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ESSAYS ON STOCK MARKET CONTAGION:

EVIDENCE FROM THE AMERICAS

A Dissertation

by

JUAN ANDRES RODRIGUEZ-NIETO

Submitted to the Graduate College of
The University of Texas Rio Grande Valley
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ESSAYS ON STOCK MARKET CONTAGION:

EVIDENCE FROM THE AMERICAS

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JUAN ANDRES RODRIGUEZ-NIETO

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August 2017

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ABSTRACT

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In this dissertation we examine the financial contagion from the U.S. to the Americas during the U.S. financial crisis.

First, we examine the relationship between the U.S. perceived market volatility (VIX), perceived credit risk (TED spread) and the U.S. financial crisis, on the stock returns of these countries. Our findings suggest that VIX has negative effects on the stock returns of all these countries and that this relationship increases significantly during the U.S. financial crisis. We also identify that increases in the TED spread have negative effects on the stock market returns of Canada and Latin America, and these effects increase during the U.S. financial crisis. We conclude that increases in market volatility and credit risk are contributing financial contagion factors, from the U.S. to the Americas, during the U.S. Financial Crisis.

Second, we explore the role of perceived market volatility (VIX), individual investor sentiment and institutional investor sentiment on the propagation of the U.S. financial crisis to the Americas. We first confirm our findings from the previous essay in regards to VIX, and then find that individual and institutional investor sentiments positively affect the stock market returns of the countries in this study. We also identify that the financial crisis has a positive effect on these relationships. We look in more detail and identify that institutional investor sentiment has a

stronger effect on stock returns than individual sentiment, highlighting the influence of institutional investors.

Third, we study the effects of the 2008-2009 U.S. financial crisis, oil price returns and U.S. market volatility, on the stock market returns of six oil producing countries in the Americas. We first find that shocks to VIX have negative effects on stock returns and that positive shocks in oil prices have positive effects. We identify that contagion from the U.S. to the other oil producers, identifying positive effects on the conditional correlations between oil price returns and the oil producers' stock returns. We find evidence that due to the U.S. financial crisis, the conditional correlations between stock market returns and oil prices increase substantially, and that these correlations remain higher than the pre-crisis period.

DEDICATION

To my wife Beatriz, thank you for your unconditional love, for your words of encouragement, for always being by my side, and for loving our children the way you do. To my Daughter Beatriz and my Son Patricio, you are my inspiration and greatest treasure. To my parents Ruben and Mau, thank you for showing me what true love is, instilling strong family values, and for always inspiring me to never give up. To my siblings Ruben and Mausita, thank you for your words of encouragement, for inspiring me to pursued my studies abroad, and for taking care of things at home. To my parents-in-law Manuel and Eugenia, thank you believing in me, for your unconditional support and for sharing with me your daughter’s love. To my siblings-in-law Eugenia, Grant, Miguel and Wendy, you are an important part of my life; thank you for your many acts of kindness. I dedicate this dissertation to all of you.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Page

CHAPTER I

INTRODUCTION AND BACKGROUND LITERATURE

1.1 Introduction

The U.S. economy suffered the worst economic downturn, since the great depression, during the late 2000s. Having officially started in late December 2007 and ending in June 2009, according to the U.S. National Bureau of Economic Research (NBER), the 2008-2009 U.S. financial crisis had financial consequences beyond the U.S borders. During the 18-month crisis, the U.S. stock markets lost over 40% of their value and this sharp stock market downturn was transmitted, through what scholars often refer to financial contagion, to the major markets in the Americas and the world.

Various scholars call the concept of contagion differently, but they all refer to the same phenomena: Masson (1999) calls these effects, based on economic fundamentals, spillovers; Forbes and Rigobon (2002) classify them as interdependence, and Kaminsky and Reinhart (2000) call them 'fundamentals based contagion'. We use the definition by Forbes and Rigobon (2002) to define that contagion exists when cross-country correlations increase during times of crisis relative to non-crisis.

The crisis contagion mechanisms are often classified into two groups of theories. The first group includes the interconnection of economic fundamentals, due to the trade of capital, goods, and services. When a country faces a crisis, it is likely that depending on the degree of interdependence, partners in the trade of goods, services, and other financial linkages, will be affected. It is likely that the crisis be spread into those countries with strong interdependence (Kaminsky and Reinhart, 2000; Rijckeghem and Weder, 2001). Other macroeconomic phenomena, such as significant oil price changes, U.S. interest rates, exchange rate changes, can influence the economic fundamentals of various countries at the same time, resulting in "fundamentals based contagions" (Kaminsky and Reinhart, 2000), which can lead to a regional crisis (Eichengreen et al., 1996).

The second group of financial contagion theories incorporate investor behavior and argue that market imperfections favor the transmission of financial crisis amongst countries (Diamond and Dybvig, 1983; King and Wadhwani, 1990; Masson, 1999; Dornbusch et al., 2000; Kodres and Pritsker, 2002). They state that information asymmetry accentuates investor uncertainty to a country's economic fundamentals, which can cause investors to follow a herding behavior when a country is under a crisis, and informed investors try to balance the risks in their international holdings by changing their portfolio composition. This herding effect may lead to excessive fund withdrawals from countries perceived to be vulnerable to the country under crisis, resulting in increased correlations amongst countries (Yuan, 2005; Pasquariello, 2007).

U.S. investors are one of the most influential groups of international equity holders in the world; Figure 1.1 represents the historical U.S. portfolio holdings of foreign equities, published by the U.S. Department of the Treasury (2016), for the larger stock markets in the Americas. We observe a growing trend before the financial crisis, followed by a downward shift during the financial crisis that is sharper for Argentina, Brazil, Canada, and Mexico and not so much for Chile, Colombia, and Peru. We observe a rebound to a positive trend for all countries after the financial crisis ended. These observations are in line with the concept of flight to safety during a financial crisis, which is when investors in an effort to balance the risk of their international positions, rather than maintaining their diversified position, tend to reduce their international holdings from countries with strong economic ties to the country in crisis.

The investor's surprise and overreaction when a crisis occurs promotes the creation of contagion, since investors' attention allocation theory tells us that important information and news will not affect prices until investors are aware of them (Mondria and Quintana-Domeque, 2013). Unanticipated and rapid changes in market expectations and confidence are also contagion promoters (Masson, 1999; Mondria and Quintana-Domeque, 2013).

According to Modern Portfolio Theory (Markowitz, 1952), a portfolio composed of international stock markets that are not perfectly positively correlated, will create a diversified portfolio of assets. Recent studies have documented that correlations amongst international stock markets vary over time, that these correlations tend to decrease in bull markets, and they tend to increase during bear markets and periods of financial distress (Ang and Bekaert, 1999; Longin and Solnik, 1995, 2001; Lin et al., 1994).

In this dissertation, we explore financial contagion mechanisms that include both economic fundamentals and investor's behavior, to explain the contagion between the U.S., Canada and the largest financial markets in the Americas during the recent U.S. financial crisis.

In our first essay, we use the multivariate DCC–GARCH model (Engle, 2002), to assess the existence of contagion from the U.S. to the Americas during the 2008-2009 financial crisis. Our sample includes daily closing prices, from January 01, 2002 to December 31, 2015, for the major stock markets in the Americas including the U.S., Argentina, Brazil, Canada, Chile, Colombia, Mexico and Peru. We assess the impact of the U.S. financial crisis on the conditional correlations between stock markets, and the perceived credit risk in the general economy represented by the *TED* spread, as well as the U.S. market volatility represented by the CBOE

Volatility Index® (*VIX*). We first identify evidence that the U.S. stock market volatility *VIX* is a promotor of contagion, from the U.S. to the stock markets in the Americas. We also find evidence that during the financial crisis period, changes in the *TED* spread have negative and statistically significant effects on the conditional correlations with Argentina, Canada, Chile, Colombia and Mexico.

In our second essay, we assess the impact of investor sentiment on the financial contagion between the U.S., Argentina, Brazil, Canada, Chile, Colombia, Mexico and Peru. We test two survey-based proxies widely used in the behavioral finance literature, as direct measures of investor sentiment. In addition to the VIX, we follow Brown and Cliff (2004) and Huerta, Egly and Escobari (2016), and differentiate the effects between individual investor sentiment, represented by the American Association of Individual Investors (*AAII*), and institutional investor sentiment, using the Investor Intelligence (*II*) Survey. We use DCC-GARCH models to obtain the dynamic conditional correlations between the U.S. market volatility, individual and institutional investor sentiments, and the stock indexes of Argentina, Brazil, Canada, Chile, Colombia, Mexico, Peru and the U.S. Our data consists of weekly closing prices, spanning from January 1, 2002 to December 31, 2015. We break our observations into three periods following Mollick and Assefa (2013). The pre-crisis period starts on January 1, 2002 and ends on December 31, 2007. The crisis period begins on January 01, 2008, right after December 2007 that is the date identified by NBER as the beginning of the U.S. financial crisis, and ends on June 30, 2009. The post-crisis period begins on July 1, 2009 and ends on December 31, 2015. We then regress the dynamic conditional correlation coefficients, using dummy variables for each of the periods. We observe significant increases in all correlation coefficients between stock returns, changes in *VIX*, and the two institutional investor sentiments during the financial crisis.

We identify that the institutional investor sentiment is a better predictor than the individual investor sentiment, which is consistent with prior research that emphasized the greater influence of institutional investors on the U.S. markets (Huerta, Egly and Escobari, 2016). Our research contributes to the literature by quantifying the influence of U.S. investor confidence on the performance of the largest stock markets in the Americas, and the role of the U.S. investor confidence on the propagation of contagion during the U.S. financial crisis.

In our third essay, we study the effects of the U.S. financial crisis on the relationship between the U.S. market volatility *VIX*, oil price returns, represented by the price per barrel West Texas Intermediate (OilWTI), and the stock returns of five of the largest oil producing countries in the Americas. Our data is composed of daily closing prices from Brazil, Canada, Colombia, Mexico and the U.S. in addition to CBOE Volatility Index *VIX*, and the oil price per barrel West Texas Intermediate (OilWTI). The sample expands from January 1, 2002 to December 31, 2015. We then break the sample into sub-periods that include the pre-crisis period from January 1, 2002 to December 2007; the crisis period from January 1, 2008 to June 30, 2009; and the post-crisis period beginning on July 1, 2009 and ending on December 31, 2015. We use a VAR model to assess the impact of shocks to ΔVIX and oil returns, on the stock returns of the major oil producers in the Americas. We first find that shocks to ΔVIX have negative effects on stock returns. We also identify that shocks to oil returns are positively directed to stock returns, and that the magnitude of these shocks seems to be related to the market capitalization for each country. We then employ a DCC-GARCH model to obtain the dynamic conditional correlations between OilWTI, VIX, Brazil, Canada, Colombia, Mexico and the U.S. We find that due to the financial crisis, the pairwise correlations between the *VIX* and each of the stock returns remains negative, significant, and increases in magnitude. This means that the relationship between the

U.S. market volatility and the stock returns of each of the oil producers increases during the financial crisis, and remains strong even after the end of the financial crisis. We also find that the relationship between oil price returns and the stock returns of the countries that produce oil increases during the U.S. financial crisis. This indicates that the stock markets in these countries are more dependent on oil-price returns after the U.S. financial crisis, and this is important since oil-prices are set globally, highlighting the interdependence of the global stock markets.

In this dissertation, we study the contagion from the U.S. to the Americas during the U.S. financial crisis, and identify evidence of both fundamental and behavioral based contagion mechanisms. This is of great concern for U.S. investors seeking to diversify their portfolios, since it appears that their own confidence in the U.S. financial markets during times of crisis may play a strong role on financial contagion.

Figure 1.1
U.S. Portfolio Holdings of Foreign Equities.

Source: U.S. Department of the Treasury (2016).

CHAPTER II

THE U.S. FINANCIAL CRISIS, MARKET VOLATILITY, CREDIT RISK AND STOCK RETURNS IN THE AMERICAS

2.1 Introduction

The 2008-2009 U.S. financial crisis, which was identified by the U.S. National Bureau of Economic Research (NBER) as having started in December 2007 and officially ending in June 2009, represented the largest U.S. market capitalization decline since the great depression. The U.S. equity markets, as represented by the Standard and Poor's 500 index (S&P 500), had a capital loss of approximately 40% during the crisis period (using data downloaded from *DataStream*), and other financial markets followed. Canada and the developing countries in Latin America were strongly affected by the U.S. financial crisis: The Peruvian equity markets suffered a loss of about 75%, the Argentinean, Brazilian and Mexican equity markets lost about 60% of their values, while Canada and Chile lost about 50% of their market value (source is *DataStream*).

Financial contagion is a popular and current topic in finance, due to the increasing investor access to international markets, collaboration and interdependence amongst countries through trade agreements, and overall market globalization. The interdependence between countries also has implications on portfolio diversification, since investors will try to diversify their portfolios by allocating funds in different industries and markets. The notion of financial contagion challenges the ability to mitigate the market interdependence and reduces the diversification properties of investing in multiple countries.

We use the definition of financial contagion proposed by Forbes and Rigobon (2002), which states that contagion occurs when cross-country correlations increase significantly during periods of crisis relative to non-crisis periods. If strong linkages exist during both crisis and non-crisis times, and no statistical difference exists between these two periods, then we say that these markets are interdependent (Forbes and Rigobon, 2002).

Empirical studies have identified the investor interdependence and contagion effects on several emerging market economies during financial crises. For example, Caporale et al. (2005) identify several financial crises during the 1990s, characterized by very rapid spread to neighboring countries, resulting in regional and global financial crises.

In this chapter, we use the multivariate DCC–GARCH model proposed by Engle (2002) to assess the existence of contagion during the 2008-2009 financial crisis, from the U.S. to Argentina, Brazil, Canada, Chile, Colombia, Mexico and Peru. We also test various factors and their role on increased conditional correlations among the U.S. and other stock markets in the Americas. We assess the impact of the perceived credit risk in the general economy, represented by the TED spread, and market volatility represented by the CBOE Volatility Index®, or VIX, on the conditional correlations between the U.S. and the stock markets of each of the countries in this study.

This chapter contributes to the literature by identifying the role of the perceived credit risk in the general economy (TED spread), and the perceived market volatility (VIX), on the financial contagion from the U.S. to the Americas during the recent U.S. financial crisis. We find evidence that the VIX is a significant contagion promotor, since the level of influence from VIX to the stock returns of the countries in the study increases during the U.S. financial crisis. We also find evidence that it is only during the financial crisis period, when changes in the TED spread have a significant influence on the stock returns of Argentina, Canada, Chile, Colombia and Mexico. This highlights how perceived risk in the general U.S. economy and perceived U.S. market volatility are significant contagion promotors, during the recent crisis period.

2.2 Literature Review and Hypotheses Development

Several techniques are used to assess variable stock market correlations, such as those that incorporate dynamic convergence properties using co-integration analysis, or employing GARCH models to identify volatility spillovers and the dynamic properties of the convergence process. The newest group of studies use Dynamic Conditional Correlation (DCC) - GARCH models, since they allow for the modeling of multiple dynamic pairwise correlations of the variables being studied.

The literature is quite extensive on stock market correlations and potential integration amongst developed markets. Hamao, Masulis, & Ng (1990) identify the existence of volatility spillovers from the U.K. and the U.S. stock markets to the Japanese stock market during the 1987 stock crash. Longin & Solnik (1995) model monthly excess returns from 1960 to 1990, for seven developed countries, finding that conditional correlations have increased over time. They also find that these conditional correlations increase during high volatility periods. Meric & Meric (1997) model linkages amongst the twelve most developed European equity markets, since the 1987 equity crisis. They apply principal components analysis and find that the market crash had a significant effect on the equity market co-movements, identifying increased correlations amongst these developed European markets and the U.S. market after the crisis. They suggest that an international equity portfolio, composed of the equity markets in the study, would have had limited diversification effects during the financial crisis.

Goetzmann, Li, & Rouwenhorst (2005) analyze the correlations amongst the world equity markets during a period of 150 years, identifying that they vary considerably, with a tendency to increase during periods of economic integration. They find that globalization has expanded investment opportunities, correlations amongst developed countries are stronger, and diversification can be achieved by investing in the emerging markets.

Access to investment opportunities in the emerging markets increases the interest from scholars to assess the diversification risks vs benefits of investing in these markets. With the elimination of the Soviet Union, and the creation of the European Union, many new emerging markets have been created in Eastern Europe, prompting attention to scholars.

Kim et al. (2005) examine the European stock market integration, after the formation of the European Monetary Union (EMU), and find evidence that the EMU has augmented the integration of EMU stock markets. Mylonidis and Kollias (2010) analyze the tendency to convergence during the first euro-decade for four major European stock markets. They show convergence is dynamic and that continues to increase within these stock markets. They identify that that the French and German markets, which were at the time the leading stock markets in the Euro Zone, have the highest level of convergence.

Studies have also analyzed the link amongst developed and developing countries. Wang and Moore (2008) use a DCC model, to investigate the interdependence amongst three emerging European markets (Czech Republic, Hungary and Poland) and the aggregate European Union market. They find that the increasing European Union participation and the recent financial crisis have increased these correlations. Syllignakis and Kouretas (2011) asses the dynamic conditional correlations between seven Central and Eastern Europe markets and the German, Russian and U.S. markets. Using weekly data from 1997–2009 they find increasing stock market correlations and note that portfolio diversification strategies in the European countries would potentially be affected by this.

Syriopoulos (2004, 2007) assess the effects of the European Monetary Union on the stock market linkages of four emerging Central European markets (Czech Republic, Hungary, Poland, Slovakia), with the German and U.S. markets. Using co-integration vector analysis, Syriopoulos finds that Central European markets have a tendency towards stronger linkages with both German and U.S. markets. Cappiello, Engle, & Sheppard (2006) identify that the conditional correlations increase during periods of financial turmoil and also find a structural break in correlations due to the introduction of the euro in January 1999.

Chen, Firth, & Rui (2002) employ co-integration analysis, and error correction vector auto-regressions (VAR), to model the interdependencies of 6 major stock markets in Latin America (Argentina, Brazil, Chile, Colombia, Mexico and Venezuela). They use data from 1995 to 2000 that includes the Asian and Russian financial crises of 1997 and 1998. They find that the six national stock price indexes share one long-term equilibrium relationship and that fluctuations in the Mexican stock market explain movements in all the other markets except Colombia. They conclude that the risk diversification potential, of a strategy that would focus on investing in Latin America as means for diversification, would be limited.

Araujo (2009) uses structural vector auto-regression models to document high degree co-movement of seven Latin American countries (Argentina, Brazil, Chile, Colombia, Mexico, Venezuela, and Peru) from January 1995 to February 2009. He also identifies that portfolio shocks help explain pairwise co-movement patterns.

Lahrech and Sylwester (2011) study the evolution of co-movements between four Latin American equity markets (Argentina, Brazil, Chile and Mexico) and the U.S. equity market. Analyzing weekly data from December 1988 through March 2004. They identify an increase in the magnitude of co-movement between the U.S. equity returns and those of each of the Latin American countries. They also identify that the speed and magnitude of these co-movements varies across these countries.

Samarakoon (2012) employs a vector auto regressions (VAR) framework to estimate the impact of stock market shocks, during non-crisis and crisis periods, and tries to determine the difference between contagion and interdependence. The sample includes 62 emerging and frontier markets, including five from Latin America (Argentina, Brazil, Chile, Peru, Venezuela), form January 2000 to march 2009. He finds mixed evidence of interdependence and contagion, from the U.S. to emerging and frontier countries, during the U.S. crisis.

We find extended literature documenting that correlations between markets vary over time and that countries with strong economic ties, such as trade of goods, services or capital can suffer from financial contagion. Since the U.S. has very strong trade agreements with North and Latin American countries, such as NAFTA, CAFTA-DR, Chile-FTA, Colombia-FTA, Peru-FTA, we expect that Canadian and Latin American stock markets will have a strong relationship with the U.S. market and that these relationships would increase during a time of crisis in the U.S. Since stock prices represent discounted future expected cash flows (Fama and Macbeth, 1973), market volatility, changes in interest rates, inflation rates and exchange rates will have an impact on stock returns (Mollick and Assefa, 2013). Daily changes in the perceived U.S. market volatility, which is represented by the VIX, are identified as having a negative and statistically significant effect on U.S. stock returns (Dennis et. al., 2006; Mollick and Assefa, 2013). We expect that increases in expected U.S. market volatility, represented by the VIX, will not only have a negative effect on U.S. capital markets, but that it will have a contagion effect on Canadian and Latin American stock returns.

Our first hypothesis is as follows:

H1: positive shocks in the perceived U.S. market volatility, represented by VIX, will have negative and statistically significant effects on stock returns of Canadian and Latin American stock markets.

The federal funds rate (FFR), which is defined by the Federal Reserve as the interest rate at which depository institutions trade federal funds (balances held at Federal Reserve Banks) with each other overnight, has been used by the U.S. Federal Reserve Board (the Fed) as the main monetary policy tool since 1987. It is documented that changes in the federal funds rate target are positively related to market interest rates, especially short –term interest rates (Thornton, 1998; Kuttner, 2001). Since stock prices reflect discounted cash flows of future earnings, and interest rates are affected by the Fed's monetary policy, there is a negative relationship between increases in the FFR, which is characteristic of contractionary monetary policy, and stock market returns (Chen et al., 1986; Bernanke and Kuttner, 2005). The prelude to the 2008-2009 U.S. financial crisis was the U.S. housing and credit crises, which started in 2007. During the financial crisis, in an attempt to stimulate the economy, the FED lowered the federal funds rate to historical lows. The expectation was for the FED to continue to stimulate the economy and by maintaining an extremely low federal funds rate it reduced the possibility of monetary policy shocks, however the federal funds rate plays an important role on defining the TED spread.

Although the federal funds rate reached historical lows, the bank sector's ability to lend to other banks, business and individuals was reduced, consequently increasing the LIBOR which in turn widen the TED spread. The TED spread is defined as the difference between interest rates on interbank loans (LIBOR) and short-term U.S. Treasury Securities. An increase in the TED spread is perceived as a sign of increased stress and risk in the financial system, while a reduction in TED is usually perceived as assign of strength in the financial system that usually results in increased economic activity. The TED spread is widely used as a proxy for perceived risk in the general economy, and it has been identified that the TED spread is reduced in periods of prosperity and it tends to increase in times of uncertainty (Lashgari, 2000). Tse and Booth (1996) identify increases in the TED spread to be influential in equity market volatility. Our second hypothesis is as follows:

H2: Increases in the TED spread will have negative and statistically significant effects on stock returns of Canadian and Latin American stock markets.

2.3 Data and empirical results

The country specific data used in this chapter are obtained from *DataStream* and consists of daily closing stock indexes, in U.S. Dollars, from January 1, 2002, through December 31, 2015, for eight of the major stock markets in the Americas. Thee dataset consists of the primary local stock indexes from Argentina (BURCAP), Brazil (BOVESPA), Canada (S&P/TSX Composite Index), Chile (IPSA), Colombia (IGBC), Mexico (BOLSA), Peru (ISBL) and the United States (S&P 500 index). The source for the effective TED spread (TED) is also *DataStream*. The use of the TED spread as a proxy for perceived risk in the general economy is widely used in literature. We use the CBOE Volatility Index® (VIX), from the *CBOE website*, as a proxy of implied market volatility.

Figure 2.1 includes the daily closing prices of all eight markets during the sample period. We observe that before the financial crisis the markets had an upward trend, that during the financial crisis, all national stock prices followed a similar pattern than the U.S. stock market and dropped dramatically, and that the markets recovered their upward trend after the financial crisis ended.

Figure 2.2 presents the daily returns for each stock market index, and the differences in TED spread and VIX during the sample period. We observe a clustering of increased volatility for all stock market returns during the U.S. Financial Crisis, except for Colombia that had another spike in 2006, which prompts us to use GARCH models to investigate the existence of contagion from the U.S. to the other stock markets.

2.4 Descriptive Statistics

Table 2.1 reports the results of the stationary tests performed to the national financial series expressed in returns, VIX and TED spread expressed in first differences. We perform the standard ADF, KPSS, and Philips-Perron tests and conclude that all series are stationary, which is not surprising since all series are in returns and first differences.

We follow Mollick and Assefa (2013) and divide the sample into subsamples. We define the sample period before the financial crisis, from January 1, 2002 to December 31, 2007, as the pre-crisis period. We then identify the financial crisis period from January 1, 2008, right after the NBER identified the month of December 2007 as the start of the U.S. financial crisis, and ending on June 30, 2009. The period from July 1, 2009 to December 31, 2015 is defined as the "post-crisis period".

Table 2.2 presents the descriptive statistics for the series. We divide Table 2.2 into four panels and present the descriptive statistics for each of the sub-periods in the study. Table 2.2A includes the pooled sample, Table 2.2B includes the pre-crisis period, Table 2.2C includes the crisis period and Table 2.2D the post-crisis period. The tables include information on the mean, standard deviation, variance, skewness coefficient, kurtosis coefficient, the Shapiro-Wilk normality test, and the Ljung–Box autocorrelation test. In all cases, the Shapiro-Wilk test statistic indicates non-normality, and the Ljung–Box test statistics suggest that all return series exhibit significant autocorrelation. For the pooled sample in Table 2.2A, we observe that Colombia, Peru, Mexico, Argentina and Chile have the highest mean returns at 0.0478, 0.0473, 0.0349, 0.0315, and 0.0241 respectively, however the standard deviation is greater for Argentina, Brazil, Peru, Colombia and Mexico at 2.2055, 2.0063, 1.8704, 1.6455, and 1.5836 in that order. We construct Sharpe ratios (mean divided by standard deviation), following a similar process to the outlined by Serban (2010) and Mollick and Assefa (2013), to compare returns against standard deviation across markets. The process allows us to compare returns, by adjusting them for risk, for all the series. Table 2.2A includes the results for the pooled data, in return/differenced form, indicating that Colombia and Peru possess the highest Sharpe ratios of 2.9% and 2.5% respectively, followed by Mexico at 2.2%, Chile at 2.1%, Argentina at 1.4%, Canada at 1.3%, and Brazil at 0.9% . Table 2.2B covers the pre-crisis period, the Sharpe ratios for Colombia and Peru continue to take the lead at 9.2% and 8.8%, followed by Chile at 8.1%, Canada at 6.9%, Brazil at 6.6%, Mexico at 6.5% and Argentina at 3.5%. Table 2.2C indicates a shift to negative mean returns during the crisis period. The Sharpe ratios indicate that Argentina had the greatest decline, adjusted for risk, of -5%, followed by Canada at -3.7%, Mexico at -3.4%, Brazil and Peru at -3.1%, Colombia at -1.8% and Chile at -1.6%. Table 2.2D focusses on the post-crisis period, where we observe a mix of positive and negative Sharpe ratios. Argentina registers the highest positive Sharpe ratio at 1.6%, followed by Mexico at 1.3% and Canada at 0.2%. We then observe Peru with a negative Sharpe ratio of -0.1%, followed by Chile at -0.9%, Colombia at -2.4% and Brazil at -2.6%.

Table 2.3 presents the unconditional correlation between the stock index returns, ΔVIX and ΔTED for the pooled sample and the three subsamples. The table is divided into Table 2.3A and Table 2.3B, with Table 2.3A including the pooled sample and the pre-crisis period, and Table 3B reporting the crisis and post-crisis periods. We observe that on Table 2.3A the results for the pooled data indicate that the correlations amongst the stock indexes are positive and significant, with the highest being those between Mexico and Brazil at 0.6925, and between Mexico and Canada at 0.6569. Another interesting finding is that correlations between changes in VIX and the stock index returns are negative and significant, observing the greater correlation coefficients for Brazil, Canada and Mexico, with correlations ranging from -0.4932 to -0.585, followed by Chile, Peru, Argentina and Colombia. As expected, the correlation coefficients between stock returns and the difference in TED are negative and significant for all stock returns, with coefficients ranging from -0.0691 for Argentina to -0.1257 for Canada. The correlations between TED differences and changes in VIX are positive and significant at 0.1188, which indicates that there is a positive but small correlation between the perceived risk in the general economy, represented by the TED spread, and the implied market volatility, represented by VIX.

The results for the pre-crisis period find that the pairwise correlations between the stock markets are also positive and significant, but the magnitude of the coefficients is lower in all cases, ranging from 0.1829 for Colombia-Argentina to 0.5625 between Mexico and Brazil. We observe similar results for all the pairwise correlations that include ΔTED and ΔVIX, showing that all coefficients followed the same direction than the pooled sample, the coefficients are smaller for the pre-crisis than the pooled sample, and with the exception of Argentina-ΔTED they are all significant. We then look at the results for the crisis period on Table 2.3B, and we observe that all pairwise correlations follow the same direction than the pooled data and pre-crisis period, that all results are significant, and that in all cases the magnitude increased considerable in comparison to the pre-crisis period. We find that the cross-country correlations range from 0.5215 to 0.8253 for Colombia-Peru and Brazil-Mexico respectively, the correlations between returns and ΔTED range from -0.1249 with Peru to -0.2475 with Colombia, and in the case of returns and ΔVIX we observe correlations ranging from -0.3884 for Colombia to -0.6489 for Mexico.

The results for the post-crisis period indicate that the pair wise correlations amongst the stock markets remained positive and significant, but they are smaller than those found during the crisis period, yet they remain higher than the pre-crisis period. We observe a similar effect for the pairwise correlations with ΔVIX, indicating that the magnitudes also decrease from the crisis period, but do not reach the levels found before the crisis period. The case of ΔTED indicates mixed results; the only statistically significant correlation observed is with Colombia, which is lower than the crisis period and slightly lower than the pre-crisis period.

We observe increased correlations for all series from the pre-crisis period to the crisis period, and we identify that correlations weaken from the crisis period to the post-crisis period for the cross-country correlations and those associated with ΔVIX, however these correlations do not reach the levels observed during the pre-crisis period. We observe that the pair wise correlations with ΔTED also increase in magnitude from the pre-crisis to the crisis period, however these correlations become non-significant for most series during the post-crisis period.

