ESSAYS ON EFFICIENCY OF THE FARM CREDIT SYSTEM AND DYNAMIC CORRELATIONS IN FOSSIL FUEL MARKETS

A Dissertation

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ABSTRACT

Markets have always changed in response to either exogenous or endogenous shocks. Many large events have occurred in financial and energy markets the last ten years. This dissertation examines market behavior and volatility in agricultural credit and fossil fuel markets under exogenous and endogenous changes in the last ten years. The efficiency of elements within the United States Farm Credit System, a major agricultural lender in the United States, and the dynamic correlation between coal, oil and natural gas prices, the three major fossil fuels, are examined.

The Farm Credit system is a key lender in the U.S. agricultural sector, and its performance can influence the performance of the agricultural sector. However, its efficiency in providing credit to the agricultural sector has not been recently examined. The first essay of the dissertation provides assessments on the performance of elements within the Farm Credit System by measuring their relative efficiency using a stochastic frontier model. The second essay addresses the changes in relationship in coal, oil, and natural gas markets with respect to changes and turbulence in the last decade, which has also not been fully addressed in literature. The updated assessment on the relative performance of entities within the Farm Credit System provides information that the Farm Credit Administration and U.S. policy makers can use in their management of and policy toward the Farm Credit System. The measurement of the changes in fossil fuel markets' relationships provides implications for energy investment, energy portfolio

management, energy risk management, and energy security. It can also be used as a foundation for structuring forecasting models and other models related to energy markets. The dynamic correlations between coal, oil, and natural gas prices are examined using a dynamic conditional correlation multivariate autoregressive conditional heteroskedasticity (MGARCH DCC) model.

The estimated results show that the FCS's five banks and associations with large assets have more efficiently produced credit to the U.S. agricultural sector than smaller sized associations. Management compensation is found to be positively associated with the system's efficiency. More capital investment and monitoring along with possible consolidation are implied for smaller sized associations to enhance efficiency. On average, the results show that the efficiency of the associations is increasing over time while the average efficiency of the five large banks is more stable. Overall, the associations exhibit a higher variation of efficiency than the five banks.

In terms of energy markets the estimates from the MGARCH DCC model indicate significant and changing dynamic correlations and related volatility between the coal, oil, and natural gas prices. The coal price was found to experience more volatility and become more closely related to oil and natural gas prices in recent periods. The natural gas price was found to become more stable and drift away from its historical relationship with oil.

DEDICATION

To my mother, with love

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NOMENCLATURE

FCS	Farm Credit System
SFA	Stochastic Frontier model
MGARCH	Multivariate Generalized Autoregressive Conditional Heteroskedasticity
DCC	Dynamic Conditional Correlation
ARCH	Autoregressive Conditional Heteroskedasticity
TFA	Thick Frontier Approach
DFA	Distribution-Free Approach
DEA	Data Envelopment Analysis
Coef.	Coefficient
Std. D.	Standard Deviation
Freq	Frequency
Bank size 1	Associations with total assets larger than or equal to $1 billion in year 2009 dollars
Bank size 2	Associations with total assets larger than or equal to $500 million and less than $1 billion in year 2009 dollars
Bank size 3	Associations with total assets larger than or equal to $250 million and less than $500 million in year 2009 dollars
Bank size 4	Associations with total assets less than $250 million in year 2009 dollars

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CHAPTER I

INTRODUCTION

The first decade of the twenty-first century has been a time of many changes and much turbulence. The collapse of housing markets in 2007, the financial crisis in 2008, the biofuel boom in agriculture with accompanying high commodity prices since 2005, and the possibility of global recession afterwards have affected and accelerated significant changes in financial sectors, economic environments, and markets worldwide. Meanwhile globalization, market liberalization, and the growth of international trade have not only opened new opportunities but also new challenges to many countries and markets. Other major challenges and risks have developed from climate change and global warming as the awareness of climate change has increased significantly given the occurrence of various climatic extremes and weather events (Leiserowitz et al., 2012). In addition, the rise of emerging markets, especially the impressive growth of the Chinese economy has had significant influences on global markets and economy. Technological advancements for energy production, environmental matters, and communications have also brought the global markets and economies to a more competitive, informative, integrated, and transparent stage. The challenges, opportunities, and risks from the global financial crisis, economic recessions, globalization, climate change, emerging markets, and technological developments include shifts in production and consumption, shifts in economic and market power, more restricted environmental regulations, and the establishment and development of environmental finance markets among other developments. With these dynamic changes coupled with new opportunities, challenges, and risks, how each element in the markets responds and operates remains as always an interesting question to discover and address.

The dissertation attempts to answer this question in a small scope by examining the performance of financial institutions and the dynamic relationships in the fossil fuel markets in the last ten years. The changes in performance of the Farm Credit System and changes in relationships between fossil fuels prices indicate how elements on each market respond to exogenous and endogenous changes. The dissertation consists of two essays. The first essay assesses comparative efficiency of associations and banks within the Farm Credit System (FCS) and the second essay estimates the relationships between fossil fuels prices.

In the first essay, the performance of associations and banks within the FCS is assessed by measuring their relative technical efficiency from 2000 to 2009. Considering the FCS's goal of providing maximum service to U.S. agricultural sector at minimum cost subject to maintaining long-run viability (Collender et al., 1991), technical efficiency can be used as an indicator of how well the FCS's is performing to maximize its service. Because the FCS is a government sponsored enterprise who is exempted from many financial regulations, and receive subsided interest rate, the estimates on the Farm Credit System's technical efficiency will provide policy implications on the effectiveness of the U.S. government sponsorship to agricultural lending sector. In addition, the first essay's results and its implications will give indications of strategies that the Farm Credit Administration and U.S. policy makers might use to improve efficiency of the U.S. Farm Credit System. The efficiency of the Farm Credit System under exogenous changes such as the biofuel boom, the financial crisis and the recent increase in farm income can be further examined to see if it can be a model for other credit and financial institutions regarding organization structure, operations, and flow of funds.

The second essay characterizes the relationship between coal, gas, and oil prices in the fossil fuel markets in North America from 2004 to 2011 by examining and evaluating their dynamic correlations. Numerous studies have been focused on the relationship and integration among energy markets or between energy markets and other markets (Meldje and Bessler, 2009; Villar and Joutz, 2006; Chevallier, 2012; Koenig, 2011). However, the dynamic correlations among fossil fuel market prices including coal have not been fully addressed. Coal, natural gas, and oil power compose 70% of the electricity generation market. There is a complex interaction and a trend of substitution between them (EIA, 2012). The relationship between these markets might have also changed due to technology and general price movements. This essay will examine the relationship between these prices to see what changes have occurred and may occur in the future. Energy producers, consumers, traders, financial institutions, governments, and hedgers, may find the estimates useful support for decisions regarding risk and portfolio management, investments, or hedging. The estimates also provide implications for other decision making process which are related to energy sector.

The dissertation is organized in four chapters. Chapter 2 presents the first essay on the efficiency of the Farm Credit System. Chapter 3 presents the second essay that covers the dynamic correlation and causal relationship among oil, natural gas, and coal markets. Chapter 4 summarizes the key findings from the previous two essays.

CHAPTER II

MEASURING THE EFFICIENCY OF THE FARM CREDIT SYSTEM

The Farm Credit System (FCS) is a nationwide network of borrower-owned lending institutions and affiliated service entities that was created to provide a reliable and permanent source of credit to U.S. agriculture. The FCS is a government sponsored enterprise (GSE) which has a very unique organizational structure and flow of funds. As of January 1, 2010, the System had five banks and 88 lending associations. The banks provide wholesale loans to their affiliated associations, other banks, and non- system lenders. Some banks can also make retail loans directly to cooperatives and other eligible entities. The banks obtain funds through the issuance of System-wide Debt Securities, common and preferred equities, plus subordinated debt (Federal Farm Credit Banks Funding Corporation, 2010). The associations provide retail loans to farmers, ranchers, aquaculture, farm related businesses, and rural homeowners. The associations may also purchase loan participations from other System entities and non-System lenders. The majority of the associations' funds arise from borrowings from their affiliated banks (Federal Farm Credit Banks Funding Corporation, 2010). As a government sponsored enterprise, in the recent Obama financial reform, the FCS is one of those financial institutions exempted from many reform regulations including securities trading, and new bank taxes. In addition, the FCS also receive subsided interest rate or lower interest rate as a result of its GSE benefits (Jensen, 2000)

The FCS has been considered a reliable and key credit source for the U.S. farmers. As of 2008, the FCS accounted for 39% of the U.S. farm business (Farm Credit Administration, 2009). The performance of FCS can therefore impact the U.S. farmers who place considerable reliance on credit. These farmers have a more than 10% debt-to-asset ratio (Schnepf, 2012). Researchers have not focused much effort on examining the efficiency of elements of the FCS in providing credit to the agricultural sector. The only published paper studying efficiency within the FCS found during a literature review was Collender et al. (1991). Collender investigated the relative profit efficiency of FCS direct-lending associations using Data Envelopment Analysis (DEA) and linear programming techniques. However, there are some concerns with this study. The results are dated and may be altered by recent developments in lending and agriculture. This thesis will assess the way relative efficiency has evolved under exogenous changes such as the biofuel boom, the financial crisis and the recently rising farm income. It is designed to provide information for the Farm Credit Administration and U.S. policy makers in their management of the FCS.

This essay's objective is therefore to develop information on the relative efficiency of elements within the Farm Credit System (FCS) in producing loans and other outputs. This will be done by examining the performance of banks and associations the system in terms of technical efficiency using data from 2000 to 2009. The FCS has a stated goal of providing maximum service to U.S. agricultural sectors at minimum cost subject to maintaining long-run viability (Collender et al., 1991). Consequently technical efficiency can be used as an indicator to evaluate the relative performance of institutions within the FCS. The efficiency of the FCS's five banks: AgFirst Farm Credit Bank, AgriBank- FC, CoBank- ACB, Farm Credit Bank of Texas, U.S. AgBank, FCB and the efficiency of their lending associations will be estimated separately as they fundamentally serve different clients with almost certainly different embodied transactions costs. The change of the system's efficiency over time under exogenous changes such as the biofuel boom, the financial crisis and the recent increase in farm income will also be examined.

The remainder of this essay is organized as follows. Section 2 discusses literature review on technical efficiency measurement. The stochastic frontier production function model is described in Section 3. Section 4 presents the empirical results and implications. Section 5 concludes and discusses further research.

2.1 Literature Review

2.1.1 Banking Efficiency Measurement

The major methods used in the literature to measure efficiency are non-parametric frontier and parametric frontier production function estimation coupled with an analysis of deviations from that frontier. Data Envelopment Analysis (DEA) is the dominant non-parametric approach. DEA uses linear programming free of parametric assumptions to estimate the frontier on which the relative performance of a decision-making-unit is compared to the most efficient one (Henderson, 2003). DEA makes several assumptions. These include:

- First, it assumes no random error and attributes all deviations from the estimated frontier to inefficiency,
- Second, it assumes a deterministic framework with no uncertainty and
- Lastly, the production set is assumed to be convex with free disposability on the production set (Henderson, 2003).

Other non-parametric approaches include Free Disposal Hull, non-parametric stochastic frontier models, and semi-parametric stochastic frontier methods Free Disposal Hull (FDH) model assumes free disposability and relaxes the convexity assumption on the production set. As defined by Kumbhakar et al. (2007), the non-parametric stochastic frontier model uses a local maximum likelihood approach in which the parameters of a polynomial model are localized with respect to the covariates of the model. The semi-parametric stochastic frontier model includes assumptions about the joint distribution of the random firm effects and the regressors along with other specifications. The non-parametric part of the semi-parametric stochastic frontier model addresses the distribution of the inefficiency terms. However, the estimators in these panel models are based on the linearity of the efficient frontier (Kumbhakar et al., 2007).

The conventional linear programming-based DEA approach has several drawbacks. These drawbacks are listed below.

- It is unable to decompose deviations from the efficient production frontier into firm effects and external factor effects, thus it considers all deviations from the frontier as inefficiencies.

- It also assumes a deterministic frontier which is constructed using the outer envelope of the observations, thus it may be influenced by outliers in the data (Wilson, 1993).
- Next, the approach generally leads to a proportion of the sample being considered as perfectly efficient but those might not be the most efficient because all observations in the data set might not be included in the reference technology. These firms in those cases are therefore "self-referencing" and their efficiency estimate is equal to one (Neff et al., 1994).
- Studies using this approach typically measure efficiency based on a single time period. They do not account for technical progress during the time period and do not consider the fact that technical efficiency for a certain firm might vary over multiple time periods (Pasiouras et al., 2007).
- The deterministic non-parametric approach does not allow uncertainty in the estimation of efficiency scores. By ignoring relevant uncertainty, estimates of economic efficiency from those studies are likely to be misleading. They may classify activities which are indeed optimal for the decision maker as inefficient (Pasour and Bruce, 1975).

Although statistical inference has been developed for non-parametric deterministic frontier models, the deterministic assumption may be too strong in many practical situations where we might expect measurement error, or random shocks (Kumbhakar et al., 2007).

Other non-parametric methodologies also have their own strengths and weakness. The robust versions of the FDH estimator do not envelop all the data therefore they are more robust to outliers but they still rely on the deterministic assumption which allows no noise. The non-parametric stochastic frontier models deal with the presence of noise in the non-parametric frontier models, however the methodology is proposed in a cross-sectional framework. The semi-parametric estimation of the stochastic frontier method is proposed for panel data but the estimators in these panel models assume linearity of the efficient frontier (Kumbhakar et al., 2007).

The parametric frontier approach specifies a functional form for the cost, profit, or production relationship among inputs, outputs, and environmental factors, and allows for random error. The three main parametric methodologies include the (a) stochastic frontier approach (SFA), (b) the thick frontier approach (TFA), and (c) the distribution-free approach (DFA). The SFA assumes that inefficiencies follow an asymmetric half-normal distribution, that the random errors follow a symmetric normal distribution, and that both the inefficiencies and random errors are orthogonal to all of the regressors. The thick frontier approach assumes that deviations from predicted performance value within a group of the highest and lowest performing entities represent random error, whereas differences in predicted performance between highest- and lowest groups represent inefficiencies. The distribution-free approach is a panel estimation method in which the efficiency for each firm is estimated as the difference between its average residual and the average residual of the firm on the frontier. It assumes that efficiency of each firm is stable, while the random error is averaged out over time (Bauer et al., 1998).

The stochastic frontier model (SFA) has several advantages over the deterministic non-parametric one (Pasiouras et al., 2007). This model allows for the possibility of external events beyond the firm's control such as the financial crisis, biofuel boom, climate, and government policy by decomposing deviations from the efficient production frontier into firm effects and external factor effects. The model uses assumptions on the distribution of the two effects and use maximum likelihood estimation to estimate them. Additionally, the SFA model allows uncertainty in the estimation of efficiency scores which the deterministic non-parametric approach does not. Lastly, the stochastic frontier model data accounts for time variations in efficiency by using time series cross sectional panel data rather than cross-section data at one point in time (Pasiouras et al., 2007).

Pasiouras et al. (2007) stated that the use of panel data accounts for time variations in efficiency given the possibility that firms might learn from previous experience, or that a firm's efficiency might change over time as a result of some regulatory or environmental factors. Panel data has also been argued to be better in studying efficiency (Carbo et al., 2002; Cornwell et al., 1990; Kumbhakar, 1993). It is because the use of panel data over a cross-section provides more degrees of freedom in the estimation of the parameters (Pasiouras et al., 2007).

However, the SFA, the thick frontier approach, and the distribution-free approach are not without defect. The SFA requires a particular functional form be estimated plus embodies assumptions about the distribution of efficiency (Neff et al., 1994). This is a disadvantage of SFA approach compared to the DEA which does not make such assumptions. Those assumptions might not truly reflect the firm's underlying technology but Van der Vennet (2002) reported that when different functions and models were estimated under different assumptions, the results were not significantly different (Pasiouras et al., 2007). Furthermore Gong and Sickles (1992) demonstrated that the stochastic model outperforms the DEA model if the employed technology is close to the given underlying technology.

Regarding the thick frontier approach, it puts no restriction on the correlations between inefficiencies and the regressors but the estimation procedure provides little information on specific firm inefficiency (Neff et al., 1994). The distribution-free approach's assumption is that for a given firm the random errors will average out over time but as Sfiridis and Daniels (2006) pointed out this might not be reasonable, especially for short time periods.

Bayesian estimation of stochastic frontier models has been developed by Van den Broeck et al. (1994), Koop et al (1995), Koop et al (1997), and Osiewalski and Steel (1998) (Koop and Steel, 2004). These models use Bayesian inference about firm-specific inefficiency in estimating the original stochastic frontier models. They are typically implemented using one of two approaches which are often called Bayesian fixed and random effects models. These two types of models are different regarding the structure of the prior information and like other models they also have weaknesses. The Bayesian fixed effects model does not make a distributional assumption about the inefficiency distribution but it implicitly makes strong and possibly unreasonable prior assumptions. Furthermore, the model can only calculate relative efficiency, as opposed to an absolute one. The random effects model allows the calculation of absolute efficiency; but it makes explicit distributional assumption about the inefficiency distribution. Those assumptions might lead to improper priors on the parameters. Improper priors in some cases can lead to invalid Bayesian inference because the posterior does not exist (Koop and Steel, 2004).

