index is calculated by establishing an aggregate market value for every component security of the index and then determining the number of shares of each security by dividing this aggregate market value by the current market price of the security. This method of calculation does not give more weight to price changes of the more highly capitalized component securities. Additionally, the weights of each component security are reset to equal values at regular intervals (e.g., quarterly). A "modified equal dollar-weighted" index resets component securities at regular intervals, but not necessarily to equal values. Securities and Exchange Commission (SEC) "Release No. 34-57148; File No. SR-Amex-2007-137", footnotes seven and eight.

[17] For more information visit http://www.wildershares.com/.

[18] Further information can be found at the following link:
https://www.invesco.com/portal/site/us/financial-professional/etfs/product-detail?productId=PBW

[19] The same series is used by Henriques and Sadorsky (2008), Kumar et al. (2012), Sadorsky (2012), and Managi and Okimoto (2013).

[20] In a "price-weighted" index, the component securities are included based on their price. The value of the price-weighted index is calculated by adding together the last transaction price for each security in the index and dividing the resulting sum by an index divisor to scale the index. Securities and Exchange Commission (SEC) "Release No. 34-57148; File No. SR-Amex-2007-137", footnote 6

[21] For more information on ADRs visit http://www.sec.gov/answers/adrs.htm

related firms. The industries comprising the index include computer hardware, software, semiconductors, telecommunications, electronics, aerospace and defense, health care equipment, and biotechnology[22].

The crude oil series used is the New York Mercantile Exchange (NYMEX) Light Sweet Crude Oil (WTI) earliest delivery date futures contract price; the most heavily traded energy product in the world[23]. The futures series is used based off of Shrestha (2014) where the author finds evidence that price discovery occurs in the futures markets for both crude oil and natural gas.

The NYMEX Henry Hub Natural Gas (NG) futures earliest delivery date contract represents the natural gas data. By volume, the Henry Hub futures contract is the third largest physical commodity in the world and is extensively used as a benchmark price for natural gas[24]. The data are obtained from `http://www.eia.gov/dnav/ng/ng_pri_fut_s1_d.htm`

The coal series is the NYMEX Coal Futures Near-Month Central Appalachian (QL) final settlement price. Central Appalachian bituminous constitutes a relatively large portion of the world export market, subsequently it is an important element for world coal prices[25]. The series is obtained from `http://www.eia.gov/coal/nymex/` and `http://www.eia.gov/coal/nymex/html/nymex_archive.cfm`.

The continuously compounded daily returns series is calculated for each of the five series by

$$r_{i,t} = 100 \cdot \ln\left(\frac{p_{i,t}}{p_{i,t-1}}\right) \tag{13}$$

where $r_{i,t}$ is the price return of the i^{th} market at day t and p_t is the daily closing price. Summary statistics are provided in Table 2. The mean of all five returns series is approximately zero with the respective standard deviations much larger than the mean value. There is relatively little skewness present in the series, but all display kurtosis. The Jarque-Bera tests statistics are large with a significance level of 0.0000 indicating the returns are not normally distributed. The five returns series are plotted Figure 1.

The five series in Figure 1 appear to have periods of high (low) volatility followed by periods of high (low) volatility; i.e., volatility clustering. Further, the graphical evidence is consistent with relatively large excess kurtosis levels found in Table 2 which suggests the variance fluctuates over time. All but the natural gas series exhibit acute volatility during late 2008 with natural gas showing this pattern later in 2009. Graphical inspection of the series is in no way causal, but is supportive of volatility spillovers, at least between some of the series. Consequently more formal methods are used to explore volatility spillover effects.

4.2 Preliminary Tests

Visual inspection of the returns series indicate that all five series are stationary with no apparent trend. Formal tests are provided to ensure unit roots are not present. Augmented Dickey-Fuller (ADF), augmented Phillips-Perron (APP), and KPSS unit root tests[26] are provided in Table 4. The augmented versions are used to increase statistical power with the lag length chosen by the largest lag from the LR, AIC, SBIC, and HQIC summary measures. Both the ADF and APP reject the null hypothesis at the 1% significance level while the KPSS unit root test fails to reject the null, indicating that all five series of price returns are stationary.

Although modeling first moment equations may remove any significant serial correlation there still exists a dynamic conditional variance process in financial asset series. Time series data displaying autocorrelation in the squared returns are unconditionally homoskedastic (i.e. constant variance), but conditionally heteroskedastic are are said to possess autoregressive conditional heteroskedastic (ARCH) effects. The Engle (1985) procedure is used to identify ARCH effects with two forms presented: F and LM versions. The squared residuals are regressed on the lagged squared residuals, one period for first-order ARCH effects. If no ARCH effects are

[22] Further details may be obtained at `http://www1.nyse.com/about/listed/pse_i.shtml`

[23] For more information see `http://www.cmegroup.com/trading/energy/light-sweet-crude-oil.html`. The data are obtained from `http://www.eia.gov/dnav/pet/pet_pri_fut_s1_d.htm`.

[24] More information may be obtained at `http://www.cmegroup.com/trading/energy/natural-gas/natural-gas.html`.

[25] For more information see `http://www.cmegroup.com/trading/energy/coal/central-appalachian-coal.html`

[26] Both the ADF and APP have unit root present as the null hypothesis and an alternative hypothesis of unit root not present whereas the opposite holds true for the KPSS test.

present the coefficient on the lagged squared residual term(s) will be statistically significantly zero and the R^2 (coefficient of determination) will be small. In large samples the test statistic is distributed chi-squared with the degrees of freedom equal to the lag order. If the test statistic is greater than the chi-squared critical value the null hypothesis of no ARCH effects present is rejected. Additionally, a multivariate ARCH test is performed on the five series jointly.

The LM and F tests (Table 3) indicate ARCH effects are clearly present for all five series with one lag as the p-values are all significant at any conventional level; i.e., there are autocorrelations in the squared residual series. The second moment equation is specified with ARCH and GARCH terms having one lag due to Hansen and Lunde (2005). Figure 2 illustrates the five return series demonstrate significant volatility time-varying and clustering characteristics; i.e., high volatility is followed by high volatility and low volatility is followed by low volatility. This implies GARCH modeling is appropriate.

The unconditional correlations are provided in Table 5. The largest unconditional correlation is between the CLEAN and TECH series. The unconditional correlations between the traditional fossil fuel series (i.e., OIL, GAS, COAL) and the CLEAN series are all positive, but noticeably smaller compared with the CLEAN and TECH relationship. The unconditional correlations between the OIL, GAS, and COAL series are all positive, but relatively small.

Table 6 shows the unconditional correlations between the squared daily returns. The pattern is quite similar to the unconditional correlations between the daily returns. The only qualitative difference occurs between GAS and TECH which is negative in the squared daily returns case.

5 Empirical Results

5.1 Second Moment Results

The main parameters of interest of the VARMA-AGARCH model for the returns series are provided in Table 7. The GARCH (β) parameters measure how volatility impacts volatility or long-term persistence. All of the own conditional GARCH parameters (β_{ii}) are statistically significant and demonstrate a high degree of persistence. The coefficients are very similar between the Normal and t-distributions with the exception of the COAL series where $\beta_{\text{coal,coal}} = 0.78$) is estimated for the Normal and $\beta_{\text{coal,coal}} = 0.92$) for the t-distribution. OIL and GAS have the largest long-term persistence with approximate estimates of $\beta_{\text{oil,oil}} = 0.88$ and $\beta_{\text{gas,gas}} = 0.91$). The CLEAN series under the Normal distribution has the smallest own conditional GARCH estimate with $\beta_{\text{clean,clean}} = 0.70$, but is still highly persistent. The only statistically significant volatility spillover (i.e., volatility in one market affecting volatility in another market) is from COAL to OIL with $\beta_{\text{oil,coal}} = 0.21$ for the Normal and $\beta_{\text{oil,coal}} = 0.13$ for the t-distribution.