2.5 The DCC model and estimation results

Following Engle (2002) we use the DCC-GARCH to quantify dynamic co-movements among the U.S., market volatility (VIX), the TED spread, Canada and six Latin American stock markets. The advantages of using the DCC-GARCH, over other estimation methods are many. By estimating the correlation coefficients of the standardized residuals, we are able to deal with heteroscedasticity, we can control for common factors that may affect the co-movements amongst stock markets, and the model is relatively parsimonious. With this model we are able to calculate and examine all possible pairwise dynamic conditional correlations from the financial series, and are able to account for possible contagion. All financial series are expressed in returns, VIX is expressed in first-differences, and the TED spread is also expressed in first-differences. We model the return dynamics by using an Autoregressive model in the form of:

$$r_t = \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{ted} + \gamma_3 r_{t-1}^{vix} + \varepsilon_t , \qquad (2.1)$$

The dynamics of the variance-covariance matrix H_t is modeled, and we assume that the vector of error returns follow a multivariate normal distribution, $\varepsilon_t \,\big|\, I\Omega_{(t-1)} \sim N(O, H_t.)$, the vector of returns is:

$$r_t = \left(r_{Argentina,t}, r_{Brazil,t}, r_{Canada,t}, r_{Chile,t}, r_{Colombia,t}, r_{Mexico,t}, r_{Peru,t}\right)'$$

and the vector of error terms is:

$$\varepsilon_t = \left(\varepsilon_{Argentina,t}, \varepsilon_{Brazil,t}, \varepsilon_{Canada,t}, \varepsilon_{Chile,t}, \varepsilon_{Colombia,t}, \varepsilon_{Mexico,t}, \varepsilon_{Peru,t}\right)'$$

We specify the variance-covariance matrix as:

$$H_t = D_t R_t D_t \tag{2.2}$$

With the (n x n) diagonal matrix D_t containing the time-varying standard deviations from the univariate GARCH models and $\sqrt{h_{ii,t}}$ on the ith diagonal, for i= 1,2,..,n. We are interested in the off-diagonal elements of the (n x n) time-varying R_t correlation matrix. We follow Engle (2002) by employing a two-step procedure and estimate the elements of H_t. We first use univariate GARCH models to calculate the standard deviations in D_t. We then adjust the first stage residuals with $u_{iti} = \varepsilon_{it} / \sqrt{h_{ii,t}}$, the resulting adjusted residuals are then used to estimate the conditional correlation residuals.

The (n x n) matrix, that captures the time-varying variance-covariance matrix of u_t, is given by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1}, \tag{2.3}$$

Where α and β are nonnegative scalars that we estimate under the restriction ($\alpha + \beta$) < 1. Each of the elements in the Q_t are denoted with $q_{ij,t}$. The (n x n) unconditional variance covariance matrix of u_t is $\bar{Q} = E(u_t \ u'_t)$. Since the correlation matrices have ones in their main diagonal we rescale R_t to be:

$$R_t = \mathrm{diag}\left(1/\sqrt{q_{11,,t}} \dots, 1/\sqrt{q_{nn,,t}}\right) Q_t \, \mathrm{diag}\left(1/\sqrt{q_{11,,t}} \dots, 1/\sqrt{q_{nn,,t}}\right) \tag{2.4}$$

If Q_t is positive then the diagonal elements in R_t will be equal to one and the off-diagonal elements will have an absolute value of less than one. The ij element in R_t is

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}\ , \quad for\ all\ i, j\ and\ i \neq j \tag{2.5}$$

For the following log likely function:

$$l_t(\theta, \phi) = -\sum_{T=1}^{T}(nlog(2\pi) + log\ |D_t|^2 + \varepsilon_t' D_t^{-2} \varepsilon_t) - \sum_{T=1}^{T}(\log|R_t| + u_t' R_t^{-1} u_t - u_t u_t') \tag{2.6}$$

We then estimate θ and ϕ for matrices D_t and R_t following the two-step approach as in Engle (2002). From the right side of the equation, we first estimate θ from the first component, followed by the estimation of ϕ located on the second component.

The results of the multivariate DCC–GARCH model are reported in Table 2.4. We split the sample into three periods and tag them as; the pre-crisis, crisis and post-crisis. Table 2.4A includes the results for the pre-crisis period, from Jan 1 2002 to Dec 31 2007, and label it as "sample I". Table 2.4B includes the crisis period, from Jan 1 2008 to Jun 30 2009, and label it as "sample II". The post-crisis period, from Jul 1 2009 to Dec 31 2015, is included on Table 2.4C as sample III.

Table 2.4A includes the results to the pre-crisis period. We first analyze the mean equations and the results indicate that the constant term, γ_0 , is positive and statistically significant for all markets. The AR(1) term, γ_1 , is statistically significant for all countries except for Mexico and Peru. Coefficients of γ_1 , for Brazil, Chile and Colombia are positive, whereas for Argentina and Canada are negative. The effect (γ_2) of the TED spread is negative and significant only for Mexico and Peru at the 10% level. One possible explanation is that the TED spread was relatively low and stable during this period (Figure 2.1), without observable shocks, and based on efficient market theory, investors would not be likely to react to anticipated TED spread changes. The effect (γ_3) of the changes in the VIX is negative and statistically significant for all countries, indicating that increases in market volatility in the U.S. are associated with lower returns of the markets in the Americas.

We then look at the parameter estimates of the mean and conditional variance equations; the coefficients are all significant, confirming the appropriate use of the GARCH (1, 1) specification. The volatility persistence (Arch + Garch coefficients) is consistently near one (1) for each of the stock indexes examined, which is indicative of high volatility persistence in the GARCH model. We observe that the estimates for the DCC (1, 1), identified as parameters lambda1 and lambda 2, are statistically significant at the 1%. If lambda 1 and Lambda 2 were found to equal to zero, then the DCC-GARCH would have been reduced to a CCC model.

Table 2.4B includes the results for the crisis period. The AR(1) term, γ_1 , is negative and statistically significant for Argentina, Brazil, Canada and Peru. The effect (γ_2) of the TED spread is only found to be negative and significant for Chile. The effect (γ_3) of the changes in the VIX is found to be negative and statistically significant for all countries, indicating that increases in market volatility in the U.S. continue to be associated with lower returns of the markets in the Americas. The results for the parameter estimates of the mean, and conditional variance equations continue to be significant, with the volatility persistence very close to 1. We also observe that Canada and Mexico report considerable higher volatility persistence during this period when compared to the pre-crisis period.

Table 2.4C reports the results for the post-crisis period. The AR(1) term, γ_1 , is negative and statistically significant for Brazil and Canada, and positive and significant for Argentina, Chile and Colombia. We find that the TED spread (γ_2) has a positive and significant effect on Argentina, Canada, Mexico and Peru. We find that changes in VIX (γ_3) has a positive and significant effect on Argentina, remaining negative and significant for Brazil, Canada, Chile, Colombia and Mexico. The results for the parameter estimates of the mean and conditional variance equations continue to be significant. The volatility persistence continues to be close to 1, except for Argentina that has a value of 1.007, which makes the model for Argentina unstable. We also observe that with the exception of Mexico and Peru, the volatility persistence increases when compared with the crisis-period.

We find evidence of different intertemporal effects, from changes in VIX to all the stock market indexes, during all the three periods. We find mixed evidence of intertemporal effects, from changes in the TED spread, to the stock market indexes, during the various periods. This prompts us examine the contemporaneous effects, by analyzing the GARCH-DCC based correlations amongst the series, throughout the three subsamples.

We construct Table 2.5 to include MGARCH-DCC based correlations, between ΔVIX, ΔTED, and the stock returns, for all three subsamples. Table 2.5A reports the conditional correlations between the ΔVIX and ΔTED and the stock returns for all countries in the study. Table 2.5B reports all possible pair-wire conditional correlations, amongst the country specific stock market indexes, during the three periods. Table 2.5A first reports that changes in *VIX* are negatively correlated and statistically significant to all stock markets. In all cases, except Peru, we observe that the coefficients during the financial crisis are higher than before the financial crisis, indicating contagion. With the exception of Peru, we find that post-financial crisis coefficients are lower than the coefficients observed during the Financial Crisis, and with the exception of Argentina and Brazil, they continue to be higher than the pre-financial crisis. We also observe that the correlation between ΔVIX and ΔTED is positive and significant only during the Financial Crisis period; indicating that the liquidity risk had a significant influence on market volatility, and vice-versa, during the financial crisis. Table 2.5A then reports that it was only during the financial crisis, that Δ*TED* are negatively associated to stock returns for all countries, being significant for all pairwise correlations except Brazil and Peru. We identify that increases in the *TED* spread are associated with increased market volatility and with negative stock market returns during the financial crisis. Tables 2.5B and 2.5C report all the pairwise correlations between stock returns of two countries. We observe statistically significant increased correlations during the financial crisis, which are indicative of financial contagion. We observe a relative reduction for most of the correlation coefficients, from the crisis-period to the post-crisis period, with the exception of the Canada-Colombia pair that reports an increase. We also identify that the majority of the pairwise correlations for the post-crisis period, continue to be higher than those of the pre-crisis period, with the exception of the Argentina-Brazil, Argentina–Chile and Argentina-Mexico pairs, which indicate lower correlations than the pre-crisis period.

2.6 Summary and Conclusions

We contribute to the literature by identifying the role that U.S. interbank credit risk (TED spread), also used as a proxy for the perceived risk in the general economy, and the perceived U.S. stock market volatility (VIX), on the financial contagion from the U.S. to the Americas, during the recent financial crisis. We use the multivariate DCC–GARCH model to identify the existence of contagion during the 2008-2009 financial crisis between the stock market volatility of the U.S., represented by the *VIX*, the perceived risk in the general economy, represented by the *TED* spread, and the stock returns of Argentina, Brazil, Canada, Chile, Colombia, Mexico and Peru. We employ daily stock-return and first differences for the period of January 1, 2002, through December 31, 2015 observing significant variation on the model's conditional correlation coefficients, especially during the 18 month-long U.S. financial crisis period.

We use three periods of interest in this analysis: the pre-crisis, financial crisis and post-crisis periods. We are able to quantify the effects of the financial crisis on the conditional correlations between the *ΔVIX* and the stock market returns from Canada and six Latin American countries, and we identify evidence of contagion from the U.S. stock market volatility, represented by the *VIX*, to the stock markets in the Americas during the financial crisis. We find that after the financial crisis ended, the conditional correlations continue at similar levels to the financial crisis period.

Our findings also suggest that it is only during the Financial Crisis period when increases in *ΔTED,* which we use as a proxy for the perceived risk in the general economy, influence the returns of Canada and most Latin American countries in the study. We find that it is only during the U.S. financial crisis that changes in the *TED* spread have a negative and significant effect on the stock returns of most countries in the study, and that changes in TED spread also have positive and significant effects on the perceived U.S. market volatility (*VIX)* during that period.

We control for *ΔVIX* throughout the subsequent chapters, since we find evidence that stock returns in the Americas are influenced by *ΔVIX* and that this relationship continues to strengthen since the financial crisis. We do not find a need to control for *ΔTED,* since we only find evidence of significant correlations between *ΔTED* and stock returns during the financial crisis. We also identify that the correlations between *ΔTED* and stock returns are relatively small when compared to those between *ΔVIX* and stock returns.

These finding have implications on portfolio diversification for U.S. investors, since we find evidence that changes in perceived U.S. market volatility, as represented by the VIX, will negatively influence the stock returns from the markets in the Americas, and that the influence increases in times of financial turmoil in the U.S. Investors need to consider this when pursuing diversification strategies that involve the markets in the Americas, since we find that this influence increases in times of financial turmoil in the U.S. Our findings suggest that stock market returns from the Americas are highly dependent on U.S. market fundamentals, and volatility, in times of U.S. financial turmoil.

Table 2.1

Unit Root Tests.

Series	ADF(k)	KPSS(k)	PHILLIPS-PERRON(k)
RET_ARG	-24.801 (5)***	0.0600	-57.826***
RET_BRA	-11.798 (23)***	0.0973	-55.642***
RET_CAN	-9.951 (29)***	0.0505	-56.506***
RET_CHI	-13.614 (18)***	0.0736	-53.054***
RET_COL	-11.511 (20)***	0.0645	-52.693***
RET_MEX	-25.896 (5)***	0.0559	-54.168***
RET_PER	-13.186 (22)***	0.0421	-57.566***
DIFF_TED	-12.486 (29)***	0.0167	-50.640***
VIX_CHG	-14.594 (17)***	0.0181	-70.938***

Notes: The results are for the pooled sample. The lag length (k) is selected as follows: for the ADF test, the Null hypothesis is unit root, we use the Campbell and Perron (1991) data dependent procedure starting with an upper bound $k_{max} = 29$, on k. if the last lag is significant then choose $k = k_{max}$, if not we reduce k by one and continue this process until this is satisfied, or else k = 0. The KPSS assumes a null that the series is stationary, we use the Bartlett-Kernel criteria to select k = 28 as truncating parameter. The critical values for the KPSS test are 0.119 (10%), 0.146 (5%), and 0.216 (1%) . The Phillips-Perron test, has a null hypothesis of unit root, ad uses the equation $k = 4(T/100)^{2/9}$ to select the maximum lag, in this case k = 8. *, **, and *** significant at 10%, 5% and 1%, respectively.

Table 2.2 A

Descriptive Statistics (Daily Data From Jan. 2002 to Dec. 2015) – Pooled Sample.

Levels	Argentina	Brazil	Canada	Chile	Colombia	Mexico	Peru	TED	VIX
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653
Mean	1928.823	391.213	10192.22	1189.258	4.5527	2169.874	898.4611	0.4342	20.0951
Standard Dev.	897.5415	202.4375	3067.304	482.2726	2.5603	936.7846	482.5596	0.465	9.1567
Variance	805580.8	40980.93	9408356	232586.9	6.5553	877565.3	232863.7	0.2163	83.8447
Skewness	0.0089	-0.028	-0.6002	-0.094	-0.1886	-0.4296	-0.1466	3.5783	2.2133
Kurtosis	2.2958	1.8804	2.1048	2.0222	1.7831	1.7222	1.6476	20.213	9.9185
Shapiro-Wilk (Normality)	10.634***	11.593***	13.425***	11.048***	12.784***	13.885***	13.171***	17.518***	15.648***
Ljung-Box test (Auto Correlation)	135,200***	139,600***	138,600***	141,600***	141,200***	141,000***	140,800***	104,500***	104,000***

Return/Differenced

	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	DIFF_TED	VIX_CHG
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653
Mean	0.0315	0.0171	0.0182	0.0241	0.0478	0.0349	0.0473	0.0001	-0.0015
Standard Dev.	2.2055	2.0063	1.3736	1.1558	1.6455	1.5836	1.8704	0.0535	1.7135
Variance	4.8641	4.0251	1.8869	1.336	2.7077	2.5079	3.4985	0.0029	2.9362
Skewness	-2.6007	-0.3006	-0.7695	-0.4386	-0.4314	-0.0926	-0.4198	0.7941	0.6591
Kurtosis	38.8719	9.6353	13.8919	13.1608	11.1119	10.4595	10.4944	84.9058	22.267
Shapiro-Wilk (Normality)	14.806***	12.703***	13.947***	13.152***	13.282***	12.997***	13.036***	17.85***	15.542***
Sharpe Ratio	0.0143	0.0085	0.0133	0.0209	0.029	0.022	0.0253		
Ljung-Box test (Auto Correlation)	63.68***	147.41***	210.32***	171.36***	144.12***	116.25***	82.26***	756.75***	184.75***

Notes: All stock indexes in levels are represented in U.S. Dollars. All variables are in returns except TED and VIX which are in differences. Sharpe Ratio = Mean/Standard-Dev.

Table 2.2 B

Descriptive Statistics (Daily Data from Jan. 2002 to Dec. 2007) – Sample I.

	Argentina	Brazil	Canada	Chile	Colombia	Mexico	Peru	TED	VIX
In levels									
Observations	1544	1544	1544	1544	1544	1544	1544	1544	1544
Mean	1267.678	230.0161	7906.54	764.0315	2.358	1347.622	441.2579	0.3909	17.8987
Standard Dev.	725.5707	161.2467	2970.306	321.0124	1.7934	741.2424	301.6147	0.3118	6.8103
Variance	526452.9	26000.5	8822715	103049	3.2163	549440.3	90971.41	0.0972	46.3808
Skewness	0.5107	1.2262	0.4682	0.5377	0.4809	0.8279	1.535	3.0552	1.3221
Kurtosis	1.8717	3.906	2.1155	2.3807	1.6376	2.3877	4.7275	13.8275	4.2843
Shapiro-Wilk (Normality)	11.51***	12.26***	10.38***	10.36***	12.42***	12.15***	12.98***	14.56***	12.17***
Ljung-Box test (Auto Correlation)	57822.69***	53698.73***	56870.25***	57249.62***	57895.27***	58056.34***	53640.18***	34460.26***	46447.92***

Returns/Differenced

	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	DIFF_TED	VIX_CHG
Observations	1544	1544	1544	1544	1544	1544	1544	1544	1544
Mean	0.0749	0.1181	0.0677	0.076	0.1587	0.0887	0.141	0.0012	-0.0006
Standard Dev.	2.1474	1.7876	0.9769	0.942	1.7225	1.3684	1.5992	0.0488	1.159
Variance	4.6113	3.1956	0.9544	0.8873	2.9669	1.8726	2.5574	0.0024	1.3432
Skewness	-3.0857	-0.1284	-0.4486	-0.4145	-0.5118	-0.19	-0.4954	1.4495	0.2747
Kurtosis	47.0868	6.3523	4.7014	4.4934	12.7899	5.0902	6.0773	36.5178	8.9985
Shapiro-Wilk (Normality)	12.76***	8.689***	7.16***	6.68***	11.42***	7.77***	9.08***	14.31***	11.11***
Sharpe Ratio	0.0349	0.0661	0.0693	0.0807	0.0921	0.0648	0.0882		
Ljung-Box test (Auto Correlation)	94.51***	82.03***	37.62	74.66***	94.55***	44.17	62.94**	505.80***	93.73***

Notes: All stock indexes in levels are represented in U.S. Dollars. All variables are in returns except TED and VIX which are in differences. Sharpe Ratio = Mean/Standard-Dev.

Table 2.2 C

Descriptive Statistics (Daily Data from Jan. 2008 to Jun. 2009) – Sample II.

	Argentina	Brazil	Canada	Chile	Colombia	Mexico	Peru	TED	VIX
In levels									
Observations	412	412	412	412	412	412	412	412	412
Mean	1840.668	537.783	10676.34	1174.707	4.344	2187.308	978.841	1.355	34.008
Standard Dev.	618.19	190.804	3034.738	224.342	0.911	622.605	299.805	0.726	14.155
Variance	382159.1	36406.15	9209633	50329.52	0.83	387636.9	89882.91	0.527	200.356
Skewness	-0.069	0.015	-0.13	-0.158	-0.156	-0.126	0.027	1.836	1.048
Kurtosis	1.267	1.38	1.32	1.621	1.581	1.396	1.507	7.138	3.357
Shapiro-Wilk (Normality)	9.02***	8.41***	8.76***	7.24***	7.54***	8.37***	7.72***	9.28***	8.29***
Ljung-Box test (Auto Correlation)	13971.73***	14081.85***	13882.24***	13296.19***	12113.57***	13656.41***	13685.91***	5375.12***	9296.11***

Returns/Differenced

	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	DIFF_TED	VIX_CHG
Observations	412	412	412	412	412	412	412	412	412
Mean	-0.137	-0.107	-0.104	-0.031	-0.041	-0.095	-0.1	-0.004	0.008
Standard Dev.	2.767	3.431	2.775	1.99	2.321	2.818	3.273	0.126	3.144
Variance	7.654	11.772	7.701	3.961	5.387	7.942	10.712	0.016	9.886
Skewness	-0.537	-0.338	-0.548	-0.276	-0.442	0.192	-0.074	0.305	0.18
Kurtosis	6.953	7.019	6.435	9.598	7.883	6.987	5.993	21.504	11.04
Shapiro-Wilk (Normality)	7.23***	7.08***	7.08***	7.65***	7.65***	7.06***	6.22***	10.38***	8.95***
Sharpe Ratio	-0.05	-0.031	-0.037	-0.016	-0.018	-0.034	-0.031		
Ljung-Box test (Auto Correlation)	77.36***	79.14***	82.24***	54.68***	35.39***	42.1***	44.87***	126.45***	70.39***

Notes: All stock indexes in levels are represented in U.S. Dollars. All variables are in returns except TED and VIX which are in differences. Sharpe Ratio = Mean/Standard-Dev.

Table 2.2 D

Descriptive Statistics (Daily Data from Jul. 2009 to Dec. 2015) – Sample III.

	Argentina	Brazil	Canada	Chile	Colombia	Mexico	Peru	TED	VIX
In levels									
Observations	1697	1697	1697	1697	1697	1697	1697	1697	1697
Mean	2551.762	502.292	12154.29	1579.679	6.6	2913.759	1294.928	0.25	18.716
Standard Dev.	612.357	120.61	1155.579	278.745	1.549	355.783	218.473	0.09	6.039
Variance	374980.5	14546.73	1335364	77698.7	2.398	126581.4	47730.44	0.008	36.472
Skewness	0.59	-0.463	-0.225	0.052	-0.972	-0.442	0.199	1.304	1.451
Kurtosis	2.584	2.529	3.069	1.897	3.016	2.924	2.784	4.579	5.306
Shapiro-Wilk (Normality)	9.56***	9.13***	6.48***	9.03***	11.74***	7.29***	6.29***	12.01***	12.25***
Ljung-Box test (Auto Correlation)	52094.76***	58574.68***	46777.17***	58872.18***	57531.81***	49895.88***	52059.58***	47297.24***	33987.55***

Returns/Differenced

	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	DIFF_TED	VIX_CHG
Observations	1697	1697	1697	1697	1697	1697	1697	1697	1697
Mean	0.033	-0.045	0.003	-0.01	-0.032	0.017	-0.002	0	-0.005
Standard Dev.	2.101	1.7	1.15	1.051	1.344	1.329	1.611	0.012	1.645
Variance	4.415	2.89	1.323	1.105	1.806	1.765	2.595	0	2.705
Skewness	-3.143	-0.109	-0.306	-0.405	-0.224	-0.351	-0.614	0.255	1.203
Kurtosis	49.986	4.782	5.044	8.841	5.458	6.17	10.913	7.707	18.83
Shapiro-Wilk (Normality)	12.72***	7.51***	8.15***	9.8***	8.77***	8.59***	9.84***	9.36***	12.87***
Sharpe Ratio	0.016	-0.026	0.002	-0.009	-0.024	0.013	-0.001		
Ljung-Box test (Auto Correlation)	49.47	37.52	82.66***	121.23***	107.26***	72.63**	54.6*	267.7***	130.26***

Notes: All stock indexes in levels are represented in U.S. Dollars. All variables are in returns except TED and VIX which are in differences. Sharpe Ratio = Mean/Standard-Dev.

Table 2.3 A

Correlation Coefficients of Daily Stock Index Returns, TED and VIX - (Pooled Sample and Pre-Crisis Period).

	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	DIFF_TED	VIX_CHG
Pooled sample									
RET_ARG	1								
RET_BRA	0.4821***	1							
RET_CAN	0.4906***	0.6276***	1						
RET_CHI	0.4064***	0.619***	0.5576***	1					
RET_COL	0.3311***	0.4601***	0.4444***	0.4658***	1				
RET_MEX	0.4537***	0.6925***	0.6569***	0.6207***	0.4587***	1			
RET_PER	0.4288***	0.5543***	0.6232***	0.4689***	0.3979***	0.5509***	1		
DIFF_TED	-0.0691***	-0.0985***	-0.1257***	-0.1114***	-0.1125***	-0.0963***	-0.0990***	1	
VIX_CHG	-0.404***	-0.4932***	-0.585***	-0.4554***	-0.3235***	-0.582***	-0.4531***	0.1188***	1

Pre-Crisis

	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	DIFF_TED	VIX_CHG
RET_ARG	1								
RET_BRA	0.3651***	1							
RET_CAN	0.335***	0.45***	1						
RET_CHI	0.2893***	0.5337***	0.4053***	1					
RET_COL	0.1829***	0.3046***	0.2264***	0.2977***	1				
RET_MEX	0.3437***	0.5625***	0.5236***	0.4855***	0.3105***	1			
RET_PER	0.2797***	0.4004***	0.4475***	0.3317***	0.2828***	0.3732***	1		
DIFF_TED	-0.0317	-0.0507**	-0.0628**	-0.0567**	-0.0653**	-0.0967***	-0.1265***	1	
VIX_CHG	-0.2858***	-0.3607***	-0.4873***	-0.3313***	-0.2042***	-0.5375***	-0.207***	0.0674***	1

Notes: All variables are in returns except TED and VIX which are in differences. *pb.10, **pb.05, ***pb.01

Table 2.3 B

Correlation Coefficients of Daily Stock Index Returns, TED and VIX - (Crisis and Post-Crisis Period).

	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	DIFF_TED	VIX_CHG
Crisis Period									
RET_ARG	1								
RET_BRA	0.7535***	1							
RET_CAN	0.7541***	0.7543***	1						
RET_CHI	0.6468***	0.7306***	0.6106***	1					
RET_COL	0.5891***	0.6168***	0.5728***	0.6199***	1				
RET_MEX	0.6809***	0.8253***	0.7039***	0.7082***	0.5687***	1			
RET_PER	0.6957***	0.7058***	0.7067***	0.5677***	0.5215***	0.6973***	1		
DIFF_TED	-0.167***	-0.1865***	-0.2026***	-0.2108***	-0.2475***	-0.138***	-0.1249***	1	
VIX_CHG	-0.5408***	-0.6397***	-0.62***	-0.5416***	-0.3884***	-0.6489***	-0.5588***	0.2032***	1

Post-Crisis

	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	DIFF_TED	VIX_CHG
RET_ARG	1								
RET_BRA	0.4411***	1							
RET_CAN	0.4763***	0.6443***	1						
RET_CHI	0.3763***	0.5905***	0.6163***	1					
RET_COL	0.3709***	0.5293***	0.591***	0.5416***	1				
RET_MEX	0.4296***	0.6828***	0.7197***	0.6514***	0.5584***	1			
RET_PER	0.4131***	0.548***	0.6731***	0.4865***	0.4396***	0.5615***	1		
DIFF_TED	-0.0251	0.0274	-0.0129	0.019	0.061**	-0.0006	-0.006	1	
VIX_CHG	-0.434***	-0.4645***	-0.609***	-0.4579***	-0.4101***	-0.5638***	-0.5226***	0.0242	1

Notes: All variables are in returns except TED and VIX which are in differences. *pb.10, **pb.05, ***pb.01

Table 2.4 A

DCC Estimations for Stock Returns, VIX and TED for Sample I. (Daily Data from Jan. 2002 to Dec. 2007).

	Argentina	Brazil	Canada	Chile	Colombia	Mexico	Peru
Mean Equations							
ϒ0	0.14686 ***	0.18533 ***	0.11064 ***	0.10648 ***	0.16915 ***	0.13999 ***	0.17606 ***
	(0.039)	(0.037)	(0.022)	(0.021)	(0.034)	(0.029)	(0.033)
ϒ1	-0.07493 ***	0.05459 **	-0.03865 *	0.05823 ***	0.10442 ***	0.01768	0.01546
	(0.026)	(0.022)	(0.023)	(0.023)	(0.027)	(0.023)	(0.023)
ϒ2 (ΔTED)	-0.61993	-1.14513	-0.11575	0.00345	-0.36551	-1.15784 *	-1.41008 *
	(0.781)	(0.886)	(0.499)	(0.491)	(0.756)	(0.645)	(0.836)
ϒ3 (ΔVIX)	-0.07887 **	-0.09459 **	-0.12594 ***	-0.12243 ***	-0.14791 ***	-0.085 ***	-0.20424 ***
	(0.038)	(0.04)	(0.023)	(0.02)	(0.031)	(0.032)	(0.031)
Variance Equations							
Cons	0.08252 ***	0.15266 ***	0.05986 ***	0.05684 ***	0.3006 ***	0.17461 ***	0.03768 ***
	(0.02)	(0.041)	(0.021)	(0.018)	(0.071)	(0.042)	(0.012)
Arch	0.08727 ***	0.08043 ***	0.06227 ***	0.06171 ***	0.15942 ***	0.10173 ***	0.05088 ***
	(0.013)	(0.013)	(0.014)	(0.013)	(0.027)	(0.02)	(0.009)
Garch	0.89874 ***	0.87183 ***	0.87501 ***	0.87176 ***	0.71609 ***	0.80389 ***	0.93509 ***
	(0.013)	(0.023)	(0.032)	(0.03)	(0.049)	(0.039)	(0.012)
Persistence	0.986	0.952	0.937	0.933	0.876	0.906	0.986
Multivariate DCC Equation							
Lambda1	0.0125 ***						
	(0.002)						
Lambda2	0.96756 ***						
	(0.006)						
Observations	1,543						
χ2	268.06						
χ2 (p-value)	0.000						

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01. The mean equation is $r_t = \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{ted} + \gamma_3 r_{t-1}^{vix} + \varepsilon_t$ where $r_t = (r_{Argentina,t}, r_{Brazil,t}, r_{Canada,t}, r_{Chile,t}, r_{Colombia,t}, r_{Mexico,t}, r_{Peru,t})'$; $\varepsilon_t = (\varepsilon_{Argentina,t}, \varepsilon_{Brazil,t}, \varepsilon_{Canada,t}, \varepsilon_{Chile,t}, \varepsilon_{Colombia,t}, \varepsilon_{Mexico,t}, \varepsilon_{Peru,t})'$ and $\varepsilon_t \mid I\Omega_{(t-1)} \sim N(O, H_t.)$. The variance equations are $h_{ii,t} = c_i + a_i \varepsilon_{i,t-1}^2 + b_i h_{ii,t-1}$ for $i = 1,2,\dots,n$. The null for the x^2test is $H_0: \alpha = \beta = 0$. Persistence is calculated as the sum of the coefficients in the variance equation (Arch and Garch).

Table 2.4 B

DCC Estimations for Stock Returns, VIX and TED for Sample II. (Daily Data from Jan. 2008 to Jun. 2009).