After considering the advantages and disadvantages of all non-parametric and parametric approaches with regards to the FCS's characteristics, we decided to use the stochastic frontier model to estimate technical efficiency in this essay. This choice is made for several reasons. First, the stochastic frontier model accounts for exogenous factors, uncertainty, and time variation of efficiency in the estimate of efficiency. Thus the estimates of efficiency using this approach therefore are likely more precise as they can incorporate recent changes as have happened in agricultural lending markets the last ten years. Second, although the SFA model requires a particular function form the findings in the literature indicate the assumption about functional form should not create too much a problem.

2.1.2 Means of Estimating Efficiency

A number of different types of efficiency such as cost, revenue, technical, and profit efficiency can be estimated (Kumbhakar and Lovell, 2000). These all require different data sets. This study estimates technical efficiency following Kumbhakar and Lovell (2000) model. It is the ratio of an entities mean production given a set of inputs to the corresponding mean production from the production function where the inputs are used most efficiently. Since the factor price data was unavailable, the technical efficiency mentioned in Kumbhakar and Lovell (2000) was a reasonable choice. Henderson (2003) also pointed out that measuring output based technical efficiency was more relevant in real life scenarios since increasing output with a given amount of inputs might be easier than decreasing inputs to produce a given amount of output.

While numerous articles were found during the literature review that dealt with the measure efficiency of the U.S. commercial banks, the only article located that discussed FCS efficiency was an article by Collender et al (1991). These researchers investigated the viability and efficiency of FCS direct-lending associations using data envelopment analysis (DEA) and linear programming. Four different types of frontiers non-parametric profit frontiers were calculated: (a) long run nationwide, (b) long run regional, (c) short run nationwide, and (d) short run regional. The results found that considerable inefficiencies exist in the FCS at the association level. Collender et al. (1991) stated that their general result about low efficiency in small associations were consistent with the banking literature at that time. However their approach contains some weaknesses. One weakness was that the researchers measured efficiency using DEA. Earlier in this essay many of the drawbacks of using DEA was discussed including taking external events and uncertainty into consideration. Second, although the authors calculated profit efficiency, it may not be reasonable to consider profit maximization as the appropriate economic objective given that the FCS's stated goal is maximizing loans at minimum cost. Generally maximizing profit is different from maximizing output at minimum cost in the sense that to obtain the highest profit they might produce less output than that demanded by their customers.

In assessing banking performance, the literature offers four approaches to identify relevant banking inputs and outputs (a) the production approach, (b) the intermediation approach, (c) the operating approach and (d) the value added approach (Sufian, 2009). Under the production approach (Benston, 1965), the number of a bank's accounts or its related transactions measure output, while the number of employees and physical capital are considered as inputs. The intermediation approach (Aly et al., 1990) defines total loans and securities as outputs, whereas deposits, labor, and physical capital are inputs. The operating approach (Jemric and Vujcic, 2002) classifies total revenue (interest and non-interest income) as banks' output and the total expenses (interest and non-interest expenses) as input. The value added approach (Drake et al., 2006) identifies deposits and loans as outputs (Sufian, 2009).

Due to data availability, the intermediation approach to identify the FCS's inputs and outputs will be used for the purpose of this essay. Banks' loans, leases, investment, interest receivables, and other earning assets are characterized as outputs, while inputs include system bonds, notes, other borrowings, labor, and fixed assets. Deposits were not defined since the FCS is not allowed to have deposits.

2.2 Methodology

2.2.1 Theoretical Conceptualization of Model

In this essay, we use a SFA stochastic frontier production function model to estimate the technical efficiency of components of the FCS. Following Battese and Coelli (1993), the frontier production function f(.) is defined as the maximum feasible volume of outputs that can be produced by a bank with a given level of inputs and technology. The actual production function of a bank can be written as:

$$Q_{it} = f(x_{it};\beta)\exp(v_{it} - u_{it}) \quad 0 \leq u_{it} < \infty \quad \text{where } i = 1,2\ldots,n \text{ and } t = 1,2\ldots T \qquad (2.1)$$

where: Q_{it} represents actual production outputs of bank i in period t, x_{it} is a (1xk) vector of values of known levels of production inputs associated with the i-th firm at the t-th period of observation; and β is a (k x l) vector of unknown parameters to be estimated, β represents the effect of a given input on the quantity of outputs produced; v_{it} and u_{it} are two components of the disturbance term which stands for deviation of the system from the efficient production frontier, v_{it} is a random noise that captures the effects of omitted variables/measurement errors which is assumed to be i.i.d normal $(0, \sigma_v^2)$; The non-positive firm effects u_{it} is a one-sided (non-negative) residual term representing the bank technical inefficiency effects which is assumed to be i.i.d truncated normal $(z_{it}^* \delta, \sigma^2)$ with z_{it} is a (1 x m) vector of bank-specific variables which may vary over time; δ is an (m x l) vector of unknown coefficients of the firm-specific inefficiency variables.

$$u_{it} = z_{it}^* \delta + W_{it} \quad \text{for } i = 1,2\ldots,n \text{ and } t = 1,2\ldots,T \qquad (2.2)$$

where: W_{it} is defined by the truncation of the normal distribution with zero mean and variance σ^2 , such that the point of truncation is - $z_{it}* \delta$, i.e. $W_{it} > -z_{it}* \delta$

U_{it} can be assumed to have a half-normal, truncated half-normal, exponential or gamma distribution, with a positive mean following Battese and Coelli (1992), and Kumbhakar and Lovell (2000). The most efficient case of each firm is obtained when the firm's effect $u_{it} = 0$, i.e. $Q_{it} = f(x_{it};\beta)\exp(v_{it})$. Thus for each firm the measure of technical efficiency is equivalent to the ratio of the production for the ith firm in any given period t, $f(x_{it};\beta)\exp(v_{it} - u_{it})$ to the corresponding production value if the firm effect u_{it} was zero, $Q_{it} = f(x_{it};\beta)\exp(v_{it})$

The technical efficiency of production for the i-th firm at the t-th observation is defined by equation:

$$TE = f(x_{it};\beta)\exp(v_{it} - u_{it}) \;/\; f(x_{it};\beta)\exp(v_{it}) = \exp(-u_{it}) = \exp(-z_{it}* \delta - W_{it})$$

Let $e_{it} = v_{it} - u_{it}$, following the model specified by equation (1) and (2), the mean prediction of TE for each firm i in period t given the values of the random variable ε_{it} is :

$$TE = E[\exp(-u_{it} \mid e_{it})] = E[\exp(-z_{it}* \delta - W_{it}) \mid e_{it}]$$

Then $E[\exp(-z_{it}* \delta - W_{it}) \mid e_{it}]$ provides the measure of TE of firm i in period t.

The system stochastic frontier production function is defined as:

$$\text{Ln } Q_{it} = \beta_0 + \beta_1 \ln B_{it} + \beta_2 \ln L_{it} + \beta_3 \ln A_{it} + \sum_{k=2000}^{2011} \beta_{4k} DY_k + \sum_{q=1}^{4} \beta_{5q} DQ_q + v_{it} - u_{it} \quad (2.3)$$

$$u_{it} = \sum_{l=1}^{4} \delta_{1t} DS_l + \sum_{p=1}^{5} \delta_{2t} DR_p + \delta_{3t} \text{Dir}_{it} + W_{it} \quad (2.4)$$

where: Q_i represents outputs which include loans, leases, investments, interest receivable, other receivables, cash and other earning assets. The value of these assets is used as a single output for the system. Inputs include input cost (B), the sum of interest paid for the system bonds, notes and other borrowings/payables; expenditures on labor (L), which is obtained from total salary and director compensation; and fixed assets (A) which is obtained from premises and fixed assets in the FCS call report data.

Following Blair and Kraft (1974), year-specific dummies DY_k with k=2001, 2002,…, 2009 were used to account for the presence of technical progress and time specific effects for those years. The resultant coefficients of the dummy variables indicate “the marginal change in output per year associated with the occurrence of technological progress in each cross section” (Blair and Kraft, 1974). Quarterly dummies with q=1,2,3, and 4 represent the 1st, 2nd, 3rd, and 4th quarter of the year is also included to account for seasonal effects on farm loan demand.

Due to the unavailability of data about specific characteristics for each association and bank, dummy variables for bank size, region, and quarter are used in the technical inefficiency equation to account for bank and association characteristics. Specifically, bank size dummy entities with (DS_1) for associations with total assets larger than$1 billion in year 2009 dollars, (DS_2) for associations with total assets between \$1 and \$500 million, (DS_3) for associations with total assets between \$500 million and \$250 million, and (DS_4) for associations with total assets less than \$250 million. Regional dummies $DR_{p,}$ with p=1,2,3,4, and 5 which stands for the bank or associations located in West, Midwest, Northeast, South, and Puerto Rico respectively. Dir_{it} is director compensation which represents management compensation.

2.2.2 Estimation Approach

MLE is used to estimate the model. As shown by Battese and Coelli (1993), the logarithm of the likelihood function is:

$$L^*(\theta; y) = -\frac{1}{2}\left(\sum_{i=1}^{N} T_I\right)\{\ln 2\pi + \ln \sigma_S^2\} - \frac{1}{2}\sum_{I=1}^{N}\sum_{t=1}^{T_i}\{(y_{it} - x_{it}\beta + z_{it}\delta)^2/\sigma_S^2\} - \frac{1}{2}\sum_{I=1}^{N}\sum_{t=1}^{T_i}\{\ln \Phi(d_{it}) - \ln\Phi(d_{it}^*)\} \quad (2.5)$$

where:

$$\sigma_s^2 = \sigma_v^2 + \sigma^2$$
$$\gamma = \sigma^2/\sigma_S^2$$
$$d_{it} = z_{it}\delta/(\gamma\sigma_S^2)^{1/2}$$
$$\mu_{it}^* = (1-\gamma)z_{it}\delta - \gamma(y_{it} - x_{it}\beta)$$
$$d_{it}^* = \mu_{it}^*/[\gamma[\gamma-\gamma)\sigma_S^2]^{1/2}$$
$$\theta = (\beta', \delta', \delta_S^2, \gamma)'$$

In turn maximizing the above log likelihood give estimates of the coefficients $\beta, \delta, \sigma_S^2$, and γ

As shown by Battese and Coelli (1993), the mean prediction of the technical efficiency of the ith firm at the tth time period $TE_{it}= \exp(-U_{it})$ is:

$$E\left((e^{-U}|E = e) = \left\{\exp[-\mu_* + \tfrac{1}{2}\sigma_*^2]\right\}\left\{\emptyset\left[\left(\frac{\mu_*}{\sigma_*}\right) - \sigma^*\right]/\emptyset(\mu_*/\sigma_*)\right\}\right) \qquad (2.6)$$

where E_i represents the (T_i x 1) vector of E_{it} 's associated with the time periods observed for the ith firm, where $E_{it} = V_{it} - U_{it}$, $\mu_* = \frac{\sigma_V^2 z\delta - \sigma^2 e}{\sigma_V^2 + \sigma^2}$, and $\sigma_*^2 = \sigma^2\sigma_V^2/(\sigma^2 + \sigma_V^2)$

The model is run separately for the banks and the associations because of their heterogeneous products. Bank size dummies are excluded in the banks' technical inefficiency equation due to their large sizes. The study uses computer program Frontier 4.1.

2.3 Data

Quarterly data for the period from Jan 2001 to Dec 2009 were obtained from the Farm Credit Administration website on the FCS five banks and associations. All data are adjusted to 2009 $ using US CPI indices (base =2009) from the Bureau of Labor website. Descriptive statistics on the variables in logarithm form for the five banks and for the associations are presented in table 1.

Two observations for particular units in selected quarters which have negative total salary and expenses are assumed to be outliers and are excluded from the data. In addition 310 observations are excluded from the data to avoid banks and associations for which the data series is too short (when less than 5 quarters of data are available).

2.4 Empirical Results and Discussion

The empirical results of the model are reported in table 2 and 3 for the 5 banks and the associations respectively. It is expected that all inputs have positive effects on output. The estimated results show that estimated coefficients for interest paid, fixed assets, and labor expenses all have positive signs and most are statistically significant at 5% level. The coefficient estimates for labor expenses and interest payable for banks are 0.33 and 0.67 respectively compared to 0.1 and 0.25 for associations. It indicates that the banks productivity is higher than the associations in using variable inputs to produce outputs. However, fixed assets seem to be more important in association's productivity where they have a higher level of significance (5%). It can be concluded that banks' output elasticity with respect to variable input is higher than that of associations while associations' output elasticity with respect to capital is more significant. These findings can be explained from the fact that small associations might still need more investment in capital assets to work more productively. The five banks might have come to a saturation point where adding more capital assets will not significantly increase outputs. Nevertheless, the five banks' dependence on the bonds and securities market explains their higher output elasticity with respect to input cost which mainly consists of interest payables.

The coefficients of year dummy variables in mean equations for banks have positive signs and all are significant at 5% level. The significantly positive sign of year dummy variables indicates that there is increasing marginal change in output per year for bank; however the magnitude varies among years. The increasing magnitude went down in 2007 then increased again in 2008 and 2009. Regarding the 5 bank estimation, the quarterly dummies and regional dummies in the technical inefficiency equation are not significant which implies that the five banks' inefficiency is not influenced by seasonal effects or regional effects. Therefore, other specific bank factors rather than regional and seasonal effects may have bigger impact to the banks' efficiency. Bank size dummies were not used for banks as all were in the large category.

When running the model for associations, the bank size dummy for bank size 4, the quarterly dummy for quarter 1 and regional dummy for the Puerto Rico are excluded from the model to avoid colinearity. Quarterly dummies are not significant in the model. Regional dummies for MidWest is positive and significant in the technical equation of associations indicating efficiency for associations located in this region might be negatively affected. It implies efficiency of associations located in MidWest in fact would be higher than the efficiency estimates if it was not because for the regional effect. The negative effect of region on efficiency of associations in the MidWest should be further investigated.

The negative and significant statistics of management compensations variable in both banks and associations' technical inefficiency equation implies a positive relation between management compensation and technical efficiency. This finding shows the possible effect of incentives on agents' effort on improving efficiency. Higher incentives for management team might help to reduce the system's technical inefficiency.

In terms of the associations, the estimates from the technical inefficiency equation show an interesting result on bank size. The dummies for bank size which stands for associations with more than $250 million in total assets are negative and statistically significant. The coefficient of bank size dummies increases in magnitude for larger banks, meaning that the larger bank size tends to have higher technical efficiency ceteris paribus. This finding is consistent with efficiency estimates presented in table 6, in which a significant gap in efficiency was found between associations with regards to their size. On average, associations which have more than $1 billion in assets average 95% efficiency, while associations which have less than $250 million in assets average 12% efficiency.

The implication from bank size dummies estimates and the low predicted efficiency of the associations with small assets are partially consistent with DeYoung et al. (2004), Mehdian et al. (2007), Wilson and Wheelock (2004), Marsh et al. (2003), Akhigbe and McNulty (2005), and many other studies. These studies showed that efficiency of US commercial banks were positively correlated with banks' size. The positive correlation between bank size and bank efficiency in these studies and the results found in our study can be explained as a result of significant economies of scale.

Tables 4 and 5 presents the average predicted technical efficiencies of the FCS five banks and associations respectively for 2000-2009. Our estimates of the system efficiency suggest that not all of the FCS's associations have efficiently utilized their inputs. A few associations have efficiency of less than 5% and the mean of the technical efficiency values is 42.03% for the associations. This indicates that on an average the system's associations realize 42.03% of the most efficient associations output using the same mix of inputs. On average the five banks have technical efficiency of 68.3%. Our efficiency estimates for associations are quite similar to Collender et al. (1991)'s results in the short run. Their results showed the efficiency in the short run for all associations was 73% regionally but only 49% nationwide. However our estimates are much higher than their results in the long run. Their results showed that in the long run, the efficiency is 28% regionally; 6% nationwide for all associations and 18% nationwide when the dominant association was dropped out of the sample. The difference in efficiency estimates likely arise because of several reasons. First, they measured profit efficiency while we measure technical efficiency. Second, the data envelopment analysis methodology assumption of a deterministic frontier constructed using the outer envelope of the observations. Pooling all associations in the model without considering the difference in bank size might falsely lower the efficiency of small banks. Third, DEA assumes all deviations from the frontier are inefficiencies. Fourth, is the time period in which the study was conducted. Collender's study used data for 1989 while this study uses data for 2001-2009.

