ESSAYS ON TIME SERIES AND CAUSALITY ANALYSIS IN FINANCIAL MARKETS

A Dissertation

by

TATEVIK ZOHRABYAN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December 2008

Major Subject: Agricultural Economics

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ABSTRACT

Essays on Time Series and Causality Analysis in Financial Markets. (December 2008)

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Financial market and its various components are currently in turmoil. Many large corporations are devising new ways to overcome the current market instability. Consequently, any study fostering the understanding of financial markets and the dependencies of various market components would greatly benefit both the practitioners and academicians. To understand different parts of the financial market, this dissertation employs time series methods to model causality and structure and degree of dependence. The relationship of housing market prices for nine U.S. census divisions is studied in the first essay. The results show that housing market is very interrelated. The New England and West North Central census divisions strongly lead house prices of the rest of the country. Further evidence suggests that house prices of most census divisions are mainly influenced by house price changes of other regions.

The interdependence of oil prices and stock market indices across countries is examined in the second essay. The general dependence structure and degree is estimated using copula functions. The findings show weak dependence between stock market indices and oil prices for most countries except for the large oil producing nations which

show high dependence. The dependence structure for most oil consuming (producing) countries is asymmetric implying that stock market index and oil price returns tend to move together more during the market downturn (upturn) than a market boom (downturn).

In the third essay, the relationship among stock returns of ten U.S. sectors is studied. Copula models are used to explore the non-linear, general association among the series. The evidence shows that sectors are strongly related to each other. Energy sector is relatively weakly connected with the other sectors. The strongest dependence is between the Industrials and Consumer Discretionary sectors. The high dependence suggests small (if any) gains from industry diversification in U.S.

In conclusion, the correct formulation of relationships among variables of interest is crucial. This is one of the fundamental issues in portfolio analysis. Hence, a thorough examination of time series models that are used to understand interactions of financial markets can be helpful for devising more accurate investment strategies.

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Thanks also go to my friends and colleagues, the department faculty and staff for making my time at Texas A&M University a great experience. Specifically, I want to thank Susan Livingston and Vicki Heard for their unconditional support and dedication. I also want to thank all those who entered my life one way or another. I cannot imagine being at this crucial stage of my career without the support and guidance of all these people. I wish one day I would be able to do the same for others in need.

NOMENCLATURE

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
Cana	Canada
CD	Consumer Discretionary
CDF	Cumulative Distribution Function
Ch	China
CS	Consumer Staple
Cze	Czech Republic
DAG	Directed Acyclic Graph
EN	Energy
ENC	East North Central
ESC	East South Central
EUR	Euro
FI	Financials
Finl	Finland
Fran	France
Germ	Germany
GICS	Global Industry Classification Sector
HC	Health Care
HK	Honk Kong

Hung	Hungary
IN	Industrials
IT	Information Technology
Ital	Italy
Jap	Japan
LLF	Log Likelihood Function
MA	Middle Atlantic
MS	Materials
MT	Mountain
NE	New England
Neth	Netherlands
PC	Pacific
Pola	Poland
Russ	Russia
SA	South Atlantic
SAC	Stable Aggregate Currency
Saud	Saudi Arabia
S&P	Standard & Poor
Spai	Spain
Swit	Switzerland
TC	Telecommunication Services
UK	United Kingdom

U.S.	United States
USD	U.S. Dollar
UT	Utilities
VAR	Vector Autoregression
VECM	Vector Error Correction Model
Vene	Venezuela
WSC	West South Central
WNC	West North Central

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CHAPTER I

INTRODUCTION

Financial markets have always been at the center of attention. Many people try to make sense of the markets and understand the dependencies of various markets and its components including the housing market, financial market (as a whole), various industries, etc. During a stable economy, linear models have been most commonly used either devising investment strategies, or modeling and forecasting the financial variables in general. Now, that many markets are in crisis, including the housing, credit, financial, and energy markets, the models that have been in use before are being revised to better capture the irregularities of financial markets. As such, more general models that are able to capture both symmetric and asymmetric relationships among various markets are of great importance.

The overall aim of this dissertation is to show the importance of dependence degree and structure in financial markets. Also, it shows the importance of time series and copula functions for modeling financial markets. How each one of the markets is linked with the other markets is examined which entails direct implications for the overall financial market. The objectives of each of the chapters are given next.

The objective of Chapter II is to investigate the dynamic interrelationship among the house prices of nine U.S. census divisions. This issue with the census division data

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This dissertation follows the format and style of the Journal of Econometrics.

has not been extensively studied especially regarding to the causal structure. The use of Directed Acyclic Graph (DAG) is intended to provide contemporaneous causal structure among the regional house prices. In addition, data-driven identification is proposed by utilizing the results of DAG and Vector Autoregression Model (VAR) or Vector Error Correction Model (VECM). Finally, the purpose of this chapter is also to understand the housing market and the interaction of the census division house prices which could be used to correctly forecast house price series.

In Chapter III, the objective is to explore the interdependence of oil prices and stock market indices. Both oil producing and oil consuming, developing and developed countries are included to obtain a more complete picture of dependence. The sample is partitioned into pre- and post-Euro periods to examine possible changes in dependencies. In addition to U.S. Dollar (USD) and Euro (EUR), Stable Aggregate Currency (SAC) is used as a base currency for both oil price and stock market index series. The reason is that a basket of currency (SAC) can minimize the exchange rate risk. Hence, it could provide more accurate results. In general, the aim is to compare the dependence structures across countries, currency-denomination cases, oil price series used, and the pre- and post-Euro periods.

The purpose of Chapter IV is to explain the interdependence of industry classification sector data in U.S. Specifically, the asymmetric dependence of stock returns across all industry aggregations in U.S. is intended to be uncovered which has not been addressed in literature before. The results of copula models that provide general dependence structure will be compared with those of linear models already studied by others.

CHAPTER II

COINTEGRATION ANALYSIS OF U.S. REGIONAL HOUSE PRICES

2.1 Introduction

Real GDP is one of the many economic and financial indicators the Federal Reserve Bank (FED) considers in devising the nation's monetary policy. Consequently, individual components of GDP also must be important indicators for assessing the well being of the economy. The largest component, comprising about 70% of the GDP, is personal consumption and real estate is an important part of the personal consumption. Real estate is probably the most interest-rate sensitive sector of the economy. Although residential investments may not represent a large share of GDP (about 5% of GDP), over the short period of time they often account for a large share of GDP changes which is mainly due to its high volatility (about 12% of GDP).[1]

Noticeable changes in house prices will have an important impact on the U.S. economy because home ownership is the primary asset held by many households. Changes in house prices will result in changes in household wealth. Changes in mortgage interest rates, also will affect the financial cost of home ownership. Moreover, the high cost of home ownership might put the labor mobility at a disadvantage, thus

[1] Various sources provide numbers especially for different time periods, but the average is about what is presented above. For more details, see McCarthy and Steindel (2007), McConnell et al. (1999), and the article in Business Week (2005). For educational purposes, Federal Reserve Bank of New York provided brief description of the economic indicators and how each of them affects the general economy and the Fed's monetary policy.

negatively affecting the economy’s efficient functioning (Alexander and Barrow, 1994). Consequently, there is growing attention centered on real estate from policy-makers, investors, researchers, and individual households. Thorough investigation of real estate markets can provide clues about the short-term and long-term performances of the economy.

This paper focuses on the regional house price data in U.S. to examine the linkages among the regional housing markets. The benefits of this study, as mentioned in the related literature, include the ripple effect, wealth distribution, labor mobility, house price prediction, and migration. The transmission of the shock in house prices of one region to another with possible time lags is referred to as ripple effect. It has been found to be significant for UK and U.S. regional housing market. Consequently, the ripple effect will have significant wealth distribution given the fact that housing comprises a large share of assets for many households (Alexander and Barrow, 1994; Holmes and Grimes, 2005). Furthermore, the regional house price analysis has an impact on the labor mobility as well as the migration, although it is weak because most households move from one region to another not only for house price differences but also for other factors (job opportunities, etc). Finally, the ability to correctly predict house prices in one region may be improved if the significant impact of other regional house prices is considered.

Although the importance of the regional house price relationship is evident, most studies in this area are mainly concerned with the UK regional housing market. Only the study by Pollakowski and Ray (1997) focuses on the interrelationship among the house price of the U.S. census divisions while the rest use metropolitan or other sub-market data. Recent methodological advances, housing market crisis, extended data set, and the need for understanding of the regional housing market call for a complete study on the interdependence of the regional house prices in U.S. Consequently, this paper attempts to uncover the dynamic interaction among the U.S. regional house prices by using innovative causality structure and identification of long-run structure. The application of the directed acyclic graphs (DAG) for analyzing the causality pattern in the U.S. housing market is one of the major contributions of this paper to the existing literature. In addition, DAG is proposed to be used for identification of the long-run structure of the cointegrated Vector Error Correction Model (VECM). The data-implied causal ordering is used to obtain impulse responses and the forecast error variance decompositions. Furthermore, house price dynamics, not been thoroughly addressed before, are studied in this paper. The detailed examination of the extended data set, including such important events as the housing market boom and busts, stock market crash, major monetary policy changes, terrorist attack in 2001, U.S. recession, oil crisis, and so on is another important addition to the existing literature. Therefore, this paper analyzes the dynamic interrelationships among the house prices of nine U.S. census regions from a new prospective.[2]

This chapter proceeds as follows: Section 2.2 provides a brief review of the previous research and the conceptual framework. Section 2.3 analyzes the time series data and its pattern. Major methodological considerations and misspecification tests are

[2] Note that division and region in this study will be used interchangeably.

covered in Section 2.4. Section 2.5 presents the empirical results and summary and the conclusions are provided in Section 2.6.

2.2 Review of Previous Research

The relationship between the house prices and their determinants has been studied by many. Numerous research projects have been done focusing on the house price fundamentals, their roles and linkages with house prices in U.S. However, little attention has been paid on investigating the interrelationship between regional house prices in U.S. On the other hand, many studies have been completed for the UK on this area of research which can be separated into various strands. One of the strands contains groups of studies attempting to empirically test the “ripple effect” hypothesis in the UK housing market. It is commonly defined as the propensity of house prices to first rise in South East of England during the upswings then filter out to other regions of UK over time (Holmans, 1990; MacDonald and Taylor, 1993; Alexander and Barrow, 1994; Drake, 1995; Ashworth and Parker, 1997; Meen, 1999; Peterson et al., 2002, Cook, 2003; Cook and Thomas, 2003; Cook, 2005; Holmes and Grimes, 2008). Results of studies on the presence of ripple effect in UK housing market have been mixed. Some studies strongly support its existence, some studies only provide very weak and limited evidence, while other studies argue against the existence of the ripple effect (Meen, 1996).[3]

The second strand of literature tackles the issues of long-run relationship, equilibrium, and convergence of house prices. Although numerous methodologies have been utilized, the findings commonly suggest that short-run regional house prices might diverge from one another, but long-run regional house prices tend to some equilibrium and relative constancy (Holmans, 1990; MacDonald and Taylor, 1993; Alexander and Barrow, 1994; Drake, 1995; Ashworth and Parker, 1997; Meen, 1999; Peterson et al., 2002, Cook, 2003; Cook and Thomas, 2003; Cook, 2005; Cook, 2006; Holmes and Grimes, 2008). Causality between the house prices of different UK regions has been another important avenue for investigation. Similar to ripple effect, the results vary across studies, but commonly suggested causal pattern runs from the South East to North via the Midlands.[4]

Lastly, the reasons and sources for such causal pattern, possible ripple effect, and the existence of long-run equilibrium are studied by some researchers. The most commonly suggested reasons are the demand factors such as income, taxes advantages, equity transfer, migration for job and non-job reasons, etc (Alexander and Barrow, 1994, Giussani and Hadjimathrou, 1991, Gordon, 1990, Holmans, 1990, Meen, 1999, Thomas,

[3] Meen (1999), Cook (2005), Cook and Thomas (2003), Drake (1995), and Holmans (1990) strongly support the existence of the ripple effect emanating from the South East of England. Conversely, Ashworth and Parker (1997) argue against the ripple effect hypothesis and were able to empirically support their argument. Finally, MacDonald and Taylor (1993), Alexander and Barrow (1994), etc found only limited and weak evidence of ripple effect.

[4] Except for Rosenthal (1986), all the studies found evidence of clear causal pattern running from the South East to the North through the Midlands (Hamnett, 1988; Bover et al., 1989; Holmans, 1990; Guissani and Hadjimatheou, 1991; MacDonald and Taylor, 1993; Alexander and Barrow, 1994).

1993, Bover et al., 1989, MacDonald and Taylor, 1993, Minford, et al. 1987). There are multiple reasons; however, there is no definite, universally accepted cause.

Interrelationships between the house prices of U.S. census divisions are uncovered in this paper. Therefore, studies that concentrate on similar issues are of great interest. The best known studies that attempt to address similar issues to this paper are by MacDonald and Taylor (1993) and Alexander and Barrow (1994) for the UK housing sector, and Pollakowski and Ray (1997) for the U.S. housing market. The former two investigate cointegrating relationships between the UK regional house prices. In other words, they examine whether or not the UK regional house prices are tied together in long-run. Both Engle-Granger and Johansen's maximum likelihood methods for bivariate and multivariate analysis, respectively, are utilized to shed light on the cointegrating relations. Quarterly regional house price indices for UK regions are used to further test for the long-run and short-run house price properties, as well as the causal pattern. Significant number of cointegrating relations is detected that evidences the interrelated housing market in the UK. The South East region of England is found to be a price determining region. Moreover, East Midlands and/or East Anglia play vital roles in transmitting the information from south to the north. While Alexander and Barrow (1994) suggest that causality flows from the South to the North passing through the Midlands, MacDonald and Taylor (1993) claim the presence of weak segmentation in UK housing market, particularly, between the North and the South. The differences of regional house prices led to the notion of "two-nation" owner-occupied housing market which in a way shares some similarities with the notion of “weak segmentation” (Hamnett, 1988).

With the emergence of new and more improved econometric and time series methods, more studies return to the question of whether or not cointegration in the UK housing market prevails. The existence of the long-run equilibrium among the UK regional house prices, even with new methods, is still strongly supported (Giussani and Hadjimatheou, 1991; Drake, 1995; Ashworth and Parker, 1997; Meen, 1999; Cook, 2003; Cook and Thomas, 2003; Cook, 2005; Holmes and Grimes, 2008). Most of these studies claim unidirectional causal flows emanating from the South (particularly South East or Greater London) to the rest of the country (mainly into North through Midlands). The most recent development in the housing literature is the use of non-parametric, asymmetric adjustment, principal component, and business cycle dating procedures.[5] In the economic literature, the cointegration analyses with the assumption of asymmetric adjustment mechanism are growing in their importance. Cook (2005) is the first to apply the methodology to analyze the housing market in the UK. Adopting the threshold autoregressive methods of Enders and Siklos (2001), Cook (2005) investigates the UK regional house price linkages from an aspect of asymmetric adjustment process. His findings show that allowing asymmetric reversion (adjustment) significantly increases the number of long-run relationships and dramatically changes the overall results of long-run relationship in UK regional house prices. On the other hand, Holmes and Grimes (2008) employed a new test that combines principal components analysis with

[5] Cook (2003), Cook and Thomas (2003), Cook (2005), Cook (2006), and Holmes and Grimes (2008) all use one or more of the mentioned methods.

unit root testing to examine long-run relationship of the UK regional house prices. UK regional house prices are driven by a single common stochastic trend which is regarded as strong convergence in the long-run.

Little research has been conducted to address the issues of possible long-run relationship between the house prices in U.S. Housing price diffusion at the local level, concentrating on the submarkets in Hartford, CT, was studied by Tirtiroglu (1992) and Clapp and Tirtiroglu (1994). The spatial aspect of the efficiency tests was applied to examine whether the house prices in a particular town are affected by the lagged own and neighboring towns' prices. They confirmed the existence of the spatial diffusion pattern where the coefficients of only the neighboring towns appear to be significant. Consequently, results consistently imply that individuals tend to overemphasize present evidence at the expense of historical evidence which is what is known as positive feedback hypothesis.[6] Subnational analysis has received large attention, although very limited for the U.S. housing market. Only Pollakowski and Ray (1997) examine the spatial and temporal house price interrelationships between the nine U.S. census divisions as well as the metropolitan areas. Moreover, informational efficiency of the U.S. housing market is tested in addition to the analysis of whether the house prices in any one location are predicted by only their own history or by the house price changes in other locations as well. Using VAR, block exogenity, and Granger-causality type tests for the period of 1975-1994, Pollakowski and Ray (1997) discovered that house prices in

[6] Positive-feedback hypothesis has been considered by Cutler, Poterba, Summers (1990), DeLong et al. (1990), Shiller (1990a, 1990b), Tirtiroglu (1992), Clapp and Tirtiroglu (1994), and Pollakowski and Ray (1997).

U.S. are interrelated. Furthermore, census division analysis provide evidence of inefficient U.S. housing market implying that shock in one location do cause any subsequent-period reactions in other locations. A survey of literature on housing market efficiency also showed considerable evidence of market inefficiency. Hence, information transfer is relevant, affecting house price movements of the other regions. On the contrary to the previous studies (Tirtiroglu, 1992; Clapp and Tirtiroglu, 1994), Pollakowski and Ray (1997) fail to show price diffusion between the contiguous regions or divisions, but rather find that price diffusion patterns for neighboring and non-neighboring divisions are not significantly different. The presumed cause for such results is the interrelated regional economies ultimately reflected in the regional housing markets. Analysis of metropolitan areas, on the other hand, has a clear contiguous region effect. That is, house price changes in a particular region (area) have much bigger effect on the house price changes of the contiguous regions (areas) than those of the non-neighboring areas.

Geographical proximity was also considered by other studies and was suggested to be important factor for house price transmission from region to region (MacDonald and Taylor, 1993; Alexander and Barrow, 1994; Giussani and Hadjimateou, 1991; Drake, 1995). Testing this hypothesis for U.S. housing market with the extended dataset and improved methodologies will provide interesting insights about the nature of the possible long-run relationship.

2.3 Data

This paper uses house price indices for the nine U.S. census divisions on a quarterly basis from 1975:1 to 2006:1. The house price indices for the nine U.S. census divisions are retrieved from Office of Federal Housing Enterprise Oversight (OFHEO). The House Price Index (HPI hereafter) for each U.S. census division is calculated using repeated observations of housing values for individual single-family residential properties on which at least two mortgages have been originated and afterwards purchased by either the Federal Home Loan Mortgage Corporation (Freddie Mac) or Federal National Mortgage Association (Fannie Mae). The HPI is commonly referred as "constant quality" house price index because the differences in quality of houses are controlled via the use of repeat transactions. Moreover, it is based on the modified version of the weighted-repeat sales methodology proposed by Case and Shiller (1987) and is available from January 1975.[7]

In real estate literature, house price indices data are commonly used for analyzing the housing market. Some studies utilize the HPI by the OFHED while others tend to construct house price indices using hedonic pricing method or others methods. For example, Pollakowski and Ray (1997) construct weighted repeat-sales index using the method of Case and Shiller (1987). Although house price index as a source for empirical analysis has been criticized based on its construction method (McCarthy and Peach, 2004; Himmelberg et al., 2005; Bourassa et al., 2006; Can and Megbolugbe, 1997), it

[7] Detailed technical description of the HPI and its construction is provided by Calhoun (1996).

still remains one of the best and readily available datasets which controls the house quality (Harter-Dreiman, 2004; Wheelock, 2006). However, there are some limitations of using this index such as the fact that it accounts for only single-family detached properties and excludes condominiums, multi-family residential properties, etc. Moreover, houses which are bought using government insured loans or more than two mortgages are not included in the construction of HPI. It is important to note that regardless of the construction method, the house price indices will always have some limitations, which implies limitations in the results. Pollakowski and Ray (1997) suggest that their results cannot be applied to predict the behavior of all single-family residences. Furthermore, additional limitations arise from the fact that data source is partially truncated. Moreover, limitations might arise from the fact that the results do not distinguish between the ripple down effect caused by an arbitrage or some regional element such as the business cycle. It has also been suggested that using sub-regional or even arbitrarily defined regional boundaries might be more appropriate than regional house price data for analyzing the interrelationship of house prices (Alexander and Barrow, 1994; Bourassa et al., 1999; Bourassa et al., 2003; Bourassa et al., 2007). Similarly, our conclusion can be made regarding to the house price indices only for single-family residential properties, even though the analyses of other type of residential properties will most likely closely resemble that of the single-family residential property.[8]

[8] Note that this is just hypothesis.

The nine U.S. census divisions used in this paper are the Pacific (PC), the Mountain (MT), the West North Central (WNC), the West South Central (WSC), the East North Central (ENC), the East South Central (ESC), the South Atlantic (SA), the Middle Atlantic (MA), and the New England (NE). Further analysis of the nine census division house prices is provided in the following subsection.

2.3.1 U.S. Economy and Housing Market

Complete understanding of the economic, financial, as well as political situations and events is necessary for modeling the interactions of the U.S. regional housing market correctly. On top of this, the graphical analysis will enhance the knowledge of U.S. housing market trend as well as the problems that have to be addressed to obtain reliable implications. Historical HPIs of nine U.S. census divisions are presented in Figure 2.1. Natural logarithmic transformation of the HPIs is used due to the assumed multiplicative effect (Johansen, 1995). The house prices in all the nine divisions have been increasing at a relatively constant rate starting from early or mid 90's, while more volatile growth rates are observed for time periods before 90s, which coincide with the booms and busts in the U.S. economy and housing sector.

The graphical examination is extremely valuable in assessing the nature of house price change, i.e. whether it is permanent or temporary shift in house prices. The distinction between the permanent and the temporary shift might vary from author to author, but, in general, at least if the change to a certain direction remains for more than several quarters (or periods), it is usually considered permanent, otherwise, temporary.

In addition, permanent change is oftentimes regarded as one that shifts the mean of the series for several periods (Juselius, 2006). Similar definition is extended to the booms and busts. For example, Wheelock (2006) defines the housing boom as an increase in the ratio of HPI to state per capita income of at least 7 percent for three or more consecutive quarters. The resulting evidence suggests that between the 1980 and 1999 U.S. states experienced about twenty house price booms. Some of those booms were followed by housing busts, while others were not (Wheelock, 2006). However, most states experienced housing booms at different time periods or at different extent, hence it is hard to define any peaks or troughs for the regional house prices as booms or busts (Wheelock, 2006). Moreover, notice that all regions experience similar shocks at different time frames with different magnitudes which brings up the question this study focuses on - which region the shock in house prices originates in? Is that shock transmitted to other regions? Does the transmission process happen immediately or with some time lags? Does it move the house prices of other regions in the same direction or the opposite? These and many other questions are intended to be answered in this chapter.

Juselius (2006) suggested using the plots on both level and differenced data to get an idea of the possible misspecification problems in the data and model. The assumption of the constant mean does not seem to hold based on the level plots (see Figure 2.1), while it appears to be more appropriate for the differenced series (see Figure

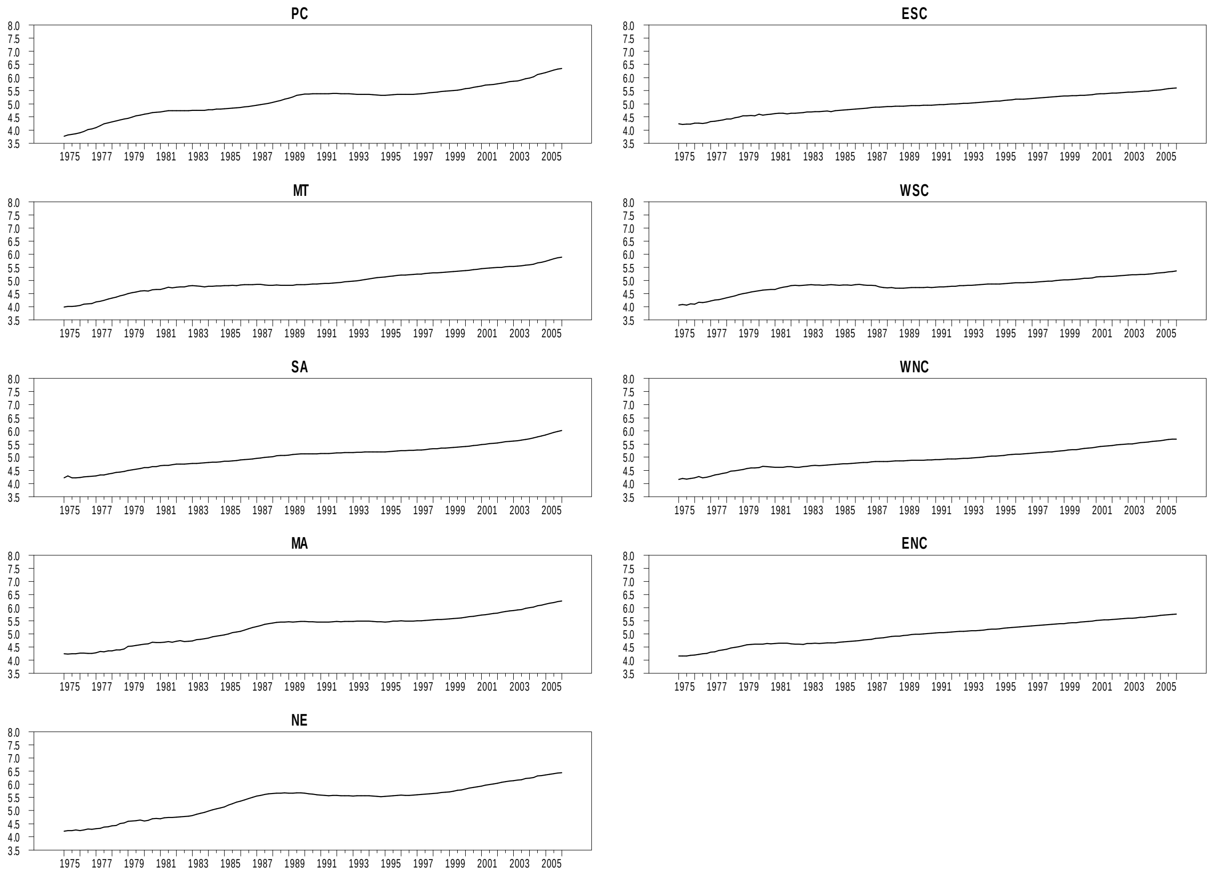

Figure 2.1 Plots of Historical Data on House Price Indices, 1975-2006.
Note that the y-axis is house price index in natural logarithm and the x-axis is time in quarters and years, 1975-2006.

2.2. Inferences about the variance constancy is harder to make from the levels of variables, hence the differenced data is of great help. From Figure 2.2, it can be seen that high variability in series is especially pronounced in the beginning of the sample period. Moreover, most series, except for the HPI changes in SA which are fairly stable over the entire sample period, appear to have relatively constant variance after the mid 1980’s. However, a few exceptions are observed. Relatively high variability is noticed for the

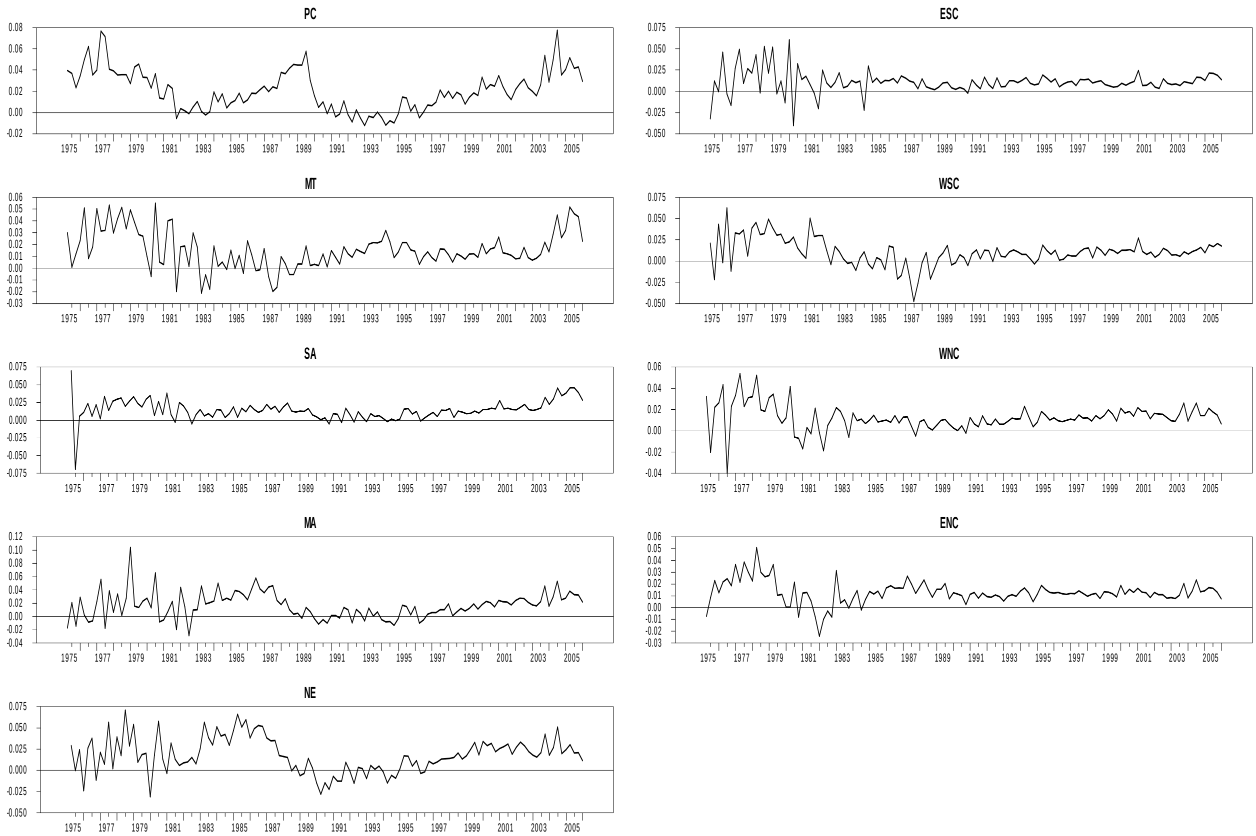

Figure 2.2 Plots of the Differenced House Price Indices, 1975-2006.
Note that the y-axis is differenced house price index in natural logarithm and the x-axis is time in quarters and years, 1975-2006.

period of 1987-1989 in changes of PC and WSC. In addition, from 2003 and on there is slight variability observed in changes of almost all the series, except for WSC and ESC.

The plot of the differenced series can also be an important tool for inspecting the normality of the marginal processes (Juselius, 2006). If the observations lie symmetrically on both sides of the mean, then marginal processes are normal. Most of the series do not seem to have symmetric observations, but rather appear to have some outlier observations emphasized mostly in the first part of the sample. Further, the detailed examination of the possible causes for such outlier observations follows which is highly important for the house price modeling.

The evolution of various events from 1970's to 1980's put the U.S. economy and its various sectors into unstable and severe situation. The first recession for the period of 1970-2006 was due to the first oil crisis which occurred in 1973 (Mishkin, 1987). The first signs of recovery was noticed in the first quarter of 1976, which then was followed by the slow growth rates, unemployment and price rise. Moreover, the trade balance dramatically fell, which was followed by a slight recovery in the fourth quarter of the same year (Supel, 1979). Although the U.S. economy commenced expanding with lower unemployment rate and increasing GDP, the inflation rate continued to increase reaching to double digits. Moreover, the second oil crisis in 1979-1980 seemed to aggravate the economy leading it to the path of another economic recession. The recession affected the nominal and real interest rates, which in turn directly influenced the current as well as the future level of investment. Consequently, Fed announced tight or contractionary monetary policy to ease the economic situation by undertaking anti-inflationary and dollar strengthening programs. As a result, investment purchases decreased until the third quarter of 1980. The recession continued becoming severe when Reagan came to power in 1980. Also as a result of the Volker's policies, recession lasted about two years, in 1980 and 1981, termed as "twin recessions". Both the real interest rate and the U.S. dollar increased sharply (Mishkin, 1987; Kim et al., 2007a). Until about 1981, the inflation rate still remained at double-digits. The international oil price rises, monetary policies and the governmental spending were commonly considered to be the main sources for high inflation in the country.