	Argentina	Brazil	Canada	Chile	Colombia	Mexico	Peru
Mean Equations							
ϒ0	0.10151	0.23805 **	0.13424	0.12009 *	0.13509	0.10484	0.10073
	(0.0956)	(0.1174)	(0.0915)	(0.0707)	(0.0844)	(0.0904)	(0.1221)
ϒ1	-0.07509 **	-0.09381 ***	-0.1075 ***	0.0282	0.01197	-0.05285	-0.11973 ***
	(0.0363)	(0.0336)	(0.0365)	(0.042)	(0.0452)	(0.0393)	(0.0388)
ϒ2 (ΔTED)	-1.32133	-1.36151	-0.94232	-1.71271 **	-1.2217	0.86165	-0.56128
	(0.968)	(1.3022)	(0.9549)	(0.8148)	(0.9969)	(0.9462)	(1.2257)
ϒ3 (ΔVIX)	-0.10574 **	-0.13969 **	-0.12887 ***	-0.07959 ***	-0.15307 ***	-0.08884 *	-0.11364 *
	(0.0467)	(0.0577)	(0.0472)	(0.0309)	(0.0355)	(0.0498)	(0.06)
Variance Equations							
Constant	0.13748 ***	0.36209 ***	0.13562 ***	0.27675 ***	0.53132 ***	0.14295 ***	0.17646 **
	(0.0475)	(0.0956)	(0.0399)	(0.079)	(0.1689)	(0.0509)	(0.071)
Arch	0.06755 ***	0.05864 ***	0.06371 ***	0.11813 ***	0.16541 ***	0.08497 ***	0.0648 ***
	(0.0147)	(0.0115)	(0.0129)	(0.0266)	(0.0467)	(0.0169)	(0.0147)
Garch	0.91371 ***	0.9026 ***	0.91613 ***	0.79288 ***	0.71388 ***	0.89589 ***	0.92137 ***
	(0.0182)	(0.018)	(0.0156)	(0.041)	(0.0684)	(0.0196)	(0.0166)
Persistence	0.981	0.962	0.980	0.911	0.879	0.981	0.986
Multivariate DCC Equation							
Lambda1	0.04391 ***						
	(0.0099)						
Lambda2	0.33586 *						
	(0.1966)						
Observations	411						
χ2	121.34						
χ2 (p-value)	0.0000						

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01. The mean equation is $r_t = \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{ted} + \gamma_3 r_{t-1}^{vix} + \varepsilon_t$ where $r_t = (r_{Argentina,t}, r_{Brazil,t}, r_{Canada,t}, r_{Chile,t}, r_{Colombia,t}, r_{Mexico,t}, r_{Peru,t})'$; $\varepsilon_t = (\varepsilon_{Argentina,t}, \varepsilon_{Brazil,t}, \varepsilon_{Canada,t}, \varepsilon_{Chile,t}, \varepsilon_{Colombia,t}, \varepsilon_{Mexico,t}, \varepsilon_{Peru,t})'$ and $\varepsilon_t \mid I\Omega_{(t-1)} \sim N(O, H_t.)$. The variance equations are $h_{ii,t} = c_i + a_i\varepsilon_{i,t-1}^2 + b_i h_{ii,t-1}$ $for\ i = 1,2,\dots,n$. The null for the x^2test is $H_0:\ \alpha = \beta = 0$. Persistence is calculated as the sum of the coefficients in the variance equation (Arch and Garch).

Table 2.4 C

DCC Estimations for Stock Returns, VIX and TED for Sample III. (Daily Data from Jul. 2009 to Dec. 2015).

	Argentina	Brazil	Canada	Chile	Colombia	Mexico	Peru
Mean Equations							
ϒ0	0.12148 ***	0.06373 **	0.06837 ***	0.05227 ***	0.04175	0.10498 ***	0.07843 **
	(0.0389)	(0.0325)	(0.0202)	(0.0198)	(0.0261)	(0.0251)	(0.0311)
ϒ1	0.09768 ***	-0.04213 **	-0.03496 *	0.07397 ***	0.06414 ***	-0.01035	0.01068
	(0.0248)	(0.0194)	(0.0181)	(0.0201)	(0.0213)	(0.019)	(0.0217)
ϒ2 (ΔTED)	8.22156 **	-0.11478	3.24677 *	2.11108	-2.1321	3.87217 *	9.2718 ***
	(3.6047)	(2.8233)	(1.7773)	(1.6604)	(2.2355)	(2.2224)	(2.7192)
ϒ3 (ΔVIX)	0.07149 ***	-0.08207 ***	-0.08225 ***	-0.05022 ***	-0.05617 ***	-0.0814 ***	-0.01032
	(0.0275)	(0.0244)	(0.0159)	(0.0147)	(0.0183)	(0.0195)	(0.0246)
Variance Equations							
Cons	-0.00705 *	0.05496 ***	0.01288 ***	0.02357 ***	0.02987 ***	0.03592 ***	0.04962 ***
	(0.004)	(0.0143)	(0.0029)	(0.0067)	(0.0091)	(0.0082)	(0.0156)
Arch	0.03424 ***	0.05167 ***	0.04288 ***	0.06334 ***	0.06031 ***	0.05272 ***	0.05765 ***
	(0.005)	(0.0074)	(0.0052)	(0.0099)	(0.0092)	(0.0074)	(0.009)
Garch	0.97285 ***	0.92558 ***	0.94297 ***	0.91155 ***	0.92198 ***	0.92366 ***	0.92158 ***
	(0.0039)	(0.0112)	(0.0067)	(0.0145)	(0.0127)	(0.0106)	(0.0134)
Persistence	1.007	0.977	0.986	0.975	0.982	0.976	0.979
Multivariate DCC Equation							
Lambda1	0.01132 ***						
	(0.0012)						
Lambda2	0.96741 ***						
	(0.0033)						
Observations	1696						
χ2	222.46						
χ2 (p-value)	0.000						

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01. The mean equation is $r_t = \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{ted} + \gamma_3 r_{t-1}^{vix} + \varepsilon_t$ where $r_t = (r_{Argentina,t}, r_{Brazil,t}, r_{Canada,t}, r_{Chile,t}, r_{Colombia,t}, r_{Mexico,t}, r_{Peru,t})'$; $\varepsilon_t = (\varepsilon_{Argentina,t}, \varepsilon_{Brazil,t}, \varepsilon_{Canada,t}, \varepsilon_{Chile,t}, \varepsilon_{Colombia,t}, \varepsilon_{Mexico,t}, \varepsilon_{Peru,t})'$ and $\varepsilon_t \,|\, I\Omega_{(t-1)} \sim N(O, H_t.)$. The variance equations are $h_{ii,t} = c_i + a_i \varepsilon_{i,t-1}^2 + b_i h_{ii,t-1}$ $for\ i = 1,2,\dots,n.$ The null for the X^2 test is $H_0:\ \alpha = \beta = 0$. Persistence is calculated as the sum of the coefficients in the variance equation (Arch and Garch).

Table 2.5 A

MGARCH-DCC Based Correlation Between ΔTED, ΔVIX and Stock Returns.

	Pre Financial Crisis Jan. 2002 – Dec. 2007	Financial Crisis Jan. 2008 - Jun. 2009	Post Financial Crisis Jul. 2009 – Dec. 2015
Between ΔVIX and stock returns			
Argentina	-0.44183 *** (0.04)	-0.56009 *** (0.0384)	-0.43548 *** (0.0307)
Brazil	-0.47012 *** (0.038)	-0.6298 *** (0.0336)	-0.4646 *** (0.0302)
Canada	-0.45605 *** (0.035)	-0.62599 *** (0.0338)	-0.60245 *** (0.0242)
Chile	-0.34063 *** (0.04)	-0.55125 *** (0.0383)	-0.43284 *** (0.031)
Colombia	-0.21813 *** (0.043)	-0.42666 *** (0.0447)	-0.40838 *** (0.0317)
Mexico	-0.53728 *** (0.035)	-0.67807 *** (0.0301)	-0.56589 *** (0.0258)
Peru	-0.28151 *** (0.045)	-0.48876 *** (0.0419)	-0.50161 *** (0.0287)
Between ΔTED and stock returns			
Argentina	-0.01188 (0.044)	-0.09926 * (0.0545)	0.027 (0.038)
Brazil	0.00937 (0.044)	-0.08236 (0.0542)	0.03663 (0.039)
Canada	-0.00789 (0.043)	-0.12603 ** (0.0535)	0.01878 (0.0389)
Chile	0.03735 (0.043)	-0.12658 ** (0.0527)	0.04139 (0.0389)
Colombia	-0.03568 (0.043)	-0.12405 ** (0.0528)	0.04173 (0.0387)
Mexico	-0.01128 (0.044)	-0.11995 ** (0.0544)	0.03588 (0.0389)
Peru	-0.06566 (0.043)	-0.04665 (0.0543)	0.01677 (0.0387)
Between ΔVIX and			
ΔTED	-0.00437 (0.043)	0.15636 *** (0.0524)	-0.00822 (0.039)

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01

Table 2.5 B
MGARCH-DCC Based Correlation Between Stock Returns.

	Pre Financial Crisis Jan. 2002 – Dec. 2007	Financial Crisis Jan. 2008 - Jun. 2009	Post Financial Crisis Jul. 2009 – Dec. 2015
Corr.(Argentina,Brazil)	0.53582 *** (0.037)	0.79146 *** (0.0208)	0.42801 *** (0.0313)
Corr.(Argentina,Canada)	0.46339 *** (0.038)	0.77061 *** (0.0223)	0.46717 *** (0.0295)
Corr.(Argentina,Chile)	0.3763 *** (0.041)	0.62849 *** (0.0335)	0.35145 *** (0.0327)
Corr.(Argentina,Colombia)	0.25416 *** (0.046)	0.52093 *** (0.0407)	0.34802 *** (0.0329)
Corr.(Argentina,Mexico)	0.47003 *** (0.04)	0.70429 *** (0.0279)	0.43225 *** (0.031)
Corr.(Argentina,Peru)	0.35761 *** (0.044)	0.71676 *** (0.0266)	0.40219 *** (0.0317)
Corr.(Brazil,Canada)	0.51227 *** (0.037)	0.80595 *** (0.0198)	0.62022 *** (0.024)
Corr.(Brazil,Chile)	0.54109 *** (0.032)	0.6842 *** (0.0294)	0.57821 *** (0.0255)
Corr.(Brazil,Colombia)	0.30793 *** (0.043)	0.58694 *** (0.0365)	0.50754 *** (0.0285)
Corr.(Brazil,Mexico)	0.62582 *** (0.032)	0.78491 *** (0.0216)	0.6711 *** (0.0211)
Corr.(Brazil,Peru)	0.42088 *** (0.041)	0.7189 *** (0.0266)	0.5315 *** (0.0275)

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01

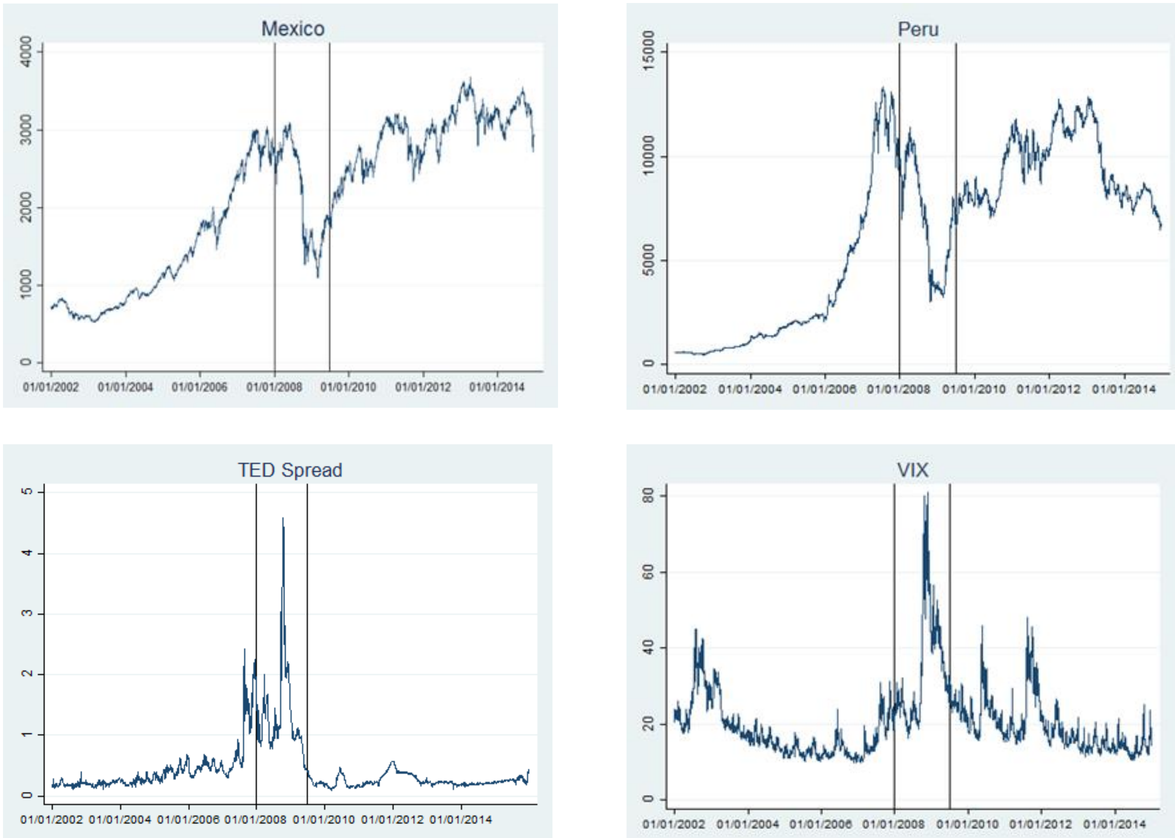
Table 2.5 C

MGARCH-DCC based Correlation between Stock Returns (Cont.).

	Pre Financial Crisis Jan. 2002 – Dec. 2007	Financial Crisis Jan. 2008 - Jun. 2009	Post Financial Crisis Jul. 2009 – Dec. 2015
Corr.(Canada,Chile)	0.38163 ***	0.61501 ***	0.57786 ***
	(0.038)	(0.0343)	(0.0253)
Corr.(Canada,Colombia)	0.21468 ***	0.55972 ***	0.57881 ***
	(0.044)	(0.0378)	(0.0253)
Corr.(Canada,Mexico)	0.50398 ***	0.70687 ***	0.67366 ***
	(0.034)	(0.0278)	(0.021)
Corr.(Canada,Peru)	0.47275 ***	0.72618 ***	0.63355 ***
	(0.038)	(0.0258)	(0.023)
Corr.(Chile,Colombia)	0.27206 ***	0.54654 ***	0.5367 ***
	(0.042)	(0.0389)	(0.0272)
Corr.(Chile,Mexico)	0.471 ***	0.68078 ***	0.62562 ***
	(0.036)	(0.0296)	(0.0232)
Corr.(Chile,Peru)	0.33071 ***	0.51044 ***	0.4801 ***
	(0.041)	(0.041)	(0.0295)
Corr.(Colombia,Mexico)	0.27117 ***	0.55253 ***	0.53731 ***
	(0.043)	(0.0388)	(0.0271)
Corr.(Colombia,Peru)	0.23922 ***	0.51066 ***	0.42762 ***
	(0.042)	(0.0405)	(0.0311)
Corr.(Mexico,Peru)	0.38283 ***	0.65073 ***	0.52361 ***
	(0.042)	(0.032)	(0.0278)

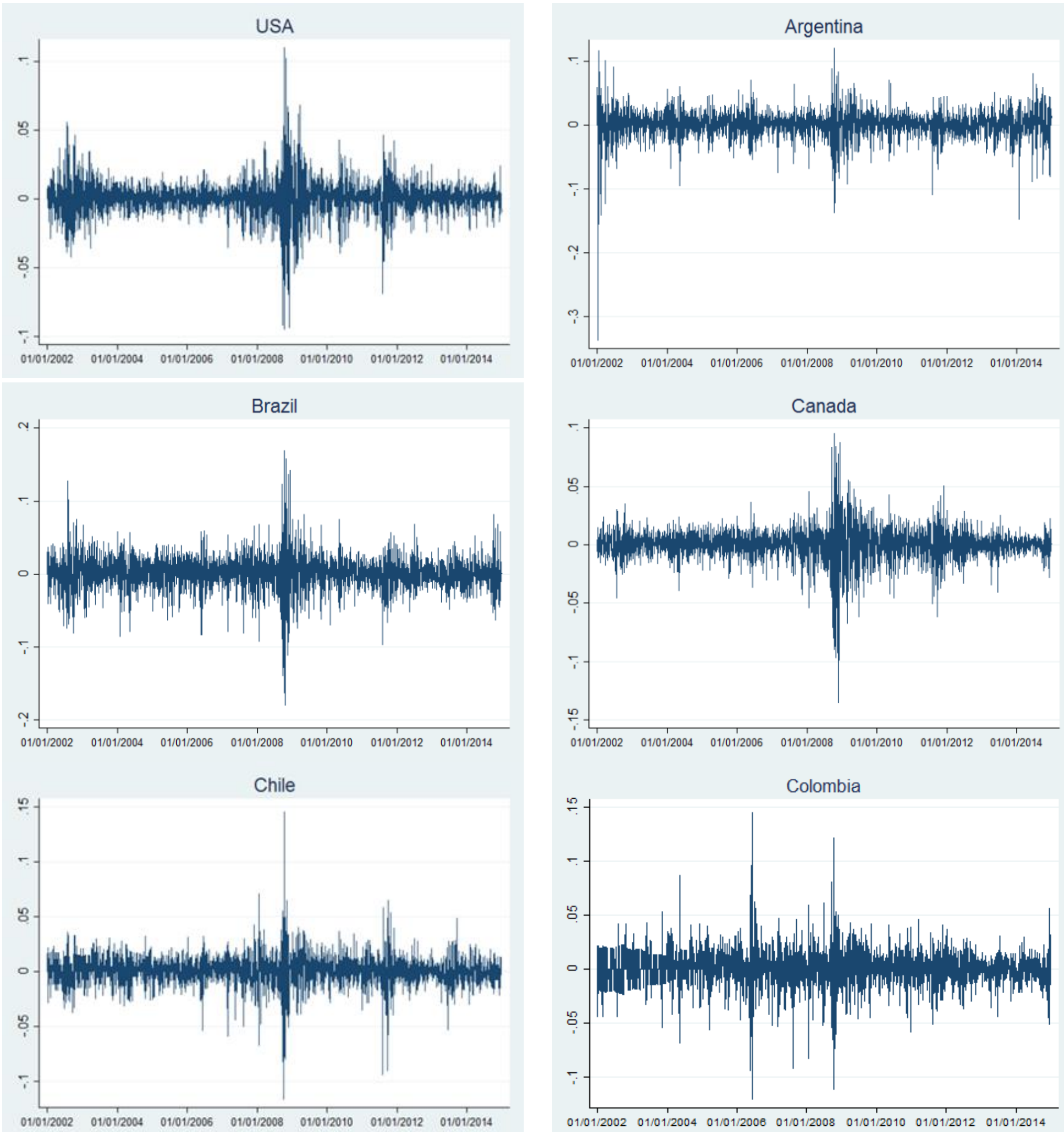
Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01

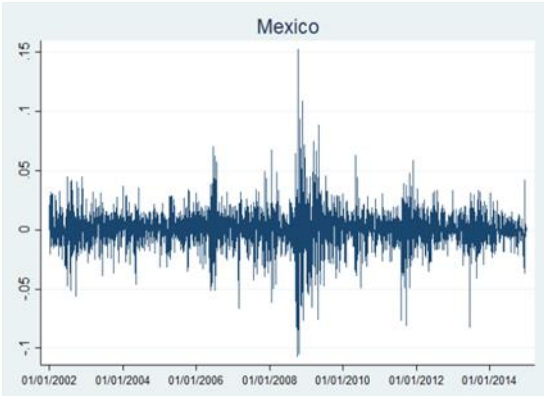
Figure 2.1
Daily Closing Prices – Stock Markets.

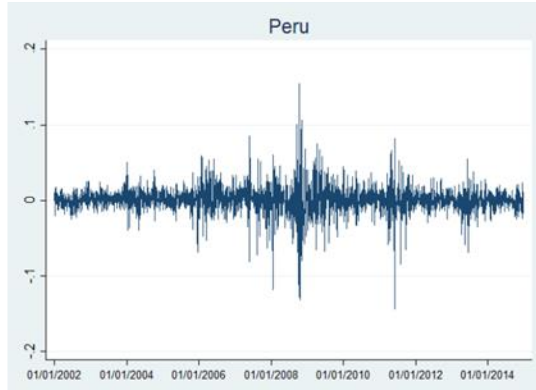


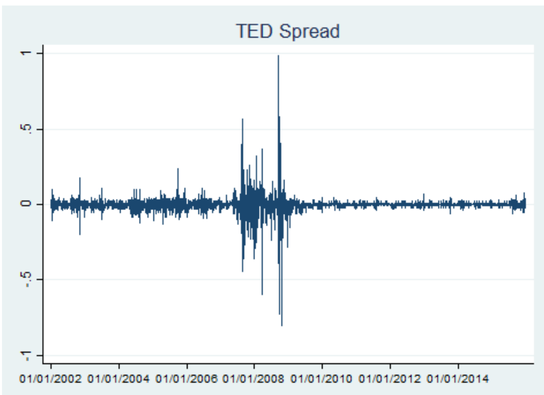
Note: Vertical lines represent the beginning and ending of the 2008-2009 financial crisis according to NBER.

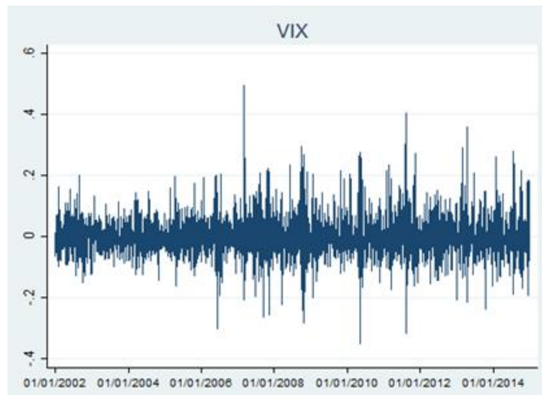
Figure 2.2
Daily Stock Returns and First Differences.




Mexico
.15
.1
.05
0
-.05
-.1
01/01/2002
01/01/2004
01/01/2006
01/01/2008
01/01/2010
01/01/2012
01/01/2014


Peru
.2
.1
0
-.1
-.2
01/01/2002
01/01/2004
01/01/2006
01/01/2008
01/01/2010
01/01/2012
01/01/2014


TED Spread
1
.5
0
-.5
-1
01/01/2002
01/01/2004
01/01/2006
01/01/2008
01/01/2010
01/01/2012
01/01/2014


VIX
.6
.4
.2
0
-.2
-.4
01/01/2002
01/01/2004
01/01/2006
01/01/2008
01/01/2010
01/01/2012
01/01/2014

CHAPTER III

THE U.S. FINANCIAL CRISIS, INVESTOR SENTIMENT, AND THE STOCK MARKETS IN THE AMERICAS.

3.1 Introduction

The 2008-2009 U.S. financial crisis is of high importance, not only because it represented largest U.S. stock market decline since the great depression of the early 20th century, but because of the rapid spread to other economies in the world. The financial contagion observed during this period challenges the ability of building diversified portfolios, by investing in different stock markets around the world, during times of crisis, and prompts us to investigate the sources of this contagion.

In addition to the fundamentals based contagion theories of Kaminsky and Reinhart (2000), other authors identify that investor behavior can also accentuate financial contagion. Investors may attempt to mitigate the risk of their international holdings, by withdrawing their funds from countries with high economic ties to the country in crisis, resulting in increased correlations between the country in crisis and its trade partners (Yuan, 2005; Pasquariello, 2007). Kodres and Pritsker (2002) develop a rational expectations model that explains financial market contagion, identifying that investors transmit shocks from one market to another when they rebalance their portfolios to adjust their exposure to macroeconomic risks.

Markowitz (1952) defines that investors are well informed and rational, when building efficient portfolios, to maximize expected returns for any given risk. Modern Financial theory states that individual investors are rational utility maximizers, who care about their investments risks and returns, and make investment decisions based on economic fundamentals (Fama, 1970). Traditional Efficient market theory states that markets are rational and that stock's values are equal to discounted future cash flows. It also states that any deviation from fundamental values should be eliminated in a short time by arbitragers, reducing the effects of investor sentiment (Fama and Macbeth, 1973)

De Long et al. (1990) highlight the role that rational and noise traders play in stock pricing, arguing that limitations to arbitrage allow for noise traders, and that stock prices consist of two elements; a fundamental value given by rational investors and a risk premium attributed to noise traders. Baker and Wurgler (2006, 2007) identify that there are two types of investors: rational traders, also known as arbitrageurs, and sentiment traders. Arbitrageurs, make informed decisions to determine expectations about the future value of an asset, while sentiment traders (i.e. noise traders) could either be optimistic or pessimistic about the market, leading them to either under-estimate or over-estimate asset prices.

Most of the investor sentiment literature focuses on the U.S. markets and finds evidence that investor sentiment affects securities pricing and stock returns. The literature also finds that investor sentiment is driven by demand shocks and/or arbitrage limitations (Lee, Shleifer, &Thaler, 1991; Lee, Jiang, & Indro, 2002; Brown & Cliff, 2004; Baker & Wurgler, 2007; Verma, Baklaci, & Soydemir, 2008; Ho &Hung, 2009; Baker, Wurgler, & Yuan, 2012; Huerta, Egly & Escobari, 2016).

A growing branch of literature investigates the effects of international investor sentiment on a country's stock valuation. Investor sentiment can be defined as, "a belief about future cash flows and investment risks that is not justified by the facts at hand" (Baker and Wurgler, 2007).

Lee et al. (2002) find that changes in investor sentiment and excess stock returns are positively correlated. They also find that bullish shifts in investor sentiment are inversely correlated to market volatility. Verma and Soydemir (2006) investigate how U.S. investor sentiment propagates to other countries, finding that that U.S. investor sentiment influences international stock market returns, varying significantly across countries. They also find that changes in institutional investor sentiment have stronger influence than individual investor sentiment, and that both are driven by both rational and irrational factors, but conclude that U.S. investor sentiment can be an important spillover factor. Investor sentiment can influence trading decisions, at both the firm and market levels, especially for firms that are difficult to value or to arbitrage (e.g., Baker and Wurgler, 2007).

Schmeling (2009) uses consumer confidence as a proxy for individual investor sentiment and assesses its impact on the stock returns for 18 industrialized countries. He finds causal effect, between investor sentiment and stock market returns, from t to t_{t+1}. He observes that individual investor sentiment negatively forecasts stock market returns and suggests that this is stronger for countries that are culturally more prone to overreaction and herd-like behavior.

Hwang (2011) find that U.S. investor sentiment can influence the demand for foreign securities, which in turn affect their price, deviating from their fundamental value. Baker et al. (2012) find evidence that investor sentiment influences market volatility and that return predictability is consistent with over-reaction corrections. They also find that investor sentiment is composed of two factors, namely “global” and “local”, and that global investor sentiment is spilled-over across markets through capital flows.

Sayim and Rahman (2015) find significant spillover from U.S. individual and institutional investor sentiment to the stock returns of the Turkish stock market. Perez-Liston, Huerta and Gutierrez (2015) use a vector auto-regressive model (VAR) to identify U.S. investor sentiment spillover to Mexican investor sentiment and the Mexican stock market returns. They attribute this spillover to the cross proximity, strong trade ties, ease of capital flows, and exchange rates.

We apply the multivariate DCC–GARCH model, introduced by Engle (2002), to identify the role of U.S. market volatility and U.S. investor sentiment as sources of contagion, from the U.S. to the Americas, during the 2008-2009 financial crisis. We first asses the existence of contagion from the U.S. to Argentina, Brazil, Canada, Chile, Colombia, Mexico and Peru. We use the CBOE Volatility Index®, or VIX, to control for the impact of market volatility on the conditional correlations obtained from the DCC-GARCH, between the U.S. and each of the stock markets. We then assess the impact of investor sentiment on these conditional correlations, by using survey-based proxies used in the literature (Brown and Cliff, 2004; Huerta, Egly and Escobari, 2016), as direct measures of investor sentiment. We distinguish the effects of the Individual Investor Sentiment, represented by the American Association of Individual Investors (AAII) survey, and Institutional Investor Sentiment, using the Investor Intelligence (II) Survey.

This chapter contributes to the investor behavior literature, by identifying the role of the perceived market volatility *VIX*, individual investor confidence *AAII*, and institutional investor confidence *II*, on the stock market returns of the major markets in the Americas during the U.S. financial crisis. We find that the institutional investor sentiment not only has greater influence than the individual investor sentiment on the stock returns of the U.S., but that this greater influence applies also to the largest markets in the Americas.

3.2 Individual and Institutional Investor Sentiment

In order to capture the effect of the institutional and individual investor sentiments, on the stock returns of the major stock markets in the Americas, we use two sentiment indexes that are widely used in the literature. Following Brown and Cliff (2004) and Huerta et.al. (2016) we first use a survey performed by the American Association of Individual Investors *AAII*, as a proxy for individual investor sentiment. The American Association of Individual Investors is a nonprofit corporation that provides education, information and research to individual investors. Since 1987, Individual investors are pooled weekly, to measure the percentage of those who are bullish, bearish, or neutral about the stock market's short-term performance. Those that are said to be bearish are individual investors that are pessimistic about the stock market performance in the next six months, those that are bullish expect for the stock prices to rise, and those neutral expect for the stock prices to remain unchanged. Following Brown and Cliff (2004), we build the *AAII* index by calculating the difference between bullish and bearish investors, the result is the bull-bear spread, commonly used as a proxy for individual investor sentiment.

We then use the Investors Intelligence, *II*, survey to build a proxy for institutional investors Intelligence. The Investors Intelligence survey analyses the market views of more than 100 investment advisor newsletters and then interprets them as being bullish, bearish and those that expect a correction or neutral. Since professional advisors are the authors of these letters, we follow Brown and Cliff (2004) and use it this survey to build a proxy for Institutional Investor Sentiment. We build the Institutional Investor index *II* by calculating the spread between the percentage of bullish newsletters and bearish newsletters.

Since we know that individual and institutional investor sentiments have positive effects on U.S. stock returns, we hypothesize that investor sentiment will also have an effect on international markets. We define three hypotheses based on individual and institutional investor sentiments:

H1: Increases in the Individual Investor Sentiment *AAII*, will have positive and statistically significant effects on the stock returns of Canadian and Latin American stock markets.

H2: Increases in the Institutional Investor Sentiment *II*, will have positive and statistically significant effects on the stock returns of Canadian and Latin American stock markets.

H3: Institutional Investor Sentiment II will have a greater influence than Individual Investor Sentiment AAII, on the stock returns of the markets in the Americas.

