Essays on Financial and Economic Risks

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Dedications

To my parents and my brother

To whom I owe lifetime gratitude

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Abstract

Essays on Financial and Economic Risks

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This dissertation consists of three essays on financial economics, focusing on different types of financial and economic risks and covering different geographical regions. These risk types are related to stock, bond and commodity markets, financial stress and country risk ratings.

The first essay investigates directional relationships, regime variances, transition probabilities and expected regime durations for two systems of economic and financial variables. The first system consists of daily series which include credit and market risks. The second system is based on monthly data, and encompasses credit, and market risks and economic activity and oil variables. The methodology is based on the Markov-Switching cointegrated VAR model. The results suggest there is a pronounced regime-specific behavior in both systems with FTP-MS model. There is a significant difference between the higher expected duration in the low volatility regime and the lower duration in the high volatility regime in both systems. Both models suggest that during the 2007/2008 Great Recession, the system stays mainly in regime 2 but returns to the normality state in the 2009 recovery period. The fundamental variables (industrial production, oil prices and the real interest rate) have varying effects in both regimes and

both systems. Quantitative easing has significant effects on the bond expected volatility index *MOVE* in the high volatility regime and industrial production in both regimes. I also examine the driving forces of the time-varying transition probabilities and find that increases of oil price will decrease the probability that the financial markets stay in the low volatility regime.

The second essay examines the asymmetric adjustments of the stock markets of the five BRICS countries (Brazil, Russia, India, China and South Africa) to changes in the economic, financial and political country risk ratings of these countries in the short run and long run, using the momentum threshold autoregression (MTAR) and the vector error-correction(VEC) models. The findings suggest that the long-run relationships between these four variables respond asymmetrically depending on the direction of the shocks. The adjustment is faster when the spread between the actual level of stock market index and the level suggested by country risk ratings is narrowing than when it is widening, except for Russia which has the opposite response. The Chinese stock market seems to have the fastest adjustments in the short-and long-run among those of the five BRICS. In terms of the three country risk ratings the financial risk ratings for the five BRICS show the most responsiveness to all the variables in the long-run, while the political risk ratings exhibit the least. The economic and political risk ratings show the fastest adjustments for Brazil, while the financial risk rating is most pronounced in Russia.

The third essay examines the Value-at-Risk for ten euro-zone equity markets individually and when divided into two groups: PIIGS and the Core, employing four

VaR estimation methods. The results are evaluated according to four statistical properties as well as the Basel capital requirements for the period including the 2007/2008 financial crisis. The estimation and the evaluation are applied to the individual assets as well as to the portfolios consisting of the two groups. The results demonstrate that the CEVT method applied to the ten individual equity assets meet all the statistical criteria the best. The two optimal equity portfolios do not show diversification benefits as the PIIGS portfolio selects Spain's *IBEX* only and that of the Core opts for Austria's ATX only. The asset class-augmented portfolio that includes the Austrian (*ATX*) index, oil and gold gives the highest diversification gains. Adding other commodities such as corn and silver, or commodities indices to the augmented portfolio does not enhance the gains. At the optimal portfolio level, the Duration-Peak-Over-the-Threshold (DPOT) is recommended the best in terms of satisfying the Basel rules.

Chapter 1: Interrelationships among Financial Risks, Economic Activity and Oil Price in a Regime-Changing Environment

1.1 Introduction

Since the 2007-2008 financial crisis, many economists have shown increasing interests in examining the behavior and interrelations between financial risk indicators which measure market, credit and volatility risks in the financial markets. These financial risk factors are related to credit risks as measured by credit default swaps (*CDS*), market risks as gauged by value-at-risk (VaR) and the spread between *LIBOR* and risk-free Treasury rates (*TED)*, and volatility risks as captured by *VIX* and *MOVE* indices. All these measures are related to the health of the economy. A decrease in the *CDS* spreads, *TED* and/or volatility is viewed as an increase in appetite for risk and a precursor for stimulation of demand to generate economic activity. On the other hand, an increase in these risks bodes ill for the real economy. Thus, it will also be interesting to link these financial risks directly to real economic activity under quantitative easing and discern the interrelations between them.

I thus focus from the financial side on the fear and volatility measures in the stock and Treasury bond markets as represented by the *S&P* 500 CBOE Volatility Index (*VIX*) and the Merrill Lynch Option Volatility Estimate Index (*MOVE*), respectively, the financial stress factors *TED* and the default risk premium, and the financial fundamental variables such as the federal funds rate (*FFR*) and the real exchange rate. From the real side, I utilize industrial production *(IP*) and oil prices.[1]

This essay addresses three major questions. First, if there are long-run equilibrium relationships between different risk measures in the stock and credit markets on one hand, and industrial production and the oil market on the other hand, should these relationships be represented as a linear VEC or a regime-switching VEC? Second, if there exists an undergoing regime-switching risk pattern, then how should different credit and market risk spreads behave over low and high volatility regimes? Third, are the transition probabilities that govern the regime switching process constant and exogenous or time-varying and affected by some information variables?

Therefore, I investigate the different patterns of interactions between financial risks, fundamental financial and real variables under one regime and in a regime-changing environment in the presence of quantitative easing. Specifically, I examine the relationships under both one regime and two regimes for expected volatility and credit risk measures including the *S&P VIX*, *MOVE, TED* and default risk spread (BAA–10 year Treasury bond rate) in the presence of monetary and oil shocks. I also investigate the short-run transmission of risks among risk measures over the single and two volatility regimes.

Since the *VIX* and *MOVE* are the underlying assets for financial derivatives[2], the results should provide useful information that is pertinent to formulation of policies and strategies. For example, the speculating types who take on significant risks can trade on

[1] My attempt to use employment and labor participation did not produce good results.
[2] *VIX* is not directly tradable, but a number of *VIX* derivatives are available in the market including *VIX* options, *VIX* futures and *VIX ETN*s.

volatility risk as represented by *VIX* using *VIX* derivatives to make money, while the hedgers can use these volatility derivatives to avoid or reduce exposure to volatility risk. The results on the regime-dependent risks should shed some light on whether those risks in a high volatility environment will persist or will disappear without regulatory actions. The finding on smooth probability can be examined to discern the expected durations for regimes related to *VIX, MOVE* and other measures of risks during and after the 2007/2008 financial crisis.

The remainder of this essay is organized as follows. Section 1.2 provides a review of the literature on the relationships between financial markets' credit and market risks in the presence of fundamental variables. Section 1.3 discusses the empirical models and section 1.4 provides the data description, the empirical findings and the results of the robustness tests. Section 1.5 concludes.

1.2 Literature Review

The different strands of the related literature focus more on the relationships between financial fundamentals and oil prices than on the relationships between financial risks, financial fundamentals and real economic activities which will be addressed in this essay.

Linkages of financial markets

Campbell and Ammer. (1993) adopt the vector autoregression (VAR) model to explain the low correlation between excess stock and bond market returns. They decompose the unexpected excess stock and the 10-year bond returns into changes in expectations of future stock dividends, inflation, short-term real interest rates, and excess stock and bond returns. They find that the primary contributor to the excess returns in stock market is the news about future excess stock returns; while the primary force driving the excess return in bond market is the innovation of future inflation rate. Their results suggest that the linkage between stock and bond excess returns is weak[3].

Another stream of the literature adopts the microeconomics perspectives to explore the behavior mechanism of investors. For example, Fleming, Kirby and Ostdiaek (1998) investigate the linkages between the volatility in the stock, bond and money markets using a trading model to capture hedging behavior across markets. Their results reveal a strong volatility linkage between these three markets due to common information. [4]

VIX and other financial risk measures

Figuerola-Ferretti, and Paraskevopoulos (2010) consider cointegration between credit risks, as represented by *CDS* spreads, and market risk embedded in the equity *VIX*. They find that *CDS* and *VIX* are cointegrated and that *VIX* has a clear lead over the *CDS* market in the price discovery process, indicating that *CDS* credit risk adjusts to *VIX* market risk when there is temporary mispricing from the long-run equilibrium. They

[3] The authors argue that the only common risk component in both markets is real interest rate. The effect of the news of future excess bond return on bond returns is trivial. There are also converse effects of the long-run expected inflation on stock and bond market excess returns.

[4] Fleming, Kirby and Ostdiaek (1998) contend that since investors' risk aversion might be varying across time and markets, it is important for economists to distinguish between the variance caused by the change in the fundamental factors and the one caused by the change in risk preference of investors. Those two components can play different roles in determining the overall risk and correlation between markets in different economic environments.

find that there are long-term arbitrage relationships between *VIX* and *CDS* for most companies, implying that excess returns may be earned using "pairs trading" strategies.[5]

Fernandes, Medeiros and Scharth (2009) examine the time series properties of daily equity *VIX*. Their results suggest that *VIX* displays long-range dependence. These authors confirm the evidence in the literature that there is a strong negative relationship between *VIX* and *S&P500* index returns, as well as a positive contemporaneous link with the value of the *S&P500* index. Moreover, they demonstrate that equity *VIX* tends to decline as the long-run oil price increases, reflecting the high demand for oil in recent years, as well as the recent trend of shorting energy prices in the hedge fund industry.

Bekaert, Hoerova and Duca (2010) decompose *VIX* into two components: the risk aversion and the expected stock market volatility, and then examine the dynamic links between those two components and the monetary policy. They find that only risk aversion component responds to the lax monetary policy. On the other hand, the increasing expected volatility leads to a laxer monetary policy.

Gogineni (2010) examines the impact of changes in daily oil price on the equity of a wide array of industries. He finds that stock returns of both industries that depend heavily on oil and those that use little oil are sensitive to changes in oil price. The latter industries are impacted because their main customers are affected by oil prices. The

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[5] The pairs trade or pair trading is a market neutral trading strategy which enables traders to profit from virtually any market conditions: uptrend, downtrend, or sideways movement. One pairs trade would be to short the outperforming asset and to long the underperforming one, betting that the "spread" between the two assets would eventually converge.

results also demonstrate that the sensitivity of industries' returns to the oil price changes depends on both the cost-side and demand-side dependence on oil.

Markov-switching model in financial economics

Most of the studies cited above use ordinary or linear VAR/VEC models and focus on one regime in examining the relationships. Long economic and financial time series are subjected to some form of structural breaks as the economy moves through different regimes or states. The concept of regime may depend on the problem at hand. Besides, the regimes may be unobservable to the statisticians carrying out ex-post analysis. Lee and Chen (2006) show Markov regime-switching models for exchange rate performs very well in prediction. They justify the use of such models and find the regimes appear to be consistent with popular known exchange rate regimes in the world. Fong and See (2002) also demonstrate validity of the use of Markov regime-switching models for volatilities in oil futures price series. Raymond and Rich (1997) use regime switching to study the role of oil prices in accounting for shifts in the mean of U.S. GDP and to predict the transition between low and high growth states. Andreopoulos (2009) estimates a Markov-switching model for the interest rate, unemployment and real oil price, without including prices of other commodities. His results suggest that real oil prices have asymmetric effects on the economy. The real oil price helps forecast unemployment in recessions only, while the real interest rate does so in expansions. The oil price, but not the real interest rate, is economically significant for unemployment in the long run.

Once the regime breakdown is achieved, then I can disentangle the relationships among the variables depending on the regime. Since it is difficult to stipulate where regime change may have occurred, I will rely on the data to decide on this. In addition, if the different regimes are allowed to have different variances or volatilities, then it also allows for heteroscedasticity in the data, which is a common occurrence in financial and economic time series. In this context, the best applicable methodology is to allow an unobserved Markov chain to drive the regimes under a time homogeneous transition probability. The most intuitively appealing way to classify the regimes is based on the level of the residual variance or in other words the surrounding level of uncertainty. If there are indeed different levels of uncertainties, then not allowing for regime differences will lead to miss-specified models and may not allow for full understanding of the relationships among the variables of interest to us.

Research on financial risks under regime-switching is expanding. Alexander and Kaeck (2008) find that within a Markov switching the determinants of the iTraxx are very sensitive to stock market volatility when the *CDS* spreads are high. On the other hand, *CDS* spreads are more sensitive to stock returns than to stock volatility during normal circumstances.

Dionne et al. (2011) explore the ability of observed macroeconomic variables and the switching in regimes to explain the proportion of corporate bonds' yield caused by credit default swaps. The model is calibrated with consumption, inflation, risk-free yields and default data for different investment grade bonds. The results show that spread variations can be related to macroeconomic undiversifiable risk.

Bollerslev, Gibson and Zhou (2011) estimate the stochastic volatility risk premium for the U.S. equity market and link the variations in the risk premium to macro-finance state variables. They extract the volatility risk premium based on the difference between the implied volatility (VIX), and the realized volatility which is the summation of intra-day high frequency squared returns. They conclude that because the VIX index is calculated through a model-free approach, it acts as a better measure of ex ante risk-neutral expectation of the integrated volatility than the traditional Black-Scholes implied volatilities.

Giot (2003) applies the Markov switching model to the *S&P 100 VIX* and the German *DAX VDAX* indices and finds that these indices switched from a low value state to a high value closer to the events of the 1997 Asian crisis, and stayed almost continuously in the high-value state for the next five years since then. In the second part of the essay, the author highlights the structural change in the asymmetric stock index volatility vs (positive and negative) returns relationship and finds that the leverage effect is much weaker after the summer of 1997 than before. The reaction of volatility to negative market returns rises much faster in the low-volatility state than in the high-volatility state. Ardia (2003), inspired by the stylized facts (leverage effect, clustering and mean-reverting behavior) of the *S&P* 500 and *VIX*, suggests a trading strategy that uses abnormally high volatility as a trading signal for long traders.

The recent literature examines whether the transition probabilities are constant and exogenous, or they can be time-varying and endogenous within the MS framework. The class of Markov Switching models which makes these probabilities time-varying and dependent on some pertinent information variables is referred as time-varying-transition-probability Markov Switching (TVTP-MS) model.

Including the proper information variables in the transition probability function is crucial for the appropriateness of the TVTP model and the strength of the regimes identified by the model. Cevik et al. (2012) explore the factors that affect the regime-switching probabilities of US stock market in both bull and bear periods using a TVTP-MS model. They consider different information variables including the US Institute for Supply Management's (ISM) manufacturing and nonmanufacturing Business Activity Indices, the industrial production. The results show that only the ISM manufacturing Business Activity Index impacts the transition probabilities in both bull and bear regimes, while nonmanufacturing index only matters in the bull periods and the TVTP model using industrial production as information variable doesn't outperform the FTV model.

Chen (2010) investigates how oil price shocks affect the transition of stock markets between bullish and bearish regimes. He uses four measures of oil price changes as the information variables in the probability function, including the percentage change of oil price, Oil Price Increase, Net Oil Price Increase and Scaled Oil Price Increase. His results suggest that the higher oil price would lead to the higher probability that the stock markets switch from bull market to bear market, as well as the higher probability of staying in the bear regime. Bhar and Nikolova (2009) apply a TVTP-MS-EGARCH model to study the impact of the world oil price changes on returns and volatilities of the stock markets in the BRIC countries, which include Brazil, Russia, India and China.

This study concludes that the level of the impact of oil price returns on equity returns and volatility in these countries depends on the extent to which these countries are net importers or net exporters of oil. It also concludes that despite the aggressive economic growth of the BRIC countries in the last 25 years, the volatility of stock returns in these economies does not have a significant impact on the volatility of global oil price returns. Emrah et al. (2012) apply a TVTP-MS model to explore the role of business confidence in affecting the US stock market returns. They choose the Institute for Supply Management (ISM) manufacturing confidence index as the information variable, which determines the regime-switching transition probabilities of the stock returns. They find this information variable to be significant in both regimes.

To my best knowledge, there is no published research on implied volatility *VIX* and *MOVE* for the stock and bond markets that accounts for the presence of financial, real economic and oil fundamentals in a regime-switching framework in comparison to their interrelations under a single regime. Additionally, this framework will also be augmented by time-varying probabilities for the switching regimes that make these probabilities dependent on the information variables relevant to this study. I will also use formal tests to compare the linear VEC versus non-linear VEC models. I will also use recent approaches (Karamé, 2011), to carry out the impulse response analysis on Markov-switching cointegrated VAR models. My study wishes to fill this gap in the literature.

1.3 Empirical Models

I proceed in three steps to examine the cointegration and VARs as related to this study. In the first step, I test for cointegration, and based on the cointegration results I then decide whether I will use a VAR or a VEC model. If the cointegration results suggest a VEC instead of an uncointegrated VAR model, I will initially follow the Johansen (1988, 1991) symmetric maximum likelihood procedure to estimate the linear VEC model. In the second step, I carry out tests to figure out if the parameters are stable and whether the presence of structural breaks or the existence of different regimes is warranted. I then follow in the third step the findings of Krolzig (1997) and the empirical work of Krolzig et al. (2002) by incorporating the cointegrating properties derived in the linear model into the Markov-Switching model.

1.3.1 Linear vector error-correction model:

Let X_t denote a *p*-dimensional column of the *I*(1) variables, which follows the following VAR(*k*) process:

$$X_t = A_1 X_{t-1} + A_2 X_{t-2} \ldots + A_k X_{t-k} + B_1 Z_1 + \cdots + B_j Z_j + \mu + \epsilon_t \quad (1)$$

where μ is a deterministic term *I*(0) elements, k is the order of lag length, Z_j are exogenous variables and ε_t is a Gaussian error term.[6] The VAR(*k*) process can be written in the following VECM representation:

$$\Delta x_t = u + \sum_{i=1}^{q-1} \Gamma_i \Delta x_{t-i} + \prod x_{t-1} + \varphi z_t + \varepsilon_t$$

[6] The deterministic time trend can be included as well.

$$\varepsilon_t \sim N(0, \sigma) \qquad (2)$$

where Π and Γ_i are *pxp* matrices of coefficients representing the long-run impacts and the short-run adjustments, respectively. The matrix Γ_i represents the interim multipliers. The hypothesis of cointegration states that the long-run impact matrix, Π, can be rewritten as:

$$\Pi = \alpha\beta' \qquad (3)$$

where α and β are *pxr* matrices. The rows of matrix α form the cointegrating vectors, while matrix β contains the loading factors which are the weights of the cointegrating vectors in the various equations. These matrices are of full rank *r* such that $0 \leq r \leq p-1$ given X_t is a *I*(1) process. If *r*=0, then no cointegration relationship exists among the elements of X_t. If the rank $0 \leq r \leq p-1$, then there are *r* cointegration vectors exist. It suggests that *r* stationary linear combinations of the elements of X_t exist with *p-r* common stochastic trends. I use the Johansen (1991) method to test the rank of the impact matrix Π. I can also perform the Granger causality test based on equation (2). If all $\Gamma_i(m,n)$ are jointly not equal to zero, then the *n*th variable in vector *X* Granger causes the *m*th variable. Otherwise the *n*th variable does not cause the *m*th variable. The joint significance can be tested by various methods such as the F test, Wald test and LR test. I will apply the linear VEC model to the daily and monthly data to account for interrelations with economic activity variables. The vector Z_t of exogenous variables includes *QE1*, *QE2* and lagged *FFR* in the daily model and the lagged *RIR* in monthly model.

I will also use both the Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SC) to determine the VAR and cointegration specifications and the lag lengths. But if there is a conflict, I will use the SC following the literature.

1.3.2 Tests for non-linearity

To investigate the linearity assumptions in both the daily and monthly VEC models in section 1.5, I will first carry out the multivariate Jarque-Bera residual normality tests which compare the third and fourth moments of the residuals to those for the normal distribution. If the results reject the null hypothesis for the residuals that they follow the multivariate normal distribution, then the presence of parameter instability in the VEC model leads us to investigate the regime dependence of the relationships between variables in the MS-VEC model.

Additionally, when the Markov-switching models have been estimated, I apply the conventional likelihood ratio LR test and the Davies test developed in Davies (1987) to test the linear specifications of VEC models versus the non-linear regime switching specification of VEC model. The conventional LR test may involve the nuisance parameter problem which means when there are unidentified parameters under the alternative hypothesis; the likelihood ratio statistic does not have the standard asymptotic χ^2 distribution. Therefore, I include the adjusted LR test, known as the Davies (1987) statistics, as a cure. It is used to calculate the approximate upper bound for the significance level of the adjusted LR statistic. Let *T* denote the LR statistic, *m* the number of coefficients in the mean that vanish under the null, and q the number of transition probabilities that vanish under the null hypothesis, then the conventional LR test is:

$$P[\chi^2(m+q) > T]$$

The approximate upper bound under the adjusted LR test is given by:

$$P[\chi^2(q) > \mathrm{T}] + 2\mathrm{T}^{1/2} exp\{\left(\frac{q}{2} - 0.5\right)\log(T) - \frac{\mathrm{T}}{2} - \frac{q}{2}\log(2) - \log\left(\frac{q}{2}\right)\}$$

If the adjusted LR test statistic exceeds the approximate upper bound, then the null hypothesis of linear specification is rejected.

3.3.the Markov regime-switching VEC Model

The VEC model discussed above presumes that the long-term cointegration, the short- term adjustments and the impacts of exogenous variables are constant over time. However, this assumption may be questionable since the comovements of relevant variables might be subject to structural breaks or regime changes, particularly when transmission of risks is under consideration.

In order to account for the regime-changing effect in the VEC model, I incorporate the Markov-switching methodology in the VEC model allowing for the presence of regime-dependence of the error correction terms, dynamics of the stationary part, and impacts of exogenous variables. The model is piecewise linear in each state but non linear across regimes. To carry the cointegrating properties derived in linear VECM to the regime-switching model, I follow the empirical works by Krolzig et al. (2002).

I aim to estimate the model with the unobservable discrete state variable s_t, which has two possible states ($s_t = 1 \; or \; s_t = 2$)[7]

$$\Delta x_{t\,=}\; u + \sum_{i=1}^{q-1} \Gamma_i(st)\Delta x_{t-i} + \Pi(s_t)x_{t-1} + \varphi_{(st)}z_t + \varepsilon_t$$

$$\varepsilon_t \sim N(0, \sigma_{(st)})$$

The coefficients of the error-correction terms Γ_i, the coefficients of the dynamics of the stationary part Π, the coefficients for exogenous variables φ, and the variance-covariance terms of the innovations σ , are all conditioned on the realization of the state variable s_t. (i.e. $\Gamma_i(s_t = 1) \neq \Gamma_i(s_t = 2)$ I place a restriction on the coefficients of the dynamics of the stationary part Π ,which states that only the β component is state dependent. while the α component is state-independent.

To determine the state transition probability, I follow Hamilton (1994). The matrix of transition probabilities is defined as:

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[7] I conduct the LR ratio tests on the number of regimes. The results support the number of regime is two against three. The result is available upon request.

$P = \begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix}$, with $\sum_{st=1}^{2} P_{st} = 1$, and $P_{st} \geq 0$ for s_t, t= 1, 2.

where the element of the i-th row and j-th column of the matrix describes the transition probability from state i to state j. The expected duration of regime i is defined as $E(S = i) = 1/(1 - P_{ii})$. A shorter expected duration is usually is expected for the high volatility state.

The log-likelihood function is given by the sum of the log-densities of the observations conditional on the history of the process:

$$L(\theta|X_T) = \sum_{t=1}^{T} \ln f(x_t\,|X_{t-1};\theta)$$

with

$$f(x_t|X_{t-1};\theta) = f(x_t, s_t = 1|X_{t-1};\theta) + f(x_t, s_t = 2|X_{t-1};\theta)$$

$$=\sum_{\delta=1}^{2} f(\,x_t|s_t = \delta, X_{t-1};\theta) prob(s_t = \delta|X_{t-1};\theta)$$

The constructed likelihood function has been is maximized to obtain parameter estimates of the model. The maximization process is based on an implementation of the Expectation Maximization (EM) algorithm introduced by Dempster, Larid and Rubin (1977) and developed by Hamilton (1990) and Krolzig (1997). Each iteration of the EM algorithm consists of two steps: the expectation step which updates the filtering and smoothing algorithms using the estimated parameter vector of the last maximization step, and the maximization step which derives an estimate of the parameter vector as the solution of the first-order conditions associated with likelihood function, where the conditional regime probabilities are replaced with the smoothed probabilities derived in the last expectation step.

1.3.4. the Time-varying Transition Probability MS-VEC model

In the previous section, I assume that the transition of states is exogenous and constant in term of the transition probabilities across regimes. Therefore, the forces that move the transition probabilities are ignored. In this section, I extend the analysis by considering the possible forces that affect the transition of states over time, and employ a time-varying transition probability (TVTP-MS-VEC) model. This model is different from that of the fixed transition probabilities as it allows these probabilities to vary across time and be associated with driving forces.