The predicted efficiencies for associations by asset size also implies that on average, efficiency of associations with more than $1 billion in assets are more stable than efficiency of smaller sized associations. Their average efficiency ranged from 94.8% to 95.1% during period 2000 to 2009 while average efficiency of associations with less than $1 billion in assets ranged from 44.7% to 51.4%, 28.5% to 36.8%, and 10.6% to 14.2% for associations with bank size 2, bank size 3, and bank size 4 respectively. The large sized associations are more stable in efficiency because they are likely more stable to risk than smaller ones as explained by Emmons et al. (2004). Emmons et al. (2004) explained that small banks have more risk inherent in their loan portfolio, because they cannot diversify away idiosyncratic risk as well as large banks. This inability to diversify comes from (a) less total loans held, (b) less diversity in borrower type and (c) geographic restrictions (Emmons et al., 2004). Therefore, their efficiency is also more likely to be influenced by exogenous changes than larger banks. This finding is consistent with Demsetz and Strahan (1997)'s results that stated that increases in bank holding companies assets lead to a reduction in firm-specific risk because large banks have better opportunities to diversify.

Despite the financial crisis which started since 2008 and the economic recession afterwards, the five banks and the associations' efficiency were stable to increasing during these times. Efficiency of the associations is on an increasing trend as presented on figure 1. The estimates are consistent with the FCS's income performance and the FCS's increasing market share in the U.S. agricultural lending market. In 2008, FCS's net income went up to $2.92 billion, rising from less than $1.77 billion in 2002 (Farm Credit Administration, 2009). Market share of the FCS in the U.S. agricultural lending market has been increasing since 2000, from 27% of total U.S. farm business debt in 2000 to 39% in 2009 (Farm Credit Administration, 2009). Rising farm income associated in part with the biofuel boom and rising crop prices are one likely reason why the associations exhibit rising efficiency. According to the Federal Reserve Bank of Kansas City, rising commodity prices followed by rise in average farm income has resulted in more spending and lending from farmers.

Another likely reason for the slightly increasing in efficiency of the associations is the consolidation of the system associations over time. The consolidation of the system associations over time might have helped to improve their efficiency as a result of increasing economics of scale. The system associations consolidated from 153 associations in 2000 to 88 associations in 2009. These findings are partially consistent with findings from Al-Sharkas et al. (2008) who investigated the cost and profit efficiency effects of bank mergers on the U.S. banking industry. These results indicated that mergers improved the cost and profit efficiencies of banks. The study also showed that merged banks had lower costs than non-merged banks because the merged banks were using the most efficient technology available (technical efficiency) as well as a cost minimizing input mix (allocative efficiency). For these reason the FCS seems somewhat immune to the financial crisis and economic recession. This finding is similar to Henderson and Akers (2010)'s finding that the U.S. agricultural banks outperformed the group of all banks nationwide during the recent financial crisis.

Technical efficiency for the individual of banks: AgFirst Farm Credit Bank, AgriBank- FC, CoBank- ACB, Farm Credit Bank of Texas, U.S. AgBank, FCB were also estimated and shown in table 7. Overall, the associations exhibit a higher variation of efficiency than the five banks due to their higher variation in size and customer base.

2.5 Concluding Remarks

The essay presents the results from an analysis of the technical efficiency of the U.S. Farm Credit system using a stochastic frontier production function model with quarterly unbalanced panel data. Overall, the results show the efficiency of the banks is quite stable while the efficiency of the associations is largely on a slightly increasing trend. The empirical results suggest that a certain number of the FCS associations especially those with small assets have not efficiently utilized their inputs compared to the most efficient of the associations. Smaller bank size and lower management compensations are indicators that explain lower efficiency estimates as implied in the significant results for the bank size variable and the management compensation variable. Moreover, fixed assets are found to be significant in explaining for associations' productivity while variable inputs are more important for the five banks. These findings indicate more consolidation or more capital investment in small associations is desirable. It is also important that the Farm Credit Administration and the U.S. policy makers take further steps in investigating whether the FCS's organizational structure, ownership structure, and operation is a good model in providing a reliable and permanent source of credit to American agriculture.

The study does not find any negative effects of the financial crisis or economic recessions to the system's efficiency, if not to say a slightly positive effect. However, further estimation of the impact of exogenous factors on the system's efficiency is necessary before deriving any conclusion about the effects of exogenous factors on the system's efficiency as the biofuel boom, increasing farm income and new regulations emerged over the same time period. Due to the unavailability of data about specific firm characteristics for each association and bank, the study has to use director compensations, bank size dummy, year dummy, regional dummy, and quarterly dummy variables to account for the technical inefficiency effects of each association and banks. Further exposure on data of the FCS's firm specific characteristics would be helpful to derive a clearer picture on each associations or banks' efficiency and how their certain characteristics might affect their technical efficiency.

CHAPTER III

THE DYNAMIC CORRELATIONS IN FOSSIL FUEL MARKETS

Coal, oil, and natural gas markets have exhibited many changes in the last decade. According to IAE et al. (2011), we have seen the following examples of change and events in the North American market:

- Decreasing market share of fossil fuels in the electric generation market
- Increasing market share of renewable fuels in the electric generation market
- Shift in fossil fuel market shares in terms of use for electrical generation
- Trend in substitution of natural gas for coal
- Increasing volatility in coal price
- Decreasing natural gas price
- Development of shale natural gas
- Stricter environmental regulations and standards
- Shutdowns of many coal-fired plants and coal mines
- Emergence of China as a large coal importer
- Greater frequency of climatic extremes and weather events

Such change and events may have altered price relationships between these fuels over time. This essay will examine these relationships and the changes in these relationships. Studying changes in relationships between coal, oil, and natural gas prices is of interest for several reasons. A main reason for the attention is that coal, oil, and natural gas are the three key fossil fuel sources for U.S. electricity generation market. Investment decisions that involve coal, oil, and natural gas are frequently considered by many energy producers and investors. As cited by Koenig (2011), price volatility and the price movement relationships with other relevant prices (hereafter called co-movement) are two important factors that motivate hedging. Understanding the price interrelationships and the changes in their relative movements can therefore help investors and producers manage investment risks and optimize portfolio returns. Another reason for interest is the study of the co-movement over time between coal, natural gas, and oil prices (hereafter called dynamic correlation) is important in energy management and security. The relative changes in price of these fuel sources have driven a significant trend of substitution among fossil fuels the last several years (EIA, 2012). Such trend might lead to natural resource vulnerability and altered energy security which, as described by the IEA (2012), is "the uninterrupted physical availability at a price which is affordable, while respecting environment concerns". Understanding the price relationships in the form of dynamic correlation is therefore useful for policy and decision makers to make energy investment decisions, or policy and regulation decisions. While many studies have examined the dynamic interrelationship between various energy prices, the relationship between the prices of oil, natural gas, and coal, the main fuel sources for electricity generation has not been fully addressed.

The objective of this study is to develop information on dynamic changes in the relationship among coal, oil, and natural gas markets. To achieve the stated objective this essay reports on an examination on how price correlation between these fossil fuels has evolved in North America from 2004 to 2011. The underlying analysis also examines the impacts of the 2008 financial crisis and economic recession on the co-movements of the three fuels by estimating their correlation before, during and after the financial crisis. The study will use the multivariate generalized autoregressive conditional heteroskedastic (MGARCH) framework developed by Engle and Sheppard (2001) to investigate the dynamic correlation between prices in these markets, identify the patterns of price transmission between these markets and examine their time-varying correlations.

The remainder of the essay is organized as follows. Section 3.2 provides market background and reviews the literature on fossil fuel markets and their price interrelationships. Section 3.3 includes the discussion of the preliminary data analysis. Section 3.4 describes the multivariate generalized autoregressive conditional heteroskedastic model that will be estimated. Section 3.5 presents the empirical estimation results along with a discussion of their nature and implications. Section 3.6 presents concluding comments and discusses further research possibilities.

3.1 Literature Review

3.1.1 Background on Fossil Fuel Markets

Many events have happened that affected in fossil fuel markets in the last ten years. First, macroeconomic events such as the financial crisis or economic recession might have indirectly impacted both demand-supply fundamentals and the level of market speculation. Lower personal income, lower economic productivity, higher unemployment rate, declining trade and altered trade finance might have affected demand for electricity and transportation which eventually might have reduced demand for fossil fuel. Rising prices of commodities during this time might have affected fossil fuel discovery, extraction and usage patterns and costs. Declining trade and trade finance plus expectations about global economic recessions might have also affected investment and market speculation in spot and futures trading.

Also, the greater frequency of climatic extremes and weather events has created bottlenecks in supply side and also increased the regional patterns of demand for energy. For example, the 2008 heavy flood in Queensland caused an increase in international demand for coal from other countries, while the 2005 Katrina and Rita hurricanes led to a substantial production shortfall and increased demand on other sources (IEA et al., 2011). Climate change also helped raise stricter environmental regulations and accelerate the growth of emission trading markets which effects on energy production costs and fuel mix demands. Other major events and factors include (a) increased volatility in fossil fuel prices, (b) increased use of combined cycle technology for power generation, (c) expansion of the natural gas pipeline network, (d) the formation and rapid development of shale natural gas starting in 2005, (e) the deregulation of the natural gas market, and (f) the rise of nuclear power and renewable energy (IEA et al., 2011). Those factors have influenced both fuel prices and the mix of energy sources used. They also created a trend where petroleum, and to a lesser extent coal, has been replaced by natural gas in electric power industry since it is a cheaper and cleaner fuel. Also, new generating facilities are more commonly fueled by natural gas resulting in an increasing market share for natural gas with less in coal and petroleum. Moreover, the rise of nuclear power and renewable energy has decreased the market share of fossil fuel in the electric generation market. Coal, oil, and natural gas's share in the U.S. electricity generation market has fallen down to 70% from 82% in 1970 (EIA, 2012).

In addition to change in total share of fossil fuels in electricity generation market, the annual share of individual fossil-fired electric power generation has also changed over time. This has occurred in response to changes in fuel prices, production cost, emission rates, allowances cost, generating capacity, and availability of competing fuels (IEA et al., 2011). Coal's share of the fossil fuel mix has declined in the last ten years from more than 70% to less than 50% in 2011. In contrast, the share of natural gas has increased from 12% in 1990 to 16% in 2000 and above 30% in 2011. Oil share in the market is now only 1% or less, down from more than 20% in the 1970s. Among the factors that have driven the shift in fossil fuel mix, relative changes in fossil fuel prices are believed to be one of the key drivers. EIA (2012) examined competition among fuels for power generation over the period 2005-2010 and found a 10% increase in the ratio of the delivered fuel price of coal to the delivered price of natural gas. This in turn led to a 1.4% increase in the use of natural gas relative to coal. Generators' use of petroleum was found to be much more responsive to relative fuel price changes. A 10% decrease in the price ratio of natural gas to petroleum was found to lead to a 19% decrease in the relative use of petroleum compared with natural gas. (EIA, 2012)

As shown in figure 4, 5 and 6, fossil fuel prices during the last ten years have been more volatile. The volatility is especially high during the 2008 financial crisis and afterwards. Coal exhibits less volatile prices due to the rather elastic coal supply, a stable demand, and a smaller and less liquid futures trading market. However, coal price volatility has also increased. In 2008, there was a marked peak in coal price volatility, as result from macroeconomic turbulence, demand shocks from Queensland flood, South Africa blackouts, and extreme volatility in freight rates. After the 2008 financial crisis, coal prices remained more volatile than they were before the crisis. The emergence of China as a large coal importer also contributes to coal price changes and volatility (IEA et al., 2011).

In the last ten years, not only did the prices and volatility in the fossil fuel markets change, but so did the co-movement among them. The 2008 financial crisis marked a period with the highest correlation. Vacha and Barunik (2012) examined the dependence among heating oil, natural gasoline, and crude oil and found that the periods of high correlation around the years 1998 and 2001. These time periods are closely related to periods of recession with falling prices. Specifically, they relate to the Asian financial crisis in 1998-2000, the 9/11 terrorist attacks, and the resulting fear in the markets in 2001-2002. Vacha and Barunik (2012) also found similar tightening of correlation during the 2008 financial crisis.

The drivers of market price volatility can be classified into two categories. The first driver is the supply and demand fundamentals in which inelastic supply meeting inelastic demand would lead to volatile prices (IEA et al., 2011). The second driver is the speculation in trading markets. Hoeven (2012) believed that market fundamentals are the primary price drivers in oil, natural gas and coal markets. Vansteenkiste (2011) examined oil future market over the period January 1992 - April 2011 and found that the period spanning to 2004, supply demand fundamentals were the key driving force behind oil price movements. However, in addition to the market interaction driven by supply and demand, the volatile macroeconomic environment in the last ten years played an important role in driving the correlation in prices and similar price movement of coal, natural gas, and oil (IEA et al., 2011).

Vansteenkiste (2011) listed three major factors that can impact oil markets and oil prices. One factored cited was the fundamental of supply and demand, and more specifically the rapid increase in demand arising from fast growing developing countries. The next factor included the excess liquidity and low interest rates. Low interest rates result in the expansion of money supply. They also decrease the demand for liquid assets by countries like China, Chile, or Dubai. Both effects would eventually lead to an increase in prices. Another factor addressed dealt with the market price speculation. The market price speculation may attribute to the upward movement in commodity prices. Vansteenkiste (2011) also identified factors that influence seasonal prices such as: market-based indices, purchasing power stability, exchange rates, and speculative pressure. It was argued that these factors have increased in relative importance. Similarly, Barnes (2010) stated that since 2002, oil prices no longer solely depend on conventional demand and supply balances.

While oil is considered a global commodity, there is no global market for natural gas. Natural gas markets are segmented due to the difficulties of transport and other factors. Consequently, natural gas price volatility is regional. Among the regions, North

America is the only natural gas market liquid enough to have financial derivatives trading at a level comparable to those for oil products. Therefore, natural gas price changes should reflect the realities of market fundamentals. Recently, unconventional natural gas production technologies have lowered entry costs and made smaller levels of supply more feasible. This has helped to increase natural gas supply elasticity and consequently decrease natural gas price volatility (IEA et al., 2011).

Coal is the least globalized of the major fossil fuel sources. Major coal users tend to have their own large resource endowments due to high transport costs and well distributed resources. Due to the complexity of coal quality measurements, only 15% of coal consumption is traded internationally. Australia, Indonesia, Russia, Colombia, South Africa and United States account for 85 % of the global exports. Coal was considered for several decades as a cheap and stable energy source. Coal prices were determined by mining costs, transportation costs, and coal fired power plants' demand. Recently with the emergence of coal demand from China, any imbalance between production and demand in China can also have significant influences on coal price. Due to its high volume to value ratio, coal is more constrained by local factors such as weather events and transportation bottlenecks than other industries (IEA et al., 2011).

Coal price volatility was historically lower than the volatility in natural gas and oil markets due to its elastic coal supply (IEA et al., 2011). Since the beginning of 2008, coal price volatility has increased. IEA et al. (2011) stated that changes in price behavior and price volatility of coal are results of rapid structural changes in recent years, with market liberalization and greater international trade among the main driving forces.

3.1.2 Relationship between Oil, Natural Gas, Coal Markets and Prices

Natural gas, oil and coal markets have complex interactions. Demand side substitution between natural gas and oil has declined as oil is increasingly used in transport where natural gas is not currently an effective substitute, and has largely been driven out of use for power generation. On the other hand, there is intensive competition between coal and natural gas in the power sector (EIA, 2012).

Natural gas and crude oil are substitutes in some forms of consumption, and are complements and rivals in production. Their relationship varies over time. They appear to be correlated in some periods and then move independently in other periods. Market behavior suggests an asymmetric relationship between the two markets when changes in oil market prices drove changes in the natural gas price, but the converse did not appear to occur (Villar and Joutz, 2006). Villar and Joutz (2006) explained the relative size of each market as one reason for the asymmetric relationship. The crude oil price is determined on the world market, while natural gas markets are more regional. Therefore, the domestic natural gas market is much smaller than the global crude oil market, and events or conditions in the U.S. natural gas market seem unlikely to have a large impact on the global price of oil. Villar and Joutz also pointed out that the relation between oil and natural gas prices is positive. The positive relation is a result from the net effect of increase in oil prices on natural gas demand and natural gas supply. The effect of increase in oil price to natural gas supply as a co-product is ambiguous, while the effect of increase in oil price to natural gas price as a substitute is clear. Following these arguments, Villar and Joutz identified a significant stable relationship between natural gas and oil prices over the period of 1989 through 2005. They found a statistically significant trend term between natural gas and oil suggesting that natural gas prices appear to be growing at a slightly faster rate than crude oil prices, narrowing the gap between the two over time during the studied period of 1989 to 2005.