3.3. Data and Descriptive Statistics

We collect country specific data from DataStream, consisting of weekly closing prices from Argentina (BURCAP), Brazil (BOVESPA), Canada (S&P/TSX Composite Index), Chile (IPSA), Colombia (IGBC), Mexico (BOLSA), Peru (ISBL) and the United States (S&P 500). Data are in U.S. Dollars, from January 1, 2002, through December 31, 2015.

We use three proxies to measure sentiment; we first use the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), as a proxy of implied market volatility. The VIX is widely used as a fear gauge, since it represents the market's expectation of stock market volatility for the next 30-day period. Following Brown and Cliff (2004), we employ two survey based weekly measures of sentiment that are collected by the American Association of Individual Investors *AAII*, and Investor's Intelligence *II*.

Table 3.1 reports the descriptive statistics for the pooled dataset, both in levels and in returns for the country stock indexes, as well as in first differences for *VIX*, *AAII* and *II*. We fist report the data in levels and provide statistics about the mean, standard deviation, variance, skewness coefficient, kurtosis coefficient, the Shapiro-Wilk normality test, and the Ljung–Box autocorrelation test. Except for *AAII*, the Shapiro-Wilk test statistic suggest that the series are non-normally distributed, and the Ljung–Box test statistics indicate that all return series are auto-correlated except for Argentina and Peru.

For the data reported in returns and differences, we observe that Colombia and Peru report the highest means at 0.24 for both, with standard deviations of 3.91 and 4.15 respectively. Followed by Mexico with mean returns of 0.17, Argentina at 0.16, and Chile at 0.12, with standard deviations of 3.83, 5.1, and 2.92 respectively. Brazil and Canada report identical mean returns of 0.09, however their standard deviations are quite different at 4.77 and 3.20 respectively. We observe that with the exception of AAII, the series are non-normally distributed, and that with the exception of the stock returns of Argentina and Peru, all series are auto-correlated.

Table 3.2 reports the unconditional correlation between the stock index returns, ΔVIX and $\Delta AAII$ and ΔII for the pooled sample. We find that all pairwise correlations amongst the stock returns are positive and significant, and the highest correlations are those between the U.S., Canada, Mexico and Brazil, with pairwise correlations ranging between 0.6487 and 0.7818. Correlations between the stock index returns and changes in VIX are negative and significant. It is not surprising to find a high correlation between the U.S. and ΔVIX of -0.7976, but it is interesting to find out that the highest correlations were also observed with Mexico, Canada and Brazil at -0.6934, -0.6655 and -0.5594 respectively, since they represent the largest stock markets in the Americas. The relationship between both investor sentiment indexes and the country specific stock indexes are positive and significant, with the individual investor sentiment *AAII* ranging from a high of 0.1919 for Canada, followed by Chile with 0.1633 and the U.S. with 0.1566, to a low of 0.1038 for Colombia. The institutional investor sentiment *II* presents greater correlations with stock returns than the individual investor sentiment *AAII* in all cases, ranging from a high of 0.4090 for the U.S., 0.3154 for Mexico and 0.3057 for Canada, with the lowest pairwise correlation being that of Peru at 0.2009. We also find a low correlation coefficient of 0.2074 between *II* and *AAII* allowing us to include both sentiment measures in the empirical model.

Table 3.3 includes the results of the stationary tests, for the country stock indexes expressed in returns, as well as VIX, individual investor sentiment AAII and institutional investor sentiment II expressed in returns. We perform the ADF, KPSS, and Philips-Perron tests, identifying that all series are stationary.

3.4. The DCC model and estimation results

We use a DCC-GARCH model, introduced by Engle (2002), to assess the changes in the conditional pair wise correlations between the stock market returns, the change in market volatility *ΔVIX*, change in the individual investor confidence *ΔAAII* and the change in institutional investor confidence represented by *ΔII*.

The model used in this study is as follows:

We model the return dynamics by using an autoregressive model in the form of:

$$r_t = \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{\Delta VIX} + \gamma_3 r_{t-1}^{\Delta AAII} + \gamma_3 r_{t-1}^{\Delta II} + \varepsilon_t , \qquad (3.1)$$

The vector of returns is:

$$r_t = (r_{Argentina,t}, r_{Brazil,t}, r_{Canada,t}, r_{Chile,t}, r_{Colombia,t}, r_{Mexico,t}, r_{Peru,t}, r_{U.S.,t})'$$

and the vector of error terms is:

$$\varepsilon_t = (\varepsilon_{Argentina,t}, \varepsilon_{Brazil,t}, \varepsilon_{Canada,t}, \varepsilon_{Chile,t}, \varepsilon_{Colombia,t}, \varepsilon_{Mexico,t}, \varepsilon_{Peru,t}, \varepsilon_{U.S.,t})'$$

The results for the multivariate DCC–GARCH model are reported in Table 3.4. The results for the mean equations indicate that the constant term γ_0 is positive and statistically significant for all markets. The AR(1) term γ_1 yields mixed results, being positive and statistically significant for Colombia, and negative and statistically significant for the U.S. and Canada. We find that the ΔVIX term is only statistically significant for Brazil, Colombia and Mexico and in all three cases, it is positive. The Individual Investor Sentiment *ΔAAII* is not significant for any country, and the Institutional Investor Sentiment *ΔII* is positive and significant for Peru and the U.S., and except for Argentina, it is found to be positive, yet not significant.

We look at the parameter estimates of the mean and conditional variance equations to verify the appropriate use of the GARCH specification, and we confirm that all coefficients are significant, thus confirming the appropriate use of the specification. The volatility persistence (a + b) is found to be near one (1) in all cases, varying from a high of 0.99 for Argentina and 0.98 for the U.S. to a low of 0.86 for Colombia, which is indicative of high volatility persistence. The lambda1 and lambda 2 parameters are statistically significant at the 1%, which verifies the appropriate use of the DCC-GARCH over a CCC model.

Table 3.5 includes the DCC-GARCH based correlations between Δ*VIX*, Δ*AAII*, and Δ*II*, and the stock returns during the pooled data period. As expected we see that correlations between the ΔVIX and stock market returns are negative and significant, indicating that the greater the volatility in the U.S., the lower the returns of these markets. We observe that the pairwise correlations between ΔVIX correlations are greater for the U.S at -0.838, followed by those of Mexico at -0.715, Canada with -0.697 and the lowest being Argentina at -0.512. The pairwise correlations with the individual investor sentiment *AAII* are all positive and significant, ranging from 0.292 for *II*, followed by Canada at 0.213, the U.S. at 0.196 with the lowest being Peru at 0.179; this indicates that positive individual investor confidence is associated with positive stock market returns. We also observe that pairwise correlations with the institutional investor confidence *II* are positive and significant; however, we observe that the magnitude of these coefficients is greater than the estimated coefficients for the individual investors. We observe that the highest pairwise correlation coefficients between *II* and the stock market returns are those associated with the U.S., Canada and Mexico, ranging from 0.603 for the U.S, 0.499 for Mexico and 0.468 for Canada. Further, the correlation between ΔVIX and ΔII is negative and statistically significant at -0.507, which is greater than that observed between the ΔVIX and ΔII at -0.143, indicating a stronger inverse relation between the fear index and institutional investor confidence, when compared to individual investors. We also observe that the pairwise correlations amongst countries are all positive and significant and it becomes clear that the highest correlations are those between the most developed countries, namely the U.S., Canada, Mexico and Brazil. We identify the highest pairwise correlations as those between Brazil-Canada at 0.839, followed by U.S.-Canada at 0.825, U.S.-Mexico at 0.806, Brazil-Mexico at 0.794, and U.S.-Brazil at 0.711.

3.5. Explaining the conditional correlation coefficients

One advantage of the DCC-GARCH model is that we are able to obtain the dynamic correlations between *ΔVIX*, *ΔII*, and *ΔAAII*, and the stock market returns and represent them graphically. Figure 3.1 includes the dynamic conditional correlations between *ΔVIX* and the various stock markets returns. We observe a downward trend, in all cases, during the pre-crisis period; indicating that the inverse relationship between *ΔVIX* and each of the stock markets grew from approximately -0.1 to levels greater than -0.5 in all cases. During the financial crisis, we observe a slight correction in the opposite direction, which sharply reverts and remains at the highest negative levels. We observe during the post-crisis period that the dynamic conditional correlations between *ΔVIX* and stock returns remain at lower levels than during the pre-crisis period, with the most notorious being those of Canada and Mexico at around -0.7 and the U.S. at -0.9.

Figure 3.2 documents the conditional correlations for all pairs between *ΔII* and the stock markets. We observe that correlations are positive and with an upward trend during the pre-crisis period. We then observe that during the financial crisis, these correlations remain at around the highest level reached during the previous period, but with apparent increased volatility. We observe that correlations during the post-crisis period remain higher than the pre- financial crisis, with a notorious upper trend for the U.S., Canada and Mexico, with dynamic conditional correlations reaching around 0.5 for the U.S. and 0.4 for Canada and Mexico.

Figure 3.3 includes all pairwise dynamic conditional correlations between individual investor sentiment *ΔAAII*, and the stock markets. We observe positive pairwise correlations, with upward trends in most cases, during the pre-crisis period. We then observe a slight downward trend after the beginning of the financial crisis period, followed by a sharp correction. We observe that during the post-crisis period the correlations remain positive and in most cases higher than the levels observed during the pre-crisis period, however they behave very erratic, with similar patterns for Brazil, Canada, Chile, Mexico, Peru and the U.S.

We are interested in defining if the financial crisis had an effect on the conditional correlation coefficients between the stock market returns, *ΔVIX*, *ΔAAII*, and *ΔII.* To capture the effect of the financial crisis on these pairwise conditional correlations we use the following regression model:

$$\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DSCRISIS_t + \epsilon_{ij,t}, \text{ for } i \neq j \tag{3.2}$$

We identify two periods in the sample: the first one runs from January 1, 2002 to December 31, 2007, and we define it as the pre-crisis period. We define the second period as since-the-crisis, because it begins at the wake of the financial crisis on January 01, 2008, and continues until the end of the pooled sample (December 31, 2015). We create a dummy variable (*DSCRISIS*) for the since-the-crisis period, which is set equal to one for such period and zero otherwise. We regress the predicted dynamic conditional correlation coefficients $\hat{\rho}_{ij,t}$, between markets and sentiment indexes *i* and *j* at time *t*, with dummy variable *DSCRISIS* for the since-the-crisis period (January 1, 2008 to December 31, 2015).

The estimation results in Table 3.6 indicate that the financial crisis has a significant impact on the conditional correlation for all the pairwise correlations. We first look at the effects on the pairwise correlations between the stock markets in the Americas and Δ*VIX* and observe that in all cases, the financial crisis has an inverse and significant impact, indicating that the relationship between Δ*VIX* and each stock index grows stronger after the financial crisis begins. We identify that Δ*VIX* has the highest negative pairwise correlations with the U.S. at -0.8157, followed by Mexico at -0.6963, Canada at -0.6628, Chile at -0.5662, Brazil at -0.5648, Peru at -0.5106, Colombia at -0.4954, and Argentina at -0.4876.

We observe that all the pairwise correlations, between these stock market indexes and the individual investor confidence *AAII*, increase significantly. We identify that the correlation with the U.S. has the greatest coefficient at 0.1902, followed by Canada at 0.1858, Chile at 0.1682, Argentina at 0.1635, Brazil at 0.1551, Mexico at 0.1493, Peru at 0.1330 and Colombia at 0.1202. This confirms that the contemporaneous relationship, between the individual investor confidence and the stock market returns, increase during the U.S. financial crisis.

We identify that effect on the relationship between the institutional investor confidence *II* and the stock market returns is also significant, and quite greater in magnitude the coefficients observed for the pairwise correlations between *AAII* and each stock index. We observe that the correlations coefficients range from a high of 0.4899 with the U.S., trailed by Mexico at 0.3780, Canada at 0.3627, Brazil at 0.3060, Chile at 0.2713, Colombia at 0.2580. Argentina at 0.2413 and Peru at 0.2306.

In an attempt to capture the effects of the financial crisis period and the following post-crisis period in more detail, we break the since-the-crisis period into two. We redefine the resulting subsamples as: pre-crisis, crisis and post-crisis. The pre-crisis period runs from January 1, 2002 to December 31, 2007. The crisis period begins on the wake of the financial crisis on January 01, 2008 and ends on June 30, 2009. The post-crisis period includes data from July 1, 2009 and ends on December 31, 2015.

To differentiate the effect of the financial crisis, and the post-crisis, on the pairwise correlations between ΔVIX, ΔAAII, ΔII and the country specific stock markets, we use the following regression model:

$$\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}, \text{ for } i \neq j \qquad (3.3)$$

We create a dummy variable for the crisis period (*DCRISIS*), and for the post-crisis period (DPOSTCRISIS), which are set equal to one, for the each of their respective periods and zero otherwise. We regress the predicted dynamic conditional correlation coefficients $\hat{\rho}_{ij,t}$, between markets and sentiment indexes *i* and *j* at time, with dummy variable *DCRISIS* for the crisis period and dummy variable DPOSTCRIS for the post-crisis period.

The estimation results for equation 5 are reported on Table 3.7. Panel A, includes the regression results for the pairwise correlations between the stock returns of the U.S. and each of the other countries. We observe that λ_0, which captures the pre-crisis period, is positive and significant for all the pairs with coefficients ranging from a high of 0.6354 for Canada, followed by Mexico at 0.6304, Brazil at 0.5340, Chile at 0.4694, Argentina at 0.4132 and Colombia at 0.3789. The effect of the financial crisis λ_1 is also positive and significant, with coefficients ranging from a high of 0.1933 for Peru, 0.1848 for Colombia, 0.1747 for Mexico, 0.151 for Argentina, 0.1359 for Brazil, 0.1354 for Chile, and 0.1007 for Canada. The effect of the post financial crisis, as indicated by λ_2, is positive and significant, ranging from a high of 0.1795 for Peru, 0.1562 for Canada, 0.1427 for Colombia, 0.1400 for Mexico, 0.1365 for Argentina, 0.1251 for Chile and 0.1147 for Brazil. We interpret that there is a strong correlation between the stock returns of the U.S. and each of the countries in this study. We observe that all countries increase their correlations with the U.S. during the financial crisis, which is indicative of contagion. With the exception of Canada, that continues to strengthen its co-movements with the U.S. after the financial crisis had ended, the other countries maintain higher correlations than those observed prior to the start of financial crisis, yet they are smaller than those from the crisis.

On table 3.7 panel B, we report the effects of the financial crisis on the pairwise correlations between the stock markets in the Americas and ΔVIX . In all cases we observe negative and statistically significant coefficients for the constant λ_0, that indicate a strong inverse relationship during the pre-crisis period. The λ_0 coefficients range from -0.6818 for the U.S., -0.5532 for Mexico, -0.5301 for Canada, -0.4507 for Brazil, -0.4299 for Chile, -0.3715 for Peru, -0.3646 for Colombia and -0.3512 for Argentina. We observe that the effect of the financial crisis λ_1 is also negative and significant for all pairs, which indicates contagion, since the inverse correlations increase during this period. The λ_1 coefficients range from a high to low starting with Mexico at -0.1683, Argentina at -0.1592, Colombia at -0.1448, Chile at -0.1434, Peru at -0.1374, U.S. at -0.1318, Brazil at -0.1303 ad Canada at -0.877. The effect of the post crisis period λ_2 is negative and significant in all cases, with most cases being smaller in magnitude than λ_1, such as Mexico at -0.1372, Chile at -0.1346, Argentina at -0.1312, Colombia at -0.1276 and Brazil at -0.1104. In the cases of Canada at -0.1460, Peru at -0.1394, and the U.S. at -0.1343, the post financial crisis coefficients for λ_2, are larger than those observed during the financial crisis. This is indicative of the long-term effects of the financial crisis on the correlations between VIX and each of the countries in the study.

The results for the effects of the financial crisis for the individual investor confidence *AAII*, and each of the country specific stock returns, are included on Table 3.7 panel C. We first observe positive and significant coefficients for λ_0, that range from 0.1651 for the U.S, followed by Canada at 0.1542, Chile at 0.1369, Brazil at 0.1312, Argentina at 0.1176, Mexico at 0.1151, Peru at 0.1083 and Colombia at 0.095. We observe mix effects of the financial crisis on these pairs, with five countries presenting inverse and statistically significant coefficients, like: Peru at -0.0324, Canada at -0.0320, the U.S. at -0.0201, Brazil at -0.0131, and Chile at -0.0059. The rest of the pairs observe positive and significant coefficients, ranging from 0.0153 for Mexico, 0.0052 for Colombia and 0.0041 for Argentina. The effect of the post-crisis period is positive and significant for all pairs, indicating that increases in the individual investor confidence, are associated with increases in stock returns. The coefficients range from 0.0555 for Argentina, 0.0462 for Canada, 0.0398 for Chile, 0.0386 for Mexico, 0.0378 for Peru, 0.0355 for the U.S. and 0.0331 for Brazil.

The last panel for Table 3.7 is panel D, which includes the results of the regressions for the pairs composed of the institutional investor confidence *II*, and the stock returns for each country. We fist observe that the constant termλ_0, which represents the pre-crisis period, is positive and significant for all the pairs. This indicates that higher institutional investor confidence is correlated to positive stock market returns in the Americas, during the pre-crisis period. The coefficients range from a high of 0.3590 for the U.S., followed by Mexico at 0.2833, Canada at 0.2602, Colombia at 0.2333, Brazil at 0.2208, Chile at 0.2107, Argentina at 0.1490 and Peru at 0.1477. The table then reports that the effect of the U.S. financial crisis, represented by λ_1, is positive and significant for all the pairs. This suggests contagion, with coefficients ranging from a high of 0.0996 for the U.S. followed by Mexico at 0.0854, Peru at 0.0789, Brazil at 0.0684, Canada at 0.0654, Argentina at 0.0604, Colombia at 0.0413 and Chile at 0.0283. Finally, the effect of the post-crisis period on the pairs is also found to be positive and significant, with coefficients that are larger than those from the crisis period in most cases with the exception of Colombia, which is smaller than the effect from the crisis. The λ_2 coefficients range from a high of 0.1381 for the U.S., followed by Canada at 0.1111, Argentina at 0.0997, Mexico at 0.0969, Brazil al 0.0891, Peru at 0.0838, Chile at 0.0680, ad Colombia at 0.0208.

We compare the coefficient of determination R^2 for each of the stock market returns, the U.S., VIX, *AAII* and *II*, to identify the regression with the highest explaining value for each of the regression models. For Argentina, we identify that *II* has the highest R^2 value of 0.5602, followed by VIX at 0.4153, the U.S. at 0.3867, and *AAII* at 0.3751. For Brazil, we identify that the highest R^2 value is from *II* at 0.4995, followed by VIX at 0.2918, the U.S at 0.2537 and *AAII* at 0.1579. For Canada, we observe a similar pattern, with a R^2value for *II* at 0.5685, followed by VIX at 0.4256, the U.S at 0.3784, tailed by *AAII* at 0.3613. For Chile, we identify that the highest R^2value is that of VIX at 0.4402, followed by the U.S. at 0.4141, *II* at 0.4019, an *AAII* at 0.115. The case of Colombia is led by the U.S. with a R^2 of 0.4834, VIX at 0.4349, *AAII* at 0.1246 and *II* at 0.0786. For Mexico, we find the highest R^2 value with *II* at 0.4443, followed by VIX at 0.369, the U.S. at 0.3069 and *AAII* at 0.0884. For Peru, the highest $R^2$is that of *II* at 0.5531, the U.S. at 0.4767, VIX at 0.4266, and *AAII* at 0.279. The Case of the U.S. has the highest R^2 value with *II* at 0.5531, followed by VIX at 0.2748, and *AAII* at 0.1608.

As we mention in chapter I, U.S. investors are some of the most influential international equity holders, and we observe on Figure 1.1 a flight to safety pattern, surrounding the U.S. financial crisis, for the Canadian and Latin American stock markets. Our findings support the flight to safety theory and indicate that investor confidence played a significant role on the contagion from the U.S. stock market to the major stock markets in the Americas, during the U.S. financial crisis. We also identify that the level of influence of the institutional investor confidence *II*, is significantly higher than that of the individual investor confidence *AAII.* These findings are in line with those of Verma and Soydemir (2006), who observe that institutional investor sentiment has a larger impact than individual investor confidence on international markets. Our findings are related to the observations made by Huerta, Egly and Escobari (2016) that large institutional investors influence the U.S. markets at a greater rate than individual investors do, attributing this to their greater access to capital and their tendency to trade in large blocks. We contribute to the literature by identifying that U.S. institutional investors not only have greater influence than individual investors do on the U.S. markets, but on the stock returns of the largest stock markets in the Americas. We observe that this influence increases during the U.S. financial crisis.

3.6. Summary and Conclusions

We examine U.S. investor sentiment as a source of contagion from the U.S. to the largest stock markets in the Americas, during the U.S. financial crisis. We use a DCC-GARCH model to obtain the dynamic conditional correlations between the U.S. market volatility, individual and institutional investor sentiments, and the stock indexes of Argentina, Brazil, Canada, Chile, Colombia, Mexico, Peru and the U.S.

We use weekly data to analyze the relationship between U.S. market volatility, individual investor sentiment, institutional investor sentiment, and the stock returns from eight countries in the Americas, before and after the U.S. financial crisis. In addition to the use of the perceived market volatility index VIX, we use the bull-bear spread from the American Association of Individual Investors *AAII* as a proxy for individual investor sentiment, and the bull-bear spread from the Investor Intelligence *II* survey as a proxy for institutional investor sentiment. We obtain the dynamic conditional correlations between the investor sentiments and the various stock market indexes, to identify the effect of the financial crisis on these pairwise correlations. We use two models to regress the predicted dynamic conditional correlation coefficients, using dummy variables for the periods that include the crisis and post-financial crisis. The dummy variables get a value of one during their period, and a value of zero otherwise. We observe a significant increase in the correlation coefficients, maintaining their sign, between U.S. stock returns, *VIX*, *AAII*, *II* and the stock market returns, due to the financial crisis.

We also observe a negative and significant correlation between changes in *VIX* and the stock market returns, and that the institutional investor confidence has a greater influence on the international stock markets, than the individual investor confidence. We also observe a significant increase in the correlation coefficients, amongst the various sentiment indexes, due to the U.S. financial crisis.

We contribute to the literature by identifying the influence that U.S. investor sentiment plays on the stock returns of the largest stock markets in the Americas. By identifying that the U.S. institutional investor sentiment has greater influence than the U.S. individual investor sentiment on the international markets of the Americas, and that this influence increases significantly during the U.S. financial crisis. We caution about the consequences of block trading, by institutional investors during times of crisis, since this flight to safety behavior can result in financial contagion.

Table 3.1

Descriptive Statistics (Weekly Data from Jan. 2002 to Dec. 2015).

Levels	Argentina	Brazil	Canada	Chile	Colombia	Mexico	Peru	U.S.	VIX	*AAII*	*II*
Observations	730	730	730	730	730	730	730	730	730	730	730
Mean	1930.15	391.68	10198.77	1191.24	4.56	2170.68	899.30	1333.68	19.97	6.86	21.82
Standard Dev.	898.52	202.55	3071.00	483.43	2.56	937.89	483.31	340.36	9.25	18.19	14.78
Variance	807340.00	41027.22	9431054.00	233704.20	6.56	879631.90	233593.10	115841.80	85.49	331.05	218.58
Skewness	0.02	-0.03	-0.60	-0.09	-0.19	-0.43	-0.15	0.79	2.33	0.03	-0.90
Kurtosis	2.31	1.88	2.11	2.02	1.79	1.72	1.65	2.88	10.89	2.91	3.58
Shapiro-Wilk (Normality)	6.405***	7.354***	9.061***	6.847***	8.465***	9.491***	8.827***	8.718***	11.256***	-1.05	8.013***
Ljung-Box test (Auto Correlation)	20045.81***	21420.17***	20977***	24122.14***	23943.21***	23931.28***	23237.52***	22284.44***	8672.29***	1946.80***	6091.48***

Returns/Differences

	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	RET_U.S.	Δ_VIX	Δ_*AAII*	Δ_*II*
Observations	730	730	730	730	730	730	730	730	730	730	730
Mean	0.16	0.09	0.09	0.12	0.24	0.17	0.24	0.08	-0.01	-0.05	-0.02
Standard Dev.	5.1	4.77	3.20	2.92	3.91	3.83	4.15	2.44	3.16	14.37	4.83
Variance	26.04	22.75	10.24	8.55	15.32	14.67	17.24	5.94	9.98	206.59	23.35
Skewness	-1.92	-0.71	-1.33	-1.68	-1.18	-0.64	-0.59	-0.85	0.73	0	0.04
Kurtosis	15.21	7.93	13.53	18.49	9.23	13.13	8.46	11.2	13.73	3.46	3.94
Shapiro-Wilk (Normality)	9.796***	7.966***	9.601***	9.413***	8.501***	9.324***	7.739***	8.684***	9.793***	1	3.201***
Ljung-Box test (Auto Correlation)	33.3	64.50***	66.66***	70.24***	58.46**	64.51**	40.04	54.55*	58.03**	108.49***	102.49***

Notes: All stock indexes in levels represented in U.S. Dollars. All variables are in returns except *VIX*, *AAII* and *II*, which are in differences. Sharpe Ratio = Mean/Standard-Dev.

Table 3.2

Correlation Coefficients of Weekly Stock Index Returns, *TED*, *AAII* and *II* - (Weekly Data from Jan. 2002 to Dec., 2015).

	Argentina	Brazil	Canada	Chile	Colombia	Mexico	Peru	U.S.	*VIX*	*AAII*	*II*
In Levels											
Argentina	1										
Brazil	0.6572***	1									
Canada	0.8741***	0.8809***	1								
Chile	0.7267***	0.8869***	0.8823***	1							
Colombia	0.7043***	0.865***	0.8858***	0.9648***	1						
Mexico	0.883***	0.8236***	0.9511***	0.9111***	0.9169***	1					
Peru	0.7618***	0.9022***	0.8885***	0.9644***	0.9307***	0.9244***	1				
U.S.	0.8234***	0.2533***	0.6345***	0.4132***	0.422***	0.6951***	0.4627***	1			
VIX	-0.295***	-0.0061***	-0.2842***	-0.142***	-0.152***	-0.2409***	-0.0729***	-0.5016***	1		
AAII	-0.0832***	-0.2382***	-0.1379***	-0.1332***	-0.1422***	-0.1403***	-0.162***	0.0796***	-0.3911***	1	
II	0.1752***	-0.0818***	0.129***	0.0641***	0.0679***	0.1257***	0.0344***	0.3789***	-0.7017***	0.5906***	1

Returns/Differenced

	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	RET_U.S.	*VIX*_CHG	*AAII*_CHG	*II*_CHG
RET_ARG	1										
RET_BRA	0.5741***	1									
RET_CAN	0.5844***	0.7537***	1								
RET_CHI	0.486***	0.6761***	0.6591***	1							
RET_COL	0.4015***	0.5508***	0.5539***	0.5423***	1						
RET_MEX	0.5346***	0.741***	0.7454***	0.6678***	0.5802***	1					
RET_PER	0.5059***	0.6769***	0.7568***	0.5785***	0.4932***	0.6651***	1				
RET_U.S.	0.519***	0.6487***	0.7818***	0.5966***	0.506***	0.7731***	0.562***	1			
*VIX*_CHG	-0.4453***	-0.5594***	-0.6655***	-0.5573***	-0.4913***	-0.6934***	-0.532***	-0.7976***	1		
*AAII*_CHG	0.1525***	0.1354***	0.1919***	0.1633***	0.1038***	0.1264***	0.1494***	0.1566***	-0.0798***	1	
*II*_CHG	0.2037***	0.265***	0.3057***	0.2516***	0.2381***	0.3154***	0.2009***	0.4090***	-0.3253***	0.2074***	1

Notes: All variables are in returns except *VIX*, *AAII* and *II*, which are in differences. *, **, and *** significant at 10%, 5% and 1%, respectively

Table 3.3

Unit Root Tests on Weekly Data from January1, 2002 to December 31, 2015

Series	ADF(k)	KPSS(19)	PHILLIPS-PERRON(k)
RET_ARG	-14.833 (2)***	0.0552	-28.642***
RET_BRA	-14.497 (2)***	0.0738	-29.400***
RET_CAN	-19.193 (1)***	0.0385	-28.760***
RET_CHI	-14.262 (2)***	0.0593	-28.560***
RET_COL	-12.769 (2)***	0.0599	-26.996***
RET_MEX	-15.498 (2)***	0.0519	-29.485***
RET_PER	-26.325 (0)***	0.0359	-26.328***
RET_U.S.	-27.962 (0)***	0.0578	-27.976***
VIX_CHG	-20.078 (1)***	0.0253	-32.042***
AAII_CHG	-20.806 (2)***	0.0188	-44.237***
II_CHG	-17.761 (1)***	0.0296	-23.538***

Notes: The lag length (k) is selected as follows: for the ADF test, the null hypothesis is unit root, we use the Campbell and Perron (1991) data dependent procedure starting with an upper bound $k_{max} = 2$, on k. if the last lag is significant then choose $k = k_{max}$, if not we reduce k by one and continue this process until this is satisfied, or else k = 0. The KPSS assumes a null that the series is stationary, we use the Bartlett-Kernel criteria to select k = 19 as truncating parameter. The critical values for the KPSS test are 0.119 (10%), 0.146 (5%), and 0.216 (1%) . The Phillips-Perron test, has a null hypothesis of unit root, ad uses the equation $k = 4(T/100)^{2/9}$ to select the maximum lag, in this case k = 7. *, **, and *** significant at 10%, 5% and 1%, respectively.

Table 3.4

DCC Estimations for Stock Returns, *VIX*, *AAII*, and *II* (weekly data from Jan. 2002 to Dec. 2015).