The ARCH (α) parameters measure how "news" impacts volatility or the short-run persistence. The only own conditional ARCH parameters (α_{ii}) that are statistically significant are GAS ($\alpha_{\text{gas,gas}} = 0.05$ for the Normal distribution) and CLEAN ($\alpha_{\text{clean,clean}} = 0.15$ for the Normal distribution), but relatively small compared with the own conditional GARCH estimates. The CLEAN series is the most responsive to own news shocks. Similar to the GARCH spillover effects, only two series news shocks impact another market besides its own: CLEAN to TECH ($\alpha_{\text{tech,clean}} = -0.04$) and TECH to CLEAN ($\alpha_{\text{clean,tech}} = -0.12$), both under the Normal distribution only.

The λ_1 and λ_2 parameters represent the impact of past shocks on current conditional correlations and of past correlations, respectively. Both estimates are positive and statistically significant. This is indicative of a DCC specification being more appropriate than a CCC one. The λ parameters sum to less than unity indicating the dynamic conditional correlations are stationary.

The γ parameters measure asymmetric effects. Under the Normal distribution only the TECH series is statistically significant whereas OIL and TECH are statistically significant under the t-distribution. This implies positive and negative shocks impact volatility in the same manner for GAS, CLEAN, and COAL, but negative shocks increase volatility more than positive shocks for both OIL and TECH.

5.2 Dynamic Conditional Correlations

The dynamic (time-varying) conditional correlations for series pairs are provided in Figure 3 for the Normal and Figure 4 for the t-distribution. The dynamic correlations clearly evolve over time with both distributions exhibiting similar patterns. The ranges of the dynamic conditional correlations that are negative indicate a possibility of portfolio diversification. However, GAS-COAL, OIL-COAL, and CLEAN-TECH show no possibility of portfolio diversification with their respective correlations positive throughout.

5.3 Diagnostic Tests

To ensure the series have been properly modeled, diagnostic tests are performed. The Ljung-Box test statistic, which has a null hypothesis of no autocorrelation, is used on the individual and multivariate residuals and squared residuals. The Normal distribution specification indicates all of the series are white noise, revealing no more useful information remains. However, the Ljung-Box test for the squared residuals of the t-distribution specification shows the CLEAN, TECH, and COAL series are not white noise[27].

6 Implications for Portfolio Design and Hedging Strategies

6.1 Portfolio Weights

Kroner and Ng (1998) developed a portfolio with the goal of minimizing risk while not lowering expected returns. The conditional volatility estimates from the multivariate GARCH Normal distribution model are used to create the weights. The portfolio weight between two assets, i and j, is given by:

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}}$$

$$w_{ij,t} = \begin{cases} 0, \text{ if } w_{ij,t} < 0 \\ w_{ij,t}, \text{ if } 0 \leq w_{ij,t} \leq 1 \\ 1, \text{ if } w_{ij,t} > 1 \end{cases}$$

where $w_{ij,t}$ is the weight of asset one in a \$1 portfolio composed of the two assets at time t, $h_{ij,t}$ is the conditional covariance between assets i and j at time t, $h_{ii,t}$ is the conditional variance of the first asset at time t, and $h_{jj,t}$ is the conditional variance of the second asset at time t.

Summary statistics for the portfolio weights are found in Table 10. The average weight for the OIL-GAS portfolio is 0.73 implying in a \$1 portfolio 73 cents should be invested in OIL and 27 cents in GAS to minimize risk. To view the dynamics of the portfolio weights, Figure 5 and Figure 6 are provided for the Normal and t-distributions, respectively.

6.2 Hedging

Another application using the conditional volatility estimates is to form hedging ratios. Following Kroner and Sultan (1993) risk-minimizing hedge ratios are calculated. To achieve this, a long (buy) position of \$1 in on asset (i) is hedged by a short (sell) position of β in another asset (j) at time t. Formally,

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}}$$

where $\beta_{ij,t}$ is the risk-minimizing hedge ratio between two assets at time t, $h_{ij,t}$ is the conditional covariance between assets i and j at time t, and $h_{jj,t}$ is the conditional variance of asset j at time t.

[27] Several first-moment specifications were tried (e.g., VAR(3) or modeling each series with ARIMA), but not presented. All failed to completely clean the series. A later paper using non-parametric techniques is able to clean the series.

The summary statistics for the average hedging ratios are given in Table 11. The average hedge ratio between OIL and GAS is 0.16. This implies a $1 long position in OIL can be hedged for 16 cents with a short position in GAS, on average. Note the average hedging ratio between CLEAN and TECH is 1.40 indicating it is fruitless to buy a long position in CLEAN shorting TECH. This finding is consistent with the persistently high positive dynamic correlation between CLEAN and TECH. Graphs of how the hedging ratios evolve over time are shown in Figure 7 and Figure 8 for the Normal and t-distributions, respectively. The CLEAN-COAL, GAS-TECH, OIL-TECH, GAS-COAL, and OIL-COAL dynamic hedging ratio exhibit periods exceeding a ratio of one.

7 Conclusion

The paper investigates conditional own volatility, spillover volatility, and correlations for a oil, natural gas, coal, alternative energy, and technology series using a multivariate asymmetric dynamic conditional correlation model. The resulting estimates are used to construct optimal two-asset portfolio weights and dynamic hedging ratios.

World energy markets are susceptible to disruptions triggered by events such as geopolitical conflicts and natural disasters. Recent examples of the former include the 2011 Libyan Civil War resulting in major oil supply disruptions and in January 2009 the dispute between the Ukraine and Russia resulting in the largest natural gas supply crisis in Europe's history[28]. Natural disasters are also a common source of oil supply disruptions with hurricanes Katrina/Rita and Gustav/Ike occurring in 2005 and 2008, respectively. Growing concerns over the economic, political, and national security ramifications of depending on foreign oil coupled with increased energy demands has led many countries to diversify the sources to meet their energy needs. For example, according to the U.S. Energy Information Administration (EIA), China, in an effort to buttress energy supply security, is diversifying its supply sources in various regions through overseas investments and long-term contracts.[29] In a continued effort to insulate itself from foreign energy sources and boost energy security, the United States increased its production of domestically produced oil and natural gas to their highest levels in fifteen years (CEA, 2013). However, sustainable and reliable sources of energy need to be balanced, in equal parts, with environmentally conscientious energy production; subsequently adding another constraint on increasing energy demand.

According to the Environmental Protection Agency (EPA 2010) nearly 90 percent of U.S. anthropogenic (i.e. human induced) emissions of all greenhouse gases are energy-related with fossil fuel combustion accounting for over 90 percent of U.S. CO_2 emissions (CEA, 2013). Many countries have pledged to lower their carbon footprint. One of the main ways to adhere to lowering carbon emissions is to switch away from more traditional fossil fuels (e.g. oil) toward cleaner or zero-emission energy sources. In an effort to attain sustainable development today and for future generations, in accordance with the United Nations Climate Change Conferences in Copenhagen and Cancún, the United States pledged to cut its CO_2 and other anthropogenic greenhouse gas emissions in the range of 17 percent below 2005 levels by 2020, and to meet its long-term goal of reducing emissions by 83 percent by 2050 (CEA, 2013). As a consequence of new policy initiatives to reduce carbon emissions both natural gas and renewable energy have grown significantly in recent years.

Natural gas is set to increase its global market share in meeting energy needs due to its relatively low supply costs, wider availability over oil, and relatively lower carbon footprint compared with oil and coal (WEO, 2013). Natural gas is seen as a cleaner alternative to petroleum and coal as an energy source enabling economies to carefully switch to renewable energies as they become more viable options through increased research and development and installation.[30] In the most recent *World Oil Outlook* OPEC predicts the fastest growing energy source will be natural gas, in terms of volume; in percentage terms natural gas growth is second behind non-hydro renewable energies (OPEC, 2013).