Coal and natural gas usage accounts for almost half of total primary energy consumption in the world and their use has been growing more rapidly than oil. In the past decade, growth of coal and natural gas supplied 60% of the growing energy needs of the world economy. Coal fired power plants generally have a higher capital cost and a less flexible operation. However, these plants might have lower marginal cost for some periods. The cross price elasticity of substitution between coal and natural gas ranges from 0.4 in the United Kingdom, which is an efficient market, to 0.05 in Japan, a non-efficient market. There was no long term structural relationship between coal and natural gas prices in the U.S. while previous studies found a declining correlation between them in recent years (IEA et al., 2011).

3.1.3 Literature Review on Methodologies and Empirical Results

Studies about price relationships in energy markets have focused on several areas. Studies of cointegration, causality, correlation, and coherence have drawn the most attention. The literature is most focused on oil and natural gas and related products, such as electricity, carbon, and emission allowances are often mentioned. The results from previous studies vary, and some findings contradict each other. These are reviewed below by type of study.

3.1.3.1 Cointegration and Causality

Meldje and Bessler (2009) studied market integration among electricity, natural gas, uranium, coal, and crude oil markets. Using a vector error correction model, they found that all prices react to market conditions and the degree of integration between markets varies but that the markets were not fully integrated. Some markets are more important drivers of price changes in other markets during particular time intervals. Among the studied markets, they found the coal market appears to be less affected by shocks than the other markets. Although when disequilibrium occurs, natural gas, oil, and coal prices exhibit high correlation, and in contemporaneous time peak, they found electricity prices move natural gas prices, which in turn influences crude oil price. In the long run, oil and coal are important in explaining natural gas prices. Bachmeier and Griffin (2006)'s show similar results using bivariate error correction models and conclude that the crude oil, coal, and natural gas markets are only weakly integrated.

Asche et al. (2006) found that the differences in the relationships between crude oil, natural gas, and electricity prices vary by different time periods. Using cointegration analysis, they found an integrated market from January 1995 to June 1998. However from July 1998–December 2002, the hypothesis of no market integration cannot be rejected, and thus that prices have decoupled. Crude oil price is found to be exogenous and is the leading price.

Villar and Joutz (2006) examined the time series econometric relationship between the Henry Hub natural gas price and the West Texas Intermediate (WTI) crude oil price using cointegration analysis and a vector error correction model. They found evidence that the WTI crude oil and Henry Hub natural gas prices have a long-run cointegrated relationship. In addition, the empirical results indicate oil prices may influence the natural gas price while the impact of natural gas prices on the oil price is negligible. Other key findings are the statistically significant short-run response of the natural gas price to contemporaneous changes in the oil price. The dynamics of the relationship suggest a one-month temporary shock to the WTI of 20% has a 5% contemporaneous impact on natural gas prices, but is dissipated to 2 % in 2 months. A permanent shock of 20% in the WTI leads to a 16% increase in the Henry Hub price one year out, all else equal.

3.1.3.2 Correlation and Coherence

Dynamics of energy markets studies have examined dynamic trend price trends and the time-varying nature of price interrelationships. Traditional methods of rolling correlation and constant conditional correlation have been used along with newer methodologies such as dynamic conditional correlations, cross-correlations, time-varying correlation, regime switching correlation, and wavelet coherence.

Mansanet-Bataller and Soriano (2009) investigated the transmission of volatility among the CO_2, oil and natural gas prices in Europe, using daily returns data over data from April 2005 to December 2008 and a version of the unrestricted Baba–Engle–Kraft–Kroner model (BEKK). They find that the natural gas market has an effect on the volatility of the CO_2 and oil markets but it is much less affected by them. In contrast, they find natural gas return volatility responds more to unanticipated events originated in its own market, such as supply interruptions or changes in reserves and stocks. They also argue changes in volatility in the CO_2 and oil markets will be highly correlated, whereas volatility in the natural gas market will be much more independent from the others.

Lanza et al. (2006) used dynamic conditional correlation to examine daily returns of WTI oil futures prices and forward prices. They found these correlations to vary significantly and the dynamic volatilities in the returns in the WTI oil forward and future prices can be either independent or interdependent over time. Ghoshray and Johnson (2010) proved that trends in energy prices change frequently. The trends are not well represented by a single positive or negative trend and therefore are difficult to predict.

Vacha and Barunik (2012) studied dynamic co-movements in crude oil, natural gasoline, heating oil, and natural gas prices from 1993 to 2010. Results from wavelet coherence showed dynamics of correlation is changing rapidly not only in time, but also in different investment horizons. They found correlations between heating oil, natural gasoline, and crude oil prices increased rapidly to the 0.8 levels at the beginning of 2009. They also found the periods of high coherence of the three commodities around the years 1998 and 2001 are closely related to periods of recession with falling prices. Those periods relate to the Asian financial crisis in 1998-2000, the 9/11 terrorist attacks, and the resulting fear in the markets in 2001-2002. Interestingly, the current financial crisis of the period 2008-2010 has shown a similarly high coherence. Consistent with other studies, natural gas seems to be unrelated to all three commodities for all investment horizons.

Vacha and Barunik (2012) also used the dynamic conditional correlation method (DCC) and unconditional constant methods to compare correlation results. The DCC correlation coefficient between crude oil and natural gas is 0.109 and the wavelet coherence coefficient is 0.186.The estimates of correlation from the wavelet coherence are closer to the unconditional correlations than the estimates from the DCC. Although in the cases with very low unconditional correlation, DCC seems to converge to a constant correlation, which is close to an unconditional one, the time-varying dynamics of correlations is confirmed using both approaches.

Chevallier (2012) modeled the dynamics of correlation between energy and emissions markets using Baba–Engle–Kraft–Kroner (BEKK), Constant Conditional Correlation (CCC) and Dynamic Conditional Correlation MGARCH (DCC-MGARCH) models on daily data from April 2005 to December 2008. He found strong empirical evidence of time-varying correlations in the range of [-0.3; 0.3] between oil and natural gas.

IEA et al. (2011) reported on a study of oil price volatility in relation to coal and natural gas prices using the dynamic conditional correlation model. They reported estimates of time-varying correlations of (0.1; 0.35) between Henry Hub and oil, (0.2; 0.4) between US coal and natural gas, and (-0.01; 0.3) between National Balancing Point (NBP) natural gas and oil. The results of this study are different from other studies and market analysis in that they found a recent decoupling co-movement of natural gas and oil.

Koenig (2011) examined correlations between daily returns of month-ahead base load electricity, fuel input and carbon emission allowance (EU-ETS) prices in Great Britain. Koenig used a dynamic conditional correlation model estimated over daily observations of month-ahead prices for natural gas, crude oil and coal estimated over during the period from April 2005 to August 2010. The results suggest that extreme weather, high commodity market volatility and seasons have no effect on correlation. However, evidence of significant price decoupling during periods of extreme relative carbon, coal and natural gas prices was found.

Wang et al (2008) examined realized volatility and correlation of the NYMEX prices for the light, sweet crude oil, and Henry-Hub natural gas futures contracts. Evidence of asymmetric volatility for natural gas was found at the five % significance level but not for crude oil futures. Natural gas volatility reacted stronger to lagged negative returns than lagged positive returns, whereas it may not be the case for crude oil futures. The realized crude oil futures volatility was found to respond with an increase in the weeks immediately before OPEC meetings where a price increase was recommended. In contrast to earlier works about a possible long-run relationship between the oil and natural gas, the researchers determined that the realized correlation between crude oil and natural gas futures does not have long-memory.

3.1.3.3 Issues on Previous Studies

All previous studies have provided interesting empirical estimations and informational findings on the interrelationship among energy prices, and between energy prices and related products. However, there are several remaining issues. One issue is that the results from previous studies are varied and in cases, contradictory. A reason for these varying results may be changes in market characteristics. Studying these markets at different point in time seems to yield different results. Lee and Lee (2008) showed energy prices are usually affected by multiple breaks, and suggested the need for controlling for multiple mean and slope shifts. Ghoshray and Johnson (2010) suggested that structural change in the global economy have profound effects on the long-run rise and fall in oil, natural gas and coal prices. However, based on literature sources, structural changes in energy markets have not been considered especially for dynamic correlation studies covering the 2008-2009 financial crisis periods. Structural breaks in commodity prices during 2008 have been found in many studies. Rohans and Ramanathan (2012) found a break in volatility structure in stock market indices in September 2008. Bichetti and Maystre (2012) identified a synchronized structural break which starts in the course of 2008 and continue thereafter on several commodity markets and on the stock market in the United States. The prices of coal, oil, and natural gas prices also appear to increase in the same manner with other commodity prices at that time. Structural breaks in their prices should therefore be checked and accounted for in the model to avoid model misspecification. The dynamic models that do not count for structural break might cause spurious results and biased forecasts (Rohans and Ramanathan, 2012). Moreover, high volatility persistence in GARCH models may originate from structural changes in the variance process. Lamoureux and Lastrapes (1990) demonstrated that any shift in the unconditional variance is likely to lead to mis-estimation of the GARCH parameters in such a way that they imply too high a volatility persistence. This study will do an analysis that considers break points so as to consider such structural changes and in particular considers the financial crisis as a possible break point.

Another issue deals with the fact that most energy market studies on cointegration and causality do not consider price volatility. Ignoring such volatility can affect estimation efficiency. Overall, the theory of cointegration provides an effective tool in modeling nonstationary data, solving the problem of spurious regressions, and exploiting useful relationships among time series (Villar and Joutz, 2006). However, Villar and Joutz (2006) stated that this does not mean that models exploiting cointegrating relations are always superior to models that do not use them as structural changes to cointegrating relations can lead to forecast failure. In addition, ignoring heteroskedasticity can lead to inefficient estimates. Consequently, this study will extend these studies and take heteroskedasticity into account. In particular, dynamic conditional correlation methods will be used to provide correlation analysis for every single point of time, and a means of forecasting into the future.

Finally, according to the author's knowledge, none of previous studies has fully addressed the dynamic changes in correlations between prices of natural gas, oil, and coal in the North American market while giving an equal analysis on the important role of coal.

In summary this study attempts to extend the literature by estimating the dynamic correlations for coal, oil, and natural gas in the North American market. In doing this it will take into consideration the volatility in the market and the possible effects of structural changes associated with the financial crisis.

3.2 Data and Preliminary Analysis

The study starts by examining data for coal, oil, and natural gas prices looking at patterns, volatility, correlation, possible structural break, and any outliers in the data. Results from preliminary analysis will be used to determine an appropriate model that measures the dynamic correlations in the fossil fuel markets.

The study uses daily price of NYMEX Natural Gas Future Contract 1, NYMEX Cushing Crude Oil Future Contract 1, and NYMEX Future Price Index for Central Appalachian coal from January 2004 to December 2011. The data is taken from Energy Information Administration (EIA) website. The summary statistics of the three absolute prices, logged prices, and first difference in logged prices are shown in table 8. The standard deviation of logged prices and first difference in logged prices show that gas is the most volatile and coal is the least volatile price. An outlier coal price in December 23 2008 is dropped out of the sample. Days when any of three price series are not reported are also dropped out of the sample.

Graphs of coal, natural gas, and oil prices show high variation in all price series. Logarithmic transformation of prices was used to stable the variance and reduce the effect of heteroskedasticity. Graphs of logged coal, natural gas, and oil prices are presented in figures 4, 5 and 6 respectively. Preliminary analysis on the absolute prices and logarithm of prices will be discussed later in this essay.

Now we address the stationary of prices which is an important determinant of which model and which transformation of data to use to avoid spurious estimations. The Dickey Fuller (DF) test is used (Dickey and Fuller, 1979) with results shown in table 10.

In three cases, the test cannot reject the null hypothesis of a unit root. Thus all three prices are non-stationary. The first differences are then checked for stationary. The DF results show the first difference of the logged prices are stationary, indicating that all the logged prices are integrated of order one I (1). Since all log prices are integrated of order one I (1), we decide to conduct further tests on both logged prices and first difference in logged prices.

Next, we test whether the prices can be modeled by a normal distribution using the Jarque-Bera test (Bera and Jarque, 1980). The p-value for the JB statistic is zero in all cases. The null hypothesis that each prices series have non-zero skewness and excess kurtosis is rejected, which means the prices are leptokurtic. Therefore, the null hypothesis of normality is rejected in favor of a non-Gaussian distribution.

Next, the Ljung-Box test (Ljung and Box, 1978) for autocorrelation in prices and squared prices, and ARCH-Lagrange Multiplier test for autoregressive conditional heteroskedasticity (ARCH) in prices are conducted with statistics shown in table 9. The Ljung-Box test is to test for autocorrelation and presence of heteroskedasticity of price series. If a price series exhibits autocorrelation, it is not a white noise process, and it is also likely to be volatile since squared of an autocorrelated price will be autocorrelated. The Ljung-Box test for squared prices is used to check for the presence of heteroskedasticity. A rejection of the null hypothesis of homoskedasticity means the variance of the price series is not constant and volatility exists in price. The ARCH-Lagrange Multiplier test is used to check for autoregressive conditional heteroskedasticity. A rejection of the null hypothesis of no autoregressive conditional heteroskedasticity means the prices exhibit volatility clustering and volatility of prices can be forecasted based on past volatility. The Ljung-Box statistic for the log prices, and their first difference show significant statistics but the autocorrelation parameters are small, close to 0. The Q statistics for squared logged prices and squared first difference in logged prices show evidence of serial dependence and volatility. From the partial-autocorrelation function (PACF) and Q(20), $Q^2(20)$ statistics, we can conclude that all three series are not serially correlated but rather are serially dependent. As presented in table 9, the null hypothesis of homoskedasticity and no autoregressive conditional heteroskedasticity are rejected in all log prices and first difference of log prices. It can be concluded that prices of coal, oil, and natural gas exhibit volatility clusterings.

Considering the above findings, the multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) is appropriate to use. In addition, to avoid spurious estimation, first differences of log prices are used and will be referred to as prices throughout the essay.

Figures 4 to 9 present the price movements in various forms. Coal prices appear to be the least volatile series. The financial crisis 2008 marked a peak in coal, oil prices and their volatility. However, the spike in coal price on 2008, according to IEA et al. (2011), is a result of the triple supply shock occurred on September 2008 together with a freight shortage. The triple supply shock includes significantly increasing coal demand in China, heavy floods in Queensland, and South Africa blackouts that restricted exports. Natural gas price volatility during this time seems to not be as affected. Natural gas price does increase and moves closely with oil and coal during the financial crisis but it takes longer to decline after the price spike. The period 2005-2006 marks another time when natural gas price and price volatility are as high as those in financial crisis. IEA et al. (2011) explains that the two price spikes in natural gas markets had different microeconomic drivers. The spike in 2005 is argued to be associated with the combination of tight supplies and storage capacity constraints while the 2008 price spike and the consequent collapse was mainly the result of the high oil price. Additionally, in 2005 Katrina and Rita hurricanes led to a substantial production shortfall (IEA et al., 2011). According to IEA et al. (2011), the year 2006 was the turning point in natural gas supply when shale natural gas production began. Since 2009, natural gas price volatility has declined due to the recession and was most probably associated with the increased price elasticity of shale natural gas production (IEA et al., 2011). The squared first difference in logged gas price in figure 11 also shows a seasonal pattern in the volatility in gas price. The volatility in gas price is always higher from June to February of the year. This likely occurs since during this period of the year, demand for electricity and energy usage is high. Thus a dummy variable will be used in the model to account for seasonal effects in gas price volatility.

As mentioned in the literature review, neglecting structural breaks in the data often lead to the biased statistical results, thus, the data are tested for structural breaks. The Quandt test (Quandt, 1960), for unknown structural break in the three price series and squared prices were performed with the break results shown in figures 13 and 14. For the prices, the most significant break found for oil price and coal price are on December 17, 2008 and December 22, 2008 respectively, while September 15, 2009 marks the most significant break in the natural gas price. For the squared prices, the most significant breaks ranged from 2008 to 2010 for coal, gas and oil.

Diebold (1986) states that with the possibility of change in regime, breaks in the variance that are not taken into account will look like autoregressive conditional heteroskedasticity (ARCH) effects when the whole sample is used. Diebold recommended that sample should be divided and tested for ARCH in the sub periods. If ARCH effects are found for the whole sample but not found for any of the sub periods, that is an indication of a break in the unconditional variance and not of ARCH effects (Diebold, 1986). Therefore, the study also tests for ARCH effects for subsamples of data. The data sub-samples are obtained by dividing the full sample using structural breaks found using the Quandt test result. The null hypothesis of constant variance is rejected for all subsamples. It is therefore sufficient to use MGARCH model.

Unconditional correlation statistics in table 11 and the rolling correlations graph in figure 3 reveal a number of relationships between the coal, natural gas and crude oil prices. The relationship between natural gas and crude oil is the strongest among the three as illustrated in the graph. Natural gasoline is related to crude oil more strongly than to coal, but in general all three pairs exhibit positive correlations. The correlation changes between the three sub-sample periods as divided by the break points, with the first period is from January 2004 to June 2008, the second period from July 2008 to January 2010, the last period from February 2010 to December 2011. In particular, in the last period we can see the correlation between coal and oil follows an increasing trend while correlation between natural gas and oil is decreasing. The same results can be seen from the rolling correlation in figure 3. The correlation changes over time and appears to be varying over time. This is evidence that three prices exhibit time varying correlations. Thus the dynamic conditional correlation MGARCH model with the data separated at break points is sufficient to examine the dynamic correlations between three price series.