The transition probability functions are then defined as a logistic function given by:

$$\mathrm{P}_{11}^{\mathrm{t}} = \frac{\exp(\sum_{i=1}^{j} \mathrm{a}_{\mathrm{i}} \mathrm{z}'_{\mathrm{t-i}})}{1 + \exp(\sum_{i=1}^{j} \mathrm{a}_{\mathrm{i}} \mathrm{z}'_{\mathrm{t-i}})}$$ [8]

$$\mathrm{P}_{22}^{\mathrm{t}} = \frac{\exp(\sum_{i=1}^{j} \mathrm{b}_{\mathrm{i}} \mathrm{z}'_{\mathrm{t-i}})}{1 + \exp(\sum_{i=1}^{j} \mathrm{b}_{\mathrm{i}} \mathrm{z}'_{\mathrm{t-i}})}$$

where, $\mathrm{a_i}$ is the estimated coefficient (or a vector of estimated coefficients) that measures the impact of the information variable(s) on the transition probabilities and $\mathrm{z_t}$

[8] As in Emrah et al. (2012), the intercept term is not included in the logistic function.

is an information variable or a vector of information variables upon which the evolution of unobserved regimes will depend.

I use different information variables in this model to evaluate the transitional effects of different oil and macroeconomic determinants which include lagged industrial production and positive net oil price shock[9].

1.4 Data Description

This essay uses two data sets: daily and monthly to allow for interrelationships between risks and economic activity. The daily sample includes the daily closing prices for two gauges of expected volatility in equity and bond markets, *VIX* for equity market and *MOVE* for bond market, the *TED*, and the West Texas Intermediate (*WTI*) crude oil futures price. The daily sample spans the period 1/2/2002 to 7/10/2010 which allows for having nonstationarity of all levels of risks.

The monthly data set includes monthly closing values for VIX, MOVE, the default risk premium (*DFR*) which is the real difference between BAA corporate bond rate and the 10-year Treasury bond rate, (real) industrial production (*IP*) and the *WTI* oil

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[9] I construct this variable (Positive Net Oil Price Shock to capture the influence of the energy price increases on the state of economy. The variable is the same as the NOPI variable used in Hamilton (1996) and Aloui and Jammzi (2009). It is defined as the difference between the current monthly closing price of oil and the maximum of the previous 12 months if the difference is positive, and all zero otherwise. PNOPS = oil_t-Max(oil_{t-1},…, $oil_{t-12,}$ if = oil_t-Max(oil_{t-1},…, oil_{t-12})>0, 0 otherwise)

price. The monthly sample period ranges from 7/1999 to 7/2011. In addition, I also sourced daily and monthly data for policy variables: the lagged federal fund rate, quantitative easing *QE1* and *QE2*. All the data have been obtained from DataStream. Table 1.1 summarizes the notation and sources for the data series in this study.

As indicated above, the equity *VIX* is an index that measures expectations of volatility of the *S&P* 500 index over the next 30 day period. It is calculated based on the options on *S&P* equity index and quoted in percentage points. [10] *VIX* is referred to as the "fear index" in equity market. An increase of *VIX* is usually associated with a decrease in the *S&P* 500 index.

The one-month *MOVE* index is a yield curve weighted index of the normalized implied volatility on one-month Treasury options, with a 40% weight on the 10-year Treasury and a 20% weight on each of the other 20- and 30-year Treasury bond maturities. The *MOVE* trades between two extremes: 80, indicating extreme complacency which presages a market problem as a result of satisfaction and contentment of the current situation, and 120 which signals extreme fear. Moves to the extremes are quite rare for this credit index. Recently, the *MOVE*'s movements signal a new regime of interest rates characterized by heightened uncertainty as market participants bid up the price for options to hedge their current risk exposure. Unlike to its equity counterpart, the CBOE's *VIX*, the *MOVE* can spike as the underlying Treasuries move in either direction. The *VIX* usually spikes as stocks go down. But the

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[10] For example, if VIX is 50, one can infer that the index options markets expect with a 68% probability the *S&P* 500 to move up or down $\frac{50\%}{\sqrt{12\text{ months}}} = 14\%$ over the next 30-day period.

jumps in the *MOVE* Index are fairly agnostic or doubtful and can be a result of yields moving in any direction.

The *TED* spread, which is here the difference between the three-month T-bill interest rates and the three-month London Interbank Offered Rates LIBOR, measures the banks' perception and caution on the credit risks of other banks. It had remained quite stable below 1% before June 2007 when its volatility dramatically increased. Right after the collapse of Lehman Brothers, the *TED* spread jumped from 1.4% to 5.6% in one month. With all the financial rescue policies adopted in U.S and any other countries, the TED spread narrowed down to 1.5% in February, 2009 but still stayed above the historical average. After the 2007/2008 financial crisis, it has been used as a signal of financial stress.

The default risk premium is the difference between the corporate BAA bond rate and the 10-year Treasury note rate, which measuring the rises and falls in corporate credit risk in anticipation of recessions and booms, respectively. This measure captures more default risk than the difference between the corporate BAA rate and the AAA government agency bond rates.

Industrial production is an index which measures real production output in U.S. released by Federal Reserve monthly, with the base year as 2007 in the sample. After it reached historical peak in March, 2008, it slid down 18% until June, 2009 and then bounced up 10% in the following year 2010.

In terms of volatility for financial risk measures, on monthly basis *TED* has the highest coefficient of variance or C.V. (0.73555), followed by the default risk (0.3547), *VIX* (0.1176) and *MOVE* (0.0498) in this sequence (See Table 1.2A). For the economic/oil variables, oil has a higher C.V (0.1856) than industrial production (0.0362). All the variables of interest except for *VIX* and *MOVE* have asymmetric distributions revealed by the Skewness statistics. The Kurtosis statistics for *TED* and *DFR* are significant higher than 3 which also imply the extreme values for these two risk measurements occur more frequently than would be predicted by the normal distribution. On the other hand, WTI oil future price and industrial production have a flatter distribution than the normal distribution. The Jarque-Bera statistics for all variables reject the null hypothesis of normal distribution at the 5% significance level.

[**Table 1.2A is about here**]

I find similar results for the daily data set. All the Jarque-Bera statistics rejected the normal distribution hypothesis

[Table 1.2B is about here]

I apply the ADF and Phillips-Perron tests to check the stationarity of variables. Table 1.3A and Table 1.3B present all the results for stationarity tests. All the tests show these variables are I(1) or in other words strongly support the presence of unit root in these series. The motivation to analyze non-stationarity is to make sure that I use the proper specification of the VAR structure.

[**Tables 1.3A and 1.3B about here]**

1.5 Empirical Results

I will present and discuss the results for the daily and monthly linear VEC models followed by those for the MS-VEC models. These models are necessary to explain the transmission of risks when there is no dramatic change in the financial and economic environment and when there is a switch in the underlying risk regimes. The monthly models are warranted to explore the transmission of risks and shocks between the financial and real sectors.

What is more important is the feedback sensitivity between the risk measures and the financial/economic/oil variables under different regimes. I can state at the outset that in the two daily and monthly MS-VEC models, the interrelationships among the variables are found to be regime-dependent, which suggests that a regime breakdown can explain these relationships better, thus reinforcing the justification of using regime-dependent models.

1.5.*1. Daily models*

1.5.1.1. Daily linear VEC model

The daily linear model includes four endogenous variables: *VIX*, *MOVE*, *TED* and oil price and three exogenous variables: *QE1*, *QE2* and lagged *FFR*. This model focuses on financial risks emanating from different asset markets. It is not possible to include oil *VIX* in this model because data on this commodity-centered volatility risk starts on May 19, 2007 while the daily data starts on January 2, 2004. Therefore, I use the oil price as a representative of commodity markets.

The results of the trace and maximum eigenvalue cointegration tests for this daily model are shown in Table 1.4. They indicate that there are two long-run equilibrium or parity equilibrium relationships among the four endogenous variables, suggesting that there are two common stochastic trends that co-move them. Specification 2 of intercept and no trend in the cointegrating and the VAR gives the best fit of all five specifications. The resulting cointegration equilibriums are listed in Table 1.4.

[Insert Table 1.4 about here]

All the drivers in both long-run equilibrium relationships are significant except for the oil price, implying that those variables drive the adjustments to the equilibrium in the VAR system as they process new information on daily basis. The error-correction terms (ECTs) in VEC models capture the deviations from the respective long-run equilibrium through the work of the drivers in the long-run (cointegrating) relationships. Most of the ECTs for both cointegrating equations in this daily model are significant; the exception is the ECT for *VIX* in the second cointegrating equation. Their significance in this model is that they cause adjustment by eliminating deviations from the long-run equilibrium. This implies that the different risk types show mean-reverting behavior and align with each other, avoiding escalations or overshooting.

The daily short-run adjustments in this linear model are dominated by changes in the *S&P500 VIX*, T-bond *MOVE* and oil. Among the exogenous variables, monetary policy through managing the *FFR* has a significant effect on all four endogenous variables. However, the dummies *QE1*[11] and *QE2* as an emergency policy have only an impact on the financial stress measure *TED* but with no effects on the volatility risks and oil return on daily basis.

This linear model shows in particular evidence of a risk spillover from the equity *VIX* to the bond risk *MOVE* and oil returns. The relationship between *VIX* and oil is bilateral but is unilateral with *MOVE* which also unilaterally receives risk from *TED*. *MOVE* and *TED* as spreads are dependent on the Treasury securities rates.

1.5.1.2. Daily MS-VEC model

This asymmetric model includes the endogenous variables *S&P* 500 volatility *VIX*, Treasury bond volatility *MOVE*, oil price and *TED*, and the exogenous variable lagged *FFR*, and the dummies *QE1* and *QE2*. The regime variances are significant for all the endogenous variables, but are higher in the second regime as expected (see Table 1.5).

[**Table 1.5 about here**]

In terms of the error-correction terms (ECTs), the results are different between low volatility regime and high volatility regime. Under the normal (low) volatility regime, among the ECTs from the first cointegration equation, only the one for *VIX* is significant; for the ECTs from the second cointegration equation, the ones for *MOV*E and TED are significant. However, in the high volatility regime, the ECTs from the first

[11] QE1 is a dummy variable, which is equal to 1 from 11/24/2008 to 03/30/2010 and equal to zero otherwise. QE2 is equal to 1 from 11/03/2010 to 6/30/2011 and equal to zero otherwise.

cointegartion equation are significant except for *VIX*. And for the ECTs from the second cointegration equation, the ones for *MOVE* and oil are significant. The results suggest that the long run equilibriums are maintained through different risk factors under two regimes.

As the short term adjustments are considered, *VIX*'s lead on all the four endogenous variables except *TED* is significant in the normal (low) volatility regime. The spillover of risk from *VIX* to the government bond market as represented by *MOVE* is positive, signaling that risk can migrate from the stock to the bond markets. Higher *VIX* risk can also lead to lower oil return on daily basis under both regimes, suggesting that higher volatility in the stock market does not bode well for the oil market on daily basis in the tranquil state of a regime-changing environment. Thus, higher risk in the stock market is negative for the oil market. The Treasury bond volatility *MOVE* does not have the spillover prowess in the normal (low) volatility regime but it has the same negative impact on the oil return as *VIX* in high volatility regime.

Oil returns have positive influence on *VIX* in the normal regime, suggesting that increases in the oil return can also invoke more volatility in stock market but this influence is not significant under the high volatility regime. Perhaps higher oil prices add to uncertainty about expected inflation which can fuel volatility in the stock market in normal times.

As far as the impacts of the exogenous variables are concerned, the lagged *FFR* representing contractionary monetary policy does not have uniform effects on the four risks and oil variables under both regimes. While higher *FFR* increases the *TED* spread which captures financial stress under both regimes, it lowers the *VIX* and *MOVE* volatility spreads and the oil returns under the normal regime. However, it increases the oil returns in the high volatility regime. Thus, monetary policy has multiple edges and should be cognizant of the state of uncertainty of the system.

It is interesting to compare the results of the daily linear VEC model with the MS VEC model under each regime respectively. While the short adjustment pattern of the linear VEC model is somewhat similar to that of the MS-VEC model under the normal regime, the error-correction terms are very dissimilar to the results under both regimes. Since the ECTs represent the stabilization factors and patterns, this dissimilarity suggests that the daily system is driven back to the long run equilibrium by different factors under the normal volatility regime and under the high volatility regime. Using the linear VEC model, which only captures the mean effect, may lead to misunderstanding of the stabilization pattern in the financial markets.

1.5.2. Monthly models

1.5.2.1 Linear VEC model

By including monthly macroeconomics indicators, I extend the daily linear model in an attempt to capture the risk migration between the financial risk indicators and real economic fundamentals, while still accounting for the emergency monetary policy. This extended model uses data series on monthly basis. I present my results in two steps: first I discuss the result for the extended VECM that includes two real economic variables *IP* (industrial production) and oil (*WTI* oil three-month future price) as additional endogenous variables.

As is the case in the daily linear model, the monthly linear VEC model has also two cointegrating vectors among the five financial, economic and oil variables, suggesting that there are three common stochastic trends. In these two long-run cointegrating (equilibrium) relationships, the default risk (*DFR*) spread, the industrial production *(IP)* and oil price all are the loading factors that drive the long-run adjustment of *VIX* to the equilibrium in the first cointegrating equation and drive the long-run adjustment of *MOVE* in the second cointegrating equation. Thus, the two long-run cointegrating (equilibrium) relationships reflect the driving forces of both financial and economic activity variables in this model.

[**Place Table 1.6 is about here]**

In the long-run adjustment for this monthly VEC model, all the financial ECTs for both cointegrating equations are significant; the exceptions are the ECTs for the economic and oil fundamentals: industrial production and oil price for both equations. This means in the long-run, the financial variables are correcting to the long-run equilibrium, but the industrial production and oil price are not.

In the short-run adjustments to the equilibrium, the financial and oil variables do participate in the adjustments. *VIX* makes the adjustment through changes in the past *MOVE* and oil return, *MOVE* through changes in its own past level and oil return, and the default risk (*DFR*) spread through changes in the past *VIX, MOVE*, its own lagged level and industrial production (*IP*), industrial production (*IP*) through changes in *MOVE*. Finally, oil return not only shows exogeneity in the long-run cointegrating (equilibrium) relationships, it also acts as exogenous in the short-run adjustment. The implementation of *QE1* has significant effect on all variables, but *QE2* only increases industrial production (*IP*) which came abruptly and only lasted for six months, lending some support to the argument that *QEs* should be done within a permanent policy framework under a transparent plan that has goals and targets and not just as an emergency monetary policy.

As part of the robustness tests, I have carried out the multivariate Jarque-Bera residual normality test for both the daily and monthly VEC model to verify the validity of these models as stated in subsection 1.3.2. The daily and monthly normality VEC results are included in Table 1.4 and Table 1.6, respectively. These results reject the null hypothesis that the residuals are following the multivariate normal distribution, which imply parameter instability in the VEC model. They suggest that accounting for regime dependence of the relationships between variables is warranted.

I also apply the adjusted LR test to test linearity versus non-linear regime switching specifications. The adjusted LR statistics are significantly above the upper bound derived from the procedure in Davies (1987). Therefore, the linear specification of VEC should be rejected.

As in the linear VEC case, I analyze the results for the daily and monthly MS-VEC models. According to the results, the difference between these two non-linear models is that the daily model works well when the financial stress is represented by *TED* which is the difference between the three-month *LIBOR* and Treasury security rate among other measures of financial stress that were tried, while in the monthly model the result are better when the financial stress is represented by *DFR* which is the corporate default risk premium that detects turnarounds in economic activity.

1.5.2.2. Monthly MS-VEC model

The results of symmetric or linear VEC models without any regime structure may simply be capturing the average effect. Within the MS-VEC model, I may likely find the parameter of a particular variable to be significant in one regime but is not in another regime. If it occurs, then the MS-VEC model provides additional insight into the background financial dynamics. Moreover, when a structural change occurs, a time-varying process poses a problem for estimation and forecasting in the single regime because there would be a shift in that parameter. This process leads to treating regime-shifts not as a singular event but rather governed by an exogenous stochastic process. Thus, regime-shifts of the past are believed to occur in the future in a like manner. By its very nature, the regime-dependent analysis makes probabilistic statements (i.e. the observation of a particular date has certain probability of being in one regime). This has the added advantage in empirical analysis, particularly when some known historical events could be associated with specific dates. The multivariate MS model is estimated using the maximum likelihood method and the likelihood function is constructed following Kim and Nelson (1999). The smoothed probabilities (i.e. the transition probabilities given the complete data) are also obtained following Kim and Nelson (1999).

In the monthly model, an across-regime comparison suggests that extent of significant regime-dependent relationships among the variables is greater in the high volatility regime than in the low volatility regime (Table 1.7). This empirical evidence suggests that the diversification benefit potential from investing be lowered under regime 2 as a result of increased dependencies and interrelations among the variables. Recent studies suggest that recent financial crises stoked greater correlations between the world's equity markets, in particular in periods of high and extreme volatility (Chan-Lau, J.A., Kim, Y.S., 2004; Diamandis, 2009). The monthly expected duration of the high variance state is only 1.93 months, while in the low state it is 6.34 months.

[**Table 1.7 about here**]

Thus, the system stays three times as much in the low state as in the high state. During the 2007-2008 financial crisis, the system had stayed most of the time in regime 2 (high volatility regime), while in the post Great Recession period the system corrected course and has been staying in regime 1 (low volatility regime) most of the time (see Figure 1.1).

[**Figure 1.1 about here**]

This finding suggests that the system has started to return back to normal stability in the post Great Recession recovery period. The high volatility regime is tremendously more volatile for all risk, financial, economic and oil variables than the low volatility regime, justifying the breakdown of the system into two regimes. The asymmetric *VIX* effect over the two regimes is similar to that of Alexander and Kaeck (2008) for *CDS* spreads, while the oil effect is consistent with the finding in Andreopoulos (2009).

As *VIX* is concerned, this measure of equity risk is influenced positively by *MOVE* and the economic activity variable industrial production (*IP*), and negatively by the oil returns in the normal volatility regime, while it is only sensitive to the industrial production (*IP*) negatively in the high volatility regime, giving a prominent but different roles for the economic activity variable on stock market volatility in both regimes. On the other hand, the bond volatility risk *MOVE* is influenced negatively by its past own changes, positively by *DFR* and negatively by oil returns in the first regime. It is also negatively responsive to oil returns in the second regime where an increase in oil returns leads to lower negative bond risk, perhaps reflecting higher economic growth and the consequently higher demand for oil. It is worth underscoring the result that higher oil returns lower both the expected volatility in both the stock and bond markets in the first regime on the monthly basis.

Changes in the corporate default risk spread (*DFR*) show much more sensitivity in the second regime than in the first one in this monthly non linear model. In the second regime, *DFR* is positively responsive to increases in *VIX*, suggesting an increase in equity market volatility leads to a higher default risk spread in the corporate bond market which purports to a turnaround in economic activity. However, *DFR* is negatively responsive to industrial production in the second regime, indicating that an improvement in this economic activity leads to lower corporate default risk or an upward turn in economic activity. The same analogy applies to the effect of real interest rate *RIR* on the default risk spread in the second regime.

Oil returns are also more sensitive in the second regime than in the first one as is the case for *DFR*. Oil returns are increased by the increases of real interest rate in that regime, probably representing a strengthening in the economy. Industrial production responses only to *MOVE* positively in the first regime but marginally, underscoring the view that volatility risk in bonds market may affect economic activity. Thus, financial volatility in the bond market can be harmful to economic activity.

QE1 and *QE2* have mixed performance in those regimes. In regime 1, *QE1* has a positive impact on *VIX*, implying that increases in quantitative easing as manifested in buying long-term securities stokes more risk in the equity market in this regime. Conversely and interestingly, *QE2* which is based on buying long-term Treasury bonds decreases *VIX* and *MOVE,* probably signaling that a longer term quantitative easing based on long-term government bonds is more effective in the normal regime. However, in regime 2, *QE1* becomes more significant than *QE2* as it displays a negative impact on *VIX, MOVE* and oil returns, while *QE2* only decreases *VIX*. In sum, quantitative easing may reduce volatility in the stock, bond and oil markets under high uncertainty environment in the monthly framework.

Finally, the lagged real interest rate (*RIR*), donated by the 10-year T Bond interest rate minus the inflation rate, reduces the changes of default risk rate (*DFR*) in the high volatility regime.

The MS-VEC model shows very different effects for the exogenous variables representing the monetary policies from the linear VEC model. Therefore, it is critically important for policy makers to understand whether the effects of the policy are regime-dependent or not. I conduct the test on the regime-dependence of the effects of the exogenous variables in the MS-VEC model.

Regime variances and smooth probabilities

[**Figures 1.1A and 1.1B are about here**]

1.5.3. Daily and monthly impulse response analysis under regime switching:

I perform the impulse response analysis with the 95% confidence bands for the daily and monthly models under two regimes based on 1000 bootstraps. For the analysis of the daily model, the lines in each column of Figure 1.2 show under the two regimes the responses of each of the three financial risk measures and the oil price to shocks coming from all these four variables over a 50-day horizon.

All the responses of the three financial risk/spread measures to the *VIX* shock (the shock to the expected volatility of the *S&P 500* index) are significant under both regimes. This suggests that there is a risk migration from equity market to the bond and credit markets. The expected volatility of the *S&P 500* index (*VIX*) leads to significant and positive responses from itself and *MOVE* in both regimes. However, the response patterns of *MOVE* are different in each regime. In the low volatility regime, the response rises modestly from the initial shock and then persists, but in the high volatility regime it jumps to the peak instantly and then drops slightly before reaching persistence throughout the 50-period horizon.

[Figure1.2 is about here]

The responses of *TED* are interesting. It seems that the *VIX* shock will cause this credit risk to slightly drop before persisting under the low volatility regime but it will cause one instant and persistent jump under the high volatility regime. This response pattern suggests that banks dealing in international interbank money markets may behave differently under different risk regimes. This finding implies that the increase in the *VIX* risk warrants more viable hedging strategies in the interbank markets on part of banks under the high volatility regime. The *VIX* shock leads to a significant drop in the oil return under the low volatility regimes. Higher expected volatility in the stock market leads to lower oil prices under tranquility.

Unlike *VIX*, the shock of *MOVE* does not have significant impacts on other risk measures under both regimes. Specifically, there is no significant response to the *MOVE* shock from *VIX* under both regimes on daily basis, which is different from the significant response of *MOVE* to a shock from *VIX*, as indicated above. However, there is a significant instant jump in *MOVE* as a result of its own shock which quickly becomes persistent under both regimes. In terms of the oil response, *MOVE* leads a slight and persistent increase of oil return under the high volatility regime, but the response is not significant under the low volatility regime. Thus, oil is more sensitive to *MOVE* shocks under turmoil. Finally, there is no daily significant response to *MOVE* shocks under both regimes from the *TED* spread which measures financial stress in the euro interbank money market.

The oil shock leads to a significant response from *VIX* under the low volatility regime. This suggests that shocks of higher oil prices lead to greater expected volatility in the stock market during tranquility times. There is no significant response to oil from *MOVE* and *TED* on daily basis. The oil return's responses to its own shocks are significant under both regimes, though the response is more steady and persistent under the high volatility regime.

The *TED* shock only affects itself under both regimes and has no significant effects on the other variables on daily basis. Only the instant response of *TED* to its own shock is slightly different under the two regimes, with an instant jump under the low volatility regime and instant drop under the high volatility regime. The consequent responses become steady and persistent under both regimes.

Figure 1.3 shows the results for impulse response analysis for monthly model.

The responses of *VIX* to its own shocks, the expected volatility of *S&P 500*, are significant on monthly basis, which instantly drop and then stay steady and persistent under both regimes. A shock from *VIX* to *MOVE* leads to a significant and positive response under the low volatility regime only. This suggests that the market risk can migrate from stocks to bond markets only under tranquility. Similarly, the response of the default risk spread (*DFR*) to the *VIX* shock is positive and significant under the low volatility regime but much more potent than the case of *MOVE*. This implies that there is a risk migration to corporate bond market from higher expected volatility in the stock market under tranquility times but with more prowess than in the Treasury bond market. There is a tiny and steady state response of industrial production to the *VIX* shock under the low volatility regime only. This suggests that the migration financial risk to the economic activity is small and limited under tranquility on monthly basis. The *VIX* shock also leads to a positive but tiny response of oil only under the low volatility regime on monthly basis. The oil response is smaller than in the case of daily data when no real economic activity variables are included. Moreover, the monthly oil response is positive while the daily response is negative.

As far as the monthly shocks from *MOVE* are concerned, there is a reciprocal positive response from *VIX* to a shock in *MOVE* under the low volatility regime, although initially the *MOVE* shock has stronger effect. Thus, the shock impacts are mutual between *VIX* and *MOVE* only when markets are less volatile. Surprisingly, on monthly basis when both markets become highly volatile the risk spillovers are not significant between stock and Treasury bond markets on monthly basis. There is an instant jump in *MOVE* as a result of its own shock, implying that the shocks in the Treasury market feed on themselves. But this response recedes quickly and it becomes persistent. The response of default risk spread (*DFR*) to the *MOVE* shock is instant and insignificant under both regimes. It decays quickly and vanishes. Unlike the response to the *VIX*, the industrial production response to *MOVE* is not significant. This result is not surprising because *VIX* represents volatility of stock options of companies that produce the industrial production, while *MOVE* is related to the volatility of the Treasury bonds.