The Obama Administration set a goal of doubling generation from wind, solar, and geothermal sources by 2020. To ensure this goal is met, a push is being made to make the renewable energy Production Tax Credit

[28] http://www.iea.org/topics/energysecurity/
[29] http://www.eia.gov/countries/cab.cfm?fips=CH
[30] http://www.npr.org/2012/02/02/146297284/could-cheap-gas-slow-growth-of-renewable-energy

permanent and refundable thereby providing incentives and certainty for investments in clean energy (CEA, 2013). According to the IEA predictions, renewable energy sources are expected to account for nearly half of the increase in global power generation to 2035 with global energy demand from renewable sources growing by 77%, per the New Policies Scenario.

The results indicate the largest driver of volatility in an individual series is the past volatility of the series itself. Own news shocks have an impact, but are relatively small. Further, little evidence is found of volatility spillover effects among the series.

8 Acknowledgments

I would like to thank Houston Stokes for his detailed comments, Georgios Karras for his comments, the audience at the Graduate Student Lunch, the audience at the Illinois Economic Association 44$^{\text{th}}$ Annual Meeting, and Scott Hegerty for his comments as a discussant.

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Journal Article	Data Range	Data Frequency	Main Result (Oil to Clean)	Research Design
Henriques and Sadorsky (2008)	2001–2007	Weekly	little impact	SVAR
Kumar et al. (2012)	2005–2008	Weekly	positive	SVAR
Sadorsky (2012)	2001–2010	Daily	positive (small)	MGARCH
Managi and Okimoto (2013)	2001–2010	Weekly	positive	MS-VAR
Lee et al. (2013)	2001–2011	Daily	positive (large)	ARJI

Table 1: Related Literature Summary

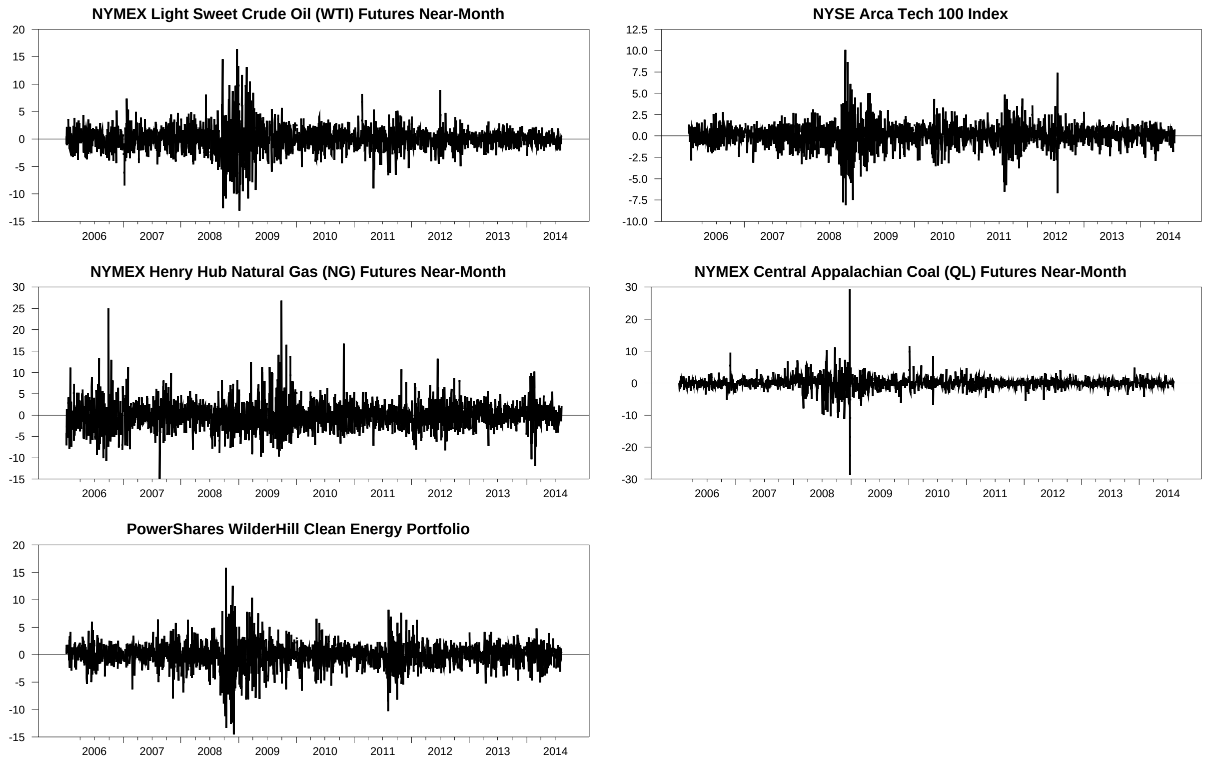

Figure 1: Returns (Daily)

	OIL	GAS	CLEAN	COAL	TECH
Mean	0.0202	−0.0458	−0.0443	0.0028	0.0359
Standard Deviation	2.3271	3.2692	2.3705	1.9510	1.3593
Minimum	−13.0654	−14.8934	−14.5550	−28.7141	−8.1202
Maximum	16.4097	26.8737	15.8199	29.3481	10.0988
Skewness	0.1152	0.8109	−0.3637	−0.0608	−0.1430
Kurtosis (excess)	5.4332	5.2767	4.6892	50.2521	5.7713
Jarque-Bera[a]	3382.0788	2885.4423	2020.9724	226644.62	2996.7586
Observations	2154	2154	2154	2154	2154

[a] The Jarque-Bera statistic is used to test for normality. All five series indicate a departure from the Normal distribution with probability values of 0.0000.

Table 2: Summary Statistics (Daily Returns)

	OIL	GAS	CLEAN	TECH	COAL
Engle's ARCH (F) Test (Lags=1)					
Statistic	122.514	11.992	174.048	91.692	576.237
Significance Level	0.00000	0.00054	0.00000	0.00000	0.00000
Engle's ARCH (LM) Test (Lags=1)					
Statistic	116.017	11.937	161.163	88.023	454.862
Significance Level	0.00000	0.00055	0.00000	0.00000	0.00000
ARCH Effects	Yes	Yes	Yes	Yes	Yes
Multivariate ARCH Test (Lags=1)					
Statistic	5920.06				
Degrees	225				
Significance Level	0.00000				
ARCH Effects	Yes				

Table 3: ARCH Tests

	OIL	GAS	CLEAN	TECH	COAL
ADF (Lags=4)					
trend	−21.7984	−22.2207	−21.7646	−22.0831	−19.6292
constant	−21.8028	−22.2160	−21.7688	−22.0333	−19.6336
APP (Lags=4)					
trend	−48.3818	−49.7159	−44.2905	−50.5415	−45.6124
constant	−48.3812	−49.7055	−44.2901	−50.5019	−45.6124
KPSS (Lags=4)					
trend	0.040498	0.031574	0.091971	0.043068	0.063527
constant	0.041897	0.075345	0.094484	0.208405	0.064481
Stationary	Yes	Yes	Yes	Yes	Yes

Four lag selection criteria are used: LR, AIC, SBIC, and HQIC. The largest lag is used for all five series.