	RET_U.S.	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER
Mean Equations								
ϒ0	0.33738***	0.42810***	0.49117***	0.38381***	0.30679***	0.52815***	0.50810***	0.45549***
	(0.0575)	(0.1390)	(0.1299)	(0.0799)	(0.0826)	(0.1213)	(0.0977)	(0.1223)
ϒ1	-0.10692***	-0.04435	-0.04263	-0.09703***	0.03277	0.07279**	-0.03726	0.01583
	(0.0321)	(0.0364)	(0.0271)	(0.0257)	(0.03164)	(0.0368)	(0.0294)	(0.0299)
ϒ2 (Δ*VIX*)	0.04792	-0.02693	0.10258**	0.01466	0.05366	0.16285***	0.10037**	-0.00924
	(0.0293)	(0.0515)	(0.05176)	(0.0347)	(0.0336)	(0.0476)	(0.0427)	(0.0089)
ϒ3 (Δ*AAII)*	-0.00296	0.00595	0.00941	-0.00403	0.00683	-0.00720	-0.00244	0.01623
	(0.0043)	(0.0096)	(0.0097)	(0.0059)	(0.0059)	(0.0087)	(0.0071)	(0.0286)
ϒ3 (Δ*II*)	0.02714*	-0.00849	0.03564	0.03094	0.01281	0.02623	0.01213	0.09922**
	(0.0152)	(0.0299)	(0.0310)	(0.0197)	(0.0192)	(0.0285)	(0.0238)	(0.0496)
Variance Equations								
Cons	0.18749***	0.76925***	1.48375***	0.41229***	0.74120***	2.8151***	0.74069***	0.76746***
	(0.0427)	(0.2682)	(0.3519)	(0.0886)	(0.2158)	(0.9571)	(0.1633)	(0.2371)
Arch	0.13326***	0.13804***	0.07856***	0.08243***	0.12714***	0.18973***	0.11673***	0.06522***
	(0.0167)	(0.0232)	(0.0128)	(0.0124)	(0.0265)	(0.0517)	(0.0168)	(0.0135)
Garch	0.85070***	0.85274***	0.85933***	0.88087***	0.79129***	0.67330***	0.84416***	0.89298***
	(0.0167)	(0.0231)	(0.0224)	(0.0164)	(0.0437)	(0.0871)	(0.0204)	(0.0220)
Persistence								
	0.98396	0.99078	0.93790	0.96330	0.91843	0.86302	0.96089	0.95820
Multivariate DCC Equation								
Lambda1	0.01079***							
	(0.0014)							
Lambda2	0.97745***							
	(0.0026)							
Observations	729							
χ2	364.19							
χ2 (p-value)	0.000							

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01. The mean equation is $r_t = \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{\Delta VIX} + \gamma_3 r_{t-1}^{\Delta AAII} + \gamma_3 r_{t-1}^{\Delta II} + \varepsilon_t$ where $r_t = (r_{Argentina,t}, r_{Brazil,t}, r_{Canada,t}, r_{Chile,t}, r_{Colombia,t}, r_{Mexico,t}, r_{Peru,t,}\ r_{U.S.,t})'$; $\varepsilon_t = (\varepsilon_{Argentina,t}, \varepsilon_{Brazil,t}, \varepsilon_{Canada,t}, \varepsilon_{Chile,t}, \varepsilon_{Colombia,t}, \varepsilon_{Mexico,t}, \varepsilon_{Peru,t}, \varepsilon_{U.S.,t})'$ and $\varepsilon_t \mid I\Omega_{(t-1)} \sim N(O, H_t.)$. The variance equations are $h_{ii,t} = c_i + a_i\varepsilon_{i,t-1}^2 + b_i h_{ii,t-1}\ for\ i = 1,2,\dots,n.$ The null for the x^2test is $H_0:\ \alpha = \beta = 0$.
Persistence is calculated as the sum of the coefficients in the variance equation (Arch and Garch).

Table 3.5

MGARCH-DCC Based Correlations Between VIX, AAII, II, and Stock Returns.

	ΔVIX	$\Delta AAII$	ΔII	RET_U.S.	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER
ΔVIX	1										
$\Delta AAII$	-0.143* (0.082)	1									
ΔII	-0.507*** (0.06)	0.292*** (0.08)	1								
RET_U.S.	-0.838*** (0.024)	0.196** (0.087)	0.603*** (0.058)	1							
RET_ARG	-0.512*** (0.057)	0.182** (0.084)	0.339*** (0.072)	0.603*** (0.05)	1						
RET_BRA	-0.597*** (0.05)	0.186** (0.089)	0.419*** (0.071)	0.711*** (0.039)	0.672*** (0.047)	1					
RET_CAN	-0.697*** (0.04)	0.213** (0.087)	0.468*** (0.068)	0.825*** (0.026)	0.647*** (0.048)	0.839*** (0.024)	1				
RET_CHI	-0.575*** (0.051)	0.188** (0.087)	0.379*** (0.073)	0.635*** (0.048)	0.541*** (0.057)	0.724*** (0.04)	0.73*** (0.041)	1			
RET_COL	-0.553*** (0.054)	0.157* (0.089)	0.305*** (0.077)	0.614*** (0.052)	0.557*** (0.055)	0.751*** (0.041)	0.743*** (0.044)	0.694*** (0.046)	1		
RET_MEX	-0.715*** (0.038)	0.18** (0.089)	0.499*** (0.066)	0.806*** (0.028)	0.628*** (0.051)	0.794*** (0.029)	0.793*** (0.03)	0.73*** (0.039)	0.674*** (0.047)	1	
RET_PER	-0.52*** (0.056)	0.179** (0.088)	0.324*** (0.077)	0.617*** (0.05)	0.572*** (0.055)	0.733*** (0.038)	0.782*** (0.031)	0.646*** (0.049)	0.648*** (0.052)	0.677*** (0.043)	1

Notes: Robust standard errors are in parentheses. *, **, and *** significant at 10%, 5% and 1%, respectively.

Table 3.6

Dynamic Correlation Coefficients and the Crisis Period

	ΔVIX	Δ*AAII*	Δ*II*
RET_ARG	-0.4876***	0.1635***	0.2413***
	(0.0119)	(0.0042)	(0.0052)
RET_BRA	-0.5648***	0.1551***	0.3060***
	(0.0151)	(0.0048)	(0.0074)
RET_CAN	-0.6628***	0.1858***	0.3627***
	(0.0174)	(0.0054)	(0.0086)
RET_CHI	-0.5662***	0.1682***	0.2713***
	(0.0143)	(0.0052)	(0.0071)
RET_COL	-0.4954***	0.1202***	0.2580***
	(0.0122)	(0.0035)	(0.0078)
RET_MEX	-0.6963***	0.1493***	0.3780***
	(0.0183)	(0.0047)	(0.0094)
RET_PER	-0.5106***	0.1330***	0.2306***
	(0.0125)	(0.0041)	(0.0052)
RET_U.S.	-0.8157***	0.1902***	0.4899***
	(0.0225)	(0.0058)	(0.0119)

Notes: Numbers in parentheses denote standard errors. *pb.10, **pb.05, ***pb.01

Table 3.7A

Regression Analysis of Conditional Correlations Coefficients and the U.S. Financial Crisis (Weekly data from Jan. 2002 to Dec. 2015).

Country/Index i:	RET_U.S	RET_U.S.	RET_U.S.	RET_U.S.	RET_U.S.	RET_U.S.	RET_U.S.
Country j:	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER
λ_0	0.4132***	0.5340***	0.6354***	0.4694***	0.3789***	0.6304***	0.3835***
	(0.0049)	(0.0057)	(0.0054)	(0.0042)	(0.0077)	(0.0062)	(0.0053)
$\lambda 1$	0.1517***	0.1359***	0.1007***	0.1354***	0.1848***	0.1747***	0.1933***
	(0.0110)	(0.0128)	(0.0120)	(0.0095)	(0.0099)	(0.1389)	(0.0119)
$\lambda 2$	0.1365***	0.1147***	0.1562***	0.1251***	0.1427***	0.1400***	0.1795***
	(0.0068)	(0.0079)	(0.0074)	(0.0059)	(0.0061)	(0.0086)	(0.0074)
Observations	730	730	730	730	730	730	730
F	230.78	124.94	222.91	258.67	342.04	162.41	333.07
F (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.3867	0.2537	0.3784	0.4141	0.4834	0.3069	0.4767

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01.

The regression equation is $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}$, for $i \neq j$

Table 3.7B

Regression Analysis of Conditional Correlations Coefficients and the U.S. Financial Crisis
(Weekly data from Jan. 2002 to Dec. 2015).

Country/Index i:	ΔVIX	ΔVIX	ΔVIX	ΔVIX	ΔVIX	ΔVIX	ΔVIX	ΔVIX
Country j:	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	RET_U.S.
λ_0	-0.3512***	-0.4507***	-0.5301***	-0.4299***	-0.3646***	-0.5532***	-0.3715***	-0.6818***
	(0.0046)	(0.0050)	(0.0044)	(0.0043)	(0.0042)	(0.0053)	(0.0045)	(0.0061)
$\lambda1$	-0.1592***	-0.1303***	-0.0877***	-0.1434***	-0.1448***	-0.1683***	-0.1374***	-0.1318***
	(0.0102)	(0.0112)	(0.0099)	(0.0096)	(0.0094)	(0.1179)	(0.0101)	(0.0136)
$\lambda2$	-0.1312***	-0.1104***	-0.1430***	-0.1346***	-0.1276***	-0.1372***	-0.1394***	-0.1343***
	(0.0063)	(0.0069)	(0.0062)	(0.0060)	(0.0058)	(0.0073)	(0.0062)	(0.0084)
Observations	730	730	730	730	730	730	730	730
F	259.9	151.15	271.07	287.67	281.54	214.18	272.17	139.09
F (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.4153	0.2918	0.4256	0.4402	0.4349	0.369	0.4266	0.2748

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01.
The regression equation is $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}$, for $i \neq j$

Table 3.7C

Regression Analysis of Conditional Correlations Coefficients and the U.S. Financial Crisis
(Weekly data from Jan. 2002 to Dec. 2015).

Country/Index i:	ΔAAII	ΔAAII	ΔAAII	ΔAAII	ΔAAII	ΔAAII	ΔAAII	ΔAAII
Country j:	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	RET_U.S.
λ_0	0.1176***	0.1312***	0.1542***	0.1369***	0.0950***	0.1151***	0.1083***	0.1651***
	(0.0020)	(0.0024)	(0.0021)	(0.0032)	(0.0021)	(0.0033)	(0.0022)	(0.0026)
λ1	0.0041***	-0.0161***	-0.0320***	-0.0059***	0.0052***	0.0153***	-0.0324***	-0.0201***
	(0.0044)	(0.0054)	(0.0047)	(0.0071)	(0.0048)	(0.0073)	(0.0049)	(0.0059)
λ2	0.0555***	0.0331***	0.0462***	0.0398***	0.0298***	0.0386***	0.0378***	0.0355***
	(0.00276)	(0.0034)	(0.0029)	(0.0044)	(0.0030)	(0.0045)	(0.0030)	(0.0037)
Observations	730	730	730	730	730	730	730	730
F	219.81	69.36	205.64	48.36	52.87	36.36	142.03	70.86
F (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.3751	0.1579	0.3613	0.115	0.1246	0.0884	0.279	0.1608

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01.
The regression equation is $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}$, for $i \neq j$

Table 3.7D

Regression Analysis of Conditional Correlations Coefficients and the U.S. Financial Crisis

(Weekly data from Jan. 2002 to Dec. 2015).

Country/Index i:	ΔII	ΔII	ΔII	ΔII	ΔII	ΔII	ΔII	ΔII
Country j:	RET_ARG	RET_BRA	RET_CAN	RET_CHI	RET_COL	RET_MEX	RET_PER	RET_U.S.
λ_0	0.1490***	0.2208***	0.2602***	0.2107***	0.2333***	0.2833***	0.1477***	0.3590***
	(0.0024)	(0.0024)	(0.0026)	(0.0022)	(0.0026)	(0.0030)	(0.0024)	(0.0033)
$\lambda 1$	0.0604***	0.0684***	0.0654***	0.0283***	0.0413***	0.0854***	0.0789***	0.0996***
	(0.0053)	(0.0054)	(0.0058)	(0.0050)	(0.0058)	(0.0066)	(0.0053)	(0.0075)
$\lambda 2$	0.0997***	0.0891***	0.1111***	0.0680***	0.0208***	0.0969***	0.0838***	0.1381***
	(0.0033)	(0.0033)	(0.0035)	(0.0031)	(0.0036)	(0.0041)	(0.0033)	(0.0046)
Observations	730	730	730	730	730	730	730	730
F	465.2	364.77	481.17	245.91	32.09	292.46	352.79	452.11
F (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R^2	0.5602	0.4995	0.5685	0.4019	0.0786	0.4443	0.4911	0.5531

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01.

The regression equation is $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DCRISIS_t + \lambda_2 DPOSTCRISIS_t + \epsilon_{ij,t}$, for $i \neq j$

Figure 3.1
Dynamic Conditional Correlations – ΔVIX to Stock Market Returns.

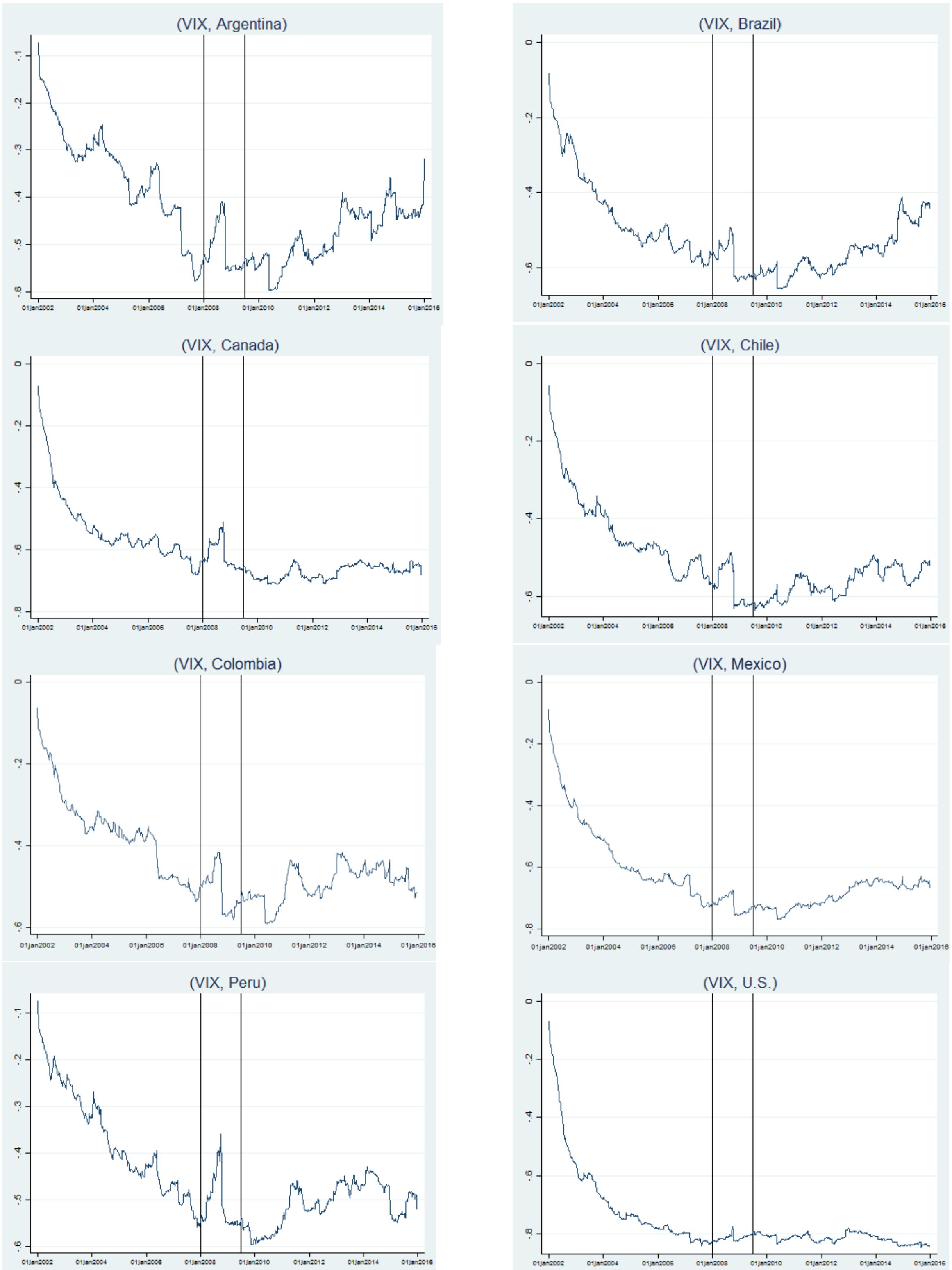


Figure 3.2
Dynamic Conditional Correlations – ΔII to Stock Market Returns.

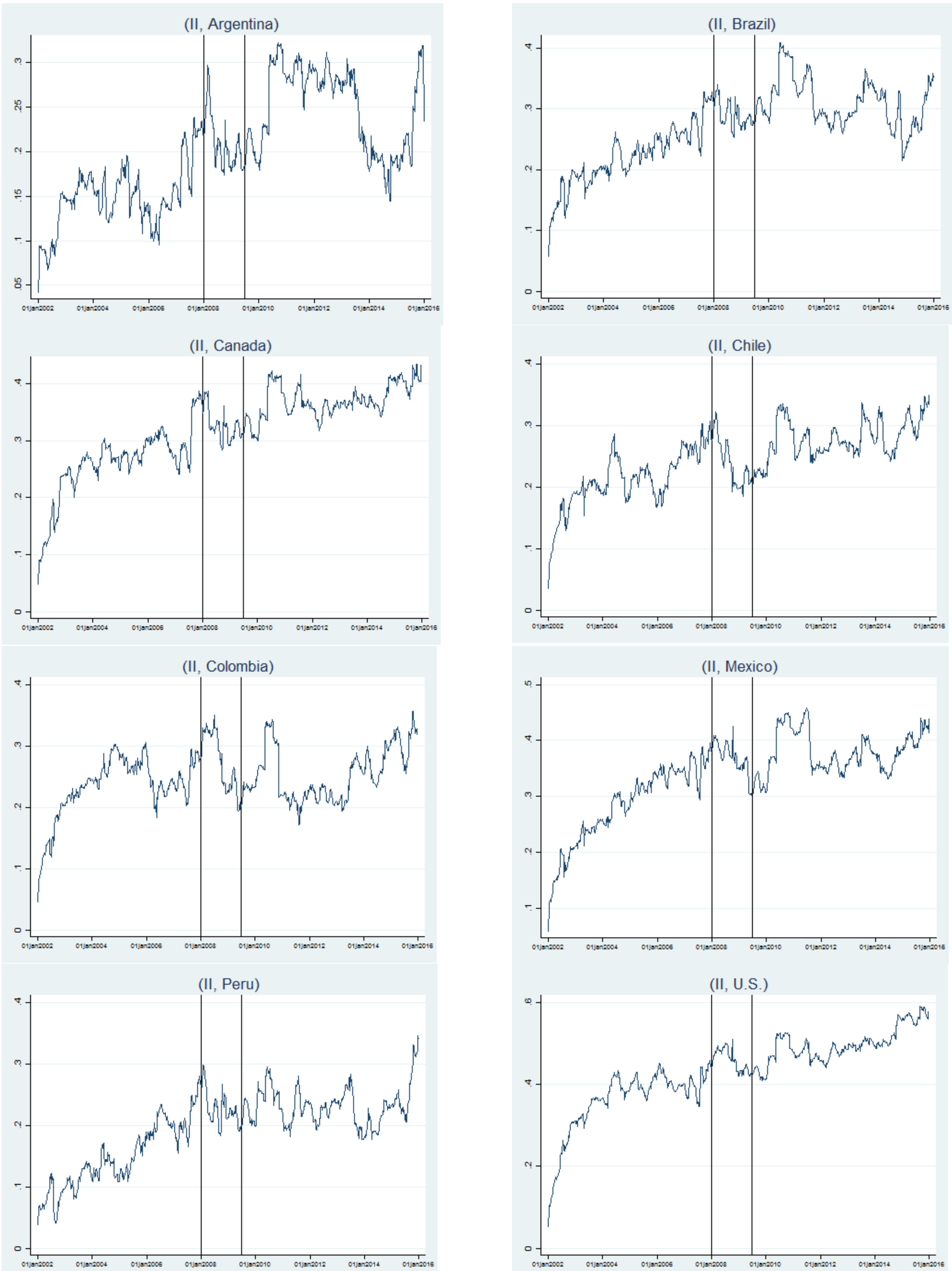


Figure 3.3
Dynamic Conditional Correlations – Δ*AAII* to Stock Market Returns.

CHAPTER IV

THE U.S. FINANCIAL CRISIS, OIL PRICES AND THE STOCK RETURNS FROM OIL PRODUCING COUNTRIES IN THE AMERICAS.

4.1. Introduction

The purpose of this chapter is to study the effects of the U.S. financial crisis, on the relationship between oil prices and five of the largest oil producing countries in the Americas. During the 2000's crude oil prices per barrel, represented by the West Texas Intermediate (OilWTI), rallied from $18/ barrel in January 2002 to a maximum of $145/barrel in July 2008, and dramatically dropped to $39/barrel by December 2008. After the financial crisis ended, oil prices followed an upward trend and eventually settled and hoovered in the $100/barrel range, until the last quarter of 2014 when oil prices began a downward turn that pushed prices back to below $50.

Forbes and Rigobon (2002) define that cross-country financial contagion, during a financial crisis period, occurs when cross-country correlations increase significantly in comparison to non-crisis periods.

Several authors have identified the effects of the oil crisis of 2008 on the 2008-2009 U.S. financial crisis. Hamilton (2009) identifies that the oil crisis of 2008 played a significant role in the 2008-2009 financial crisis. Bhar and Malliaris (2011) attribute the oil price crash of 2008, to investors' rapid closing of oil positions, deleveraging of speculative funds, and loss of liquidity during the 2008-2009 financial crisis. Mollick and Assefa (2013) find that the conditional correlations between the S&P 500 and oil prices had a significant increase during and after the 2008-2009 U.S. financial crisis.

We study the effects of shocks to oil price returns and perceived U.S. market volatility, during the 2008-2009 financial crisis, on stock market returns of oil producing countries from the Americas. We know from Mollick and Assefa (2013) that the U.S. financial crisis produced a shift on the relationship between oil price returns and U.S. stock returns, from being non-significant to significant after the financial crisis. We are interested in identifying if similar effects are present with other oil producing countries.

We first confirm that the level of influence from *VIX* to the stock returns of the major oil producers in the Americas increased due to the financial crisis. This means that U.S. market volatility was a strong promoter of contagion from the U.S. to the other countries in the Americas, and that these oil producers continue to pay strong attention to the U.S. market performance, the official end of the U.S. financial crisis. Our findings are in line with those from Mollick and Assefa (2013), who identify that stock returns in the U.S. are positively affected by oil prices after the U.S. financial crisis. We find that due to the financial crisis, oil prices not only affect U.S. stock returns, but similar effects are also present on other major oil producers in the Americas. We observe that the effects of the oil-price returns, on the stock returns of the major oil producers in the Americas, are significantly greater after the start of the U.S. financial crisis.

4.2. Literature Review and Hypotheses Development

Global oil supply and demand are the key determinants of global oil prices; with global income identified as the principal driver of global oil demand (Hamilton, 2009). In addition to global income, geopolitical events affecting oil supply can be contributing factors of price shocks

(Hamilton, 2009; Hamilton 2011). Increased demand for oil by China and other countries, transitioning from agricultural to industrial economies together with stagnant global production, are contributing factors of the oil price increase in the 2000's (Hamilton, 2009).

Several recent papers study the relationship between oil prices and equity markets during times of high market volatility. A few authors identify a positive relationship between the prices of oil and the stock market in Norway (e.g., Bjørnland , 2009; Jung and Park, 2011). Malik and Hammoudeh (2007) model the relationship between the global oil market, U.S. equity market, and Gulf equity markets finding evidence of spillover for Saudi Arabia. Arouri et al. (2011) detect volatility spillovers between oil prices and stock markets in the Gulf Cooperation Council countries (GCC) over the period of 2005 to 2010. Lizardo and Mollick (2010) find that oil price fluctuations have an effect on the exchange rates between the U.S. and net oil exporting countries; identifying that oil price increases weaken the U.S. dollar against countries such as Canada, Mexico and Russia.

Mollick and Assefa (2013) use GARCH and MGARCH-DCC models to assess the dynamic correlations amongst several U.S. stock indexes, oil price returns and several macroeconomic and financial variables; they use daily data from January 1999 to December 2011 and consider three subsamples to differentiate these effects: before, during, and after the 2008-2009 financial crisis. They find that the relationship amongst these variables changed after the financial crisis; during the pre-financial crisis the conditional correlations between stock returns and oil prices changes is slightly negative, switching to positive after the financial crisis, highlighting the changing correlations between stock markets and oil.

A few studies investigate the effects of oil prices on oil exporting countries and include some Latin American countries in their sample. Wang et al. (2013) use the Vector Auto

Regression Framework (VAR) to study the reaction of oil-exporting and oil-importing countries to price shocks of oil. They use monthly data from January 1999 to December 2011 of nine oil-importing countries and seven oil-exporting countries including Mexico, Venezuela and Canada. They identify that the shocks depend on the importance of oil to the national economy of each country, shocks are stronger and longer for oil-exporting countries than for oil-importing countries, and oil-exporters tend to move together during these shocks.

Ghorbel et.al. (2013) also use monthly data, from January 1997 to June 2011, to identify shocks and contagion between the oil and stock markets. They find evidence of herding contagion during the U.S. financial crisis period of 2008-2009, between oil prices and 22 oil-importing and exporting countries that include Argentina and Brazil. Sadorsky (2014) models the volatility and correlations between oil, copper and wheat and an index made of 21 emerging market stock prices, which include Brazil, Chile, Colombia, Mexico and Peru. His daily data spans from January 2000 to June 2012 and he finds evidence of long-term volatility spillovers from oil to emerging markets.

Jubinski and Lipton (2013) use a GARCH model to study the relationship between the West Texas Intermediate (OilWTI), Gold and Silver prices, and the CBOE Volatility Index (VIX) from January 1990 to December 2010. They find that oil has a negative and statistically significant relationship with the VIX, and that this relationship increases during recessionary periods.

Several authors such as Dennis et. al. (2006), and Mollick and Assefa (2013) have documented that increases in perceived U.S. market volatility, represented by the VIX, have a negative effect on U.S. stock returns. In our previous chapters, we also identified that these effects expand beyond the U.S. indicating that increases in expected market volatility in the U.S., as represented by the VIX, have inverse effects on Canadian and Latin American stock returns.

A number of studies investigate the evolution of co-movements amongst Latin American stock markets over the past two decades, as well as their interdependence with the U.S. stock market. Most studies find evidence of increased co-movements, although the speed and magnitude of these increases varies between countries, but begin to question the risk diversification potential of investing in Latin America (Chen, Firth, & Rui, 2002; Araujo, 2009; Lahrech and Sylwester, 2011).

Mellado and Escobari (2015) investigate the Latin American Integrated Market, also known as MILA for its name in Spanish (Mercado Integrado Latino Americano), and its effects on the Chilean, Colombian and Peruvian stock markets. They find increased levels of conditional correlations between stock returns after the creation of MILA.

We expect that increases in the expected U.S. market volatility (VIX) will have a negative effect on the stock returns of the major oil producing countries in the Americas. We also expect that the findings from Mollick and Assefa (2013) will expand to other oil producing countries in the Americas, that is: that the 2008-2009 financial crisis will have a long lasting effect on the increased relationship between oil prices and stock market returns form oil producing countries in the Americas. We also expect for the VIX to Oil correlation to be dynamic and for it to strengthen during the financial crisis.

4.3. Data and empirical results

The country specific data used in this chapter consists of daily closing indexes, in U.S. Dollars, from January 1, 2002, through December 31, 2015, for six (6) top oil-producing countries in the Americas. The data set, obtained from DataStream, consists of the primary local stock indexes from Brazil (BOVESPA), Canada (S&P/TSX Composite Index), Colombia (IGBC), Mexico (BOLSA), and the United States (S&P 500 index). We use the CBOE Volatility Index® (VIX) as a proxy of implied market volatility, and use the oil price per barrel West Texas Intermediate (OilWTI), obtained from DataStream, to represent the price of oil.

We follow Mollick and Assefa (2013) and define the financial crisis period from January 1, 2008 to June 30, 2009. Since we are assessing the impact of the financial crisis on the relationship between stock market returns, oil price returns, and the VIX, we analyze three sub-periods. The first period runs from January 1, 2002 to December 31, 2007, and we identify it as the "pre-crisis period". The "crisis period" begins on January 1, 2008 and continues until June 30, 2009, the third period runs from July1, 2009 to December 31, 2014, and we define it as the "post-crisis" period.

Figure 4.1 includes the daily closing prices of the five stock markets, oil, and VIX during the pooled sample. We observe that during the pre-crisis period, all stock indexes and oil had an upward trend. We also observe a sharp decrease for all stock indexes and oil during the crisis period and a reverse and general upward trend for most countries during the post-crisis period. We also observe that the VIX has a dramatic increase during the 18-month length of the U.S. financial crisis and that volatility tends to decrease afterwards.

Figure 4.2 presents the daily returns for all six stock market indexes, oil, and first differences in market volatility (VIX). We observe increased volatility during the 2008-2009 financial crisis for all series, motivating us to use a GARCH model in this study.

Table 4.1 contains the descriptive statistics both in levels and in returns/differences. For the data reported in levels, we observe that the Shapiro-Wilk test statistic indicates non-normality and the Ljung–Box test statistics indicate significant autocorrelation.

For the data reported in returns, we observe that Colombia has the highest mean returns at 0.048, followed Mexico at 0.035, with close standard deviations at 1.646 and 1.584 respectively. On the other hand, Brazil and Canada have similar mean returns at 0.017 and 0.018 in that order, but Brazil has higher standard deviation at 2.006, than Canada at 1.374. In the case of the U.S., we observe that it has the lowest mean return at 0.016 as well as the lowest standard deviation at 1.228. We observe that the Shapiro-Wilk test statistic indicates non-normality. The results for the Ljung–Box test indicate autocorrelation for all series. The mean returns are all positive for all series and the change in VIX is negative.

Table 4.2 presents the unconditional correlation for the series, expressed in returns and differences, for the pooled sample. We observe that the correlations with the changes in VIX are negative as expected, from a high of -0.2046 for Oil, -0.3235 for Colombia, -0.4932 for Brazil, -0.5820 for Mexico, -0.5850 for Canada and -0.8272 for the U.S. The pairwise correlations between U.S. returns and other countries is positive ranging from 0.3051 for Colombia, 0.5439 for Brazil, 0.6847 for Canada and 0.6666 for Mexico. The correlations between OilWTI range from a low of 0.2160 with the U.S., 0.2556 For Mexico, 0.2602 for Colombia, 0.2954 for Brazil and 0.4266 for Canada.