The shock of default risk (*DFR*) spread has positive impacts on both *VIX* and *MOVE* only under the low volatility regime but the former is greater than the later because *DFR* represents the financial stress in the corporate bond market. The response increases over four periods before becoming steady and converging to the long-run equilibrium. The default risk spread responses positively to its own past shock under both regimes, but unlike *VIX* and *MOVE* this impact increases from the initial jump for both regimes. The impact of *DFR* on industrial production is marginal significant under the high volatility regime only, underlying its property as a predictor of changes in economic activity which holds here only during turmoil. The oil to *DFR* shock is no different than its response to the *TED* shock under daily basis. It underlines the importance of shocks related to the fundamentals over shocks related to financial risks.

An *IP* shock can significantly increase *VIX* during the first period under both regimes. That is, initially a shock in *IP* can increase the expected volatility in stock market, probably because of an outset increase in the level of uncertainty under both tranquility and turmoil. Then the *VIX* response drops slightly before it stabilizes to the long-run equilibrium under the low volatility regime; but *VIX* rises without any drops under the high volatility regime. This highlights the importance of the shocks in real economic variables on *VIX* over the importance shocks in stock market risks on economic activity. On the other hand, the response of *MOVE* to the *IP* shock is negative and marginally significant only under the high volatility regime. *DFR* responds differently to the *IP* shock under each regime. Under the low volatility regime *IP* shock leads to a significant rise of *DFR* while under the high volatility regime *IP* leads to a marginally significant drop of *DFR*. *IP* responds positively to its own shocks under both regimes.

The positive oil shock leads to a significant and positive response from *VIX* under the high volatility regime, implying the risk migrates from oil price to stock market on monthly basis. However, the oil shocks lead to negative, although marginally significant, drops in *MOVE* and *DFR*, signaling improvement in economic activity and a reduction in demand for the Treasury securities as safe haven. This implies that the shocks from the real economic activities may have different impacts on different financial markets. The industrial production (*IP*) also responses positive to the oil shock under the high volatility regime only which confirms the above interpretation on economic activity. Finally, the oil return responds positively to its own shock under the high volatility regime only.

1.5.4. Monthly time-varying transition probability Markov switching VEC model

The monthly MS-VEC estimated above is set under the fixed transition probabilities specification which does not allow the transition probabilities governing the switch of risk regimes to be endogenous and varying over time. In this section, I estimate the MS-VEC model under time-varying transition probabilities, which use the selected information variables to explain the evolution of the transition probabilities governing the switches of risk regimes. As my primary interest here is to identify the impacts of two variables (the industrial production and oil price changes) on the transition of risk regimes in financial markets, I construct a TVTP-MS-VEC model with three financial risk measures (*VIX*, *MOVE* and Default Risk Premium), and use the changes in industrial production and the oil price as the information variables in the probabilities function respectively. Both models indicate that two different regimes can be identified, (a low volatility regime and a high volatility regime), despite which information variable is used.

Table 1.8 presents the results of the TVTP-MS-VEC using the WTI oil price change as the information variable. The results show that the oil price change has significant effects on the transition probabilities only in the low volatility (regime 1). When the markets are in the low volatility regime, the increase in the WTI price will decrease the probability that the low volatility regime will persist. In other words, the positive oil price shock will pull the financial markets away from the tranquil state and push them to the turbulent state. On the other hand, if the markets are in the high volatility regime (regime 2), a rising oil price has no significant effects on the probability of switching to the low volatility regime, negating the oil price the stabilizing status. The role of the oil price in the transitional probabilities documented here is consistent with the findings in Chen (2010). However, Chen (2010) only focuses on the returns and volatility in the US stock market, while in this essay I look at the volatilities in US stock and bond markets as well as the default risk.

Table 1.8B reports the results of TVTP-MS-VEC estimation when the industrial production is used as the information variable. The results suggest that the industrial production has significant influence on the transition probability P_{12}, which is the probability of switching from the high volatility regime (regime 2) to the low volatility regime (regime 1). However, the industrial production surprisingly doesn't affect the transition probability in the low volatility regime.

[**Table 1.8B is about here**]

1.6 Conclusions

This essay examines the dynamic relationship among different measures of financial risks including expected volatilities in the stock and Treasury bond market and gauges of financial stress on the daily and monthly bases. The expected stock market volatility is represented by the *S&P 500 VIX* while the expected volatility in the Treasury securities market is measured by *MOVE*. The financial stress is measured by changes in spread between *LIBOR* and Treasury bill rates, which is known as the *TED* spread for the daily data, and by the default risk (*DFR*) premium which gauges the spread between the BAA corporate rate and the 10 year Treasury bond rate for monthly data.

Since these risk measures are sensitive to the state of the economy and different environment regimes, I construct two VEC models: the conventional VEC model that has one single regime, and the two-regime MS-VEC model as warranted by the regime specification tests. Both models are also applied to the daily and monthly data. In the monthly models, economic activity as represented by industrial production is added to detect migration of risk between the financial and real sectors.

I underscore the importance of the source of the shock of the variable by distinguishing between financial and real economic activity shocks. I are keen to know whether financial or economic shocks have the upper hand in influencing different risks.

In terms of financial risk migration, it appears from the empirical evidence that risk spreads from stock market to the Treasury bond market but this spread does not impact the financial stress in the international interbank market on daily basis. Additionally, there is risk migration in the case of the inter-bank financial stress to the expected volatility in the treasury securities market. There is no risk spread from the treasury securities market to the stock and interbank markets. MS-VEC model confirms the risk migration from *VIX* to *MOVE* in the low (normal) volatility regime. This finding also underlines the importance of *VIX* in spreading risks to other markets.

The monthly result of the conventional VEC model does not give *VIX* a major role to play as in the daily model. In fact, it suggests that the expected volatility in the Treasury bond market affects the corresponding volatility in the stock market. This result is confirmed by the MS-VEC model which suggests *MOVE* as well as *DFR* play the most important role in terms of financial risk spreading under the normal volatility regime. This finding contradicts the role *VIX* plays in the daily model.

The most interesting feature of the monthly model is the relationship between the financial risks and the economic activity represented by the industrial production (IP). Interestingly, it is *MOVE* not *VIX* that impacts *IP* in the conventional monthly VEC model. The industrial production (*IP*) receives no impacts from other financial risk spreads. However, the MS-VEC model under the normal volatility regime confines this

IP impact role to only *DFR* which is known as a detector of changes in economic activity. On the other hand, the conventional VEC model suggests that the industrial production (*IP*) does not impact any financial risk measures except for *DFR*. However, the MS-VEC result shows that *IP* affects the expected volatility in stock market (*VIX*) as well as *DFR* under both regimes, although the effects are reversed across regimes.

On monthly basis, increases in oil price returns in the conventional model reduce *VIX* and *MOVE*. This result is confirmed by the MS-VEC model under the normal volatility regime, implying that the oil return may be a better indicator than *IP* to capture the effect of real economic activity on the expected volatilities in both stock and bond markets. Similarly, the oil return acts exogenously except for being affected by *DFR* under the high volatility regime.

When it comes to the impacts of the exogenous lagged real long-run interest rate on financial risks, this rate increases the stock market risk, industrial production and oil prices in the conventional monthly VEC model. There is no corresponding result of this impact in the normal volatility regime of the MS-VEC model. On the other hand, under the high volatility regime a higher lagged long-run interest rate reduces DFR, underscoring the impact of fiscal policy on corporate risk in the long-run. This result suggests that the conventional monthly VEC model captures the long-run interest rate impacts better than the MS-VEC model.

In terms of the effects of the emergency monetary policies on financial risk measures, the conventional monthly VEC results suggest that *QE1*is much more effective than *QE2* in calming the volatilities in stock and bond markets and reducing

DFR. The results of MS-VEC model indicate that both *QE1* and *QE2* are effective under both regimes. This should not be a surprise because quantitative easing is not a conventional policy and should be examined in a regime changing environment.

In conclusion, for a study that deals with different measures of financial and economic risks, the MS-Model captures more effects and provides more useful information.

Chapter 2: Asymmetric Adjustments of the Responses of Stock Markets to Disaggregated Country Risk Ratings for the BRICS

2.1 Introduction

The five BRICS (Brazil, Russia, India, China and South Africa) are currently viewed as fastest growing economies with relative political, economic and financial stability, and believed to have the prospect of inducing a major reallocation in world powers in the future. Their current stability and the future promise should have positive implications for these countries' economic, financial and political risks currently and in the future, with the spillover to their financial markets including the stock markets.

The country risk ratings are used to measure the overall risk for investments in countries. This aggregated country risk factor also includes disaggregated components such as financial, economic and political measures of stability. The impacts of country risk on the performance of the economic and financial sectors are catching increasingly more attention given risk events such as the bailout in Greek, the turmoil in Middle East and the nuclear crisis in Japan. There is extensive literature on the effects of corporate credit on individual stock prices. Meanwhile, the relationship between Country Credit Risk (CCR) and the economic and financial performance also starts to catch more attention. Erb, Harvey and Viskanta (1996b), for example, examine the symmetric impacts of political, financial and economic risks on expected fixed-income returns. They investigate the performance of forty national equity markets on the indices released by Morgan Stanley Capital International (MSCI), International Finance Corporation (IFC) and World Bank. This essay is different from Erb, Harvey and

Viskanta (1996b) in three ways. First, I use the decomposed country risks into three components to identify the effects of financial, economic and political risks on the individual stock markets. Second, since it is known that positive and negative shocks in CCR have asymmetric effect on financial market and real economy, I use the Momentum Threshold Cointegration (MTAR) model to examine whether the positive and negative shocks in those risk components have symmetric or asymmetric effects on the stock market performance.

The objective in this essay is to focus on the five fastest growing economies, known as BRICS, which include Brazil, Russia, India, China and South Africa. These countries are having strong impacts on the global GDP growth and are showing strong stock market performance. More resources are being channeled to these countries. It will be interesting and valuable to discern how the stock markets in these high growth countries behave in the face of asymmetric risks.

The remaining parts of this chapter are organized as follows: Section 2.2 provides a review of the relevant literature and section 2.3 introduces the ICRG country risk ratings and the background information of BRICS countries. Section 2.4 presents the empirical framework of my research, and section 2.5 discusses the empirical results. Section 6 concludes.

2.2 Review of the Literature

There is extensive literature on the effects of corporate credit on individual firms' behavior and performance (see Klymaz 2009). However, the research focusing on the impacts of the changes of the country risk rating on the economic and financial performance of the country is limited, especially in the context of the equity market performance for the emerging economies including BRICS.

Given the increasing global investment opportunities, finding the appropriate measures of country risks becomes very important for international portfolio managers, investors and regulatory agents. Oetzel, Bettis and Zenner (2001) summarize eleven widely used measures of country risk and evaluate their usefulness across seventeen countries. They find all the country risk indicators are adequate and reliable measures of country risk during period of normal environment but work poorly in the periods when there exist dramatic country risk changes. They use the monthly percentage changes in the value of a national currency as a proxy of real country risks. The periods of dramatic country risk changes are classified into two categories. One category refers to those periods when the currency value drops by 10% or more in one month, while the other entails the drops by 40% or more.

Erb, Harvey and Viskanta (1995) investigate the relationships between the survey-based country credit ratings and the expected returns and volatilities of their equity market indices for forty countries, including both developed and emerging nations. On the one hand, they find the lower country risk ratings (i.e., higher country risks) are associated with the higher average equity returns for most of the countries expect for Argentina and Brazil. On the other hand, they find there is a negative relation between the country risk ratings and the local equity return volatilities, which means a higher country risk indicates a higher equity return volatility. Erb, Harvey and Viskanta (1996b) extend their analysis by adding three lagged country risk rating measures from International Country Risk Guide (ICRG)—political risk, economic risk and financial risk credits. Their time-series/cross-sectional regression results show that, when all the countries are pooled together, the financial risk credit has the most explanatory power on the expected equity index return, while the economic risk credit has the least. However, if the emerging countries are estimated separately from the developed countries, no risk attribute is statistically significant in determining the expected equity returns. Since the authors don't distinguish the positive changes of the country risk credits from the negative ones, their result may be misleading if there exist asymmetric effects. Diamonte, Liew and Stevens (1996) investigate how the political risk affects equity market returns in emerging and developed markets. They use the same ICRG political risk measure and focus on the pre-Iraq-war period from 1985 to 1995. They find the political risks have greater influence on the level of the expected market returns in emerging markets than in developed markets. Alexei and Alexei (2006) study the risk factors that affected the Russian stock market returns from 1995 to 2005. They use a linear regression model with a rolling data window of one year to capture the changes of the importance of different risk factors on stock market return. They find that the emerging market index has the most influence on the Russian stock market return, and the world oil price increase would increase the stock return in Russia only in 23% of the time.

Among the studies that focus on the impacts of sovereign credit ratings on national financial markets, Kaminsky and Schmukler (2002) examine the influence of changes in the sovereign debt ratings and the outlooks developed by the three major rating agencies, Moody's , S&P and Fitch-IBCA, on 16 emerging bond and stock markets in East Asia, Eastern Europe and Latin America. They find that the changes in sovereign debt ratings and outlooks will significantly affect both domestic bond and stock markets. Additionally, Kaminsky and Schmuker (2002) classify these countries into transparent and non-transparent as suggested in Mehrez and Kaufmann (2000), and find the impacts of rating changes are stronger in the non-transparent economies than in the transparent ones.

Lin, Wang and Gau (2007) investigate the influence of financial and macroeconomic domestic factors on the excess returns of eight emerging bond markets. They find that although the explanatory power of the local instruments on excess returns may vary across different bond markets, the local instruments can forecast excess bond returns in general. For example, the domestic credit risk spread, which is the difference between the domestic bond yield and the yield of a US Treasury bond of similar maturity, has a significant and positive effect on the domestic excess bond returns.

Hail and Leuz (2006) study the effect of countries' disclosure and securities regulations on the cross-country differences in the cost of equity capital. They find that the disclosure requirements, securities regulations and enforcement mechanisms in one country can significantly affect the cost of capital in that country.

Sari, Uzunkaya and Hammoudeh (2011) explore the relationships between country risk ratings and equity market movements in Turkey. They find that a long-run relationship exists between the equity market movements and the disaggregated country risk ratings. Moreover, the political and financial risk ratings significantly and positively impact the equity market movements in the short-run.

To my best knowledge, most of the studies on the influence of country risks on domestic financial markets apply the symmetric approach to examine the effect of changes of country risk ratings. However, previous studies suggest the presence of asymmetry of the responses of financial markets to changes of country risk ratings. My study aims to address this issue by employing the threshold cointegration model to test and identify this asymmetry in the relationship between equity market index and country risk ratings of the five BRICS countries.

2.3 ICRG Country Risk Ratings and the BRICS Countries

2.5.1 The BRICS countries

The BRICS together account for more than a quarter of the world's land area, more than 40% of the world's population and about 15% of global GDP. These countries are believed to be now at a stage similar to that of newly advanced economies. China's GDP exceeded that of Japan in 2011. Goldman Sachs expects the BRICS' nominal total GDP (excluding South Africa) to reach $128 trillion in 2050, compared to $66 trillion for the G7 countries. It also expects the four BRICS (excluding South Africa) to account for 41%

of the world's market capitalization by 2030. China might overtake the United States in equity market capitalization terms by 2030 and turn to be the largest equity market in the world. Despite the common strong economic growth, these five countries are dissimilar in many political, financial and economic characteristics, which have strong bearing on their risk ratings. As I focus on their equity markets, I notice that the developments of those markets are different. For example, the equity market capitalization to GNP ratio varies from the 35 percent for China, to the 72 for Russia. [Table 2.3 for the details about BRICS]

2.5.2 ICRG country risk ratings

The International Credit Risk Group (ICRG) rating system is based on a set of 22 indicators in three risk categories or groups: political risk, financial risk and economic risk. Three indices are created for each group: Political Risk rating (political risk) with risk points ranging from zero to 100 points; Financial Risk rating (financial risk) and Economic Risk rating (economic risk), each with risk points ranging from zero to 50 points. The composite Country Risk Rating (CR) is the sum of the political risk, financial risk and economic risk ratings divided by two, ranging from zero to 100. The greater the number of points assigned for a risk rating, the lower the risk represented by that rating. Thus, an ascending number indicates a descending level of risk.

The Political Risk rating focuses on 12 preset indicators measuring political stability of the country. The five indicators with highest weights are government stability; socioeconomic conditions; investment profile; internal conflict and external conflict. As indicated above the Political Risk rating accounts for 50% of the Composite Country Risk rating. The Financial Risk rating is based on five financial risk indicators including foreign debt as a percentage of GDP, foreign debt service as a percentage of exports of goods and services, current account as a percentage of exports of goods and services, net international liquidity as months of imports cover, and exchange rate stability. It is worth mentioning that the appreciation and depreciation of the currency against the US dollar are assigned different points for the same percentage of changes (e.g., 10% appreciation is assigned 9.5 points, while 10% depreciation is assigned 8.5 points). In order words, the same percentage of depreciation is associated with higher risk in exchange rate stability than appreciation. The Economic Risk rating includes five economic risk indicators such as GDP per head, real GDP growth, annual inflation rate, budget balance as a percentage of GDP, and current account as a percentage of GDP. The details for each risk indices are explained in Table 2.1.

2.4 Econometric Framework

This essay investigates the relationships between the equity market indices and the three types of country risk ratings for each of the BRICS countries. In particular, I aim to examine the long-run cointegration relationships and the short-term adjustments to equilibrium among those variables. The cointegrating relationship embodies the spread between the equity market index and the predicted level by economic, financial and political risks for each country. It can be interpreted as the equity index adjusted to risks in the country. Previous studies suggest that stock market returns, volatilities and correlations may asymmetrically respond to positive and negative shocks of critical economic variables, financial market risks and regulatory policies (See Lobo, 2000; Bernanke and Kuttner, 2005 and Chuliá et al., 2010).

The traditional cointegration model as Johnansen (1988), which assumes that the adjustment to long-run equilibrium is symmetric, is unable to capture the possible asymmetries resulting from the positive and negative shocks. Therefore, I consider a set of cointegration and error-correction models with Threshold Autoregressive (TAR) or Momentum Threshold Autoregressive (MTAR) processes, which allow asymmetric adjustment. Technically, I take three steps to reach my goals. In the first step, I follow an extension of the empirical work of Enders-Siklos (2001) to test the cointegration model which allows for asymmetric adjustments toward the long run equilibrium. The result will be compared against those of the linear cointegration model which assumes symmetric adjustments. I focus on a system that consists of the stock market index and the three risk ratings for each country.

I estimate the regression model of the stock index on the three components of country risks, using the ordinary least square method.

$$Stock_{it} = c_i + \beta_1 F_{it} + \beta_2 E_{it} + \beta_3 P_{it} + e_{it} \tag{1}$$

where $Stock_{it}$ is the logarithmic value of the stock index in country i at period t, the F_{it}, E_{it} and P_{it} are the logarithmic financial, economic and political risk scores for country i at the same period respectively.

Then I take the residuals from Eq. (1) and estimate the following TAR and MTAR models, respectively.

$$\Delta\hat{e}_t = \rho_1 M_t \hat{e}_{t-1} + \rho_2 (1 - M_t)\hat{e}_{t-1} + \sum_{i=1}^{n} \gamma_i \Delta\hat{e}_{t-1} + \varepsilon_t \tag{2}$$

where $\varepsilon_t \sim I.I.D(0, \sigma^2)$ and the lagged values of $\Delta\hat{e}_t$ are meant to yield uncorrelated residuals. The coefficients ρ_1 and ρ_2 are expected to be negative for convergence to occur. The absolute values of these coefficients measure the speeds of the widening and narrowing adjustments of stock index changes to long-run equilibrium, without specifying which variable(s) is (are) making the adjustment.

The indicator function for TAR model is denoted as follows:

$$M_t = \{ \begin{matrix} 1 & if\, \hat{e}_{t-1} > \tau \\ 0 & if\ \hat{e}_{t-1} < \tau \end{matrix} \tag{3a}$$

In order to let the threshold τ be determined endogenously, I use the method developed in Chan (1993) by sorting the series $\{\hat{e}_{t-1}\}$ in ascending order and excluding the lowest and highest 15 percent. The consistent estimate of the threshold τ is the $\hat{e}_{t-1}$that yields the smallest Residual Sum of Squares from the remaining 70 percent of $\{\hat{e}_{t-1}\}$. The length of the lagged values of $\hat{e}_{t-1}$ is selected according to AIC criterion.

The indicator function for MTAR model is constructed as follow:

$$M_t = \{ \begin{matrix} 1 & if\ \Delta\hat{e}_{t-1} > \tau \\ 0 & if\ \Delta\hat{e}_{t-1} < \tau \end{matrix} \tag{3b}$$

In the following, I present the equations for the MTAR-VEC model which relates Δe_{t-1} to the threshold τ. The corresponding equations for the TAR-VEC model require the modification in the indicator function of Δe_{t-1} to e_{t-1}. After the asymmetric effect is identified, I estimate the following MTAR-VEC model using the estimated threshold τ.

$$\Delta stock_t = \begin{cases} \lambda^{\mathrm{stock}^+}\widehat{\mathrm{e}_{t-1}} + \sum_{k=1}^{p}\alpha_k^{\mathrm{stock}+}\Delta\mathrm{stock}_{t-k}^{+} + \sum_{k=1}^{p}\beta_1^{\mathrm{stock}+}\Delta ER_{t-k} + \sum_{k=1}^{p}\beta_2^{\mathrm{stock}+}\Delta\mathrm{FR}_{t-k}^{+} + \sum_{k=1}^{p}\beta_3^{\mathrm{stock}+}\Delta PR_{t-k}^{+} \text{ if } \widehat{\Delta\mathrm{e}_{t-1} >} \tau \\ \lambda^{\mathrm{stock}^-}\widehat{\mathrm{e}_{t-1}} + \sum_{k=1}^{p}\alpha_k^{\mathrm{stock}-}\Delta\mathrm{stock}_{t-k}^{-} + \sum_{k=1}^{p}\beta_4^{\mathrm{stock}-}\Delta ER_{t-k}^{-} + \sum_{k=1}^{p}\beta_5^{\mathrm{stock}-}\Delta\mathrm{FR}_{t-k}^{-} + \sum_{k=1}^{p}\beta_6^{\mathrm{stock}-}\Delta\mathrm{PR}_{t-k}^{-} \text{ if } \widehat{\Delta\mathrm{e}_{t-1} >} \tau \end{cases} + \vartheta_t^{\mathrm{stock}} \tag{4a}$$

$$\Delta ER_t = \begin{cases} \lambda^{ER^+}\widehat{e_{t-1}} + \sum_{k=1}^{p}\alpha_k^{ER+}\Delta stock_{t-k}^{+} + \sum_{k=1}^{p}\beta_1^{ER+}\Delta ER_{t-k} + \sum_{k=1}^{p}\beta_2^{ER+}\Delta FR_{t-k}^{+} + \sum_{k=1}^{p}\beta_3^{ER+}\Delta PR_{t-k}^{+} \; if \; \widehat{\Delta e_{t-1} >} \tau \\ \lambda^{ER^-}\widehat{e_{t-1}} + \sum_{k=1}^{p}\alpha_k^{ER-}\Delta stock_{t-k}^{-} + \sum_{k=1}^{p}\beta_4^{ER-}\Delta ER_{t-k}^{-} + \sum_{k=1}^{p}\beta_5^{ER-}\Delta FR_{t-k}^{-} + \sum_{k=1}^{p}\beta_6^{ER-}\Delta PR_{t-k}^{-} \; if \; \widehat{\Delta e_{t-1} >} \tau \end{cases} + \vartheta_t^{ER} \tag{4b}$$

$$\Delta FR_t = \begin{cases} \lambda^{\mathrm{FR}^+}\widehat{\mathrm{e}_{t-1}} + \sum_{k=1}^{p}\alpha_k^{\mathrm{FR}+}\Delta\mathrm{stock}_{t-k}^{+} + \sum_{k=1}^{p}\beta_1^{\mathrm{FR}+}\Delta ER_{t-k} + \sum_{k=1}^{p}\beta_2^{\mathrm{FR}+}\Delta\mathrm{FR}_{t-k}^{+} + \sum_{k=1}^{p}\beta_3^{\mathrm{FR}+}\Delta PR_{t-k}^{+} \text{ if } \widehat{\Delta\mathrm{e}_{t-1} >} \tau \\ \lambda^{\mathrm{FR}^-}\widehat{\mathrm{e}_{t-1}} + \sum_{k=1}^{p}\alpha_k^{\mathrm{FR}-}\Delta\mathrm{stock}_{t-k}^{-} + \sum_{k=1}^{p}\beta_4^{\mathrm{FR}-}\Delta ER_{t-k}^{-} + \sum_{k=1}^{p}\beta_5^{\mathrm{FR}-}\Delta\mathrm{FR}_{t-k}^{-} + \sum_{k=1}^{p}\beta_6^{\mathrm{FR}-}\Delta\mathrm{PR}_{t-k}^{-} \text{ if } \widehat{\Delta\mathrm{e}_{t-1} >} \tau \end{cases} + \vartheta_t^{\mathrm{FR}}$$

$$(4c)$$

$$\Delta PR_t = \begin{cases} \lambda^{PR^+}\widehat{e_{t-1}} + \sum_{k=1}^{p} \alpha_k^{PR+}\Delta stock_{t-k}^{+} + \sum_{k=1}^{p} \beta_1^{PR+}\Delta ER_{t-k} + \sum_{k=1}^{p} \beta_2^{PR+}\Delta FR_{t-k}^{+} + \sum_{k=1}^{p} \beta_3^{PR+}\Delta PR_{t-k}^{+} \text{ if } \Delta\widehat{e_{t-1}} > \tau \\ \lambda^{PR^-}\widehat{e_{t-1}} + \sum_{k=1}^{p} \alpha_k^{PR-}\Delta stock_{t-k}^{-} + \sum_{k=1}^{p} \beta_4^{PR-}\Delta ER_{t-k}^{-} + \sum_{k=1}^{p} \beta_5^{PR-}\Delta FR_{t-k}^{-} + \sum_{k=1}^{p} \beta_6^{PR-}\Delta PR_{t-k}^{-} \text{ if } \Delta\widehat{e_{t-1}} > \tau \end{cases} + \vartheta_t^{PR}$$

$$(4d)$$

If the long-run speeds of adjustments $\lambda^{stock^+} \neq \lambda^{stock^-}$ in Eq. (4a), then the stock indices respond to the deviation from the long-run equilibrium asymmetrically (asymmetric mean- reverting) when the deviation/the speed of deviation is higher or lower than the threshold value in the MTAR models. The same logic applies to λ^+ and λ^- in Eqs. (4b) – (4d) for the risk ratings. In the stock return equation in Eq. (4a), both the above and below the long-run equilibrium speeds of adjustment λ^{stock+} and λ^{stock-}, respectively, should be negative for the stock return to revert to the long-run equilibrium. As indicated above, if the spread, e_{t-1}, is negative after a negative shock, but also widening (that is, $\hat{e}_{t-1} < 0$ and $\Delta\hat{e}_{t-1} > \tau$), and thus the change in this spread, Δe_{t-1}, is increasing, the spread is widening (that is, M_t is 1 in eq. (3b)), and the stock index will need to increase for the spread to revert to the long-run position. Thus, λ^{stock+} needs to be negative. Similarly, if the spread, e_{t-1}, is positive but narrowing (that is, $\hat{e}_{t-1} > 0$ and $\Delta\hat{e}_{t-1} < \tau$) and $\Delta\hat{e}_{t-1}$ is decreasing (that is, $M_t = 0$), then the speed λ^{stock-} also needs to be negative, indicating that the stock index needs to fall for the spread to revert to its long-run position. Thus, λ^{stock-} should also be negative.