Table 4: Unit Root Tests

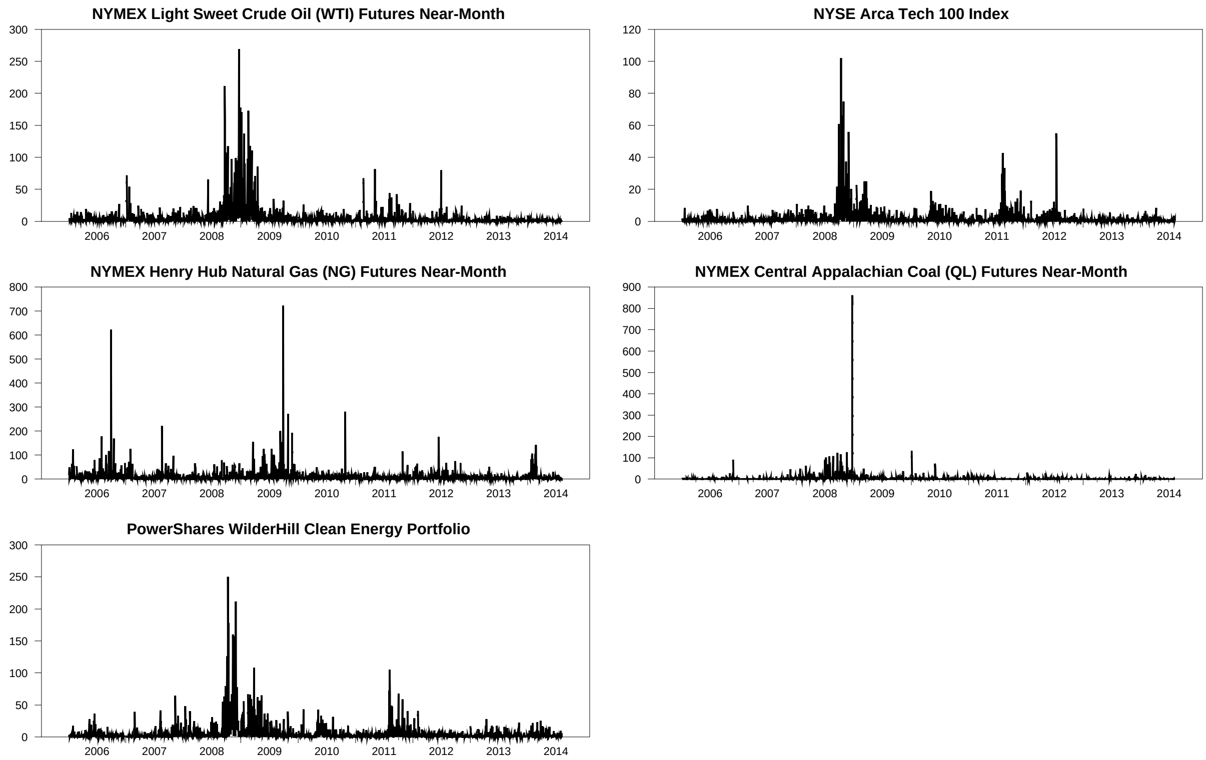

Figure 2: Squared Returns (Daily)

	OIL	GAS	CLEAN	COAL	TECH
OIL	1.0000	0.2147	0.3461	0.2953	0.2915
GAS	0.2147	1.0000	0.0969	0.1843	0.0579
CLEAN	0.3461	0.0969	1.0000	0.1603	0.8036
COAL	0.2953	0.1843	0.1603	1.0000	0.1136
TECH	0.2915	0.0579	0.8036	0.1136	1.0000

Table 5: Correlations (Daily Returns)

	OIL	GAS	CLEAN	COAL	TECH
OIL	1.0000	0.0280	0.3010	0.1480	0.2904
GAS	0.0280	1.0000	0.0246	0.0335	−0.0082
CLEAN	0.3010	0.0246	1.0000	0.0855	0.7615
COAL	0.1480	0.0335	0.0855	1.0000	0.0607
TECH	0.2904	−0.0082	0.7615	0.0607	1.0000

Table 6: Correlations (Squared Daily Returns)

	Normal			t		
Variable	Coefficient	Standard Error	t-Statistic	Coefficient	Standard Error	t-Statistic
$\omega_{\text{oil,oil}}$	0.0640	0.0307	2.0825	0.0420	0.0267	1.5733
$\omega_{\text{gas,gas}}$	0.1199	0.0388	3.0916	0.1778	0.0577	3.0805
$\omega_{\text{clean,clean}}$	0.1824	0.0865	2.1091	0.1604	0.1618	0.9916
$\omega_{\text{tech,tech}}$	0.0243	0.0138	1.7549	0.0271	0.0197	1.3804
$\omega_{\text{coal,coal}}$	0.0778	0.1676	0.4639	0.0178	0.0256	0.6969
$\alpha_{\text{oil,oil}}$	0.0197	0.0156	1.2620	0.0198	0.0180	1.1038
$\alpha_{\text{oil,gas}}$	0.0236	0.0124	1.9033	0.0109	0.0114	0.9518
$\alpha_{\text{oil,clean}}$	0.0467	0.0334	1.3987	0.0059	0.0319	0.1865
$\alpha_{\text{oil,tech}}$	−0.0912	0.0518	−1.7626	−0.0602	0.0520	−1.1574
$\alpha_{\text{oil,coal}}$	−0.0304	0.0291	−1.0426	−0.0311	0.0238	−1.3086
$\alpha_{\text{gas,oil}}$	0.0103	0.0198	0.5214	−0.0074	0.0226	−0.3295
$\alpha_{\text{gas,gas}}$	0.0523	0.0137	3.8287	0.0700	0.0144	4.8483
$\alpha_{\text{gas,clean}}$	−0.0102	0.0383	−0.2666	−0.0097	0.0235	−0.4140
$\alpha_{\text{gas,tech}}$	−0.0697	0.0608	−1.1469	−0.0744	0.0414	−1.7989
$\alpha_{\text{gas,coal}}$	−0.0261	0.0236	−1.1052	−0.0241	0.0244	−0.9841
$\alpha_{\text{clean,oil}}$	−0.0030	0.0288	−0.1047	−0.0061	0.0161	−0.3788
$\alpha_{\text{clean,gas}}$	−0.0039	0.0166	−0.2379	−0.0019	0.0176	−0.1083
$\alpha_{\text{clean,clean}}$	0.1494	0.0495	3.0155	0.1399	0.1080	1.2952
$\alpha_{\text{clean,tech}}$	−0.1192	0.0592	−2.0142	−0.1281	0.1270	−1.0087
$\alpha_{\text{clean,coal}}$	−0.0036	0.0276	−0.1304	0.0089	0.0243	0.3660
$\alpha_{\text{tech,oil}}$	−0.0015	0.0112	−0.1375	−0.0099	0.0100	−0.9891
$\alpha_{\text{tech,gas}}$	−0.0047	0.0082	−0.5693	−0.0046	0.0101	−0.4563
$\alpha_{\text{tech,clean}}$	−0.0435	0.0161	−2.7094	−0.0270	0.0221	−1.2205
$\alpha_{\text{tech,tech}}$	0.0394	0.0231	1.7099	0.0141	0.0235	0.6014
$\alpha_{\text{tech,coal}}$	0.0347	0.0221	1.5671	0.0285	0.0243	1.1743
$\alpha_{\text{coal,oil}}$	−0.0473	0.0465	−1.0173	−0.0082	0.0161	−0.5102
$\alpha_{\text{coal,gas}}$	−0.0026	0.0158	−0.1637	−0.0128	0.0107	−1.1973
$\alpha_{\text{coal,clean}}$	−0.0243	0.0449	−0.5400	−0.0072	0.0204	−0.3507
$\alpha_{\text{coal,tech}}$	0.0362	0.0643	0.5632	0.0325	0.0306	1.0621
$\alpha_{\text{coal,coal}}$	0.1120	0.0990	1.1308	0.0531	0.0344	1.5421
$\beta_{\text{oil,oil}}$	0.8830	0.0502	17.6063	0.8819	0.0421	20.9722
$\beta_{\text{oil,gas}}$	0.0134	0.0442	0.3027	0.0321	0.0381	0.8432
$\beta_{\text{oil,clean}}$	−0.0601	0.0830	−0.7245	0.0482	0.0698	0.6904
$\beta_{\text{oil,tech}}$	0.1168	0.1260	0.9268	0.0178	0.1160	0.1534
$\beta_{\text{oil,coal}}$	0.2093	0.0963	2.1725	0.1297	0.0614	2.1131
$\beta_{\text{gas,oil}}$	−0.0444	0.0385	−1.1513	−0.0164	0.0266	−0.6179
$\beta_{\text{gas,gas}}$	0.9169	0.0116	78.9648	0.9098	0.0133	68.5123
$\beta_{\text{gas,clean}}$	0.1658	0.1063	1.5593	0.2162	0.0792	2.7283
$\beta_{\text{gas,tech}}$	−0.0332	0.1632	−0.2036	−0.1342	0.1185	−1.1329
$\beta_{\text{gas,coal}}$	0.0806	0.0673	1.1970	0.0781	0.0366	2.1345
$\beta_{\text{clean,oil}}$	−0.0368	0.0939	−0.3920	−0.0598	0.0875	−0.6840
$\beta_{\text{clean,gas}}$	−0.0140	0.0612	−0.2287	−0.0043	0.0447	−0.0970
$\beta_{\text{clean,clean}}$	0.7019	0.1435	4.8914	0.7599	0.2458	3.0916
$\beta_{\text{clean,tech}}$	0.3593	0.2362	1.5208	0.2959	0.3891	0.7604
$\beta_{\text{clean,coal}}$	0.1391	0.1112	1.2508	0.0956	0.1065	0.8980
$\beta_{\text{tech,oil}}$	0.0132	0.0356	0.3715	0.0153	0.0282	0.5424
$\beta_{\text{tech,gas}}$	−0.0001	0.0225	−0.0062	0.0020	0.0171	0.1141
$\beta_{\text{tech,clean}}$	0.1028	0.0623	1.6511	0.0906	0.0714	1.2693
$\beta_{\text{tech,tech}}$	0.7959	0.0878	9.0675	0.8087	0.1249	6.4754
$\beta_{\text{tech,coal}}$	−0.0815	0.0798	−1.0212	−0.0365	0.0804	−0.4540
$\beta_{\text{coal,oil}}$	0.2154	0.4642	0.4641	−0.0010	0.0818	−0.0120
$\beta_{\text{coal,gas}}$	−0.0080	0.0652	−0.1232	0.0267	0.0204	1.3052
$\beta_{\text{coal,clean}}$	0.4525	0.6663	0.6791	0.1504	0.0992	1.5161
$\beta_{\text{coal,tech}}$	−0.8013	1.3838	−0.5791	−0.2669	0.2330	−1.1457
$\beta_{\text{coal,coal}}$	0.7754	0.3341	2.3213	0.9217	0.0765	12.0446
γ_{oil}	0.0602	0.0338	1.7828	0.0898	0.0249	3.6088
γ_{gas}	0.0274	0.0204	1.3415	−0.0063	0.0198	−0.3177
γ_{clean}	0.0155	0.0216	0.7159	0.0250	0.0237	1.0553
γ_{tech}	0.1292	0.0325	3.9809	0.1309	0.0544	2.4052
γ_{coal}	0.0124	0.0746	0.1657	−0.0032	0.0175	−0.1836
λ_1	0.0160	0.0035	4.5383	0.0156	0.0048	3.2326
λ_2	0.9780	0.0062	157.7099	0.9804	0.0074	132.2147
Shape				8.1569	0.3694	22.0826
AIC		18.842			18.573	
SBIC		19.084			18.819	
HQIC		18.930			18.663	
Log-Liklihood		−20191.0911			−19901.3160	
Observations		2153			2153	