Table 4.3 includes the results of the unit root tests performed to the stock indexes and oil prices expressed in returns, and the VIX expressed in first differences. We perform the standard ADF, KPSS, and Philips-Perron tests and conclude that these series are stationary.

4.4 Intertemporal Relationship of Oil, VIX and Stock Returns

We employ a standard vector autoregressive model (VAR) to test the intertemporal relationship between stock returns, oil returns and changes in VIX. This method allows us to test the responses of stock returns to oil and ΔVIX innovations (shocks), and to capture the short-run dynamics amongst variables. We begin our analysis by verifying the order of integration of the variables, since the VAR model requires that the variables be of the same order to perform the causality tests. We review the results from the ADF, KPSS and Phillips-Perron tests reported on Table 4.3, and conclude that all the series are stationary, proceeding with the estimation of the VAR model.

The VAR estimation begins by determining the lag length for each variable to be included in the model, by using four selection-order statistics: we first compute the final prediction error (FPE) followed by the Akaike's information criterion (AIC), the Hannan and Quinn information criterion (HQIC), as well as the Schwarz's Bayesian information criterion (SBIC), determining that four lags are appropriate. Appendix A includes the selection-order statistics for the VAR analysis.

The vector autoregressive model is of the following form:

$$(OilWTI)_t = \propto_{2_0} + \sum_{n=1}^{N} \propto_{2_{2n}} (OilWTI)_{t-n} + \sum_{n=1}^{N} \propto_{2_{3n}} (VIX)_{t-n} + \sum_{n=1}^{N} \propto_{2_{1n}} r_{t-n} + e_{2t}, \quad (4.1)$$

$$(VIX)_t = \propto_{3_0} + \sum_{n=1}^{N} \propto_{3_{2n}} (OilWTI)_{t-n} + \sum_{n=1}^{N} \propto_{3_{3n}} (VIX)_{t-n} + \sum_{n=1}^{N} \propto_{3_{1n}} r_{t-n} + e_{3t}, \quad (4.2)$$

$$r_t = \propto_{1_0} + \sum_{n=1}^{N} \propto_{1_{2n}} (OilWTI)_{t-n} + \sum_{n=1}^{N} \propto_{1_{3n}} (VIX)_{t-n} + \sum_{n=1}^{N} \propto_{1_{1n}} r_{t-n} + e_{1t}, \quad (4.3)$$

With:

$$r_t = \left(r_{Canada,t}, r_{Colombia,t}, r_{Mexico,t}, r_{Peru,t}, r_{US,t} \right)'$$

The ordering of this model runs from the most exogenous (OilWTI) to the most endogenous (stock returns), with VIX in between. Where r_t is the vector of stock returns at time *t*, $(OilWTI)_t$ are the oil returns at time *t*, $(VIX)_t$ are the changes in VIX at time *t*. $(OilWTI)_{t-n}$, $(VIX)_{t-n}$ and r_{t-n} , are lags of oil returns, the changes in *VIX* and stock returns at time *t-n*. $\propto_{1_0}$ is a vector of constant terms and e_{1t} is a vector of error terms.

We investigate the contributions of shocks on changes in VIX, and oil returns to the fluctuations in stock returns. To do this, we extract the forecasted error variance decompositions and the generalized impulse functions, using asymptotic normal approximations.

Table 4.4 reports the variance decomposition of the VAR model for Brazil. We report the results at 1,3, 5 and 7 days, observing only minor changes after the fifth day. Since we identify that results are unchanged after 7 days, we proceed to report them as ∞ to represent long-term effects. We find that after 7 days, shocks in oil price returns, ΔVIX, and changes in Brazil stock returns are able to explain, respectively, 8.54%, 22% and 69.46% respectively of the variance of Brazil's stock returns. Since we use daily data and identify long-term effects after 7 days, we describe the long-term effects for the subsequent tables.

Table 4.5 reports the variance decomposition of the VAR mode for Canada. In this case, we find that shocks in oil price returns, and ΔVIX, account for 17.94% and 30.14% respectively, of Canada's stock returns variance, with shocks to Canada's returns explaining its own stock returns.

Results for Colombia are reported on Table 4.6 We identify that shocks in Colombia's stock returns explain 81.56% of the variance of Colombia's stock returns, while shocks on oil price returns and ΔVIX account for 6.51% and 11.90% respectively. For Mexico, we find on

Table 4.7 that shocks to Mexico's stock returns account for 61.69% of the variance, while shocks to ΔVIX explain 32.06% and shocks on oil returns explain 6.26%.

Table 4.8 indicates that shocks to U.S. stock returns explain 30.98% of U.S. stock returns variance, while shocks to ΔVIX explain 63.86%, and shocks to oil price returns 5.16%. These results highlight the impact of shocks to ΔVIX, on the stock returns of the U.S. and the rest of the oil producers. We notice that; the larger the market cap and oil production (U.S., Canada, Mexico, Brazil), the larger the proportion of the stock returns variance that can be explained by shocks to oil price returns and ΔVIX.

We also identify in all cases, oil price returns are explained by shocks on oil prices at about 98% to 99%, that shocks to ΔVIX only explain about 1%, and shocks to stock returns explain less than 1%. For the variance in ΔVIX, we find that shocks on ΔVIX can explain about 94% to 95% of the variance, while shocks on oil price returns account for about 4% to 5%, and shocks to stock returns account for less than 1%.

We then obtain the graphical representation of the impact of shocks on the OilWTI returns and ΔVIX, by the impulse response functions (IRFs). Figures 4.3-4.7 include the impulse responses to one standard deviation increase in oil price returns as well as the impulse responses to one standard deviation increase to ΔVIX. In all cases, we identify that: stock returns react positively to shocks on stock returns, that shocks in oil price returns result in positive stock returns, and shocks to changes in VIX have negative effects on stock returns.

Figure 4.3 includes the impulse responses to one standard deviation increase to Brazil, OilWTI and ΔVIX. We focus on the responses of Brazil to the shocks to itself, changes in oil prices and changes in VIX. We first identify that stock returns react positively to shocks on itself, with a 1% increase in stock returns shock leads to about a 1.6% increase in stock returns, and this effect disappears after one week. We also find that shocks in oil price returns result in positive stock returns, with a 1% shock increase in oil price returns resulting in stock return increases of about 0.7%, and these effects also disappear after one week. The figure also shows that shocks to changes in VIX have a negative effect on stock returns, with a 1% shock increase resulting in a 1% decrease in stock returns, and disappearing after 2 weeks.

Figure 4.4 includes the impulse responses to one standard deviation increase to Canada, OilWTI and ΔVIX . We find that a shock of 1% increase in Canadian stock returns, results in a 1% increase in Canadian stock returns. Results indicate that a shock of 1% increase in oil price returns will result in an increase of about 0.6% stock returns, and that a similar shock to changes in VIX will result in a 0.8% decrease in stock returns. In the three cases, the effects of those shocks dissipate after two weeks.

Figure 4.5 represents the impulse responses to one standard deviation increase to Colombia, OilWTI and ΔVIX. Results indicate that a shock of 1% in stock returns, will result in an increase of about 1.5% in Colombian stock returns. Similar shocks in oil price returns and changes in VIX will result in increases of 0.5% and decreases of -0.4% respectively. Shocks to stock returns and oil price returns will dissipate in one week, and shocks to changes in VIX will dissipate in two weeks.

Figure 4.6 reports the impulse responses to one standard deviation increase to Mexico, OilWTI and ΔVIX. We find that shocks of 1% to stock returns, oil price returns, and ΔVIX, will result in changes in stock returns of 1.2%, 0.4% and -1 % respectively. Furthermore, these shocks dissipate in 1 week for stock returns and oil price returns, taking 2 weeks to dissipate for ΔVIX.

Figure 4.7 reports the impulse responses to one standard deviation increase to U.S., OilWTI and ΔVIX. Results indicate that 1% shocks to U.S. stock returns result in positive increases of 0.8% on U.S. stock returns. Similar shocks to oil price returns will result in increases of about 0.25%, and shocks to ΔVIX will result in U.S. stock return decreases of 1%.

In order for our results to be valid, the system VAR equations must be stationary and the model stability conditions, which require the moduli of the eigenvalues of the dynamic matrix to lie within the unit circle, must hold. Failure to meet these stability conditions would result in shocks that would not dissipate, causing permanent effects and spurious VAR results. We include the results from the eigenvalue stability condition tests on Appendix B. Our tests indicate that for all series, the eigenvalues lie inside the unit circle, and that each of the VAR models satisfies the stability condition.

4.5. The DCC model and estimation results

Since we find that shocks to oil price returns, and shocks to ΔVIX, influence the stock returns of the major oil producing countries in the Americas; we are interested in identifying the dynamic influence of the U.S. financial crisis on the relationship between oil price returns, ΔVIX, and stock returns.

We use the Dynamic Conditional Correlation - GARCH (DCC-GARCH) model developed by Engle (2002) to measure the pairwise dynamic correlations between oil returns and the major oil producers in the Americas.

The model used is as follows:

Mean Equations: $r_{t=}\gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{OilWTI} + \gamma_3 r_{t-1}^{\Delta VIX} + \varepsilon_t$,

$$where\ \ r_t = (r_{Brazil,t}, r_{Canada,t}, r_{Colombia,t}, r_{Mexico,t}, r_{U.S.,t}\ )'$$

$$\varepsilon_t = \ (\varepsilon_{Brazil,t}, \varepsilon_{Canada,t}, \varepsilon_{Colombia,t}, \varepsilon_{Mexico,t}, \varepsilon_{U.S.,t}\ )' and\ \ \varepsilon_t \,|\, I_{(t-1)} \sim N(O, H_t.) \qquad (4.2)$$

Variance Equations: $h_{ii,t} = \omega_i + \alpha_{i,1}\varepsilon_{i,t-1}^2 + \beta_{i,1}h_{ii,t-1}, \quad for\ i = 1,2, \dots, n.$

$$q_{ij,t} = \bar{\rho}_{ij}(1 - a - b) + bq_{ij,t-1} + a\eta_{i,t-1}\eta_{j,t-1} \qquad (4.3)$$

DCC equation: $$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}\ , \quad where\ i,j = 1,2, \dots, 6.\ and\ i \neq j \qquad (4.4)$$

We apply the described DCC–GARCH to the pooled data, expanding from January 2002 to December 2015, and present the results in Table 4.4. Results for the mean and variance equations (1) and (2) are as follows: for the mean equation, the constant term, γ_0 , is positive and statistically significant for all markets, varying from a high of 0.1274 for Brazil to a low of 0.0881 for the U.S.. The AR(1) term, γ1, shows mixed results, being positive and statistically significant for Colombia at 0.0803, and negative and statistically significant for the U.S. at -0.1028 and Canada at -0.0385.

The effect γ2, representing the impact of OilWTI returns on each of the market returns, is positive and statistically significant for all countries, except Mexico, with coefficients for Brazil at 0.0306, Canada at 0.3, Colombia at 0.0209, and the U.S. at 0.0081. The effect of γ3, representing changes on the U.S. Market Volatility (VIX), is negative and significant for all countries and rages from a high of -0.135 for Mexico, followed by Canada at -0.1281, Brazil at -0.1226, Colombia at -0.1121 to a low of -0.0632 for the U.S, confirming the influence of the U.S. market volatility on these oil producers.

The table also then includes parameter estimates of the mean and conditional variance equations; the coefficients are all positive and significant, confirming the appropriate use of the GARCH (1, 1) specification. The volatility persistence (Arch + Garch coefficients) is consistently near to one (1) and as high as 0.988 for Canada and 0.987 for the U.S. to a low of 0.947 for Colombia, indicating high volatility persistence in the GARCH model.

Table 4.9 also includes the estimates for the DCC -GARCH estimates Lambda 1, and Lambda 2. We find both parameters to be statistically significant, indicating that the DCC-GARCH model is appropriate for the sample. The sum of these parameters is greater than 0.94 and less than 0.99, which indicates strong co-movement over time, and high level of persistence.

4.6. Explaining the conditional correlation coefficients

In this section, we study the impact of the U.S. Financial Crisis, on the dynamic conditional correlations between oil prices represented by OilWTI, *VIX* and the stock indexes from 6 oil producing countries. We find that changes in OilWTI prices $\gamma 2$ have a positive effect on the oil producers in the Americas, and are interested in assessing the impact of both the financial crisis and the post-crisis, on these pairwise correlations. We are also interested in asesing the pairwise correlations between these oil producers and the U.S. market volatility (VIX).

One of the advantages of using the MGARCH-DCC model is that we are able to obtain all possible dynamic pairwise correlations between *VIX*, OilWTI with each of the stock markets, as well as all possible pairwise correlations between the stock markets. Figures 3, 4 and 5 include the pairwise conditional correlations between OilWTI, the U.S. and *VIX* with the oil producer, in which we observe the changing nature of these correlations, and how they seem to follow different patterns due to the U.S. Financial Crisis. We build an empirical regression model, presented on equation 4, to analyze the conditional correlation dynamics.

$$\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DV1_t + \lambda_2 DV2_t + \epsilon_t, \text{ for } i \neq j \tag{4.5}$$

The dependent variable $\hat{\rho}_{ij,t}$ represents the predicted conditional correlation by the DCC-GARCH between markets *i* and *j* at time *t*. We then include two dummy variables; $DV1_t$ is the dummy variable for the financial crisis (January 1, 2008 to June 30, 2009), and $DV2_t$ is the dummy variable for the post-crisis period (July 1, 2009 to December 31, 2015). Each dummy variable is set equal to one for each of the periods and zero otherwise.

We regress the dynamic conditional correlation coefficients on the dummy variables, for the financial crisis and post-financial crisis periods, and omit the pre-financial crisis period. By omitting the pre-financial crisis period, and including the constant λ_0, we are able to capture the dynamic properties of the correlations, and the effects of each period relative to the pre-financial crisis.

The estimation results of the regressions, for all possible pairwise correlations, are included in Table 4.10. We first report on Table 4.10A, the regression results for the pairwise correlations between the U.S. stock returns and the other four oil producers, and partial results for the pairwise correlations between OilWTI and the oil producing countries. Table 4.5B includes the remainder of the pairwise correlations between OilWTI and the oil producers, and it reports all pairwise correlations between VIX and the oil producers.

On table 4.10A, we fist identify the regression coefficients for the pairwise correlations between stock returns of the U.S. and each of the oil producing countries. The constant term λ_0 captures the pre-crisis period, and it is positive and significant in all cases. The coefficients range from 0.2279 for Colombia, 0.4897 for Brazil, 0.6045 for Canada and 0.6176 for Mexico, indicating a high correlation during the pre-crisis period. The estimates of λ_1 capture the effects of the financial crisis period, indicating that the co-movements increased significantly for each pair, which is evidence of contagion.   The estimates are all positive and significant, and range from 0.0577 for Canada, 0.1113 for Brazil, 0.1144 for Mexico, to 0.1382 for Colombia. The effect of the post financial crisis λ_2 is also positive and significant, indicating that all pairwise correlations are significantly higher during the post-crisis period than the pre-crisis period. The coefficients are larger than the financial crisis in the cases of Canada at 0.1127, and Colombia at 0.1671, and lower for Brazil-U.S. at 0.085 and Mexico-U.S. at 0.599. We find evidence of contagion during the U.S. financial crisis, from the U.S. to the four oil-producing countries, and observe that the contagion persists during the post-crisis period.

Since we identify that there is evidence of contagion, from the U.S. to the four oil producers, we investigate oil prices as a source of contagion. On tables 4.10B we report the correlations between OilWTI and each country, observing that the constant term λ_0 is positive and significant, indicating that for the pre-crisis period, each of the stock markets from the four oil-producers move in the same direction as oil prices do. The coefficients range from 0.1255 for Colombia, 0.1283 for Mexico, 0.1618 for Brazil to 0.3135 for Canada. We also identify that in the case of the U.S., λ_0 is also positive and significant, with a coefficient of 0.0635. The effect of the financial crisisλ_1, is also positive and significant for all countries, including the U.S. with coefficients ranging from 0.0309 for Mexico, 0.0635 for the U.S., 0.1139 for Canada, 0.1623 for Brazil ad 0.176 for Colombia. The increased correlations indicate contagion, during the U.S. financial crisis, from oil prices to each of the oil producers. The effects of the post financial crisis λ_2 are positive and significant in all cases and with greater coefficients than those of observed during the crisis. The coefficients for λ_2 range from 0.162 for Canada, 0.1961 for Brazil, 0.1998 for Colombia, 0.2009 for Mexico and 0.245 for the U.S., These estimates reveal that the relationship between oil prices and the oil producers continue to strengthen beyond the U.S. financial crisis.

We also observe the coefficients for the OilWTI –*VIX* relationship are negative and significant for the constant term λ_0, at -0.0852, we then observe that the financial crisis term λ_1, is also significant at -0.0575, and that the post crisis term λ_2, is higher than the crisis term at -0.1795. This indicates that the relationship OilWTI-*VIX* increases in magnitude as the U.S. financial crisis unveils, and it continues to strengthen after the crisis ended.

The last pairwise correlations are reported on table 4.10C, including *VIX* and each of the stock returns across countries. We observe that the constant term λ_0, is negative and significant for all pairs indicating a strong inverse correlation during the pre-crisis period, which ranges from -0.2461 for Colombia, -0.4303 for Brazil, -0.4976 for Canada, -0.5249 for Mexico and -0.7831 for the U.S. The effect of the financial crisis λ_1, is negative and significant for all pairs and indicates contagion, with coefficients ranging from -0.0695 for the U.S., -0.0772 for Canada, -0.0949 for Colombia, -0.1063 for Brazil and -0.1097 for Mexico.

The effect of the post financial crisis λ_2, is also negative and significant in all cases, indicating that relative to the pre-crisis period, the inverse relationship between *VIX* and each of the stock returns is stronger during the post-crisis. We observe two cases, Canada at -0.1108 and Colombia at -0.1264, where the post-crisis coefficients are greater than the corresponding coefficients for the financial crisis period. The coefficients for Mexico at -0.0552 and U.S. at -0.0492, are smaller than the crisis period, yet indicate that there was indeed an increase in the inverse correlation for these pairs, even after the crisis officially ended.

The estimation results in Table 4.10 indicate the existence of contagion during the financial crisis, from the U.S. to the oil producing countries. We investigate two sources of contagion; market volatility represented by then *VIX* and Oil prices as represented by the OilWTI prices. We confirm that significant impact of the financial crisis on increased conditional correlations between changes in the *VIX* and the stock market returns across countries. We are also able to confirm the strengthening relationship between OilWTI and the stock returns of the Oil Producing Countries, due to the financial crisis, which continues to strengthen even after the crisis, is officially over. This is of great importance, since oil is an important revenue source for all of these countries, and their stock markets seem to be paying more attention to oil price changes after the wake of the financial crisis.

4.7. Robustness Check

Since we are assessing the impact of the financial crisis on the relationship between stock market returns, OilWTI price returns, and the *VIX*, we break the pooled sample into three sub-samples. We first break the pooled sample into the periods described before, namely the pre-crisis, crisis and post-crisis period, and apply the DCC-GARCH model described on section 4.2 to each of these sub samples. Since the model does not converge for the crisis period, we consolidate the crisis and post-crisis periods, leaving us with two sample periods. For this robustness check, our Sample I runs from January 1, 2002 to December 31, 2007, right before the beginning of the financial crisis. Sample II begins on January 1, 2008 and continues until December 31, 2015, covering the crisis and post-crisis periods.

We replicate the DCC-GARCH model described on equations 1 and 2, for each of the periods and obtain the specific dynamic conditional correlations for each period. We then compare the conditional correlation coefficients and asses de degree of contagion.

Table 4.11 contains the results for the DCC GARCH for Sample I, which covers the pre-crisis period. We first report the results for the mean equations; the constant term γ_0 is positive and significant for all oil producing countries. The AR(1) term γ_1, is positive and significant for Brazil at 0.06476 an Colombia at 0.1171, negative and significant for the U.S. at -0.1001, and not-significant for Canada and Mexico. The term γ_2, representing the effect of changes in OilWTI prices, is positive for all countries, and statistically significant for all except for Colombia. The coefficients for γ_2 vary from 0.0124 for the U.S., 0.0198 for Mexico, 0.0354 for Brazil and 0.0367 for Canada. The effect of the U.S. Market Volatility (VIX) is included on γ_3, and it is negative and significant for all countries, ranging from -0.0712 for the U.S., -0.157 for Canada, -0.1669 for Mexico, -0.1752 for Brazil and -0.1825 for Colombia.

The coefficients for the parameter estimates of the mean and conditional variance equations are all positive and significant, and the volatility persistence is close to one in all cases. The DCC estimates Lambda 1, and Lambda 2 are also statistically significant, indicating that the DCC Model is appropriate.

Table 4.12 reports the DCC GARCH results for sample II. The constant term, γ_0, is positive and statistically significant for all markets, however with the exception of the U.S., the coefficients are smaller than those reported for Sample I. The AR(1) term, $\gamma 1$, shows mixed results since it is found to be negative and significant for Brazil, Canada and the U.S. and positive and significant for Colombia.

The term $\gamma 2$, representing OilWTI returns is positive for all countries, but only statistically significant for Canada at 0.0318, Colombia at 0.0351 and Brazil at 0.0373. These results seem counter intuitive, however, as we report on Table 4.13, the correlation coefficients between the pairs OilWTI-U.S. and OilWTI-Mexico, experience the largest increase from Sample I to Sample II. When we consider these results, we infer that the possible explanation is that both U.S. and Mexican stock markets, shifted from reacting to the first differences of the OilWTI prices from the previous period, to increased contemporaneous co-movements with OilWTI.

The term $\gamma 3$, represents the VIX, and it remains negative and significant for all countries, ranging from -0.0564 for the U.S., -0.089 for Colombia, -0.1113 for Canada, -0.1137 for Brazil and -0.1176 for Mexico, reflecting the influence of the U.S. market volatility in these oil producing countries.

The coefficients for the parameter estimates of the mean and conditional variance continue to be positive and significant, and the volatility persistence (Arch + Garch) is near one in all cases. The parameter estimates Lambda 1, and Lambda 2 are also statistically significant, and the sum of the parameters is greater than 0.90 indicating the appropriateness of the model.

One of the advantages of using the DCC-GARCH model is that are able to identify the long lasting effects of the financial crisis on the conditional correlations between OilWTI, *VIX*, and the stock market returns of the oil producing countries. Table 4.13 includes the DCC-GARCH based correlations, between OilWTI, VIX, and the stock market returns for the pooled sample, Sample I (pre-crisis period) and Sample II (crisis and post-crisis periods).

For the Pooled data sample, we observe that the correlation coefficients between OilWTI and the oil producers are positive and significant, ranging in descending order from 0.4184 for Canada, followed by Brazil at 0.3279. Colombia at 0.2808, Mexico at 0.2799 and the U.S. at 0.2675. We also identify that the correlation between OilWTI and *VIX* is negative and significant at a rate of -0.2115, indicating an inverse relationship between changes in oil prices and changes in market volatility. As expected, we observe that the correlation between *VIX* and the country specific stock markets is negative and significant in all cases, and not surprising; the highest correlation is that between *VIX* and the U.S. at -0.8349. The rest of the countries report correlations from -0.5865 for Canada, -0.5774 for Mexico, -0.5096 for Brazil and -0.3542 for Colombia. We then analyze the cross-country conditional correlations between the U.S. market and each of the other oil producers, observing that the highest coefficients are those with Canada, Mexico and Brazil at 0.6954, 0.6752 and 0.6031, respectively, trailing by Colombia at 0.392.

We compare the pairwise correlations for both sub-samples. We fist analyze the results for Sample I, representing the pre-crisis period. We observe that the pairwise correlations between OilWTI and the stock markets are only significant for Brazil at 0.1648 and Canada at 0.3472. The coefficients for the pairwise correlations between *VIX* and each stock index are negative and significant in all cases, ranging from -0.8677 for the U.S., -0.6975 for Mexico, -0.6033 for Brazil, -0.566 for Canada and -0.3458 for Colombia. The cross country correlations between the U.S. and each of the studied countries is positive and significant in all cases, ranging from 0.7642 for Mexico, 0.6962 for Brazil, 0.65 for Canada and 0.3713 for Colombia. These results shade light to the strong relationship between the largest stock markets in the Americas, and the influence of the U.S. market returns and U.S. market volatility on the stock returns for each of them prior to the U.S. financial crisis.

The last section of table 4.13, includes the correlation coefficients for Sample II, which captures the period following the beginning of the financial crisis, and it includes the post finical crisis period as well.

We observe that the correlations coefficients between OilWTI, and each of the oil producers is positive and significant. During this sample period, the coefficients range for a high of 0.533 for Canada, 0.4526 for Brazil, 0.4282 for the U.S., 0.4194 for Mexico and 0.4058 for Colombia. These observations are in line to the findings of Mollick and Asseffa (2013), since the correlations between the OilWTI and the U.S. have negative and not statistically significant relationships during the pre-crisis period, yet they change to positive and significant for the period that includes the financial crisis. We observe similar results for Brazil, Colombia and Mexico. These findings highlight the substantial influence of the financial crisis, on the correlations between OilWTI and each of the oil producing countries, indicating contagion.

For the pairwise correlations between *VIX* and each of the stock markets, we observe that the coefficients are negative and significant. When contrasting the coefficients from Sample II and Sample I, we notice that the coefficients for Canada (-0.648) and Colombia (-0.4423) are greater during sample II, and are reduced for the U.S. (-0.8492), Brazil (-0.5466), and Mexico (-0.6118). We then review the pairwise correlations between the U.S. and each of the stock markets, and observe that for Canada (0.7564) and Colombia (0.4927) the coefficients increase in magnitude, and that for Brazil (0.6497) and Mexico (0.7125), the coefficients are reduced.

These results highlight the significant increase in influence between oil prices and stock returns from all oil producing countries because of the U.S. financial crisis. Since we are not able to separate the crisis and post-crisis periods, we are not able to distinguish the intra-sample II differences for the pairwise correlations between *VIX*-Stock and U.S.-Stock. However, we observe that the post-crisis period reports higher correlations than the pooled data sample in all cases, prompting us to review our findings from the robustness test with our results from section 4.5. When comparing the results from the robustness check with the results from Table 4.5A, we observe that for the pairs *VIX*-Stock and U.S.-Stock, the correlation coefficients of the crisis dummy variable are significantly higher than the dummy variable for the pre-crisis period, indicating a strong contagion during the financial crisis followed by a reduced correlation during the post-crisis period. At the same time, we observe that the relationship between these two countries and OilWTI increased significantly during this period.

A new strand of literature distinguishes demand and supply shocks in the oil market to explore their effects on the U.S. economy and the real price of oil (Kilian, 2008; Kilian, 2009; Kilian and Park, 2009). These studies use monthly data that includes measures of global real activity to capture demand, global oil production to compute supply, real prices of oil imported by the U.S., as well as aggregate U.S. stock returns. We are not able to assess these differences in this study since we use daily data but we will consider using monthly data in future research.

4.8. Summary and Conclusions

We employ VAR and DCC-GARCH models to study the influence of the 2008-2009 financial crisis on the relationship between oil price returns (OilWTI), U.S. market volatility (VIX), and the stock market returns of five of the largest oil-producing countries in the Americas.

Our sample includes daily closing prices from January 1, 2002, through December 31, 2015, of five major oil-producing countries in the Americas including: Brazil (BOVESPA), Canada (S&P/TSX Composite Index), Colombia (IGBC), Mexico (BOLSA), and the United States (S&P 500 index). To measure the U.S. implied market volatility we use the CBOE Volatility Index® (VIX) and use the oil price per barrel West Texas Intermediate (OilWTI), to represent the price of oil.

We test the effects of shocks to changes in VIX and oil returns, on stock returns from the principal oil producers in the Americas, by using VAR models. We find that shocks to VIX have short-run negative effects on stock returns, followed by a reversal and eventual dissipation of the effects by the fifth day. In the case of shocks to OilWTI, we identify that shocks to OilWTI will result in increases on stock returns of all oil producers and that the magnitude of these reactions to shocks is directly related to the market cap and oil production of the oil producers. Overall, we confirm the influence of shocks to VIX and OilWTI on the stock returns of oil producers in the Americas.

To assess the dynamic relationship between oil price returns, changes in VIX and stock returns, we employ the DCC-GARCH for the pooled data and obtain the pairwise dynamic conditional correlations between OilWTI, *VIX*, the U.S. Brazil, Canada, Colombia and Mexico. We then regress these pairwise dynamic conditional correlation coefficients with two dummy variables, representing the financial crisis and post-financial crisis periods. We are able to capture the effects of each period, on each pairwise conditional correlation, relative to the pre-financial crisis.