3.3 Methodology

To examine the dynamic correlation between prices of coal, oil, and natural gas, the study uses Dynamic Conditional Correlation for multivariate GARCH model (DCC MGARCH) proposed by Engle and Sheppard (2001). According to Chiang et al. (2007), this model has several advantages over other estimation methods that measure the time-varying correlation. First, it accounts for heteroskedasticity directly. Second, explanatory variables can be included in the mean equation and in the conditional variance for a better model specification. Third, the model is flexible and can be used to examine multiple series without adding too many parameters. The estimates of time-varying correlation coefficients enable us to examine the dynamic correlation of price of fossil fuels when there are multiple regime shifts in response to market changes, shocks, and crises (Chiang et al., 2007). Previous studies have proved that the DCC MGARCH model is as flexible as the varying conditional correlation MGARCH model, more flexible than the conditional correlation MGARCH model, and more parsimonious than the diagonal vech MGARCH model (StataCorp, 2012).

3.3.1 Theoretical Conceptualization of Model

Following Engle and Sheppard (2001), the DCC MGARCH model assumes that returns from k assets are conditionally multivariate normal with zero expected value and covariance matrix H_t. The returns can be either mean zero or the residuals from a filtered time series.

$$r_t | F_{t-1} \sim N(0, H_t)$$

$$\text{and } H_t = D_t R_t D_t$$

where D_t is the kxk diagonal matrix of time varying standard deviations from univariate GARCH models with $\sqrt{h_{it}}$ on the ith diagonal, and R_t is the time varying correlation matrix.

The DCC MGARCH model is estimated with a two stage process. In the first stage, univariate GARCH models are estimated for each residual series. In the second stage, the residuals, transformed by their standard deviation estimated during the first stage, are used to estimate the parameters of the dynamic correlation. The conditional correlation matrix is simply the covariance matrix of the standardized residuals. A stochastic process is proposed to be an approximation to the correlation matrix, named quasi-correlation matrix Q. Finally, the log likelihood and model estimates are derived (Engle, 2009)

In the first stage, R_t is replaced with I_k, an identity matrix of size k. Let the parameters of the model, θ, be written in two groups $(\emptyset_1, \emptyset_2, \ldots\ldots, \emptyset_k, \psi) = (\phi, \psi)$

where the elements of $\emptyset$ correspond to the parameters of the univariate GARCH model for the ith asset series $(\phi_i) = (\omega, \alpha_{1i}, \ldots\ldots,, \alpha_{P_I i}, \beta_{1i}, \beta_{Q_I i})$

The resulting first stage quasi-likelihood function is the sum of the log-likelihoods of the individual GARCH models for each asset:

$$QL_1(\phi|r_t) = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + \log(|I_k| + 2\log(|D_t| + r_t' D_t^{-1} I_k D_t^{-1} r_t)$$
$$= -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + \sum_{n=1}^{k}(\log(h_{it}) + \frac{r_{it}^2}{h_{it}})$$
$$= -\tfrac{1}{2}\textstyle\sum_{n=1}^{k}(T\log(2\pi) + \sum_{t=1}^{T}(\log(h_{it}) + \frac{r_{it}^2}{h_{it}}) \qquad (3.1)$$

The second stage is estimated using the correctly specified likelihood, conditioning on the parameters estimated in the first stage likelihood:

$$QL_1(\phi|r_t) = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + 2\log(|D_t| + \log(|R_t| + r_t' D_t^{-1} I_k D_t^{-1} r_t)$$
$$= -\tfrac{1}{2}\textstyle\sum_{t=1}^{T}(k\log(2\pi) + 2\log(|D_t| + \log(|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t) \qquad (3.2)$$

where $\varepsilon_t \sim N(0, R_t)$ are the residuals standardized by their conditional standard deviation.

Engle and Sheppard (2001) propose to write the elements of D_t as univariate GARCH models, so that:

$$h_{i,t} = w_i + \textstyle\sum_{p=1}^{P_I}\alpha_{Ip} r_{it-p}^2 + \sum_{q=1}^{Q_I}\beta_{Iq} h_{it-q} \qquad (3.3)$$

for i = 1; 2; : : : ; k with the usual GARCH restrictions for non-negativity and stationary being imposed, such as non-negativity of variances and

$$\sum_{p=1}^{P_I} \alpha_{Ip} + \sum_{q=1}^{Q_I} \beta_{Iq} < 1$$

The proposed dynamic correlation structure is:

$$Q_t = (1 - \textstyle\sum_{m=1}^{M} \alpha_m - \sum_{m=1}^{M} \beta_n)\overline{Q} + \sum_{m=1}^{M} \alpha_m(\epsilon_{t-m}\epsilon'_{t-m}) + \sum_{n=1}^{N} \beta_n Q_{t-n} \quad (3.4)$$

where Q is the unconditional covariance of the standardized residuals resulting from the first stage estimation, and $R_t = Q_t^{*^{-1}} Q_t Q_t^{*^{-1}}$

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11}} & 0 & 0 \cdots & 0 \\ 0 & \sqrt{q_{22}} & 0 \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 \ldots & \sqrt{q_{kk}} \end{bmatrix}$$

so that Q_t^* is a diagonal matrix composed of the square root of the diagonal elements of Q_t.

The typical element of R_t is of the form : $\rho_{ijt} = \frac{q_{ijt}}{\sqrt{q_{ii} q_{jj}}}$

3.3.2 Model Estimation Procedure

As explained in the preliminary data analysis, the prices of coal, natural gas, and oil are all integrated of order one I (1). The first differences of the logged prices, which will be addressed as the price series throughout the remaining parts of the essay, are used for model estimation to avoid the problem of spurious regression.

Although results from Quandt test show multiple breaks in the data and different break period in three price series, they appear to be most significant during year 2008, 2009, and 2010. Combined with visual inspection of the prices and squared prices, the study will use 3 dummy variables to capture the structural break in the data. The dummy variables 1, 2, 3 represent periods from January 2004 to June 2008, July 2008 to February 2010, and March 2010 to December 2011 respectively. The time period from July 2008 to February 2010 also represents the financial crisis period.

3.3.2.1 Estimation of the Mean Equation and Conditional Variance

In the first stage, univariate GARCH (1.1) models are estimated for each residual series. The mean equation refers to the equation in which the sample mean of price is removed from the data if it is significantly different from zero (Tsay, 2005). The purpose of the mean equation is to demean the prices, and capture any autocorrelation in the series. As stated in previous section, the model is fitted over the full sample using 3 dummy variables to differentiate sub-samples between the break periods. For the full sample, autocorrelation of each series appears to be small, close to 0. Therefore the mean equation of the each series contains the series itself and dummy variables.

Mean equation:

$$y_{i,t}=\alpha+\Sigma\,\beta_k{*}\,DM_{k,t}+\varepsilon_{i,t} \tag{3.5}$$

where DM_k are dummy variables k=1,2,3 stand for sub sample periods from January 2004 to June 2008, July 2008 to February 2010, and March 2010 to December 2011 respectively.

Conditional variance:

$$h_{i,t}=a_o+a_1h_{i,t-1}+b_1\,\varepsilon^2_{i,t-1}+\sum_{k=1}^{3}d_k\,DM_{k,t} \tag{3.6}$$

3.3.2.2 Estimation of the Conditional Variance-Covariance Matrix

The standardized residuals, which are equal to the residuals divided by their standard deviation estimated in the first stage, will subsequently be used to estimate the parameters of the dynamic correlation. Standardized residuals: $s_{i,t}=\varepsilon_{i,t}/\sqrt{h_{i,i,t}}$

Then the MGARCH DCC model's residuals are checked for any remaining serial correlation. In case, heteroskedasticity still presents, the mean equation is checked again for omitted variable and the order determination of GARCH term is examined from high order of 5 to lower order of 1. The study uses GARCH (1, 1). The mean equations and GARCH order are displayed in table 5. The seasonal dummy variable and dummy variables for sub-samples are also used in the variance equations. However, the seasonal dummy variables are dropped out of the oil and coal variance equations due to insignificant test results. Dummy 3 is excluded from the model to avoid colinearity. The model specification is confirmed by checking the residuals for any remaining serial correlation

3.4 Empirical Results

The estimated model parameters are shown is table 13. The null-hypothesis of constant correlation is rejected at 1% indicating a dynamic co-movement between the coal, natural gas, and oil prices. It means the correlations among the fossil fuel markets are not constant over time. The residuals and squared residuals from the DCC MGARCH are checked for autocorrelation and serial dependence. The autocorrelation function (ACF) and PACF of the residuals and squared residuals show no serially autocorrelation or heteroskedasticity remaining. Sixteen out of thirty coefficients estimates are statistically significant. The model is therefore well specified.

Estimates for dummy 2 variable, which stands for the time from July 2008 to February 2010, are significant at 5% level in all three variance equations. Meanwhile, dummy 1, which stands for the time from January 2004 to June 2008, is not significant at 5% in all three equations. It implies coal, oil, and natural gas prices exhibit higher volatility during 2008 to 2010. Furthermore, the estimated conditional quasi-correlation between the volatilities of the coal and gas, coal and oil, and gas and oil is positive and significant at 1% implying volatility in the three markets are related.

The seasonal dummy variable for the time from July to February of the year was included in all 3 variance equations at first but is not significant for coal and oil's. The estimate for seasonal dummy in natural gas variance equation is significant at 1% level indicating that natural gas price is more volatile during July to February of the year.

As shown in table 14 and figure 15, although having different movement patterns, the dynamic correlation estimates are quite consistent with market observations and the rolling correlation estimates. In particular, the correlations between oil, natural gas, and coal are varying and fluctuating. The correlation between oil and natural gas ranges from -0.002 to 0.61, and is experiencing a declining trend since 2009. Table 14 presents summary correlation between coal, oil, and gas for full sample and for the three sub samples. The correlation in sub sample 3 for the time from February 2010 to December 2011 is only 0.18 compared to 0.356 and 0.354 in other two periods. In particular, the correlation even went to negative on September and October 2010. The expansion of shale natural gas and the higher supply elasticity of natural gas appear to have made the natural gas price more stable to overall changes in the market. Furthermore, the increasing share of natural gas and the less than 1% share of oil in electricity generation market have lessened the dependence between oil and natural gas as substitutes.

On the contrary, the correlation between coal versus oil and coal versus natural gas is rising. The correlation between coal versus oil ranges from -0.18 to 0.55 while the correlation between coal versus natural gas ranges from -0.07 to 0.44. Coal appears to be more and more correlated to oil than to gas. The increasing correlation between coal and other energy markets, together with its increasing volatility indicates a more vulnerable and risky situation for coals and its producers.

As shown in figure 11, the correlation of the three pairs all increased in 2008 during the time of financial crisis and decreased in 2009. This result is consistent with finding from Mjelde and Bessler (2009) that when market disequilibrium occurs, the energy prices become more correlated. The asymmetric relationship between oil price and other energy commodities partially explains this movement. Increasing oil price might have a large contemporaneous shock on the prices of other commodities while decreasing oil price might not. In addition, the coal price asymmetric reaction to shock between the North American markets (IEA et al., 2011), market uncertainty, and volatility when the economic recession begins might be other reasons why correlation between energy prices fell in 2009. As a consequence, energy portfolios or hedging might work better in term of minimizing risk in recession time or when the oil price decreases.

3.5 Concluding Remarks

Countless studies have been done to examine and discover the dependence or interrelationship between energy prices. Oil and natural gas are the two energy commodities that receive a great deal of attention and focus. However, the dynamic correlation in between these market prices and coal prices has not been fully addressed. Many changes have occurred and will continue to happen in fossil fuel markets. The EIA (2011) has reported that there has been a rising share of natural gas in North American electricity market, replacement of oil with natural gas in electricity markets, increased attention paid to greenhouse gas emissions, decreasing productivity in coal mining, and shutdowns of many coal-fired plants and coal mines recently among other developments. These changes can influence the relationship between these markets substantially.

This essay uses a multivariate GARCH model for Dynamic Conditional Correlation (MGARCH DCC) to examine the changes in co-movement between coal, oil, and natural gas market prices. The empirical results show evidence that there exists a dynamic correlation and a related volatility between prices which are significant at the 1% level. Coal price which seemed to be the most stable energy price is now facing a more uncertain and risky future. On contrast, natural gas has become less correlated with oil. The increasing correlation between coal and the other two fuel prices and the declining correlation between natural gas and oil reflects the changes in fossil fuels' interactions and interrelationship.

The resulting estimates indicate that while the correlations between the three energy prices vary over time, the three price series tended to move more closely during the financial crisis. In particular, during that period coal prices became more related to oil and natural gas prices exhibiting more volatility. Simultaneously, natural gas exhibited more stable prices and showed a weaker correlation with oil price. In addition, natural gas prices were found to exhibit more volatility from July to February of the year. The year period 2008 to 2010 experienced the most volatility in oil, natural gas, and coal prices.

Engle (2001) stated that "The goal of volatility analysis must ultimately be to explain the causes of volatility. While time series structure is valuable for forecasting, it does not satisfy our need to explain volatility. .... Thus far, attempts to find the ultimate cause of volatility are not very satisfactory." The MGARCH DCC model used in this study has not detected the cause of volatility in the fossil fuel prices. Neither has the study answered the question about the causes of dynamic correlation between coal, oil, and natural gas price. Moreover, with such dynamic co-movements, an interesting question can be raised about the dynamic causality between the three markets. Previous studies have come up with different results about causal relationship among energy prices. However, structural changes at times in markets might change price discovery behavior and put the causality relationship to a completely different stage. Future research can address these directions.

CHAPTER IV

CONCLUSIONS

Markets have always changed in response to either exogenous or endogenous shocks. Many large events have occurred in global markets as well as in financial markets and energy markets the last ten years. The dissertation examines market behavior and volatility in agricultural credit and fossil fuel markets. The efficiency of elements within the United States Farm Credit System, a major agricultural lender in the Unites States, and the dynamic correlations between coal, oil and natural gas prices, the three major fossil fuels, are examined.

The dissertation consists of two essays. The first essay addresses relative efficiency of elements within the Farm Credit System from 2000 to 2009. The Farm Credit System (FCS) is considered by many a successful model for the U.S. credit system. Examination of the technical efficiency of elements within the FCS will provide information as to whether the FCS has utilized its government sponsorship and privileges in obtaining inputs to producing outputs efficiently. This essay also examines differences in productivity and efficiency of the five banks versus the associations. In addition, it addresses how efficiency changed over time and space.

In studying the efficiency of the Farm Credit System, the banks' efficiency is quite stable while the efficiency for the associations is increasing. The empirical results also suggest that the FCS's five banks and associations with large assets have more efficiently produced credit than smaller sized associations. Moreover, smaller bank size in term of assets and lower management compensation are indicators that explain lower efficiency estimates. In addition, the level of fixed assets held is found to be significant in explaining for associations' productivity while variable inputs are more important for the five banks. These findings indicate more consolidation or more capital investment in small associations may be desirable. The 2008 financial crisis which caused foreclosure and bankruptcy of many financial institutions appeared to have little impact on the FCS operations although the boom in bioenergy and farm income may be an important countervailing force.

The second essay reports on an examination of the dynamic correlation of fossil fuel prices in North America from 2004 to 2011. Numerous studies have been focused on the relationship and integration among energy markets or between energy market and other markets. Nevertheless, the dynamic correlation relationships among fossil fuel markets have not been fully addressed. This essay reports on the measurement of the correlation between price of oil, natural gas, and coal and an examination of how correlations have changed over time including an investigation of their relationship during the 2008 financial crisis. The resulting estimates of possible dynamic changes in fossil fuel price relationships can provide helpful information for risk managements, portfolio managements, hedging decisions, and energy regulations.

While the research reported in the first essay finds little evidence of an the impact of the 2008 financial crisis on system efficiency, the second essay finds some effects of the crisis on price movements in fossil fuel markets and the relation between those prices. During the time 2008-2010, coal price was found to experience more volatility and become more closely related to oil and natural gas prices. The natural gas price was found to become more stable and drift away its historical relationship with oil. The increasing substitution of natural gas for coal and decreasing substitution of natural gas for oil may be the reason. Hybrids and plug in transportation means may also be increasing coal-oil substitution.

In studying market responses to exogenous shocks, the dissertation has used a rather naïve and indirect approach. Rather than directly estimating how the exogenous factors impact behaviors of market elements, the analysis has examined the behaviors of the market elements over time to make inference about effects of exogenous factors. Further estimation of the impact of exogenous changes on the FCS's efficiency as well as the dynamic correlations of fossil fuel prices is necessary to derive any conclusion about the effects.