Table 7: VAR(1)-ADCC: Parameter Estimates

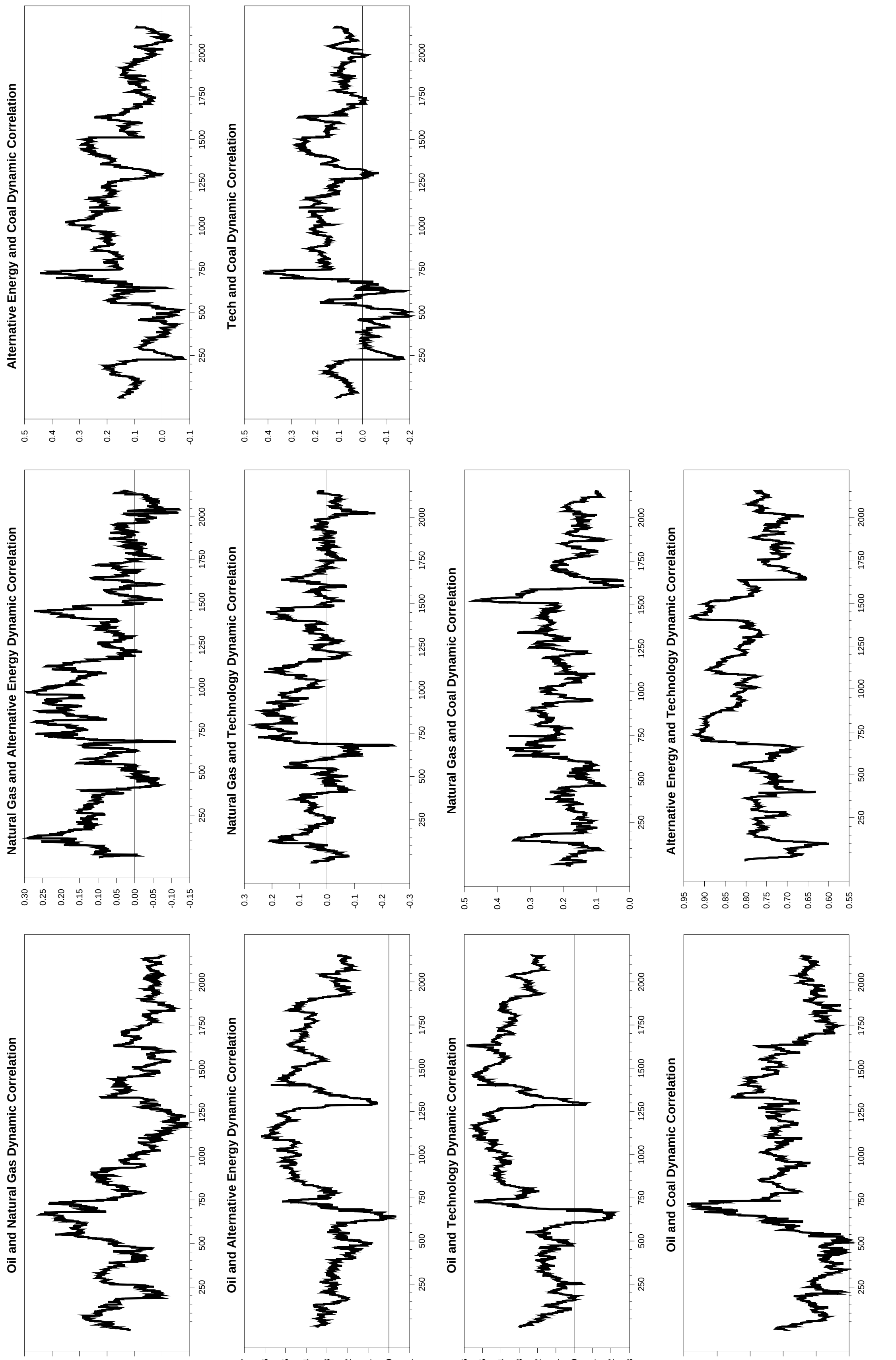

Figure 3: Dynamic Correlations (Normal)

	OIL	GAS	CLEAN	TECH	COAL
z (AC=10)					
Q	4.7682	7.4788	4.4556	8.6227	10.8180
Significance	0.9061	0.6796	0.9245	0.5682	0.3719
z (AC=20)					
Q	13.4111	19.6113	17.4055	14.2383	20.3915
Significance	0.8591	0.4825	0.6265	0.8182	0.4337
z^2 (AC=10)					
Q	7.5605	9.7535	15.3511	15.0998	10.8638
Significance	0.6717	0.4624	0.1198	0.1285	0.3682
z^2 (AC=20)					
Q	13.1771	18.9861	25.4710	23.9747	19.9902
Significance	0.8697	0.5227	0.1840	0.2435	0.4585
White Noise	Yes	Yes	Yes	Yes	Yes
Multivariate Q (AC=10)	z	z^2			
Q	206.0664	261.7906			
Significance	0.9805	0.2915			
Multivariate Q (AC=20)					
Q	433.0996	509.9531			
Significance	0.9860	0.3693			
White Noise	Yes	Yes			

Table 8: Ljung-Box Diagnostic Test for Standardized Residuals (Normal Distribution)