In the case of Eq. (4b) for economic risk *ER*, the long-run speed of adjustment in the case of widening λ^{ER^+} should be positive as this risk rating should go down, implying a higher economic risk level, for the adjustment to the equilibrium to take traction. In the case of narrowing where the spread is positive and decreasing, *ER* must increase in value, implying a lower risk level, for the adjustment to converge to the equilibrium. This signifies that λ^{ER^-} must also be positive. In sum, the widening and narrowing adjustments require different movements of the risk levels.

2.5 Empirical Results

2.5.1 Data Description

I use the monthly International Country Risk Guide (ICRG) country risk ratings for economic, financial and political risk ratings. I consider the five BRICS countries. The full sample ranges from September 1995 to April 2011, which is constrained by the start of the country ratings for Russia. Table 2.2A presents the descriptive statistics for the levels of the three country risk ratings for these countries. Among the five BRICS, Brazil has the lowest historical mean for the financial risk rating, which implies that there exists a concern about this country's financial stability. Russia carries the highest level of political risk, which is confirmed by both the second lowest historical mean political risk rating and the highest volatility as defined by the variance-to-mean ratio.

All of the risk ratings have a negatively skewed distribution except for the political risk rating in South Africa. This implies a longer left tail and the mass of the distribution is concentrated on the right. This signifies that the risk ratings are bunched up on the high end of the spread scale. The highest skewness is in China's economic and financial risk and Russia's political risk. The kurtosis is positive for all the ratings, which implies the distribution is more leptokurtic (peaked) than the normal distribution. The Jarque-Bera test results reject the normal distribution hypothesis except for Brazil's financial and political risks.

Table 2.2B details the contemporaneous correlations of the three risk ratings political risk, financial risk and economic risk for each BRICS country based on the monthly observations from September 1995 to April 2011. The correlations are lower than the grouping would imply. The highest correlation of the rating levels is 0.8137 which is between the political risk and the financial risk ratings in Russia, followed by the correlation between the political risk and the economic risk ratings in India, which is 0.723. These are the only two correlations that are above 50% among the 15 correlations I considered. These correlations signify the importance of political risk in Russia and India. The relatively low correlations between three types of risk ratings for the BRICS suggest that these risk ratings focus on different aspects of the individual economy and may have different impacts on the associated stock markets. As a result, it is valid to incorporate all the risk ratings in one model, assessing the effect of different risks on stock market prices of those countries. Moreover, the correlation patterns across the BRICS are very different, which reflects strong country specific characteristics. For example, there are only two negative correlations between the political risk and each of the economic risk ratings and the financial risk ratings for China, which shows the unique influence of the political risk in this country on its financial and economic performances. The domestic stock market indices are listed in Table 2.3.

The stationary test results for both the stock market indices and country risk ratings for the five BRICS countries are presented in Table 2.4. I carry out both the ADF (constant & trend) test and PP (constant & trend) tests. For all BRICS, the country risk factors are all I(0) at 1% significance level according to the results.

2.5.1 Cointegration and Asymmetry Tests

I employ an extension of the Enders-Siklos (2001) process to test the presence of asymmetry in the long-run cointegration relationship among the equity market index and country risk ratings for each of the five BRICS. Table 2.5 and Table 2.6 present the results for asymmetric cointegration tests for TAR and MTAR specifications, respectively.

The estimates of the endogenously-derived thresholds range between -0.5 and +0.5 in the TAR model for all the BRICS countries except for China which has a positive threshold equal to 0.352. The estimates in the MTAR models range between -0.15 and + 0.15 for all the countries, but only Russia which has a positive threshold of 0.1425. The threshold estimates of the M-TAR model for the BRICS are higher than what is provided in the commodity price and stock market literature (see for example, Hammoudeh et al., 2010).

The null hypothesis of no cointegtation ($\rho_1 = \rho_2 = 0$) in Eq. (2) is rejected for all countries in both TAR and MTAR specifications, implying that there exists a significant long-run cointegration relationship between every BRICS country's stock market index and its disaggregated country risk ratings. I then test whether the adjustment to the long-run equilibrium is symmetric (i.e., $\rho_1 = \rho_2$) or asymmetric (i.e., $\rho_1 \neq \rho_2$). The results suggest that the adjustments to the long-run equilibrium between stock index and country risk ratings are asymmetric under the MTAR specification in all of the BRICS countries, but only Brazil also has the asymmetric long-run adjustment under the TAR model. This may suggest that Brazil's financial markets are more sensitive to asymmetry in mild and sharp positive and negative shocks than the other BRICS countries, and this instability may explain the lowest financial risk ratings (or higher risk level) of Brazil. As shown in Table 2.6, I also find that the adjustment of the spread to equilibrium is faster during widening after negative shocks than narrowing in only Russia, while for Brazil, India, China and South Africa this adjustment is slightly faster during narrowing which follow a positive shock. The result implies that that are more profitable opportunities and thus traders are more active in taking advantage of the spread between the stock markets and risks in Russia, when Russian stock market index is climbing or the country risk levels (country risk ratings go down) are raising. This can happen either when there is a positive shock in stock markets or a negative shock to country risk ratings. For the other four BRICS countries, investors are more active when the spread is narrowing, when the stock indices are declining or the country risk ratings are increasing.

2.5.2 MTAR-VEC Model

The results on asymmetric cointegration in the previous section have confirmed the existence of the asymmetric long-run (cointegration) relationships between domestic stock market indices and country risk ratings for all of the BRICS countries. In this section, I apply the MTAR-VEC model to further investigate the asymmetric dynamic individual behaviors of the domestic stock market indices and the country risk ratings for each country. My goals are twofold. First, I am interested in the Granger causalities between the disaggregated country risk ratings and the associated stock market indices, which may help reveal how domestic stock markets respond to the changes in different types of country risks in the long-run and short-run. The results also show which type of the country risks has the most influence on domestic equity market performance in each BRICS country. Additionally, the results of the Granger causalities between the individual country risk ratings provide international investors with insights on the risk migrations within each BRICS country. Second, the MTAR specification allows us to study the asymmetric feature of those dynamic relationships when the speed of the deviation of the stock market indices from the long-run equilibrium with the country risk ratings is greater (widening) or less than (narrowing) the estimated threshold level.

Table 2.7 presents the results of asymmetry tests for the estimated Eq. (4a) of the MTAR-VEC model for the five BRICS. The results suggest that, under the long-run symmetry hypothesis, and the joint long-term and short-term symmetry hypothesis, only the stock market indices of China and South Africa reject the null symmetric hypothesis and exhibit significant asymmetric adjustments in the long run and the combined long-run and short-run. Additionally, China is the only country whose stock market rejects every short-run symmetry hypotheses. This result implies that the fast growing Chinese stock market responds asymmetrically to negative and positive risk shocks in the short run. This probably has to do with the fast growth of the Chinese economy which averaged more than 10% in the years preceding the 2007/2008 financial crisis, where this kind of high economic growth leads to the varying responses of China's stock market index to country risk ratings shock.

I present the individual short-run adjustments of stock market indices and the three country risk ratings for the five BRICS in Table 2.8 (Panel A-D). Panel A of this table shows the long-run and the short-run adjustments of the individual stock market indices of these countries (Eq.4a). Generally, the stock markets in BRICS make stronger adjustments in the long run when the spreads are narrowing than widening, expect the Brazilian and Russian stock markets which show no significant adjustments whatsoever in the long-run. The convergence to the long-run equilibrium during narrowing implies that the adjustment may be caused by a declining stock market and/or an increase in the country risk ratings in the long-run. That is, in China, India and South Africa, an improvement in the risk ratings or a reduction in the risk levels may lead to convergence to the long-run equilibrium. The Chinese market also makes adjustment during widening. That is, the convergence in China may also happen because of an increase in the risk levels. In the short run, the adjustments in the individual countries' stock markets and risk ratings are mixed during widening and narrowing. The increases in the stock market indices during widening lead to adjustments to the equilibrium in the short-run for Brazil, India, China and South Africa. However, decreases in the stock indices during narrowing lead to adjustments in the cases of Russia as well as China. Thus, the Chinese stock market is active in the long- and short-run during both narrowing and widening.

In terms of the changes in stock market indices in response to the changes of country risk ratings, I find that the financial risk ratings changes have the most influence on the country stock markets, followed by economic risk ratings. The changes of political risk rating only have a significant effect on stock market index in China and Russia only, which implies that investors have special concerns of the political risk in these countries. In China, the three lagged changes of country risk ratings are significant and have the negative signs during narrowing. This suggests that the risk ratings should go up for the stock market to decline. However these risk ratings have the positive but not significant during widening.

Concerning the economic risk rating in Eq.(4b) in Panel B, the long-run adjustments lead to equilibrium only for Brazil during narrowing and for Russia during widening as these countries have the desired positive signs for their error-correction terms. This suggests that for the adjustments to equilibrium in the long run take traction during narrowing, the economic risk ratings should improve, while for Russia the economic risk ratings should decline or the economic risk level should increase. On the other hand, there is a divergence in India during narrowing whose error-correction term has negative sign, while in China and South Africa the error-correct effects are not significant. In the short run, the economic risk ratings are marginally affected by the changes in the lagged stock market index during narrowing in India only. This is not surprising because the economic risk ratings have to do with the real sector of the economy but not directly with the stock market. The responsiveness of the economic risk ratings to its own past changes is significant but different for Russia during widening and for Brazil during narrowing. It converges for Brazil and diverges for Russia. The results also show that the financial risk ratings will positively affect the economic risk ratings during widening for these two countries. Moreover, it is affected by political risk ratings during widening and narrowing in the case of Russia. The impacts of the lagged financial risk ratings on the economic risk ratings are positive during widening for Brazil and Russia, and during narrowing for Russia. In contrast to the impact of past economic risk ratings on itself, here the positive past financial risk ratings lead to convergence for both countries. Finally, the economic risk rating is affected by the political risk ratings only during widening for Russia. In sum, the economic risk in Brazil and Russia and the most sensitive to all three country risk ratings.

For the financial risk ratings Eq. (4c) in Panel C, there is convergence to long-run equilibrium during widening for Brazil and Russia, while for Russia and South Africa during narrowing. In the short run, the changes in the lagged stock market index affect the financial risk rating in Russia during narrowing while South Africa during widening only. Changes in the past political risk ratings lead to convergence to the equilibrium in the short-run during widening for Russia and during narrowing for China. Changes of the lagged financial risk ratings affect own for Russia and China during widening, leading to convergence in the first period but the impact is negative in the second period leading to divergence. In sum, Russia's financial risk ratings seems to be the most affected among the five BRICS by the three country risk ratings.

Finally, the findings for the political risk ratings are in Panel D of Table 2.8. The long-run adjustment for the political risk ratings is the least significant. It is only significant during narrowing for India. Additionally, the adjustments of political risk ratings to changes in the past stock markets in the short run is confined to Russia during widening and narrowing, and to China in the second period during widening only. Changes in past economic risk ratings impact the political risk ratings for India and China during widening. Changes in lagged financial risk ratings affect political risk ratings in Brazil and Russia during narrowing. Past own political risk ratings affect their own for Brazil and South Africa during widening and during narrowing for Brazil, Russia and China as well. The adjustments here diverge for Brazil during narrowing. In sum, most of the adjustments for the political risk ratings take place during the short-run and not during the long-run. They are also more apparent during widening than during narrowing. Again the most affected countries are Brazil and Russia as have been the case for the economic risk rating.

2.6 Conclusion

This essay examines the asymmetric cointegration relationship between stock market indices and three country risk ratings: economic, financial and political for the five BRICS countries (Brazil, Russia, India, China and South Africa). It also examines the adjustments of stock market indices and these country risk ratings to the equilibrium in the long- and short run. The results show that there are cointegration relationships between the domestic stock market index and the three country risk ratings for each of these countries. Moreover, the results also suggest the cointegration relationship for each country is asymmetric. This implies that the adjustment over time to the long-run equilibrium has different speeds depending on whether the shock is positive or negative. The adjustment is faster during narrowing than widening for all the countries except Russia.

In the VEC model, Brazil and Russia are the two countries which have the most significant adjustments for economic and political risk ratings. Russia also shows strong adjustment for financial risk ratings. Decision makers in those two countries should be aware of the sensitivity of their stock markets to the political risk ratings announcements related particularly to government stability, socioeconomic conditions and internal and external conflicts. Decision makers in Russia should pay attention to financial risk announcements particularly foreign debt share in GDP, foreign debt service, current account balance and exchange rate stability. China's stock market expresses the most responsiveness to the three country risk ratings. The Chinese decision makers should be sensitive to all the economic, financial and political risk announcements. The economic risk announcements are related largely to GDP per capita, GDP growth, inflation rate, budget balance and current account.

Most of the adjustments to the equilibrium take traction during widening not during narrowing. Among the three country risk ratings, the political risk rating displays the least adjustment in the long run.

Chapter 3: Downside Risk in the Eurozone Equity Markets with Commodity Portfolio Diversification

3.1 Introduction

The recent financial turmoil in the eurozone countries has brought into focus the importance of financial risk management in those countries. The eurozone debt crisis has affected their stock markets which are highly correlated because of increasing integration and harmonization in this area. The mounting risk and uncertainty have confounded investors, portfolio managers and policy-makers in the eurozone as well as in other countries. In such an environment, it will be valuable and useful to examine the downside risk for these assets and figure out ways to diversify away risks. It will also be particularly important to estimate risks during periods of extreme events like the 2007/2008 financial crisis that affected essentially all asset markets. Under such crisis circumstances, significant and extreme drops in prices and returns of these assets have become highly probable, with potentially damaging consequences on portfolios of individuals and institutions. These circumstances have also made risk management strategies for highly volatile stocks become more challenging, particularly when the percentages of violations of confidence targets have compounded.

The quantification of the size of potential losses and the assessment of risk levels for individual markets and their portfolios are fundamental in designing prudent risk management and portfolio strategies. Value-at-risk (VaR) models have become an important instrument within the financial markets for quantifying and assessing downside market risks associated with asset price fluctuations. They determine the maximum expected loss an asset or a portfolio can generate over a certain holding period, with a pre-determined probability value. Therefore, a VaR model can be used to evaluate the performance of individual asset and portfolio managers by providing downside risk quantification. It can also help investors and portfolio managers to determine the most effective risk management strategy for a given situation. Moreover, quantification of the extreme losses in those asset markets is important in the current market environment. Extreme value theory (EVT) provides a comprehensive theoretical forum through which statistical models describing extreme scenarios can be developed.

There is a cost of inaccurate estimation of the VaR in equity markets which affects efficiency and accuracy of risk assessments. Surprisingly, despite the increasing importance and rising correlations of the eurozone markets, and the need for more portfolio diversification with other asset classes, there are only few studies that analyze the VaRs of these markets, the VaR-based optimal portfolio constructions and their efficient VaR frontiers. The studies that examine European portfolio diversification emphasize diversification through industries instead of countries. In this essay, I underscore the importance of diversification of equity markets with other asset classes, particularly commodities. Standing as hedges and safe havens against risk and during uncertainty, commodities like the precious metals and oil have experienced extraordinary surges in prices and returns in the last few years, which have elevated the potential downside risk and subjected them to black swan-types of events. These assets have therefore become important elements of diversified portfolios.

My current study expands the spectrum of asset diversifications in the eurozone and deals with events that are more extreme than the regular behavior dynamics of the stock indices. Therefore, it constructs VaR-based optimal portfolios, examines their characteristics and performance for this zone, and ranks those optimal portfolios using VaR-based risk performance measure.[12]

The objective of this essay is to fill this gap in the financial risk management for the eurozone equity markets and construct diversified optimal portfolio strategies by using more up-to-date techniques and designing optimal diversified portfolios that take into account volatility asymmetry and clustering, as well as diversification with different asset classes. This topic has not been researched adequately for the harmonious eurozone, despite its potential to provide diversification within broad investment portfolios and hedging capability. To achieve these objectives, this essay computes VaRs for ten eurozone market indices, using four estimation methods including RiskMetrics, Duration-based Peak Over Threshold (DPOT), conditional EVT (CEVT) (using normal and skewed t-distributions) and GARCH-based filtered historical simulation. These ten markets are grouped into the PIIGS (Portugal, Ireland, Italy, Greece and Spain) and the Core (Germany, France, Austria, Finland and the Netherlands). Several portfolios have been constructed from those two groups, in addition to including in the portfolios the S&P 500 index, oil, gold, silver and corn to the equity portfolio.

[12] I have constructed the efficient VaR frontiers for the portfolios. However, the frontiers constructed don't have the proper shape to allow a tangency point. The graphs are available upon request.

The results show that each of these two well-integrated groups should have only one asset in the optimal portfolio. Combing the two groups, the evidence shows that the expended optimal equity portfolio should have one index, which is the Austrian ATX index. Diversifying with commodities improves the performance of the optimal augmented equity portfolios. Specifically, diversifying with oil and gold gives the best return/risk reward. In terms of the Basel capital requirement rules, the DPOT seems to give a more satisfying result at the optimal portfolio level.

The reminder of this chapter is organized as follows. After this introduction, Section 3.2 presents a review of the VaR literature on eurozone and Europe. Section 3.3 provides the VaR estimation methods and the construction of the optimal portfolios for the eurozone. Section 3.4 discusses the empirical results and Section 3.5 concludes.

3.2 Literature Review

The review of the literature does not produce many studies that apply the various VaR estimation methods to the eurozone and European stock markets, whether as individual assets, portfolios and/or portfolios diversified with other asset classes. Commodities offer an effective hedge against both expected and unexpected inflation. They are real assets and possess intrinsic values that reflect changes in the price level. Moreover, commodities are not income-producing assets as they do not yield an ongoing stream of cash flows as stocks do. There also exists a high degree of heterogeneity among individual commodities (Fabozzi, Füss and Kaiser, 2008; Erb and Harvey, 2006; Kat and Ooman, 2007). On the other hand, similar to stocks, most commodities have positive excess kurtosis which implies a leptokurtic return distribution. This distribution has fatter tails with the higher probability for extreme events, compared to normally distributed returns. However, in contrast to stocks most commodities are positively skewed. This characteristic is beneficial to investors because it implies a lower downside risk and an upward return bias of an investment portfolio. These characteristics distinguish commodities from stocks, particularly from the integrated eurozone's individual country stock market indices, and give rise to expectations of low correlations with those stock indices.

Cotter (2004) applies the extreme value theory, among others, to measure the downside risk for five European equity indices: the *ISEQ* (Ireland), *FTSE100* (UK), *CAC* 40 (France), *DAX* 100 (Germany) and *IBEX* 35 (Spain) from the beginning of 1998 to the end of April 1999. Cotter's results show that the EVT-VaR dominates alternative approaches, such as the variance/covariance and Monte Carlo methods, in the tail estimation for those equity indices. Moreover, his results also suggest that there is a significant difference across those equity indices in terms of the downside risk during the sample period. Allen (2005) assesses five models which estimate the VaR thresholds for an equally-weighted portfolio comprising three European equity indices, *CAC* 40 (France), *FTSE* 100 (UK) and Swiss Market Index *(SMI*), and the S&P 500 index. Allen finds the Portfolio-Spillover GARCH model (PS-GARCH) (see McAleer and Veiga, 2008a for more information) provides the best result in terms of meeting the requirement of the Basel Accord among the five models considered.

Billio and Pelizzon (2000) use a multivariate regime-switching (RS) model to estimate the VaRs for 10 individual Italian stocks and also for a portfolio based on these stocks. They find the RS approach outperforms the RiskMetrics and GARCH(1,1) models both in the single asset VaR forecasts and the portfolio VaR estimation.

In the context of optimal portfolio selection, many studies generally focus on using the VaR as an alternative risk measure to the traditional measures of risk that rely on the standard deviation (or variance). The literature includes: Jansen, Koedijk and Vries (2000); Basak and Shapiro (2001); Gaivoronski and Pflug (2005); Palmquist and Krokhmal (1999); and Campbell, Huisman and Koedijk (2001). Campbell et al. (2001) solve for the optimal portfolios based on a Sharpe-like portfolio performance index, using the VaR from the historical distribution as the risk measure. The optimal portfolio they find is the one which maximizes the expected return subject to the specified levels of VaR constraints. They conclude that their method outperforms the traditional mean-variance framework because the latter is rooted in the assumption of normality which usually underestimates the downside risk. Gaivoronski and Pflug (2005) provide a method to calculate the mean-VaR efficient frontier using a smoothed VaR estimation. Their experimental results show that the mean-VaR efficient portfolios differ substantially from the mean-variance efficient portfolios. Particularly, for the portfolios which consist of 16 market indices: eight Morgan Stanley Equity Price Indices for USA, UK, Italy, Japan, Russia, Argentina, Brazil and Mexico, and eight Morgan Stanley Bond Indices for the same markets, the VaR optimal portfolios constitute a substantial improvement over the variance optimal portfolios in term of the magnitude of the estimated portfolio VaRs. In 50% of their experiments, the improvement is over 10%.

The literature on equity portfolio diversification in Europe and eurozone focuses on comparing diversification over countries with diversification over industries. In 1990 and before the creation of the eurozone, some studies find that diversification over countries yields more efficient portfolios than diversification over industries (see Heston and Rouwenhorst, 1995). This result has been attributed to the unification process and the harmonization of economic policies in eurozone. In the 2000s, the literature finds evidence of increasing consequences for the industry factors in driving asset returns in European financial market but the dominance remained for the country factors (see Rouwenhorst, 1999; Carrieri, Errunza and Sarkissian , 2004; Ge´rard et al., 2002; Adjaoute´ and Danthine, 2001; 2004). This result has been aided by the information technology/internet ‘‘bubble’’ (known as IT-hype). Adaoute and Danthine (2001) find that diversification opportunities within the 15 member eurozone at that time have been reduced. The authors find the culprit to be the convergence of economic structures and homogenization of economic shocks than the disappearance of risk.

More recently, employing the mean–variance approach and using recent data, Moerman (2008) finds strong evidence that diversification over industries yields more efficient portfolios than diversification over countries even when the IT-hype is accounted for. Therefore, the evolution of the literature on eurozone equity market diversification increasingly supports diversification within industries instead of across national markets.