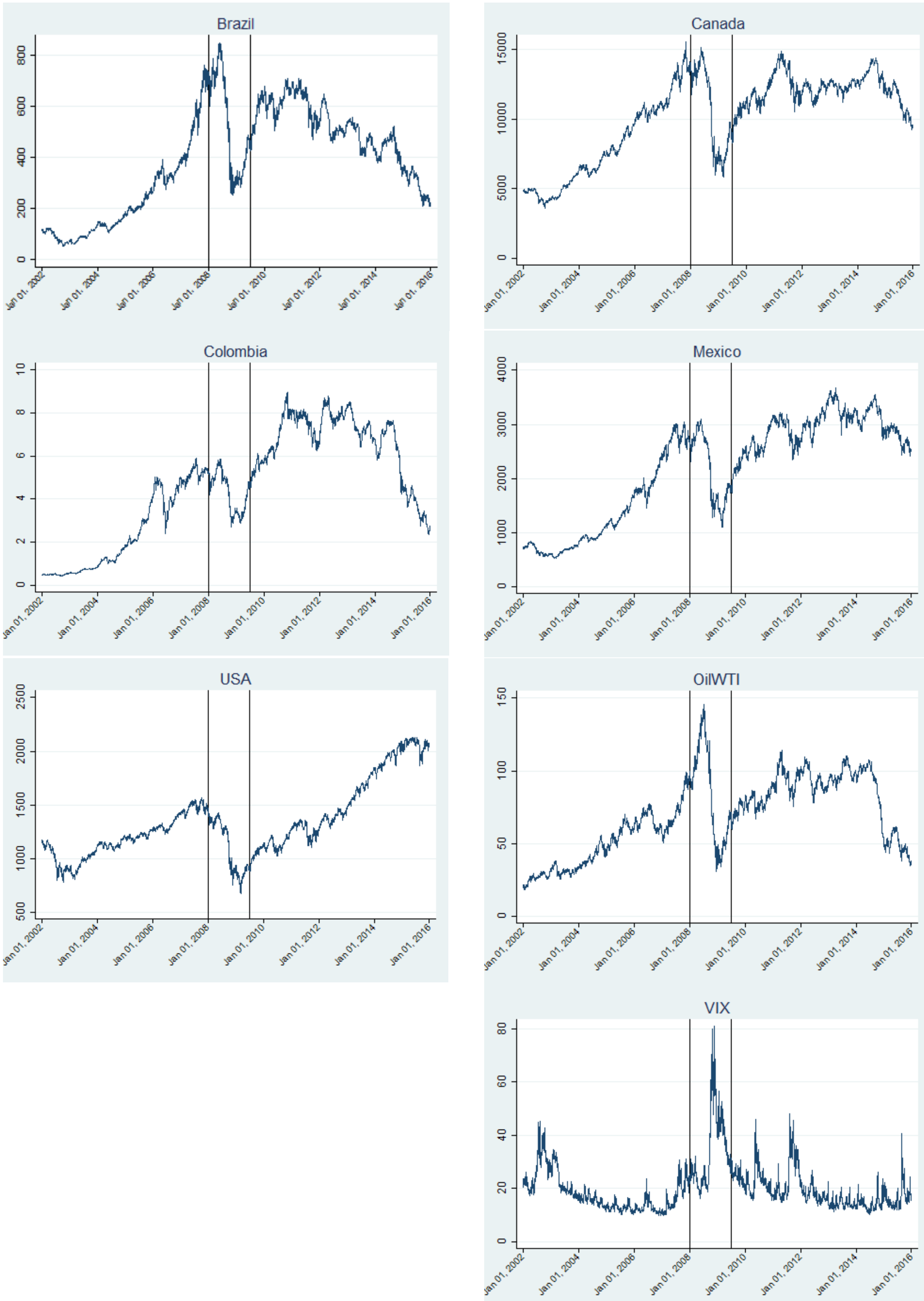
Our findings suggest that the U.S. financial crisis had a positive, statistically significant, and long-lasting effect on the correlation between oil price returns (OilWTI) and the stock returns of the largest oil producers in the Americas. We observe significant increase during the financial crisis, and identify that coefficients remained higher than the pre-crisis period, but slightly lower than that of the crisis period.

We also identify increase correlation coefficients between the U.S. and the other oil producers, due to the financial crisis, indicating the existence of contagion. We find a similar pattern, but with negative sign, for the pairwise correlations between the VIX and the stock markets, indicating the role of the U.S. stock market volatility on this contagion.

We conduct a robustness check by breaking the pooled data into two samples; Sample I, includes the pre-crisis and Sample II includes both crisis and post-crisis periods. We then apply the DCC GARCH model for each period, compare the generated conditional correlations for each sample, and find evidence of contagion. We find that during the pre-financial crisis period, the correlation between the OilWTI and the stock returns is positive and significant only for Brazil and Canada. We find that the correlation between OilWTI and the U.S has a slight negative, but not significant coefficient. The correlation coefficients between OilWTI, Colombia and Mexico are positive but not significant. For the post-crisis period, we find that all pairwise correlations between OilWTI and the oil producing countries are positive and significant, confirming the influence of oil price changes on the stock returns of oil producers in the Americas after the financial crisis.

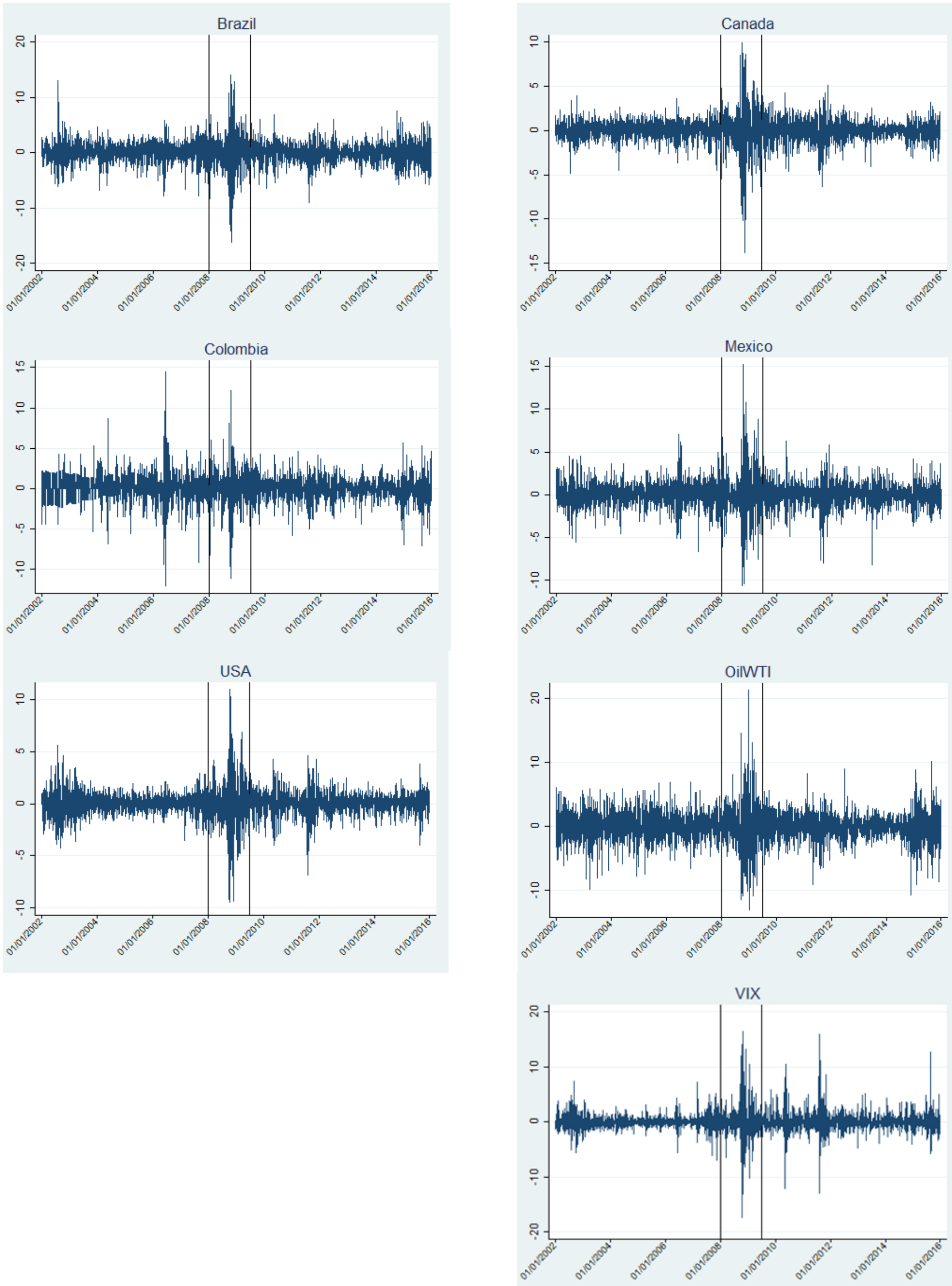
Our contribution to the literature is identifying how the U.S. financial crisis significantly changed the relationship between oil price returns, and the stock returns from the major oil producers in the Americas. We observe that before the U.S. financial crisis, the oil producing countries are highly influenced by the performance and volatility of the U.S. financial markets, and that this relationship is strengthened during the financial crisis, continuing to be strong after the financial crisis ends. We then identify that with the exception of Brazil and Canada, the relationship between oil price returns and the stock returns from the oil producers is not significant before the financial crisis. We also find that it is only after the financial crisis begins, that oil price returns influence significantly the stock markets of the oil producers, and this influence continues even after the crisis ends.

Figure 4.1
Daily Closing Prices – Stock Markets.



Note: Vertical lines represent the beginning and ending of the 2008-2009 financial crisis according to NBER.

Figure 4.2
Daily Stock Returns and Calculated Changes or Differences.



Note: Vertical lines represent the beginning and ending of the 2008-2009 financial crisis according to NBER.

Figure 4.3

Impulse Responses to One Standard Error Shocks to Brazil, OilWTI and ΔVIX.

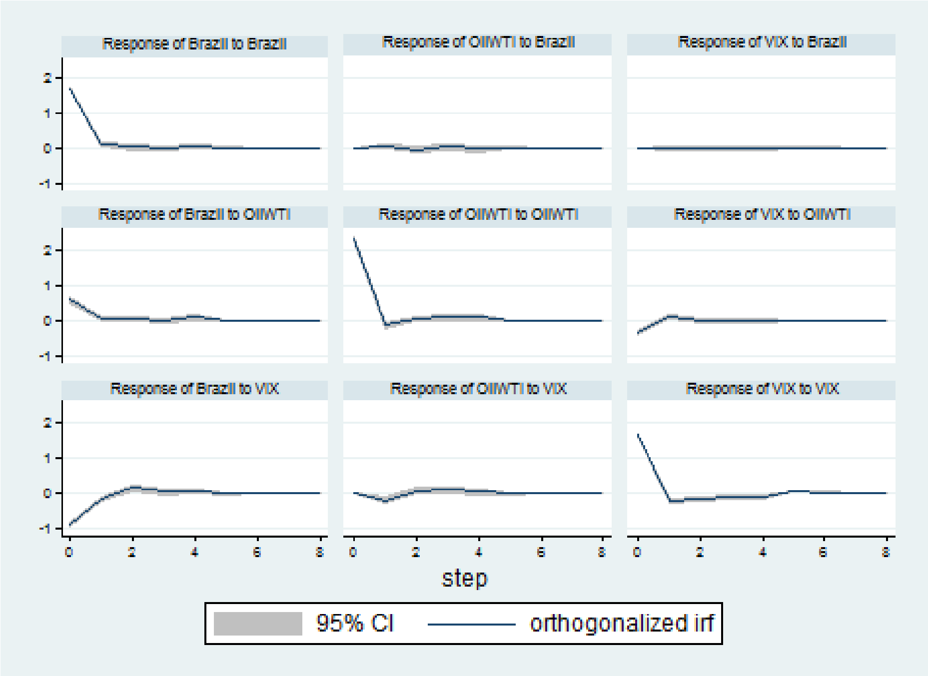


Figure 4.4

Impulse Responses to One Standard Error Shocks to Canada, OilWTI and ΔVIX.

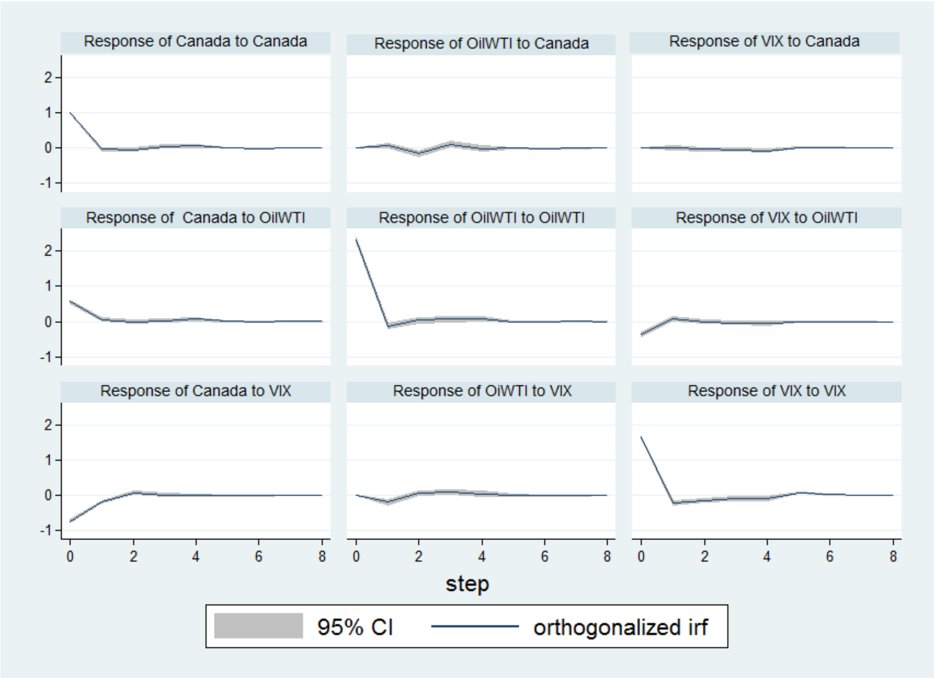


Figure 4.5
Impulse Responses to One Standard Error Shocks to Colombia, OilWTI and ΔVIX.

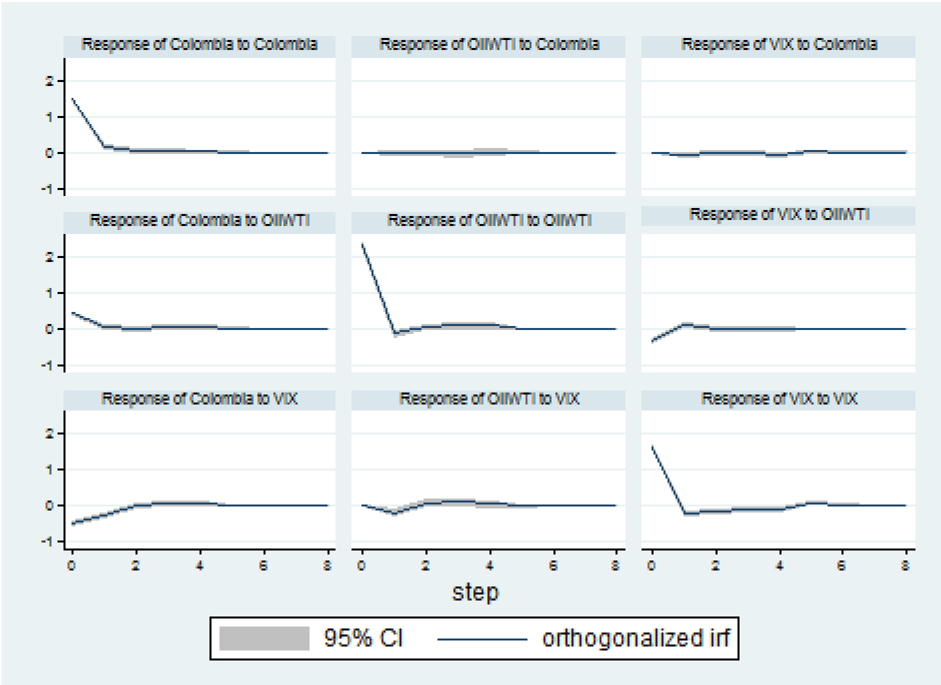


Figure 4.6
Impulse Responses to One Standard Error Shocks to Mexico, OilWTI and ΔVIX.

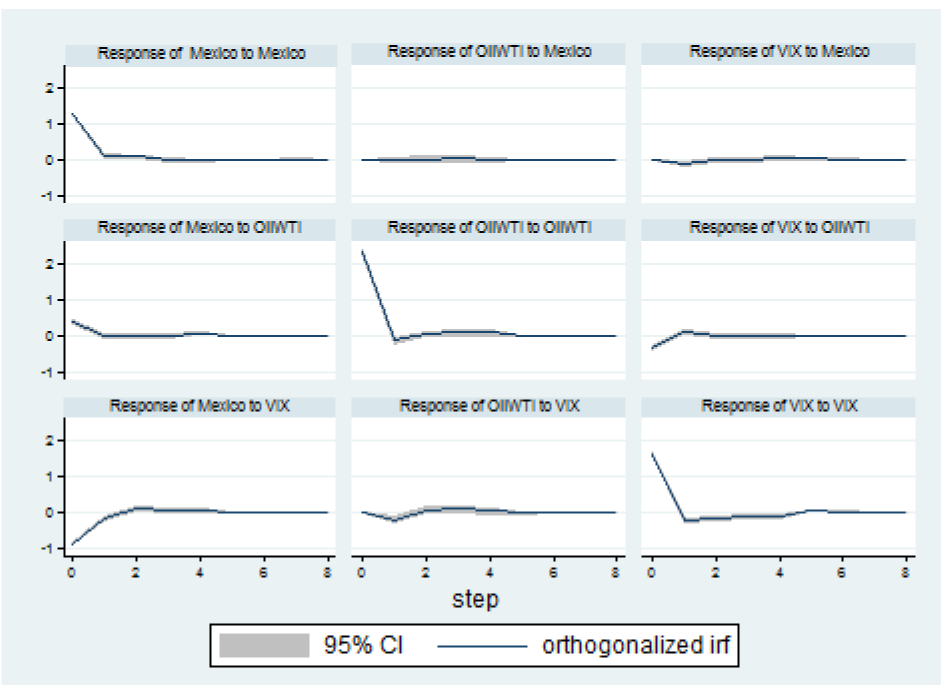


Figure 4.7
Impulse Responses to One Standard Error Shocks to U.S., OilWTI and ΔVIX.

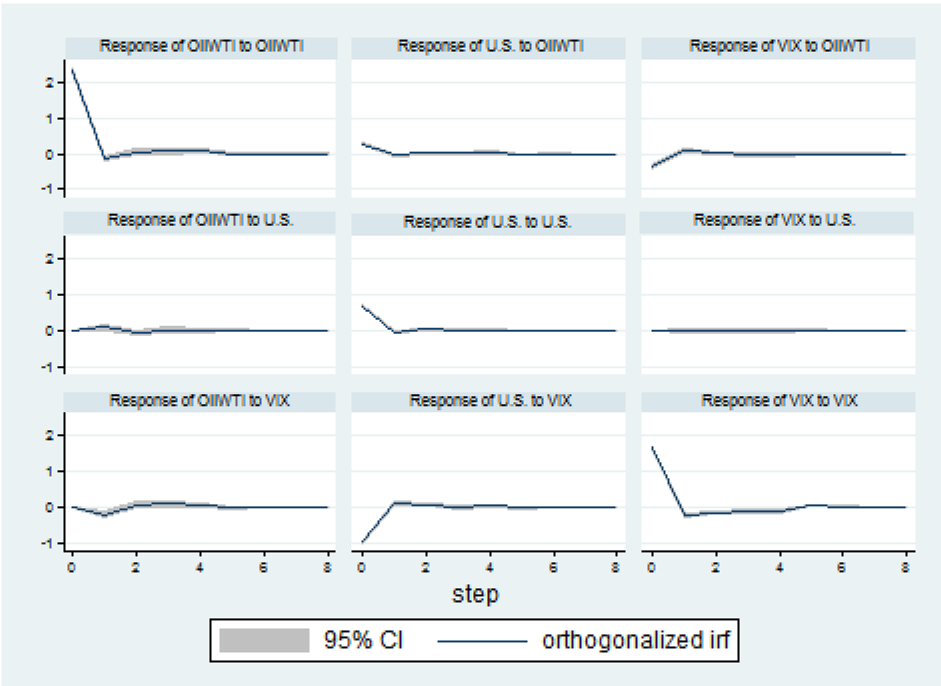
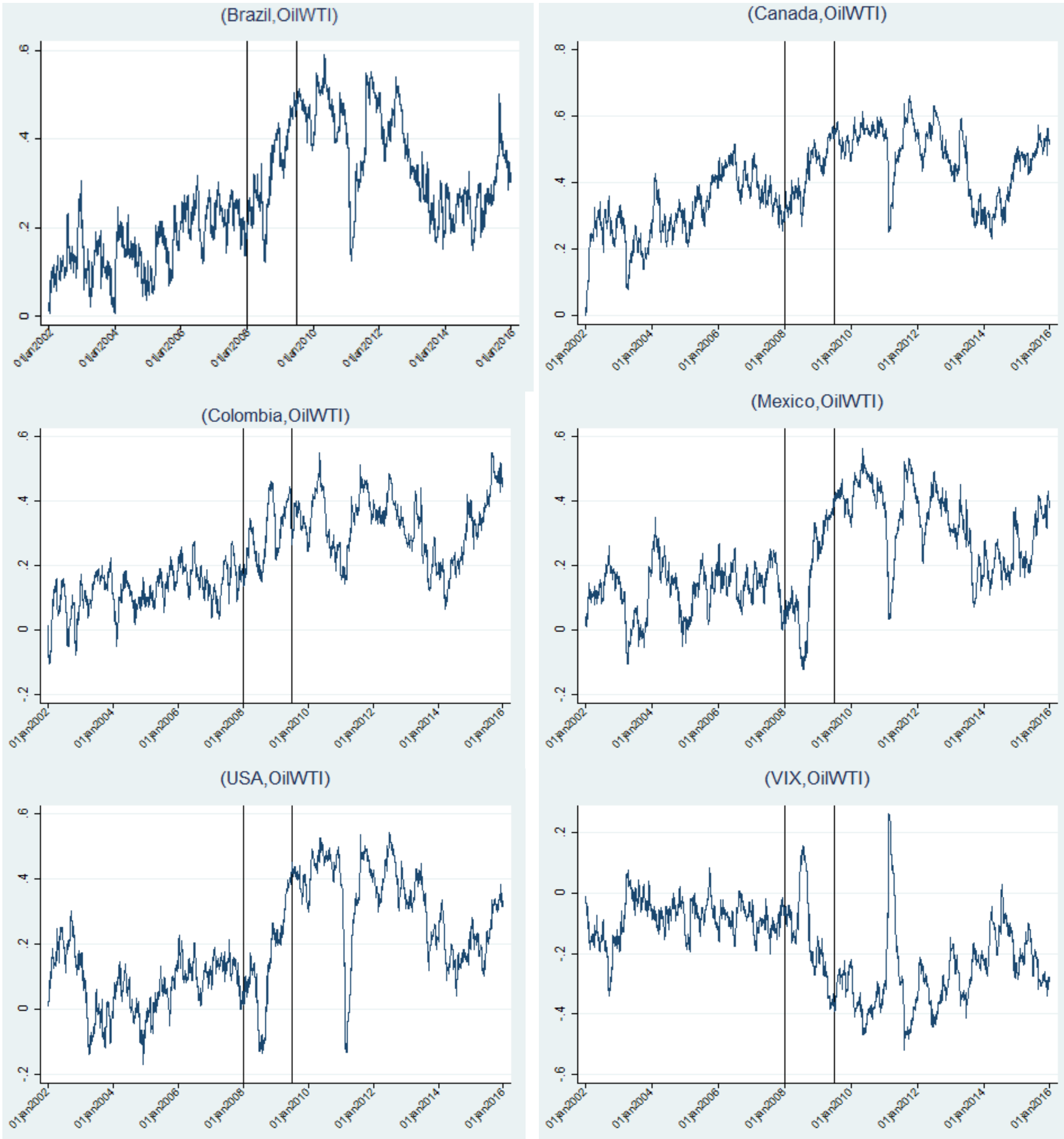


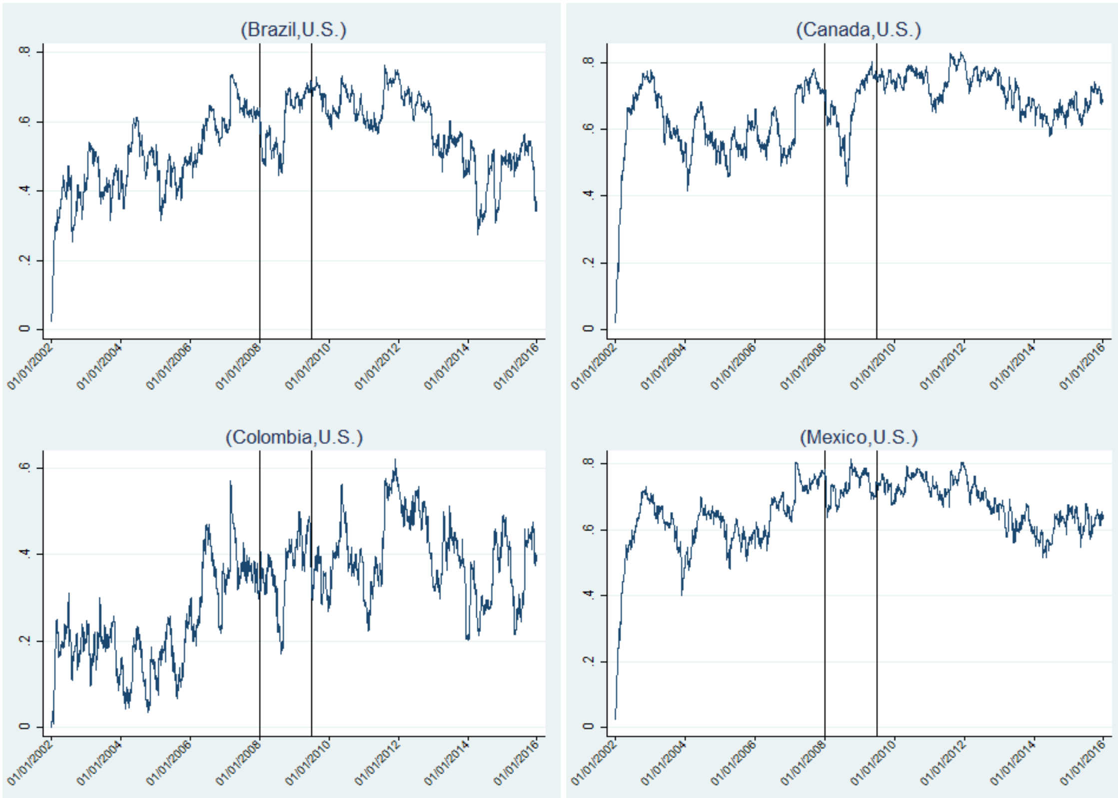
Figure 4.8
Dynamic Conditional Correlations Between OilWTI and Oil Producers.



Note: Vertical lines represent the beginning and ending of the 2008-2009 financial crisis according to NBER.

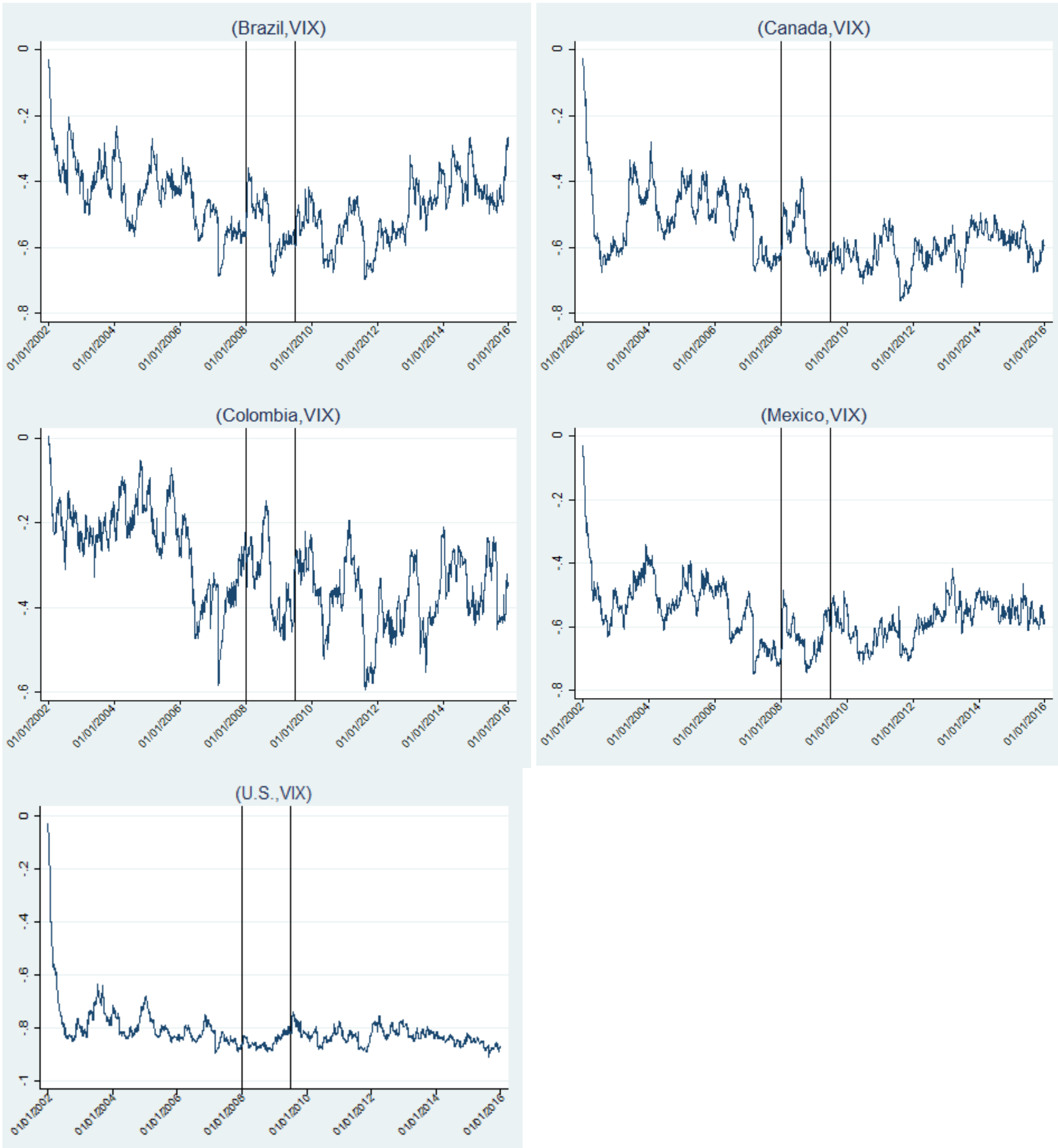
Figure 4.9

Dynamic Conditional Correlations Between U.S. and Other Oil Producers.



Note: Vertical lines represent the beginning and ending of the 2008-2009 financial crisis according to NBER.

Figure 4.10
Dynamic Conditional Correlations Between VIX and Oil Producers.



Note: Vertical lines represent the beginning and ending of the 2008-2009 financial crisis according to NBER.

Table 4.1
Descriptive Statistics (Daily Data from Jan. 2002 to Dec. 2015).