The two-year severe recession was shortly followed by the two-year robust recovery in 1982. However, it should be mentioned that until 1983, the economy followed an erratic pattern. For example, the slowdown of the GDP growth in 1979 was followed by an actual fall in GDP after the second quarter of 1980. Starting from about 1982, the economy continued growing, inflation and unemployment rates dropped, level of investment increased, pushing the nation into the economic boom. In addition, the law of the largest tax cut in U.S. was signed by Reagan in 1981. Consequently, tax cuts, the increased government purchases and the anti-inflation program put the U.S. economy on the prosperous path from about 1983, which were later termed as the “Reagan Boom”. The economic boom of the early and mid-eighties, however, coincided with a number of alarming developments. Among those, perhaps the most outstanding are the federal tax reform in 1986 and the stock market crash in 1987 (Kim et al., 2007a).

Most of the above mentioned economic events and distresses were reflected in the housing market. Years later a couple of more recessions occurred, however, they did not seem to have any significant impact on the real estate market.[9] Other factors that are worth mentioning due to their direct effect on the housing sector are the emergence of the new institutions, financial system, products, etc. In the evolution of the U.S. housing system, the era of securitization from 1970s to 1980s is very important and coincided with the above mentioned economic events. Due to the increase of interest rates, there

[9] The recession in 1991 and the 2000 recession which was due to the burst of the dot-com-bubble did not have significant influence on the log HPIs.

was duration mismatch of assets and liabilities. This was more crucial for the Savings and Loans (S&L) institutions in 1980s. Consequently, many banking institutions (predominantly S&Ls) defaulted, which then initiated the need for new reforms and laws (Integrated Financial Engineering, Inc., 2006).

All the above discussed events that took place in U.S. from 1970's to 2000's will be incorporated with the appropriate methodological procedures. In addition, the knowledge of the possible outlier observations will be used in the following section which deals with the modeling of the regional house prices.

2.4 Methodology

A list of methodologies is presented here, starting with the background information about the common methodologies that similar studies have used. Then, the cointegration test is described followed by the misspecification tests that are used to ensure the best model is of use. The following subsection details the identification issue and the proposed method of obtaining identification of long-run structure.

The list of the methodologies used to study the housing market has been expanding over time. It already has been two decades since more powerful statistical and/or econometric tools have emerged and been in use by economists in various fields. Cointegration analysis, pioneered by Engle and Granger (1987) and Johansen (1988), has been extensively used for modeling house price determination. Observed spatial pattern in regional house prices directed researchers to consider time-series properties of regional price data. Numerous studies that attempted to include explanatory variables for housing market investigation, had to tolerate the variable selection problem which has been an important empirical issue. The data limitation and the peculiar house price pattern certainly impose restrictions in terms of number of variables in the model. Researchers have sought various ways to approach these limitations. For instance, some used reduced-form approach to identify and estimate appropriate supply and demand variables. This approach however, presumes that housing market is in the steady-state equilibrium (Meese and Wallace, 1993). Another group of researchers specify that equilibrium house prices are implied by fundamental variables (Abraham and Hendershott, 1996). Furthermore, the cointegration approach used by Giussani and Hadjimatheou (1991), MacDonald and Taylor (1993), Alexander and Barrow (1994), Pollakowski and Ray (1997), Meen (1999) enables them to explain the spatial differences in regional house prices. The notion of cointegration is concerned with the long-run relationships among variables or sets of variables. This typically tests if the long-run movement in house price in one region is related to the long-run price changes in another region(s). This study, similar to the above mentioned ones, utilizes the cointegration approach in addition to more recently developed procedures (e.g. DAGs, data-driven identification, and innovation accounting) to examine the long-run relationships of U.S. regional house prices.

2.4.1 Cointegration Tests

Similar to most studies conducting multivariate cointegration tests, this study uses Johansen (1988) procedure. The initial step of statistical analysis starts with the unrestricted vector autoregressive model (VAR). The p-dimensional VAR model of order k with Gaussian errors is expressed by the following equation:

$$Y_t = \alpha + \sum_{i=1}^{k} A_i Y_{t-1} + \varepsilon_t \qquad t = 1,\ldots,125 \tag{2.1}$$

where Y_t is a $px1$ vector of p series with $p = 9$ representing the HPIs for each nine divisions used in this paper. A_i is a (9 x 9) coefficient matrix, α is a 9 x 1 drift vector, ε_t is a (9 x 1) innovation vector which are normal independent identically distributed ($N_p(0,\Omega)$), and the k is the maximum lag length. Fitting the unrestricted VAR model with the k lags does not involve complications; they arise when the necessary assumptions of the underlying model need to be checked. In particular, the lag lengths k needs to be determined, the serial correlation and the conditional heteroskedasticity, as well as the distribution of the errors should be checked (Johansen, 1988, 1991, 1995; Juselius, 2006). More detailed discussion of the misspecification tests is given in the following section.

Since there is no prior information about the cointegration rank, it is determined using the likelihood ratio test or trace test proposed by Johansen (1988, 1991) (Bruggemann et al., 2006). The null hypothesis of the trace test statistics of Johansen (1991) is that there are at most r cointegrating vectors, which in our case is 8, i.e. $r = 0,\ldots,8.$ Furthermore, three cases are possible. First, if the rank of Π is full ($r = p$), then the Y_t is stationary and VAR at levels is appropriate. Second, if the rank is zero ($r = 0$), all series are nonstationary and there is no combination of two or more nonstationary series that is stationary at levels. Hence, VAR at first differences should be used for analyzing dynamic relationships of the series. Finally, if the rank is between zero and full rank, i.e. $0 < r < p$, then the existence of r cointegrating vectors indicates the presence of r linear combinations of the series that make the process stationary. In this case, error-correction model is used (Johansen, 1995, Juselius, 2006). To determine the cointegrating vector r, the trace test results are compared with only two models: the first model includes constant (intercept) in the cointegration relations, and the second model includes the first model in addition to the deterministic trend in levels (outside the cointegration relations). These two models are the best to use for such data. Because there are deterministic variables included in the model, the critical values of Johansen (1996) are no longer valid. For this purpose, the critical values are simulated specifically for our model.[10]

Results of the trace test indicate that the VAR in error-correction form is appropriate to use, thus further analysis are conducted using the vector error correction model (VECM). Juselius (2006) provides several advantages of the ECM formulation. Among those, the multicollinearity effects are significantly reduced in ECM formulation and the distinction between the short-run and the long-run effects is very clear and their interpretations are more intuitive. Error correction model (ECM) can be presented based on VAR component in first differences with the order of k-1:

[10] Note that all the time series analysis are conducted using CATS in RATS software grounded on Dennis, Hansen, Johansen, and Juselius (2006).

$$\Delta Y_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \Pi Y_{t-1} + \varepsilon_t \tag{2.2}$$

$\Pi = \alpha\beta'$ has a reduced rank where α and β are $p \times r$ matrices, $r \leq p$. Here Δ represents the first differences, Γ_i and Π are short-run and long-run coefficient matrices, respectively; μ is a vector of constant or drift, and k is the appropriate number of lags. In addition, ΠY_{t-1} term is the error correction component at levels for $t = 1,\ldots,125$ of total observations in this study. Furthermore, under the hypothesis of nonstationary $I(1)$ processes, cointegrated VAR model is given by:

$$\Delta Y_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \alpha\beta' Y_{t-1} + \varepsilon_t \tag{2.3}$$

where $\beta' Y_{t-1}$ is an $r \times 1$ vector of stationary cointegration relations, where α is the loadings. The importance of Π comes from the fact that its rank determines the number of cointegrating vectors. Hence, alternative formulation of the trace test includes the rank of Π. The null hypothesis of the rank Π is $r = 0$ at 5% significance level which implies that no cointegrating vector exits between the two series. The alternative hypothesis of the rank Π is that $r \geq 1$, indicating that at least one cointegrating vector exists. Depending on the decision, null goes up to $r = 8$.

2.4.2 Misspecification Tests

The model presented above is the basic one, assuming that the model is well specified. However, real world examples oftentimes have one or more specification problems. The importance of misspecification analysis of the model comes from the fact that a study might fail to convey reliable implications, thus the results may not be fully trusted. Hence, a thorough examination of the data and the model is critical.

The descriptive statistics on HPI for each division are presented in Table 2.1. New England appears to have the highest mean HPI, followed by the Middle Atlantic and Pacific. It is interesting to note also that these three divisions have the most volatile HPIs. On the contrary, West South Central has the lowest mean HPI as well as standard deviation. Furthermore, to avoid spurious results, all the nine series were tested for stationarity condition. Series are stationary if their mean and the variance are stable over time. According to Figures 2.1 and 2.2, all the nine series exhibit unit root or nonstationary pattern. Several techniques are known in the literature to overcome the nonstationarity problem in levels and one of the most commonly used and easy method is differencing the series until they are stationary (Engle and Granger, 1987; Johansen, 1988; Juselius, 2006). In this paper, we conduct Dickey-Fuller test of stationarity, the results of which are reported in Table 2.2.[11] Series are nonstationary at levels and stationary at the first difference, thus to sustain stationarity, all of the nine series are first differenced. In other words, all the series are integrated of order one, i.e. $I(1)$. Hence, cointegration analysis can be conducted.

As suggested by Juselius (2006), every assumption is based on the presumption that others are satisfied. For example, to check for normality of the series, it is assumed

[11] However, because Dickey-Fuller test of stationarity is proven to have low power, other tests such as Phillips and Perron, KPSS, and ADF have conducted for robustness purposes (DeJong et al., 1990; Diebold and Rudebusch, 1990; Kwiatkowski, Phillips, Schmidt, and Shin, 1992; MacDonald and Taylor, 1993; Hansen, 1994; Johansen, 1988; so on). The results of these tests are not reported but are available upon the request from authors. Note that the conclusions of the stationarity tests are the same regardless of the test used.

Table 2.1 Descriptive Statistics on House Price Indices for Nine U.S. Census Regions, 1975-2006

Census Regions (House Price Index)	Mean (Price Index)	Mean Rank	Min. (Price Index)	Max. (Price Index)	SD (Price Index)	SD Rank	CV	CV Rank	Skewness	Kurtosis
PC	5.1365	3	3.7675	6.3542	0.5897	2	0.1148	1	-0.2970	-0.2668
MT	4.9615	6	3.9845	5.8923	0.4428	4	0.0892	4	-0.1368	-0.3109
SA	5.0555	4	4.2138	6.0113	0.4384	5	0.0867	6	-0.1017	-0.5272
MA	5.2429	2	4.2299	6.2524	0.5434	3	0.1036	3	-0.3768	-0.8368
NE	5.3778	1	4.2103	6.4424	0.6062	1	0.1127	2	-0.3930	-0.8081
ESC	4.9486	7	4.2101	5.6074	0.3717	8	0.0751	8	-0.1743	-0.8599
WSC	4.8144	9	4.0635	5.3625	0.2966	9	0.0616	9	-0.6463	0.4705
WNC	4.9344	8	4.1551	5.6951	0.3901	7	0.0790	7	0.0707	-0.6229
ENC	4.9960	5	4.1537	5.7569	0.4379	6	0.0877	5	-0.0558	-1.0165

Note: HPIs are in logarithms. The “Mean” labeled column is the simple mean price index for census divisions listed on the far left-hand-most column of each row over the observation period 1975:1 – 2006:1. The columns labeled “Min” and “Max” refer to the minimum and maximum numbers for the far left-hand-most column over the period mentioned above. The column headed “SD” shows the standard deviation of each divisions’ house price index over the observed time period. Entries in the column labeled “CV” refer to the coefficient of variation, which is SD/Mean for each division. The table also provides the ranks on mean, standard deviation, and coefficient of variation respectively for the far left-hand-most column. In the rankings, the order is from 1 to 9, “1” being the highest value and “9” being the least one.

Table 2.2 Dickey-Fuller Test Results of House Price Indices of Each Nine U.S. Census Division, 1975-2006

Series	Number of Differences	DF test
PC	1	-4.163
MT	1	-6.426
SA	1	-5.307
MA	1	-7.907
NE	1	-5.343
ESC	1	-14.443
WSC	1	-5.329
WNC	1	-7.371
ENC	1	-6.120

Note: This table shows the results of Dickey-Fuller test of non-stationarity. The first column labeled “Series” shows the logarithmic transformation of the HPI series, the second column labeled “Number of Differences” is the number of differences needed to make the data stationary. Finally, the last column labeled “DF-test” gives the Dickey-Fuller test value. All the values are significant at 5% and 10% significance levels.

that every other assumption of the underlying model is satisfied. Hence, specification tests have to be performed after each assumption is checked for to confirm that the rest is unchanged (Juselius, 2006). The maximum number of lags (k) is estimated using the Schwartz Loss (SIC) and Hannan and Quinn (HQ) loss matrices. Given the small sample size of 125 and VAR of 9 (p) dimension, the maximum lag length is restricted to be 5.

The results, which are reported in Table 2.3, are somewhat odd. VAR with one lag is suggested by the SIC, while HQ metrics results in optimal lag length of 5.[12] Sometimes when the results of the information criteria do not match and large lag length is found to be optimal by one of the measures, there is a possibility that it is not correctly determined due to some specification problems such as outlier observations and mean shifts (Juselius, 2006). Hence, we initially start with a VAR of order two.

Table 2.3 Lag Length Selection Tests

Model	K	T	Regr	Log-Lik	SC	H-Q	LM(1)	LM(k)
VAR(5)	5	120	46	5750.242	-79.321	-85.032	0.000	0.090
VAR(4)	4	120	37	5565.389	-79.471	-84.065	0.000	0.060
VAR(3)	3	120	28	5378.156	-79.582	-83.059	0.000	0.000
VAR(2)	2	120	19	5263.055	-80.895	-83.254	0.000	0.000
VAR(1)	1	120	10	5121.032	-81.760	-83.002	0.000	0.000

Note: The table gives five different criteria for selecting a lag length of the VAR model. The far-left-most column, “Model”, is the VAR model at different lags. The following column gives the number of lags in the model (“K”). The third column (“T”) is the number of observations. The fourth column (“Regr”) is the number of parameters to be estimated. The lag length selection criteria starts with the fifth column (“Log-Lik”) which is the log-likelihood ratio of the VAR with k lags (at each row k is a different lag), which is maximized. The next column is the Schwartz Information Criteria (“SC”) which is minimized. The following column is the Hannan and Quinns Information Criteria (“HQ”) which is also minimized. The last two far-most-right columns (“LM(1)” and “LM(k)”) are the Lagrange multiplier values for one and k lags.

[12] Different lag lengths with a variety of deterministic components, such as seasonal dummy variables, constant, drift, and dummy variables for outliers, have been used. However, the results of the lag length have remained unchanged except for the case when we used maximum lag length of 6 and more. In those cases, the largest lag is found to be optimal by HQ loss metrics. These results are not reported, but available upon request from author.

Generally, for time series data a list of misspecification tests are of importance and need to be checked. Univariate misspecification tests include the normality test for each series using Jarque-Bera test and the ARCH effect of each series for autoregressive conditional heteroskedasticity. In addition, the first four moments are also highly important to find the source of the problem, if any. Multivariate tests, on the other hand, include the LM test for residual autocorrelation, Ljung-Box test for correlation, and Doornik and Hansen (1994) test for normality of all the series.

Table 2.4 provides the results of the misspecification tests for an unrestricted VAR(2). The multivariate tests for normality and residual autocorrelation are rejected at even 10% significance level. On the other hand, univariate test for normality is not rejected for the MT, SA, and NE regions at 5% significance level. This might be due to the moderate skewness and kurtosis for these series. Most series, except for the MT and ESC, pass the ARCH test at least at 10% significance level. The R^2 for each equation (i.e. $\Delta PC, \Delta MT, \ldots, \Delta ENC$) is not high. However, the R^2 values are misleading and should not be subject to much emphasize when it is calculated for the unrestricted VAR in levels. Similarly, the overall measure of goodness of fit in the VAR model is given by the trace correlation statistic which is not significantly high. It can be approximately considered as an average R^2 in the p VAR equations (Juselius, 2006). Overall, the model is not well specified and from the skewness and kurtosis it can be concluded that there are large residuals. In addition, graphical inspection of both the level and the

Table 2.4 Misspecification Tests Based on the Unrestricted VAR (2)

Trace Correlation	0.53								
Log(|Ω|)	-86.79								
Multivariate Tests									
Residual Autocorrelation									
	LM(1):	$X^2(81)$		218.3		p-val.		0.00	
	LM(4):	$X^2(81)$		169.7		p-val.		0.00	
Normality									
	LM:	$X^2(81)$		197.9		p-val.		0.00	
Univariate Tests									
	ΔPC	ΔMT	ΔSA	ΔMA	ΔNE	ΔESC	ΔWSC	ΔWNC	ΔENC
ARCH(2)	0.89	17.86	8.25	1.67	5.72	14.67	4.04	2.72	1.67
p-value	0.64	0.00	0.02	0.43	0.06	0.00	0.13	0.26	0.44
Normality	15.91	4.02	1.28	31.29	4.98	15.43	15.90	31.22	14.29
p-value	0.00	0.13	0.53	0.00	0.08	0.00	0.00	0.00	0.00
Skewness	0.95	-0.21	-0.15	1.35	-0.43	-0.56	0.41	-0.52	0.74
Kurtosis	5.33	3.65	3.21	8.87	3.70	5.07	4.94	6.25	5.15
Std. Deviation	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
R^2	0.76	0.47	0.68	0.56	0.71	0.38	0.63	0.55	0.58

Note: The table provides the results of Equation 2.1. Specifically, it gives the results of unrestricted VAR model with 2 lags.

differenced data reveals that series have seasonal and trending patterns.[13] This may also create some specification problems. Hence, detrending and seasonal adjustment procedures are performed on all the series (Harvey and Trimbur, 2003). It is known that each series are composed of seasonal factor, trend-cycle, and the irregular component.

[13] Juslieus (2006) suggests that graphical analysis for the specification checking is highly recommended and even might reveal specification problems that tests fail to find.

Multiplicative model with the seasonal span of four and linear trend is calculated and extracted leaving only the irregular component in the series.[14]

The new series (detrended and seasonally adjusted) are well-behaved without rough spikes. Consequently, VAR is re-estimated using the new dataset. The misspecification tests using the new, corrected series show huge improvement in terms of the problems that were present before. However, the problem with the residual autocorrelation and normality still exist. Further analyses provide evidence of large residuals which need to be carefully considered given their importance to the econometric results.

Usually, residuals larger than $|3.3\sigma_{\varepsilon}|-|3.5\sigma_{\varepsilon}|$ should be treated with care since they indicate possible outlier observations (Juselius and MacDonald, 2004; Juselius, 2006). The residuals of most series are relatively large at the beginning of the sample period. Given the U.S. economy at the time, the high residuals are quite intuitive indicating that some sort of intervention took place. For example, the rising inflation rate perhaps accounts for the pre-recession shock in the WNC at 1977:01 that caused the residuals to exceed $|3.5\sigma_{\varepsilon}|$. Other series, except for PC, MT, SA, and NE also appear to fluctuate greatly perhaps as a result of the inflation rate changes. The announcement of the tight monetary policy by the Fed appears to have had its effect on the housing market. Furthermore, the lagged effect of the monetary policy and the twin recessions influenced housing market as well, with more pronounced effect on MA in 1980:1 and

[14] The classical decomposition of the series, say PC, into a trend-cycle (TC), seasonal (S) and irregular (I) components can be modeled either as additive (PC=TC+S+I) or multiplicative (PC=TC×S×I). The later model is used in this paper because the seasonality of the series seems to increase with the trend. @classicalDecomp procedure in RATS does this type of decompositions.

WNC in 1980:04. Furthermore, a large residual is observed in the ENC series for the date of 1985:03. Unlike most other shocks, this shock does not appear to be intuitive since it does not coincide with any major events either in U.S. economy as a whole or the housing sector. The large residual in the MT series in 1986:04 and 1987:01 is explained by the federal tax reforms and perhaps the conditions that later caused the stock market crash (Kim et al., 2007a). The final observation of abnormal residuals is for PC in 2004:1. Volatile residuals for most of the series were observed during the period of 2004-2006. In fact, late 2005 and the beginning of 2006 was actually the start of the housing market slowdown. Very large residuals are detected for most series at this time, therefore these two observations (i.e. 2006:01 and 2005:04) are not used. Certainly, these dates are highly informative of the housing sector, however, the loss (arising specification problems) from including the observations for those dates outweighs the gain. Hence, the further analysis proceed with 123 observation rather than 125.

It is common to consider the observations with large residuals as outlying observations. Outliers can seriously distort the autocorrelation structure of the time series (Chernick et al., 1982). If the outliers are ignored and left in the time series they may seriously bias the autocorrelation function (ACF) and partial autocorrelation function (PACF) of series (Mills and Prasad, 1992). In practice, it is common to treat outlying observations to be the results of intervention, structural break, etc. Thus, to overcome the outlier problems, the addition of the dummy variables in the model is very common. However, one needs to be careful about the type of outliers since each type of outlier should be treated differently. For example the additive outliers should be corrected for before proceeding with any analysis. On the other hand, the transitory and the permanent outliers need to be included in the model due to the important information they convey.[15]

Outlier observations are corrected with the addition of the seven dummy variables in the VAR model. Permanent blip dummies, which take a value of 1 on the date of shock and 0 otherwise, are added for the following observations: 1980:04, 1985:03, and 2004:01. In the case of +/- effect of the residuals which has a dynamic effect on the later observations, transitory dummy variable is used. Hence, transitory dummy variables, that take a value of 1 on the shock date, -1 for the next observation, and 0 otherwise, are set for 1977:01 and 1980:01 observations. Further, a dummy variable that takes a value of 1 on two consecutive dates is included for 1986:04. The difference of the last dummy variable is also included due to its importance for the shock and the model. All of them are included as restricted deterministic components in the VECM.

Although the misspecification tests may improve with the inclusion of the dummy variables and suggest the goodness of the model, the parameters of the model can still suffer from non-constancy. Various methods (tests) are used in this paper to tackle the parameter constancy problem thoroughly. Both backward and forward recursive tests are conducted, each of which is useful for testing different time periods of the entire sample. The main purpose of these tests is to find out if the sample period of 1975-2006 is appropriate for analysis or if there is any structural change that suggests

[15] More detailed information about the outliers, their detection, type, and the ways of fixing them see Franses and Lucas (1997), Nielsen (2004), Juselius (2006).

the model needs to be re-specified for the sample period, perhaps partitioning it into several sub-periods. All the following tests performed here are recursive meaning that the models are first estimated for sub-sample of 1 to T1, then increasing the unit period until it covers the full sample, whereas in case of backward recursion, the models are estimated first for the subsample of T to T1, then increasing the unit period until it covers the beginning of the sample (full sample). These procedures are fully covered in Hansen and Johansen (1999) and Juselius (2006).

There is some evidence of parameter instability, however, the time range the parameters are the most volatile is the beginning of the sample which coincides with the high inflation rates, tight monetary policy, twin recessions, oil shocks, etc. In other words, it is somewhat expected even looking at the plot of the differenced series. The significance and the importance of these shift dummies are further tested to get the best and the most parsimonious model. It is common practice to partition the sample into two (if there is one structural break) sub-samples and estimated each subsample separately (Hansen and Johansen, 1999). However, the small sample size puts restrictions on the estimation methods. Therefore, it is not optimal to partition the sample into various parts to account for the structural breaks. The next popular method of dealing with the parameter non-constancy is by the use of dummy variables, particularly shift dummies (Juselius, 2006). Consequently, shift dummies are included in the model. Interestingly, the goodness of the model and the parameters did not change much with the shift dummies either each separately or combined.[16] Hence, insignificance of the shift dummies leads to considering the model with no shift dummy variables.

Reconciling all the above changes, the VAR(k) model in ECM form is now given by:

$$\Delta Y_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \alpha\beta' Y_{t-1} + \Phi D_t + \varepsilon_t \qquad t = 1,\ldots,123 \qquad (2.4)$$

The model has the same specification as Equation (2.3) with the only addition of the vector of dummy variables (D_t); Φ is the vector of coefficients for the dummy variables. The estimated model is then checked for the validity of the underlying assumptions. A clear improvement in terms of univariate normality, the trace correlation (goodness of fit of the model), and standard deviations is revealed. Although the multivariate normality statistics, ARCH statistics, and LM(1) and LM(k) values are greatly reduced, the null hypothesis for these tests is still rejected. Hence, there are a few specification issues remaining in the model.

It is well evidenced that small sample size will likely cause the series to deviate from normality assumption, which further will cause some additional problems with respect to residual autocorrelation, ARCH, etc. Hence, some misspecification in the model is not considered to be unusual given the limited sample size and large dimension (Franses and Haldrup, 1994; Bruggemann et al., 2006; Juselius, 2006). Consequently, model in Equation (2.4) does seem to be acceptable given the limited sample size and the number of parameters to be estimated.

[16] The results with shift dummies are not reported in this paper.

Cointegration analysis is conducted to shed light on the long-run relations that may exist among the nine series. Some authors suggest that the unrestricted VAR has to be well specified before estimating the restricted VECM, while others claim that the model will be well specified after the estimation of the reduced form. The proponent of the first approach is Juselius (2006), who proposes to test for cointegration once the model is well specified. On the other hand, it has been suggested that some of the misspecification problems that prevail should be checked again after the determination of the correct cointegration rank. In other words, reduced form model has to be checked again for specification issues (Juselius, 2006; Bruggemann et al., 2006). However, one needs to be cautious regarding the model check due to the small sample size distortions.

Johansen's trace test is used to determine the number of common cointegrating relations in the model. Although the trace test has been criticized for not accounting for the small sample size and deterministic components, the corrected version of trace test is "Bartlett corrected" for small samples and accounts for deterministic components added to the model.[17] To calculate the corrected version of the trace test, we simulated the critical values for 2000 replications and length of the random walks of 123 (i.e. number of observations used). The importance of simulation comes from the fact that small samples usually tend to deviate from the normality assumption and asymptotic distribution does not seem to hold for small samples. Hence, the corrections are vital for

[17] See Johansen (2000, 2002) and Juselius (2006) for more details about Bartlett correction and the trace test for more sophisticated models.

correct results. The results of trace test are reported in Table 2.5. It can be seen that the difference between the corrected and not corrected tests is enormous. Without Bartlett correction for small samples and the deterministic components, the rank of 8 would have been accepted at 4.5% significance level, while with Bartlett correction the rank of 4 is accepted at even 1% significance level. Thus, the small sample size distortion and the inclusion of the deterministic component could mask the true long-run relations among the series.

After the determination of the cointegration rank, the tests of long-run exclusion of a variable (i.e. a zero row restriction on β), unit vector of alpha for a variable, and the weak exogenity of a variable (i.e. a zero row restriction on α) are conducted which later will have bearings on the identification of the model. The results indicate that none of the variables are weakly exogenous which implies that in short-run all of them respond to the perturbations in long-run relations. Unit vector test is rejected for all the variables

Table 2.5 Trace Test Results

Decision	p-r	R	Eig. Value	Trace	Frac95	P-value	Trace*	P-value*
F/F*	9	0	0.781	536.974	189.418	0.000	271.730	0.000
F/F*	8	1	0.560	356.492	155.041	0.000	188.928	0.000
F/F*	7	2	0.499	258.926	124.951	0.000	128.037	0.032
F/F*	6	3	0.413	176.577	96.621	0.000	101.808	0.020
F/R*	5	4	0.248	113.117	72.605	0.000	54.439	0.524
F/R*	4	5	0.242	79.132	50.450	0.000	38.527	0.412
F/R*	3	6	0.161	46.172	33.022	0.001	18.571	0.715
F/R*	2	7	0.129	25.348	18.588	0.004	11.758	0.402
R/R*	1	8	0.073	8.961	8.730	0.045	5.891	0.180

Note: * represents the Barlett corrected trace test which accounts for the small sample size and the inclusion of the dummy (deterministic) component. The trace test is accepted at >5% significance level for the Barlett-corrected trace test, while it is only boarder line accepted (4.5%) for the traditional, not-corrected trace test.

as well. On the other hand, the result of the long-run exclusion test suggests that MT is not included in the cointegration space. Therefore, it should be omitted from the cointegration space and from the long-run relations at 5% and higher significance levels. This information is further used to test various restrictions. The test of restriction given the hypothesis that MT should be omitted from the cointegration relations for

$$Y_t^{'} = [PC_t \quad MT_t \quad SA_t \quad MA_t \quad NE_t \quad ESC_t \quad WSC_t \quad WNC_t \quad ENC_t]$$

is given by: $H_1 : \beta^r = H\varphi \quad or \quad R'\beta = 0$. Although the hypothesis of four zero restrictions on the MT is accepted with the p-value of 0.24, the model is not identified. Thus, as mentioned in Juselius (2006), completely omitting the MT series will affect the long-run identification negatively.

Various restrictions that are either suggested by the data (using the DAG), model (significance levels), or by the tests (such as long-run exclusion) are investigated. The following section will shed light on the identification problem and the proposed method using DAG which is discussed next.

2.4.3 Identification

The issue of identification is central for the complete understanding of economic models. Unique identification is necessary for estimation and interpretation of the parameters of the dynamics of the system of the vector autoregressive model. Alternatively stated, the reduced form model with correlated innovations has to be transformed into a structural form with uncorrelated, economically interpretable shocks. This problem is especially pronounced in the case of non-stationary data (variables) that allows us to formulate two separate identification problems: identification of the long-run (cointegration relations) and short-run (equations of systems) structures. The identification of the long-run structure imposes long-run economic structure on the unrestricted cointegration relations, whereas the identification of the short-run structure imposes short-run dynamic adjustment structure on the equations for the differenced process (Johansen, 1991, 1995; Juselius, 2006).

Cointegrated VAR model both in reduced-form and the structural form can be used for analyzing the long-run structure. The reduced form cointegrated VAR is used in this paper, which eliminates the worries about the identification of the short-run structure as its parameters are uniquely defined in this case. Although the long-run parameters are also uniquely defined based on the normalization of the eigenvalue problem, just-identifying restrictions on the long-run structure are necessary.

Three different aspects of identification is acknowledged which are the generic identification (statistical model), empirical identification (parameter significance), and the economic identification (Johansen and Juselius, 1994). The first two conditions are satisfied if one follows the correct steps of model estimation, while the last condition is much more complicated. For example, if one examines a micro or macroeconomic problem, theory and the existing literature is almost always used for identification of the long-run and short-run structures. The problem arises when research involves either something absolutely new for which there is no set theory or dynamic relationships (linkages) among certain variables for which no formal theory exists.[18] Hence, the

[18] Brief history of the identification problem is well introduced by Lack and Lenz (1999).

achieved identification is not based on solid economic or econometric arguments (Lack and Lenz, 2005). In this paper we offer a new method for long-run identification by utilizing the causal structure which is a direct result of the DAG.

The DAG, discussed in the next section, is used to obtain the causal structure among the variables. The graph along with the results of the test for exclusion is used to get just-identifying restrictions on the long-run structure. The DAG without MT (excluded) confirms the above findings of four cointegrating vectors. Moreover, it provides important information as to what are the cointegrating relations and which variables are included in it. The four major divisions (Figure 2.3) which have arrowheads directed to them are the four cointegrating relations where only the regions that cause these four regions are included in the model and the others are restricted in the long-run structure. As a result, the long-run system has the following form[19]

$$\beta' X_{t-1} = \begin{bmatrix} \beta_{11} & 0 & \beta_{13} & 0 & \beta_{15} & 0 & 0 & 0 & \beta_{19} & \beta_{01} \\ \beta_{21} & 0 & 0 & 0 & 0 & 0 & \beta_{17} & 0 & \beta_{19} & \beta_{02} \\ 0 & 0 & 0 & \beta_{34} & \beta_{35} & 0 & 0 & \beta_{38} & 0 & \beta_{03} \\ 0 & 0 & 0 & 0 & \beta_{45} & \beta_{46} & \beta_{47} & \beta_{48} & \beta_{49} & \beta_{04} \end{bmatrix} \begin{bmatrix} PC_{t-1} \\ MT_{t-1} \\ SA_{t-1} \\ MA_{t-1} \\ NE_{t-1} \\ ESC_{t-1} \\ WSC_{t-1} \\ WNC_{t-1} \\ ENC_{t-1} \\ 1 \end{bmatrix}$$

[19] Note that in the third relation which corresponds to the ESC equation on the graph, the effect of MA is not accounted for because its innovation is transferred to ESC via NE. Hence, NE is included but not the MA.