I explore in this study diversification among eurozone national stock markets and commodities since as indicated earlier the correlations with commodities are much lower than between the eurozone national stock indices

The literature on diversification with commodities is rising in importance because this diversification can enhance returns and/or reduce risk. Satyanarayan and Varangis (1996) and Idzorek (2007) detect diversification benefits, analyzing the shift of the efficient frontier when the investment universe is extended to a commodity index. Georgiev (2001) and Gibson (2004) constitute portfolios with different commodity allocations and compare their risk-return characteristics in the mean-variance space. You and Daigler (2010) detect the diversification benefits of commodity futures by employing the mean-variance and Sharpe optimization models.

3.3 VaR Forecasts Models and Optimal Portfolios

In this section, I explicitly explain the empirical models that I use to estimate the VaRs for the ten individual equity index returns and the return for the optimal portfolio based on VaRs.

3.3.1 RiskMetrics

The first method I apply in this essay to estimate the VaRs is the RiskMetrics approach, which is mostly widely used by financial institutions, regulatory departments and portfolio investors. This method is developed by J.P. Morgan (1996). The conditional volatility is estimated based on the exponentially weighted moving average (IGARCH) method:

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)\varepsilon_{t-1}^2$$

where σ_t^2 is the forecast of conditional volatility, $\lambda = 0.94$ is the decay parameter[13], and ε_{t-1} is the last period residual which follows the standard normal distribution. The VaR is calculated as follows:

$$VaR_t = Z_p \sigma_t$$

where Z_p is the standard normal quantile for $p = 0.01$.

The RiskMetrics model is relatively easier to implement than other methods. However, this model is subject to criticism because it ignores the asymmetric effect, the violation of the normality and risk in the tails of the distribution as often observed in the equity return data. As a remedy, I apply the Extreme Value Theory in the following two promising methods CEVT and DPOT to get a better proxy of the tail distribution.

3.3.2 Conditional extreme value theory (CEVT)

This approach is a hybrid of a time-varying volatility model and the Peaks-Over-Threshold (POT) method suggested by the Extreme Value Theory (Appendix A provides more details about the POT method). As proposed by Diebold et al. (1998) and McNeil and Frey (2000), I take a two-step process to forecast the VaRs. I first fit an AR(1)-GARCH(1,1) framework with the index return data, estimate $\hat{\mu}_{t+1|t}$ and $\hat{\sigma}_{t+1|t}$ and calculate the implied residuals. In the second step, I obtain the *p*-quantile value for the residual distribution by applying the POT method based on the EVT. Although the filter with normal innovations can remove the majority of clustering, it may still generate a

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[13] λ is set at 0.94 for the daily data as suggested in RiskMetrics.

misspecified model. In order to address the misspecification, I also use the filter with skewed student's-t distribution.

The one-day-ahead VaR forecast of CEVT method is calculated with the following equation:

$$\widehat{VaR}_{t+1|t}^{CEVT}(P) = \hat{\mu}_{t+1|t} + \hat{\sigma}_{t+1|t}\hat{z}_p$$

where $\hat{\mu}_{t+1|t}$ is the estimated conditional mean, $\hat{\sigma}_{t+1|t}$ is the estimated conditional standard deviation, which are obtained from the AR(1)-GARCH(1,1) process. Moreover, the quantile $\hat{z}_p$ for the significance level p is obtained through a Peak-Over-Threshold procedure. [14]

3.3.3 Duration-based peaks over threshold (DPOT)

The benefit for using the duration-based estimation methodology to forecast the VaRs is to eliminate the tendency of clustering which could be generated through the POT method. The DPOT model focuses on excesses and the durations between excesses instead of the extreme values themselves. This class of models was recently proposed by Araújo Santos and Fraga Alves (2012).

Let $x_1, x_2, \ldots x_n$ be the excess returns above the threshold u, d_1 is the duration until the first excess, and $d_i = t_i - t_{i-1}$, and $d_{i,v} = d_i + \cdots + d_{i-v+1} = t_i - t_{i-v}$. At day t, after the excess n, I define $d_{t,1} = d^t$, $d_{t,2} = d^t + d_n$ and for $v = 3,4, \ldots$, $d_{t,v} = d^t + d_n + \cdots + d_{n-v+2}$, which represents the duration until day t since the proceeding v

[14] The detail of the POT method is discussed in the Appendix A.

excesses. I assume a Generalized Pareto Distribution for the excess Y_i, which is above the threshold u, such that

$$Y_t \sim GPD(\gamma, \sigma_t = g(\alpha_1, \dots, \alpha_{k,} d^t, d_n + \cdots + d_{n-v+2}))$$

where $\gamma, \alpha_1, \dots, \alpha_{k,}$ are parameters to be estimated.

The one-day-ahead VaR forecast by the POT method is calculated with the following equation as derived in Appendix A:

$$\widehat{VaR}_{t+1|t}^{POT}(P) = \mu + \frac{\widehat{\sigma_t}}{\hat{\gamma}}((\frac{n}{n_x p})^{\hat{\gamma}} - 1)$$

where $\widehat{\sigma_t} = g(\alpha_1, \dots, \alpha_{k,} d^t, d_n + \cdots + d_{n-v+2})$

Both the conditional expected value and the conditional variance for the excesses depend on d^t and the last v durations between excesses, respectively, as follows:

$$E[Y_t|\Omega_t] = \frac{\sigma_t}{1-\gamma}, (\gamma < 1); and\ V[Y_t|\Omega_t] = \frac{(\sigma_t)^2}{(1-2\gamma)}, (\gamma < \frac{1}{2})$$

where Ω_t is the information set which is available until t.

The empirical study of the equity indices suggests an inverse relationship between the expected value and variance of excesses, and the durations between excesses. This relationship is captured by the duration-based term $1/(d_{i,v})^c, c > 0$, which is incorporated in the parameter σ_t:

$$\sigma_t = \alpha \frac{1}{(d_{i,v})^c}$$

Therefore, the DPOT VaR estimator turns to be

$$\widehat{VaR}_{t+1|t}^{DPOT(v,c)}(p) = \mu + \frac{\hat{\alpha}}{\hat{\gamma}(d_{i,v})^c}((\frac{n}{n_x p})^{\hat{\gamma}} - 1)$$

To estimate the parameters $\hat{\gamma}$ and $\hat{\alpha}$, I set $v = 3$, and $c = 0.75$ and apply the Nelder and Mead algorithm to maximize the following log likelihood function:

$$\log L(\gamma, \alpha) = \log \prod_{i=v}^{n} fY_i(y_i) = \log \prod_{i=v}^{n} (\frac{\alpha}{(d_{i,v})^c})^{-1}(1 + \frac{\gamma}{\alpha} y_i (d_{i,v})^c)^{-\left(\frac{1}{\gamma}+1\right)}$$

$$= -\sum_{i=v}^{n} \log\left(\frac{\alpha}{(d_{i,v})^c}\right) - \left(\frac{1}{\gamma} + 1\right) \sum_{i=v}^{n} \log(1 + \frac{\gamma}{\alpha} y_i (d_{i,v})^c)$$

3.4 Empirical Results

3.4.1 Descriptive statistics

In this section, I present the descriptive statistics for country equity indices in the eurozone, the individual commodity prices and composite commodity indices.

I use daily percentage log returns based on the closing spot values for equity indices for countries in two groups of the eurozone. The first group includes the five PIIGS countries: Portugal, Italy, Ireland, Greece and Spain; and the second group called the Core consists of: Austria, Finland, France, Germany and the Netherlands. The countries in the second group are chosen to match the countries in the first group but have less issues of sovereign debt. To be consistent with the dates of all countries' memberships in the eurozone, I select the sample period which ranges from January 2, 2001 to November 30, 2011, yielding a total of 2,848 observations of percentage log returns, $r_t = 100 \times (lnp_t - lnp_{t-1})$. These indices are considered as the composite assets, and it is assumed that investors can choose portfolios which reproduce these indices. All the commodity prices and indices' series have the same sample size as chosen equity indices.

Table 3.1 summarizes the notation and sources for the ten country equity indices included in this essay. The descriptive statistics are given in Table 3.2. Over the sample period, the Austrian Traded Index (ATX) has the highest average return among the equity indices, while the Greek ATHEX Composite Share Price Index (ATHEX) yields the lowest. It's interesting to note that the positive average return goes across the two groups for these countries: Portugal, Spain, Austria and Germany. This across group positive performance is not strongly affected over the whole period by the recent sovereign debt crisis. The un-weighted average returns for the PIIGS group is -0.03, while the average for the Core group is -0.01.

In terms of volatility as defined by the standard deviation, the Finnish *OMX* has the highest volatility, while the Portuguese *PSI* has the lowest over the sample period. Higher volatility also goes across both groups. The un-weighted average volatility for the PIIGS is 1.625, while the average for the Core is 1.818.

The results for the skewness test are also mixed across groups: seven indices (*AEX* for the Netherlands, *ATX* for Austria, *DAX* for Germany, *FTSE* for Italy, *ISEQ* for Ireland, *OMX* for Finland and *PSI* for Portugal) have negative skewness statistics, which means the mass of the distribution of returns is concentrated on the right part. However, the returns for the other three countries (*ATHEX* for Greece, *CAC* for France and *IBEX* for Spain) are positively skewed, which implies a higher chance of getting lower return in the equity markets of these countries. All the series have a Kurtosis value higher than 3, which means their distributions are more peaked than the normal distribution. Moreover, The Jarque-Bera statistic suggests a rejection of the normality hypothesis for the distributions of all the series.

Considering the commodities and commodity indices, all series have positive average daily returns, expect for the Dow-Jones UBS commodity index (*DJUBSCI*). Silver has the highest mean daily return, followed by the other two goods gold and oil. Oil has the highest standard deviation which reflects the frequent fluctuations in the energy market over the sample period due to transitional factors that affect the oil markets. Similar to equity indices, all commodities have a negative skewness statistics with the exception of corn. All the Kurtosis statistics for the commodities and commodity indices are greater than three, which also suggests that the distribution for their returns are more peaked than the normal distribution. Moreover, all the results for Jarque-Bera normality tests reject the normality null hypothesis for the commodities and commodity indices.

3.4.2. Back-testing results

In this section, I assess the accuracy and the performance of the VaR models used in this paper. Following the approach proposed by Campbell (2001), I obtain one-day-ahead VaR forecasts for each model. For every equity index, the VaR forecast is calculated with a moving window of size of 1,000 days. Therefore, I get 1,848 one-day-ahead VaR forecasts for each index per method. The programs that are used to obtain one-day-ahead VaR forecasts and to apply the accuracy tests are written in the R language (R Development Core Team, 2008). The primary tool for assessing the accuracy of the interval forecasts is to monitor the binary sequence generated by observing whether the return r_t on day t is in the tail region specified by the VaR at time t − 1. This sequence is referred to as the hit sequence:

Christoffersen (1998) shows that assessing the goodness for VaR forecasting methods can be condensed to examining whether the hit sequence h_t satisfies the two properties: the unconditional coverage (UC) and the independence (IND). The unconditional coverage property means that the nominal coverage is equal to the true coverage p:

$$E(h_t) = p \text{ for all t,}$$

The independence property states that the expected $h_t = p$ is independent of the historical realizations of h_t. It can be presented as

$$E\{h_t | h_{t-1}, h_{t-2}, \dots h_1\} = p$$

When both properties are validated, I say that the hit sequence satisfies the conditional coverage (CC) property.

$$h_t = \{ \begin{matrix} 1, if\ r_t < VaR_{t|t-1(p)} \\ 0, if\ r_t \geq VaR_{t|t-1(p)} \end{matrix}$$

Christoffersen (1998) shows that evaluating interval forecasts can be reduced to examining whether the hit sequence satisfies the unconditional coverage (UC) and independence (IND) properties. When both properties are validated, the hit sequence satisfies the conditional coverage (CC) property. In order to test the UC hypothesis, I apply the Kupiec test (Kupiec, 1995), while to test the CC hypothesis I apply the conditional coverage test developed by Christoffersen (1998). To test the IND hypothesis alone, I apply the independence test that was recently introduced in the literature by Araújo Santos and Fraga Alves (2012). This test is based on durations between consecutive violations and until the first violation. I refer to this test as the MM independence test.

3.4.2.1. Percentage of violations

The RiskMetrics method gives the highest percentage of violations among all the methods for all of the equity indices. The PIIGS indices have generally similar percentage of violations compared to the Core group according to the RiskMetrics model. In the PIIGS group, Ireland and Italy have the highest percentage of violations, while in the Core group the Netherlands has the highest violations. The DPOT generally gives slightly more violation percentages to the PIIGS than to the Core. The CEVT methods give lower percentage of violations compared to the DPOT method only for the PIIGS countries.

3.4.2.2 Unconditional coverage test (UC test)

This test is to monitor the binary hit sequence h_t, namely:

$$h_t = \{ \begin{matrix} 1, if\ r_t < VaR_{t|t-1(p)} \\ 0, if\ r_t \geq VaR_{t|t-1(p)} \end{matrix}$$

where r_t is the index return on day *t*.

I test the UC hypothesis against the alternative of $E(h_t) \neq p$, using the following the Likelihood Ratio test proposed by Kupiec (1995):

$$LR_{UC} = -2\ln\{(1-p)^{T-X}p^X\}/ln\{(1-\hat{p})^{T-X}\hat{p}^X\}$$

where $p = 0.01$ is the target exception rate, $\hat{p}$ is the sample violation rate, *X* is the total number of violations, *T* is the number of observations, and *LR* is asymptotically distributed as $\chi^2(1)$.

The results of the UC test are given in Table 3.3. The RiskMetrics approach performs poorly with the rejection of the UC hypothesis for all the hit sequences of the ten equity indices at the 1% significance level, which suggests that the percentages of violations are higher than 1% in all cases. This implies the evolving nature of the volatilities in equity market. The DPOT method improves the results for only three out of the ten indices over RiskMetrics method. The three indices are for Austria and Finland from the Core group, and for Ireland from the PIIGS. The UC hypothesis is rejected for *CAC*, *DAX* and *PSI* at the 10% significance level, for *ATHEX*, *FTSE* and *IBEX* at the 5% level and for *AEX* at the 1% level. Both the CEVT models provide more reliable results in terms of the UC property for all the equity indices compared to the RiskMetrics and DPOT methods, except for FTSE in PIIGS for which the UC hypothesis is rejected at the 5% significance level for the CEVT-normal, and at the 10%

level for the CEVT-skewed-student. This implies that the application of the extreme value theory in approximating the tail distributions of return can help improve the accuracy of the VaR forecasts significantly.

The above UC test only focuses on the frequency of the violations of VaR forecasts, but does not consider the case of the clustering zeros and ones in the hit consequence. As a remedy, I conduct the following conditional coverage (CC) test as in Christoffersen (2009), accounting for the dynamics of the exceptions by jointly testing for the unconditional coverage and the serial independence of the hit sequence.

3.4.2.3 Conditional coverage test (CC test)

Consider a binary first order Markov chain, $\{h_t\}$, with the transition probability matrix:

$$\pi_1 = \begin{bmatrix} 1-\pi_{01} & \pi_{01} \\ 1-\pi_{11} & \pi_{11} \end{bmatrix}$$

where $\pi_{ij} = \Pr(h_t = j | \quad h_{t-1} = i). for\ i, j \in \{0,1\}$. The conditional coverage test statistic is:

$$LR_{cc} = -2[lnL(p) - lnL(\widehat{\pi_{01}}, \widehat{\pi_{11}})]$$

where $lnL(p) = (1-p)^{n_0} p^{n_1}, lnL(\widehat{\pi_{01}}, \widehat{\pi_{11}}) = (1-\widehat{\pi_{01}})^{n_{00}} \widehat{\pi_{01}}^{n_{01}} (1-\widehat{\pi_{11}})^{n_{10}} \widehat{\pi_{11}}^{n_{11}}$, and $\widehat{\pi_{01}} = \frac{n_{01}}{n_{01}+n_{00}}, \widehat{\pi_{11}} = \frac{n_{11}}{n_{10}+n_{11}}, n_{ij}$ is the number of observations with a *j* following an *i*, n_i is the total number of observations with an *i*. This LR_{cc} has an asymptotic distribution of $\chi^2(2)$.

The results for the CC test are also presented in Table 3.3. In terms of the conditional coverage property, the RiskMetrics still performs very poorly with the rejection of the null hypothesis for all the ten equity indices. With the DPOT approach, the results have been improved for six out of the ten indices over the RiskMetrics method. The CC hypothesis is rejected at the 10% confidence level for *ATHEX*, *FTSE* and *IBEX*, which all are countries belonging to the PIIGS group, and for *AEX* which is in the Core group at the 5% level. For the CEVT models, all the VaR forecasts for all the indices pass the CC test; with the only exception is *FTSE* which is rejected at the 5% level under the CEVT-normal specification.

3.4.2.4 Maximum-Median independence (MM) test

In order to provide more insights into the independence property of the equity indices returns, I apply the MM independence test. This more recent test has more power than the CC test in testing the independence hypothesis because it considers all types of clustering, while the CC test is only sensitive to the violations following the Markov-Chain process[15]. The MM test statistic is as follows:

$$T_{N,[\frac{N}{2}]} = log2\left(\frac{D_{N:N-1}}{D_{[\frac{N}{2}]:N}}\right) - logN$$

[15] The CC test is based on the assumption that the probability of a violation is only affected by the most recent period.

where N is the nth violation, $D_{\left[\frac{N}{2}\right]:N}$ and $D_{N:N}$ are, respectively, the median and the maximum of durations between two consecutive violations. Under the null, the asymptotic distribution for the MM statistics is Gumbel.

The results of MM test are included in Table 3. RiskMetrics fails the MM test for two indices: *OMX* and *AEX*. The DPOT model passes the MM test for all indices except *CAC*, *DAX* and *AEX*. However, the CEVT models outperform the RiskMetrics and DPOT models since they pass the MM test for all the countries.

Based on the four evaluation criteria, the CEVT methods stand out as the best models for back-testing properties for the ten eurozone equity indices.

3.4.2.5 Basel capital requirement

In 1996 the Basel Committee on Banking Supervision (BCBS) issued an Amendment to the Basel I Capital Accord, in which the financial institutions are required to calculate their market risk Minimum Capital Requirement (MCR) based on their own VaR models by using the following formula:

$$MCR_{t+1} = \max(\frac{m_c}{60}\sum_{i=1}^{60} VaR_{t-i+1}; VaR_t)$$

where $m_c = 3 + k$ and $k \in [0,1]$. The MCR is the maximum between the previous day's VaR and the average of the last 60 daily VaRs increased by the multiplier m_c. The multiplier m_c is determined by the backtesing results for the internal VaR models. Essentially, the greater the number of the violations when the actual loss exceeds the daily VaR forecast during the last 250 trading days, the higher the value of the multiplier m_c. The details of this three-zone approach is included in Table 3.4.

I present the daily capital requirements results for the ten individual equity indices in Table 3.4 using the four VaR methods. The two CEVT methods are more reliable and accurate than the RiskMetrics and DPOT methods with zero number of entering the red zone. It is interesting to note that CEVT-sstd has the lowest violation number among all the methods, but it doesn't give the lowest average daily capital charges for all the indices. The CEVT-normal method generates lower capital charges than CEVT-sstd for five indices: *PSI*, *ISEQ*, *IBEX*, *OMX* and *AEX*.

I estimate the daily capital requirement for the optimal portfolio which consists of *ATX*, gold and oil, using the four VaR estimation methods. The results demonstrate that the RiskMetrics method gives the lowest average capital requirement for this portfolio. However, this method gives 102 days in the red zone, which reflects lack of accuracy of this model. For this portfolio, the better estimation method is the DPOT method which gives zero entry days in the red zone and still has lower average capital requirement than the two CEVT methods. Based on the Basel rules, the DPOT is the preferred method.

3.4.3 Optimal portfolio

In this section, I apply the VaR to the portfolio selection issue, using the forecast VaR as the risk measure of the portfolio. Following the approach developed in Campbell (2001), I elaborate on finding the optimal portfolio which maximizes the expected return of the portfolio at the given level of the Value-at-Risk forecasts. The results are presented in **Table 3.5**.

Our initial strategy is to construct an optimal portfolio for group 1 (PIIGS) and another for group 2 (the Core). The results show that each of these portfolios is overwhelmingly dominated by one market index, with negligible weights for the other members of the group. The PIIGS portfolio is dominated by Spain's *IBEX*, while the Core portfolio is overwhelmed by the Austrian *ATX* index which has the highest average historical return among the ten markets. When the two groups are merged to one grand portfolio (Portfolio #3), the Austrian *ATX* dominates the ten market indices. Therefore, these portfolios should be diversified with other asset classes.

Our attempt to include the *S&P* 500 index and the dollar-euro exchange rate in each group portfolio and in the total portfolio did not change the dominance of *IBEX* in the PIIGS portfolio, and of *ATX* in the Core and the total portfolios. My next strategy is to follow the literature that diversifies equity portfolios with another asset classes, specifically commodities. This literature examines the sources of diversification benefits that commodities can attribute to portfolio gains. It confirms that energy and precious metals contribute to those diversification gains by reducing risk and enhancing returns. It finds the contribution of agricultural commodities to gains to be due to reducing risk.

Therefore, I added oil and gold to the portfolio that contains *IBEX* and *ATX* and called this four-asset portfolio Portfolio #4. The addition of energy and precious metal have changed the portfolio weights, reduced risk and enhanced return. Due to its spectacular performance in the last two decades, gold accounts for about 75% of this portfolio. On the other hand, oil, *ATX* and *IBEX* have 5%, 20% and less than 1%, respectively.

Other attempts to include silver and corn in Portfolio #4 did not reduce the risk and improve the return, despite the relative low correlation between corn and the other assets. I also added the two commodity indices: *S&PCI* and *DJCI* to Portfolio #4, respectively. The inclusion of commodity indices improves the return but increases the risk as well. Thus, the implication of this portfolio exercise is that investors and portfolio managers who invest in the eurozone equity market should augment their equity portfolios by adding oil and gold to gain both the benefits of diversification (which include a reduction in risk) and the enhancement in returns. Commodities such as silver and corn do not yield any of these diversification benefits.

With the optimal diversified portfolios at hand, I evaluate the performance of the aforementioned VaR methods applied to those portfolios by using the same estimation back-tests used in assessing the same VaR methods for individual equity indices.

The most notable finding is that the CEVT methods, although still providing the lowest percentage of violations, perform poorly in the Kupiec unconditional coverage (UC) test and the Christoffersen conditional coverage (CC) test. This is very different from what I have in the single asset case. Because the UC and the CC statistics only test the equality between the percentage of violations and the 1% confidence level, the results don’t necessarily suggest that the CEVT methods underestimate the downside risk of the portfolios, but only reflect the fact that the percentage of violations differs from the 1% confidence level. Actually, the percentage of violations is far below the 1%

level. For example, in the case of the portfolio that includes gold, oil and *ATX*, both CEVT methods only have four violations over the period from 11/2/2004 to 12/1/2011 that has 1,847 observations. The actual percentage of violations is 0.22%.

This result suggests that the CEVT method may overestimate the downside risk for the portfolios, at least when it is applied through the historical simulation approach.

3.5 Conclusions

Using the recent daily data from 2001 to 2011, I explore the downside risks for ten individual equity indices in the eurozone countries divided into two groups: the PIIGS countries and the Core countries, using four VaR methods. These estimation methods are: RiskMetrics, DPOT, CEVT-normal and CEVT-student-t. I also explore this downside risk for portfolios for the two groups comprised of these countries.

I test for the most appropriate value-at-risk (VaR) method for these individual eurozone indices and the diversified portfolios of the groups. I apply different evaluation criteria including the percentage of violations, maximum-median independence (MM) test, unconditional coverage test and conditional coverage test. I also apply the minimum capital requirements as stated in the Basel capital accord to these equity indices and portfolios, which allows us to evaluate the performance of the aforementioned VaR methods from a more practical perspective. Finally, I augment the equity portfolios with other asset classes.

Given the evidence I collected for the individual equity index VaR forecasts, the CEVT methods are the best performer among all the estimation methods because they satisfy all the back-testing statistical criteria better than the other methods. However, if the minimum capital requirement is the only concern, the RiskMetrics method gives the lowest mean capital requirement for the individual indices, which rewards the financial institutions who apply this method the opportunity to earn higher profits than other institutions who utilize different advanced VaR estimation methods such the CEVT methods.

I first examine portfolio diversifications across the ten equity indices. By assessing the historical performance of the VaR-based equity portfolios for the PIIGS and Core groups, the results demonstrate that the optimal portfolio contain one index for each group. I find that the optimal PIIGS portfolio is comprised of 99% of the Spanish *IBEX* index. Similarly, the optimal Core portfolio consists of 99% of the Austrian *ATX* index. If the ten indices are included in one portfolio, the results show that the resulting augmented optimal equity portfolio is 99% dominated by *ATX*. These results should not be surprising given the fact that the eurozone financial markets are highly integrated. Thus, any diversification within the eurozone markets does not produce diversification gains.

Following the suggestions from the recent literature on equity portfolio diversification, I diversify the full eurozone optimal equity portfolio with different asset classes including individual commodity assets, composite commodity indices and the S&P 500 index.