Levels	Brazil	Canada	Colombia	Mexico	U.S.	OilWTI	VIX
Observations	3653	3653	3653	3653	3653	3653	3653
Mean	391.213	10192.22	4.553	2169.874	1333.98	68.822	20.095
Standard Dev.	202.438	3067.304	2.56	936.785	340.325	26.93	9.157
Variance	40980.93	9408356	6.555	877565.3	115821	725.25	83.845
Skewness	-0.028	-0.6	-0.189	-0.43	0.786	0.047	2.213
Kurtosis	1.88	2.105	1.783	1.722	2.88	2.078	9.919
Shapiro-Wilk (Normality)	11.60***	13.43***	12.78***	13.89***	13.06***	10.85***	15.65***
Ljung-Box test (Auto Correlation)	139,600***	138,600***	141,200***	141,000***	139,300***	133,800***	104,000***

Return/Differenced

	RET_BRA	RET_CAN	RET_COL	RET_MEX	RET_U.S.	RET_OilWTI	VIX_CHG
Observations	3653	3653	3653	3653	3653	3653	3653
Mean	0.017	0.018	0.048	0.035	0.016	0.017	-0.002
Standard Dev.	2.006	1.374	1.646	1.584	1.228	2.346	1.714
Variance	4.025	1.887	2.708	2.508	1.508	5.504	2.936
Skewness	-0.301	-0.77	-0.431	-0.093	-0.22	0.119	0.659
Kurtosis	9.635	13.892	11.112	10.46	12.776	8.146	22.267
Shapiro-Wilk (Normality)	12.70***	13.95***	13.28***	12.99***	13.98***	12.04***	15.54***
Ljung-Box test (Auto Correlation)	147.41***	210.32***	144.12***	116.25***	121.96***	111.51***	184.75***

Notes: All stock indexes in levels are represented in U.S. Dollars. All variables are in returns except VIX which is in differences. Sharpe Ratio = Mean/Standard-Dev.

Table 4.2
Correlation Coefficients of Daily Stock Index Returns, OILWTI and VIX
(daily data from Jan. 2002 to Dec., 2015)

	Brazil	Canada	Colombia	Mexico	U.S.	OilWTI	VIX
In Levels							
Brazil	1.0000 ***						
Canada	0.8807 ***	1.0000 ***					
Colombia	0.8649 ***	0.8860 ***	1.0000 ***				
Mexico	0.8239 ***	0.9515 ***	0.9165 ***	1.0000 ***			
U.S.	0.2525 ***	0.6335 ***	0.4200 ***	0.6940 ***	1.0000 ***		
OILWTI	0.8674 ***	0.8740 ***	0.8649 ***	0.8278 ***	0.3693 ***	1.0000 ***	
VIX	-0.0141	-0.2947 ***	-0.1577 ***	-0.2469 ***	-0.5069 ***	-0.1503 ***	1.0000 ***

Returns/Differenced

	RET_BRA	RET_CAN	RET_COL	RET_MEX	RET_U.S.	RET_OilWTI	VIX_CHG
RET_BRA	1						
RET_CAN	0.6276 ***	1					
RET_COL	0.4601 ***	0.4444 ***	1				
RET_MEX	0.6925 ***	0.6569 ***	0.4587 ***	1			
RET_U.S.	0.5439 ***	0.6847 ***	0.3051 ***	0.6666 ***	1		
RET_OilWTI	0.2954 ***	0.4266 ***	0.2602 ***	0.2556 ***	0.2160 ***	1	
VIX_CHG	-0.4932 ***	-0.5850 ***	-0.3235 ***	-0.5820 ***	-0.8272 ***	-0.2046 ***	1

Notes: All variables are in returns except TED and VIX which are in differences. *, **, and *** significant at 10%, 5% and 1%, respectively

Table 4.3

Unit Root Tests (Daily Data from Jan. 2002 to Dec., 2015).

Series	ADF(k)	KPSS(29)	PHILLIPS-PERRON(k)
RET_BRA	-11.798 (23)***	0.0973	-55.642***
RET_CAN	-9.951 (29)***	0.0505	-56.506***
RET_COL	-11.511 (20)***	0.0645	-52.693***
RET_MEX	-25.896 (5)***	0.0559	-54.168***
RET_U.S.	-14.198 (18)***	0.0629	-67.033***
RET_OilWTI	-22.030 (8)***	0.0412	-64.183***
VIX_CHG	-14.594 (17)***	0.0181	-70.938***

Notes: The lag length (k) is selected as follows: for the ADF test, the ull hypothesis is unit root, we use the Campbell and Perron (1991) data dependent procedure starting with an upper bound k_{max} = 29, on k. if the last lag is significant then choose k = k_{max}, if not we reduce k by one and continue this process until this is satisfied, or else k = 0. The KPSS assumes a null that the series is stationary, we use the Bartlett-Kernel criteria to select k = 28 as truncating parameter. The critical values for the KPSS test are 0.119 (10%), 0.146 (5%), and 0.216 (1%) . The Phillips-Perron test, has a null hypothesis of unit root, ad uses the equation $k = 4(T/100)^{2/9}$ to select the maximum lag, in this case k = 8. *, **, and *** significant at 10%, 5% and 1%, respectively

Table 4.4
Variance Decomposition of VAR Model for Brazil

Variance decomposition across days									
	Innovation								
	Shock in OilWTI			Shock in VIX			Shock in Brazil		
	fevd	Lower	Upper	fevd	Lower	Upper	fevd	Lower	Upper
OilWTI									
1	100.00	100.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
3	99.08	98.45	99.70	0.85	0.25	1.45	0.08	-0.11	0.26
5	98.84	98.15	99.52	1.05	0.40	1.70	0.11	-0.11	0.34
7	98.84	98.15	99.52	1.05	0.40	1.70	0.11	-0.11	0.34
∞	98.84	98.15	99.52	1.05	0.40	1.70	0.11	-0.11	0.34
VIX									
1	4.43	3.13	5.74	95.57	94.26	96.87	0.00	0.00	0.00
3	4.59	3.24	5.95	95.39	94.04	96.75	0.01	-0.06	0.08
5	4.64	3.29	5.99	95.34	94.00	96.69	0.02	-0.05	0.09
7	4.63	3.29	5.98	95.35	94.00	96.69	0.02	-0.06	0.09
∞	4.63	3.29	5.98	95.35	94.00	96.69	0.02	-0.06	0.09
Brazil									
1	8.46	6.73	10.19	20.99	18.74	23.25	70.55	68.06	73.03
3	8.40	6.68	10.12	21.98	19.67	24.29	69.62	67.11	72.13
5	8.54	6.81	10.27	21.99	19.68	24.30	69.47	66.95	71.98
7	8.54	6.81	10.27	22.00	19.69	24.31	69.46	66.94	71.97
∞	8.54	6.81	10.27	22.00	19.69	24.31	69.46	66.94	71.97

Table 4.5
Variance Decomposition of VAR Model for Canada

Variance decomposition across days	Innovation								
	Shock in OilWTI			Shock in VIX			Shock in Canada		
	fevd	Lower	Upper	fevd	Lower	Upper	fevd	Lower	Upper
OilWTI									
1	100.00	100.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
3	98.69	97.94	99.43	0.80	0.22	1.38	0.51	0.04	0.98
5	98.27	97.42	99.11	1.00	0.37	1.63	0.73	0.16	1.30
7	98.26	97.41	99.11	1.00	0.37	1.64	0.73	0.16	1.31
∞	98.26	97.41	99.11	1.00	0.37	1.64	0.73	0.16	1.31
VIX									
1	4.51	3.20	5.83	95.49	94.17	96.80	0.00	0.00	0.00
3	4.68	3.31	6.04	95.26	93.89	96.64	0.06	-0.10	0.22
5	4.71	3.35	6.06	94.97	93.59	96.36	0.32	-0.01	0.65
7	4.70	3.35	6.05	94.96	93.57	96.35	0.35	0.00	0.70
∞	4.70	3.35	6.05	94.96	93.57	96.35	0.35	0.00	0.70
Canada									
1	17.95	15.70	20.21	28.96	26.67	31.25	53.09	50.73	55.45
3	17.70	15.46	19.94	30.34	28.00	32.67	51.96	49.61	54.31
5	17.94	15.68	20.20	30.14	27.81	32.47	51.92	49.56	54.28
7	17.94	15.68	20.20	30.14	27.82	32.47	51.92	49.56	54.28
∞	17.94	15.68	20.20	30.14	27.82	32.47	51.92	49.56	54.28

Table 4.6

Variance Decomposition of VAR Model for Colombia

Variance decomposition across days									
	Innovation								
	Shock in OilWTI			Shock in VIX			Shock in Colombia		
	fevd	Lower	Upper	fevd	Lower	Upper	fevd	Lower	Upper
OilWTI									
1	100.00	100.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
3	99.13	98.52	99.74	0.86	0.25	1.46	0.01	-0.06	0.08
5	98.91	98.25	99.57	1.05	0.40	1.70	0.04	-0.08	0.16
7	98.90	98.24	99.57	1.06	0.41	1.71	0.04	-0.08	0.16
∞	98.90	98.23	99.57	1.06	0.41	1.71	0.04	-0.08	0.16
VIX									
1	4.48	3.16	5.79	95.52	94.21	96.84	0.00	0.00	0.00
3	4.61	3.26	5.97	95.19	93.81	96.57	0.20	-0.08	0.47
5	4.65	3.31	5.99	94.99	93.61	96.37	0.36	0.01	0.71
7	4.64	3.30	5.98	94.99	93.61	96.37	0.37	0.01	0.72
∞	4.64	3.30	5.98	94.99	93.61	96.37	0.37	0.01	0.72
Colombia									
1	6.52	4.97	8.06	9.15	7.42	10.87	84.34	82.17	86.50
3	6.45	4.90	7.99	11.55	9.58	13.52	82.00	79.68	84.32
5	6.51	4.96	8.06	11.92	9.92	13.91	81.57	79.24	83.91
7	6.51	4.96	8.07	11.92	9.93	13.92	81.56	79.22	83.90
∞	6.51	4.96	8.07	11.92	9.93	13.92	81.56	79.22	83.90

Table 4.7

Variance Decomposition of VAR Model for Mexico

Variance decomposition across days									
	Innovation								
	Shock in OilWTI			Shock in VIX			Shock in Mexico		
	fevd	Lower	Upper	fevd	Lower	Upper	fevd	Lower	Upper
OilWTI									
1	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.99	0.99	1.00	0.01	0.00	0.01	0.00	0.00	0.00
5	0.99	0.98	1.00	0.01	0.00	0.02	0.00	0.00	0.00
7	0.99	0.98	1.00	0.01	0.00	0.02	0.00	0.00	0.00
∞	0.99	0.98	1.00	0.01	0.00	0.02	0.00	0.00	0.00
VIX									
1	4.46	3.15	5.77	95.54	94.23	96.85	0.00	0.00	0.00
3	4.59	3.24	5.94	94.92	93.51	96.33	0.49	0.06	0.92
5	4.63	3.29	5.98	94.79	93.38	96.20	0.57	0.11	1.04
7	4.63	3.29	5.97	94.79	93.38	96.20	0.58	0.11	1.05
∞	4.63	3.29	5.97	94.79	93.38	96.20	0.58	0.11	1.05
Mexico									
1	6.19	4.67	7.70	31.30	28.87	33.73	62.51	60.03	65.00
3	6.08	4.58	7.57	32.04	29.58	34.50	61.88	59.38	64.38
5	6.26	4.76	7.76	32.05	29.58	34.52	61.69	59.18	64.19
7	6.26	4.75	7.76	32.06	29.59	34.52	61.69	59.18	64.19
∞	6.26	4.75	7.76	32.06	29.59	34.52	61.69	59.18	64.19

Table 4.8

Variance Decomposition of VAR Model for U.S.

Variance decomposition across days	Innovation								
	Shock in OilWTI			Shock in VIX			Shock in U.S.		
	fevd	Lower	Upper	fevd	Lower	Upper	fevd	Lower	Upper
OilWTI									
1	100.00	100.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
3	98.94	98.27	99.61	0.85	0.25	1.45	0.21	-0.09	0.52
5	98.74	98.02	99.45	1.05	0.40	1.70	0.21	-0.09	0.52
7	98.74	98.02	99.45	1.05	0.40	1.70	0.22	-0.09	0.52
∞	98.74	98.02	99.45	1.05	0.40	1.70	0.22	-0.09	0.52
VIX									
1	4.45	3.14	5.76	95.55	94.24	96.86	0.00	0.00	0.00
3	4.61	3.26	5.97	95.37	94.01	96.73	0.02	-0.07	0.10
5	4.66	3.31	6.01	95.30	93.94	96.65	0.05	-0.08	0.18
7	4.65	3.31	6.00	95.30	93.95	96.65	0.05	-0.09	0.19
∞	4.65	3.31	6.00	95.30	93.95	96.65	0.05	-0.09	0.19
U.S.									
1	5.02	3.64	6.40	63.68	61.70	65.65	31.30	29.62	32.99
3	5.05	3.66	6.45	63.89	61.90	65.89	31.05	29.36	32.75
5	5.16	3.76	6.56	63.85	61.85	65.84	30.99	29.30	32.69
7	5.16	3.76	6.56	63.86	61.86	65.85	30.98	29.29	32.68
∞	5.16	3.76	6.56	63.86	61.86	65.85	30.98	29.29	32.68

Table 4.9
DCC Estimations for Stock Returns, OilWTI and VIX (Daily Data from Jan. 2002 to Dec. 2015).

	Brazil	Canada	Colombia	Mexico	U.S.
Mean Equations					
ϒ0	0.1274***	0.0935***	0.0988***	0.1269***	0.0881***
	(0.0235)	(0.0142)	(0.02)	(0.0181)	(0.0118)
ϒ1	0.0007	-0.0385***	0.0803***	-0.006	-0.1028***
	(0.0141)	(0.0136)	(0.0163)	(0.0136)	(0.0144)
ϒ2 (ΔOilWTI)	0.0306***	0.03***	0.0209**	0.0129	0.0081**
	(0.0108)	(0.0064)	(0.0093)	(0.0079)	(0.0038)
ϒ3 (ΔVIX)	-0.1226***	-0.1281***	-0.1121***	-0.135***	-0.0632***
	(0.0183)	(0.011)	(0.0145)	(0.0144)	(0.0107)
Variance Equations					
Constant	0.0835***	0.0189***	0.1348***	0.0505***	0.0166***
	(0.0133)	(0.0032)	(0.0233)	(0.0078)	(0.0022)
Arch	0.0747***	0.0654***	0.131***	0.079***	0.081***
	(0.0067)	(0.0056)	(0.0128)	(0.0072)	(0.0052)
Garch	0.9043***	0.9226***	0.8158***	0.9011***	0.9058***
	(0.0086)	(0.0065)	(0.0193)	(0.0089)	(0.0058)
Persistence	0.980	0.9880	0.9469	0.9802	0.9869
Multivariate DCC Equation					
Lambda1	0.014***				
	(0.0009)				
Lambda2	0.9764***				
	(0.0016)				
Observations	3652				
χ2	361.85				
χ2 (p-value)	0				

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01.
The mean equation is $r_t = \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{WTI} + \gamma_3 r_{t-1}^{\Delta VIX} + \varepsilon_t$
where $r_t = (r_{Brazil,t}, r_{Canada,t}, r_{Colombia,t}, r_{Mexico,t}, r_{U.S.,t})'$; $\varepsilon_t = (\varepsilon_{Brazil,t}, \varepsilon_{Canada,t}, \varepsilon_{Colombia,t}, \varepsilon_{Mexico,t}, \varepsilon_{U.S.,t})'$
and $\varepsilon_t \mid I\Omega_{(t-1)} \sim N(O, H_t.)$. The variance equations are $h_{ii,t} = c_i + a_i \varepsilon_{i,t-1}^2 + b_i h_{ii,t-1}$ for $i = 1,2, \dots, n$.
The null for the x^2test is $H_0 : \alpha = \beta = 0$. Persistence is calculated as (Arch + Garch).

Table 4.10A

Regression Analysis of Conditional Correlations Coefficients and the Post Financial Crisis (U.S).

Country/Index i:	U.S.	U.S.	U.S.	U.S.
Country j:	Brazil	Canada	Colombia	Mexico
λ_0	0.4897***	0.6045***	0.2279***	0.6176***
	(0.0027)	(0.0022)	(0.0025)	(0.0021)
$\lambda 1$	0.1113***	0.0577***	0.1382***	0.1144***
	(0.006)	(0.0048)	(0.0055)	(0.0047)
$\lambda 2$	0.085***	0.1127***	0.1671***	0.0599***
	(0.0037)	(0.003)	(0.0034)	(0.0029)
Observations	3652	3652	3652	3652
F	326.64	710.44	1228.55	386.23
F (p-value)	0.000	0.000	0.000	0.000
Ajusted R^2	0.1514	0.2799	0.4021	0.1743

Table 4.10B

Regression Analysis of Conditional Correlations Coefficients and the Post Financial Crisis (OilWTI).

Country/Index i:	OilWTI	OilWTI	OilWTI	OilWTI	OilWTI	OilWTI
Country j:	Brazil	Canada	Colombia	Mexico	U.S.	VIX
λ_0	0.1618***	0.3135***	0.1255***	0.1283***	0.0772***	-0.08516***
	(0.0023)	(0.0024)	(0.0022)	(0.0027)	(0.0029)	(0.0026)
$\lambda 1$	0.1623***	0.1139***	0.176***	0.0309***	0.0635***	-0.0575***
	(0.0052)	(0.0053)	(0.0048)	(0.006)	(0.0066)	(0.0058)
$\lambda 2$	0.1961***	0.162***	0.1998***	0.2009***	0.245***	-0.1795***
	(0.0032)	(0.0033)	(0.003)	(0.0037)	(0.0041)	(0.0036)
Observations	3652	3652	3652	3652.00	3652.00	3652.00
F	1924.71	1253.25	2338.13	1559.05	1849.39	1231.02
F (p-value)	0.000	0.000	0.000	0.00	0.00	0.00
Ajusted R^2	0.5131	0.4069	0.5615	0.46	0.50	0.40

Notes: *** Represent statistical significance at the 1% level. Standard errors are in the parenthesis. The regression equation is $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DV1_t + \lambda_2 DV2_t + \epsilon_t$, for $i \neq j$, where $\hat{\rho}_{ij,t}$, represents the predicted conditional correlation by the DCC-GARCH in table 4.4 between markets *i* and *j* at time *t*.

Table 4.10C

Regression Analysis of Conditional Correlations Coefficients and the Post Financial Crisis (VIX).

Country/Index i:	VIX	VIX	VIX	VIX	VIX
Country j:	Brazil	Canada	Colombia	Mexico	U.S.
λ_0	-0.4303***	-0.4976***	-0.2461***	-0.5249***	-0.7831***
	(0.0024)	(0.0021)	(0.0024)	(0.002)	(0.0017)
λ1	-0.1063***	-0.0772***	-0.0949***	-0.1097***	-0.0695***
	(0.0054)	(0.0047)	(0.0053)	(0.0045)	(0.0039)
λ2	-0.0598***	-0.1108***	-0.1264***	-0.0552***	-0.0492***
	(0.0033)	(0.0029)	(0.0033)	(0.0028)	(0.0024)
Observations	3652.00	3652.00	3652.00	3652.00	3652.00
F	270.48	746.78	766.81	369.77	277.92
F (p-value)	0.00	0.00	0.00	0.00	0.00
Ajusted R^2	0.16	0.29	0.30	0.17	0.13

Notes: *** Represent statistical significance at the 1% level. Standard errors are in the parenthesis. The regression equation is $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DV1_t + \lambda_2 DV2_t + \epsilon_t$, for $i \neq j$, where $\hat{\rho}_{ij,t}$, represents the predicted conditional correlation by the DCC-GARCH in table 4.4 between markets *i* and *j* at time *t*.

Table 4.11

DCC Estimations for Stock Returns, OilWTI and VIX - Sample I

	Brazil	Canada	Colombia	Mexico	U.S.
Mean Equations					
ϒ0	0.1929***	0.1131***	0.1607***	0.1444***	0.0571***
	(0.037)	(0.0217)	(0.0339)	(0.0288)	(0.0173)
ϒ1	0.0676***	-0.0212	0.1171***	0.0234	-0.1001***
	(0.0227)	(0.0227)	(0.0267)	(0.0221)	(0.0223)
ϒ2 (ΔOilWTI)	0.0354**	0.0367***	0.005	0.0198*	0.0124**
	(0.016)	(0.0092)	(0.0151)	(0.0119)	(0.0055)
ϒ3 (ΔVIX)	-0.1752***	-0.157***	-0.1825***	-0.1669***	-0.0712***
	(0.0386)	(0.0208)	(0.0313)	(0.0292)	(0.0188)
Variance Equations					
Constant	0.1813***	0.0603***	0.3221***	0.1915***	0.008***
	(0.0458)	(0.0184)	(0.0774)	(0.0425)	(0.0029)
Arch	0.0962***	0.0642***	0.1723***	0.1197***	0.0412***
	(0.0148)	(0.0129)	(0.0292)	(0.0213)	(0.0079)
Garch	0.8541***	0.8759***	0.6971***	0.7913***	0.9516***
	(0.0243)	(0.0278)	(0.0533)	(0.0361)	(0.0102)
Persistence	0.9503	0.9402	0.8695	0.9110	0.9928
Multivariance DCC Equations					
Lambda1	0.0034***				
	(0.0011)				
Lambda2	0.9923***				
	(0.0011)				
Observations	1564				
$\chi 2$	209.66				
$\chi 2$ (p-value)	0				

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01. Persistence is calculated as the sum of the coefficients in the variance equation (Arch + Garch). Sample I includes daily data from Jan. 2002 to Dec. 2007.

Table 4.12

DCC Estimations for Stock Returns, OilWTI and VIX – Sample II

	Brazil	Canada	Colombia	Mexico	U.S.
Mean Equations					
ϒ0	0.0755**	0.0761***	0.0475*	0.1058***	0.1108***
	(0.0311)	(0.0195)	(0.025)	(0.0239)	(0.0168)
ϒ1	-0.0446**	-0.0501***	0.0463**	-0.0211	-0.1075***
	(0.0181)	(0.0174)	(0.0205)	(0.0176)	(0.0192)
ϒ2 (ΔOilWTI)	0.0373**	0.0318***	0.0351***	0.0127	0.0086
	(0.0153)	(0.0093)	(0.0123)	(0.0108)	(0.0055)
ϒ3 (ΔVIX)	-0.1137***	-0.1113***	-0.089***	-0.1176***	-0.0564***
	(0.0208)	(0.013)	(0.016)	(0.0167)	(0.0131)
Variance Equations					
Constant	0.0705***	0.0181***	0.057***	0.0451***	0.0279***
	(0.0134)	(0.0035)	(0.015)	(0.0076)	(0.0038)
Arch	0.0682***	0.0685***	0.0951***	0.0772***	0.0949***
	(0.0074)	(0.0067)	(0.0124)	(0.0078)	(0.0075)
Garch	0.9137***	0.9231***	0.8835***	0.9057***	0.8853***
	(0.009)	(0.0071)	(0.0164)	(0.0089)	(0.0083)
Persistence	0.9820	0.9918	0.9785	0.9828	0.9802
Multivariate DCC Equation					
Lambda1	0.0179***				
	(0.0018)				
Lambda2	0.954***				
	(0.0052)				
Observations	2087				
χ2	217.14				
χ2 (p-value)	0				

Notes: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01. Persistence is calculated as the sum of the coefficients in the variance equation (Arch + Garch). Sample II includes daily data from January 2008 to Dec. 2015.

Table 4.13

Correlation Coefficients of Daily Stock Index Returns, OilWTI and VIX

	Pooled Data	Sample I	Sample II
OilWTI, VIX	-0.2115***	0.021	-0.3454***
	0.0387	0.072	0.0331
OilWTI, U.S.	0.2675***	-0.0036	0.4282***
	0.0386	0.0759	0.0316
OilWTI, Brazil	0.3279***	0.1648**	0.4526***
	0.0371	0.0752	0.0301
OilWTI, Canada	0.4184***	0.3472***	0.5333***
	0.0336	0.0658	0.0268
OilWTI, Colombia	0.2808***	0.104	0.4058***
	0.0379	0.0736	0.031
OilWTI, Mexico	0.2799***	0.0493	0.4194***
	0.0381	0.0738	0.0313
VIX, U.S.	-0.8349***	-0.8677***	-0.8492***
	0.0122	0.017	0.0102
VIX, Brazil	-0.5096***	-0.6033***	-0.5466***
	0.0297	0.0462	0.0258
VIX, Canada	-0.5865***	-0.566***	-0.648***
	0.0264	0.0491	0.0216
VIX, Colombia	-0.3542***	-0.3458***	-0.4423***
	0.0353	0.0654	0.0302
VIX, Mexico	-0.5774***	-0.6975***	-0.6118***
	0.0265	0.0419	0.0229
U.S., Brazil	0.6061***	0.6962***	0.6497***
	0.0259	0.0435	0.0219
U.S., Canada	0.6954***	0.65***	0.7564***
	0.0212	0.0447	0.0164
U.S., Colombia	0.392***	0.3713***	0.4927***
	0.0348	0.0693	0.0289
U.S., Mexico	0.6752***	0.7642***	0.7125***
	0.0218	0.0375	0.0183

Note: Robust standard errors are in parentheses. *pb.10, **pb.05, ***pb.01

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APPENDIX A

Appendix A

LAG SELECTION CRITERIA

This table presents the selection-order statistics used to select the appropriate number of lag(s) to be included in the VAR for stock returns, OilWTI returns and ΔVIX. The four selection-order statistics: final prediction error (FPE), the Akaike's information criterion (AIC), the Hannan and Quinn information criterion (HQIC), and the Schwarz's Bayesian information criterion (SBIC). * indicates the appropriate number of lags selected by each selection order criteria.

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-42231.9				26.7308	23.151	23.1552	23.1629
1	-41792.5	878.93	49	0	21.5809	22.9369	22.9708*	23.0321*
2	-41710.6	163.74	49	0	21.1955	22.9189	22.9825	23.0974
3	-41632.4	156.33	49	0	20.8594	22.9029	22.9962	23.1647
4	-41554.5	155.91*	49	0	20.531*	22.8871*	23.01	23.2321

APPENDIX B

Appendix B

VAR RESULTS: STABILITY CONDITIONS

Vector Auto Regression (VAR). Brazil, OilWTI, and ΔVIX

Eigenvalue stability condition

Eigenvalue			Modulus
0.298289	+	.4617617i	0.549727
0.298289	-	.4617617i	0.549727
-0.39024	+	.3458793i	0.521459
-0.39024	-	.3458793i	0.521459
-0.07844	+	.4430083i	0.449899
-0.07844	-	.4430083i	0.449899
-0.4305	+	.105775i	0.443308
-0.4305	-	.105775i	0.443308
0.423053	+	.0372613i	0.42469
0.423053	-	.0372613i	0.42469
0.096712	+	.3798896i	0.392007
0.096712	-	.3798896i	0.392007

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition

Vector Auto Regression (VAR). Canada, OilWTI, and ΔVIX

Eigenvalue stability condition

Eigenvalue			Modulus
0.32483	+	.5064157i	0.601641
0.32483	-	.5064157i	0.601641
-0.43452	+	.3722106i	0.572145
-0.43452	-	.3722106i	0.572145
-0.06071	+	.4956397i	0.499344
-0.06071	-	.4956397i	0.499344
0.494855	+	.05861445i	0.498314
0.494855	-	.05861445i	0.498314
-0.44764	+	.114307i	0.462003
-0.44764	-	.114307i	0.462003
-0.00072	+	.4410049i	0.441005
-0.00072	-	.4410049i	0.441005

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition

Vector Auto Regression (VAR). Colombia, OilWTI, and ΔVIX

Eigenvalue stability condition

Eigenvalue			Modulus
0.273162	+	.497743i	0.567772
0.273162	-	.497743i	0.567772
-0.39985	+	.3422627i	0.52633
-0.39985	-	.3422627i	0.52633
0.454299			0.454299
-0.05392	+	.4225453i	0.425972
-0.05392	-	.4225453i	0.425972
-0.41278			0.412775
0.345717	+	.1920449i	0.395476
0.345717	-	.1920449i	0.395476
-0.25334	+	.2783728i	0.376395
-0.25334	-	.2783728i	0.376395

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition

Vector Auto Regression (VAR). Mexico, OilWTI, and ΔVIX

Eigenvalue stability condition

Eigenvalue			Modulus
0.296241	+	.4811794i	0.565059
0.296241	-	.4811794i	0.565059
-0.37268	+	.3296493i	0.497557
-0.37268	-	.3296493i	0.497557
0.45868			0.45868
0.30975	+	.3043398i	0.434244
0.30975	-	.3043398i	0.434244
-0.0669	+	.4181589i	0.423476
-0.0669	-	.4181589i	0.423476
-0.33367	+	.17708i	0.377748
-0.33367	-	.17708i	0.377748
-0.30378			0.303776

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition

Vector Auto Regression (VAR). U.S., OilWTI, and ΔVIX

Eigenvalue stability condition

Eigenvalue			Modulus
0.31622	+	.4745313i	0.570241
0.31622	-	.4745313i	0.570241
-0.4014	+	.347744i	0.531085
-0.4014	-	.347744i	0.531085
0.426488	+	.0397647i	0.428338
0.426488	-	.0397647i	0.428338
-0.01047	+	.4114526i	0.411586
-0.01047	-	.4114526i	0.411586
-0.38387	+	.08893044i	0.394036
-0.38387	-	.08893044i	0.394036
-0.0909	+	.3596594i	0.37097
-0.0909	-	.3596594i	0.37097

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition

BIOGRAPHICAL SKETCH

Juan Andres Rodriguez-Nieto earned the degree of Doctor of Philosophy in Business Administration with concentration in Finance at the University of Texas – Rio Grande Valley in 2017. He received his Masters of Business Administration as well as a Certificate in Applied Finance and Economics from Southern Oregon University. He also obtained a Bachelor of Science in Mining Engineering from Universidad de Guanajuato, Mexico in 1994. His research interests include behavioral finance, international finance, investments, energy economics and corporate finance. He has presented his research at the PhD Project- Finance Doctoral Student Association conference, where he received recognition for the second-best student paper in 2015. Juan Andres Rodriguez-Nieto is the Director of the University Career Center at the University of Texas Rio Grande Valley, and he served as adjunct professor of finance at the same institution. Juan Andres Rodriguez-Nieto can be contacted at: 2943 Old Spanish Trail, Brownsville, Texas 78520, by phone at (956) 266-5641 or by e-mail at juan.rodrigueznieto@utrgv.edu