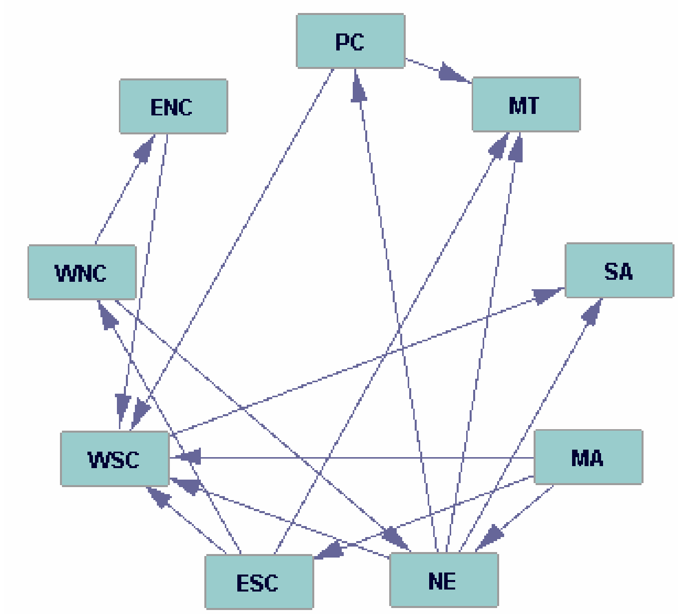

Figure 2.3 Directed Acyclic Graph with the Knowledge Tier for the Causality Purposes.

The restriction is just-identifying and model is accepted with $X^2(9) = 16.389$ and $p - value = 0.059$. The first three relations are invariant to MT inclusion, and only the fourth relation is altered due to MT. Therefore, the confidence of the first three relations to achieve long-run identification is very high due to its robustness. Conversely, the last relation is dependent upon the test of exclusion (i.e. MT exclusion) which is why confidence of the last relation as identifying is limited. However, even in this case the contribution of the DAG to the identification issue is enormous. Unlike the automated identification available from CATS in RATS which is not based on data inferences or economic theory, the identification procedure proposed in this paper bases completely on the observed innovations among the variables, data, and model inferences using the causal structure. This is especially useful when the supporting economic theory is incomplete or non-existent. The description and application of DAG in impulse response functions is presented next.

2.4.4 Directed Acyclic Graphs (DAG)

In real estate literature that focuses primarily on the dynamic interrelations of regional house prices, no study has ever used the Directed Acyclic Graphs (DAG). This paper employs DAG to investigate the contemporaneous causal relationships among innovations of the nine series. In addition, its importance for price discovery implications which is later discussed and the above mentioned identification issues is inevitable. Besides its importance in model identification, DAG is also highly important in VAR-type innovation accounting as it enables us to assign the contemporaneous causal ordering of the variables based on the data. Hence, instead of randomly choosing the causal pattern, data-inferred pattern can be used and justified through DAG when studying the dynamics of the system.

The orthogonality among the innovations is very important for VAR. Furthermore, modeling the contemporaneous causal relationship among innovations is vital for the accuracy and consistency of the innovation accounting. Early papers tend to use Choleski factorization of contemporaneous covariance to find the orthogonalized innovations. Another approach, which relaxes the Cholesky ordering, is used by Bernanke (1986). The Bernanke factorization puts “over-identified” restrictions based on the existing theoretical information related to the variables. Recently, a more sophisticated DAG approach is being used which is based on the observed innovations among the variables. This approach has been used for innovation accounting from VAR which provides data-based ordering of the innovations (Bessler and Akleman, 1998; Hoover, 2005; Kim et al., 2007a).

A directed graph is a graphical representation of causal relationship among a set of vertices (for this paper - among innovations from the VECM).[20] There are three possibilities that the lines and the arrowheads between the variables can be arranged. First, it is the unidirectional causal flow such as A→B, which indicates that variable A causes variable B. Second, it is the undetermined causal direction, A − B, which means that there is some relationship between A and B, however, the direction of the causation is undetermined. Finally the third, in which case there is bidirectional causation presented as A ↔ B implying that A causes B and B causes A. If this happens, most likely there is an omitted variable between A and B.

The direction of the causal flows among the variables is assigned using D-separation which formally represents the screening-off phenomenon (Pearl, 2000). Among three variables A, B, and C the following causal patterns can be formed. "Causal fork" is formed as $A \leftarrow B \rightarrow C$, where B is the common cause of A and C, thus the measure of unconditional association between A and C is non-zero. However, the association between A and C will be zero if B is conditioned on. Another causal pattern, which is observationally equivalent to the causal fork, is the "causal chain": $A \rightarrow B \rightarrow C$. Similar to the case of causal fork, the unconditional association between A and C is non-

[20] This paper will introduce the DAG in a simple and concise way, but for readers who are motivated to read about the DAG more detailed, we refer them to Spirtes et al. (1993), Pearl (2000), Bessler and Yang (2003) and Kim et al. (2007). The latter articles explore the DAG in economics field and motivate its applications in applied economics.

zero, while it becomes zero as one conditions on B. In both cases, variable B screens-off the association between the two end variables. Finally, the last causal pattern called "causal inverted fork" is given by $A \rightarrow B \leftarrow C$ and is observationally different from the above two cases. In this case, the unconditional association between the two end variables is zero, while if we condition on the common effect B, the association becomes non-zero. The common effect B does not screen-off the association between its common causes.

The GES algorithm is used to assign causal flows among a set of variables using the covariance of innovations. Alternatively stated, the algorithm builds directed graph. Notice that directed graph, or more precisely the directed acyclic graph does not allow causal flows among the variables such that the variable that causes another one will eventually be caused indirectly by its own cause (i.e. acyclic graph can contain only one of each variables). It starts with the DAG with no edges. Furthermore, the addition of edges one-by-one with all possible directions is evaluated using the Bayesian scoring function. As a result, causal structure that obtains the maximum Bayesian score is chosen. It is important to note that only the acyclic causal structures are considered.[21] The advantage of this algorithm is the independence of the final causal structure from the significance level, while the drawback is exponentially increasing models to consider when there are many variables. However, the TETRAD IV software which is used to estimate the GES algorithm simplifies the matter.[22]

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[21] For more information about the GES algorithm, see Chickering (2002).
[22] The web site of Carnegie-Melon University, Philosophy department provides free TETRAD IV software (http://www.phil.cmu.edu/projects/tetrad/).

The complete correlation matrix resulting from the just-identifying model is fed into TETRAD to obtain the contemporaneous causal structure among the nine U.S. census divisions. Given the results of the exclusion test and the negligible role of MT in the U.S. housing market, a tier (knowledge) is added which restricts the MT to cause any other region contemporaneously. The resulting graph in DAG pattern illustrates how the U.S. regions interact with each other instantaneously. Further, the results of it have bearing on the dynamic structure of the overall system. Afterwards, due to the relative limitation of coefficient interpretation from the reduced form (just-identified) model, the innovation accounting is utilized (Bessler and Yang, 2003). It facilitates the interpretation and summary of the dynamic relationship between regional house prices using the findings of the above mentioned procedures (i.e. just-identified model and DAG).

2.5 Results

The above estimated just-identified model and the DAG facilitate the calculation of the innovation accounting. Particularly, the impulse response function and the forecast error variance decomposition are used to shed light on the dynamics of the U.S. housing market. The role of the DAG in directing the causal flows among the series contemporaneously and the further use in the innovation accounting is fully elaborated.

The results from the DAG with MT and a tier which is provided in Figure 2.3 and DAG without MT (Figure 2.4) differ slightly boosting the confidence in the

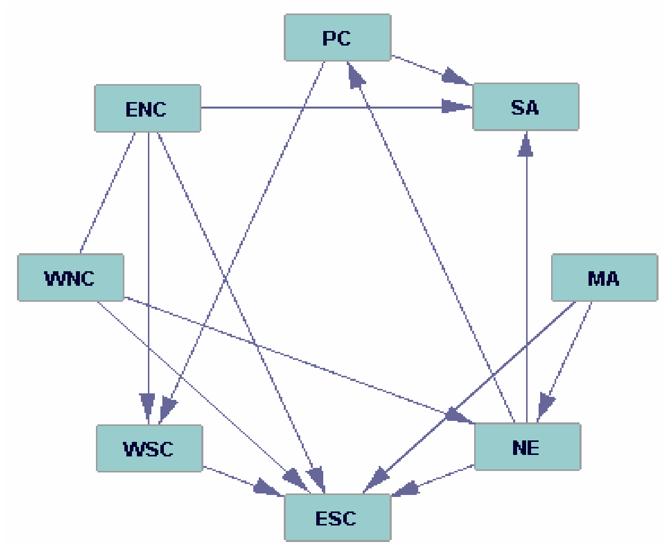

Figure 2.4 Directed Acyclic Graph with MT Excluded for Identification Purposes.

resulting causal structure. The robust orderings of causal flows show how the house price innovations of certain census divisions cause house price changes in others. Among the robust causal structures is the contemporaneous causal effect of NE on PC, MA and WNC on NE, NE on SA, MA on ESC, PC and ENC on WSC. Hereafter, the DAG with MT and a tier will be used for interpreting the instantaneous causal ordering. The MA appears to be the only exogenous region at contemporaneous time. Hence, shocks arising in this region are transmitted into other regions affecting their housing markets by changing the house prices. The exogenity of the MA is expected due to its importance in both economic and financial sectors in the nation. All the states included in MA, New York, New Jersey, and Pennsylvania, have very important roles and do affect the dynamics of the national economy. Consequently, the finding of MA being the source of house prices changes in the U.S. is consistent with its role in the overall economy. While the exogenity of MA is expected due to the high house prices and the leading role of the region in the overall economy, it is very surprising to find that NE and PC are not exogenous in the short run. This is perhaps due to the fact, that in the short run a region affecting house prices in other regions is not intuitive given that the housing market cycle is over 6-8 years (Rosenthal, 1986, Alexander and Barrow, 1994, Pollakowski and Ray, 1997).

The housing prices in SA, WSC, and MT are completely influenced by other regions' house price shocks. In other words, they are information "sinks" in the U.S. regional housing market. The insignificant role of MT can be explained by the fact that it has very negligible influence in the overall economy, although some of the states included in the region are somewhat important in agricultural sector. The explanation of the WSC which is somewhat logical as house prices in those states (thus in the region overall) are lower relative to the national average and the growth has not been outstanding. Conversely, it would be more logical to see SA, which includes states that have very high house prices (such as Washington D.C., Virginia, Florida, North Carolina, etc) and high growth, as an important player in the housing marker rather than as information "sink". Other regions that extensively take part in transmitting the received shocks to the other regions include PC, NE, ESC, WNC, and ENC. While the results might be somewhat debatable regarding to the importance of PC and NE, they are more intuitive with respect to the WNC, ENC, and ESC as house price shock transmitters.

Overall, the results based on the DAG are generally intuitive and are used in ordering of causal flows for the VAR-type innovation accounting. It provides the user imputed causal ordering among the variables in Bernanke decomposition which further provides impulse response functions and the forecast error variance decompositions. The later two help to summarize the structural form of the model. The impulse response function describes the in-sample effect of a typical shock to the system and can be used to economically interpret the behavior of the system (Lack and Lenz, 1999). Figure 2.5 presents the impulse response functions for one-time-only positive shocks in information from house prices in each U.S. region. In each graph, the vertical axis represents the standardized responses with the range of -5 to +12. The horizontal axis, on the other hand, represents time periods (in quarters) following the information shock. In each graph we use maximum of 35 quarters (eight years and 3 quarters). Note that Figure 2.5 does not intend to explicitly show the numbers of each axis, instead, the purpose for reporting the figures is to show the pattern of the curves.

Large negative responses are generated by most regions due to the innovations in the ENC house price. The responses become more negative with the time horizon and the adjustment process back to equilibrium appears to be very slow. On the contrary, innovations in house price of WNC and NE generate large positive responses which adjust very slowly as well. Similarly, innovations in ESC house prices generate large positive responses in house prices of all other regions except for the MT and SA which tend to respond by small positive changes with shorter adjustment periods. It is interesting to note that the responses to shocks in MA are mostly positive at the shorter horizons (in short-run), becoming negative at intermediate and longer time periods, with exception of MT that does not respond and the SA which responds positively for the

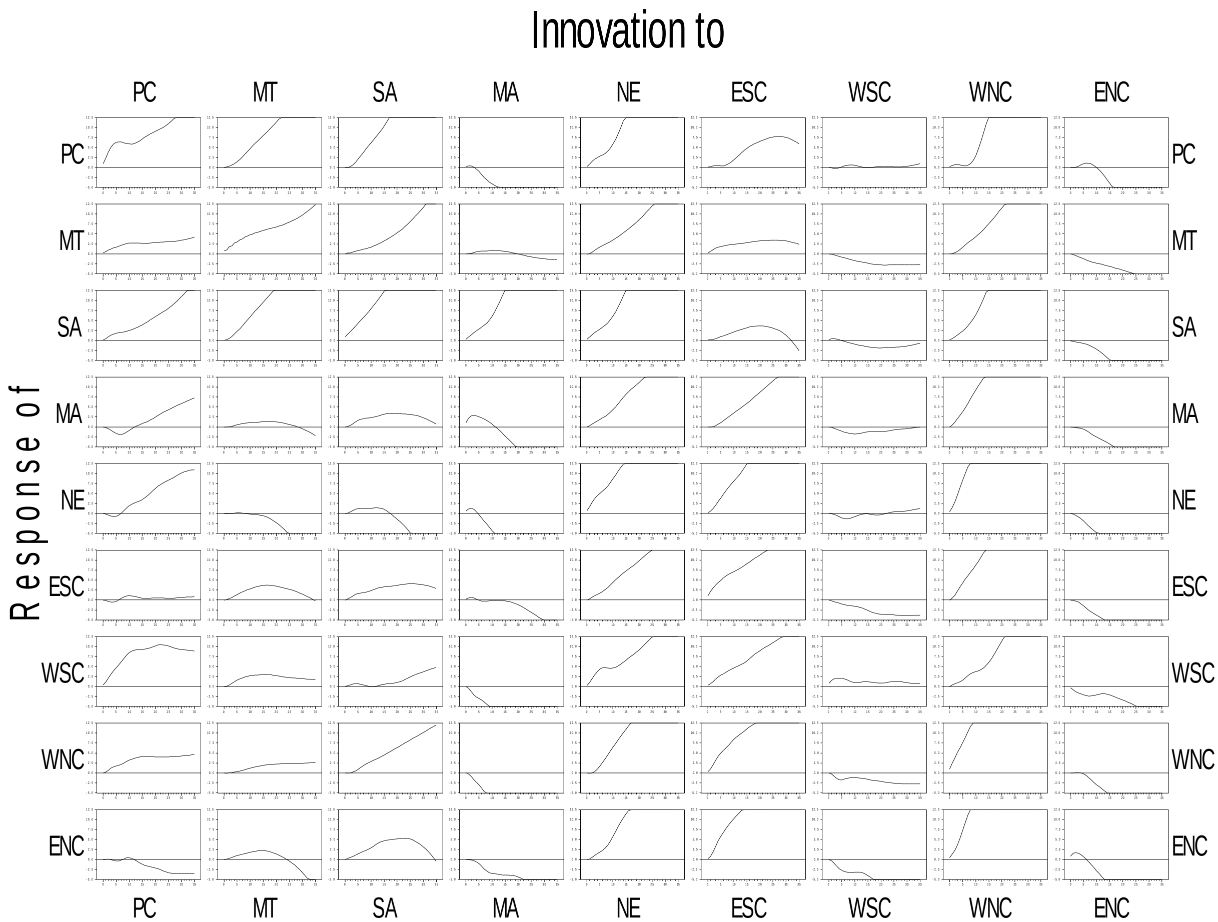

Figure 2.5 Impulse Response Functions for the U.S. Regional House Prices.

whole period of analysis. With some exceptions, moderate positive responses are originated in house prices series of all the regions due to the shocks in PC, MT, and SA. However, in some cases insignificant responses outweigh the significant ones (i.e. innovations in SA). Lastly, the DAG-based insignificance of the WSC is also confirmed by observing the impulse response functions where shocks in WSC generate nearly no response in the U.S. housing market.

Overall, it can be seen that innovations in most house price series generate quite volatile responses from other regions. The adjustment back to equilibrium for most cases is slow. It can be concluded from the impulse response function that the house prices in WSC appear to be the least influential generating the least responses from other series followed by the SA and MT. On the other hand, the WNC and NE generate the largest positive responses in other regions with slow adjustment periods. The opposite applies to ENC and MA which have similar rate of adjustment but negative responses.

Although the impulse response function gives good intuition about the pattern created by the shocks, the decomposition of forecast error variance is numerically more informative. The variance decomposition assesses the importance of different shocks by determining relative share of variance that each structural shock contributes to the total variance of each variable (Lack and Lenz, 2005). More detailed information about the uncertainty in each region's price series at different time horizons in future is reported in Table 2.6. Forecast error variance decomposition is given for every series at horizons of 0, 1, 8, 16, and 28 quarters ahead. It shows how the innovations in each region affects the house prices of the same and other regions at the specified time horizons. The maximum time horizon of 28 quarters is chosen due to the suggested notion of Pollakowski and Ray (1997) about the real estate cycle being 6-8 years.

In the short-run, uncertainty in PC is mainly explained by the innovations in its own series (84%). However, 8 periods ahead (2 years), the innovations in NE and SA comprise large portion of uncertainty in PC (14% and 12%). At the longer horizons the role of shocks in its own series fades away becoming less significant in explaining the

Table 2.6 Variance Decomposition of House Price Indices from Nine Census Regions Based on Bernanke Decomposition

Horizon	PC	MT	SA	MA	NE	ESC	WSC	WNC	ENC
					PC				
0	84.199	0.000	0.000	5.556	6.613	0.418	0.000	3.213	0.000
1	83.297	0.196	0.003	2.995	9.370	0.507	0.187	3.435	0.010
8	59.132	6.214	12.281	5.161	14.622	0.487	0.244	0.807	1.053
16	16.268	10.416	17.745	6.661	25.115	3.016	0.052	19.024	1.702
28	5.190	7.463	15.428	3.529	30.136	1.987	0.007	32.398	3.864
					MT				
0	11.564	80.138	0.000	0.064	0.164	7.992	0.000	0.079	0.000
1	15.474	62.819	2.229	0.141	0.371	17.257	0.087	0.467	1.154
8	11.372	36.556	2.800	1.213	12.008	12.217	2.856	14.485	6.492
16	6.897	25.855	5.037	0.610	17.392	6.754	3.316	27.915	6.225
28	2.795	14.529	9.835	0.176	23.472	3.171	1.915	39.027	5.080
					SA				
0	1.298	0.000	75.762	3.939	8.734	1.938	4.974	2.523	0.830
1	4.542	0.545	60.347	8.480	15.370	0.869	4.233	4.414	1.200
8	5.721	13.987	40.734	2.544	18.153	2.113	0.355	14.734	1.659
16	2.887	15.186	27.481	0.316	22.767	1.805	0.423	25.880	3.255
28	2.320	11.487	22.598	0.471	28.256	0.619	0.168	30.581	3.501
					MA				
0	0	0	0	100	0	0	0	0	0
1	0.384	0.030	0.188	94.068	1.207	0.000	0.181	3.688	0.253
8	5.354	0.924	6.291	17.299	10.473	5.296	3.212	48.869	2.282
16	0.930	0.654	3.670	3.110	16.766	9.359	1.279	59.376	4.855
28	1.372	0.202	1.599	6.123	17.979	11.591	0.305	55.653	5.176
					NE				
0	0	0	0	35.162	41.855	2.646	0	20.337	0
1	0.271	0.013	0.219	22.152	41.137	4.379	0.046	31.476	0.307
8	0.252	0.007	0.822	1.776	19.677	13.878	0.762	58.782	4.045
16	1.002	0.023	0.301	5.795	17.936	15.406	0.145	53.811	5.582
28	2.209	0.764	0.720	11.408	12.913	18.681	0.033	48.022	5.250
					ESC				
0	0	0	0	4.326	0	95.674	0	0	0
1	0.394	0.177	1.095	4.771	1.193	88.145	0.629	3.414	0.181
8	0.389	3.618	3.870	0.289	6.544	42.659	1.760	35.221	5.651
16	0.249	3.715	3.066	0.055	11.538	25.981	1.601	45.842	7.952
28	0.067	1.508	1.854	0.561	13.053	18.407	1.430	55.523	7.597
					WSC				
0	15.451	0	0	0.005	6.997	8.435	59.183	0.047	9.882
1	20.096	0.081	0.574	3.161	13.601	8.034	40.859	2.037	11.558
8	33.011	3.662	0.409	13.587	21.655	11.315	5.301	5.323	5.739
16	33.367	3.470	0.130	22.197	15.044	12.635	1.517	9.048	2.592
28	18.009	1.419	0.442	23.145	16.289	13.602	0.450	24.069	2.577
					WNC				
0	0	0	0	0.518	0	11.454	0	88.028	0
1	0.623	0.019	0.000	0.720	0.020	13.921	1.026	83.651	0.017
8	2.704	0.188	1.369	10.093	5.333	21.696	1.702	56.319	0.597
16	2.291	0.380	2.144	9.456	11.794	16.326	0.501	54.433	2.673
28	1.188	0.300	2.811	6.847	15.263	12.123	0.337	57.348	3.782
					ENC				
0	0	0	0	0.121	0	2.672	0	20.534	76.674
1	0.062	0.225	1.108	0.023	0.328	9.811	1.624	32.228	54.592
8	0.050	0.855	1.884	2.139	3.795	29.480	5.291	55.062	1.443
16	0.078	0.578	2.003	1.824	9.727	20.805	2.100	59.629	3.258
28	0.244	0.153	1.100	1.252	10.782	16.172	1.441	63.885	4.971

uncertainty in PC house prices. Instead, SA which only influences PC, NE, and WNC becomes more significant (about 17%, 30%, and 32%). The percentage of uncertainty in PC explained by other series is smaller than 10%. Furthermore, PC itself along with the ESC explains about 15% uncertainty in MT in short-run becoming less important with time and reaches to about 3% 7 years ahead. On the other hand, NE and WNC become more significant in explaining the MT variance in long time horizons reaching to 23% and 39%, respectively. Similar to the PC case, the self-explanatory power of MT drops dramatically from about 80% to 14% as the time horizon increases. The MT, on the other hand, becomes significant after about 2 years accounting for up to 15% of the SA variance.

Interestingly, MA which was found to be the only exogenous series by DAG explaining all the uncertainty in itself, is about 86% explained by other series in the long-term being mainly influenced by NE (17%) and WNC (59%). However, its role in leading the NE in short-run and WSC in long-run cannot be left unnoticed. Up to 35% of the uncertainty in NE is attributed to the innovations arising in MA in short-run, leaving about 58% and 18% of uncertainty to be explained by WNC and ESC in longer horizons. NE itself appears to be one of the main leaders in the housing market affecting all regions significantly. However, its effect on house prices in ESC and ENC is relatively small. The findings regarding to the NE are consistent with those of Pollakowski and Ray (1997) who showed the lagged NE price changes are quite significant in 6-9 census divisions. However, our findings do not support the notion that NE is a “leading indicator" which was suggested in the previous studies, but it certainly confirms the finding of Pollakowski and Ray (1997) regarding to the NE's explanatory power.

WNC appears to have the major influence on the house prices in ESC reaching to about 55%. Surprisingly, ESC itself explains large portion of its uncertainty and dies off slowly relative to the others. The exact opposite is observed in WSC series which accounts for only 59% of its uncertainty in short-run exponentially dropping to 0.5%. In addition, this is perhaps the only region where the house price dynamics are greatly influenced by innovations of more than five regional house price series: PC (up to 33%), MA (23%), NE (21%), ESC (13%), WNC (24%), and ENC (11%). It is the only region that has nearly no influence on other regions' house prices. The exact opposite is observed for the WNC house price series, which are the main leaders in the U.S. housing market and remain relatively exogenous over time accounting for 88%-54% of its uncertainty over time. However, three other regions explain relatively significant portion in the WNC house price uncertainty: NE (15%), MA (10%), and ESC (21%). It is the main contributor of the house price dynamics in ENC explaining up to 63% of the uncertainty. Similar to the WSC series, uncertainty in ENC house prices explained by innovations arising in the own series comprises only very small percentage (2%) in long-run. The other regions that have significantly large affect on the ENC house prices include the NE (10%) and ESC (29%).

The overall results suggest that house prices of most regions are being influenced by innovations in other regions more in longer time horizons than in short-run. The most influential region - WNC, followed by NE, MA, and ESC appear to always have vital role for price discovery in the U.S. housing market. On the contrary, WSC, SA, and ENC do not seem to be part of the long-run house price determination, and are rather greatly influenced by the other regional house price dynamics. These results appear to be consistent with the restricted model and the DAG results. Overall, highly interrelated U.S. regional house prices are found regardless of the methods applied.

2.6 Conclusions

Real estate market has proven to be important in many aspects. This fact has attracted many researchers to do various analysis involving house prices and other variables. Mostly UK studies explored the long-run relationships between the UK regional house prices. Only Pollakowski and Ray (1997) use the U.S. census division house price data to explore the long-run relationship. However, the techniques and methodology used in their study are very simplistic and do not allow thorough analysis of housing market.

The data used in this study is deseasoned and detrended to allow only the irregularities in the series. Model specification and identification is extensively analyzed leading to a highly significant and just-identifiable model. We use a method which facilitates identification of the long-run structure using the Directed Acyclic Graphs and the results of exclusion tests. Four cointegrating relations among the nine variables are found. Furthermore, using the proposed identification procedure, we find that the four cointegrating relations are those of ESC, WSC, SA, and NE. All the house price series are found to facilitate the adjustment back to equilibrium, but not all are part of the cointegration space (e.g. MT). Furthermore, DAG results suggest that MA appears to be the most exogenous, leading house prices in other regions. Somewhat different results are found based on the impulse response functions and the forecast error variance decomposition suggesting the central role of WNC followed by NE. The importance of NE in the overall U.S. housing market is also suggested by Pollakowski and Ray (1997), who claim that it is significant for 6-9 census divisions.

In addition, our findings provide evidence that PC, MA, ESC, and ENC have moderate impact on house price determination. WSC, followed by the SA and MT, appears to be the least exogenous region not being part of any price discovery process. The house prices of these regions are considerably influenced by the rest of the market. Moreover, all the regions appear to explain less of their own price uncertainty as the time horizon increases. Put another way, at longer time horizons, such as 16 (4 years) and 28 (7 years), the uncertainty in house prices of most regions is mostly explained by other regions.

The overall findings provide strong evidence of U.S. regional house prices being highly interrelated which is consistent with the findings of Pollakowski and Ray (1997). This implies that U.S. regional housing market is inefficient and that shocks arising in one census division do cause the same and subsequent-period reactions in other census divisions. In addition, the DAG results indicate the importance of the information transfer for house price determination. Furthermore, the causality results are not necessarily consistent with the geographical locations of the regions, i.e. regions do not necessarily influence the adjacent region more than the non-adjacent regions. This pattern of price diffusion is consistent with that of Pollakowski and Ray (1997) who showed that the price diffusion pattern does not differ for neighboring and non-neighboring census divisions in terms of their statistical significance.

Several possible explanations for the observed dynamics in the U.S. housing market can be very exhaustive including migration, income, local economy, zoning restrictions, etc. Migration, which was offered mainly to explain the empirical findings in UK, is often associated with the availability of jobs, unemployment, labor market, demographics, as well as the lifestyle (Minford et al., 1987, Bover, 1989, Gordon, 1990, Holmans, 1990, Giussani and Hadjimatheou, 1991, McDonalds and Taylor, 1993, Alexander and Barrow, 1993, Meen, 1999). Our findings regarding the nonspatial diffusion of the regional house price changes are probably direct effect of the regional economic interactions (Pollakowski and Ray, 1997). In other words, innovations in particular regional economy will directly affect that region’s housing market in addition to transmitting the shock to other regions’ economies eventually having an impact on the housing market. Moreover, some authors suggest that zoning restriction and the difficulty of getting building permits might explain the observed dynamics and high prices in east and west of the U.S. (Glaeser and Gyourko, 2002). Although many possible causes for such findings can be offered as hypothesis, it will be interesting to study the actual cause if the data permits.

CHAPTER III

INTERDEPENDENCE OF OIL PRICES AND STOCK MARKET INDICES: A COPULA APPROACH

3.1 Introduction

Everyday major news channels discuss at least one story about oil, its demand and supply, present and future price movements, or the potential effect on financial markets. Record high (crude) oil prices have been reported every single day from the beginning to the middle of 2008. More and more policies are being devised to cope with the rising oil prices. All this attention on oil is a direct result of its importance for most of the economies in the world (Nandha and Faff, 2008). Moreover, the demand for oil is increasing as countries become more developed. For example, the demand for oil by China and India which are in the process of rapid development is growing over time. On the other hand, the demand by developed countries for oil is not decreasing in spite of the vigorous search for alternative fuel which translates into less oil consumption. That means that oil supply will remain an important factor for the global economic progression at least for some time. Hence, the large oil producing countries will continue having very decisive role in determining the oil production and the pricing strategies. It is therefore important to thoroughly comprehend the effect of oil prices and pricing strategies on the world economy.

Theoretically, the oil prices influence the state of economy, however, it is not clear how the relationship changes depending upon the availability and usage of the oil in a particular country/region. For instance, the oil prices are likely to positively influence the GDP of Saudi Arabia, whereas the opposite would perhaps be the case for France. Empirically, many papers showed a link between the oil price and the state of economy. Studies from 1983 up to 2007 have shown that the economies of most countries are inversely related with the oil price changes (Hamilton, 1983; Burbidge and Harrison, 1984; Gisser and Goodwin, 1986; Loungani, 1986; Mork, 1989; Lee, Ni, and Ratti, 1995; Mork, Olsen, Mysen, 1994; Mussa, 2000; IEA, 2004; Jones et al, 2004). The data and methodologies applied in these studies vary, but most of them come to a similar conclusion – oil is an important factor for the economy. However, the issue of whether this relationship changes for the oil rich and high-consumption countries still remains unanswered. Inclusion of various countries such as large oil producing, oil consuming, or the combination of both in this study will help to illustrate how much, if any, and to which direction the relation between the oil and the financial markets changes.

The reported relationship of oil prices and the economy brought forth new ideas and avenues of research. The reasoning behind many of the recent studies arises from the empirical evidence that oil price has an impact on the overall economy; hence it may have an impact on the individual industries as well. Consequently, many studies examined the relationship between the various industry sectors and the oil prices. Faff and Brailsfort (1999) claimed that oil, gas and diversified resources industries are positively correlated with the oil prices, while negative correlation is observed for industries, such as paper and packaging, financials and transport. Furthermore, the individual stocks have become the focus of many studies. Combining the equity returns of different industries these studies also had some industry implication and confirmed the results of Faff and Brailsfort (1999).

Equity markets have later been studied for possibility of being influenced by oil price shocks. The rationale for the possible oil price impact on stock returns comes from the fact that oil, being a major input, directly affects the cost structure of firms. The increased cost, ceteris paribus, will result in smaller profit which will negatively affect the expected earnings and will result in depressed aggregate stock prices (Ciner, 2001; Nandha and Faff, 2008). These hypotheses have been empirically accepted for Greece (Papapetrou, 2001) and for UK (El-Sharif et al., 2005). They show that oil price shocks have negative and weak influence on the non-oil or non-gas stock returns. On the other hand, if one looks from the perspective of oil producing company, the above mentioned notion will be reversed resulting in positive impact of oil price increases on stock returns of mainly oil and gas industries (companies from these industries). This notion seems to be supported by some studies that use stock returns of oil and gas industries, individual companies (or oil-intensive companies) and oil prices (Al-Mudhaf and Goodwin, 1993; Sadorsky, 1999; Faff and Brailsford, 1999; Sadorsky, 2001; Papapetrou, 2001; Hammoudeh and Li, 2004; El Sharif et al., 2005; Nandha and Faff, 2008; Boyer and Filion, 2007).