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APPENDIX A

TABLES

Table 1 Descriptive Statistics for the FCS's Five Banks and Associations

Variable	Obs	Mean	Std. D.	Min	Max
Banks					
Log (earning assets)	161	16.76	0.73	15.13	17.99
Log (premises and fixed assets)	161	9.09	0.77	6.70	10.15
Log (laborexpenses)	161	8.76	0.63	6.75	10.24
Log (interest payable)	161	11.71	0.85	9.95	13.06
Log(directors' compensation)	161	5.36	0.48	4.09	6.35
Associations					
Log (earning assets)	4196	12.70	1.54	0.00	16.93
Log (premises and fixed assets)	4196	7.16	1.70	0.00	11.43
Log (laborexpenses)	4196	6.70	1.37	0.69	10.30
Log (interest payable)	4196	7.05	2.29	-0.18	12.44
Log(directors' compensation)	4197	3.25	1.09	-0.18	6.81

Source: Farm Credit Administration

Table 2 Maximum Likelihood Estimates of Stochastic Frontier Functions for Five Banks

Variable	Coefficient	Std. D.	t-ratio
Constant	5.67	0.33	17.31
Log (premises and fixed assets)	0.03	0.02	1.55
Log (laborexpenses)	0.33	0.03	9.37
Log (interest payable)	0.67	0.04	18.3
Dummy year 2001	0.22	0.08	2.66
Dummy year 2002	0.53	0.09	5.83
Dummy year 2003	0.79	0.09	9.12
Dummy year 2004	0.67	0.09	7.71
Dummy year 2005	0.45	0.08	5.63
Dummy year 2006	0.29	0.08	3.64
Dummy year 2007	0.27	0.08	3.36
Dummy year 2008	0.44	0.08	5.61
Dummy year 2009	0.64	0.08	8.43
Dummy quarter 2	0.01	0.03	0.32
Dummy quarter 3	-0.01	0.03	-0.23

Table 2 Continued

Variable	Coefficient	Std. D.	t-ratio
Dummy quarter 4	-0.04	0.03	-1.28
Constant	0.69	0.51	1.34
Dummy region West	0.47	0.5	0.94
Dummy region Midwest	0.07	0.5	0.14
Dummy region Northeast	0	1	0
Dummy region South	0.15	0.5	0.3
Mgmt compensation	-0.09	0.03	-2.81
Sigma-squared	0.02	0	6.6
Gamma	1.00	0.01	145.48

Table 3 Maximum Likelihood Estimates of Stochastic Frontier Functions for Associations

Variable	Coefficient	Std.D.	t-ratio
Constant	11.12	0.16	71.00
Log (premises and fixed assets)	0.05	0.02	2.64
Log (laborexpenses)	0.10	0.02	4.30
Log (interest payable)	0.25	0.01	19.17
Dummy year 2001	-0.04	0.06	-0.61
Dummy year 2002	0.09	0.06	1.40
Dummy year 2003	0.12	0.07	1.72
Dummy year 2004	0.09	0.07	1.36
Dummy year 2005	-0.08	0.06	-1.28
Dummy year 2006	-0.17	0.06	-2.56
Dummy year 2007	-0.08	0.06	-1.28
Dummy year 2008	0.01	0.06	0.16
Dummy year 2009	0.10	0.06	1.60
Dummy quarter 2	0.04	0.04	1.11
Dummy quarter 3	0.04	0.04	1.05
Dummy quarter 4	-0.02	0.04	-0.56
Constant	2.66	0.19	14.02
Dummy bank size 1	-4.62	0.30	-15.29
Dummy bank size 2	-1.16	0.06	-19.10
Dummy bank size 3	-0.83	0.04	-21.76
Dummy region West	0.11	0.16	0.68
Dummy region Midwest	0.43	0.16	2.70

Table 3 Continued

Variable	Coefficient	Std.D.	t-ratio
Dummy region Northeast	0.01	0.17	0.03
Dummy region South	0.17	0.15	1.08
Mgmt compensation	-0.26	0.03	-9.12
Sigma-squared	0.55	0.02	25.62
Gamma	0.29	0.05	6.16

Table 4 Predicted Efficiency Value for the Five Banks 2000-2009

Year	Mean	Std. D.	Freq
2000	0.66	0.08	8
2001	0.66	0.17	8
2002	0.67	0.16	8
2003	0.64	0.13	17
2004	0.67	0.10	20
2005	0.68	0.11	20
2006	0.69	0.12	20
2007	0.70	0.12	20
2008	0.70	0.15	20
2009	0.68	0.19	20
Average	0.68	0.13	161

Table 5 Predicted Efficiency Value for Associations 2000-2009

Year	Mean	Std. D.	Freq
2000	0.26	0.28	436
2001	0.31	0.28	516
2002	0.37	0.29	456
2003	0.40	0.29	420
2004	0.42	0.30	412
2005	0.45	0.30	408
2006	0.48	0.30	403
2007	0.51	0.30	396
2008	0.53	0.31	386
2009	0.54	0.31	363
Average	0.42	0.31	4196

Table 6 Predicted Efficiency Value for Associations 2000-2009 by Bank Size

	Bank Size 1			Bank Size 2			Bank Size 3			Bank Size 4		
Year	Efficiency	Std.D.	Freq	Efficiency	Std.D.	Freq	Efficiency	Std.D.	Freq	Efficiency	Std.D.	Freq
2000	0.949	0.01	54	0.447	0.10	29	0.285	0.08	75	0.106	0.04	278
2001	0.948	0.01	67	0.458	0.10	70	0.286	0.05	122	0.114	0.04	257
2002	0.948	0.01	75	0.453	0.09	89	0.295	0.06	117	0.121	0.04	175
2003	0.949	0.01	77	0.460	0.09	95	0.309	0.05	109	0.130	0.04	139
2004	0.950	0.02	82	0.462	0.10	93	0.318	0.06	110	0.137	0.04	127
2005	0.950	0.01	89	0.501	0.08	86	0.334	0.06	122	0.137	0.05	111
2006	0.951	0.01	98	0.514	0.07	90	0.346	0.06	119	0.137	0.06	96
2007	0.950	0.01	108	0.515	0.07	89	0.350	0.07	119	0.140	0.06	80
2008	0.951	0.01	116	0.506	0.08	95	0.365	0.07	100	0.142	0.05	75
2009	0.950	0.01	117	0.487	0.06	77	0.368	0.08	106	0.132	0.04	63
Average	0.950	0.01	883	0.483	0.09	813	0.326	0.07	1099	0.124	0.04	1401

Table 7 Predicted Time Varying Efficiency Value for Individual Bank 2000-2009

Year	AgFirst, FCB			AgriBank, FCB			FCB of Texas			US AgBank, FCB			CoBank ACB		
	Mean	Std. D.	Freq	Mean	Std. D.	Freq	Mean	Std. D.	Freq	Mean	Std. D.	Freq.	Mean	Std. D.	Freq
2000	0.73	0.01	4				0.58	0.04	4						
2001	0.78	0.14	4				0.54	0.08	4						
2002	0.80	0.13	4				0.55	0.06	4						
2003	0.77	0.11	4	0.65	0.05	4	0.55	0.05	4	0.91	0.00	1	0.52	0.05	4
2004	0.74	0.10	4	0.72	0.03	4	0.68	0.13	4	0.64	0.02	4	0.57	0.08	4
2005	0.70	0.07	4	0.78	0.03	4	0.75	0.05	4	0.68	0.02	4	0.49	0.04	4
2006	0.72	0.03	4	0.83	0.00	4	0.73	0.04	4	0.69	0.02	4	0.49	0.03	4
2007	0.72	0.03	4	0.88	0.03	4	0.64	0.05	4	0.71	0.04	4	0.54	0.04	4
2008	0.76	0.08	4	0.89	0.06	4	0.55	0.04	4	0.76	0.08	4	0.55	0.03	4
2009	0.86	0.10	4	0.87	0.08	4	0.49	0.02	4	0.73	0.08	4	0.47	0.01	4
Average	0.76	0.09	40	0.80	0.09	28	0.61	0.10	40	0.71	0.07	25	0.52	0.05	28

Table 8 Data Statistics for Coal, Oil, and Gas Price

Variable	Obs	Mean	Std. D.	Min	Max
Coal price	1993	60.59	17.42	37.5	143.25
Gas price	1969	6.31	2.32	2.51	15.37
Oil Price	1993	71.81	22.45	32.48	145.29
Logged coal	1993	4.06	.25	3.62	4.96
Logged natural gas	1969	1.78	.34	.92	2.73
Logged oil	1993	4.22	.32	3.48	4.97
Δ Logged coal	1992	.0002	.02	-.28	.29
Δ Logged natural gas	1968	-.0003	.03	-.14	.26
Δ Logged Oil	1992	.0005	.02	-.13	.16

Source: EIA

Table 9 Diagnostics Test of Data

Variable	Normality test			ARCH LM (5)	Q(20)	Q2(20)
	Pr(Skewness)	Pr(Kurtosis)	Prob>chi2	Prob > chi2	Prob > chi2	Prob > chi2
Logged coal	0.00	0.00	0.00	0.00	0.00	0.00
Logged natural gas	0.00	0.00	0.00	0.00	0.00	0.00
Logged oil	0.00	0.00	0.00	0.00	0.00	0.00
Δ Logged coal	0.07	0.00	0.00	0.00	0.00	0.00
Δ Logged natural gas	0.00	0.00	0.00	0.00	0.00	0.00
Δ Logged oil	0.50	0.00	0.00	0.00	0.00	0.00

Table 10 Dickey Fuller Test

Variable	Deterministic term	Test value	Critical value (%)		
			1	5	10
Logged Coal	Constant, trend	-2.08	-3.43	-2.86	-2.57
Δ Logged coal	Constant, trend	-44.67	-3.43	-2.86	-2.57
Logged natural gas	Constant, trend	-1.73	-3.43	-2.86	-2.57
Δ Logged natural gas	Constant, trend	-47.11	-3.43	-2.86	-2.57
Logged Oil	Constant, trend	-2.28	-3.43	-2.86	-2.57
Δ Logged Oil	Constant, trend	-46.54	-3.43	-2.86	-2.57

Table 11 Unconditional Correlation from Jan 2004 to Dec 2012

Variable	Coal	
Gas	0.15	
	(0.00)	
Oil	0.26	0.27
	(0.00)	(0.00)

Table 12 The Mean Equations and GARCH Order

Dependent variable	Mean Equation	GARCH (1,1)
Coal	$y_{i,t}=\alpha+ \Sigma\ \beta_k{*}\ DM_{k,t}$ $+\varepsilon_{i,t}$	$h_{i,t} = a_o + a_1 h_{i,t-1} + b_1$ $\varepsilon^2_{i,t-1}+\sum_{k=1}^{3} d_k\ DM_{k,t}$
Gas	$y_{i,t}=\alpha+ \Sigma\ \beta_k{*}\ DM_{k,t}$ $+\varepsilon_{i,t}$	$h_{i,t} = a_o + a_1 h_{i,t-1} + b_1$ $\varepsilon^2_{i,t-1}+\sum_{k=1}^{3} d_k\ DM_{k,t} + d_s DS_{s,t}$
Oil	$y_{i,t}=\alpha+ \Sigma\ \beta_k{*}\ DM_{k,t}$ $+\varepsilon_{i,t}$	$h_{i,t} = a_o + a_1 h_{i,t-1} + b_1$ $\varepsilon^2_{i,t-1}+\sum_{k=1}^{3} d_k\ DM_{k,t}$

Table 13 Model Estimation Results

Variable	Coef.	Std. D.	z	P>|z|	95% Confidence Interval	
Coal mean equation						
Dummy sub 1	-0.02	0.05	-0.33	0.74	-0.12	0.09
Dummy sub 2	-0.14	0.07	-2.09	0.04	-0.28	-0.01
Dummy sub 3	0	(omitted)				
_constant	0.06	0.04	1.3	0.19	-0.03	0.14
Coal variance equation						
arch						
L1.	0.05	0.02	2.69	0.01	0.01	0.09
garch						
L1.	-0.43	0.17	-2.58	0.01	-0.77	-0.1
Dummy sub 1	0.13	0.08	1.79	0.07	-0.01	0.28
Dummy sub 2	0.2	0.09	2.23	0.03	0.02	0.37
Dummy sub 3	0	(omitted)				

Table 13 Continued

Variable	Coef.	Std. D.	z	P>|z|	95% Confidence Interval	
_constant	0.23	0.15	1.55	0.12	-0.06	0.51
Gas mean equation						
Dummy sub 1	0.06	0.05	1.1	0.27	-0.04	0.16
Dummy sub 2	-0.07	0.07	-1.04	0.3	-0.21	0.06
Dummy sub 3	0	(omitted)				
_constant	-0.03	0.04	-0.59	0.56	-0.11	0.06
Gas variance equation						
arch						
L1.	-0.02	0	-4.31	0	-0.03	-0.01
garch						
L1.	0.78	0.12	6.32	0	0.53	1.02
Dummy sub 1	0.04	0.07	0.61	0.54	-0.09	0.18
Dummy sub 2	0.2	0.09	2.3	0.02	0.03	0.36
Dummy sub 3	0	(omitted)				
Seasonal dummy	0.2	0.07	3.02	0	0.07	0.33
_constant	-1.64	0.51	-3.24	0	-2.63	-0.65
Oil mean equation						
Dummy sub 1	0.02	0.05	0.37	0.71	-0.08	0.12
Dummy sub 2	-0.08	0.07	-1.15	0.25	-0.21	0.06
Dummy sub 3	0	(omitted)				
_constant	0.03	0.04	0.76	0.45	-0.05	0.12
Oil variance equation						
arch						
L1.	0.03	0.02	1.64	0.1	-0.01	0.06
garch						
L1.	0.49	0.35	1.38	0.17	-0.2	1.18
Dummy sub 1	-0.03	0.08	-0.4	0.69	-0.19	0.12
Dummy sub 2	0.16	0.1	1.67	0.1	-0.03	0.35
Dummy sub 3	0	(omitted)				
_constant	-0.75	0.72	-1.04	0.3	-2.16	0.67
Correlation						
Coal vs Gas	0.24	0.07	3.42	0	0.1	0.37

Table 13 Continued

Variable	Coef.	Std. D.	z	P>|z|	95% Confidence Interval	
Coal vs Oil	0.27	0.07	3.86	0	0.13	0.4
Gas vs Oil	0.27	0.07	3.94	0	0.14	0.41
Adjustment						
Lambda1	0.02	0	6.99	0	0.01	0.02
Lambda2	0.97	0	273.24	0	0.97	0.98

Table 14 Summary of Predicted Correlation between Fossil Fuels Markets

Correlation	Obs	Mean	Std. D.	Min	Max
Full sample					
Oil vs Coal	1977	0.19	0.15	-0.18	0.55
Oil vs Gas	1977	0.31	0.14	0.00	0.61
Coal vs Gas	1977	0.17	0.10	-0.07	0.45
Sub sample 1					
Oil vs Coal	1096	0.08	0.08	-0.18	0.30
Oil vs Gas	1096	0.36	0.14	0.01	0.61
Coal vs Gas	1096	0.11	0.09	-0.07	0.32
Sub sample 2					
Oil vs Coal	396	0.32	0.07	0.17	0.47
Oil vs Gas	396	0.35	0.10	0.18	0.57
Coal vs Gas	396	0.24	0.06	0.09	0.36
Subsample 3					
Oil vs Coal	485	0.32	0.09	0.19	0.55
Oil vs Gas	485	0.19	0.10	0.00	0.44
Coal vs Gas	485	0.23	0.07	0.04	0.45