For the eurozone optimal equity portfolio that includes *ATX*, a diversification strategy that adds gold and oil to this portfolio gives the following optimal weights: 8.3% for *ATX*, 18% for oil, and 73.6% for gold. This strategy underscores the importance of equity diversification with oil and gold for investors in the harmonized eurozone. The gain of this portfolio diversification with gold and oil is significant, compared to all other portfolios. The average daily return increases from 0.031% to 0.059%, while the estimated VaR is reduced from $56.1 to $28.8 for an investment of $1,000. My other attempts to widen the diversification with other commodities such silver and corn have not improved the reward-risk ratio as measured by the VaR-based Sharpe ranking criterion. I have also replaced oil and gold by the two benchmark commodity indices, the Standard & Poor Goldman Sachs Commodity Index (*SPGSCI*) and the Dow Jones UBS Commodity Index (*DJ/UBSCI*). However, this diversification doesn't improve the performance.

Contrary to their results on satisfying all the VaR statistical properties for the individual assets, the two CEVT methods don't pass all the VaR back-tests in the case of the optimal portfolios because they overestimate the downside risk. On the other hand, the statistical property results for the portfolios under the RiskMetrics are still the worst among all the methods. However, in terms of the Basel rules on capital requirements, the RiskMetrics surprisingly gives the lowest average capital requirements, but it doesn't fare well in terms of the number of days in the red zone. Overall, the DPOT method has the second lowest capital requirement but still has zero days in the red zone, and, the DPOT method satisfies the statistical properties better than the RiskMetrics method.

Therefore, for the mostly diversified optimal portfolio, the DPOT is recommended in terms of satisfying the Basel rules.

Appendix A: The POT method for VaR forecasts

I consider the following Generalized Pareto Distribution (GPD):

$$G_{\gamma,\sigma}(y) = \begin{cases} 1-(1+\gamma y/\sigma)^{-\frac{1}{\gamma}}, & \gamma \neq 0 \\ 1-\exp\left(-\frac{y}{\sigma}\right), & \gamma = 0 \end{cases} \qquad (1)$$

where $\sigma > 0$, and the support is $y > 0$ when $\gamma \geq 0$; and $0 \leq y \leq -\sigma/\gamma$ when $\gamma < 0$.

The probability that a random variable X assumes a value that exceeds a threshold u by at most y, given that it does exceed that threshold, can be represented by the excess distribution:

$$F_u(y) = P[X-u \leq y | X > u] = \frac{F(y+u)-F(u)}{1-F(u)} \qquad (2)$$

for $0 \leq y \leq x^F - u$, where x^F is the right endpoint of F. The Extreme Value Theory (EVT) suggests the GPD (i.e., Eq.(1)) as an approximation for the excess distribution (i.e., Eq.(2)), for a sufficiently high threshold u for a wide class of distributions.

Let $\overline{F(y)} = 1 - F(y)$, Eq. (2) can be transformed as:

$$\overline{F_u(y)} = 1 - P[X-u \leq y | X > u] = \frac{\overline{F(y+u)}}{\overline{F(u)}} \qquad (3)$$

Let $x = y + u$, $\overline{F_u(x-u)} = \frac{\overline{F(x)}}{\overline{F(u)}}$ (4).

Smith (1987) proposed a tail estimator based on the approximation of a GPD to the excess distribution. For a sample of size of n_x, let *n* be the number of observations that are above the threshold u. Then, $\frac{n}{n_x}$ is an estimator of $\overline{F(u)}$. Plug in $\overline{F_u(x-u)}$, the term $(1+\gamma y/\sigma)^{-\frac{1}{\gamma}}$ obtained from Eq.(1) to Eq.(4), I get the tail estimator:

$$\widehat{\overline{F(x)}} = \frac{n}{n_x}(1+\hat{\gamma}\frac{x-u}{\hat{\sigma}})^{-1/\hat{\gamma}}, \text{ valid for } x > u. \qquad (5)$$

When I forecast the VaRs, I need to know the quantile z_p responding to the specified significance level p. For $p = \overline{F(x)}$, I invert Eq. (5) and get the VaR POT estimator:

$$\widehat{VaR}_{t+1|t}^{POT}(P) = \mu + \frac{\hat{\sigma}}{\hat{\gamma}}((\frac{n}{n_x p})^{\hat{\gamma}} - 1)$$

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Appendix of Tables

Table 1.1 Variables' Notation

Name	Description	Source
Financial Indicators		
DFR	Default Risk Premium =10 Year T-bill- BAA bond interest rate	DataStream
FFR	Effective Federal Fund Rate	Federal Reserve
MOVE	Merrill Lynch Option Volatility Estimate Index	DataStream
RIR	Real Interest Rate = DSG10-Inflation Rate	Federal Reserve Bank of St. Louis
S&P 500	Standard & Poor index	DataStream
TED	TED spread = LIBOR-3M T-bills	DataStream
VIX	Chicago Board Options Exchange's Market Volatility Index on near-term volatility of *S&P*500 stock index	DataStream
Real Economic Indicators		
IP	Industrial production (base year=2007)	Federal Reserve
Oil_M	WTI 3-month oil future price	Energy Information Administration

Table 1.2A Monthly Descriptive Statistics

	VIX	*MOVE*	*TED*	*DFR*	*OIL*	*IP*
Mean	2.952294	4.605517	0.533224	2.276808	3.573846	4.406456
Median	2.969388	4.628398	0.456000	2.060000	3.378952	4.474483
Maximum	4.092510	5.365509	2.962500	6.100000	4.943854	4.612385
Minimum	2.343727	4.041295	0.121940	1.300000	2.347558	4.096108
Std. Dev.	0.347197	0.229269	0.392213	0.807623	0.663477	0.159484
Skewness	0.418946	0.215868	2.464903	1.997461	0.233234	-0.669396
Kurtosis	2.841965	3.773454	12.79088	8.578059	1.833223	1.995173
C.V	0.117602	0.049781	0.73555	0.354717	0.185648	0.036193
Jarque-Bera	7.876236	8.500125	1301.780	591.9700	13.09222	30.23870
Probability	0.019485	0.014263	0.000000	0.000000	0.001436	0.000000
Observations	260	260	260	260	260	260

Notes: VIX, MOVE, Oil and IP are in natural logarithm. C.V (Coefficient of Variance) is defined as standard deviation over the mean. The sample period is from 1999/07 – 2011/07.

Table 1.2B Daily Descriptive Statistics

	VIX	*MOVE*	*TED*	*OIL*
Mean	2.997226	4.602994	0.538648	3.605071
Median	3.008155	4.614130	0.450000	3.413126
Std. Dev.	0.358247	0.249470	0.442000	0.630604
Skewness	0.390341	0.173332	2.908630	0.229704
Kurtosis	3.247373	3.500068	17.50789	1.754709
Jarque-Bera	120.4108	66.47420	43865.50	316.3175
Probability	0.000000	0.000000	0.000000	0.000000
C.V.	0.119526	0.054197	0.820573	0.174921
Observations	4309	4309	4309	4309

Notes: The sample period is from 2004/01/01 – 2011/07/01

Table 1.3A Daily Unit Root Tests

Levels	ADF (constant)	ADF (const & trend)	PP (constant)	PP(const & trend)
LN_VIX	-2.459568	-2.523121	-2.960422	-3.048831
LN_MOVE	-2.426803	-2.435187	-2.966311	-2.976552
TED	-3.172567	-3.219230	-3.197645	-3.249462
LN_OIL	-1.868506	-2.183161	-1.769948	-2.150383
FFR	-0.168217	-0.455855	-0.472116	-0.665888

First Difference	ADF (constant) t-statistic	ADF (const & trend) t-statistic	PP (constant) Adj. t-statistic	PP(const & trend) Adj. t-statistic
LN_VIX	-17.08005***	-17.07615***	-59.46751***	-59.45108***
LN_MOVE	-10.54207***	-10.54056***	-48.04079***	-48.03806***
TED	-9.526710***	-9.545140***	-55.76711***	-56.03671***
LN_OIL	-21.89891***	-21.91208***	-50.92704***	-50.93319***
FFR	-24.06426***	-24.15001***	-55.94709***	-56.45939***

Notes: The sample period is from 2004/01/01 – 2011/07/01
Lag length is determined by the results of SC. Test's crucial values are:

	1% level -3.433724 5% level -2.862917 10% level -2.567550	1% level -3.963068 5% level -3.412267 10% level -3.128065	1% level -3.433701 5% level -2.862907 10% level -2.567544	1% level -3.963035 5% level -3.412251 10% level -3.128055

Table 1.3B Monthly Unit Root Tests (1999M7-2011M07)

Levels	ADF (constant)	ADF (const & trend)	PP (constant)	PP(const & trend)
LN_VIX	-2.566649*	-2.638932	-2.938552**	-2.924525
LN_MOVE	-2.567140*	-2.444888	-2.285197	-2.567140
DFR	-2.119984	-2.472468	-1.700234	-1.958869
RIR	-2.834597*	-2.802704	-2.362891	-2.340025
LN_IP	-2.505087	-2.609941	-1.457527	-1.670023
LN_OIL	-1.171384	-1.674460	-1.333929	-1.811996

Notes: Lag length is determined by the results of SC.

First Difference	ADF (constant)	ADF (const & trend)	PP (constant)	PP(const & trend)
LN_VIX	-12.92804***	-12.88353***	-13.80710***	-13.74740***
LN_MOVE	-11.71691***	-11.65210***	-12.23470***	-12.15849***
FFR	-5.857165***	-5.824061***	-5.723876***	-5.688922***
RIR	-6.489044***	-6.463327***	-6.439448***	-6.411265***
LN_IP	-2.861939*	-2.102662	-7.574699***	-7.553405***
LN_OIL	-8.791758***	-8.772499***	-8.795638***	-8.777184***

Notes: The sample period is from 1999/07 – 2011/07.
Lag length is determined by the results of SC. The critical values for the unit root tests and their significance are respectively :

1% level -3.433724	1% level -3.963068	1% level -3.433701	1% level -3.963035
5% level -2.862917	5% level -3.412267	5% level -2.862907	5% level -3.412251
10% level -2.567550	10% level -3.128065	10% level -2.567544	10% level -3.128055

Table 1.4 Daily Linear VEC Model

Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	2	2*	4	2	2
Max-Eig	2	2*	2	2	2

Cointegrating Eqs.:	CointEq1	CointEq2
LN_VIXEI(-1)	1.000000	0.000000
LN_MOVE(-1)	0.000000	1.000000
LN_OIL(-1)	-0.016345	0.079402
TED3(-1)	-0.520736***	-0.506618***
C	-2.774555***	-4.819756***

Error Correction Model:	D(LN_VIX)	D(LN_MOVE)	D(LN_OIL)	D(TED3)
CointEq1	-0.040138***	0.012671***	-0.004870*	0.029004***
CointEq2	0.005524	-0.028149***	0.011994***	0.039174***
D(LN_VIX(-1))	-0.089139***	0.039411***	-0.058984***	0.001045
D(LN_MOVE(-1))	0.054672	0.043640*	-0.016756	0.057764
D(LN_OIL(-1))	0.112467*	-0.023223	-0.046638**	-0.100278
D(TED(-1))	-0.018373	0.025979**	-0.002556	0.203028***
QE1	0.005368	-0.003733	0.001661	-0.014031***
QE2	-0.003466	-0.000563	0.000696	0.002255
FFR_LAG	-0.003483***	-0.001166**	0.000816**	0.007265***

Log likelihood	13413.67
Akaike information criterion	-13.66837
Schwarz criterion	-13.53718

VEC residual normality test:

Component	Jarque-Bera	df	Prob.
1	2483.067	2	0.0000
2	2066.546	2	0.0000
3	481.9619	2	0.0000
4	558940.6	2	0.0000
Joint	569090.1	55	0.0000

H_0: the distribution of residuals is following the multivariate normal distribution.

Table 1.5 Daily MS VEC Model with Two Regimes

		D_VIX	D_MOVE	D_OIL	D_TED
Regime 1 (Low Variance)					
	Intercept	-0.001242	0.000503	0.000735	0.000564
	D_VIX(-1)	-0.059120**	0.030463*	-0.05158***1	-0.009651
	D_MOVE(-1)	0.027097	0.011934	0.011299	0.015813
	D_Oil(-1)	0.140860**	0.028479	-0.034681	-0.024675
	D_TED(-1)	-0.006207	-0.025861	-0.002598	0.029191*
	Coin 1	-0.058555***	0.000078	-0.004382	0.004471
	Coin2	-0.004945	-0.027113***	0.003524	0.008647**
	FFR_LAGGED	-0.007326***	-0.003053***	-0.000188	0.001181*
	QE1	0.008199*	-0.000229	0.001124	-0.005088***
	QE2	-0.008461*	-0.001449	0.000251	0.000371
	Variance	0.048400***	0.033136***	0.018497***	0.019482***
Regime 2 (High Variance)					
	Intercept	-0.001242	0.000503	0.000735	0.000564
	D_VIX(-1)	-0.149830***	0.031626	-0.062394***	-0.009931
	D_MOVE(-1)	0.094775	0.091011	-0.062058**	0.131870
	D_OIL(-1)	0.057320	-0.090173	-0.074696	-0.245478
	D_TED(-1)	-0.017367	0.033779	0.001749	0.242999***
	Coin 1	-0.030230	0.040007***	-0.013382*	0.060293*
	Coin 2	0.020558	-0.046545***	0.027976***	0.053109
	FFR_LAGGED	0.002434	0.000730	0.001632**	0.011978***
	QE1	0.025684	-0.020105*	0.006617	-0.031711
	QE2	0.132896***	-0.004630	-0.007826	-0.005070
	Variance	0.096770***	0.057548***	0.028935***	0.138903***

Transition Probabilities

	Regime 1	Regime 2	Durations
Regime 1	0.9418	0.0582	17.18
	0.2043	0.7957	4.9
Regime 2			

Notes: t-statistics are below the parameters with two decimal places***,** and * represent 1%, 5% and 10% significance level, respectively. The sample period is from 2004/01/01 – 2011/07/01

Table 1.6 Monthly Linear VEC Model

Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	3	2*	2	2	2
Max-Eig	1	2*	3	2	2

Cointegrating Eqs:	CointEq1	CointEq2
LN_VIX(-1)	1.000000	0.000000
LN_MOVE(-1)	0.000000	1.000000
DFR(-1)	-1.366903***	5.687647***
LN_IP(-1)	-17.15573***	99.08704***
LN_OIL(-1)	2.259915***	-10.89246***
C	70.64497***	-430.7904***

Error Correction:	D(VIX)	D(MOVE)	D(DFR)	D(IP)	D(OIL)
CointEq1	-0.2297***	-0.0807	0.3258***	0.0062*	-0.0020
CoinEq2	-0.0423***	-0.0135	0.0530***	8.42e-05	-0.0002
D(VIX(-1))	-0.0581	0.1451	0.2880**	-0.0021	-0.0115
D(MOVE(-1))	0.2567***	-0.2488***	0.0690	0.0067*	0.0177
D(DFR(-1))	0.0459	0.0107	0.2030**	0.0033	-0.0130
D(IP(-1))	-2.6489	-2.8878	-5.7356*	-0.0571	-0.6800
D(OIL(-1))	-1.1565***	-1.1276***	-0.8042	-0.0096	0.0992
QE1	-0.0973**	-0.0097***	-0.1611***	-0.0029*	-0.0219***
QE2	-0.0489	-0.0216	0.0252	0.0056***	-0.0028
LAGGED_RIR	0.0171**	0.0088	-0.0093	0.0009***	0.0027*

Log likelihood	1064.517
Akaike information criterion	-13.82782
Schwarz criterion	-12.55501

VEC residual normality test

Component	Jarque-Bera	df	Prob.
1	13.01010	2	0.0015
2	69.62420	2	0.0000
3	147.7607	2	0.0000
4	219.4764	2	0.0000
5	27.52187	2	0.0000
Joint	4390.311	105	0.0000

Notes: H_0: the distribution of the residuals is multivariate normal distribution. The sample period is from 1999/07 – 2011/07. ***,** and * represents 1%.5% and 10% significance level respectively.

Table 1.7 Monthly MS-VEC Model

	D_VIX	D_MOVE	D_DFR	D_IP	D_OIL
Constant	0.013399	-0.010389	-0.005996	0.000827	0.004164
Regime 1					
D_VIX_1	-0.135911	0.063917	0.033516	-0.004237	-0.021427
D_MOVE_1	0.294609***	-0.227243***	-0.139064	0.005515	0.008188
D_DFR_1	0.134901	0.097650*	0.102529	0.004860*	-0.011110
D_IP_1	4.873319*	-0.605523	5.556359*	-0.067046	-0.316090
D_OIL_1	-0.988474**	-0.781776**	-0.730215	-0.013203	0.004140
LAGGED_RIR	0.006695	0.007129	-0.003483	0.000503	0.000193
QE1	0.175826***	-0.049082	-0.106125	0.003387	0.010376
QE2	-0.075334	-0.080557*	-0.033078	0.001781	-0.003552
COIN1	-0.477407***	-0.117278	0.117389	0.000781	0.009559
COIN2	-0.074984***	-0.015300*	0.029021	-0.000520	0.002528
Variance[1] $_{regime1}$:	0.015728***	0.008205***	0.018256****	1.65E-05***	0.000079***
Regime 2					
D_VIX_1	0.323873	0.364826	1.236952***	-0.009394	-0.025640
D_MOVE_1	-0.245683	-0.472050*	-0.146171	0.015236	0.042811
D_DFR_1	-0.083425	-0.112109	-0.042525	0.011789	0.049687*
D_IP_1	-10.24042***	-4.687139	-12.84492***	-0.035095	-1.307759*
D_OIL_1	-1.283974	-1.973613**	-0.034133	0.005396	0.378641***
LAGGED_RIR	0.014419	0.022125	-0.067961*	0.001846	0.008514*
QE1	-0.230813***	-0.114986	-0.045289	-0.005987	-0.043195***
QE2	-0.248753*	0.103411	-0.255534	0.012473*	-0.011846
COIN1	0.082373	-0.051915	0.708359**	0.006895	-0.092692**
COIN2	0.011676	-0.009246	0.121447**	-0.000194	-0.018195***
Variance $_{regime2}$:	0.025598***	0.037352***	0.061509***	6.42E-05***	0.00094***

F-test[2]	1.48***	4.21***	3.72***	3.22***	1.98***
Transition probabilities			Regime 1	Regime 2	Duration
	Regime 1		0.8422	0.1578	6.34
	Regime 2		0.5181	0.4819	1.93

MS-VEC Model		*Linear VEC*	
Log likelihood	1146.5483	Log likelihood	1058.2263
Akaike AIC	-14.0215	Akaike AIC	-13.7254

LR linearity tst:

176.6439 Chi(65)=[0.0000]** Chi(67)=[0.0000]** DAVIES=[0.0000]**

Notes: The sample period is from 1999/07 – 2011/07. ***, **, and * indicate statistical significance at the 1%, 0.5% and 10% levels, respectively. The variances are the expected variances derived from 1,000 bootstraps. The F-test is for H_0: *variance in regime 1 = variance in regime 2.* H_a: *variance in regime 1 < variance in regime 2*. The test rejects the linearity hypothesis at 1% significance level.

Table 1.8A Time-varying Transition Probability MS-VEC Model (Information variable: oil price change)

	D(VIX)	D(MOVE)	D(DFR)
Regime 1			
D_VIX(-1)	-0.1702	0.1272	0.4907*
D_MOVE(-1)	0.5051**	0.1278	0.5951*
D_DFR(-1)	0.0477	-0.0295	0.3497*
COIN1	-0.0338	0.0154	-0.0662*
COIN2	0.2539	-0.1775	0.4900
Variance	0.0192	0.0063	0.0363
(p-value)	(0.0009)	(0.0003)	(0.0003)
Regime 2			
D_VIX(-1)	-0.2012	0.0596	0.3445
D_MOVE(-1)	0.1178	-0.4495*	-0.1217
D_DFR(-1)	-0.0367	0.1335	0.0130
COIN1	-0.0148	-0.0234	-0.0175
COIN2	-0.1019	0.0001	0.0540
Variance	0.0307	0.0236	0.4907
(p-value)	(0.0006)	(0.0000)	(0.0937)
P(1,1)	α1=-19.283489*		
(p-value)	(0.08)		
P(1,2)	β1= 6.5493		
(p-value)	(0.6040)		
LogLik	177.2321		

Notes: The time-varying transition probability MS model includes three financial risks variables: VIX, MOVE, and Default Risk Premium. The information variable is the percentage changes in WTI oil prices $(\Delta \log(wti_t) = \log(wti_t) - \log(wti_{t-1})$.

α_i are the coefficients for the ith lagged value in the transition probability function

of P_{11}; $\frac{\exp(\sum_{i=1}^{j} a_i z'_{t-i})}{1+\exp(\sum_{i=1}^{j} a_i z'_{t-i})}$[16], and β_i is the coefficient of the ith lag in the transition probability function of P_{12}.[17] $\frac{\exp(\sum_{i=1}^{j} b_i z'_{t-i})}{1+\exp(\sum_{i=1}^{j} b_i z'_{t-i})}$

[16] As in Emrah et al. (2012), the intercept term is not included in the logistic function.
[17] The calculation is accomplished by using the MATLAB package MS_Regress, which is originally developed by Marcelo Perlin and is extended by Ding, Zhuanxin (2012) to time-varying transition probability case. Ding estimates the parameter of P_{12} first and derives P_{22} from the equation: P_{22} =1- P_{12}.

Table 1.8B Time-varying Transition Probability MS-VEC Model (Information variable: industrial production changes)

	D(VIX)	D(MOVE)	D(DFR)
Regime 1			
D_VIX(-1)	-0.1515	0.1821*	0.3459*
D_MOVE(-1)	0.6001**	-0.0930	0.8695**
D_DFR(-1)	-0.0469	0.0187	0.1067
COIN1	0.0216	-0.0055	-0.0031
COIN2	-0.0535	-0.0003	0.2884
Variance	0.0098	0.0057	0.0250
(p-value)	(0.0001)	(0.0004)	(0.0000)
Regime 2			
D_VIX(-1)	-0.3531	-0.1016	0.3662
D_MOVE(-1)	0.1673	-0.1508	-0.2730
D_DFR(-1)	-0.0039	0.0119	0.1586
COIN1	-0.0576	-0.0186	-0.0594
COIN2	0.0902	-0.1394	0.1808
Variance	0.0359	0.0277	0.0517
(p-value)	(0.0004)	(0.0000)	(0.0002)
P(1,1)	α1=140.5842		
(p-value)	(0.1821)		
P(1,2)	β3=-95.9945*		
(p-value)	(0.08)		
LogLik	184.366		

Notes: Information variable is the last period oil price shock, which is the percentage change in the monthly industrial production ($\Delta \log(IP_t) = \log(IP_t) - \log(IP_{t-1})$. β3 is the parameters

Notes: The sample period is from 1999/07 – 2011/07. ***, **, and * indicate statistical significance at the 1%, 0.5% and 10% levels, respectively. The variances are the expected variances derived from 1,000 bootstraps. The F-test is for H_0: *variance in regime 1 = variance in regime 2.* H_a: *variance in regime 1 < variance in regime 2*. The test rejects the linearity hypothesis at 1% significance level.

Table2.1 Details of the ICRG Rating System

	Points	Percentage of Composite Country Risk
Political Risk		
Government Stability	12	6
Socioeconomic Conditions	12	6
Investment Profile	12	6
Internal Conflict	12	6
External Conflict	12	6
Corruption	6	3
Military in Politics	6	3
Religious Tensions	6	3
Law and Order	6	3
Ethnic Tensions	6	3
Democratic Accountability	6	3
Bureaucracy Quality	4	2
Total political points	100	50
Economic Risk		
GDP per Head	5	2.5
Real GDP Growth	10	5
Annual Inflation Rate	10	5
Budget Balance as a Percentage of GDP	10	5
Current Account as a Percentage of GDP	15	7.5
Total economic points	50	25
Financial Risk		
Foreign Debt as a Percentage of GDP	10	5
Foreign Debt Service as a Percentage of Exports of Goods and Services	10	5
Current Account as a Percentage of Exports of Goods and Services	15	7.5
Net International Liquidity as Months of Import Cover	5	2.5
Exchange Rate Stability	10	5
Total financial points	50	25
Overall points	200	100

Note: ICRG is International Country Risk Guide.