Although the individual stock returns are indeed influenced by the oil price movements, overall stock market indices have been shown to be unrelated to the oil price shocks, at least in statistical sense. The stock market indices are viewed as important indicators of the state of economies, thus the relationship should be well studied for the complete understanding of an economy. Despite the importance of such study, only limited number of studies examined it. Among those limited studies, most find that the two markets are independent (Huang et al., 1996). However, the analysis of nonlinear or asymmetric relationship between the oil prices and economy, as well as stock markets showed the existence of nonlinear relation such that an oil price increase is more detrimental to the U.S. economy and financial markets, than an oil price decrease is beneficial (Mork, 1989; Hamilton, 1996; Balke, Brown, and Yucel, 2002). In addition, nonlinear Granger causality from oil futures return to S&P 500 index return is found (Ciner, 2001). This study investigates the relationship between stock market indices and oil price series for many countries using copula functions and Stable Aggregate Currency (SAC) to explore the general dependence without the currency effect.

Oil prices have been mainly denominated in U.S. dollars, however, the decline of the U.S. dollar value against other currencies have led OPEC to think of an alternative currency for crude oil pricing (Amuzegar, 1978; Haughton, 1991; Samii et al., 2004; Verleger, 2003). This issue has emerged late 1970's and early 1980's when the U.S. dollar was devalued. It again has become a current issue with the U.S. dollar quickly losing its value and dominance in the global economy. The importance of the appropriate currency for crude oil pricing stems from the claims that oil price movements are partially due to the currency movements, meaning that exchange rate fluctuations cause oil price movements (Samii and Clemenz, 1988; Basher and Sadrosky, 2006). This is an important issue that needs to be accounted for in such studies since the possible significant relationship between stock markets and oil prices might be masked by the exchange rate movements. Moreover, numerous studies showed that stock markets of many countries are influenced by exchange rate movements as well. Hence, exchange rates are common causes for both variables of interest and thus the appropriate actions for consideration are imperative. However, very few studies controlled for exchange rates when studying the relationship between the oil prices and stock market indices. For example, Cologni and Manera (2008) included the exchange rate as an explanatory variable in the VAR to control for the exchange rate risk. Similarly, Basher and Sardosky (2006) included a weighted average of the foreign exchange value of the U.S. dollar against a subset of the broad index currencies in the OLS regression to account for the exchange rate effect. This paper uses a relatively stable currency basket which greatly eliminates the exchange rate risk and accounts for currency movements. Specifically, SAC is employed as the base currency (Hovanov et al., 2003). Moreover, for comparison purpose we included the U.S. dollar and Euro as alternative base currencies. However, unlike the Cologni and Manera (2007) and Basher and Sadordky (2006), all the series (oil prices and stock market indices) are transformed into SAC, Euro, and U.S. dollar. The results with these modifications will provide us more accurate answers as to whether the oil prices really affect the stock markets when we eliminate the effects of the exchange rate changes.

Another contribution of this paper is the examination of oil price and stock market relationship from an asymmetric perspective. Although there is some limited evidence of asymmetry in the relationship, no one has looked at the application of copula functions in this field. It facilitates flexible modeling of univariate marginal distributions. In addition, the dependence can be estimated based on the entire dependence structure rather than just univariate measures (Chollete et al., 2005).

This paper is organized as follows. Section 3.2 presents the construction of the SAC, the data and its transformations into series with minimum exchange-rate exposure. The copula functions and the estimation procedure are briefed in Section 3.3. Main results of the paper are given in Section 3.4 followed by the implications and conclusion of the results which are reported in Section 3.5.

3.2 Stable Aggregate Currency (SAC) and Data Transformation

This section details the oil prices and stock market indices data for different countries including both developed and developing among which are some of the large oil producing countries. Two different oil price series are used for the purposes of comparison and robustness of the results. This is important as the existing studies have used different oil prices series which may be another reason for some of the results that are not quite consistent with each other. In addition, a brief review of the SAC methodology and the techniques for data transformation is presented.

3.2.1 Review of SAC

In the literature on oil prices and stock markets, several studies have only included specific currencies as explanatory variables in OLS or VAR analysis. Most common ones are the U.S. dollar or Euro. However, even the most stable currencies such as U.S. dollar and Euro fluctuate, especially during extreme events. The series denominated in either currency will be affected by the exchange rate dynamics and the results of the studies that employ either currency as the base will be highly dependent upon the dynamics of the base currency chosen. Hence, the conclusion of a study may change depending on which currency is used due to their fluctuations over time. In essence, the exchange rate fluctuates as a direct result of both currencies. Therefore, to sustain the stability of the exchange rates, the choice of the base currency is important. For example, using U.S. dollar as a base currency as opposed to British pound, changes the relationship between the Euro and Yen (Hovanov et. al., 2003).

On the other hand, the use of a basket of hard currencies, such as the U.S. dollar, German mark, British pounds, Japanese yen, and French franc would greatly minimize the aggregate volatility by combining the currencies at some fixed proportion (Seymour, 1980; Hovanov et. al., 2003). This principle is used to construct both the Special

Drawing Rights (SDR) and the SAC[23]. In this paper we propose the use of SAC in order to achieve minimal exchange rate movement. Unlike many studies on oil prices and stock markets, this study proposes the denomination of all the series into one standard currency or basket of currencies.

The complete details on SAC construction are given in Hovanov et al. (2003), while this paper presents a brief introduction of SAC. It starts with the Invariant Currency Value Index (ICVI) which is the same for a fixed set of currencies regardless of the base currency choice. The invariance property of the ICVI has important implications especially if it is used as a base currency. Moreover, the fluctuation of a particular currency and not the exchange rate (which changes due to the change in numerator and/or denominator currencies) can be demonstrated through the use of ICVI.

Furthermore, Normalized Index of Value (*NVal)* in exchange is used to mathematically express the ICVI through the following equation:

$$NVal_{ij} = \frac{c_{ij}}{\sqrt[n]{\prod_{i=1}^{n} c_{ij}}} \qquad (3.1)$$

where $NVal_{ij}$ is the normalized value in exchange, c_{ij} is the exchange coefficient (i.e. the exchange rate of the i^{th} currency for the j^{th} currency), where j^{th} currency is the base currency. The geometric mean of values in exchange (i.e. c_{ij}) is expressed by $\sqrt[n]{\prod_{i=1}^{n} c_{ij}}$.

Given that the $NVal_{ij}$ is invariant upon the base currency choice, it can be substituted by $NVal_i$. Furthermore, the Reduced Normalized Value in Exchange

[23] The SDR is proposed by International Monetary Fund which is a basket of currency comprised of hard currencies at fixed proportions.

($RNVal_i(t/t_0)$) is used instead of $NVal_i$ because of its convenience of further demonstration.

$$RNVal_i(t/t_0) = \frac{NVal_i(t)}{NVal_i(t_0)} \tag{3.2}$$

Equation (3.2) expresses the $RNVal_i(t/t_0)$ starting from t_0 (t_0 =1), where i is the number of currencies included in the SAC, i.e. i=1,…,5 and i=1,…,4 for pre- and post-Euro periods, respectively.. The time series of the $RNVal_i$ at moment t_0 =1 (January 8, 1982) for each of the five and four currencies included in pre- and post-Euro periods, respectively is computed as $USD(t/1) = RNValUSD(t/1)$, $JPY(t/1) = RNValJPY(t/1)$, $GBP(t/1) = RNValGBP(t/1)$, $DEM(t/1) = RNValDEM(t/1)$, $FRF(t/1) = RNValFRF(t/1)$, where t is the number of observations (e.g. t=1,…, 4290 and t=1,…,2256 for the pre- and post-Euro periods, respectively).[24] In addition, the sum product of $RNVal_i(t/t_0)$ and the weight vector w is calculated to determine the Index Value ($Ind(w;t)$), which is mathematically presented as:

$$Ind(w;t) = \sum_{i=1}^{n} w_i RNVal_i(t/t_0) \tag{3.3}$$

Optimal weights of the key international currencies included in the currency basket are obtained by minimizing the variance subject to these constraints: $w_i \geq 0$ and $w = w_1 + w_2 + \ldots + w_i = 1$. Formally, the variance $S^2(w)$ can be presented as:

[24] In the post-Euro period, $DEM(t/1) = RNValDEM(t/1)$ and $FRF(t/1) = RNValFRF(t/1)$ are replaced by $EUR(t/1) = RNValEUR(t/1)$.

$$S^2(w) = \sum_{i,k=1}^{n} w_i w_k \operatorname{cov}(i,k) = \sum_{i=1}^{n} w_i^2 s_i^2 + \sum_{\substack{i,k=1 \\ i<k}}^{n} w_i w_k \operatorname{cov}(i,k) \tag{3.4}$$

where $\operatorname{cov}(i,k)$ is the covariance of time series *RNVal*$_i$*(t/t*$_0$*)* and *RNVal*$_k$*(t/t*$_0$*)*, s_i^2 is the variance of the time series *RNVal*$_i$*(t/t*$_0$*)*, and $w_1,\ldots,w_i$ are the weight-coefficients calculated as given:

$$w_i = \frac{q_i c_{ij}(t_0)}{\sum_{i=1}^{n} q_i c_{ij}(t_0)} \tag{3.5}$$

The calculated optimal weights are further used to calculated the optimal quantities of currencies ($q_1^*,\ldots,q_5^*$) through the following equation:

$$q_i^* = \frac{w_j^*}{c_{ij}(t_0)}\mu \tag{3.6}$$

Finally, the SAC is constructed by incorporating the key currencies at calculated optimal proportions (amounts).[25] It will later be used to transform both the oil price and stock market index data into SAC-denominated series.

3.2.2 Data

The data used in this study includes daily oil price series and stock market indices from both developed and developing countries over the period of January 7, 1982 to December 31, 2007. The reason for the chosen starting period is due to the fact that both oil price series are available from that date. The stock market indices include the Nikkei 225 Average Composite Index (Japan), FTSE 100 Index (UK), DAX 30

[25] The currencies included in the SAC are exactly the same currencies that comprise the SDR.

Performance Index (Germany), DS Total Market Index (France), AEX 30 Ordinary Index (Netherlands), DS Total Market Index (Italy), S&P 500 Composite Index (U.S.), IBEX 35 Index (Spain), OMX Helsinki Index (Finland), S&P/TSX Composite Index (Canada), Swiss Market Index (Switzerland), WSE WIG Index (Poland), Prague Stock Exchange Index (Czech Republic), Budapest Stock Exchange Index (Hungary), Shanghai SE Composite Index (China), RTS (Russia), Hang Seng Index (Hong Kong), Venezuela Stock Index (Venezuela), and S&P/IFCG Index (Saudi Arabia). The two oil price series used include Brent crude oil spot FOB price and the OPEC oil basket price. The former is used as it is the main benchmark for Asia, Middle East, and Europe. The latter is used for the sensitivity purposes to test if results change substantially when the benchmark is not used. All the data is retrieved from DataStream database.

The creation of Euro as a common currency for most of the EU countries has been shown to have an influence on the dynamics of financial series (Patton, 2006a). The hypothesis of results being different pre- and post-Euro periods is empirically tested in this paper. The overall time period is partitioned into pre- and post-Euro periods and the series that are available at a later date are only included in the post-Euro period. Pre-Euro period starts at the starting date mentioned above and ends on December 31, 1998. It includes eight stock market indices (Nikkei 225 Average Composite Index (Japan), FTSE 100 Index (UK), DAX 30 Performance Index (Germany), DS Total Market Index (France), DS Total Market Index (Italy), S&P 500 Composite Index (U.S.), S&P/TSX Composite Index (Canada), Hang Seng Index (Hong Kong)) and both oil price series. In addition to these series, the rest of stock market indices are also included in the Post-

Euro period which ranges from January 1, 1999 to December 31, 2007. The results of the two periods (for the series that are available for both periods) are compared for the possibility of changed interactions.

3.2.3 Data Transformation

Each series is denominated into the same base currency or currency basket. This way, the exchange rate effect is minimized resulting in more accurate results. When stock market indices are denominated in local currencies, they incorporate both local currency and stock market movements. Similarly, the oil price series in local currencies fluctuate due to price changes and currency movements. This way results would not represent the pure stock market and the oil price dependence since the currency movement will have an influence on both series. Moreover, if both oil prices and stock market indices are denominated in U.S. dollars (Euro), the series will in addition depend on the exchange rate changes, i.e. the relation between the local currency and the U.S. dollar (Euro). Consequently, studies examining the stock markets of various countries, oil prices and other macroeconomic variables incorporate exchange rate risk, thus it is possible that the results are inaccurate. To overcome this problem, this paper proposes to denominate all the stock market indices and oil prices series in a basket of currency (SAC), which essentially minimizes the volatilities of comprised currencies (Hovanov et al., 2003; Maung, 2004; Zohrabyan, 2005). The data transformation follows according to the following equation:

$$P_{it}^{SAC_t} = P_{it}^{C_{it}} \times \frac{SAC_t}{C_{it}}, \qquad t = 1, \ldots, T \tag{3.7}$$

where $P_{it}^{C_{it}}$ is the i^{th} stock market index or the i^{th} oil price series at time t in the i^{th} country's currency. Similarly, $P_{it}^{SAC_t}$ is the i^{th} stock market index (or the i^{th} oil price series) at time t in SAC, where SAC is the base currency, and $\frac{SAC_t}{C_{it}}$ is the exchange rate of SAC for the i^{th} country's currency at time t. All the series are then denominated into SAC to minimize the currency movements for further analysis. As mentioned earlier, the U.S. dollar and the Euro (only for the post-Euro period) are applied as numeraire for comparison purposes. The data transformation under these two alternative base currencies is the same as the Equation (3.7) with SAC being changed into U.S. dollar and Euro. Hereinafter, the data used will be transformed unless otherwise mentioned.[26]

3.3 Copula Functions

Copula function which joins the marginal distribution functions to restore their joint multivariate distribution function was first introduced over 50 years ago (Sklar, 1959). However, it only became popular several years ago. In his paper Mikosch (2005) stated that within 2003 and 2005 the Google search of "copula" has increased by about 65 times.[27] This shows that the application of copula functions in various studies has skyrocketed in a short time-span. Copula functions have been widely used in finance, economics and other social science fields. In fact, in risk management studies, copulas

[26] Exchange rate data for all the countries used in this study are obtained from Oanda Pacific Exchange database. The time period for these dataset is the same as for the stock market indices.
[27] Notice that not all of the items from "copula" search were pertaining to the copula functions used in statistics, mathematics, finance, economics, etc.

are now one of the most common methodologies used. Researches in finance, statistics, and economics also have increasingly used these exotic and flexible functions. It is apparent that copulas are useful in nonlinear analysis, specifically modeling the structure of dependence. It has been used in spillover analysis where its importance stems from the fact that various copula families tackle different aspects of dependence structure.

There is an extensive theoretical research done on copulas and, as a result, wide variety of functional forms, copula families, and methods of estimation are available. For example, both parametric and non-parametric copulas can be used and over ten parametric copula families or classes can be chosen. The basic definition of the copula functions, their functional forms, properties, and estimation methods are detailed below. The most important and fundamental theorem on copulas is the Sklar's theorem given by Theorem 1 below.

Theorem: Given a *2*-dimensional cumulative distribution function $H(x, y)$ of any pair (X, Y) of continuous random variables whose marginal cumulative distributions are $F(x)$ and $F(y)$, there exists a unique *2*-dimensional copula $C:[0,1]^2 \rightarrow [0,1]$ such that

$$H(x, y) = C(F(x), F(y)) \tag{3.8}$$

Conversely, if C is a *2*-copula and $F(x)$ and $F(y)$ are the marginal distribution functions, then $H(x, y)$ is a *2*-dimensional joint distribution function with margins $F(x)$ and $F(y)$ (Rodriguez, 2007). Copula functions have several important properties such as copulas are grounded, *2*-increasing, and if at least one of the coordinates is zero, then the copula will also be zero (Marshal and Zeevi, 2002).[28]

The increasing importance of copulas stems from the fact that it facilitates an easy and flexible multivariate distribution calculation using the marginal distributions and the copula function, which is invariant under increasing and continuous transformations of data (Chollete et al., 2005). That is the margins can be estimated with the best fitting distribution, filtered, and modified as necessary. Following the model selection for the margins, copula functions are used to restore the joint distribution with the correctly specified marginal distributions and the proper dependence structure. Moreover, copula is a measure of dependence which is more informative and appropriate than the linear dependence measures.

Cherunini et al. (2004) provide different approaches to estimate the copula functions. The most popular one is the Inference Function Marginal (IFM) approach which consists of two stages. In the first stage the margins are being modeled with the best fitting distribution. The parameters of the univariate marginal distribution are estimated by:

$$\hat{\theta}_1 = ArgMax_{\theta_1} \sum_{t=1}^{T} \sum_{j=1}^{n} \ln f_j(x_{jt};\theta_1) \tag{3.9}$$

The estimated parameters of margins $\hat{\theta}_1$ are then used in the second stage of copula parameter θ_2 estimation.

[28] Detailed information on copula functions, properties, their applications in finance area, and more can be found in Joe (1997), Nelson (2006), Cherubini et al. (2004), Bouye et al. (2000), Embrechts et al. (2002), Embrechts et al. (2003), Marshal and Zeevi (2002), and Patton (2004).

$$\hat{\theta}_2 = ArgMax_{\theta_2} \sum_{t=1}^{T} \ln c(F(x_t), F(y_t); \theta_2, \hat{\theta}_1) \tag{3.10}$$

According to IFM approach, the parameters of the margins and copulas are separately estimated. Specifically, the two-stage semi-parametric procedure is used in this paper where the first-stage is estimated non-parametrically. IFM estimator is defined as the vector:

$$\hat{\theta}_{IFM} = (\hat{\theta}_1, \hat{\theta}_2)' \tag{3.11}$$

Essentially, this way the specification errors of margins are minimized to nearly zero implying more accurate results. The IFM approach is computationally more attractive and is less complex in general than the alternative approach in which case the parameters of both marginal distribution and copulas are estimated simultaneously. Moreover, Patton (2006b) shows that IFM estimator is consistent and asymptotically normal. Comparing the exact maximum likelihood and the IFM estimators, Xu (1996) reported nearly the same mean square errors.

3.3.1 Stage One – Univariate Marginal Distributions

It is a common practice to transform the price series into logarithmic differences (i.e. returns) which generally results in stationary series. Many of the return series of this study are fairly volatile. This is the case especially for the stock market indices of developing countries. Moreover, most of the financial series tend to deviate from the i.i.d. assumption and are usually conditional heteroskedastic resulting in inaccurate estimation of the degree of dependence (Hu, 2006). This is certainly the case with the return data of this study. In addition, many of the series also suffer from serial correlation[29]. To solve both the autocorrelation and the conditional heteroskedasticity problems, autoregressive (AR) and generalized autoregressive conditional heteroskedastic (GARCH) models are used. Following Patton (2006a), we assumed that the conditional means evolve according to an autoregressive (AR) process. On the other hand, the conditional variance evolves according to an asymmetric GARCH model.

Each of the individual return series is modeled by fitting k order autoregressive model.[30] It is given by the following equation:

$$r_t = c + \sum_{k=1}^{10} \theta_k r_{t-k} + \varepsilon_t \qquad (3.12)$$

In addition, the conditional variance of each series is modeled by fitting an asymmetric GARCH model as given:

$$\sigma_t^2 = \kappa + \alpha\sigma_{t-1}^2 + \phi\varepsilon_{t-1}^2 + \psi[\varepsilon_{t-1} < 0]\varepsilon_{t-1}^2 \qquad (3.13)$$

The asymmetric GARCH model includes the leverage or asymmetry term by a Boolean indicator taking the value of 1 if the prior model residual is negative and 0 otherwise. This model was introduced by Glosten et al. (1992). Franses and Dijk (1996) showed that GJR model can improve on the standard symmetric GARCH model mainly due to the fact that it accounts for the negative (positive) skewness of financial returns. In fact, when $\psi > 0$, impact is much greater in case of negative shocks than positive shocks. Therefore, because many of the series in this study have observed negative skewness, it

[29] LM test is performed for up to 10 lags. It was rejected for most of the series and lag inclusion was necessary in most cases to cure the autocorrelation problem.
[30] Order k of the autoregressive model differs for each return series as some required more lags than others.

is more appropriate to use GJR-GARCH than the standard symmetric GARCH. The GJR-GARCH (p, q) model is used with innovations modeled by a Student-t asymmetric generalized distribution of Hansen (1994).[31]

The resulting standardized residuals from the GJR-GARCH model are then used to calculate the unit cumulative distributions (CDF's). Moreover, the non-parametric kernel CDF's of each filtered series is estimated which are shown to be the best for interior of the distribution where most of the data is found. The advantage of the non-parametric estimation of margins is that it does not entail any specification errors. However, evidence shows that it is not the best for the tails of the distribution. The extreme value theory (EVT) is therefore applied to the standardized residuals that fall in each tail in order to estimate the tails of the distribution. As a result, 10% of the standardized residuals for the upper and lower threshold is used in order to estimate the parametric Generalized Pareto Distribution (GPD) (Embrechts et al., 1997; Mikosch, 2003; McNeil et al., 2005). Furthermore, the maximum likelihood estimation is utilized to fit the amount by which the extreme residuals in each tail fall beyond the associated threshold to a GPD. The negative log-likelihood function is then optimized to estimate the tail index and scale parameters of the GPD. The resulting distribution of margins captures the heavy-tails of the series better and provides more accurate CDF estimation.

[31] Models for each series and each case are available upon request from authors.

3.3.2 Stage Two - Copula Functions

Given the parameter estimates of the margins, copula parameters can be estimated in the second stage using the maximum likelihood estimator. However, to estimate the copula parameters copula function, family, and class have to be specified. This study uses the following nine different constant parametric copula functions from various copula families and classes: Normal copula, Clayton copula, Rotated Clayton copula, Frank copula, Plackett copula, Gumbel copula, Rotated Gumbel copula, Student copula, and Symmetricized Joe-Clayton (SJC) copula.[32]

The most appropriate copula function for each bivariate model is selected based on the log-likelihood functions and three information metrics (selection criteria). The latter includes the Akaike Information Criterion (AIC) and Bayesian Information Criteria (BIC). All three measures use somewhat different approach as given below:

$$AIC = -2 \times LLF + 2 \times Parameters \tag{3.14}$$

$$BIC = -2 \times LLF + \log(T) \times Parameters \tag{3.15}$$

where *LLF* is the log-likelihood function, *Parameters* is the number of parameters, and the T is the number of observations (4290 and 2256 for pre- and post-Euro, respectively). The number of parameters for each copula function is one except for the Student t and SJC copula functions.

Large number of observations result in different criteria values among the three Goodness-of-Fit measures. Hence, the copula model chosen by the information criteria

[32] Patton (2004) provides the functional forms for all the copula functions used in this study.

to be the best fitting copula may slightly differ depending on the measure used. All the 9 copula functions used in this study will be ranked based on all three criteria.

3.3.3 Dependence Measures

As mentioned earlier, copula functions describe the structure of dependence and are adequate indicators of the possible co-movement between the series (Patton, 2006b). Moreover, copulas are related to all the association concepts such as concordance, linear correlation, tail dependence, positive quadrant dependency, and some of the related measures such as Kendall’s tau, Spearman’s rho, Pearson’s rho, index of tail dependency (Cherubini et al., 2004). This study uses four dependence measures: Pearson’s rho, Kendall’s tau, Spearman’s rho, and index of tail dependency.

Pearson’s correlation (aka linear correlation), which has been in common use for many years, measures the linear dependence between the variables of interest. According to Emnrechts et al. (2003), it is invariant under strictly increasing linear transformation and is easy to manipulate under linear operations which is one of the main reasons for such popularity. Moreover, it is also a natural scalar measure of dependence in elliptical distributions; however, in cases of non-elliptical distributions it provides a false measure of dependence. For instance, if the best fit of the model are the heavy-tailed distributions, which have infinite second moments, the Pearson’s correlation can not even be defined. The existence of outliers, unequal variances, non-normality, and non-linearity all influence the linear correlation coefficient (Carmona, 2004). Hence, only under special circumstances linear correlation is appropriate and accurate measure of dependence.

The other commonly used dependence measures, Spearman's rho and Kendall's tau, are non-parametric dependence (concordance) measures and are often considered to be the best dependence measures for nonelliptical distributions (Embrechts et al., 2003). These concordance measures are based on the order statistics of the sample. Moreover, the distortions that affect the linear correlation coefficient are greatly minimized resulting in rank correlations that are robust measures of correlation. In fact, Spearman's rho computes the correlation between pairs of ranks by mimicking the approach of linear correlation (Genest and Favre, 2007). Specifically, it measures the probability of concordance and discordance. Spearman's rho, given the ordered statistics or ranks of X and Y, is defined as:

$$\rho_s = 3\left[\Pr((X_1 - X_2)(Y_1 - Y_2) > 0) - \Pr((X_1 - X_2)(Y_1 - Y_2) < 0)\right] \tag{3.16}$$

Spearman's rho is very closely related to the Kendall's tau which measures the difference between the probability of concordance and probability of discordance. Given that it is also a rank correlation, Kendall's tau for the ordered statistics of X and Y is given by:

$$\tau = \Pr((X_1 - X_2)(Y_1 - Y_2) > 0) - \Pr((X_1 - X_2)(Y_1 - Y_2) < 0) \tag{3.17}$$

Similar to linear correlation coefficient, both $\tau \in [-1,1]$ and $\rho_s \in [-1,1]$. Both Kendall's tau and the Spearman's rho can be represented in terms of copula functions as below:

$$\tau = 4\int_0^1\int_0^1 C(u,v)\,dC(u,v) - 1 \tag{3.18}$$

$$\rho_s = 12\int_0^1\int_0^1 uvdC(u,v) - 3 \tag{3.19}$$

Copula parameters can be estimated either through maximum likelihood or through Kendall's tau estimator (Equation 3.18). The Kendall's tau estimator is efficient and can be used as a Goodness-of-Fit measure of copula models (Embrechts et al., 2002; Chollete et al., 2005; Hu, 2006). Specifically, if the dependence parameter is relatively the same regardless of the estimation method, then there is no difference whether it is obtained from the rank of data or via the copula functions. Essentially, this would imply that the copula functions are well specified.[33]

Lastly, tail dependence is also used in this paper as a measure of dependence. In fact, tail dependence is a property of an underlying copula function and is used to summarize the potential for extreme co-movements among a set of variables (Marshal and Zeevi, 2002). It is important to note that the tail dependence differs widely for different class or family of copulas (Rodriguez, 2007). For example, Normal, Frank, and Plackett copulas have zero tail dependences and would not be able to capture any of the information about the extreme co-movements or the dependence structure in the tails. The tail dependence for Student t-copula is given as (Marshal and Zeevi (2002)):

$$\lambda_L = 2\times\left(1 - t_{\nu+1}\left(\frac{\sqrt{\nu+1}\sqrt{\rho+1}}{\sqrt{\rho+1}}\right)\right) \tag{3.20}$$

[33] The relationship between the Kendall's tau and parameters of different copulas is given in Embrechts et al. (2003), Cholete et al. (2005), Hu (2006), and Genest and Favre (2007). For example, the Clayton and Gumbel copula parameters and Kendall's tau are related through these equations: $\tau_\theta = \frac{\theta}{\theta+2}$ and $\tau_\theta = 1 - \frac{1}{\theta}$. In this study we computed the copula parameters both ways. We find that they are fairly close to each other. Hence, it can be concluded that the copula models are well specified.

Student t copula captures only the symmetric tail dependence (e.g. $\lambda_L = \lambda_U$) which is more informative than the case of independence but still lacks to explain possible asymmetries in the tails. On the other hand, Clayton, Rotated Clayton, Gumbel, Rotated Gumbel, and SJC all are very informative and provide information on asymmetric depe-ndence.[34] The tail dependence of Clayton copula is given as (Embrechts et al., 2003):

$$\lambda_L = 2^{-1/\theta} \tag{3.21}$$

where θ is the Clayton copula parameter. Note that Clayton copula has λ_L and zero lower and upper tail dependences, respectively. Conversely, Rotated Clayton copula has zero and λ_U lower and upper tail dependences, respectively. The equation for λ_U is exactly the same as λ_L (lower tail dependence of Clayton copula) only replacing the θ Clayton copula parameter with that of Rotated Clayton. Similar relation is observed for the Gumbel and Rotated Gumbel copulas. The upper tail dependence of the Gumbel copula is the following:

$$\lambda_U = 2 - 2^{1/\theta} \tag{3.22}$$

where θ is the Gumbel copula parameter. The lower tail dependence of the Gumbel copula is zero. Changing only the copula parameters and the tail dependencies, the Rotated Gumbel copula has the same tail dependence equation for the lower tail as the Gumbel copula has for its upper tail dependence.

Lastly, the tail dependencies for the SJC copula are the SJC copula parameter estimated in the reverse order. Tail dependencies that tackle only the specific tails or

[34] Tail dependences for each of the copula functions used in the study are provided in Nelsen (2006), Embrechts et al. (2002), Marshal and Zeevi (2002), Patton (2004), Chollete et al. (2005), and in most copula papers.

both tails unequally would provide sufficient information on whether or not the dependence of oil price series and stock market indices is higher during the crash than booms.

3.4 Results

The results of this paper are summarized in this section. The results of conventional dependence measures for oil price series and the stock market indices such as Kendall’s tau, Spearman’s rho, and the linear correlation are illustrated first. The copula parameter estimates, tail dependences, and log-likelihood functions are all represented next followed by the information criteria results. In other words, the nature of the relationship, the direction of the dependence, and the best fitting dependence structure of oil price series and the stock market indices are illustrated in this section.