	OIL	GAS	CLEAN	TECH	COAL
z (AC=10)					
Q	3.7581	8.0893	5.0150	8.5311	9.2443
Significance	0.9576	0.6201	0.8902	0.5771	0.5091
z (AC=20)					
Q	11.0924	20.5999	17.7037	14.4364	18.7611
Significance	0.9438	0.4210	0.6069	0.8077	0.5374
z^2 (AC=10)					
Q	9.8706	9.9396	19.4832	31.3191	22.4916
Significance	0.4519	0.4458	0.0345	0.0005	0.0128
z^2 (AC=20)					
Q	14.4488	18.0140	28.5621	42.0899	27.1033
Significance	0.8070	0.5865	0.0967	0.0027	0.1324
White Noise	Yes	Yes	No/Yes	No	No/Yes
Multivariate Q (AC=10)	z	z^2			
Q	207.7194	299.7930			
Significance	0.9761	0.0169			
Multivariate Q (AC=20)					
Q	433.6036	538.6040			
Significance	0.9853	0.1128			
White Noise	Yes	No/Yes			

Table 9: Ljung-Box Diagnostic Test for Standardized Residuals (t Distribution)

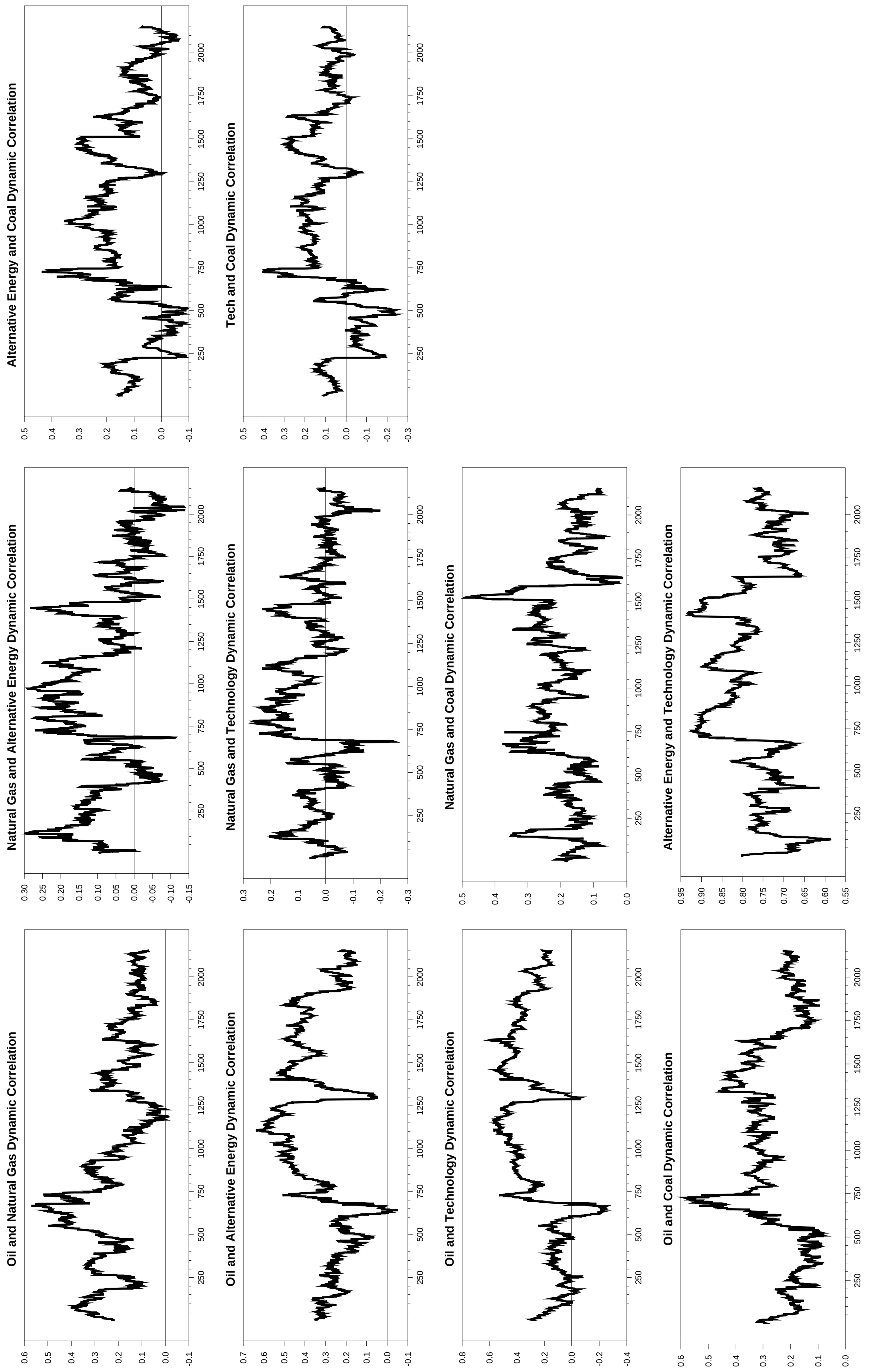

Figure 4: Dynamic Correlations (t Distribution)

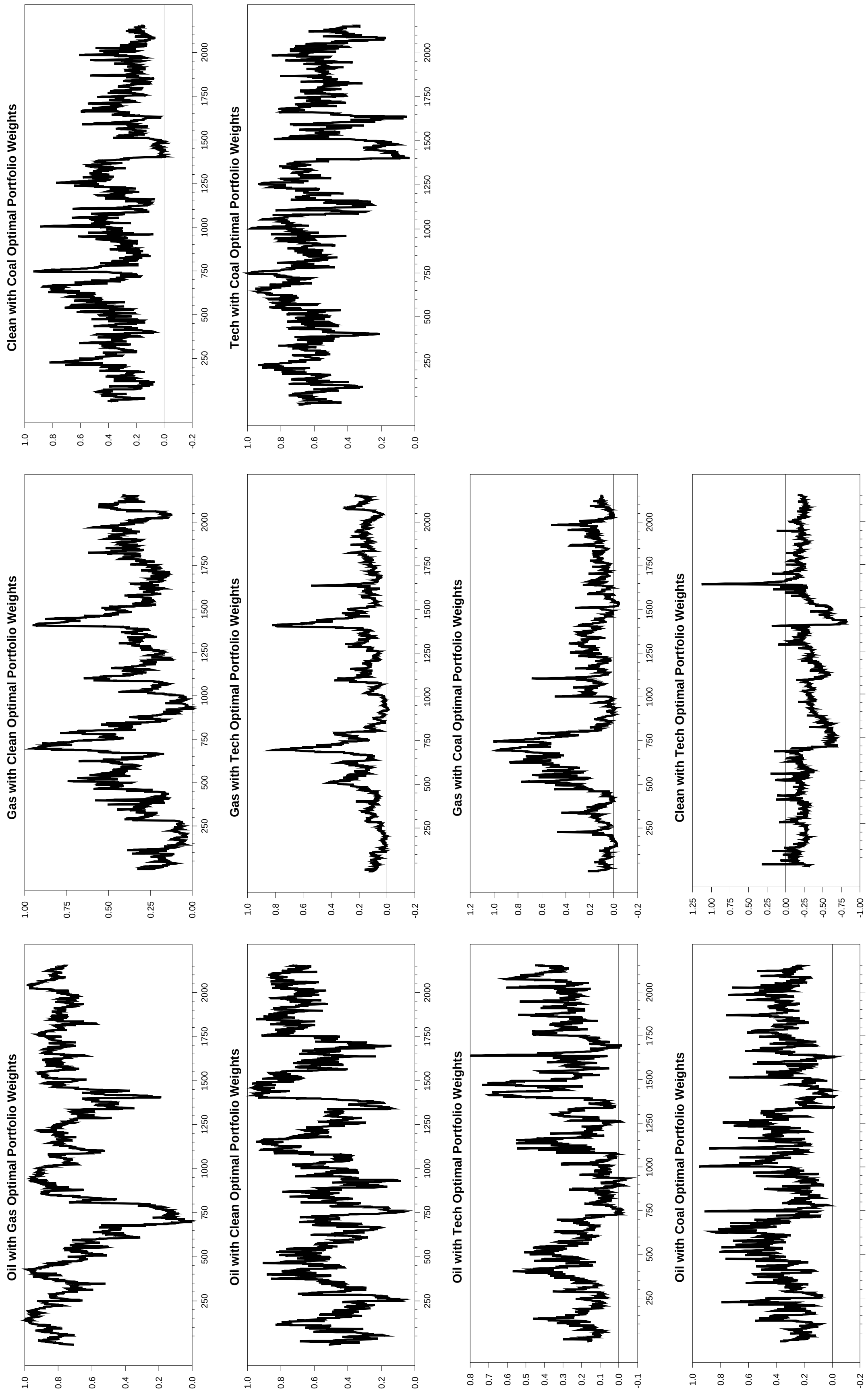

Figure 5: Portfolio Weights (Normal)