APPENDIX B

FIGURES

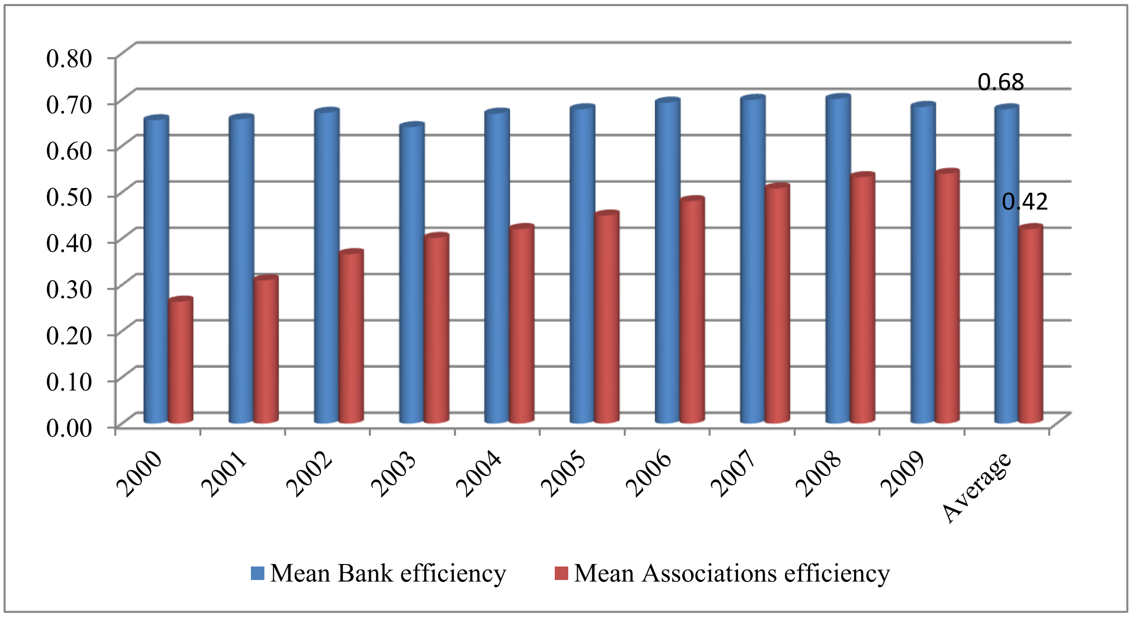

Figure 1 Mean Efficiency Estimates of Five Banks versus Associations

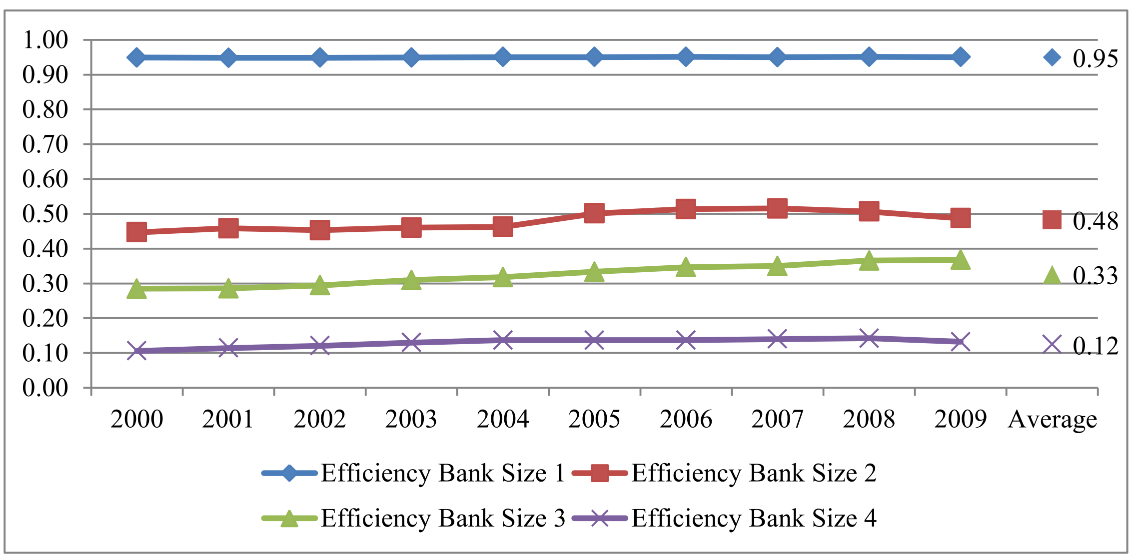

Figure 2 Mean Efficiency Estimates of Associations by Bank Size

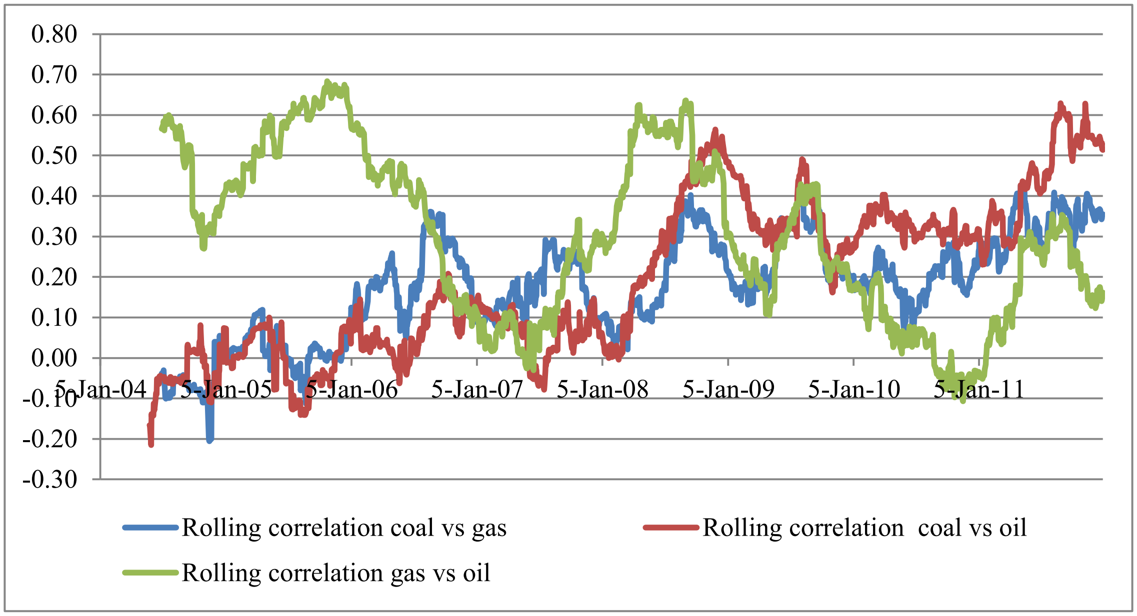

Figure 3 Rolling Correlation Window 100

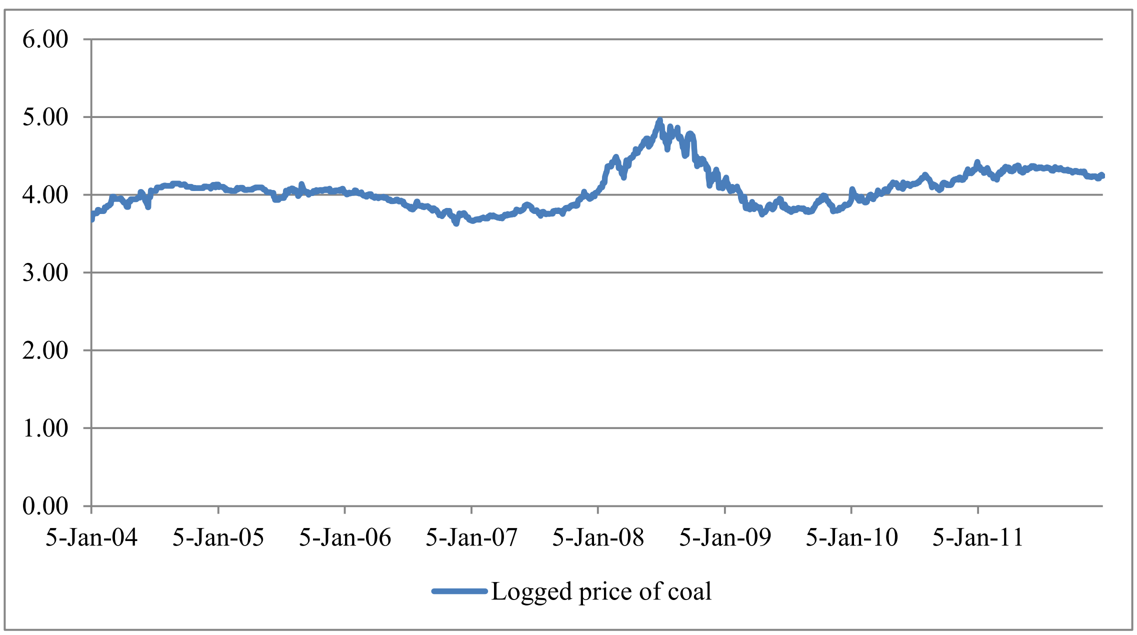

Figure 4 Logged Prices of Coal

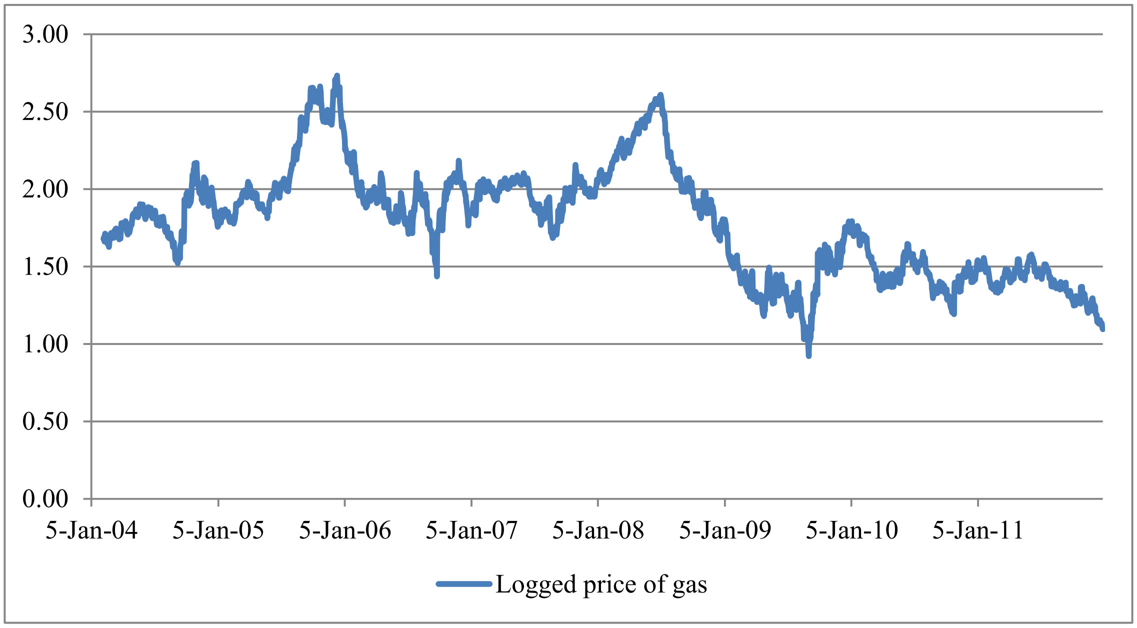

Figure 5 Logged Prices of Natural Gas

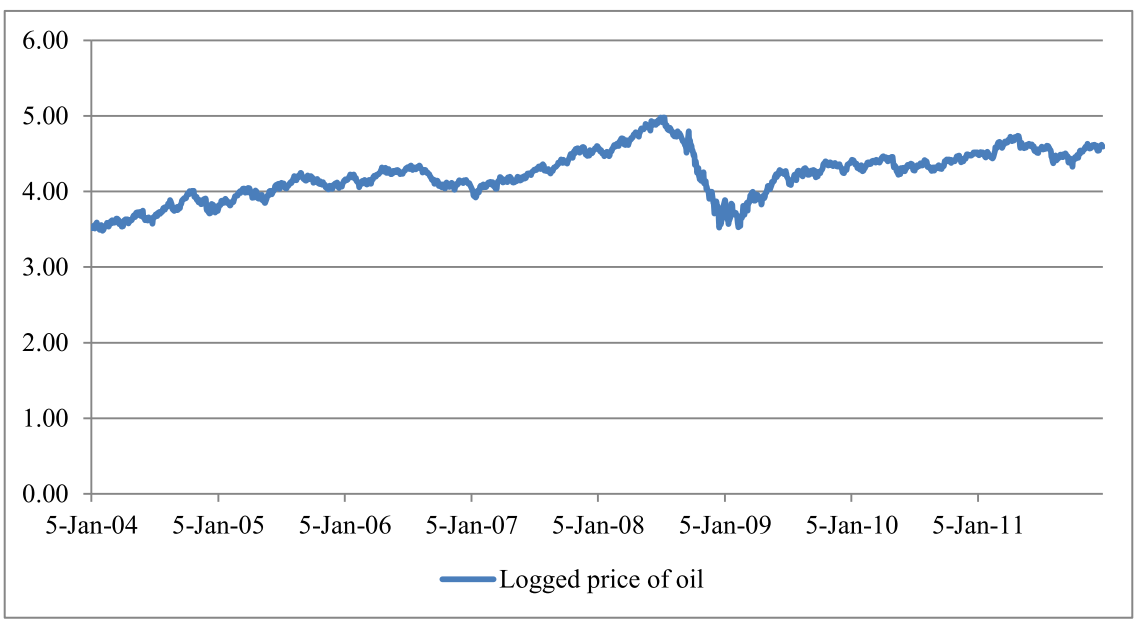

Figure 6 Logged Prices of Oil

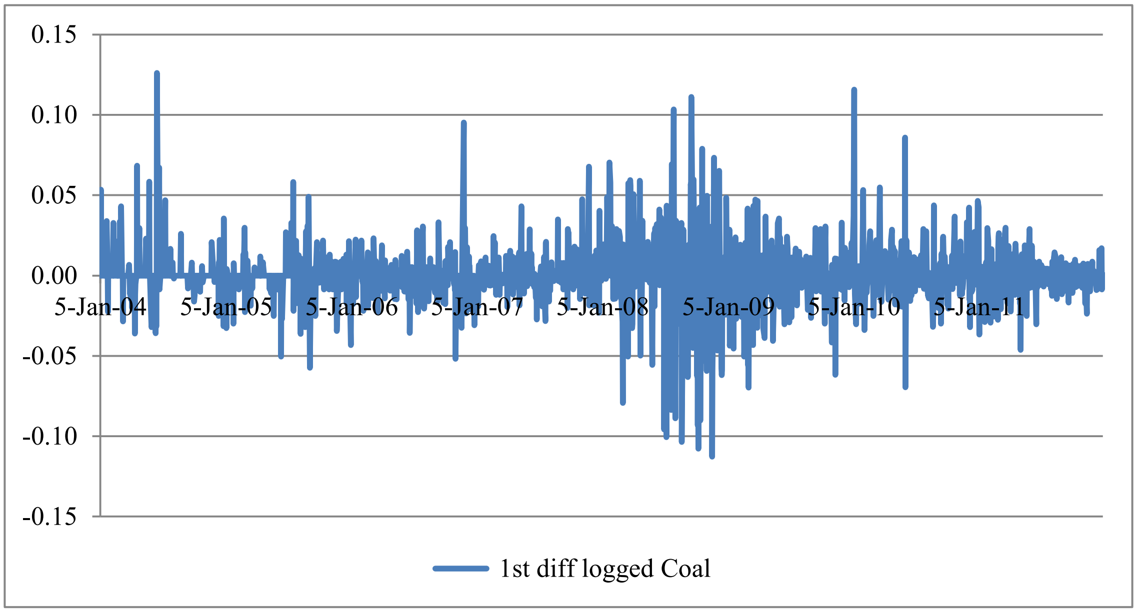

Figure 7 First Difference in Logged Prices of Coal

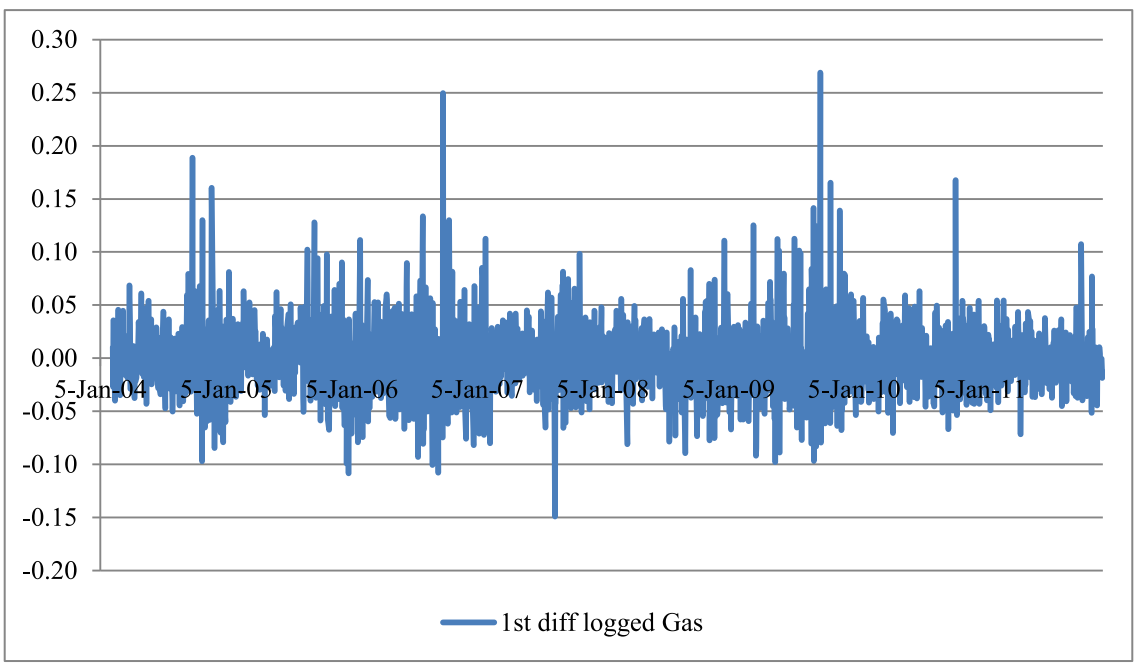

Figure 8 First Difference in Logged Prices of Natural Gas

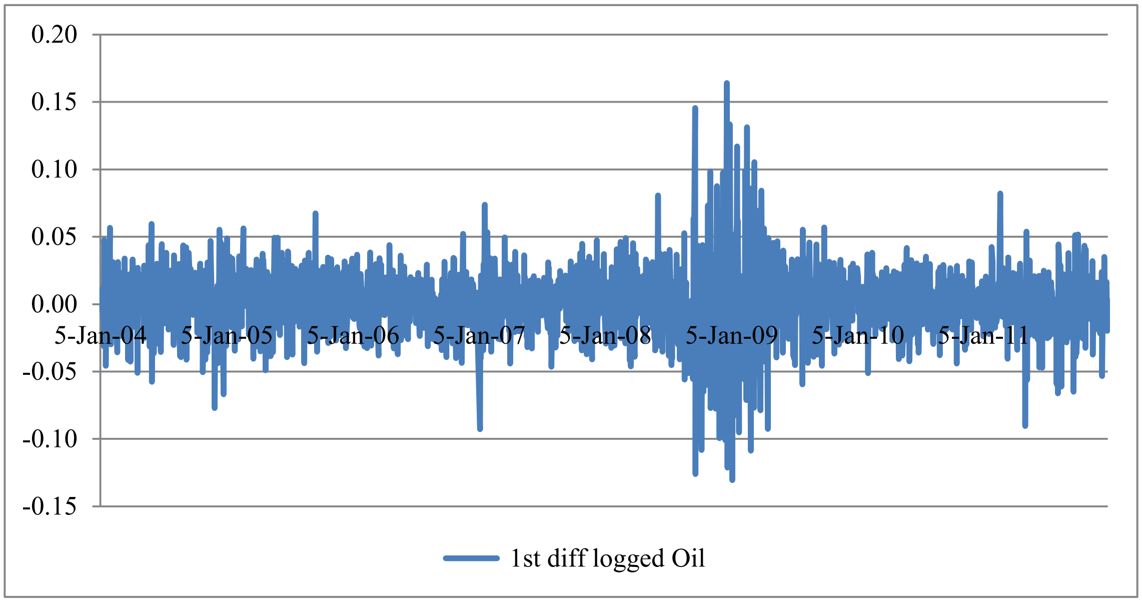

Figure 9 First Difference in Logged Prices of Oil

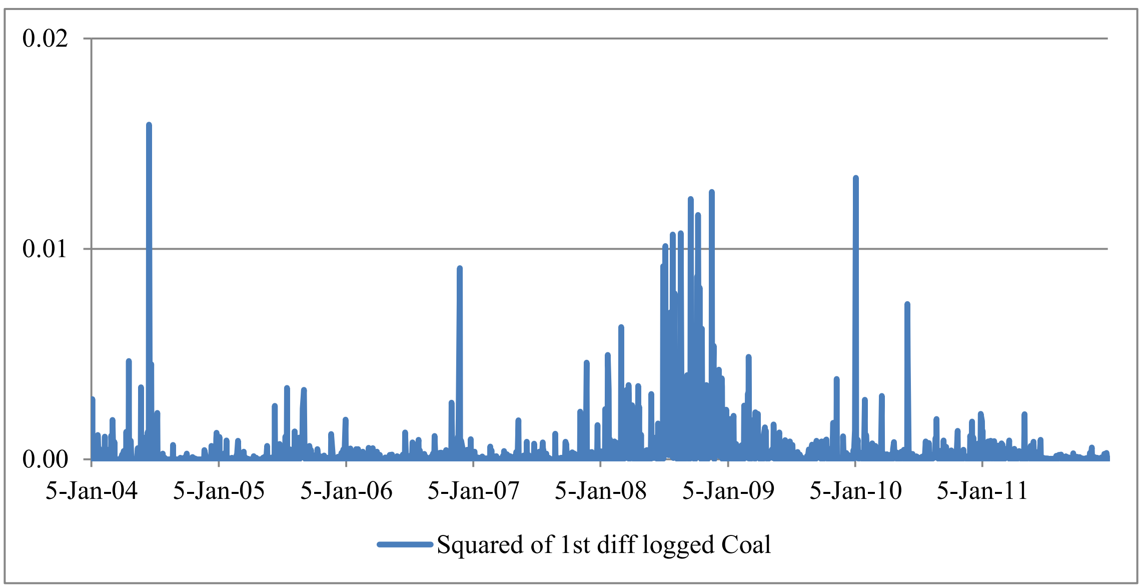

Figure 10 Squared of First Difference in Logged Prices of Coal

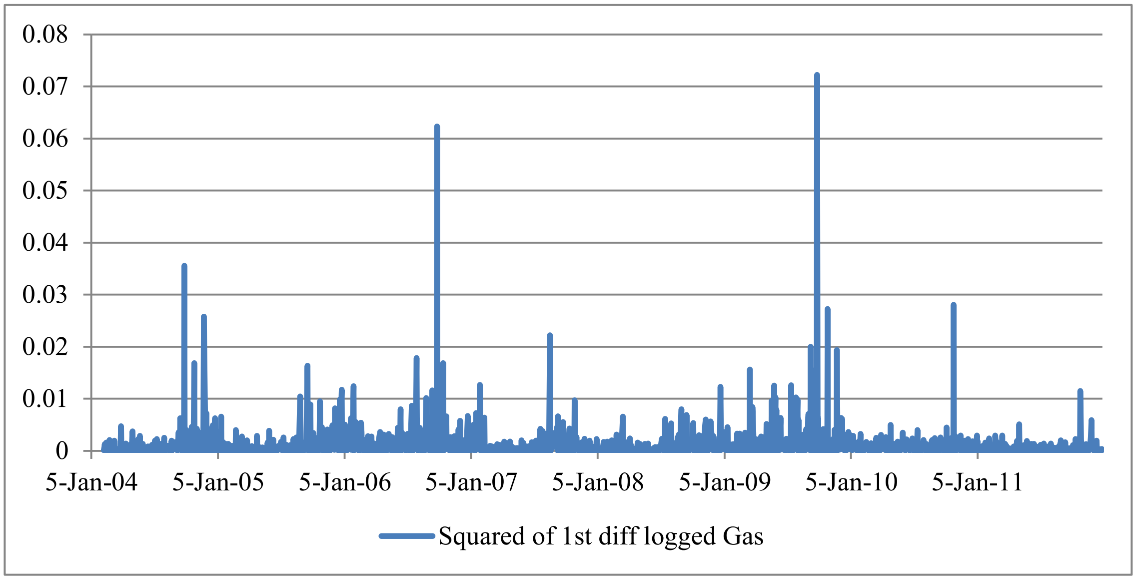

Figure 11 Squared of First Difference in Logged Prices of Natural Gas

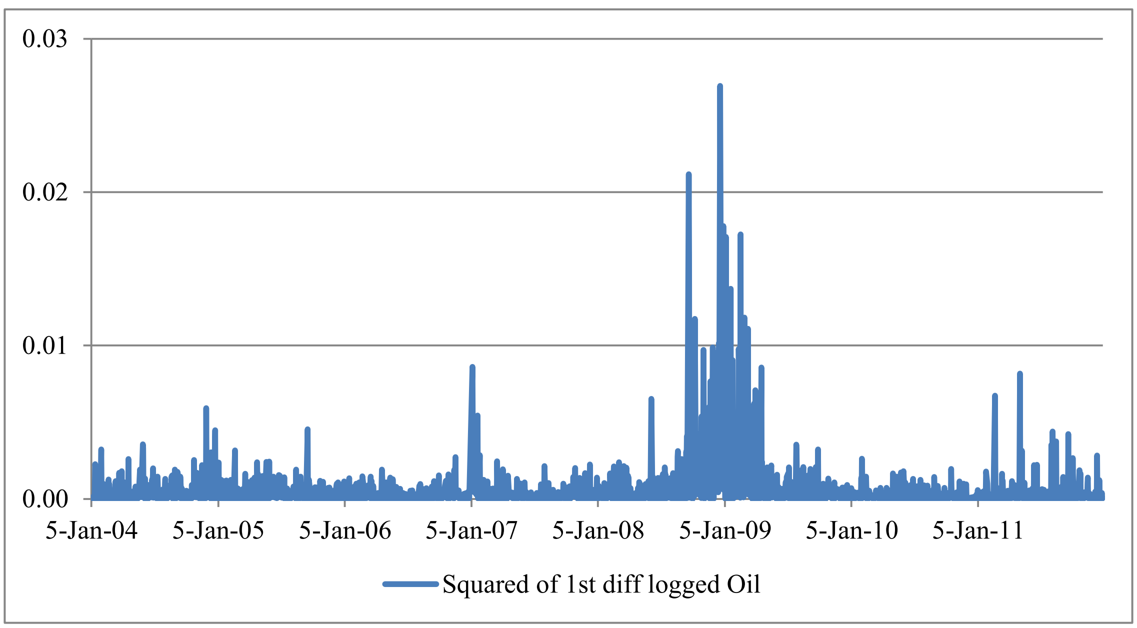

Figure 12 Squared of First Difference in Logged Prices of Oil

A B C

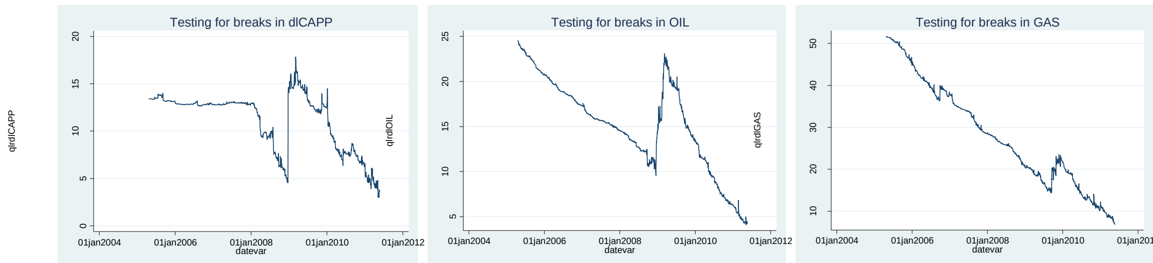

Figure 13 Testing for Structural Breaks in Coal (A), Natural Gas (B), and Oil (C)

A B C

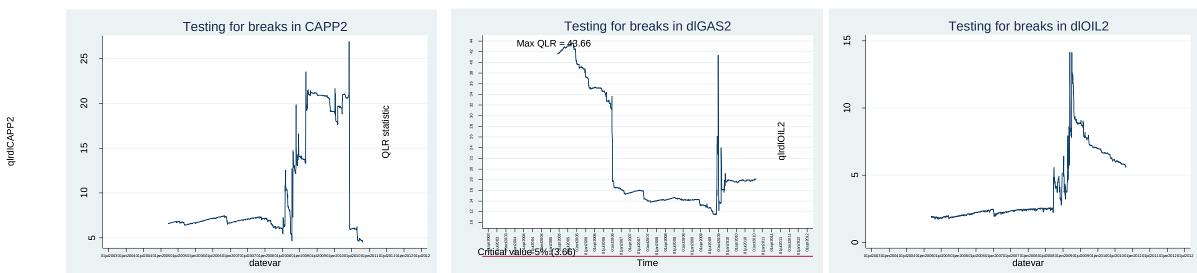

Figure 14 Testing for Structural Breaks in Squared Price of Coal (A), Natural Gas (B), and Oil (C)

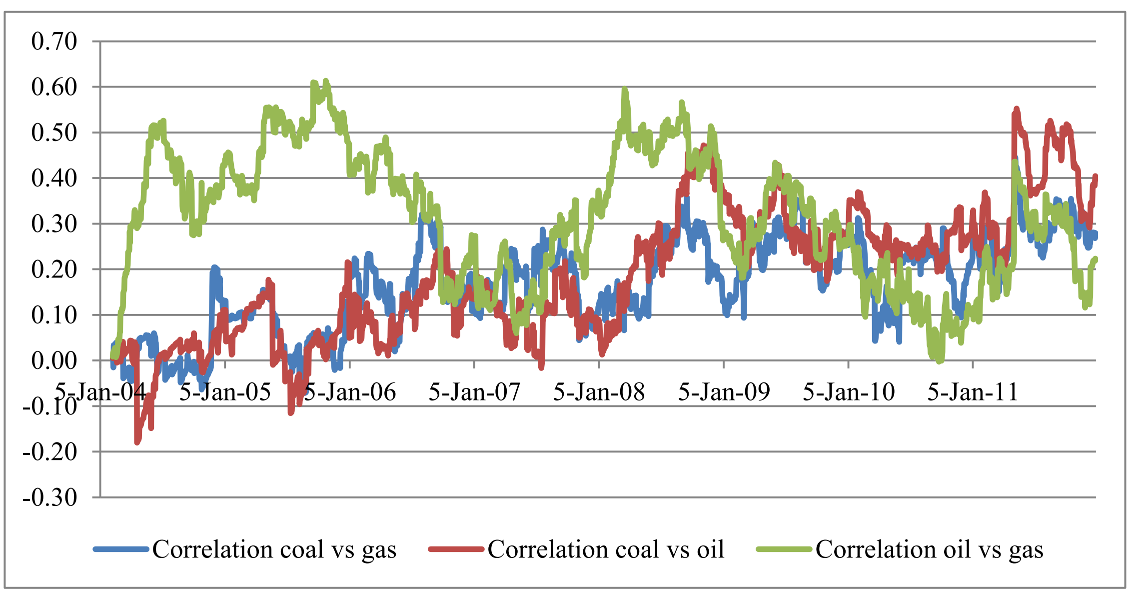

Figure 15 Predicted Correlation between Fossil Fuels Markets

APPENDIX C

VARIABLE DESCRIPTIONS

Table 15 Variable Descriptions

Variable	Descriptions
Log (earning assets)	Logarithm of loans, leases, investments, interest receivable, other receivables, cash and other earning assets
Log (premises and fixed assets)	Logarithm of premises and fixed assets
Log (laborexpenses)	Logarithm of labor expenses
Log (interest payable)	Logarithm of interest payables for the system bonds, notes and other borrowings/payables
Log(directors' compensation)	Logarithm of director compensation
Dummy year 2001	Dummy variable for year 2001
Dummy year 2002	Dummy variable for year 2002
Dummy year 2003	Dummy variable for year 2003
Dummy year 2004	Dummy variable for year 2004
Dummy year 2005	Dummy variable for year 2005
Dummy year 2006	Dummy variable for year 2006