3.4.1 Results of Degree and Structure of Dependence

The results of the dependence measures are summarized in Tables 3.1 and 3.2 for Brent oil and Opec oil price series, respectively. First, we compare whether or not the Brent oil and Opec price series result in different measures of dependence. Depending on the oil price series used, the association degree measures result in different values especially in the post-Euro period (with the exception of pre-Euro Japan). For instance, all the measures of dependence between the Swiss stock market index and Opec oil price series are statistically significant even at 10% significance level, whereas in case of

Table 3.1. Correlation between Each Stock Market Index and Brent Oil Price Returns

	Pre-Euro-USD			Pre-Euro-SAC			Post-Euro-USD			Post-Euro-SAC			Post-Euro-EUR		
	K. Tau	S. Rho	P. Rho	K. Tau	S. Rho	P. Rho	K. Tau	S. Rho	P. Rho	K. Tau	S. Rho	P. Rho	K. Tau	S. Rho	P. Rho
UK	0.010	0.014	-0.006	-0.054	-0.080	-0.057	0.041	0.060	0.033	0.023	0.034	0.013	0.046	0.068	0.056
	0.334	*0.351*	*0.686*	*0.000*	*0.000*	*0.000*	*0.004*	*0.004*	*0.117*	*0.104*	*0.103*	*0.539*	*0.001*	*0.001*	*0.007*
Japan	0.027	0.039	-0.031	-0.024	-0.034	-0.064	0.041	0.061	0.071	0.008	0.012	0.029	0.048	0.069	0.092
	0.008	*0.010*	*0.043*	*0.024*	*0.025*	*0.000*	*0.004*	*0.004*	*0.001*	*0.566*	*0.573*	*0.167*	*0.001*	*0.001*	*0.000*
US	-0.029	-0.043	-0.082	0.081	0.119	0.036	-0.012	-0.016	-0.016	0.012	0.019	0.018	0.061	0.090	0.101
	0.006	*0.005*	*0.000*	*0.000*	*0.000*	*0.018*	*0.413*	*0.447*	*0.440*	*0.393*	*0.366*	*0.397*	*0.000*	*0.000*	*0.000*
Germany	0.006	0.009	-0.058	-0.107	-0.156	-0.151	0.017	0.026	0.007	-0.002	-0.003	-0.021	-0.014	-0.021	-0.026
	0.536	*0.556*	*0.000*	*0.000*	*0.000*	*0.000*	*0.222*	*0.222*	*0.756*	*0.886*	*0.881*	*0.323*	*0.308*	*0.311*	*0.226*
France	0.006	0.009	-0.031	-0.098	-0.144	-0.135	0.038	0.057	0.031	0.008	0.013	-0.006	-0.006	-0.009	-0.018
	0.556	*0.550*	*0.040*	*0.000*	*0.000*	*0.000*	*0.006*	*0.007*	*0.136*	*0.549*	*0.541*	*0.768*	*0.654*	*0.657*	*0.389*
Italy	0.010	0.014	-0.046	-0.048	-0.063	-0.079	0.044	0.065	0.035	0.014	0.019	-0.009	-0.010	-0.014	-0.026
	0.355	*0.374*	*0.003*	*0.000*	*0.000*	*0.000*	*0.002*	*0.002*	*0.101*	*0.359*	*0.357*	*0.668*	*0.515*	*0.518*	*0.218*
Canada	-0.004	-0.006	0.006	0.084	0.124	0.099	0.099	0.147	0.136	0.106	0.157	0.149	0.130	0.191	0.194
	0.687	*0.679*	*0.715*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
HK	0.019	0.029	0.004	0.067	0.100	0.049	0.010	0.015	0.028	0.030	0.044	0.044	0.071	0.107	0.108
	0.064	*0.061*	*0.781*	*0.000*	*0.000*	*0.001*	*0.468*	*0.477*	*0.190*	*0.033*	*0.036*	*0.036*	*0.000*	*0.000*	*0.000*
China							0.005	0.008	0.000	0.018	0.026	0.009	0.065	0.096	0.071
							0.698	*0.709*	*0.999*	*0.211*	*0.219*	*0.662*	*0.000*	*0.000*	*0.001*
Czech Rep.							0.036	0.054	0.045	-0.014	-0.019	-0.029	-0.004	-0.005	-0.004
							0.010	*0.011*	*0.034*	*0.355*	*0.357*	*0.166*	*0.798*	*0.796*	*0.854*
Netherlands							0.025	0.038	0.006	-0.002	-0.003	-0.022	-0.015	-0.022	-0.028
							0.072	*0.072*	*0.790*	*0.890*	*0.897*	*0.303*	*0.289*	*0.302*	*0.188*
Finland							0.037	0.055	0.029	0.020	0.030	0.012	0.011	0.017	0.012
							0.009	*0.009*	*0.163*	*0.159*	*0.161*	*0.578*	*0.423*	*0.416*	*0.569*
Hungary							0.044	0.066	0.057	0.036	0.048	0.024	0.026	0.035	0.052
							0.002	*0.002*	*0.007*	*0.024*	*0.022*	*0.248*	*0.098*	*0.097*	*0.014*
Poland							0.050	0.075	0.080	0.034	0.051	0.052	0.041	0.061	0.071
							0.000	*0.000*	*0.000*	*0.015*	*0.015*	*0.014*	*0.004*	*0.004*	*0.001*
Russia							0.066	0.096	0.069	0.075	0.109	0.068	0.097	0.141	0.110
							0.000	*0.000*	*0.001*	*0.000*	*0.000*	*0.001*	*0.000*	*0.000*	*0.000*
Saudi Arabia							0.015	0.021	0.022	0.045	0.067	0.048	0.097	0.144	0.107
							0.304	*0.308*	*0.301*	*0.001*	*0.001*	*0.023*	*0.000*	*0.000*	*0.000*
Venezuela							0.027	0.042	0.033	0.032	0.048	0.033	0.059	0.089	0.066
							0.052	*0.048*	*0.114*	*0.023*	*0.022*	*0.122*	*0.000*	*0.000*	*0.002*
Spain							0.026	0.039	0.007	-0.005	-0.007	-0.031	-0.022	-0.032	-0.049
							0.060	*0.066*	*0.733*	*0.724*	*0.730*	*0.140*	*0.125*	*0.126*	*0.021*
Switzerland							0.023	0.034	0.014	-0.013	-0.019	-0.029	-0.032	-0.047	-0.044
							0.105	*0.106*	*0.512*	*0.372*	*0.361*	*0.171*	*0.024*	*0.024*	*0.036*

Note: The table reports the dependence measures including the Kendall's Tau (K. Tau), Spearman's Rho (S. Rho), and Pearson's Rho (P. Rho) for pre- and post-Euro periods and three denominations: Stable Aggregate Currency (SAC), U.S. Dollar (USD), and Euro (EUR). The p-values are in italics.

Brent oil price, all of the coefficients are insignificant. However, these results are only observed for SAC- and EUR-denominated data in post-Euro period. Overall, it can be concluded that the dependence measures change somewhat depending on the type of oil price series used. This result is somewhat different from that of Ciner (2001), who used WTI and Brent oil price series and concluded that there is no significant difference between the two series and one can choose either one for such analysis.

Table 3.2 Correlation between Each Stock Market Index and Opec Oil Price Returns

	Pre-Euro-USD			Pre-Euro-SAC			Post-Euro_USD			Post-Euro-SAC			Post-Euro-EUR		
	K. Tau	S. Rho	P. Rho	K. Tau	S. Rho	P. Rho	K. Tau	S. Rho	P. Rho	K. Tau	S. Rho	P. Rho	K. Tau	S. Rho	P. Rho
UK	0.008	0.011	-0.014	-0.072	-0.105	-0.067	0.029	0.044	0.013	0.008	0.012	-0.013	0.039	0.058	0.047
	0.443	*0.462*	*0.360*	*0.000*	*0.000*	*0.000*	*0.038*	*0.037*	*0.542*	*0.554*	*0.559*	*0.538*	*0.005*	*0.006*	*0.027*
Japan	0.006	0.008	-0.065	-0.050	-0.071	-0.103	0.032	0.048	0.059	-0.010	-0.014	0.003	0.049	0.071	0.099
	0.584	*0.595*	*0.000*	*0.000*	*0.000*	*0.000*	*0.022*	*0.023*	*0.005*	*0.491*	*0.493*	*0.871*	*0.001*	*0.001*	*0.000*
US	-0.024	-0.037	-0.084	0.109	0.159	0.059	-0.012	-0.017	-0.031	0.023	0.035	0.021	0.085	0.125	0.128
	0.018	*0.017*	*0.000*	*0.000*	*0.000*	*0.000*	*0.399*	*0.426*	*0.135*	*0.096*	*0.093*	*0.315*	*0.000*	*0.000*	*0.000*
Germany	-0.008	-0.012	-0.081	-0.138	-0.202	-0.186	0.008	0.012	-0.015	-0.021	-0.032	-0.052	-0.033	-0.049	-0.053
	0.429	*0.420*	*0.000*	*0.000*	*0.000*	*0.000*	*0.573*	*0.574*	*0.479*	*0.127*	*0.125*	*0.013*	*0.020*	*0.021*	*0.012*
France	0.003	0.005	-0.060	-0.121	-0.177	-0.174	0.026	0.038	0.006	-0.014	-0.020	-0.044	-0.028	-0.041	-0.054
	0.735	*0.752*	*0.000*	*0.000*	*0.000*	*0.000*	*0.068*	*0.071*	*0.791*	*0.330*	*0.337*	*0.038*	*0.049*	*0.049*	*0.010*
Italy	0.007	0.010	-0.051	-0.049	-0.064	-0.071	0.033	0.050	0.003	-0.007	-0.009	-0.047	-0.037	-0.049	-0.068
	0.479	*0.495*	*0.001*	*0.000*	*0.000*	*0.000*	*0.017*	*0.018*	*0.879*	*0.668*	*0.676*	*0.026*	*0.019*	*0.020*	*0.001*
Canada	0.000	0.000	0.006	0.108	0.159	0.121	0.075	0.112	0.094	0.083	0.124	0.111	0.114	0.169	0.173
	0.974	*0.986*	*0.677*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
HK	0.009	0.014	-0.014	0.069	0.103	0.041	0.016	0.024	0.019	0.045	0.067	0.047	0.095	0.140	0.130
	0.358	*0.350*	*0.374*	*0.000*	*0.000*	*0.007*	*0.254*	*0.260*	*0.371*	*0.001*	*0.001*	*0.024*	*0.000*	*0.000*	*0.000*
China							0.006	0.051	0.000	0.027	0.041	0.019	0.084	0.125	0.097
							0.695	*0.699*	*0.982*	*0.055*	*0.052*	*0.379*	*0.000*	*0.000*	*0.000*
Czech Rep.							0.035	0.054	0.038	-0.026	-0.037	-0.053	-0.016	-0.023	-0.031
							0.013	*0.015*	*0.070*	*0.078*	*0.081*	*0.012*	*0.285*	*0.280*	*0.142*
Netherlands							0.013	0.020	-0.011	-0.021	-0.032	-0.048	-0.033	-0.049	-0.051
							0.354	*0.347*	*0.611*	*0.130*	*0.130*	*0.021*	*0.019*	*0.020*	*0.016*
Finland							0.026	0.039	0.018	0.004	0.006	-0.007	-0.005	-0.007	-0.003
							0.062	*0.066*	*0.385*	*0.788*	*0.768*	*0.747*	*0.717*	*0.751*	*0.890*
Hungary							0.044	0.065	0.055	0.033	0.044	0.025	0.019	0.025	0.043
							0.002	*0.002*	*0.009*	*0.037*	*0.036*	*0.243*	*0.230*	*0.228*	*0.039*
Poland							0.046	0.069	0.057	0.028	0.042	0.037	0.038	0.056	0.064
							0.001	*0.001*	*0.007*	*0.043*	*0.045*	*0.077*	*0.007*	*0.008*	*0.002*
Russia							0.082	0.120	0.098	0.095	0.138	0.101	0.123	0.178	0.152
							0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Saudi Arabia							0.024	0.036	0.027	0.066	0.098	0.069	0.130	0.192	0.144
							0.087	*0.087*	*0.199*	*0.000*	*0.000*	*0.001*	*0.000*	*0.000*	*0.000*
Venezuela							0.025	0.037	0.030	0.041	0.061	0.042	0.078	0.116	0.084
							0.074	*0.076*	*0.159*	*0.004*	*0.004*	*0.047*	*0.000*	*0.000*	*0.000*
Spain							0.014	0.021	-0.006	-0.026	-0.038	-0.057	-0.044	-0.066	-0.073
							0.305	*0.312*	*0.785*	*0.066*	*0.068*	*0.007*	*0.002*	*0.002*	*0.001*
Switzerland							0.009	0.013	-0.022	-0.038	-0.057	-0.076	-0.058	-0.086	-0.090
							0.534	*0.523*	*0.299*	*0.007*	*0.007*	*0.000*	*0.000*	*0.000*	*0.000*

Note: The table reports the dependence measures including the Kendall's Tau (K. Tau), Spearman's Rho (S. Rho), and Pearson's Rho (P. Rho) for pre- and post-Euro periods and three denominations: Stable Aggregate Currency (SAC), U.S. Dollar (USD), and Euro (EUR). The p-values are in italics.

Dependence measures are also compared based on the chosen base currency. In pre-Euro period there is a large economic and statistically significant difference across all the correlation measures for USD- and SAC-denominated data. The latter case yields significant, large, and often negative dependence measures (e.g. -0.107 Kendall's tau parameter for Germany under SAC-denomination case), while the former results in mostly insignificant and somewhat weak coefficients (e.g. 0.006 Kendall's tau parameter for Germany under USD-denomination case). The picture changes greatly after the creation of Euro. The dependence measures for most series become the exact opposites. In other words, the coefficients that were not significant in pre-Euro period become statistically significant in post-Euro period and vice versa. This pattern is observed for both SAC and USD denomination cases. The only exception is Canadian stock market index which in almost all cases appears (except for USD-denominated data in pre-Euro period) to be strongly and significantly associated with Brent oil price series. Similar results are found for Russian, Saudi Arabian, and Venezuelan stock market index returns and oil price returns. To a smaller degree, these findings can be applied to Polish, Swiss, and Hungarian stock index returns and oil price series as well.

The choice of currency appears to be important as the dependence results greatly change for most of the stock market indices. For majority of cases, EUR- and SAC-denominated series yield similar and more consistent dependence results than USD-denominated series (e.g. Finland, Saudi Arabia, Czech Republic, etc). Moreover, there appears to be a significant difference between the dependence structure of developed and developing countries (e.g. Germany and US versus Russia and Poland). Stock markets of most developed countries exhibit no correlation with oil price series, whereas weak but significant measures of dependence are observed for most of the developing countries. The possible explanation for such results is the fact that most developed countries have better functioning financial markets and are less susceptible to small changes, while the developing countries are largely affected by small changes.

Finally, the three dependence measures are compared. Spearman's rho and Kendall's tau result in nearly the same association measures, and only in few cases the Pearson's rho differs in both significance and the degree of dependence (e.g. UK for post-Euro period under the USD denomination case, Venezuela for post-Euro period under the SAC denomination case, Italy for pre-Euro period under USD-denomination case). Hence, results are not greatly affected by the dependence measure and the oil price series used. However, there is a marked difference in pre-and post-Euro periods implying that the creation of Euro changed the dynamics of the financial markets of the developed countries (e.g. UK, US, France, Italy, Germany, etc). In addition, the development status of countries is important and plays critical role in understanding the relationship between the oil price series and the stock market indices. Finally, the choice of the base currency greatly changes the dependence measures implying its crucial role in obtaining accurate results. Most of the stock market indices have very small and mostly insignificant dependence measures which are highly sensitive upon different scenarios. This is consistent with the results reported by Huang et al. (1996) who found that oil futures returns have no impact on stock market indices such as S&P 500. We find that the only relatively strong and significant association is observed for Canadian stock market index returns and Brent oil price returns regardless of the different scenarios. Strong association is also found for Russian, Saudi Arabian, Venezuelan, Polish, and Hungarian stock market index returns and oil price returns.

3.4.2 Copula Results

The estimated copula parameters for each scenario are reported in Tables 3.3 to 3.7. There are some differences noticed for different denomination scenarios. For example, in pre-Euro period SAC-denominated series have slightly larger copula parameters than the USD-denominated cases. For example, Gumbel copula parameter estimates for USD-denominated data is 1.001 and 1.012 for Canada and HK (with Brent oil price series), respectively, whereas, the estimates change under the SAC-denomination case becoming 1.083 and 1.058, respectively. On the other hand, in post-Euro period USD-denominated series have larger parameter estimates than EUR-denominated series, and those have larger parameters than the SAC-denominated series. Hence, in copula estimation the choice of a base currency is crucial and depending on that, copula results can change.

The use of Brent oil price series versus Opec oil price series changes the results somewhat, but there is no consistency to be able to make solid conclusions as to how results change. In some cases and for some copula functions, the parameters are larger when Opec oil series is used, whereas, in some cases the opposite is true. Hence, the only possible conclusion made is that the copula parameters are not the same under different oil price series.

Table 3.3 Estimated Copula Parameters for USD-denominated Data in Pre-Euro Period

	Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t		SJC	
UK-Brent	0.028	0.037	0.024	1.087	0.162	1.015	1.017	0.028	27.606	0.000	0.000
Jap-Brent	0.024	0.014	0.036	1.118	0.219	1.017	1.008	0.029	27.411	0.000	0.000
US-Brent	-0.036	-0.025	-0.009	0.893	-0.222	1.001	1.000	-0.037	19.777	0.000	0.000
Germ-Brent	0.009	0.019	0.012	1.063	0.121	1.009	1.011	0.014	16.809	0.000	0.000
Fran-Brent	0.011	0.018	0.017	1.042	0.081	1.009	1.012	0.014	19.359	0.000	0.000
Ital-Brent	-0.002	0.003	0.004	1.034	0.065	1.002	1.002	0.003	18.178	0.000	0.000
Cana-Brent	0.012	0.023	0.001	1.022	0.043	1.001	1.010	0.012	52.505	0.000	0.000
HK-Brent	0.025	0.034	0.015	1.096	0.182	1.012	1.016	0.027	41.976	0.000	0.000
UK-Opec	0.029	0.040	0.032	1.088	0.161	1.018	1.022	0.028	14.970	0.000	0.000
Jap-Opec	0.000	-0.007	0.012	1.045	0.086	1.007	1.000	0.004	27.350	0.000	0.000
US-Opec	-0.035	-0.032	-0.021	0.926	-0.153	1.000	1.000	-0.033	27.509	0.000	0.000
Germ-Opec	-0.002	-0.001	0.008	1.020	0.040	1.004	1.000	0.002	21.046	0.000	0.000
Fran-Opec	0.001	0.000	0.004	1.037	0.072	1.006	1.000	0.005	27.515	0.000	0.000
Ital-Opec	0.005	0.018	-0.009	1.063	0.120	1.000	1.003	0.009	27.451	0.000	0.000
Cana-Opec	0.019	0.020	0.013	1.063	0.123	1.006	1.008	0.020	52.395	0.000	0.000
HK-Opec	0.017	0.024	0.006	1.077	0.148	1.007	1.008	0.019	50.691	0.000	0.000

Note: The table contains the estimated parameters for the following copula functions: Normal, Clayton, Rotated Clayton (R. Clayton), Plackett, Frank, Gumbel, Rotated Gumbel (R. Gumbel), Student t, and Symmetricized Joe-Clayton (SJC).

Table 3.4 Estimated Copula Parameters for SAC-denominated Data in Pre-Euro Period

	Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t		SJC	
UK-Brent	-0.078	-0.031	-0.046	0.754	0.000	1.000	1.000	-0.088	11.796	0.000	0.000
Jap-Brent	-0.051	-0.041	-0.027	0.863	0.000	1.001	1.000	-0.052	27.616	0.000	0.000
US-Brent	0.142	0.142	0.169	1.628	0.947	1.099	1.089	0.154	12.044	0.041	0.015
Germ-Brent	-0.177	-0.073	-0.098	0.558	0.000	1.000	1.000	-0.188	10.591	0.001	0.001
Fran-Brent	-0.163	-0.076	-0.090	0.579	0.000	1.000	1.000	-0.172	10.372	0.000	0.000
Ital-Brent	-0.057	-0.023	-0.050	0.734	0.000	1.000	1.000	-0.076	21.045	0.000	0.000
Cana-Brent	0.147	0.163	0.136	1.576	0.909	1.083	1.091	0.152	27.798	0.008	0.035
HK-Brent	0.102	0.115	0.094	1.415	0.679	1.058	1.066	0.109	19.095	0.000	0.021
UK-Opec	-0.114	0.000	-0.059	0.660	0.000	1.000	1.000	-0.129	8.437	0.000	0.000
Jap-Opec	-0.088	-0.063	-0.066	0.787	0.000	1.000	1.000	-0.087	27.859	0.000	0.000
US-Opec	0.184	0.189	0.228	1.913	1.263	1.136	1.122	0.202	10.777	0.081	0.023
Germ-Opec	-0.233	-0.084	-0.112	0.465	0.000	1.000	1.000	-0.247	9.302	0.000	0.000
Fran-Opec	-0.218	-0.100	-0.100	0.501	0.000	1.000	1.000	-0.225	10.126	0.000	0.000
Ital-Opec	-0.056	-0.033	-0.053	0.762	0.000	1.000	1.000	-0.074	44.182	0.000	0.000
Cana-Opec	0.181	0.195	0.191	1.796	1.165	1.116	1.117	0.189	20.691	0.091	0.108
HK-Opec	0.108	0.127	0.097	1.445	0.716	1.064	1.072	0.117	15.849	0.000	0.103

Note Note: The table contains the estimated parameters for the following copula functions: Normal, Clayton, Rotated Clayton (R. Clayton), Plackett, Frank, Gumbel, Rotated Gumbel (R. Gumbel), Student t, and Symmetricized Joe-Clayton (SJC).

Table 3.5 Estimated Copula Parameters for USD-denominated Data in Post-Euro Period

	Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t		SJC	
UK-Brent	0.061	0.058	0.067	1.230	0.404	1.037	1.033	0.064	19.323	0.001	0.001
Jap-Brent	0.065	0.056	0.065	1.196	0.358	1.034	1.028	0.068	100.000	0.001	0.001
US-Brent	-0.016	0.006	0.000	0.951	0.001	1.005	1.005	-0.018	15.014	0.001	0.001
Germ-Brent	0.020	0.019	0.036	1.075	0.140	1.018	1.011	0.021	15.506	0.001	0.001
Fran-Brent	0.053	0.067	0.047	1.191	0.342	1.027	1.035	0.055	15.948	0.000	0.002
Ital-Brent	0.059	0.076	0.048	1.234	0.413	1.031	1.044	0.065	18.311	0.000	0.006
Cana-Brent	0.157	0.177	0.164	1.618	0.954	1.095	1.105	0.163	14.030	0.023	0.043
HK-Brent	0.030	0.029	0.042	1.049	0.095	1.020	1.017	0.027	27.529	0.000	0.000
Ch-Brent	0.005	0.000	0.018	1.016	0.031	1.006	1.002	0.005	57.351	0.000	0.000
Cze-Brent	0.053	0.068	0.041	1.191	0.344	1.027	1.035	0.057	27.611	0.000	0.003
Neth-Brent	0.035	0.040	0.035	1.140	0.259	1.019	1.020	0.038	27.553	0.001	0.001
Finl-Brent	0.060	0.057	0.057	1.241	0.425	1.030	1.034	0.065	46.946	0.001	0.001
Hung-Brent	0.067	0.073	0.053	1.224	0.407	1.030	1.041	0.070	79.989	0.001	0.001
Pola-Brent	0.084	0.087	0.086	1.273	0.474	1.047	1.047	0.085	27.711	0.003	0.002
Russ-Brent	0.099	0.114	0.086	1.410	0.671	1.052	1.066	0.105	27.681	0.001	0.017
Saud-Brent	0.036	0.074	0.008	1.089	0.164	1.011	1.034	0.034	18.747	0.001	0.001
Vene-Brent	0.037	0.036	0.033	1.129	0.240	1.018	1.022	0.040	100.000	0.001	0.001
Spai-Brent	0.026	0.042	0.017	1.127	0.233	1.016	1.022	0.032	18.888	0.001	0.001
Swit-Brent	0.028	0.016	0.050	1.109	0.204	1.023	1.013	0.030	17.376	0.001	0.001
UK-Opec	0.042	0.044	0.039	1.155	0.284	1.021	1.026	0.045	27.513	0.001	0.001
Jap-Opec	0.050	0.039	0.060	1.131	0.245	1.029	1.020	0.051	65.174	0.001	0.001
US-Opec	-0.027	0.000	0.000	0.946	0.001	1.002	1.002	-0.025	27.583	0.001	0.001
Germ-Opec	0.002	0.001	0.010	1.024	0.047	1.003	1.005	0.003	27.425	0.001	0.001
Fran-Opec	0.027	0.043	0.013	1.098	0.185	1.005	1.023	0.030	27.456	0.000	0.000
Ital-Opec	0.034	0.056	0.007	1.141	0.264	1.006	1.030	0.039	27.445	0.000	0.000
Cana-Opec	0.111	0.141	0.096	1.414	0.689	1.059	1.079	0.119	16.453	0.000	0.043
HK-Opec	0.031	0.045	0.019	1.072	0.139	1.009	1.024	0.032	62.090	0.000	0.000
Ch-Opec	0.009	0.003	0.025	1.042	0.080	1.011	1.005	0.010	27.482	0.000	0.000
Cz-Opec	0.056	0.067	0.053	1.199	0.357	1.032	1.037	0.060	17.235	0.000	0.001
Neth-Opec	0.016	0.010	0.033	1.068	0.129	1.017	1.009	0.019	18.883	0.001	0.001
Finl-Opec	0.036	0.035	0.033	1.127	0.236	1.016	1.020	0.038	70.185	0.001	0.001
Hung-Opec	0.069	0.080	0.060	1.237	0.419	1.036	1.044	0.072	27.684	0.001	0.002
Pola-Opec	0.066	0.077	0.053	1.235	0.420	1.029	1.040	0.070	27.583	0.001	0.001
Russ-Opec	0.111	0.132	0.097	1.455	0.735	1.060	1.075	0.118	19.331	0.001	0.028
Saud-Opec	0.028	0.064	0.009	1.069	0.127	1.009	1.032	0.026	14.031	0.000	0.002
Vene-Opec	0.029	0.030	0.027	1.103	0.194	1.013	1.015	0.031	56.447	0.001	0.001
Spai-Opec	0.012	0.015	0.017	1.053	0.101	1.012	1.010	0.014	27.468	0.001	0.001
Swit-Opec	0.012	0.000	0.035	1.071	0.134	1.015	1.004	0.016	19.136	0.001	0.001

Note: The table contains the estimated parameters for the following copula functions: Normal, Clayton, Rotated Clayton (R. Clayton), Plackett, Frank, Gumbel, Rotated Gumbel (R. Gumbel), Student t, Symmetricized Joe-Clayton (SJC).

Table 3.6 Estimated Copula Parameters for SAC-denominated Data in Post-Euro Period

	Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t		SJC	
UK-Brent	0.027	0.027	0.031	1.107	0.203	1.018	1.011	0.029	27.434	0.001	0.001
Jap-Brent	0.017	0.023	0.013	1.029	0.058	1.005	1.010	0.018	100.000	0.001	0.001
US-Brent	0.026	0.040	0.036	1.075	0.142	1.021	1.024	0.026	12.013	0.001	0.001
Germ-Brent	-0.016	0.000	0.007	0.964	0.001	1.006	1.002	-0.016	18.180	0.001	0.001
Fran-Brent	0.006	0.024	0.004	1.033	0.064	1.006	1.010	0.008	19.298	0.000	0.000
Ital-Brent	0.010	0.032	0.000	1.077	0.145	1.002	1.014	0.014	27.362	0.000	0.000
Cana-Brent	0.167	0.188	0.184	1.699	1.039	1.110	1.113	0.177	12.582	0.039	0.042
HK-Brent	0.050	0.044	0.056	1.144	0.271	1.029	1.024	0.050	27.532	0.001	0.000
Ch-Brent	0.021	0.006	0.025	1.099	0.187	1.009	1.002	0.023	100.000	0.000	0.000
Cze-Brent	-0.012	0.013	0.000	0.967	0.001	1.002	1.006	-0.012	27.474	0.000	0.000
Neth-Brent	-0.008	0.000	0.000	0.993	0.001	1.002	1.002	-0.007	27.508	0.001	0.001
Finl-Brent	0.033	0.030	0.026	1.125	0.234	1.013	1.018	0.035	85.920	0.001	0.001
Hung-Brent	0.024	0.011	0.010	1.048	0.095	1.003	1.002	0.018	100.000	0.001	0.001
Pola-Brent	0.056	0.063	0.051	1.185	0.333	1.029	1.033	0.057	27.620	0.001	0.001
Russ-Brent	0.106	0.128	0.094	1.474	0.749	1.063	1.075	0.117	15.864	0.001	0.026
Saud-Brent	0.074	0.108	0.038	1.257	0.451	1.027	1.054	0.077	27.640	0.001	0.013
Vene-Brent	0.044	0.048	0.039	1.165	0.300	1.023	1.029	0.047	27.450	0.001	0.001
Spai-Brent	-0.022	0.000	0.000	0.968	0.001	1.002	1.002	-0.019	27.581	0.001	0.001
Swit-Brent	-0.027	0.000	0.002	0.932	0.001	1.008	1.002	-0.028	27.546	0.001	0.001
UK-Opec	0.001	0.002	0.004	1.027	0.053	1.008	1.002	0.002	62.478	0.001	0.001
Jap-Opec	-0.013	0.000	0.000	0.933	0.001	1.002	1.002	-0.015	100.000	0.001	0.001
US-Opec	0.036	0.047	0.036	1.133	0.245	1.024	1.025	0.040	15.436	0.001	0.001
Germ-Opec	-0.046	0.000	0.000	0.880	0.001	1.002	1.002	-0.049	100.000	0.001	0.001
Fran-Opec	-0.034	0.000	0.000	0.912	0.001	1.002	1.002	-0.036	100.000	0.000	0.000
Ital-Opec	-0.018	0.008	0.000	0.988	0.001	1.002	1.002	-0.017	100.000	0.000	0.000
Cana-Opec	0.121	0.149	0.113	1.456	0.744	1.068	1.084	0.129	14.991	0.003	0.036
HK-Opec	0.068	0.070	0.052	1.222	0.408	1.027	1.037	0.071	100.000	0.000	0.002
Ch-Opec	0.040	0.029	0.042	1.187	0.339	1.018	1.017	0.044	45.051	0.000	0.000
Cz-Opec	-0.023	0.006	0.000	0.933	0.001	1.002	1.003	-0.024	27.338	0.000	0.000
Neth-Opec	-0.041	0.000	0.000	0.894	0.001	1.002	1.002	-0.042	27.293	0.001	0.001
Finl-Opec	-0.004	0.003	0.000	0.988	0.001	1.002	1.002	-0.004	100.000	0.001	0.001
Hung-Opec	0.021	0.017	0.007	1.041	0.081	1.006	1.004	0.016	100.000	0.001	0.001
Pola-Opec	0.038	0.059	0.011	1.140	0.262	1.007	1.027	0.040	80.029	0.001	0.001
Russ-Opec	0.133	0.160	0.122	1.599	0.918	1.079	1.092	0.145	18.041	0.002	0.044
Saud-Opec	0.087	0.112	0.067	1.316	0.538	1.039	1.062	0.091	18.157	0.001	0.012
Vene-Opec	0.053	0.053	0.050	1.206	0.366	1.025	1.030	0.057	51.186	0.001	0.001
Spai-Opec	-0.050	0.000	0.000	0.867	0.001	1.002	1.002	-0.051	44.303	0.001	0.001
Swit-Opec	-0.065	0.000	0.000	0.838	0.001	1.002	1.002	-0.066	46.493	0.001	0.001

Note: The table contains the estimated parameters for the following copula functions: Normal, Clayton, Rotated Clayton (R. Clayton), Plackett, Frank, Gumbel, Rotated Gumbel (R. Gumbel), Student t, Symmetricized Joe-Clayton (SJC).