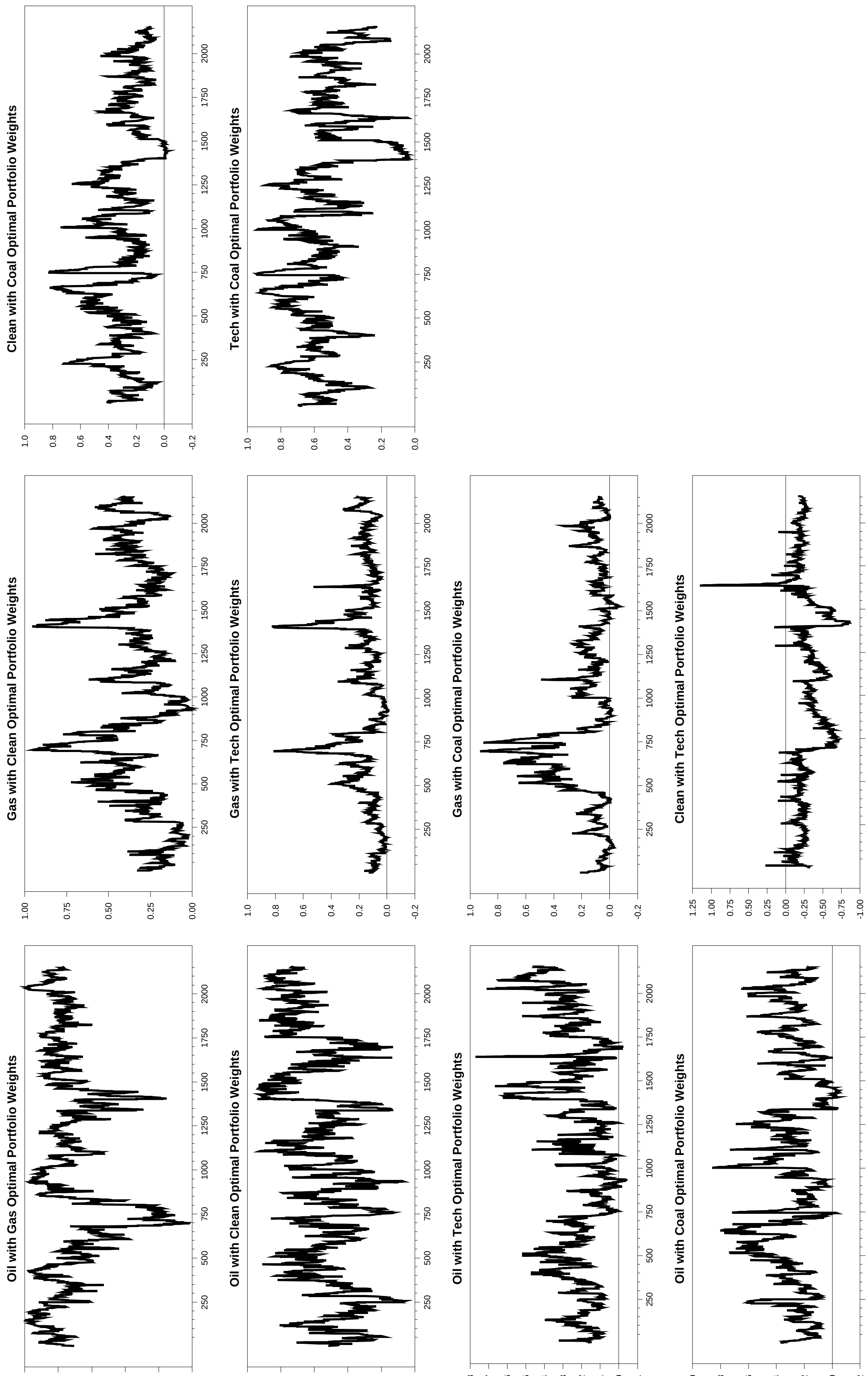

Figure 6: Portfolio Weights (t)

Variables	Obs	Normal Mean	Normal Std. Dev.	Normal Min.	Normal Max.	t Mean	t Std. Dev.	t Min.	t Max.
$w_{\text{oil,gas}}$	2153	0.7303	0.196	0.0069	0.9953	0.7331	0.1836	0.0172	0.9944
$w_{\text{oil,clean}}$	2153	0.5638	0.1999	0.0585	0.9738	0.5611	0.1967	0.0618	0.9406
$w_{\text{oil,tech}}$	2153	0.2236	0.1424	−0.0433	0.7965	0.2167	0.1347	−0.0444	0.7697
$w_{\text{oil,coal}}$	2153	0.3269	0.1617	−0.0219	0.9538	0.2815	0.1707	−0.047	0.8592
$w_{\text{gas,clean}}$	2153	0.3261	0.1817	0.006	0.9534	0.3265	0.1817	0.0057	0.9555
$w_{\text{gas,tech}}$	2153	0.1489	0.1229	−0.011	0.8229	0.148	0.121	−0.0115	0.8252
$w_{\text{gas,coal}}$	2153	0.1748	0.1881	−0.0478	1.005	0.1452	0.1726	−0.0725	0.9274
$w_{\text{clean,tech}}$	2153	−0.2798	0.1777	−0.8201	1.1314	−0.2832	0.1864	−0.8712	1.1529
$w_{\text{clean,coal}}$	2153	0.3217	0.1709	−0.0097	0.9394	0.2831	0.1644	−0.0242	0.8319
$w_{\text{tech,coal}}$	2153	0.5946	0.1785	0.032	0.9941	0.5494	0.1843	0.0345	0.9479

Table 10: Portfolio Weights Summary Statistics

Variables	Obs	Normal Mean	Normal Std. Dev.	Normal Min.	Normal Max.	t Mean	t Std. Dev.	t Min.	t Max.
$\beta_{\text{oil,gas}}$	2153	0.1645	0.1503	0.0027	0.9659	0.1604	0.1426	−0.0054	0.921
$\beta_{\text{oil,clean}}$	2153	0.3186	0.1415	−0.0408	0.8255	0.3205	0.1552	−0.056	0.8606
$\beta_{\text{oil,tech}}$	2153	0.4393	0.3027	−0.8401	1.4368	0.4335	0.3192	−0.8257	1.4367
$\beta_{\text{oil,coal}}$	2153	0.3693	0.1702	0.0714	1.2019	0.4047	0.2261	0.0688	1.464
$\beta_{\text{gas,clean}}$	2153	0.1362	0.1746	−0.3519	0.9148	0.1324	0.1843	−0.3858	0.921
$\beta_{\text{gas,tech}}$	2153	0.1182	0.2515	−0.8634	1.4745	0.1098	0.2598	−1.0034	1.5024
$\beta_{\text{gas,coal}}$	2153	0.4536	0.2566	0.037	1.7163	0.5051	0.2879	0.0298	1.7265
$\beta_{\text{clean,tech}}$	2153	1.3981	0.2373	0.3304	3.1262	1.3913	0.2165	0.3069	2.7441
$\beta_{\text{clean,coal}}$	2153	0.2048	0.188	−0.1242	1.129	0.2205	0.2497	−0.2392	1.5436
$\beta_{\text{tech,coal}}$	2153	0.0898	0.1181	−0.1878	0.6674	0.0982	0.1509	−0.2441	0.7484