Table2.2A Data Statistics

Risks	Brazil	Russia	India	China	South Africa
Economic Risk					
Mean	34.8597	36.4473	34.2117	39.6805	35.5988
Median	35.0000	38.2500	34.5000	39.5000	36.0000
Std. Dev.	3.0424	7.2520	1.6886	1.3722	2.1406
C.V.	0.0872	0.1990	0.0493	0.03458	0.0601
Skewness	-0.4954	-0.8876	-0.5271	0.1518	-0.9298
Kurtosis	3.3509	2.9139	2.5388	2.0362	3.2838
Jarque-Bera	8.6545	24.7468	10.3724	7.9984	27.7224
Probability	0.0132	0.0000	0.0055	0.018	0.0000
Financial Risk					
Mean	33.9228	39.1409	41.1516	45.0638	38.1755
Median	34.0000	40.50000	41.0000	45.5000	38.5000
Std. Dev.	4.9325	6.4056	2.8603	3.0126	2.1534
C.V.	0.1454	0.1636	0.0695	0.0668	0.0564
Skewness	0.0234	-0.7543	-0.3249	-1.2591	-0.6323
Kurtosis	2.2872	2.4098	1.6662	3.8045	2.8544
Jarque-Bera	1.0930	20.5557	17.2436	54.7472	12.6932
Probability	0.5789	0.0000	0.0001	0.0000	0.0017
Political Risk					
Mean	66.2180	62.1755	60.6941	66.8377	68.8218
Median	66.0000	61.0000	61.5000	67.5000	69.0000
Std. Dev.	2.4826	5.8771	3.5098	2.9734	3.4577
C.V.	0.0374	0.0945	0.0578	0.0444	0.0502
Skewness	-0.1401	-1.3770	-0.4297	-0.6214	0.3768
Kurtosis	2.2872	4.5499	2.4848	2.4407	2.7112
Jarque-Bera	4.5954	78.2381	7.8659	14.5489	5.1021
Probability	0.1004	0.00000	0.0195	0.0006	0.0779
Stock Returns					
Mean	0.0114	0.0168	0.0084	0.0088	0.0067
Median	0.0237	0.0317	0.0210	0.0123	0.0141
Std. Dev	0.1227	0.1555	0.0950	0.0876	0.0827
C.V.	10.7631	9.2559	11.3095	9.9545	12.3432
Skewness	-0.8597	-1.3136	-0.5364	0.1718	-1.2663
Kurtosis	5.1377	7.8403	4.7051	4.1532	6.4671
Jarque-Bera	58.6442	236.3336	31.6245	11.2838	143.6427
Probability	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: The sample period ranges from September 1995 to April 2011. Coefficient of Variation is defined at the ratio of the standard deviation to the mean.

Table2.2B Correlations of Risk Rating Levels

Brazil	Economic Risk	Financial Risk	Political Risk
Economic Risk	1.0000		
Financial Risk	0.3176	1.0000	
Political Risk	0.1879	0.2479	1.0000
Russia			
Economic Risk	1.0000		
Financial Risk	0.4859	1.0000	
Political Risk	0.4445	0.8137	1.0000
India			
Economic Risk	1.0000		
Financial Risk	0.4650	1.0000	
Political Risk	0.7230	0.4256	1.0000
China			
Economic Risk	1.0000		
Financial Risk	0.3635	1.0000	
Political Risk	-0.0021	-0.1388	1.0000
South Africa			
Economic Risk	1.0000		
Financial Risk	0.0599	1.0000	
Political Risk	0.0477	0.4224	1.0000

Table 2.3 BRICS and U.S. Data Description:

	Brazil	Russia	India	China	South Africa	USA
GDP (PPP) (in trillion, 2011 est.)	\$2.282	\$2.38	\$4.463	\$11.29	\$0.555	\$15.04
GDP per capita (PPP2011 est.))	\$11,600	\$16,700	\$3,700	\$8,400	\$11,000	\$48,100
Index of Economic Freedom (2011)	56.3(113)	50.5(143)	54.6(124)	52(135)	62.7(74)	77.8(9)
Freedom of corruption (2011)	37(75)	22(146)	34(84)	36(79)	47(55)	75(19)
Population (in thousands)	196,343	140,702	1,140,566	1,317,066	48,783	313,232
competitiveness rank (2010-2011)	58	63	51	27	54	4
Stock market indices	BOVESPA	Russia RTS	India BSE(100)	Shanghai SE A	FTSE/JSE	S&P 500

Notes: The information on GDP is collected from CIA world fact book. Countries' scores of the Index of economic freedom (overall, freedom of corruption) are collected from Heritage Foundation. The number in the parentheses is the ranking of the country in all 180 countries. Competitiveness ranking is from "The Global Competitiveness Report 2010-2011" on World Economic Forum. The U.S. is included as a reference for comparison purpose.

Table 2.4 Unit Root Tests

	Stock	Economic Risk	Financial Risk	Political Risk
Brazil				
level				
ADF	-1.6742	-3.5226**	-2.8667	-2.9275
PP	-1.9096	-3.5792**	-2.7816	-3.0826
first difference				
ADF	-12.0892***	-13.6725***	-15.2817***	-12.5115***
PP	-12.0867***	-13.6971***	-15.2797***	-12.4822***
Russia				
level				
ADF	-2.5222	-3.5226**	-2.7195	-2.0094
PP	-2.5248	-3.5792**	-2.9376	-2.3048
first difference				
ADF	-10.9501***	-13.6725***	-10.9265***	-13.4306***
PP	-11.0366***	-13.6971***	-11.6412***	-13.4822***
India				
level				
ADF	-2.0910	-3.3121*	-2.2612	-2.5220
PP	-2.2868	-3.2878*	-2.4309	-2.3366
first difference				
ADF	-11.9848***	-14.8798***	-12.2434***	-13.9019***
PP	-11.9830***	-15.0569***	-12.1769***	-14.4294***
China				
level				
ADF	-1.9004	-3.7563**	-2.2279	-1.6520
PP	-2.3681	-3.7103**	-2.2279	-1.4312
first difference				
ADF	-12.6779***	-15.2808***	-13.9584***	-15.2255***
PP	-12.9053***	-15.6254***	-13.9694***	-15.4771***
South Africa				
level				
ADF	-2.0135	-2.2099	-3.8572**	-2.0823
PP	-2.0135	-2.5273	-3.9869***	-2.2740
first difference				
ADF	-12.8786***	-14.3456***	-13.8268***	-11.8622***
PP	-12.8802***	-14.5003***	-13.8283***	-11.8659***

Notes: I employ the ADF (constant & trend) test and PP (constant & trend) test. The critical values are 1% (-3.9630) marked by ***, 5% (-3.4127) denoted by ** and 10% (-3.1281). All variables are in logarithm. The sample period is from 1995/9 to 2011/1.

Table 2.5 Estimates of the TAR Cointegration Spread Model

	Brazil	Russia	India	China	S. Africa
τ	-0.4505	-0.40754	-0.5050	0.3528	-0.3287
Φ_{μ}[a]	11.5433***[18]	4.8800***	4.3646	6.4851***	3.4722**
$\rho_1=\rho_2$[b]	11.2215***	2.3746	0.656171	0.7883	2.6988
ρ_1	-0.0416	-0.0469	-0.05253*	-0.1296***	-0.0228
ρ_2	-0.2609***	-0.1493***	-0.0922**	-0.0768*	-0.1132**
Lags[c]	0	2	0	0	1
Q(4)[d]	13.5287	11.8457	12.2580	10.7824	1.9233
	(0.5567)	(0.9956)	(0.2133)	(0.8409)	(0.7499)
AIC	528.3728	441.0939	423.7532	417.3924	308.5117
SBC	535.2577	453.9753	430.6381	424.2773	318.2210

Notes: [a] The Φ test is an F-test that examines the joint hypothesis of $\rho_1 = \rho_2 = 0$.

[b] $\rho_1=\rho_2$ tests the null hypothesis that there is symmetric adjustment. The estimated ρ_1 and ρ_2 measure the speeds of the widening and narrowing adjustments, respectively.

[c] The lag used for each test is determined using the general-to-specific method (Ng and Perron, 1995) with a maximum lag order of 12 allowed.

[d] *Q(4)* are the Box-Pierce Q statistics for the first 4 autocorrelations of the residuals are jointly equal to zero. The p-values corresponding to individual test statistics are given in parenthesis. Statistical significance is indicated by double asterisks (**) for the 5% level. The sample period is 01/1992-04/2011.

[18] The critical values for F-statistics for Φ test and T-statistics for ρ_1 and ρ_2 are calculated through the bootstrap method suggested by Enders and Siklos. (2001) and Wane et al. (2005). The critical values are available upon requested.

Table 2.6 Estimates of the M-TAR Cointegration Model for the Five BRICS

	Brazil	Russia	India	China	S. Africa
τ	-0.1407	0.1425	-0.1287	-0.1264	-0.1485
Φ_{μ}[a]	9.0877***	10.1416***	10.5384***	9.4061***	5.8784***
ρ_1=ρ_2[b]	6.5415**	14.4904***	12.5845***	6.3360**	7.4048***
ρ_1	-0.05593*	-0.4051***	-0.0277	-0.0763	-0.0272
ρ_2	-0.2271***	-0.0613*	-0.2353***	-0.3029***	-0.2297***
Lags[c]	0	2	0	0	1
Q(4)[d]	12.5406	13.0594	13.6129	9.3639	1.4614
	(0.3166)	{0.9836}	(0.4896)	(0.9807)	(0.8335)
AIC	532.9176	431.1599	412.0563	411.8816	303.8562
SBC	539.8025	444.0414	418.9411	418.7665	313.5656

Notes: [a] The Φ test is an F-test that examines the joint hypothesis of $\rho_1 = 0$ and $\rho_2 = 0$.

[b] ρ_1=ρ_2 tests the null hypothesis that there is symmetric adjustment. The estimated ρ_1 and ρ_2 measure the speeds of the widening and narrowing adjustments, respectively. [c]The lag used for each test is determined using the general-to-specific method (Ng and Perron, 1995) with a maximum lag order of 12 allowed. [d] *Q(4)* are the Box-Pierce Q statistics for the first 4 autocorrelations of the residuals are jointly equal to zero. The p-values corresponding to individual test statistics are given in parenthesis. Statistical significance is indicated by double asterisks (**) for the 5% level. The sample period is 01/1992-04/2011.

Table 2.7 MTAR-VEC Model's Hypothesis Testing for the Five BRICS Stock

	Brazil	Russia	India	China	South Africa
HO: Long term symmetry[a]	0.7620 (0.3838)	1.0780 (0.3006)	0.6878 (0.4080)	5.6390** (0.0189)	3.6927* (0.056)
HO: Long term + Short-term symmetry[a]	1.18127 (0.3202)	1.2326 (0.2782)	1.0833 (0.3712)	4.6751*** (0.0000)	2.0497* (0.073)
HO: Short-term symmetry in Stock Index	1.3785 (0.2419)	0.9342 (0.3949)	0.4311 (0.512)	2.3050** (0.0476)	2.6348 (0.1063)
HO: Short-term symmetry in Economic Risk Rating[a]	0.7620 (0.3838)	0.1245 (0.8829)	1.4811 (0.2252)	6.7926*** (0.000)	0.3289 (0.5669)
HO: Short-term symmetry in Financial Risk Rating[a]	0.049222 (0.8246)	2.0125 (0.1368)	1.2376 (0.2674)	5.7966*** (0.000)	1.4138 (0.2360)
HO: Short-term symmetry in Political Risk Rating[a]	1.8389 (0.1768)	1.2475 (0.2898)	0.8585 (0.3554)	1.2422 (0.2926)	0.4123 (0.5216)
Lags[b]	1	2	1	5	1

Notes: Statistical significance is indicated by ** (***) for the 5% (1%) level. .

[a] These are F-statistics with their correspondent significance in parenthesis.

[b] The lag used for each test is determined using the general-to-specific method (Ng and Perron, 1995) with a maximum lag order of 12 allowed.

Table 2.8 Estimation of the MTAR-VEC Models for the Five BRICS

Panel A- Stock Market Indices Adjustments

Error Correction:	Brazil	Russia	India	China	South Africa
$\lambda^{\text{stock}^{+}}$	-0.0129	-0.0793	-0.0184	-0.0598**	-0.0010
$\lambda^{\text{stock}^{-}}$	-0.0158	0.0020	-0.0745**	-0.3343***	-0.0713*
D(Stock^{+}(-1))	0.1895**	0.2336	0.1713**	0.1887**	0.1738*
D(Stock^{-}(-1))	0.0404	0.2753***	0.0674	-0.3780***	-0.1118
D(ER^{+}(-1))	0.0243	0.0460	-0.6652*	0.4088	0.1068
D(ER^{-}(-1))	0.3245	-0.0265	-0.0452	-2.2150***	-0.2683
D(FR^{+}(-1))	0.0996	-0.8211*	1.8181***	0.3053	-0.2412
D(FR^{-}(-1))	-0.5529	0.0565	-0.4104	-1.6408**	0.2747
D(PR^{+}(-1))	0.3247	0.1528	0.2321	0.4221	0.2177
D(PR^{-}(-1))	-0.8539	1.2049**	0.6981	1.1364	-0.8810
D(Stock^{+}(-2))	N/A	N/A	N/A	N/A	N/A
D(Stock^{-}(-2))	N/A	N/A	N/A	0.3599***	N/A
D(ER^{+}(-2))	N/A	0.5429**	N/A	N/A	N/A
D(ER^{-}(-2))	N/A	N/A	N/A	N/A	N/A
D(FR^{+}(-2))	N/A	N/A	N/A	N/A	N/A
D(FR^{-}(-2))	N/A	N/A	N/A	N/A	N/A
D(PR^{+}(-2))	N/A	N/A	N/A	N/A	N/A
D(PR^{-}(-2))	N/A	N/A	N/A	-3.1865***	N/A

Note: The estimated equation of the MTAR-VEC model in this table is Eq. (4a).

Panel B- Economic Risk Ratings Adjustments

Error Correction:	Brazil	Russia	India	China	South Africa
λ^{ER^+}	0.0073	0.0756**	-0.0013	0.0016	-0.0019
λ^{ER^-}	0.0349***	0.0015	-0.0242***	-0.0002	-0.0043
D(Stock$^+$(-1))	-0.0362	-0.0690	0.0136	0.0101	-0.0309
D(Stock$^-$(-1))	-0.0276	0.0315	0.0574*	0.0275	0.0330
D(ER$^+$(-1))	0.2997***	-0.3543**	0.1295	0.1028	-0.1217
D(ER$^-$(-1))	-0.1297	0.0012	-0.1025	-0.0293	0.0506
D(FR$^+$(-1))	0.1323**	0.8941***	-0.0782	-0.1542	0.0648
D(FR$^-$(-1))	-0.0638	0.2019	-0.0129	-0.1159	0.0299
D(PR$^+$(-1))	0.1185	1.099***	0.0671	0.0945	0.0852
D(PR$^-$(-1))	-0.2519	0.0517	-0.0288	0.4434	-0.1484
D(Stock$^+$(-2))	N/A	N/A	N/A	N/A	N/A
D(Stock$^-$(-2))	N/A	N/A	N/A	N/A	N/A
D(ER$^+$(-2))	N/A	N/A	N/A	N/A	N/A
D(ER$^-$(-2))	N/A	N/A	N/A	N/A	N/A
D(FR$^+$(-2))	N/A	N/A	N/A	N/A	N/A
D(FR$^-$(-2))	N/A	0.3939*	N/A	N/A	N/A
D(PR$^+$(-2))	N/A	N/A	N/A	N/A	N/A
D(PR$^-$(-2))	N/A	N/A	N/A	N/A	N/A

Note: The estimated equation of the MTAR-VEC model in this table is Eq. (4b).

Panel C- Financial Risk Rating Adjustments

Error Correction:	Brazil	Russia	India	China	South Africa
$\lambda^{FR^{+}}$	0.0134*	0.0324*	0.0016	0.0015	0.0049
$\lambda^{FR^{-}}$	0.0030	0.0104**	0.0013	-0.0077	0.0269**
D($Stock^{+}$(-1))	0.0206	0.0301	0.0143	-0.0094	0.0709**
D($Stock^{-}$(-1))	-0.0007	0.0339*	0.0148	0.0124	0.0807
D(ER^{+}(-1))	0.1821	-0.1681**	0.0645	0.1181	-0.0510
D(ER^{-}(-1))	-0.1056	0.0110	-0.0469	-0.1019	-0.1818
D(FR^{+}(-1))	-0.0056	0.4694***	0.1378	0.2573**	-0.0721
D(FR^{-}(-1))	-0.3112**	-0.1647	-0.0257	-0.1387	0.0635
D(PR^{+}(-1))	-0.0074	0.9358***	0.0001	0.0306	0.2189
D(PR^{-}(-1))	-0.6590	-0.0061	0.0136	0.3900**	-0.2245
D($Stock^{+}$(-2))	N/A	0.0695**	N/A	0.0530***	N/A
D($Stock^{-}$(-2))	N/A	N/A	N/A	-0.0348***	N/A
D(ER^{+}(-2))	N/A	N/A	N/A	N/A	N/A
D(ER^{-}(-2))	N/A	N/A	N/A	N/A	N/A
D(FR^{+}(-2))	N/A	-0.3036***	N/A	-0.2107*	N/A
D(FR^{-}(-2))	N/A	0.3530**	N/A	N/A	N/A
D(PR^{+}(-2))	N/A	N/A	N/A	N/A	N/A
D(PR^{-}(-2))	N/A	N/A	N/A	N/A	N/A

The estimated equation of the MTAR-VEC model in this table is Eq. (4c).

Panel D- Political Risk Rating Adjustments

Error Correction:	Brazil	Russia	India	China	South Africa
λ^{FR^+}	-0.0001	0.0043	-0.0013	0.0004	-0.0016
λ^{FR^-}	0.0064	0.0050	0.0177**	-0.0059	0.0006
D(Stock$^+$(-1))	0.0064	-0.0361	0.0060	-0.0040	-0.0066
D(Stock$^-$(-1))	-0.0103	0.0602***	0.0309	0.0098	0.0034
D(ER$^+$(-1))	-0.0100	-0.0942	0.1691*	0.1321*	0.0173
D(ER$^-$(-1))	0.0174	0.0146	-0.0693	-0.0954	-0.0138
D(FR$^+$(-1))	0.0417	0.0168	0.0081	-0.0580	-0.0525
D(FR$^-$(-1))	-0.0825**	-0.1615**	0.1624	-0.0884	0.0455
D(PR$^+$(-1))	0.1518**	-0.096	-0.0612	-0.064	0.2509***
D(PR$^-$(-1))	-0.3217**	0.0995	-0.0085	0.2132	0.1135
D(Stock$^+$(-2))	N/A	0.0565**	N/A	0.0228**	-0.0725
D(Stock$^-$(-2))	N/A	N/A	N/A	N/A	N/A
D(ER$^+$(-2))	N/A	N/A	N/A	N/A	N/A
D(ER$^-$(-2))	N/A	N/A	N/A	N/A	N/A
D(FR$^+$(-2))	N/A	N/A	N/A	N/A	N/A
D(FR$^-$(-2))	N/A	N/A	N/A	N/A	N/A
D(PR$^+$(-2))	N/A	N/A	N/A	N/A	N/A
D(PR$^-$(-2))	N/A	0.2442**	N/A	0.3641*	N/A

Note: The estimated equation of the MTAR-VEC model in this table is Eq. (4d).

Table 3.1 List of Stock Market Indices

Name	Symbol	Description	Country
Amsterdam Exchange Index	*AEX*	This market capitalization weighted index is composed of a maximum of 25 of the most actively traded[19] securities on the exchange.	The Netherlands
ATHEX Composite Share Price Index	*ATHEX*	This market capitalization weighted index is composed of the 60 largest[20] companies that traded in the Big Cap category of the Athens stock exchange.	Greece
Austrian Traded Index in EUR	*ATX*	This market capitalization weighted index comprises the 20 with the highest liquidity and market value.	Austria
CAC 40	*CAC*	This market capitalization weighted index composes the 40 largest equities measured by free-float market capitalization and liquidity companies listed on Euronext Paris equity market.	France
Deutscher Aktien Index	*DAX 30*	This market capitalization weighted index composes the 40 largest equities measured by free-float market capitalization and liquidity companies listed on Frankfurt Stock Exchange.	Germany
FTSE MIB (Milano Italia Borsa)	*FTSE*	This index consists of the 40 most-traded stock classes on the exchange.	Italy
IBEX 35(Iberia Index)	*IBEX*	This index is composed of the 35 most liquid securities traded on the Spanish Market	Spain
IBEQ overall index	*ISEQ*	This index is composed of the 20 companies with the highest trading volume and market capitalization liquid securities traded on the Irish Stock Exchange.	Ireland
	OMX	OMX HELSINKI (OMXH) – FINLAND	Finland
	PSI	PORTUGAL *PSI* GENERAL	Portugal

Notes: All data are obtained from DataStream.

[19] The selection is made on an annual review date in March. It is based on the share turnover over the previous year.
[20] The companies are ranked on the basis of their trading value excluding blocks.

Table 3.2 Descriptive Statistics for Index Returns

Group 1	*ATHEX*	*FTSE*	*IBEX*	*ISEQ*	*PSI*
Mean	-0.0442	-0.0178	0.0099	-0.0136	0.0073
Median	0.0122	0.0517	0.0357	0.0689	0.0589
Maximum	14.6373	8.5290	14.9682	9.9495	11.5957
Minimum	-11.3663	-10.7525	-10.6569	-15.1514	-12.9159
Std. Dev.	1.8572	1.4528	1.7446	1.6997	1.3726
Skewness	0.0078	-0.4435	0.0502	-0.6492	-0.2092
Kurtosis	8.4497	8.0997	9.5961	10.0708	12.6228
Jarque-Bera	3524.344	3179.520	5164.200	6132.842	11009.05

Group 2	*AEX*	*ATX*	*CAC*	*DAX*	*OMX*
Mean	-0.01415	0.0312	-0.0097	0.0104	-0.0176
Median	0.0337	0.0728	0.0308	0.0701	0.0194
Maximum	12.3159	12.6114	12.1434	12.3697	9.9142
Minimum	-11.8565	-12.5361	-11.7370	-9.6010	-16.3145
Std. Dev.	1.7703	1.8014	1.7607	1.7994	1.9612
Skewness	-0.0889	-0.3165	0.0273	-0.0494	-0.2472
Kurtosis	9.2257	10.1130	8.9285	7.4737	7.4640
Jarque-Bera	4603.209	6051.500	4171.100	2376.132	2393.665
Probability	0.00	0.00	0.00	0.00	0.00

Commodities & commodity indices	*Corn*	*Gold*	*Oil*	*Silver*	*SPGSCI*	*DJUBSCI*
Mean	0.03304	0.065312	0.05522	0.06892	0.00631	-0.00408
Median	0	0.37446	0.03362	0.19231	0	0
Maximum	12.75710	6.84143	18.12974	13.16316	7.21586	5.39012
Minimum	-10.40878	-7.97189	-19.8907	-20.3851	-9.16951	-5.70218
Std. Dev.	1.90911	1.18505	2.349135	2.09915	1.60211	1.12156
Skewness	0.13445	-0.26737	-0.23805	-1.34823	-0.29083	-0.20030
Kurtosis	5.53413	7.75507	8.91320	13.22466	5.38094	4.56494
Jarque-Bera	770.6379	2717.06	4173.185	13268.66	712.8545	309.66
Probability	0.00	0.00	0.00	0.00	0.00	0.00
Observations	2848	2848	2848	2848	2848	2848

Notes: The indices and their associated market are as follows:

ATHEX (Greece), *FTSE* (Italy), *IBEX* (Spain), *ISEQ* (Ireland), *PSI* (Portugal), *AEX* (the Netherlands), *ATX* (Austria), *CAC* (France), *DAX* (Germany), *OMX* (Finland). S*PGSCI* (S&P Golden Sachs Commodity Index), *DJUBSCI* (Dow-Jones UBS Commodity Index).

Table 3.3: Back-testing Results for Individual Equity Index (2001 -2011)

Panel A: PIIGS countries

Panel A_1: Portugal (*PSI*)

	RiskMetrics	DPOT	CEVT-n	CEVT- sstd
% of viol.	0.0183	0.0146	0.0113	0.011
Kupiec uc	10.5496(0.00)	3.4737 (0.06)	0.3324(0.56)	0.3324(0.56)
MM ind	-0.3741(0.77)	3.1735(0.13)	2.8693(0.18)	2.5139(0.21)
Christ. cc	10.7641(0.00)	4.1596(0.12)	1.7341(0.42)	1.7341(0.42)

Panel A_2: Ireland (*ISEQ*)

	RiskMetrics	DPOT	CEVT-n	CEVT- sstd
% of viol.	0.0238	0.0129	0.0091	0.0097
Kupiec uc	25.6577(0.00)	1.5222 (0.21)	0.1230(0.72)	0.0127(0.91)
MM ind	1.4560(0.28)	3.2615(0.10)	0.3437(0.65)	0.2865(0.59)
Christ. cc	26.4095(0.00)	2.5230(0.28)	2.2304(0.32)	1.9220(0.38)

Panel A_3: Italy *(FTSE*)

	RiskMetrics	DPOT	CEVT-n	CEVT- sstd
% of viol.	0.0238	0.0151	0.0167	0.0146
Kupiec uc	25.6577(0.00)	4.2785 (0.03)	7.1183(0.07)	3.4737(0.06)
MM ind	1.4560(0.14)	2.1774(0.19)	-0.0470(0.72)	0.2161(0.65)
Christ. cc	26.4095(0.00)	4.8760(0.08)	8.1905(0.01)	4.1596(0.12)

Panel A_4: Greece (*ATHEX*)

	RiskMetrics	DPOT	CEVT-n	CEVT- sstd
% of viol.	0.0200	0.0151	0.0119	0.0113
Kupiec uc	14.5210(0.00)	4.2785 (0.03)	0.6383(0.42)	0.3324(0.56)
MM ind	1.8104(0.26)	1.5198(0.29)	1.0539(0.39)	1.1004(0.45)
Christ. cc	16.0836(0.00)	4.8760(0.08)	1.1726(0.55)	0.8182(0.66)

Panel A_5: Spain (*IBEX*)

	RiskMetrics	DPOT	CEVT-n	CEVT- sstd
% of viol.	0.02110	0.0156	0.01244	0.0124
Kupiec uc	17.4470(0.00)	5.1558(0.02)	1.0362(0.30)	1.0362(0.30)
MM ind	1.5947(0.29)	1.5063(0.34)	1.1774(0.42)	1.1004(0.44)
Christ. cc	17.5066(0.00)	5.6725(0.05)	1.6212(0.44)	1.6212(0.44)

Notes: The numbers in parenthesis are the *p*-values.