Table 3.7 Estimated Copula Parameters for EUR-denominated Data in Post-Euro Period

	Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t		SJC	
UK-Brent	0.069	0.062	0.076	1.244	0.432	1.039	1.033	0.072	27.588	0.003	0.001
Jap-Brent	0.075	0.078	0.072	1.223	0.402	1.040	1.040	0.078	52.406	0.001	0.002
US-Brent	0.104	0.130	0.104	1.360	0.601	1.063	1.072	0.107	10.443	0.003	0.028
Germ-Brent	-0.033	0.000	0.000	0.905	0.001	1.003	1.002	-0.035	15.641	0.001	0.001
Fran-Brent	-0.018	0.002	0.000	0.948	0.001	1.002	1.002	-0.019	100.000	0.000	0.000
Ital-Brent	-0.033	0.000	0.000	0.931	0.001	1.002	1.002	-0.036	100.000	0.000	0.000
Cana-Brent	0.208	0.244	0.227	1.912	1.278	1.138	1.146	0.217	12.777	0.054	0.080
HK-Brent	0.110	0.107	0.114	1.376	0.645	1.061	1.060	0.113	27.640	0.010	0.007
Ch-Brent	0.089	0.079	0.086	1.373	0.633	1.046	1.044	0.095	100.000	0.003	0.001
Cze-Brent	0.003	0.022	0.004	1.000	0.001	1.004	1.012	0.003	18.245	0.000	0.000
Neth-Brent	-0.029	0.000	0.000	0.924	0.001	1.002	1.002	-0.029	27.532	0.001	0.001
Finl-Brent	0.020	0.016	0.017	1.076	0.144	1.008	1.010	0.021	93.195	0.001	0.001
Hung-Brent	0.031	0.021	0.035	1.138	0.259	1.016	1.008	0.044	100.000	0.001	0.001
Pola-Brent	0.070	0.082	0.062	1.226	0.397	1.036	1.043	0.071	27.670	0.001	0.003
Russ-Brent	0.143	0.168	0.147	1.645	0.960	1.093	1.100	0.156	11.964	0.013	0.043
Saud-Brent	0.150	0.191	0.125	1.602	0.937	1.079	1.106	0.157	19.273	0.001	0.072
Vene-Brent	0.093	0.107	0.089	1.351	0.585	1.053	1.062	0.098	17.821	0.001	0.014
Spai-Brent	-0.051	0.000	0.000	0.879	0.001	1.002	1.002	-0.050	27.603	0.001	0.001
Swit-Brent	-0.053	0.000	0.000	0.851	0.001	1.006	1.002	-0.056	19.521	0.001	0.001
UK-Opec	0.054	0.042	0.066	1.182	0.327	1.034	1.021	0.055	27.529	0.001	0.001
Jap-Opec	0.075	0.067	0.078	1.209	0.381	1.037	1.035	0.078	94.832	0.001	0.001
US-Opec	0.133	0.154	0.142	1.511	0.806	1.084	1.089	0.140	10.961	0.017	0.031
Germ-Opec	-0.061	0.000	0.000	0.831	0.001	1.002	1.002	-0.063	27.286	0.001	0.001
Fran-Opec	-0.058	0.000	0.000	0.838	0.001	1.002	1.002	-0.061	100.000	0.000	0.000
Ital-Opec	-0.071	0.000	0.000	0.814	0.001	1.002	1.002	-0.076	100.000	0.000	0.000
Cana-Opec	0.175	0.211	0.176	1.690	1.039	1.107	1.122	0.182	13.588	0.021	0.073
HK-Opec	0.144	0.149	0.142	1.527	0.863	1.080	1.084	0.148	56.699	0.013	0.027
Ch-Opec	0.123	0.120	0.125	1.534	0.858	1.071	1.072	0.131	27.163	0.011	0.007
Cz-Opec	-0.014	0.000	0.000	0.957	0.001	1.002	1.003	-0.015	27.317	0.000	0.000
Neth-Opec	-0.063	0.000	0.000	0.829	0.001	1.002	1.002	-0.065	27.261	0.001	0.001
Finl-Opec	-0.020	0.000	0.000	0.935	0.001	1.002	1.002	-0.021	100.000	0.001	0.001
Hung-Opec	0.037	0.005	0.063	1.168	0.304	1.028	1.006	0.052	100.000	0.001	0.001
Pola-Opec	0.061	0.082	0.033	1.204	0.368	1.020	1.040	0.063	72.303	0.001	0.003
Russ-Opec	0.185	0.214	0.198	1.859	1.218	1.124	1.127	0.198	14.423	0.033	0.063
Saud-Opec	0.184	0.218	0.185	1.792	1.155	1.111	1.129	0.193	14.543	0.016	0.080
Vene-Opec	0.115	0.124	0.116	1.469	0.746	1.067	1.073	0.122	27.222	0.006	0.015
Spai-Opec	-0.081	0.000	0.000	0.781	0.001	1.002	1.002	-0.084	48.975	0.001	0.001
Swit-Opec	-0.098	0.000	0.000	0.747	0.001	1.002	1.002	-0.102	27.159	0.001	0.001

Note: The table contains the estimated parameters for the following copula functions: Normal, Clayton, Rotated Clayton (R. Clayton), Plackett, Frank, Gumbel, Rotated Gumbel (R. Gumbel), Student t, Symmetricized Joe-Clayton (SJC).

Finally, observing the results across pre- and post-Euro periods, one can see that the creation of Euro certainly changes the copula results. Nearly all the copula parameters become larger after the creation of Euro, except for the Normal and Student copula parameters. This implies that similar to the dependence measures, copula parameters do change in the post-Euro period. Although the choice of oil price series, base currency, and the creation of Euro changes the copula results, overall, the parameters of almost all the copula functions are quite small in all cases. Moreover, in some cases the parameters are at the lowest limits of copula functions. Therefore, one major implication is that oil prices and stock market indices are nearly independent in almost all scenarios. In addition, the development status of a country appears to have no bearings on the copula results implying that weak to no dependence between the oil prices and stock market indices is a global phenomenon. The only strong relation is found between Canadian stock market index and the oil price series which in almost all cases has quite large parameter estimates.

3.4.3 Tail Dependency Results

Examination of tail dependencies which are based on the estimated copula parameters will illustrate potential asymmetries in relationship between oil price series and stock market indices. Appendix A provides the tail dependencies for all scenarios. As mentioned earlier, Normal, Plackett, and Frank copulas have zero tail dependencies. Student t copula provides symmetric tail dependencies which are rather small in all cases.

In pre-Euro period tail dependencies of Clayton and Rotated Clayton copulas in most cases are zero (or very small) except for SAC-denominated Canada, U.S., and HK stock market indices. Moreover, (lower) tail dependence of Clayton copula is much higher than the (upper) tail dependence of Rotated Clayton copula for Canada and HK series. This means that oil prices and stock market indices for Canada and HK have higher dependencies in case of a crash than a boom. Specifically, oil price decrease affects the stock market indices for Canada and HK more than oil price increase. Similar results are reported for post-Euro period. The opposite is true for U.S. implying that oil price increase has more influence on U.S. stock market index than oil price decrease in pre-Euro period. This result is also observed in post-Euro period for EUR-denominated data. The finding that U.S. has the observed asymmetry is consistent with the results of Ciner (2001) who reported that oil prices affect the S&P 500 returns in a nonlinear fashion. In post-Euro period, Russia and Saudi Arabia appear to have the same pattern as Canada and HK. In addition, EUR-denominated stock market indices of China, Poland, and Venezuela are observed to have asymmetric tail dependencies as well implied by Clayton and Rotated Clayton copulas.

For most series in pre-Euro period, the tail dependence implied by Rotated Gumbel copula which captures the left tail dependence is larger than that of Gumbel copula (captures the right tail dependence). Moreover, the highest tail dependencies are reported for U.S. and Canada in pre-Euro period for SAC-denominated data. Similar results are also observed in post-Euro period when tail dependencies implied by Gumbel and Rotated Gumbel copulas are the largest for Canada (i.e. 0.136 vs. 0.132 for Rotated

Gumbel and Gumbel, respectively).[35] In general, most series have higher left tail dependence (Rotated Gumbel) than right tail dependence (Gumbel). Among those, the largest and most prominent left tail dependencies are for Canada, Russia, Saudi Arabia, Venezuela, and HK. This implies during market recession or downturns, the relation of stock market index returns and oil price returns become stronger for these countries. The only exceptions are for UK, Japan, U.S., Germany, HK, and China which have larger right tail dependence implying higher dependence in case of bull markets than bear markets.

In general, SJC copula tail dependences are rather small across the scenarios and series. The largest dependencies are observed for Canada, Russia, and Saudi Arabia (HK is large only in pre-Euro period). Moreover, they have higher left (lower) tail dependencies than upper tail dependencies which again imply that the relationships between oil price and stock index returns are stronger during the market downturn for Canada, Russia, and Saudi Arabia.

Overall, the tail dependencies change depending on the oil price series used, but not significantly. Moreover, there is also noticeable difference in tail dependence measures among the three denomination cases (two denomination cases for pre-Euro period). For example, if considering SAC-denominated data for the post-Euro period, we can see the there is a pattern according to which developed countries tend to have smaller tail dependence measures than the developing countries. However, such pattern vanishes with the use of other base currencies. Thus, it can be concluded that the choice

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[35] Numbers are reported from the Appendix A (A.7).

of base currency and the oil price series is important and can change the tail dependences.

3.4.4 Copula Selection Results

To select the best copula model, three selection criteria, reported in Appendix B, are used: Log Likelihood Functions (LLF), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC).[36]According to the log-likelihood measure, Student t copula is found to be the best copula model in the pre-Euro period (except for the case of Canada for which Placket copula is the best) regardless of base currency choice. These results do not change upon the choice of the oil price series. On the other hand, the post-Euro period provides quite different results. Student t copula model is ranked the highest for many bivariate cases regardless of the base currency choice. However, the Opec and Brent oil series result in somewhat different model rankings in each case. Overall, the pre-Euro and post-Euro periods (for the same series) are very different in some cases. For example, in pre-Euro period, Gumbel, Rotated Gumbel, and SJC copula models were never reported to be ranked the first, while in post-Euro period, few bivariate models are explained the best by these copula models. Overall, Student t, Clayton, Gumbel, Rotated Gumbel, and Placket models are ranked the highest among the nine copula models available. This finding is consistent with all the available cases analyzed. However, so far we have analyzed and ranked the models based on only log-

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[36] In addition, as a Goodness-of-Fit test the copula parameters are estimated from the Kendall's tau coefficient. In addition, as a Goodness-of-Fit test the copula parameters are estimated from the Kendall's tau coefficient.

likelihood functions. To get a robust ranking, one needs more than one selection criterion. Therefore, AIC and BIC selection criteria are applied.

In the pre-Euro period all three information criteria (i.e., AIC and BIC) mostly show the superiority of the Student t and Placket copula models. However, slight difference between the SAC- and USD-denomination cases is observed, with the main difference being that Student t copula is found to be the best for more series under the SAC-denomination case than the USD-denomination case. Among the other copula models Gumbel, Rotated Gumbel, Clayton, and Normal copulas are also ranked the highest for some series in the USD-denomination case. These information criteria results are mostly consistent with the log-likelihood function results and imply that for the majority of the series in the pre-Euro period Student t and Placket copula functions fit the best. This result is unchanged regardless of the oil price series used.

On the other hand, the post-Euro period provides very diverse results both in terms of the denominations and the oil price series used. Student t, Normal, and Rotated Gumbel copulas are the top ranked models under the EUR-denomination and Brent oil case. Although top ranked Normal copula models dominate for most of the series similar to the Brent oil case, Placket copula is also found to be the best fitting models in the Opec oil case. In the USD-denomination case, Opec and Brent oil series provide quite similar results. The best models in this case are Student t, Rotated Gumbel, Gumbel, and Placket copula models. The results are partially consistent with the log-likelihood results.

Finally, the case of SAC-denomination is analyzed and the large difference between the Opec and Brent oil price scenarios is observed. For the former case Normal, Plackett, and Gumbel copulas dominate, and only for several series Clayton, Students t, and Rotated Gumbel copulas are ranked the highest. In case of the Brent oil price scenario, Student t, Clayton, and Placket copula models are the most frequently observed best models, and for only few Gumbel and Rotated Gumbel copula models are ranked the highest. The log-likelihood results for this scenario are not consistent with the information criteria results.

Overall, Student t copula model is ranked high for most of the bivariate models in almost all the cases. Similarly, Normal copula model is also ranked high, followed by the Gumbel, Rotated Gumbel, and Placket copulas. Lastly, Clayton and Rotated Clayton copulas also fit the models the best in some cases. Among the least favorable copula models are the SJC and Frank. Note that there is a very distinct difference between the pre- and post-Euro periods. The pre-Euro period is mostly explained by the elliptical copulas while the post-Euro period is characterized by a mixture of the copula models, hence not leaning towards one common copula model. Moreover, the denomination scenarios are somewhat different from one another and in some special cases, they are completely different. Hence, it can be concluded that the choice of the best copula model is very sensitive to the choice of base currency. Finally, the Opec and Brent oil price scenarios provide generally similar outcome except for a few cases when the highly ranked models completely change upon scenarios used. It is worth noting that there is no specific ordering of copulas for the models based on the development status of a country.

Therefore, it can be concluded that the best copula models do not change depending on the developed and developing countries.[37]

Patton (2004) and others have stated that Student t copula is appropriate for most models which is certainly true for this study. However, for some cases if there is any observed asymmetry in the tails, then other copulas such as Gumbel or Clayton would fits the model better.

3.5 Conclusions

Given the increasing importance of oil for global economic progress, more and more articles emerge aiming to explain the impact of increasing demand for oil and oil prices on the global economy. However, only a few study the relationship of oil prices and stock market indices. There still is a gap in understanding the oil price and stock market co-movement. Moreover, the inclusion of various countries with different levels of economic development is not well explored. There is also limited information about the asymmetric dependence between oil prices series and stock market indices. There is no information on adjustment for exchange rate dynamics in the existing literature on oil and stock market series in order to obtain results that without exchange rate risk. Hence, this paper addresses all these issues to fully understand the relationship between the oil price series and stock market indices. Specifically, we address the following questions:

[37] To save space only the post-Euro period with EUR denomination for both Opec and Brent oil price scenarios is reported in Appendix B. The other scenarios (i.e. USD and SAC denominations for pre- and post-Euro periods) are available upon request.

do oil prices and stock market indices move together? Is there any asymmetry in the relationship? Does the dependence (if any) increase during extreme events? Does the dependence change for pre- and post-Euro periods? Does the choice of oil price series matter? Does the choice of base currency matter? Is there a specific dependence pattern for developed and developing countries?

The application of copula functions enables us to model with greater flexibility and explore various dependence measures. We find that the choice of oil price series, base currency, and the creation of Euro is indeed important. With regard to oil price series, we find that the copula parameter estimates and the tail dependences moderately change depending on which oil prices series is used. Moreover, the information criteria and log-likelihood functions also differ based on the use of a particular oil price series. On the other hand, almost all the results change depending on the base currency chosen. Given the minimum variance of SAC, it can be assumed that SAC-denominated data would provide more accurate results as the exchange rate effect is nearly eliminated in this case. However, because nearly no difference in ranking copula models was observed in pre-Euro period, we can conclude that the oil price series is not an important issue in pre-Euro period. This is not the case for the post-Euro period. Lastly, the creation of Euro (1999) alters the results greatly, especially in case of the correlation or dependence measures. Hence, it can be concluded that dynamics of the dependence structure and degree between the oil prices and stock market indices changes as new major events (i.e. creation of Euro) occur.

Overall, the dependence measures, copula parameters, as well as the tail dependence measures are quite small throughout the scenarios. One of the major bivariate case that stands out to be relatively strong all the time is the oil price series and the Canadian stock market index, regardless of the scenario used (e.g. time periods, oil price series, currency denomination, etc). Moreover, we found that left tail dependence is relatively stronger for this relationship than the right one implying that the two series are more likely to crash together than boom together. In other words, association of oil price return and Canadian stock market index return becomes stronger during the market downturn. Similarly, Russian and Saudi stock market index returns also appear to be more correlated with the oil price series during a market downturn than market progress. In most cases, this notion holds for Venezuela as well. One of the possible explanations is that Canada, Russia, Saudi Arabia, and Venezuela are all large (Canada is relatively large) oil producing countries; hence any oil price decrease is viewed adversely in the eyes of investors and results in larger adverse impact on stock markets than if the oil prices had to rise.

On the other hand, many large oil consuming countries such UK, U.S., HK (in some cases), Germany (in some cases), and China do not have such relatively strong association with oil price returns. Moreover, asymmetry in the form of right tail dependence is observed for these countries. This implies that the association of oil prices and stock market index returns for these countries becomes stronger during the market upturn (boom) than market downturn. This finding can perhaps be explained by Ciner (2001) findings that there is bidirectional non-linear causality between the stock index returns and oil price returns. In other words, stock market returns also affect the oil prices. Perhaps, that's the reason that both oil price and stock market index returns move together more when both markets are booming. Furthermore, there seems to be a pattern of developed countries and developing countries having different tail dependences. The former ones tend to have lower tail dependences relative the developing countries. This is perhaps due to the fact that financial markets of developing countries are less efficient and tend to overreact to even a slight oil price change.

Investors are the main beneficiaries of this study as it presents broad empirical evidence of relationship between the oil price and stock market index returns. Presented for various possible scenarios, results will provide more options for investors to evaluate the possible co-movement between the two series. In addition, the results also provide important information regarding the diversification and possible gains from it.

CHAPTER IV

THE STRUCTURE AND DEGREE OF DEPENDENCE AMONG U.S. INDUSTRY SECTORS

4.1 Introduction

Portfolio diversification is a common strategy to mitigate investment risk. Previous researchers have presented alternative investment strategies with the aim of minimizing the variance and/or maximizing the returns. Hence, any new methodology that addresses portfolio risk is of interest to both investors and academicians. The recent developments in the area of statistics, mathematics, and finance, particularly the correct formulation of the dependence among various assets are becoming more and more attractive for risk management purposes. Investors' utility from a portfolio of investments is affected by the dependence structure because it will directly affect the distribution of portfolio returns and have a direct impact on the optimal investment portfolio and diversification.

There are a limited number of studies that provide some information on relationships among stock prices indices of industry classification sectors in U.S. (Alli et al., 1994; Kim and Bessler, 2007). However, there are many limitations and the provided information is not complete. This fact emphasizes the importance of empirical analysis that would foster our knowledge regarding the inter-industry dependency. Kim and

Bessler (2007), attempted to fill this gap by examining the price transmission among ten aggregations of U.S. equity prices. Their findings show strong interaction among the sectors. Moreover, Information Technology is reported to be exogenous and along with Industrials and Health Care sectors has significant influence on the other sectors. However, they explored the causality structure from the linear perspective (e.g. linearity assumption is imposed). Moreover, most of the papers investigating the dependence structure among a set of stock indices from different industries or international markets assume multivariate normality and use linear correlation statistics. However, more recent studies find strong evidence of the presence of asymmetry in the dependence structure such as higher correlation during the market downturns than upturns (Longin and Solnik, 2001; Ang and Chen, 2002; Chen, Fan, and Patton, 2004; Chollete et al., 2005; Hu, 2006). As a result, models that allow more flexibility are proposed. With this regard, copulas (Sklar, 1959) have gained much attention in modeling possible nonlinear dependence structure of multivariate time series. Its increasing importance stems from the fact that it facilitates an easy and flexible multivariate distribution calculation using only the marginal distributions and the copula function which is invariant to transformation (Chollete et al., 2005). Moreover, the tail dependence which measures the dependence structure of upper and lower tails for various copula families is a direct property of a copula function. Hence, general dependence, including symmetric and asymmetric, and linear and non-linear, can simply be calculated via copulas.

The use of copula functions in portfolio investment and dependence structure among the stock indices of various industry sectors will lead to more accurate results relative to the conventional methods used before. Hence, the purpose of this paper is to study the general relationship of aggregations of U.S. equity prices from a copula perspective. Specifically, we want to explore the inter-industry dependence structure and the presence of possible asymmetries in the relationship. The rest of this chapter is organized as follows. Section 4.2 covers the data used in this paper, followed by the copula functions which are introduced in Section 4.3. Section 4.4 introduces the estimation model followed by the interpretation of the results which is covered in Section 4.5. Finally, conclusions close the chapter in Section 4.6.

4.2 Data

This chapter uses data comprised of Standard & Poor (S&P) 500 Global Industry Classification Sector (GICS) indices for ten sectors. The series are daily for the period of January 2, 1995 – July 1, 2008. The starting date is taken according to the availability of the GICS index. The GICS is an enhanced industry classification system which was developed by S&P and MSCI Barra (www.standardandpoors.com). Its creation was benefited by global financial community in a way that they now have a consistent set of global sector and industry definitions, which is used for portfolio analysis, asset management, and the sector and industry comparisons (www.standardandpoor.com). Unlike other existing industry classifications (SICS and NAICS), the GICS is based on the company’s financial performance. The GICS indices start with the initial value of

100 on January 2, 1995 and change over time due to the changes in market valuation of the individual equities (Kim and Bessler, 2007).

The GICS is a four-level structure. The highest level is comprised of 10 sectors: Consumer Discretionary (CD), Consumer Staple (CS), Energy (EN), Financials (FI), Health Care (HC), Industrials (IN), Information Technology (IT), Materials (MS), Telecommunication Services (TC), and Utilities (UT). The second level is broken down into 24 industry groups. The third level breaks down the industry groups into 68 industries which in turn are comprised of 154 sub-industries (fourth level). [38]

The majority of the sectors have changed over time according to Figure 4.1. However, the most notable change is observed for the IT sector during the IT bubble period (1999). The FI has increased until the beginning of 2007 when signs of housing market crisis, credit crunch, and overall economic meltdown became more noticeable causing the FI to decrease. On the other hand, gradual increase in oil prices especially last couple of years caused the increase in EN. Similarly, UT shows increasing trend especially starting from 2004. In general, most of the sectors increased largely from 2003-2004 to the end of the sample, except for the IT and TC. The descriptive statistics is reported in Table 4.1 which shows that IT has the highest mean, followed by the FI and HC. On the other hand, UT has the smallest mean. In terms of standard deviation, again IT has the highest standard deviation followed by the EN and FI. In addition, the normality assumption for all the series is rejected. The series are also non-stationary at

[38] Interested readers are referred to Standard & Poor’s website (www.gics.standardandpoors.com) for more information on GICS. In addition, details about the sectors, industry groups, industries, and sub-industries are also given in Kim and Bessler (2007).

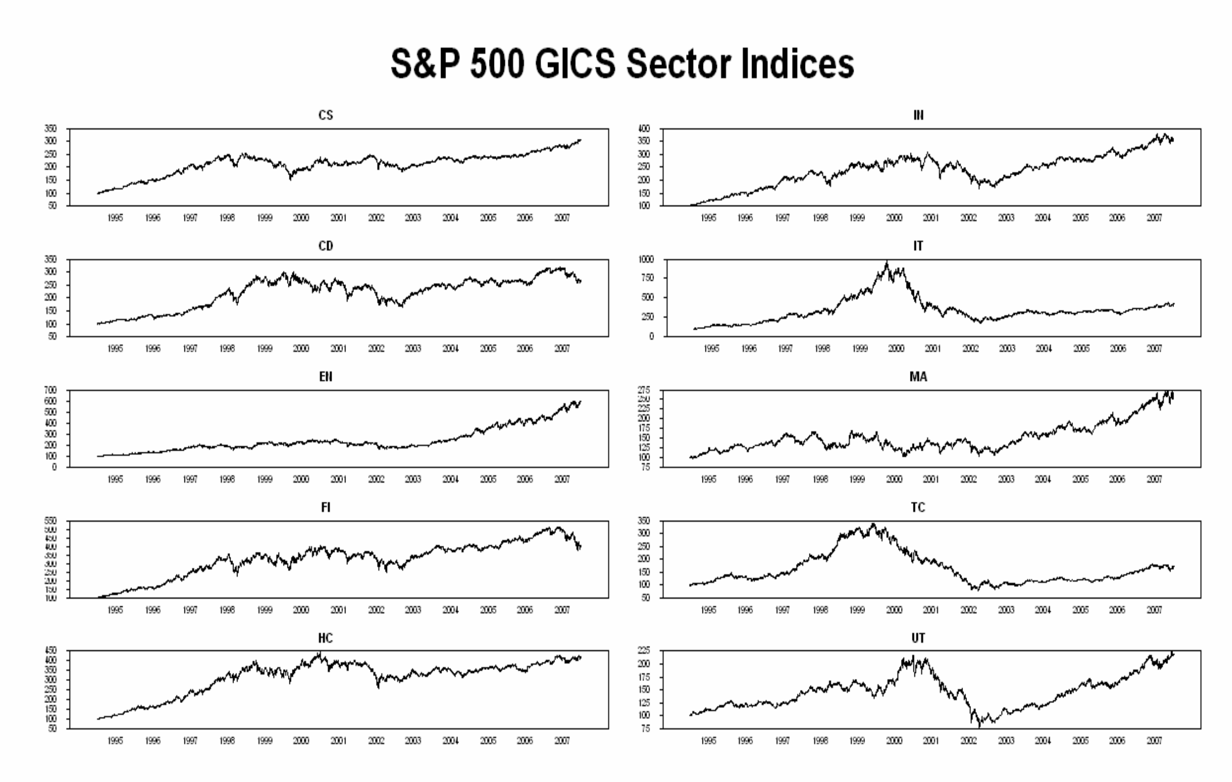

Figure 4.1 Historical Plot of S&P 500 GICS Indices for Period of January 2, 1995 to December 31, 2007

Table 4.1 Descriptive Statistics on Levels of Sector Data

	CD	CS	EN	FI	HC	IN	IT	MS	TC	UT
Mean	222.1477	215.2949	259.1996	326.9154	317.0029	241.7135	345.2631	156.4919	162.8089	148.1306
Median	242.6050	220.5400	214.4500	342.1400	347.5500	250.8850	318.2650	142.9500	138.7500	147.8900
Maximum	318.5400	306.6100	668.8100	509.5500	444.9800	381.1600	988.4900	285.9100	339.2800	223.9100
Minimum	99.65000	98.73000	99.15000	100.0000	98.31000	100.0000	99.04000	96.04000	79.00000	77.27000
Std. Dev.	57.39984	43.79138	129.1449	96.83920	85.70080	63.48212	164.6054	41.24536	61.58628	32.97880
Skewness	-0.656710	-0.624623	1.287404	-0.563319	-1.129144	-0.233029	1.439383	1.258757	1.213328	0.330697
Kurtosis	2.278586	3.267205	3.757687	2.766102	3.104883	2.489208	5.232200	3.838559	3.470623	2.200747
Jarque-Bera	329.5284	239.4978	1057.147	194.3001	750.0201	70.16404	1947.374	1033.276	896.6641	157.9394
P-value	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

levels, but the transformation of all the series into logarithmic difference induces stationarity (Table 4.2).[39] More detailed analyses of the data and residuals follows.

Table 4.2 Dickey-Fuller Test of Stationarity for Sector Returns Data

	CD	**CS**	**EN**	**FI**	**HC**	**IN**	**IT**	**MS**	**TC**	**UT**
T-test Statistics	-57.76	-60.59	-61.07	-58.25	-57.18	-59.33	-59.89	-58.83	-60.71	-57.81

Note: All the returns data are stationary in levels at 1% significance level.

4.3 Copula Approach

Most of the existing papers studying the linkage and interdependence among the industry sectors overlook the possible existence of asymmetric or nonlinear relationships, and instead concentrate on commonly used linear dependence. To fill the gap and study the dependence between the GICS indices from broader perspective, this paper proposes the use of copula functions. The latter has been extensively used in modeling both the contemporaneous dependence between variables and temporal dependence structure of time series variables (Fermanian and Scaillet, 2003; Chen and Fan, 2006; Patton, 2006, and Ng, 2006). Moreover, copula functions have been largely used in modeling observations using flexible functional forms (Kim et al., 2007b). The use of copula in many other areas is growing and many new uses of copula functions are being researched in recent studies. In general, it has become one of the hot subjects and tools currently used in finance and economics literature. The details about copula

[39] The DF results are only reported for the transformed data. The DF result for the levels data is available from author upon request.

functions, their uses, and possible extensions are the essence of many books and papers, such as Joe (1997), Nelsen (2006), Cherubini et al (2004), Patton (2004, 2006a, 2006b), Embrechts et al. (2002), Genest and Rivest (1993), and Genest and Favre (2007). The brief review of copula for bivariate observations which can be extended to higher dimensions is given next.

The copula function is defined by the famous Sklar's (1959) theorem. Let's consider that X_1 and X_2 are two continuous random variables with univariate distribution functions $F_1(X_1)$ and $F_2(X_2)$, and joint distribution function $F_{12}(X_1, X_2)$. The Sklar's theorem states that there is a unique function C, such that

$$F_{12}(X_1, X_2) = C(F_1(X_1), F_2(X_2)). \tag{4.1}$$

In a nutshell, copula function is the joint distribution of (U_1, U_2) where $U_1 = F_1(X_1)$ and $U_2 = F_2(X_2)$ are uniformly distributed on (0, 1) (Kim et al., 2007b). Consequently, the uniform distribution of the variables of interest is obtained separately from the dependence structure between them. Bivariate copula functions have three properties:

1. $C(U_1, U_2)$ is increasing in U_1 and U_2.
2. $C(0, U_2) = C(U_1, 0) = 0$ and $C(1, U_2) = U_2$, $C(U_1, 1) = U_1$.
3. If $U_{11} < U_{12}$ and $U_{21} < U_{22}$, then

   $C(U_{12}, U_{22}) - C(U_{12}, U_{21}) - C(U_{11}, U_{22}) + C(U_{11}, U_{21}) \geq 0$.

In words, copula function (joint probability) will increase if at least one of the marginal distributions increases given that the other marginal distribution is constant. Likewise, it will increase if both margins increase. In addition, joint distribution is zero if at least one of the margins has zero probability. Similarly, the copula function equals the marginal distribution if the other margin has probability of one (Rockinger and Jondeau, 2001).

Copula functions are also linked with some association measures, such as Kendall's tau and Spearman's rank correlation (Venter, 2002; Hu, 2006; Marshal and Zeevi, 2002).[40] Conversely, the Pearson's correlation coefficient is dependent not on copula but the marginal distributions which fails to provide information on strengths on different parts of the distribution. Moreover, for any correlated variates with the same copula Kendall's tau is constant, whereas Pearson's correlation can change with the same copula. In fact, copula parameters can be directly estimated via Kendall's tau and vice versa given the following relation (Venter, 2002):

$$\tau = 4\int_0^1\int_0^1 C(u,v)dC(u,v) - 1 . \tag{4.2}$$

Given that the tail dependencies of each parametric copula function emphasize different parts of the probability distribution, it is detrimental to use as many copula functions (with varying tail dependencies) as necessary to understand the dependence for the whole probability distribution. For such purpose, the following six copula functions are used in this paper: Normal, Clayton, Gumbel, Rotated Gumbel, Student t, and SJC. Gumbel, Rotated Gumbel, Symmetricized Joe-Clayton (SJC), and Clayton copulas are asymmetric and have more probability concentrated on the tails. On the other hand, Normal and Student t copulas are symmetric. The functional forms for each of the six

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[40] The Kendall's tau is defined as the probability of concordance and probability of discordance, such that $\tau = \Pr((X_1 - X_2)(Y_1 - Y_2) > 0) - \Pr((X_1 - X_2)(Y_1 - Y_2) < 0)$. It is calculated from the rank of data, rather than the sample which is the case for Pearson's correlation. Therefore, it gives the non-parametric measure of dependence (Nelsen, 2006; Marshal and Zeevi, 2002; Venter, 2002; Hu, 2006).

copula functions used are given in Table 4.3.[41] In addition, Table 4.3 contains information on the relationship between the Kendall's tau and each of the copula functions. Finally, the tail dependencies of each copula function are given in Table 4.3.

Table 4.3 Functional Forms, Tail Dependences, and Kendall's Tau Relations for Five Copula Functions

Normal Copula	
CDF	$\left[C_N(u,v;\rho)=\Phi_\rho(\Phi^{-1}(u),\Phi^{-1}(v))\right]$
PDF	$c_N(u,v;\rho)=\frac{1}{\sqrt{1-\rho^2}}\exp\left\{\frac{\Phi^{-1}(u)^2+\Phi^{-1}(v)^2-2\rho\Phi^{-1}(u)\Phi^{-1}(v)}{2(1-\rho^2)}+\frac{\Phi^{-1}(u)^2\Phi^{-1}(v)}{2}\right.$
Parameter Range	$\rho\in(-1,1)$
Kendall's Tau	$\tau_\rho=\frac{2\arcsin(\rho)}{\pi}$
Tail Dependency	$\lambda_L=\lambda_U=0$
Clayton Copula	
CDF	$C_C(u,v;\theta)=(u^{-\theta}+v^{-\theta}-1)^{-\frac{1}{\theta}}$
PDF	$c_C(u,v;\theta)=(1+\theta)(uv)^{-\theta-1}(u^{-\theta}+v^{-\theta}-1)^{-2-\frac{1}{\theta}}$
Parameter Range	$\theta\in[-1,\infty)\setminus\{0\}$
Kendall's Tau	$\tau_\theta=\frac{\theta}{\theta+2}$
Tail Dependency	$\lambda_L=2^{-1/\theta}$, $\lambda_U=0$
Gumbel Copula	
CDF	$C_G(u,v;\delta)=\exp\left\{-((-\log u)^\delta+(-\log v)^\delta)^{\frac{1}{\delta}}\right\}$

[41] The functional form of SJC copula function is not provided in this paper because it is very long. Interested reader is referred to see Patton (2004).