Dummy year 2007	Dummy variable for year 2007
Dummy year 2008	Dummy variable for year 2008
Dummy year 2009	Dummy variable for year 2009
Dummy quarter 2	Dummy variable for quarter 2
Dummy quarter 3	Dummy variable for quarter 3
Dummy quarter 4	Dummy variable for quarter 4
Dummy region West	Dummy variable for banks or associations that is located in West region
Dummy region Midwest	Dummy variable for banks or associations that is located in MidWest region

Table 15 Continued

Variable	Descriptions
Dummy region Northeast	Dummy variable for banks or associations that is located in NorthEast region
Dummy region South	Dummy variable for banks or associations that is located in South region
Mgmt compensation	Dummy variable for management compensation
Dummy bank size 1	Dummy variable for associations with total assets larger than or equal to $1 billion in year 2009 dollars
Dummy bank size 2	Dummy variable for associations with total assets larger than or equal to $500 million and less than $1 billion in year 2009 dollars
Dummy bank size 3	Dummy variable for associations with total assets larger than or equal to $250 million and less than $500 million in year 2009 dollars
Sigma-squared	Variance of technical inefficiency effects
Gamma	Variance of technical inefficiency effects divided by the sum of variance of technical inefficiency effect and variance of the random errors
Coal price	Absolute price of coal
Gas price	Absolute price of natural gas
Oil price	Absolute price of oil
Logged coal	Logged price of coal
Logged natural gas	Logged price of natural gas
Logged oil	Logged price of oil
Δ Logged coal	First difference in logged price of coal
Δ Logged natural gas	First difference in logged price of natural gas
Δ Logged oil	First difference in logged price of oil
Dummy sub 1	Dummy variable that stands for time period from January 2004 to June 2008
Dummy sub 2	Dummy variable that stands for time period from July 2008 to February 2010
Dummy sub 3	Dummy variable that stands for time period from March 2010 to December 2011
Seasonal dummy	Seasonal dummy variable that stands for time period from July to Feb of the year

Table 15 Continued

Variable	Descriptions
Lambda1	First parameter that governs the dynamics of conditional quasicorrelations
Lambda2	Second parameter that governs the dynamics of conditional quasicorrelations