Table 11: Hedge Ratios (Long/Short) Summary Statistics

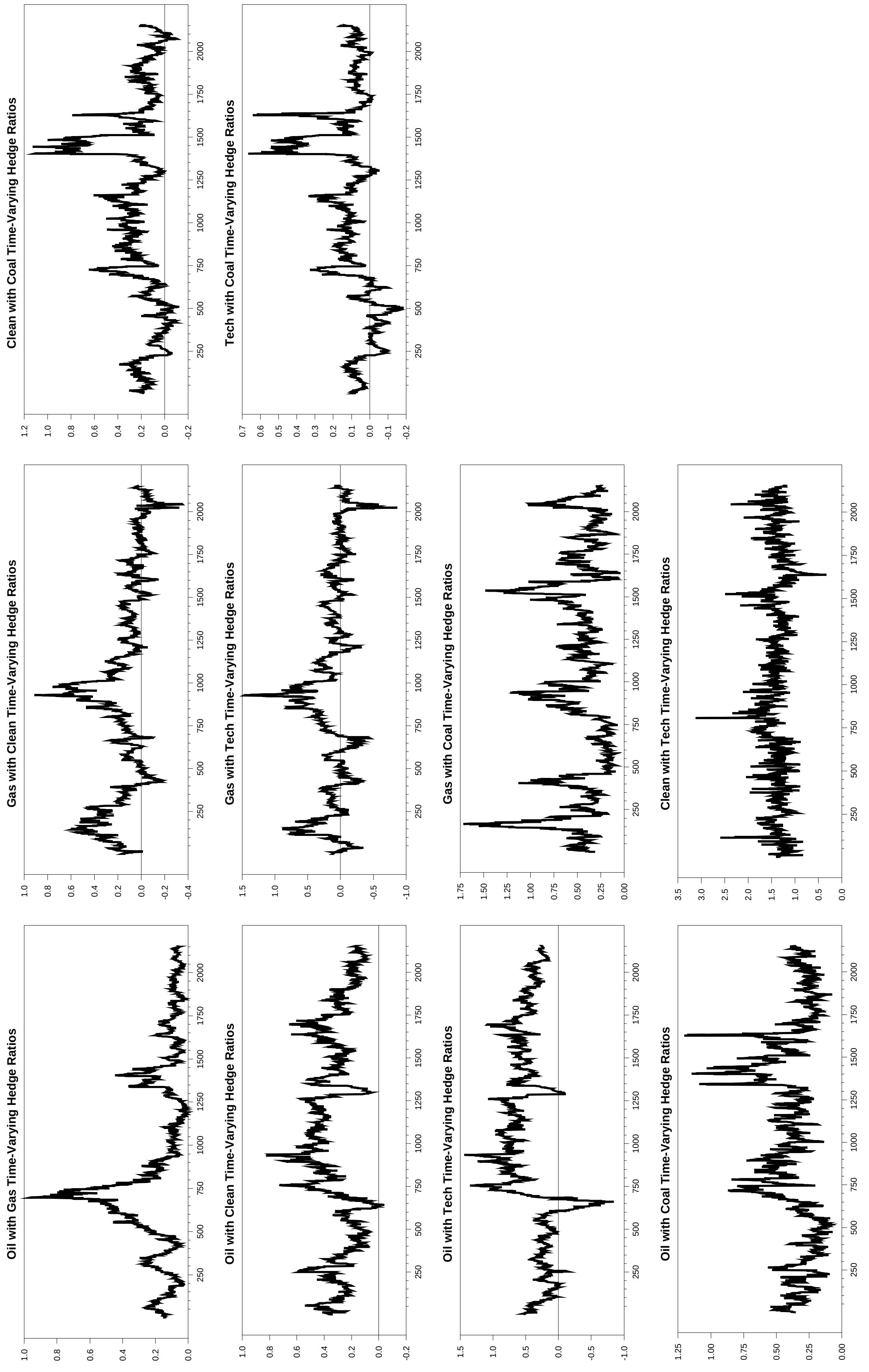

Figure 7: Dynamic Hedging Ratios (Normal)

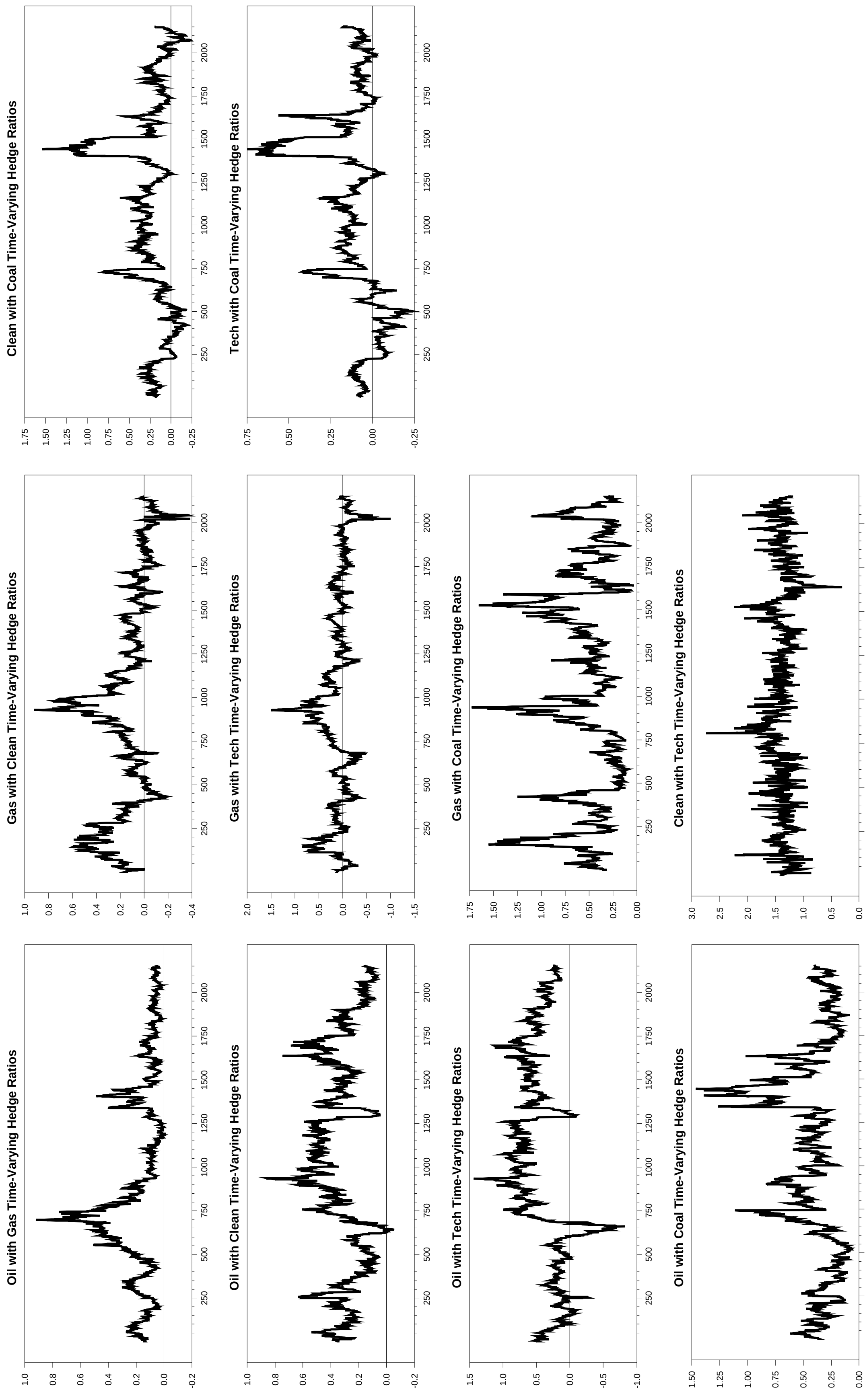

Figure 8: Dynamic Hedging Ratios (t)