Table 4.3 (Continued)

PDF	$c_G(u,v;\delta)=\dfrac{C_G(u,v;\delta)(\log u\cdot\log v)^{\delta-1}}{uv((-\log u)^{\delta}+(-\log v)^{\delta})^{2-\frac{1}{\delta}}}\left(((-\log u)^{\delta}+(-\log v)^{\delta})^{\frac{1}{\delta}}+\delta-1\right)$
Parameter Range	$\delta\in[1,\infty)$
Kendall's Tau	$\tau_\theta=1-\frac{1}{\theta}$
Tail Dependency	$\lambda_L=0$, $\lambda_U=2-2^{1/\theta}$
Rotated Gumbel Copula	
CDF	$C_{RG}(u,v;\delta)=u+v-1+C_G(1-u,1-v;\delta)$
PDF	$c_{RG}(u,v;\delta)=c_G(1-u,1-v;\delta)$
Parameter Range	$\delta\in[1,\infty)$
Kendall's Tau	$\tau_\theta=1-\frac{1}{\theta}$
Tail Dependency	$\lambda_L=2-2^{1/\theta}$, $\lambda_U=0$,
Student t Copula[42]	
CDF	$C_S(u,v;\rho,\nu)=T_{\rho,\nu}(T_\nu^{-1}(u),T_\nu^{-1}(v))$
PDF	$c_S(u,v;\rho,\nu)=\dfrac{\Gamma(\nu+2/2)t_\nu(T_\nu^{-1}(u))^{-1}t_\nu(T_\nu^{-1}(v))^{-1}}{\nu\pi\Gamma(\nu/2)\sqrt{1-\rho^2}}\times\left(1+\left(\dfrac{T_\nu^{-1}(u)^2+T_\nu^{-1}(v)^2-2\rho T_\nu^{-1}(u)T_\nu^{-1}(v)}{\nu(1-\rho^2)}\right)^{-\frac{\nu+2}{2}}\right.$
Parameter Range	$\rho\in(-1,1),\nu>2$
Kendall's Tau	$\tau_{\rho\nu}=\frac{2\arcsin(\rho)}{\pi}$
Tail Dependency	$\lambda_L=2\times\left(1-t_{\nu+1}\left(\dfrac{\sqrt{\nu+1}\sqrt{\rho+1}}{\sqrt{\rho+1}}\right)\right)$

It can be observed that only normal copula has zero tail dependence. Student t copula has symmetric tail dependence, whereas Clayton, Gumbel, and Rotated Gumbel copulas

[42] In Student t copula function, T_ν^{-1} and t_ν are the inverse cdf and pdf of Student t, respectively. In addition, $T_{\nu,\rho}$ is the bivariate Student t cdf.

have asymmetric tail dependencies. Finally, the tail dependencies of SJC are the SJC copula parameters in reverse order (Marshal and Zeevi, 2002; Patton, 2004).

4.4 Estimation Methods

Copula functions allow separation of the margins to find the best distributions before restoring the joint distribution. This is especially important if the series are not independently and identically distributed (i.i.d.). The industry sectors used in this paper are tested for serial correlation and heteroskedasticity. We find that the common technique of filtering data with AR-GJR(1,1) model cures these problems and makes data i.i.d. The filtered standardized residuals are then used to obtain the marginal distribution functions for stock returns of each of the ten sectors. Following the Canonical Maximum Likelihood (CML) estimation method, the marginal distributions are estimated using the empirical distribution (kernel smoothing). On the other hand, following the Inference for the Margins (IFM), 10% of the tails of distributions are estimated using the Generalized Pareto Distribution (GPD) (Embrechts et al., 1997; Mikosch, 2003; McNeil et al., 2005). In essence, this induces more accurate distribution estimation that better captures heavy-tails of the residuals. The estimated distribution is then transformed into uniform distribution to facilitate the estimation of the copula functions.

The second stage of the CML estimation method deals with the copula parameter estimation. For such purpose, the estimated marginal distributions from the first stage are used. Copula parameters are then estimated through Maximum Likelihood Estimation (MLE) method, such that

$$\hat{\theta}_2 = \arg\max_{\theta_2} \sum_{t=1}^{T} \ln c(\hat{F}_1(X_{1t}), \hat{F}_2(X_{2t}); \theta_2) \tag{4.3}$$

where θ_2 is the copula parameter and $\hat{F}_i(X_{it})$ is the estimated i^{th} marginal distribution (Cherubini et al., 2004). Besides the fact that copula parameters provide useful information on the structure of dependence between the series of interest, they are useful in estimating other dependence measures such as tail dependencies and Kendall's tau.[43]

Each of the six copulas provide unique information about the pairwise relations among the industry sectors. However, it is important to explore which copula describes each relationship best. We adopt the commonly used Log Likelihood Function (LLF), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) methods to rank the copula functions (Dias and Embrechts, 2004; Rodriguez, 2007; Chollete et al., 2005). The LLF is essentially maximized and the copula model with the highest LLF is ranked the highest. Conversely, the AIC and BIC information matrices are minimized, hence the copula model with the lowest AIC and BIC value is ranked the highest. The AIC and BIC are given as:

$$AIC = -2 \times LLF + 2 \times Parameters \tag{4.4}$$

$$BIC = -2 \times LLF + \log(T) \times Parameters \tag{4.5}$$

[43] Table 4.1 above illustrates these relationships.

where T is the number of observations (e.g. 3521) and the Parameters is the number of copula parameters.[44] Furthermore, as a goodness-of-fit test, the parameters of the highest ranked copula models are also calculated from the rank of the data, i.e. through the Kendall's tau given the equations in Table 4.3. Small difference between the copula parameters estimated through maximum likelihood or ranks of data implies that copula model is well specified.

4.5 Results

The degree of dependence in this paper is measured with Kendall's tau and Pearson's correlation coefficient. The results of both dependence measures are reported in Table 4.4. According to Table 4.4, stock returns of sector aggregations in U.S. are very interrelated with large overall degree of dependence. Moreover, all the relationships are statistically significant with p-value close to zero. The weakest degree of dependence is 0.19 found between IT and MS and IT and EN sectors. Conversely, 0.60 is the highest degree of dependence observed between IN and CD sectors. Other strong relationships, which are higher than 0.50, are found between FI and CD, FI and IN, and IN and MS sectors. Similar results are reported for Pearson's correlation. The only difference is the degree of dependence which is slightly higher reaching up to 0.81 in case of Pearson's correlation. The strength and the weakness of the relationships are consistent under both dependence measures. Although it is hard to pick a particular industry sector having the

[44] Only the Student t and SJC copula functions have two parameters. The rest of the copula models have only one parameter.

Table 4.4 Degree of Dependence Measured by Kendall's Tau and Pearson's Rho

	CD	EN	FI	HC	IN	IT	MA	TC	UT	
Kendall's Tau	0.431	0.266	0.436	0.459	0.451	0.259	0.346	0.332	0.317	**CS**
Pearson's Rho	0.566	0.398	0.591	0.662	0.605	0.296	0.505	0.435	0.443	
Kendall's Tau		0.269	0.558	0.415	0.603	0.457	0.452	0.412	0.300	**CD**
Pearson's Rho		0.396	0.763	0.570	0.819	0.651	0.642	0.584	0.408	
Kendall's Tau			0.262	0.256	0.323	0.191	0.364	0.225	0.316	**EN**
Pearson's Rho			0.396	0.393	0.471	0.267	0.522	0.332	0.472	
Kendall's Tau				0.428	0.565	0.395	0.416	0.394	0.335	**FI**
Pearson's Rho				0.585	0.780	0.556	0.600	0.567	0.472	
Kendall's Tau					0.437	0.302	0.313	0.326	0.289	**HC**
Pearson's Rho					0.606	0.389	0.442	0.442	0.411	
Kendall's Tau						0.455	0.514	0.402	0.324	**IN**
Pearson's Rho						0.657	0.723	0.578	0.467	
Kendall's Tau							0.315	0.347	0.190	**IT**
Pearson's Rho							0.426	0.516	0.253	
Kendall's Tau								0.300	0.283	**MA**
Pearson's Rho								0.423	0.408	
Kendall's Tau									0.293	**TC**
Pearson's Rho									0.389	

Note: All the coefficients are significant at 1%, 5%, and 10% significance levels.

highest dependence across all the other sectors, we can observe that EN has relatively weak relationship with the other industry sectors which is consistent under the two dependence measure.

Consistent with the Kendall's tau and Pearson's rho, copula parameters, reported in Table 4.5, reveal that the EN has the smallest copula parameters with almost all other industry sectors, except for the IN, MS, and UT. Similarly, UT and TC sectors also have relatively small copula parameters with some of the other sectors. Furthermore, in

Table 4.5 Parameter Estimates of Six Copula Functions

	Normal	Clayton	Gumbel	R. Gumbel	Student		SJC	
CD-CS	0.618	1.151	1.727	1.757	0.643	4.357	0.406	0.483
CS-EN	0.390	0.559	1.309	1.335	0.402	8.910	0.133	0.278
CS-FI	0.625	1.156	1.730	1.765	0.647	4.950	0.406	0.482
CS-HC	0.660	1.249	1.801	1.834	0.673	5.611	0.444	0.504
CS-IN	0.639	1.247	1.768	1.818	0.662	4.412	0.409	0.515
CS-IT	0.410	0.596	1.361	1.375	0.434	5.422	0.206	0.278
CS-MS	0.496	0.822	1.468	1.511	0.519	5.182	0.232	0.398
CS-TC	0.499	0.787	1.469	1.498	0.517	6.079	0.265	0.367
CS-UT	0.486	0.755	1.438	1.472	0.498	6.622	0.230	0.365
CD-EN	0.388	0.583	1.318	1.347	0.408	6.577	0.129	0.296
CD-FI	0.751	1.691	2.261	2.301	0.766	5.956	0.536	0.597
CD-HC	0.589	1.088	1.666	1.705	0.619	4.119	0.368	0.470
CD-IN	0.790	2.038	2.520	2.662	0.803	5.949	0.558	0.661
CD-IT	0.646	1.181	1.778	1.798	0.665	5.685	0.437	0.482
CD-MS	0.630	1.186	1.722	1.772	0.650	6.011	0.375	0.503
CD-TC	0.590	1.003	1.619	1.651	0.604	8.694	0.349	0.440
CD-UT	0.447	0.676	1.396	1.418	0.468	6.819	0.206	0.326
EN-FI	0.392	0.571	1.327	1.347	0.410	6.188	0.165	0.276
EN-HC	0.373	0.563	1.295	1.332	0.390	6.736	0.099	0.295
EN-IN	0.461	0.727	1.416	1.449	0.483	6.011	0.208	0.353
EN-IT	0.294	0.397	1.220	1.237	0.310	7.134	0.091	0.184
EN-MS	0.503	0.826	1.475	1.515	0.527	6.489	0.231	0.395
EN-TC	0.327	0.452	1.251	1.269	0.345	7.848	0.104	0.216
EN-UT	0.470	0.713	1.411	1.440	0.483	8.899	0.204	0.348
FI-HC	0.601	1.116	1.679	1.725	0.628	4.516	0.366	0.480
FI-IN	0.765	1.841	2.297	2.325	0.803	5.949	0.535	0.631
FI-IT	0.574	0.923	1.631	1.625	0.310	7.135	0.091	0.184
FI-MS	0.586	1.037	1.629	1.670	0.608	5.947	0.335	0.459
FI-TC	0.571	0.931	1.600	1.611	0.587	7.008	0.364	0.402
FI-UT	0.513	0.816	1.503	1.518	0.531	5.424	0.303	0.370
HC-IN	0.608	1.175	1.709	1.763	0.639	3.722	0.378	0.499
HC-IT	0.448	0.718	1.413	1.449	0.481	4.638	0.209	0.351
HC-MS	0.442	0.734	1.402	1.448	0.475	4.399	0.178	0.368
HC-TC	0.466	0.743	1.437	1.466	0.498	5.143	0.231	0.354
HC-UT	0.435	0.656	1.378	1.405	0.452	6.037	0.190	0.322
IN-IT	0.647	1.157	1.764	1.783	0.662	7.229	0.437	0.473
IN-MS	0.702	1.462	1.921	1.979	0.717	5.842	0.460	0.564
IN-TC	0.568	0.968	1.594	1.624	0.587	5.845	0.340	0.428
IN-UT	0.488	0.773	1.457	1.483	0.506	5.701	0.250	0.367
IT-MS	0.475	0.742	1.453	1.473	0.502	4.771	0.269	0.344
IT-TC	0.495	0.753	1.459	1.482	0.512	7.671	0.266	0.347
IT-UT	0.301	0.402	1.225	1.240	0.315	7.674	0.094	0.187
MS-TC	0.431	0.666	1.378	1.409	0.456	5.783	0.185	0.327
MS-UT	0.419	0.623	1.360	1.383	0.438	6.075	0.178	0.306
TC-UT	0.429	0.611	1.372	1.384	0.448	8.184	0.208	0.283

Note: This table reports the parameter estimates of the six copula models. The parameters are reported for each sector combination.

addition to the same pairs which are strongly correlated according to the dependence measures (i.e. FI and CD, FI and IN, and IN and MS), strong relationships are also found between CD and CS, CS and FI, CS and HC, CS and IN, CD and IT, CD and MS, FI and HC, HC and IN, and IN and IT. These results, to some degree, are consistent with the Kim and Bessler's (2007) Directed Acyclic Graph (DAG) results where they estimate the inter-sector relationship using contemporaneous causal model. Although causality is not studied in this paper, the relationships detected in Kim and Bessler (2007) mostly coincide with the strong dependencies reported in this study (through copula parameters). However, copula-based model results in more interrelated U.S. sectors. Also, there is a strong evidence of asymmetric relationships which is not detected in Kim and Bessler's (2007) paper.

The Rotated Gumbel copula parameter estimates for the majority cases are higher than Gumbel copula parameter estimates. Consequently, the dependence on the left tail of the distribution is higher than that on the right hand implying asymmetry for most relations. Tail dependencies are considered to be more informative about the dependence structure, than the copula parameters.

Similar to the degree of dependence and copula parameter results, EN has relatively small tail dependencies with nearly all the industry sectors (Table 4.6). The highest tail dependencies are found for CD and IN, FI and IN, and FI and CD pairs. Nearly in all cases, the lower tail dependence is higher than the upper tail dependence which is consistent either for the Gumbel and Rotated Gumbel copulas, or for the SJC

Table 4.6 Upper and Lower Tail Dependences for Five Copula Functions

	CD		EN		FI		HC		IN		IT		MS		TC		UT		
	λ_L	λ_U	λ_L	λ_U	λ_L	λ_U	λ_L	λ_U	λ_L	λ_U	λ_L	λ_U	λ_L	λ_U	λ_L	λ_U	λ_L	λ_U	
Clayton	0.548	0.000	0.289	0.000	0.549	0.000	0.574	0.000	0.574	0.000	0.313	0.000	0.431	0.000	0.414	0.000	0.399	0.000	
Gumbel	0.000	0.506	0.000	0.302	0.000	0.507	0.000	0.531	0.000	0.520	0.000	0.336	0.000	0.396	0.000	0.397	0.000	0.381	
R. Gumbel	0.517	0.000	0.319	0.000	0.519	0.000	0.541	0.000	0.536	0.000	0.344	0.000	0.418	0.000	0.412	0.000	0.398	0.000	CS
Student	0.327	0.327	0.067	0.067	0.303	0.303	0.295	0.295	0.339	0.339	0.159	0.159	0.210	0.210	0.176	0.176	0.150	0.150	
SJC	0.483	0.406	0.278	0.133	0.482	0.406	0.504	0.444	0.515	0.409	0.278	0.206	0.398	0.232	0.367	0.265	0.365	0.230	
Clayton			0.305	0.000	0.664	0.000	0.529	0.000	0.712	0.000	0.556	0.000	0.557	0.000	0.501	0.000	0.359	0.000	
Gumbel			0.000	0.308	0.000	0.641	0.000	0.484	0.000	0.683	0.000	0.523	0.000	0.504	0.000	0.466	0.000	0.357	
R. Gumbel			0.327	0.000	0.648	0.000	0.498	0.000	0.703	0.000	0.530	0.000	0.521	0.000	0.478	0.000	0.369	0.000	CD
Student			0.114	0.114	0.369	0.369	0.321	0.321	0.412	0.412	0.286	0.286	0.262	0.262	0.154	0.154	0.132	0.132	
SJC			0.296	0.129	0.597	0.536	0.470	0.368	0.661	0.558	0.482	0.437	0.503	0.375	0.440	0.349	0.326	0.206	
Clayton					0.297	0.000	0.292	0.000	0.385	0.000	0.175	0.000	0.432	0.000	0.215	0.000	0.378	0.000	
Gumbel					0.000	0.314	0.000	0.292	0.000	0.368	0.000	0.235	0.000	0.400	0.000	0.260	0.000	0.366	
R. Gumbel					0.327	0.000	0.317	0.000	0.387	0.000	0.248	0.000	0.420	0.000	0.273	0.000	0.382	0.000	EN
Student					0.125	0.125	0.104	0.104	0.162	0.162	0.072	0.072	0.169	0.169	0.068	0.068	0.093	0.093	
SJC					0.276	0.165	0.295	0.099	0.353	0.208	0.184	0.091	0.395	0.231	0.216	0.104	0.348	0.204	
Clayton							0.537	0.000	0.686	0.000	0.472	0.000	0.513	0.000	0.475	0.000	0.428	0.000	
Gumbel							0.000	0.489	0.000	0.648	0.000	0.471	0.000	0.470	0.000	0.458	0.000	0.414	
R. Gumbel							0.506	0.000	0.653	0.000	0.468	0.000	0.485	0.000	0.462	0.000	0.421	0.000	FI
Student							0.308	0.308	0.412	0.412	0.072	0.072	0.234	0.234	0.187	0.187	0.207	0.207	
SJC							0.480	0.366	0.631	0.535	0.184	0.091	0.459	0.335	0.402	0.364	0.370	0.303	
Clayton									0.554	0.000	0.381	0.000	0.389	0.000	0.394	0.000	0.348	0.000	
Gumbel									0.000	0.500	0.000	0.367	0.000	0.361	0.000	0.380	0.000	0.346	
R. Gumbel									0.518	0.000	0.387	0.000	0.386	0.000	0.396	0.000	0.362	0.000	HC
Student									0.357	0.357	0.213	0.213	0.220	0.220	0.200	0.200	0.147	0.147	
SJC									0.499	0.378	0.351	0.209	0.368	0.178	0.354	0.231	0.322	0.190	
Clayton											0.549	0.000	0.623	0.000	0.489	0.000	0.408	0.000	
Gumbel											0.000	0.519	0.000	0.565	0.000	0.455	0.000	0.391	
R. Gumbel											0.525	0.000	0.580	0.000	0.468	0.000	0.404	0.000	IN
Student											0.231	0.231	0.325	0.325	0.225	0.225	0.184	0.184	
SJC											0.473	0.437	0.564	0.460	0.428	0.340	0.367	0.250	
Clayton													0.393	0.000	0.398	0.000	0.178	0.000	
Gumbel													0.000	0.389	0.000	0.392	0.000	0.239	
R. Gumbel													0.399	0.000	0.404	0.000	0.251	0.000	IT
Student													0.218	0.218	0.130	0.130	0.064	0.064	
SJC													0.344	0.269	0.347	0.266	0.187	0.094	
Clayton															0.353	0.000	0.329	0.000	
Gumbel															0.000	0.346	0.000	0.335	
R. Gumbel															0.365	0.000	0.350	0.000	MS
Student															0.157	0.157	0.140	0.140	
SJC															0.327	0.185	0.306	0.178	
Clayton																	0.322	0.000	
Gumbel																	0.000	0.342	
R. Gumbel																	0.350	0.000	TC
Student																	0.093	0.093	
SJC																	0.283	0.208	

Note: Normal copula has zero tail dependencies, thus is not included in the table. The tail dependencies are estimated according to the equations in Table 4.3

copula. This confirms the long existing theory that during a market downturn, stock prices of most companies tend to be more correlated than during the market upturn. Similarly, in the case of industry sectors the idea is the same and the results show that the relationships among the sectors are higher during the market downturn than a market boom. However, the asymmetric copula models may not be the best relative to the more conventional copula models. Hence, the LLF, AIC, and BIC are used to rank the copula models (Table 4.7).

The Student t copula model is found to be the best in all cases except for the EN and HC and FI and IT sectors. The best fitting copula model for EN and HC sectors is the Rotated Gumbel copula, while for the latter pair Normal copula model appears to be the best. Consequently, it was found that most of the dependencies are heavy-tailed distributed but not necessarily asymmetrically. In other words, most models seem to have symmetric tail dependencies which capture the fat tails of the distributions.

The best copula models are then tested using the Kendall’s tau and copula relation. The estimated Student t copula parameters using Kendall’s tau are very close to those estimated using maximum likelihood. Similarly, the difference is nearly zero for copula parameter estimates of Rotated Gumbel and Normal copula for EN-HC and FI-IT pairs, respectively. Consequently, the copula functions are well specified. In other words, there are negligible or no specification errors in terms of parametric copula estimation, specifically, highest ranked copula estimation (i.e. Student t, Rotated Gumbel, and Normal copulas).

Table 4.7 The LLF, AIC, and BIC for the Highest Ranked Copula Models

	CD	EN	FI	HC	IN	IT	MS	TC	UT	
LLF	964.96	313.63	963.67	1066.91	1035.65	380.41	565.10	552.26	510.45	
AIC	-1925.93	-623.26	-1923.35	-2129.83	-2067.30	-756.83	-1126.19	-1100.53	-1016.90	**CS**
BIC	-1913.59	-610.93	-1911.01	-2117.50	-2054.96	-744.49	-1113.86	-1088.19	-1004.57	
LLF		329.96	1537.70	872.96	1799.47	1016.58	956.67	778.57	439.96	
AIC		-655.93	-3071.39	-1741.92	-3594.94	-2029.17	-1909.35	-1553.15	-875.93	**CD**
BIC		-643.60	-3059.06	-1729.59	-3582.61	-2016.84	-1897.02	-1540.82	-863.59	
LLF			339.50	***303.99***	473.59	190.12	562.97	226.94	461.53	
AIC			-674.99	***-605.98***	-943.18	-376.24	-1121.94	-449.87	-919.05	**EN**
BIC			-662.66	***-599.82***	-930.84	-363.90	-1109.61	-437.54	-906.72	
LLF				885.92	1799.47	***704.63***	798.16	732.53	605.45	
AIC				-1767.84	-3594.94	***-1407.26***	-1592.32	-1461.05	-1206.91	**FI**
BIC				-1755.51	-3582.61	***-1401.09***	-1579.99	-1448.72	-1194.58	
LLF					945.61	476.38	478.18	498.02	411.43	
AIC					-1887.22	-948.75	-952.37	-992.05	-818.86	**HC**
BIC					-1874.89	-936.42	-940.03	-979.71	-806.53	
LLF						997.15	1254.45	734.73	530.86	
AIC						-1990.30	-2504.90	-1465.47	-1057.71	**IN**
BIC						-1977.97	-2492.56	-1453.14	-1045.38	
LLF							525.08	525.86	193.73	
AIC							-1046.16	-1047.73	-383.46	**IT**
BIC							-1033.83	-1035.40	-371.13	
LLF								411.84	384.99	
AIC								-819.68	-765.97	**MS**
BIC								-807.35	-753.64	
LLF									387.00	
AIC									-770.00	**TC**
BIC									-757.67	

Note: The best copula models for each two-sector combinations are chosen based on the maximum LLF and minimum AIC and BIC values. Minimum Student t copula is the highest ranked copula model for all the pairs except for the HC-EN and IT-FI which are in bold and italics. Rotated Gumbel copula fits HC-EN pairs the best and Normal copula is ranked the highest for IT-FI pair.

Table 4.8 Parameter Estimates of Highest Ranked Copula Models via Kendall's Tau

CD	EN	FI	HC	IN	IT	MS	TC	UT	
0.626	0.405	0.633	0.660	0.651	0.396	0.517	0.499	0.478	**CS**
	0.411	0.768	0.606	0.812	0.657	0.652	0.603	0.454	**CD**
		0.401	***1.343***	0.486	0.295	0.541	0.346	0.476	**EN**
			0.623	0.775	***0.581***	0.608	0.580	0.503	**FI**
				0.634	0.456	0.472	0.490	0.438	**HC**
					0.656	0.722	0.591	0.488	**IN**
						0.474	0.518	0.294	**IT**
							0.454	0.430	**MS**
								0.445	**TC**

Note: The table reports the Student t copula parameter estimates using Kendall's tau. The two pairs that are best described by Rotated Gumbel and Normal Copula are in bold and italics. HC-EN pair is described best by Rotated Gumbel copula, thus the parameter is estimated using the relation between the Kendall's tau and the Rotated Gumbel copula. Similarly, the parameter for FI-IT pair is estimated using the relation between the Kendall's tau and Normal Copula. These numbers are intended to be compared with the parameter estimates of the selected copula models from Table 4.5.

4.6 Conclusions

Failure of many financial variables to satisfy the normality assumption originated the need for more restrictive models to analyze the dependencies among them. In investment analysis such models are of great interest due to the possible improvement of risk management techniques. The diversification which is considered to be central for reducing investment risk can also be assessed through such models. Particularly, the formulation of the “true” dependence among a set of variables can be used to calculate the diversification gain (loss) (Hu, 2006).

The interdependence between the aggregations of ten U.S. sector equity prices is explored in this paper. The detection of possible asymmetries in dependence is specifically analyzed by using copula functions. The use of copula functions eases the modeling of joint distribution in such a way that marginal distributions can initially be separately modeled. This is especially critical when the variables deviate from the normality assumption and the only way to model joint distribution is by breaking it down into margins and the copula. In addition, copula functions are used for estimating the dependence structure across ten industry sectors in the U.S.

Overall, the results are very consistent across different dependence measures applied in this paper. The industry sectors are highly dependent upon each other which are consistent with the results Kim and Bessler (2007). Although the lower tail dependence structure is more signified than the upper tail dependence indicating some degree of asymmetry, the best model that helps explain dependencies between most of the industry sectors appears to be the Student t copula which is symmetric and captures the heavy tails of the distributions.

The Consumer Discretionary, Consumer Staples, Financials, and Industrials sectors have strong relationships with other sectors. Conversely, the Telecommunication Services, Utilities, and Energy sectors do not have a strong relationship with other sectors. Most of these findings are consistent with the Kim and Bessler's (2007) DAG results which provide contemporaneous linear dependence. Consequently, it can be implied that linear and non-linear (general) models do provide somewhat similar results in showing sectors are strongly related with each other, but they differ greatly in terms of providing information of possible asymmetries which was detected by the copula-based models. Moreover, the high interdependence across the aggregations of U.S. stock prices implies that industry diversification gains may be fairly small.. One of the reasons for such findings might be the fact that the data used in this study is aggregate masking any possible inverse or no dependencies across certain industries disappear. Hence, these results should be used with care especially for investment purposes.

CHAPTER V

CONCLUSIONS

Time series modeling and dependence formulation for financial markets is the focus of this dissertation. Time series models are used to investigate interrelationships among the U.S. housing market, interdependence between oil prices and stock market indices, and inter-industry dependence across the aggregations of U.S. equity prices.

Housing prices of nine U.S. census divisions are studied in the first essay. House price series are found to be cointegrated, thus are modeled by VECM. Furthermore, the Directed Acyclic Graphs (DAGs) are used to build the contemporaneous causal structure among the house price series. The combination of VECM and DAG results are used in order to obtain data-driven identification. Just-identified models can be obtained by placing restrictions on the VECM according to the DAG results. This proposed identification method is data-driven and explains the model much better than the automatic identification included in many software programs. The findings suggest highly interrelated regional housing market in U.S. Moreover, West North Central is the leading cause for house price changes in other regions. Similarly, Middle Atlantic and New England also have significant influence in house price changes in the country. On the contrary, the East North Central has the least important role in the U.S. housing market. Overall, it can be concluded that house prices of other regions, especially the leading regions, should be considered for forecasting house price of any census divisions.

Interdependence of oil prices and stock market indices across many countries is investigated in the second essay. Both oil producing and oil consuming, developing and developed countries are included to obtain a more complete picture of dependence. In addition to U.S. Dollar (USD) and Euro (EUR), Stable Aggregate Currency (SAC) is used as a base currency for both oil price and stock market index series. The reason is that a basket of currency (SAC) can minimize the exchange rate risk. Hence, it provides more accurate results free of exchange rate risk. All these scenarios are studied using copula functions which allow flexible calculation of joint distributions and measurement of structure and degree of dependence.

The evidence shows weak (strong) dependence between oil prices and stock market indices for oil consuming (producing) nations. Moreover, the detected asymmetry in the dependence suggests that during market downturn (upturn) oil prices and stock market indices are more correlated in case of oil producing (consuming) countries such as Canada, Russia, Saudi Arabia, and Venezuela (UK, France, Germany, U.S., and China). There is negligible difference between the copula results for developed and developing countries. However, significant change is detected between the pre- and post-Euro period results. Specifically, the dependence between the oil prices and stock market indices become more significant after the creation of Euro.

Third essay analyzes the inter-industry dependence among the U.S. equity aggregations. The series are filtered by AR-GARCH models. The univariate distributions of the filtered residuals are further used in copula modeling. The results offer strong sector interdependence which is consistent across all the dependence measures. The least connected sectors include the Utilities, Telecommunication Services, and the Energy. Conversely, the most interrelated sectors are the Consumer Discretionary, Consumer Staple, and Industrials. Although the dependence measure is higher for the lower tails than the upper tails potentially implying asymmetric dependence, the copula model that describes the relationships the best is the Student t copula. The latter is symmetric but captures the heavy-tails of distribution. Overall, results of this essay are very similar to those reported by Kim and Bessler (2007) which are obtained using linear causality models. Hence, it can be concluded that for this particular dataset the linear and non-linear, asymmetric models provide essentially similar results. Lastly, given that U.S. equity aggregations are strongly interrelated, the diversification gains resulting from inter-industry investments may be small.

All the three essays can be extended further either analyzing certain points that were not considered in this dissertation, or by focusing on the limitations of each of the essays. The limitations of dissertation are given for each of the three essays. In Chapter II the limited dataset imposes certain restrictions on the number of lags and possible exogenous variable inclusion. Also, census division data is used which averages out house price changes at state level resulting in smoother house price series over time. In Chapter III, bivariate parametric copula functions are used instead of multivariate and non-parametric copula functions. Limitations in Chapter IV include the data set which is aggregate and thus masks some of the industry-specific information that could potentially result in profitable investment. There is room for improvement and extension for each of the essays as detailed below:

1. In Chapter II, out-of-sample forecasting should be used to test the accuracy of the VECM model and DAG's causal structure results.
2. In Chapter III, multivariate copula models with the non-linear causal structure should be used to investigate general causal structure. This would be very helpful in determining the direction of the causality (i.e. whether stock market indices affect the oil prices or vice versa).
3. In Chapter IV, analyzing the data with VAR-Copula approach and applying non-linear DAG will allow direct comparison of results of non-linear and linear models.

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APPENDIX A

TAIL DEPENDENCE PARAMETERS

A.1 Tail Dependence Parameters for Nine Copulas in pre-Euro period for USD-Denominated Data

		Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Brent	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.023	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.020	0.000	0.000	0.000
Jap-Brent	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.011	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.023	0.000	0.000	0.000
US-Brent	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.000	0.000
Germ-Brent	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.001	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.012	0.000	0.001	0.000
Fran-Brent	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.016	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.012	0.000	0.000	0.000
Ital-Brent	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.000	0.000
Cana-Brent	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.014	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
HK-Brent	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.022	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.016	0.000	0.000	0.000

Note: For each of the copula function, the lower (left) and upper (right) tail dependences are reported.

A.2 Tail Dependence Parameters for Nine Copulas in pre-Euro period for USD-Denominated Data

		Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Opec	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.030	0.001	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.024	0.000	0.001	0.000
Jap-Opec	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.010	0.000	0.000	0.001
US-Opec	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Germ-Opec	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.006	0.000	0.000	0.000
Fran-Opec	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.009	0.000	0.000	0.000
Ital-Opec	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cana-Opec	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.011	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.000	0.000
HK-Opec	Lower	0.000	0.000	0.000	0.000	0.000	0.000	0.011	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.010	0.000	0.000	0.000

Note: For each of the copula function, the lower (left) and upper (right) tail dependences are reported.

A.3 Tail Dependence for Copulas in pre-Euro period for SAC-Denominated Data

		Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.002	0.000
Jap-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
US-Brent	**Lower**	0.000	0.007	0.000	0.000	0.000	0.000	0.110	0.009	0.015
	Upper	0.000	0.000	0.016	0.000	0.000	0.121	0.000	0.009	0.041
Germ-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.002	0.001
Fran-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000
Ital-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cana-Brent	**Lower**	0.000	0.014	0.000	0.000	0.000	0.000	0.112	0.000	0.035
	Upper	0.000	0.000	0.006	0.000	0.000	0.103	0.000	0.000	0.008
HK-Brent	**Lower**	0.000	0.002	0.000	0.000	0.000	0.000	0.084	0.001	0.021
	Upper	0.000	0.000	0.001	0.000	0.000	0.074	0.000	0.001	0.000

Note: For each of the copula function, the lower (left) and upper (right) tail dependences are reported.

Table A.4 Tail Dependence for Copulas in pre-Euro period for SAC-Denominated Data

		Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.006	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.006	0.000
Jap-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
US-Opec	**Lower**	0.000	0.026	0.000	0.000	0.000	0.000	0.145	0.016	0.023
	Upper	0.000	0.000	0.048	0.000	0.000	0.159	0.000	0.016	0.081
Germ-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000
Fran-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
Ital-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cana-Opec	**Lower**	0.000	0.029	0.000	0.000	0.000	0.000	0.140	0.001	0.108
	Upper	0.000	0.000	0.027	0.000	0.000	0.139	0.000	0.001	0.091
HK-Opec	**Lower**	0.000	0.004	0.000	0.000	0.000	0.000	0.091	0.002	0.103
	Upper	0.000	0.000	0.001	0.000	0.000	0.081	0.000	0.002	0.000

Note: For each of the copula function, the lower (left) and upper (right) tail dependences are reported.

A.5 Tail Dependences USD-Denominated Data in post-Euro period

		Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.044	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.048	0.000	0.000	0.001
Jap-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.037	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.045	0.000	0.000	0.001
US-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.007	0.001	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.006	0.000	0.001	0.001
Germ-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.001	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.025	0.000	0.001	0.001
Fran-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.046	0.001	0.002
	Upper	0.000	0.000	0.000	0.000	0.000	0.036	0.000	0.001	0.000
Ital-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.058	0.001	0.006
	Upper	0.000	0.000	0.000	0.000	0.000	0.041	0.000	0.001	0.000
Cana-Brent	**Lower**	0.000	0.020	0.000	0.000	0.000	0.000	0.127	0.005	0.043
	Upper	0.000	0.000	0.015	0.000	0.000	0.117	0.000	0.005	0.023
HK-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.023	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.028	0.000	0.000	0.000
Ch-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.000	0.000
Cze-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.046	0.000	0.003
	Upper	0.000	0.000	0.000	0.000	0.000	0.036	0.000	0.000	0.000
Neth-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.027	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.026	0.000	0.000	0.001
Finl-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.045	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.040	0.000	0.000	0.001
Hung-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.054	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.040	0.000	0.000	0.001
Pola-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.062	0.000	0.002
	Upper	0.000	0.000	0.000	0.000	0.000	0.061	0.000	0.000	0.003
Russ-Brent	**Lower**	0.000	0.002	0.000	0.000	0.000	0.000	0.084	0.000	0.017
	Upper	0.000	0.000	0.000	0.000	0.000	0.068	0.000	0.000	0.001
Saud-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.045	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.015	0.000	0.000	0.001
Vene-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.030	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.024	0.000	0.000	0.001
Spai-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.029	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.022	0.000	0.000	0.001
Swit-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.017	0.001	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.031	0.000	0.001	0.001

Note: For each of the copula function, the lower (left) and upper (right) tail dependences are reported.

A.6 Tail Dependences USD-Denominated Data in post-Euro period

		Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.035	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.028	0.000	0.000	0.001
Jap-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.027	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.039	0.000	0.000	0.001
US-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001
Germ-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.007	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.001
Fran-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.031	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.006	0.000	0.000	0.000
Ital-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.041	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.000	0.000
Cana-Opec	**Lower**	0.000	0.007	0.000	0.000	0.000	0.000	0.099	0.002	0.043
	Upper	0.000	0.000	0.001	0.000	0.000	0.076	0.000	0.002	0.000
HK-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.032	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.012	0.000	0.000	0.000
Ch-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.007	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.015	0.000	0.000	0.000
Cze-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.049	0.001	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.043	0.000	0.001	0.000
Neth-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.012	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.023	0.000	0.000	0.001
Finl-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.028	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.022	0.000	0.000	0.001
Hung-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.057	0.000	0.002
	Upper	0.000	0.000	0.000	0.000	0.000	0.047	0.000	0.000	0.001
Pola-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.053	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.039	0.000	0.000	0.001
Russ-Opec	**Lower**	0.000	0.005	0.000	0.000	0.000	0.000	0.094	0.001	0.028
	Upper	0.000	0.000	0.001	0.000	0.000	0.077	0.000	0.001	0.001
Saud-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.043	0.002	0.002
	Upper	0.000	0.000	0.000	0.000	0.000	0.013	0.000	0.002	0.000
Vene-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.021	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.018	0.000	0.000	0.001
Spai-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.014	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.016	0.000	0.000	0.001
Swit-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.020	0.000	0.000	0.001

Note: For each of the copula function, the lower (left) and upper (right) tail dependences are reported.

A.7 Tail Dependences SAC-Denominated Data in post-Euro period

		Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.024	0.000	0.000	0.001
Jap-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.013	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.007	0.000	0.000	0.001
US-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.032	0.004	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.029	0.000	0.004	0.001
Germ-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.009	0.000	0.000	0.001
Fran-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.014	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.000	0.000
Ital-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.019	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000
Cana-Brent	**Lower**	0.000	0.025	0.000	0.000	0.000	0.000	0.136	0.008	0.042
	Upper	0.000	0.000	0.023	0.000	0.000	0.132	0.000	0.008	0.039
HK-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.032	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.038	0.000	0.000	0.001
Ch-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.012	0.000	0.000	0.000
Cze-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000
Neth-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001
Finl-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.024	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.017	0.000	0.000	0.001
Hung-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.001
Pola-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.043	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.039	0.000	0.000	0.001
Russ-Brent	**Lower**	0.000	0.004	0.000	0.000	0.000	0.000	0.094	0.002	0.026
	Upper	0.000	0.000	0.001	0.000	0.000	0.080	0.000	0.002	0.001
Saud-Brent	**Lower**	0.000	0.002	0.000	0.000	0.000	0.000	0.070	0.000	0.013
	Upper	0.000	0.000	0.000	0.000	0.000	0.036	0.000	0.000	0.001
Vene-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.039	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.031	0.000	0.000	0.001
Spai-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001
Swit-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.011	0.000	0.000	0.001

Note: For each of the copula function, the lower (left) and upper (right) tail dependences are reported.

A.8 Tail Dependences SAC-Denominated Data in post-Euro period

		Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.011	0.000	0.000	0.001
Jap-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001
US-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.034	0.001	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.032	0.000	0.001	0.001
Germ-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001
Fran-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000
Ital-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000
Cana-Opec	**Lower**	0.000	0.009	0.000	0.000	0.000	0.000	0.105	0.003	0.036
	Upper	0.000	0.000	0.002	0.000	0.000	0.087	0.000	0.003	0.003
HK-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.048	0.000	0.002
	Upper	0.000	0.000	0.000	0.000	0.000	0.036	0.000	0.000	0.000
Ch-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.024	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.025	0.000	0.000	0.000
Cze-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000
Neth-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001
Finl-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001
Hung-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.006	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.000	0.001
Pola-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.036	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.010	0.000	0.000	0.001
Russ-Opec	**Lower**	0.000	0.013	0.000	0.000	0.000	0.000	0.114	0.001	0.044
	Upper	0.000	0.000	0.003	0.000	0.000	0.099	0.000	0.001	0.002
Saud-Opec	**Lower**	0.000	0.002	0.000	0.000	0.000	0.000	0.079	0.001	0.012
	Upper	0.000	0.000	0.000	0.000	0.000	0.052	0.000	0.001	0.001
Vene-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.040	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.033	0.000	0.000	0.001
Spai-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001
Swit-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001

Note: For each of the copula function, the lower (left) and upper (right) tail dependences are reported.

A.9 Tail Dependences EUR-Denominated Data in post-Euro period

		Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.044	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.051	0.000	0.000	0.003
Jap-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.052	0.000	0.002
	Upper	0.000	0.000	0.000	0.000	0.000	0.052	0.000	0.000	0.001
US-Brent	**Lower**	0.000	0.000	0.005	0.000	0.000	0.000	0.091	0.011	0.028
	Upper	0.000	0.000	0.000	0.001	0.000	0.080	0.000	0.011	0.003
Germ-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.001	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.001	0.001
Fran-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000
Ital-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000
Cana-Brent	**Lower**	0.000	0.059	0.000	0.000	0.000	0.000	0.169	0.010	0.080
	Upper	0.000	0.000	0.047	0.000	0.000	0.161	0.000	0.010	0.054
HK-Brent	**Lower**	0.000	0.002	0.000	0.000	0.000	0.000	0.077	0.000	0.007
	Upper	0.000	0.000	0.002	0.000	0.000	0.078	0.000	0.000	0.010
Ch-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.058	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.061	0.000	0.000	0.003
Cze-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.016	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.006	0.000	0.000	0.000
Neth-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001
Finl-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.014	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.011	0.000	0.000	0.001
Hung-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.012	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.022	0.000	0.000	0.001
Pola-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.057	0.000	0.003
	Upper	0.000	0.000	0.000	0.000	0.000	0.048	0.000	0.000	0.001
Russ-Brent	**Lower**	0.000	0.016	0.000	0.000	0.000	0.000	0.122	0.009	0.043
	Upper	0.000	0.000	0.009	0.000	0.000	0.115	0.000	0.009	0.013
Saud-Brent	**Lower**	0.000	0.027	0.000	0.000	0.000	0.000	0.128	0.001	0.072
	Upper	0.000	0.000	0.004	0.000	0.000	0.099	0.000	0.001	0.001
Vene-Brent	**Lower**	0.000	0.002	0.000	0.000	0.000	0.000	0.079	0.001	0.014
	Upper	0.000	0.000	0.000	0.000	0.000	0.069	0.000	0.001	0.001
Spai-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001
Swit-Brent	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.000	0.001

Note: For each of the copula function, the lower (left) and upper (right) tail dependences are reported.

A.10 Tail Dependences EUR-Denominated Data in post-Euro period

		Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.029	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.045	0.000	0.000	0.001
Jap-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.046	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.049	0.000	0.000	0.001
US-Opec	**Lower**	0.000	0.011	0.000	0.000	0.000	0.000	0.110	0.011	0.031
	Upper	0.000	0.000	0.007	0.000	0.000	0.105	0.000	0.011	0.017
Germ-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001
Fran-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000
Ital-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000
Cana-Opec	**Lower**	0.000	0.037	0.000	0.000	0.000	0.000	0.145	0.006	0.073
	Upper	0.000	0.000	0.019	0.000	0.000	0.130	0.000	0.006	0.021
HK-Opec	**Lower**	0.000	0.010	0.000	0.000	0.000	0.000	0.105	0.000	0.027
	Upper	0.000	0.000	0.007	0.000	0.000	0.100	0.000	0.000	0.013
Ch-Opec	**Lower**	0.000	0.003	0.000	0.000	0.000	0.000	0.091	0.000	0.007
	Upper	0.000	0.000	0.004	0.000	0.000	0.090	0.000	0.000	0.011
Cze-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.000
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000
Neth-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001
Finl-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001
Hung-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.038	0.000	0.000	0.001
Pola-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.053	0.000	0.003
	Upper	0.000	0.000	0.000	0.000	0.000	0.027	0.000	0.000	0.001
Russ-Opec	**Lower**	0.000	0.039	0.000	0.000	0.000	0.000	0.150	0.006	0.063
	Upper	0.000	0.000	0.030	0.000	0.000	0.147	0.000	0.006	0.033
Saud-Opec	**Lower**	0.000	0.042	0.000	0.000	0.000	0.000	0.153	0.005	0.080
	Upper	0.000	0.000	0.024	0.000	0.000	0.134	0.000	0.005	0.016
Vene-Opec	**Lower**	0.000	0.004	0.000	0.000	0.000	0.000	0.092	0.000	0.015
	Upper	0.000	0.000	0.003	0.000	0.000	0.085	0.000	0.000	0.006
Spai-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001
Swit-Opec	**Lower**	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001
	Upper	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.001

Note: For each of the copula function, the lower (left) and upper (right) tail dependences are reported.

APPENDIX B

COPULA MODEL RANKING

B.1 Log-Likelihood Functions for EUR-Denominated Data in post-Euro Period

	Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Brent	5.411	3.413	5.512	5.549	5.470	7.192	3.126	6.683	6.593
	7	8	5	4	6	1	9	2	3
Jap-Brent	6.417	5.715	4.571	4.721	4.702	5.164	6.119	6.823	7.340
	3	5	9	7	8	6	4	2	1
US-Brent	12.341	14.391	9.761	10.759	10.456	13.904	18.993	22.042	19.068
	6	4	9	7	8	5	3	1	2
Germ-Brent	1.226	-0.005	-0.001	1.118	-0.011	0.117	-0.223	5.405	-9.985
	2	6	5	3	7	4	8	1	9
Fran-Brent	0.360	0.004	-0.003	0.334	-0.006	-0.002	-0.099	1.396	-2.309
	2	4	6	3	7	5	8	1	9
Ital-Brent	1.171	-0.005	-0.006	0.499	-0.007	-0.185	-0.131	1.303	-4.054
	2	4	5	3	6	8	7	1	9
Cana-Brent	49.929	41.849	37.544	48.037	46.412	47.217	50.159	55.909	55.723
	4	8	9	5	7	6	3	1	2
HK-Brent	13.780	9.753	11.631	12.264	12.338	12.621	11.475	14.814	15.484
	3	9	7	6	5	4	8	2	1
Ch-Brent	8.991	4.937	6.289	11.817	11.753	5.689	4.965	9.079	7.427
	4	9	6	1	2	7	8	3	5
Cze-Brent	0.011	0.509	0.015	0.000	0.000	0.067	0.633	3.271	-0.473
	6	3	5	7	8	4	2	1	9
Neth-Brent	0.918	-0.003	-0.004	0.733	-0.009	-0.151	-0.166	2.426	-10.211
	2	4	5	3	6	7	8	1	9
Finl-Brent	0.436	0.233	0.285	0.618	0.610	0.236	0.359	0.545	-3.271
	4	8	6	1	2	7	5	3	9
Hung-Brent	0.997	0.253	0.957	0.877	0.875	1.108	0.147	0.874	-0.371
	2	7	3	4	5	1	8	6	9
Pola-Brent	5.513	6.315	3.576	4.709	4.585	4.714	6.922	7.263	7.034
	5	4	9	7	8	6	3	1	2
Russ-Brent	23.409	21.450	16.357	27.379	26.136	21.028	26.746	29.729	26.742
	6	7	9	2	5	8	3	1	4
Saud-Brent	25.691	28.750	12.189	25.800	25.404	15.015	30.772	28.676	30.242
	6	3	9	5	7	8	1	4	2
Vene-Brent	9.692	9.186	6.974	9.984	9.671	8.604	11.145	12.512	11.608
	5	7	9	4	6	8	3	1	2
Spai-Brent	2.882	-0.006	-0.010	1.903	-0.015	-0.297	-0.221	4.387	-13.805
	2	4	5	3	6	8	7	1	9
Swit-Brent	3.139	-0.010	-0.002	3.050	-0.019	1.809	-0.413	6.359	-12.432
	2	6	5	3	7	4	8	1	9

Note: Copula models are ranked according to the highest log-likelihood function. 1 to 9 are the rankings of each of the nine copula models, where 1 is the best fitting copula model and 9 is the worst fitting copula model.

B.2 Log-Likelihood Functions for EUR-Denominated Data in post-Euro Period

	Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Opec	3.272	1.597	4.397	3.212	3.148	6.234	1.316	4.545	4.038
	5	8	3	6	7	1	9	2	4
Jap-Opec	6.414	4.264	5.481	4.241	4.253	4.511	4.452	6.352	6.745
	2	7	4	9	8	5	6	3	1
US-Opec	20.280	18.967	16.666	19.373	18.716	21.772	22.739	29.498	26.002
	5	7	9	6	8	4	3	1	2
Germ-Opec	4.213	-0.010	-0.009	3.980	-0.021	-0.452	-0.381	4.919	-15.884
	2	5	4	3	6	8	7	1	9
Fran-Opec	3.835	-0.008	-0.012	3.694	-0.021	-0.544	-0.389	3.907	-6.605
	2	4	5	3	6	8	7	1	9
Ital-Opec	5.487	-0.010	-0.015	4.211	-0.020	-0.635	-0.514	4.879	-9.531
	1	4	5	3	6	8	7	2	9
Cana-Opec	35.133	33.397	23.812	31.985	31.201	30.756	39.402	40.794	41.612
	4	5	9	6	7	8	3	2	1
HK-Opec	23.588	17.668	16.421	21.873	22.099	18.164	20.408	24.012	23.995
	3	8	9	5	4	7	6	1	2
Ch-Opec	17.186	10.935	12.517	21.642	21.534	12.918	12.535	17.778	15.350
	4	8	9	1	2	6	7	3	5
Cz-Opec	0.218	0.000	-0.001	0.218	-0.005	-0.078	0.063	2.660	-2.055
	3	5	6	2	7	8	4	1	9
Neth-Opec	4.451	-0.011	-0.008	4.114	-0.022	-0.374	-0.429	6.070	-15.786
	2	5	4	3	6	7	8	1	9
Finl-Opec	0.429	-0.002	-0.005	0.531	-0.008	-0.252	-0.110	0.369	-9.683
	2	4	5	1	6	8	7	3	9
Hung-Opec	1.410	0.014	3.044	1.225	1.197	2.629	0.095	1.545	0.861
	4	9	1	5	6	2	8	3	7
Pola-Opec	4.246	6.415	0.970	4.030	3.996	1.147	6.008	4.438	4.248
	5	1	9	6	7	8	2	3	4
Russ-Opec	39.220	33.370	26.982	43.719	42.171	33.793	39.544	43.983	40.852
	6	8	9	2	3	7	5	1	4
Saud-Opec	38.799	34.895	25.915	39.181	38.092	28.671	42.171	44.050	41.836
	5	7	9	4	6	8	2	1	3
Vene-Opec	15.051	12.220	11.170	16.280	15.682	12.063	13.655	17.133	15.654
	5	7	9	2	3	8	6	1	4
Spai-Opec	7.441	-0.014	-0.013	7.150	-0.029	-0.532	-0.560	7.912	-19.249
	2	5	4	3	6	7	8	1	9
Swit-Opec	10.977	-0.019	-0.012	9.934	-0.034	-0.495	-0.706	12.461	-21.356
	2	5	4	3	6	7	8	1	9

Note: Copula models are ranked according to the highest log-likelihood function. 1 to 9 are the rankings of each of the nine copula models, where 1 is the best fitting copula model and 9 is the worst fitting copula model.

B.3 Akaike Information Criteria for EUR-Denominated Data in post-Euro Period

	Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Brent	-8.821	-4.826	-9.024	-9.097	-8.939	-12.385	-4.252	-9.366	-9.187
	7	8	5	4	6	1	9	2	3
Jap-Brent	-10.835	-9.429	-7.142	-7.441	-7.403	-8.329	-10.237	-9.645	-10.680
	1	5	9	7	8	6	3	4	2
US-Brent	-22.682	-26.781	-17.523	-19.518	-18.911	-25.808	-35.985	-40.083	-34.137
	6	4	9	7	8	5	2	1	3
Germ-Brent	-0.451	2.010	2.003	-0.237	2.023	1.765	2.447	-6.809	23.971
	2	6	5	3	7	4	8	1	9
Fran-Brent	1.280	1.992	2.005	1.332	2.012	2.005	2.197	1.208	8.619
	2	4	6	3	7	5	8	1	9
Ital-Brent	-0.342	2.010	2.012	1.001	2.014	2.369	2.261	1.393	12.108
	1	4	5	2	6	8	7	3	9
Cana-Brent	-97.859	-81.698	-73.088	-94.074	-90.824	-92.435	-98.319	-107.817	-107.447
	4	8	9	5	7	6	3	1	2
HK-Brent	-25.561	-17.505	-21.263	-22.527	-22.675	-23.243	-20.949	-25.629	-26.969
	3	9	7	6	5	4	8	2	1
Ch-Brent	-15.981	-7.874	-10.578	-21.633	-21.506	-9.378	-7.930	-14.159	-10.854
	3	9	6	1	2	7	8	4	5
Cze-Brent	1.979	0.981	1.970	2.000	2.000	1.867	0.734	-2.542	4.947
	6	3	5	7	8	4	2	1	9
Neth-Brent	0.163	2.006	2.009	0.534	2.019	2.302	2.332	-0.851	24.423
	2	4	5	3	6	7	8	1	9
Finl-Brent	1.127	1.535	1.431	0.764	0.780	1.528	1.282	2.910	10.541
	3	7	5	1	2	6	4	8	9
Hung-Brent	0.007	1.494	0.087	0.246	0.250	-0.216	1.705	2.252	4.742
	2	6	3	4	5	1	7	8	9
Pola-Brent	-9.025	-10.630	-5.152	-7.418	-7.170	-7.429	-11.843	-10.526	-10.068
	5	2	9	7	8	6	1	3	4
Russ-Brent	-44.818	-40.899	-30.714	-52.758	-50.272	-40.056	-51.493	-55.458	-49.484
	6	7	9	2	4	8	3	1	5
Saud-Brent	-49.381	-55.500	-22.378	-49.599	-48.809	-28.030	-59.543	-53.351	-56.485
	6	3	9	5	7	8	1	4	2
Vene-Brent	-17.385	-16.373	-11.947	-17.967	-17.343	-15.208	-20.290	-21.024	-19.215
	5	7	9	4	6	8	2	1	3
Spai-Brent	-3.765	2.011	2.021	-1.807	2.030	2.595	2.442	-4.775	31.609
	2	4	5	3	6	8	7	1	9
Swit-Brent	-4.278	2.021	2.005	-4.101	2.038	-1.617	2.826	-8.719	28.863
	2	6	5	3	7	4	8	1	9

Note: Copula functions are ranked based on the AIC model and the model with the smallest AIC value is ranked the highest. 1 to 9 are the rankings of each of the nine copula models, where 1 is the best fitting copula model and 9 is the worst fitting copula model.

B.4 Akaike Information Criteria for EUR-Denominated Data in post-Euro Period

	Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Opec	-4.543	-1.194	-6.795	-4.425	-4.296	-10.468	-0.632	-5.090	-4.077
	4	8	2	5	6	1	9	3	7
Jap-Opec	-10.828	-6.528	-8.962	-6.483	-6.505	-7.023	-6.904	-8.703	-9.491
	1	7	3	9	8	5	6	4	2
US-Opec	-38.559	-35.933	-31.333	-36.747	-35.431	-41.545	-43.479	-54.996	-48.005
	5	7	9	6	8	4	3	1	2
Germ-Opec	-6.427	2.021	2.018	-5.959	2.043	2.905	2.763	-5.837	35.768
	1	5	4	2	6	7	8	3	9
Fran-Opec	-5.669	2.015	2.025	-5.388	2.042	3.088	2.779	-3.814	17.211
	1	4	5	2	6	8	7	3	9
Ital-Opec	-8.975	2.020	2.031	-6.422	2.041	3.271	3.028	-5.758	23.061
	1	4	5	2	6	8	7	3	9
Cana-Opec	-68.267	-64.794	-45.624	-61.971	-60.401	-59.512	-76.804	-77.588	-79.223
	4	5	9	6	7	8	3	2	1
HK-Opec	-45.177	-33.336	-30.843	-41.746	-42.199	-34.327	-38.816	-44.023	-43.991
	1	8	9	5	4	7	6	2	3
Ch-Opec	-32.371	-19.870	-23.033	-41.284	-41.068	-23.836	-23.070	-31.555	-26.699
	3	9	8	1	2	6	7	4	5
Cz-Opec	1.564	2.000	2.002	1.563	2.010	2.156	1.873	-1.320	8.110
	3	5	6	2	7	8	4	1	9
Neth-Opec	-6.903	2.022	2.016	-6.227	2.044	2.749	2.858	-8.140	35.572
	2	5	4	3	6	7	8	1	9
Finl-Opec	1.142	2.004	2.009	0.937	2.016	2.503	2.220	3.262	23.365
	2	3	4	1	5	7	6	8	9
Hung-Opec	-0.821	1.972	-4.088	-0.450	-0.395	-3.258	1.810	0.910	2.277
	3	8	1	4	5	2	7	6	9
Pola-Opec	-6.492	-10.829	0.060	-6.059	-5.992	-0.293	-10.016	-4.877	-4.496
	3	1	9	4	5	8	2	6	7
Russ-Opec	-76.440	-64.741	-51.963	-85.437	-82.342	-65.586	-77.088	-83.966	-77.704
	6	8	9	1	3	7	5	2	4
Saud-Opec	-75.599	-67.790	-49.829	-76.362	-74.183	-55.342	-82.343	-84.100	-79.673
	5	7	9	4	6	8	2	1	3
Vene-Opec	-28.101	-22.439	-20.340	-30.560	-29.364	-22.125	-25.309	-30.265	-27.307
	4	7	9	1	3	8	6	2	5
Spai-Opec	-12.882	2.028	2.026	-12.300	2.058	3.064	3.120	-11.825	42.499
	1	5	4	2	6	7	8	3	9
Swit-Opec	-19.954	2.038	2.025	-17.867	2.068	2.990	3.411	-20.922	46.712
	2	5	4	3	6	7	8	1	9

Note: Copula functions are ranked based on the AIC model and the model with the smallest AIC value is ranked the highest. 1 to 9 are the rankings of each of the nine copula models, where 1 is the best fitting copula model and 9 is the worst fitting copula model.

B.5 Bayesian Information Criteria for EUR-Denominated Data in post-Euro Period

	Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Brent	-3.100	0.895	-3.303	-3.376	-3.218	-6.663	1.469	2.077	2.256
	5	6	3	2	4	1	7	8	9
Jap-Brent	-5.114	-3.708	-1.421	-1.720	-1.682	-2.607	-4.516	1.797	0.763
	1	3	7	5	6	4	2	9	8
US-Brent	-16.961	-21.060	-11.802	-13.797	-13.190	-20.087	-30.264	-28.640	-22.694
	6	4	9	7	8	5	1	2	3
Germ-Brent	5.270	7.732	7.724	5.485	7.744	7.487	8.168	4.634	35.413
	2	6	5	3	7	4	8	1	9
Fran-Brent	7.001	7.713	7.726	7.053	7.734	7.726	7.919	12.651	20.061
	1	3	5	2	6	4	7	8	9
Ital-Brent	5.379	7.731	7.733	6.723	7.735	8.091	7.982	12.836	23.551
	1	3	4	2	5	7	6	8	9
Cana-Brent	-92.137	-75.977	-67.366	-88.353	-85.102	-86.713	-92.598	-96.374	-96.004
	4	8	9	5	7	6	3	1	2
HK-Brent	-19.839	-11.784	-15.541	-16.806	-16.954	-17.521	-15.228	-14.186	-15.526
	1	9	5	4	3	2	7	8	6
Ch-Brent	-10.260	-2.153	-4.857	-15.912	-15.784	-3.656	-2.208	-2.716	0.588
	3	2	3	1	2	6	7	8	9
Cze-Brent	7.700	6.702	7.691	7.721	7.721	7.588	6.456	8.900	16.390
	5	2	4	6	7	3	1	8	9
Neth-Brent	5.885	7.727	7.730	6.255	7.740	8.023	8.054	10.591	35.865
	1	3	4	2	5	6	7	8	9
Finl-Brent	6.849	7.256	7.152	6.486	6.501	7.249	7.004	14.353	21.984
	3	6	5	1	2	7	4	8	9
Hung-Brent	5.728	7.215	5.808	5.967	5.971	5.505	7.427	13.695	16.185
	2	6	3	4	5	1	7	8	9
Pola-Brent	-3.304	-4.909	0.570	-1.696	-1.449	-1.707	-6.122	0.916	1.374
	3	2	7	5	6	4	1	8	9
Russ-Brent	-39.097	-35.178	-24.993	-47.037	-44.551	-34.334	-45.771	-44.016	-38.041
	5	7	9	1	3	8	2	4	6
Saud-Brent	-43.660	-49.779	-16.656	-43.878	-43.087	-22.308	-53.822	-41.909	-45.042
	5	2	9	4	6	8	1	7	3
Vene-Brent	-11.664	-10.651	-6.226	-12.246	-11.621	-9.487	-14.568	-9.581	-7.772
	3	5	9	2	4	6	1	7	8
Spai-Brent	1.957	7.732	7.742	3.915	7.751	8.316	8.163	6.668	43.052
	1	4	5	2	6	8	7	3	9
Swit-Brent	1.444	7.742	7.726	1.620	7.759	4.104	8.548	2.724	40.306
	1	6	5	2	7	4	8	3	9

Note: Copula functions are ranked based on the BIC model and the model with the smallest BIC value is ranked the highest. 1 to 9 are the rankings of each of the nine copula models, where 1 is the best fitting copula model and 9 is the worst fitting copula model.

B.6 Bayesian Information Criteria for EUR-Denominated Data in post-Euro Period

	Normal	Clayton	R. Clayton	Plackett	Frank	Gumbel	R. Gumbel	Student t	SJC
UK-Opec	1.178	4.527	-1.073	1.297	1.425	-4.747	5.090	6.353	7.366
	3	6	2	4	5	1	7	8	9
Jap-Opec	-5.107	-0.806	-3.240	-0.761	-0.784	-1.302	-1.183	2.739	1.952
	1	5	2	7	6	3	4	9	8
US-Opec	-32.838	-30.212	-25.611	-31.025	-29.710	-35.824	-37.758	-43.553	-36.562
	5	7	9	6	8	4	3	1	2
Germ-Opec	-0.706	7.742	7.739	-0.238	7.764	8.626	8.484	5.605	47.211
	1	5	4	2	6	8	7	3	9
Fran-Opec	0.052	7.737	7.746	0.333	7.763	8.809	8.500	7.629	28.654
	1	4	5	2	6	8	7	3	9
Ital-Opec	-3.253	7.742	7.752	-0.700	7.762	8.992	8.750	5.685	34.504
	1	4	5	2	6	8	7	3	9
Cana-Opec	-62.546	-59.073	-39.903	-56.249	-54.680	-53.790	-71.082	-66.145	-67.781
	4	5	9	6	7	8	1	3	2
HK-Opec	-39.455	-27.615	-25.121	-36.025	-36.477	-28.606	-33.094	-32.581	-32.548
	1	8	9	3	2	7	4	6	5
Ch-Opec	-26.650	-14.148	-17.312	-35.563	-35.347	-18.115	-17.349	-20.113	-15.256
	3	9	7	1	2	5	6	4	8
Cz-Opec	7.286	7.722	7.723	7.284	7.731	7.877	7.595	10.123	19.553
	2	4	5	1	6	7	3	8	9
Neth-Opec	-1.181	7.744	7.737	-0.506	7.765	8.470	8.580	3.303	47.015
	1	5	4	2	6	7	8	3	9
Finl-Opec	6.863	7.726	7.730	6.659	7.737	8.224	7.941	14.704	34.808
	2	3	4	1	5	7	6	8	9
Hung-Opec	4.900	7.693	1.634	5.272	5.327	2.463	7.531	12.353	13.720
	3	7	1	4	5	2	6	8	9
Pola-Opec	-0.771	-5.108	5.782	-0.338	-0.271	5.428	-4.295	6.566	6.947
	3	1	7	4	5	6	2	8	9
Russ-Opec	-70.719	-59.019	-46.242	-79.716	-76.621	-59.865	-71.367	-72.523	-66.261
	5	8	9	1	2	7	4	3	6
Saud-Opec	-69.878	-62.069	-44.108	-70.641	-68.462	-49.620	-76.621	-72.657	-68.230
	4	7	9	3	5	8	1	2	6
Vene-Opec	-22.380	-16.718	-14.618	-24.839	-23.643	-16.404	-19.588	-18.822	-15.864
	3	6	9	1	2	7	4	5	8
Spai-Opec	-7.160	7.749	7.747	-6.579	7.779	8.785	8.842	-0.382	53.941
	1	5	4	2	6	7	8	3	9
Swit-Opec	-14.233	7.759	7.746	-12.146	7.789	8.711	9.132	-9.479	58.155
	1	5	4	2	6	7	8	3	9

Note: Copula functions are ranked based on the BIC model and the model with the smallest BIC value is ranked the highest. 1 to 9 are the rankings of each of the nine copula models, where 1 is the best fitting copula model and 9 is the worst fitting copula model.

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