Panel B: Other countries

Panel B_1: Austria (*ATX*)

	RiskMetrics	DPOT	CEVT-n	CEVT- sstd
% of viol.	0.0216	0.0108	0.0124	0.0124
Kupiec uc	18.9893(0.00)	0.1229(0.72)	1.0362(0.30)	1.0362(0.30)
MM ind	-0.2423(0.72)	1.3329(0.34)	-0.9520(0.94)	-0.9520(0.94)
Christ. cc	20.1594(0.00)	1.6807(0.43)	2.1602(0.33)	2.1602(0.33)

Panel B_2: Finland (*OMX*)

	RiskMetrics	DPOT	CEVT-n	CEVT- sstd
% of viol.	0.01893	0.0091	0.0102	0.0102
Kupiec uc	11.8157(0.00)	0.1230(0.72)	0.01464(0.90)	0.01464(0.90)
MM ind	5.3528(0.02)	2.1787(0.27)	1.8660(0.31)	1.8660(0.31)
Christ. cc	11.9883(0.00)	0.4372(0.80)	0.4101(0.81)	0.4101(0.81)

Panel B_3: France (*CAC*)

	RiskMetrics	DPOT	CEVT-n	CEVT- sstd
% of viol.	0.0189	0.0140	0.0091	0.0097
Kupiec uc	11.8157(0.00)	2.7441(0.09)	0.1230(0.72)	0.0127(0.91)
MM ind	2.0187(0.23)	12.1836(0.00)	0.6671(0.57)	0.1534(0.63)
Christ. cc	11.9883(0.00)	3.5264(0.17)	0.4372(0.80)	0.3664(0.83)

Panel B_4: Germany (*DAX*)

	RiskMetrics	DPOT	CEVT-n	CEVT- sstd
% of viol.	0.0205	0.0140	0.0091	0.0091
Kupiec uc	15.9571(0.00)	2.7441(0.09)	0.1230(0.72)	0.1230(0.72)
MM ind	2.2390(0.17)	11.9503(0.00)	1.4758(0.39)	1.4758(0.39)
Christ. cc	17.3809(0.00)	3.4948(0.17)	0.4372(0.80)	0.4372(0.80)

Panel B_5: The Netherlands (*AEX*)

	RiskMetrics	DPOT	CEVT-n	CEVT- sstd
% of viol.	0.0227	0.0167	0.0124	0.0119
Kupiec uc	22.2260(0.00)	7.1183(0.00)	1.0362(0.30)	0.6383(0.42)
MM ind	4.8400(0.02)	13.8080(0.00)	-0.3288(0.81)	0.5516(0.51)
Christ. cc	25.2392(0.00)	7.4947(0.02)	1.6212(0.44)	1.1726(0.55)

Optimal portfolio

	RiskMetrics	DPOT	CEVT-n	CEVT- sstd
% of viol.	0.0221	0.1244	0.0021	0.0021
Kupiec uc	20.5827(0.00)	1.0362(0.30)	16.8312(0.00)	16.8312(0.00)
MM ind	0.2887(0.61)	0.7555(0.52)	-0.0259(0.79)	-0.0259(0.79)
Christ. cc	23.8087(0.00)	5.6484(0.05)	16.8327(0.00)	16.8327(0.00)

Table 3.4: Daily Capital Charges for Individual Assets

Panel A: PIIGS countries

Panel A_1: Portugal (*PSI*)

Model	Number of days in the red zone	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	0	10.9640	33.2698	3.4327
DPOT	201	11.6680	22.7905	3.3396
CEVT - n	0	11.6042	39.2014	4.1513
CEVT - sstd	0	11.6743	38.9670	4.3172

Panel A_2: Ireland (*ISEQ*)

Model	Number of days in the red zone	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	245	14.7052	43.2118	5.2024
DPOT	0	15.8000	32.8284	5.7656
CEVT - n	0	14.7057	39.8311	6.2626
CEVT - sstd	0	14.9953	45.2623	6.3504

Panel A_3: Italy (*FTSE*)

Model	Number of days in the red zone	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	0	11.6222	33.9931	4.6084
DPOT	125	12.5459	29.4808	4.3003
CEVT - n	0	11.9144	36.5122	4.9281
CEVT - sstd	0	11.6840	35.6879	4.9829

Panel A_4: Greece (*ATHEX*)

Model	Number of days in the red zone	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	135	15.0462	39.6072	5.3262
DPOT	0	16.5353	29.6643	6.0816
CEVT - n	0	15.4974	39.4312	6.5435
CEVT - sstd	0	15.2526	38.7487	6.5970

Panel A_5: Spain (*IBEX*)

Model	Number of days in the red zone	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	5	13.5022	40.1655	5.9758
DPOT	56	14.7562	29.8339	5.3909
CEVT - n	0	14.1332	42.1524	5.7435
CEVT - sstd	0	14.2761	43.2859	5.6790

Panel B: Core countries

Panel B_1: Austria (*ATX*)

Model	Number of days in the red zone	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	84	15.1524	51.9809	6.0915
DPOT	0	16.2824	34.0806	5.9129
CEVT - n	0	15.2313	51.4433	6.7238
CEVT - sstd	0	15.1695	50.9051	6.9044

Panel B_2: Finland (*OMX*)

Model	Number of days in the red zone	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	0	13.0033	34.8865	5.5072
DPOT	0	14.7110	31.9103	6.2303
CEVT - n	0	13.2025	32.8482	6.5030
CEVT - sstd	0	13.2676	32.4414	6.6856

Panel B_3: France (*CAC*)

Model	Number of days in the red zone	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	0	12.7300	39.0219	4.7203
DPOT	248	14.4378	29.7777	5.5496
CEVT - n	0	12.9721	38.2298	5.5943
CEVT - sstd	0	12.8597	37.3102	5.6134

Panel B_4: Germany (*DAX*)

Model	Number of days in the red zone	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	67	12.6742	41.8530	4.6088
DPOT	248	13.6343	19.2133	5.2954
CEVT - n	0	12.8075	42.1473	5.4419
CEVT - sstd	0	12.7208	41.4742	5.3828

Panel B_5: The Netherland (*AEX*)

Model	Number of days in the red zone	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	76	12.6043	42.6374	4.5256
DPOT	244	13.5109	32.8023	4.7890
CEVT - n	0	12.9354	46.2049	4.8742
CEVT - sstd	0	12.9417	45.8070	4.8980

Basel Accord Penalty Zones

Zone	Number of Violations	k
Green	0 to 4	0.00
Yellow	5	0.40
	6	0.50
	7	0.65
	8	0.75
	9	0.85
Red	10+	1.00

Note: The number of violations is accumulated for the last 250 trading days.

Optimal Portfolio (Gold, Oil, ATX)

Model	Number of days in the red zone	Daily Capital Charges		
		Mean	Maximum	Minimum
RiskMetrics	102	9.5075	23.3308	4.8078
DPOT	0	10.6395	24.5572	4.7453
CEVT - n	0	13.6369	28.9107	8.7613
CEVT - sstd	0	13.6167	28.8848	8.8412

Table 3.5: Estimated VaR- Optimal Portfolios

Portfolio 1: PIIGS equity indices

PSI (%)	ISEQ(%)	ETSE (%)	ATHEX (%)	IBEX (%)	Portfolio VaR ($)	Portfolio Return	Risk-return ratio
0.02	0.09	0	0.39	99.5	-50.07	0.000099	0.00000029

Notes: Portfolio 1 includes the five equity indices for PIIGS countries. Daily returns are used to find the optimal portfolio at the point where the risk-return trade-off the return-risk ratio S(P) is maximized. The risk-return ratio equation is given by $P': \max_P S(P) = \frac{(r(P)-r_f)}{(\varphi(p,P))}$, where P is the optimal portfolio, $\varphi(p,P) = W(0)r_f - VaR(p,P)$ is the performance measure for risk, W(0) is the amount invested, r_f is the the 10 year Treasury rate available on the last day of the sample period which is equal to 2.08%, and VaR(p,P) is the Value-at-Risk for portfolio P. The VaR for $1000 held in the portfolio is given for a daily time horizon and a 99% confidence level, where the historical distribution is used to estimate the VaR. % is the weight of the individual equity indices in the portfolio.

Portfolio 2: Core countries equity indices

ATX (%)	OMX(%)	CAC(%)	DAX(%)	AEX(%)	Portfolio VaR ($)	Portfolio Return	Risk-return ratio
99.44	0.24	0.15	0.03	0.14	-56.16	0.0003096	0.00000401

Notes: Portfolio 2 includes the five equity indices for Core countries.

Portfolio 3: 10 equity indices

ATX (%)	DAX(%)	Portfolio VaR ($)	Portfolio Return	Risk-return ratio
99.06	0.94	-56.10	0.0003097	0.00000401

Notes: Portfolio 3 includes all the ten equity indices mentioned above.

Portfolio 4: Gold, ATX

Gold (%)	ATX (%)	Portfolio VaR ($)	Portfolio Return	Ratio
81.4	19.6	-30.29	0.00059	1.698E-05

Back-tests results

	RiskMetrics	DPOT	CEVT-n	CEVT- sstd
% of viol.	0.0216	0.0075	0.0021	0.0021
Kupiec uc	18.9893(0.00)	1.1972(0.2738)	16.8311(0.00)	16.8311(0.00)
MM ind	-1.6919(0.99)	0.8422(0.46)	0.2768(0.70)	0.2768(0.70)
Christ. cc	19.0336(0.00)	9.6935(0.00)	16.8327(0.00)	16.8327(0.00)

Portfolio 5: Gold, oil, ATX

Gold (%)	ATX (%)	Oil(%)	Portfolio VaR ($)	Portfolio Return	Ratio
73.6	8.3	18	-28.83	0.00060	1.803E-05

	RiskMetrics	DPOT	CEVT-n	CEVT- sstd
% of viol.	0.0227	0.0113	0.0021	0.0021
Kupiec uc	22.2260(0.00)	0.3324(0.56)	16.8311(0.00)	16.8311(0.00)
MM ind	-1.0420(0.93)	1.7337(0.32)	0.0259(0.79)	0.0259(0.78)
Christ. cc	23.1728(0.00)	1.7341(0.42)	16.8327(0.00)	16.8327(0.00)

Portfolio 6: Gold, Oil, ATX, IBEX [incrementally adding gold, oil respectively]

Gold (%)	Oil(%)	ATX (%)	IBEX (%)	Portfolio VaR ($)	Portfolio Return	Risk-return ratio
74.9	5.0	20	0.1	-29.876	0.000599	0.00001723

	RiskMetrics	DPOT	CEVT-n	CEVT- sstd
% of viol.	0.0227	0.0108	0.0021	0.0021
Kupiec uc	22.2260(0.00)	0.1229(0.72)	16.8130(0.00)	16.8130(0.00)
MM ind	-0.6096(0.83)	-0.0413(0.68)	0.2768(0.70)	0.2768(0.70)
Christ. cc	23.1728(0.00)	5.7832(0.05)	16.8327(0.00)	16.8327(0.00)

Portfolio 7: Gold, Oil, Silver, ATX, IBEX

Gold (%)	Oil (%)	Silver (%)	ATX (%)	IBEX (%)	Portfolio VaR ($)	Portfolio Return	Risk-return ratio
13.98	11.03	56.587	6.16	12.3218	-45.09	0.000579	0.0000109

Portfolio 8: Gold, Oil, ATX, IBEX, S&PGSCI

Gold (%)	Oil (%)	ATX (%)	IBEX(%)	S&PGSCI	Portfolio VaR ($)	Portfolio Return	Risk-return ratio
99.7	0.03	8E-04	0	0.0729	-32.7539	0.000652	0.00001706

Portfolio 9: Gold, Oil, ATX, IBEX, CORN

Gold (%)	Oil(%)	ATX (%)	IBEX (%)	CORN	Portfolio VaR ($)	Portfolio Return	Risk-return ratio
74.7	13.8	8	34	0	-29.78	0.000599	0.00001731

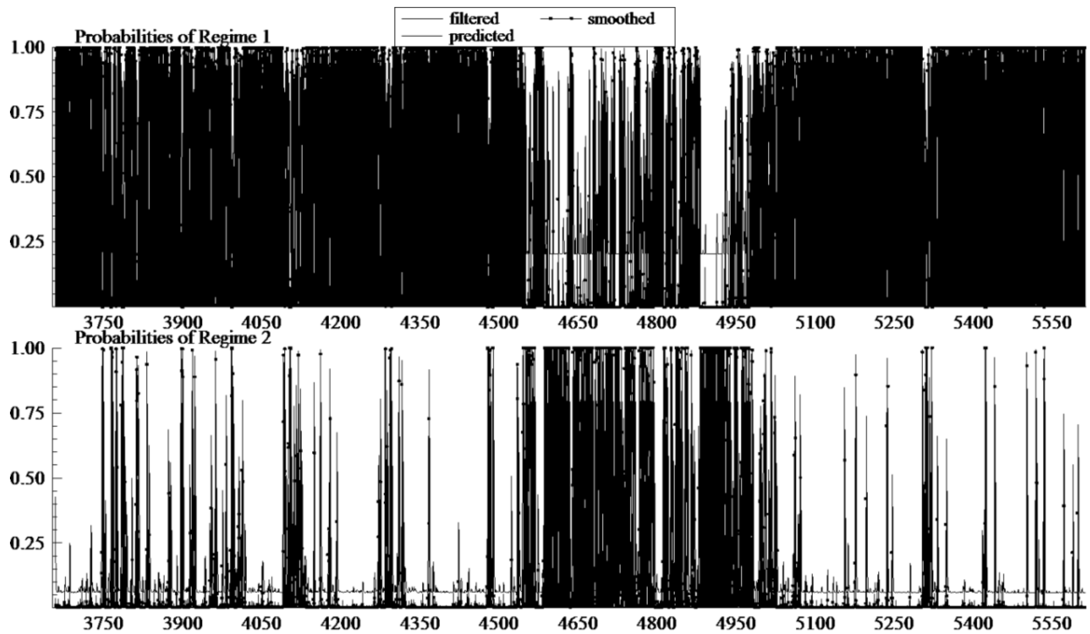
Portfolio 10: Gold, Oil, ATX, IBEX, DJUBSCI

Gold (%)	Oil(%)	ATX (%)	IBEX (%)	DJUBSCI	Portfolio VaR ($)	Portfolio Return	Risk-return ratio
99.1	0.8	0.001	0.0375	0.0626	-33.217	0.000651	0.00001708

Appendix of Figures

Figure 1.1: Smoothed Regime Probabilities

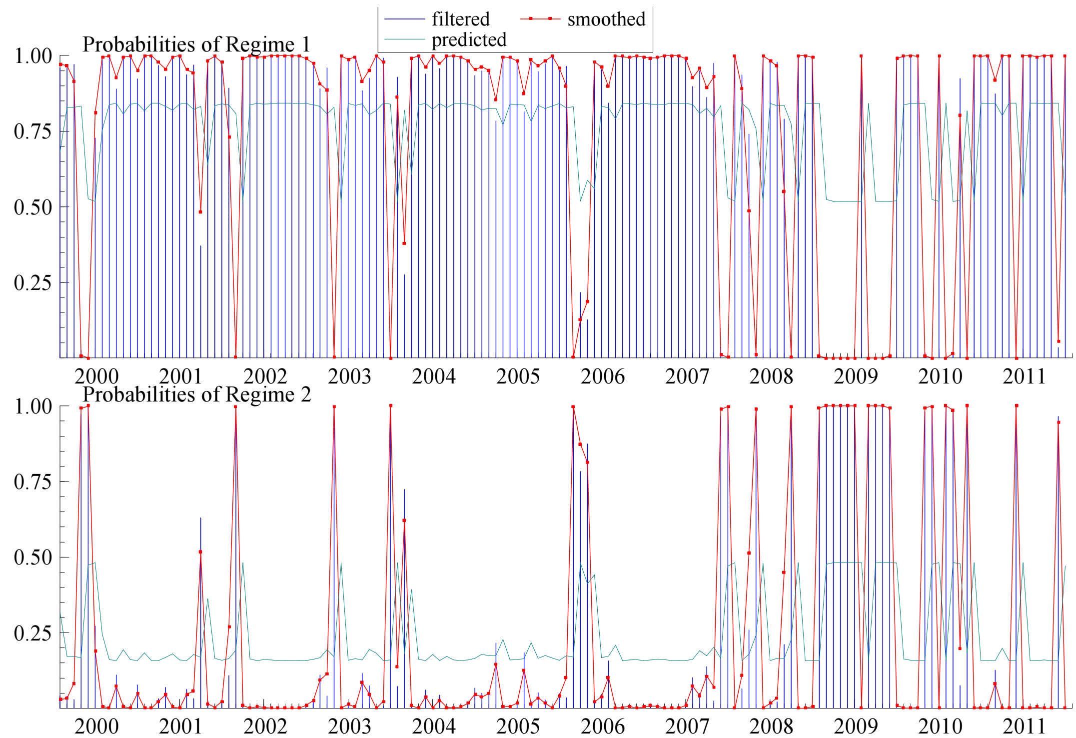
Figure 1A Daily



Notes: The time period is from 1/02/2004 to 7/01/2011.

Smoothed Regime Probabilities

Figure 1.1B Monthly

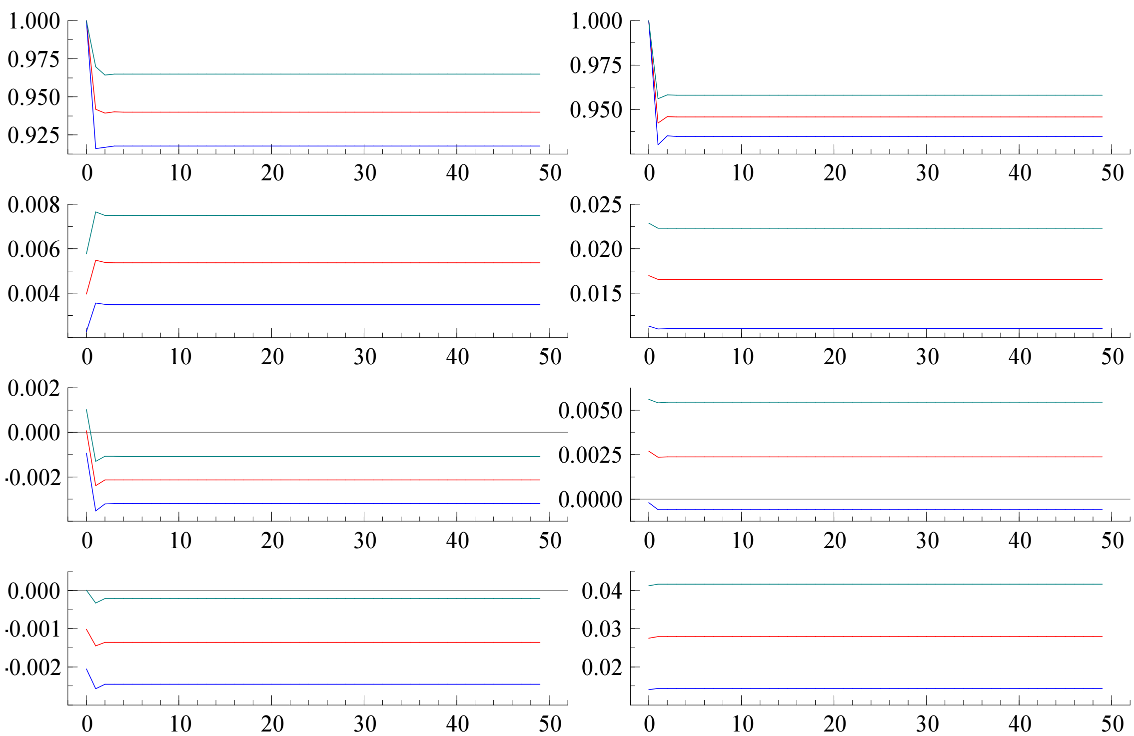


Notes: the time period ranges from 1999M07 to 2011M07. The predicted, filtered and smoothed probabilities are defined as the time paths of the conditional regime probability $\widehat{\xi_t}$. For a specified observation set $Y_\tau, \tau < T$, $\widehat{\xi_{t|\tau}}, \tau < t$ predicted regime probabilities; $\widehat{\xi_{t|\tau}}, \tau = t$ filtered regime probabilities; $\widehat{\xi_{t|\tau}}, t < \tau \leq T$ smoothed regime probabilities

Figure 1.2 Daily Impulse Response Function

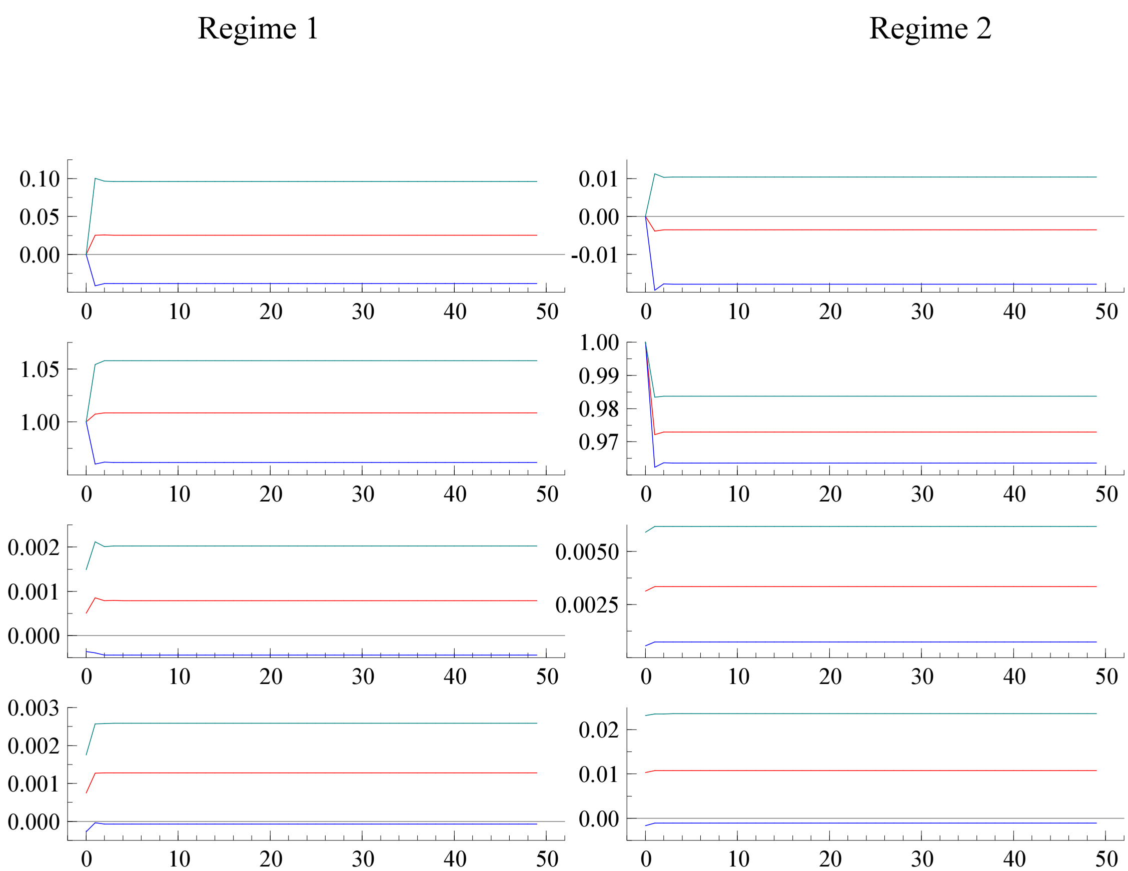
Responses to one unit shock of *VIX*:

Daily: Regime 1 Regime 2



Notes: The first column is the responses in regime 1. The second column is the responses in regime 2. The order of variables is *VIX*, *MOVE*, *OIL* and T*ED*.

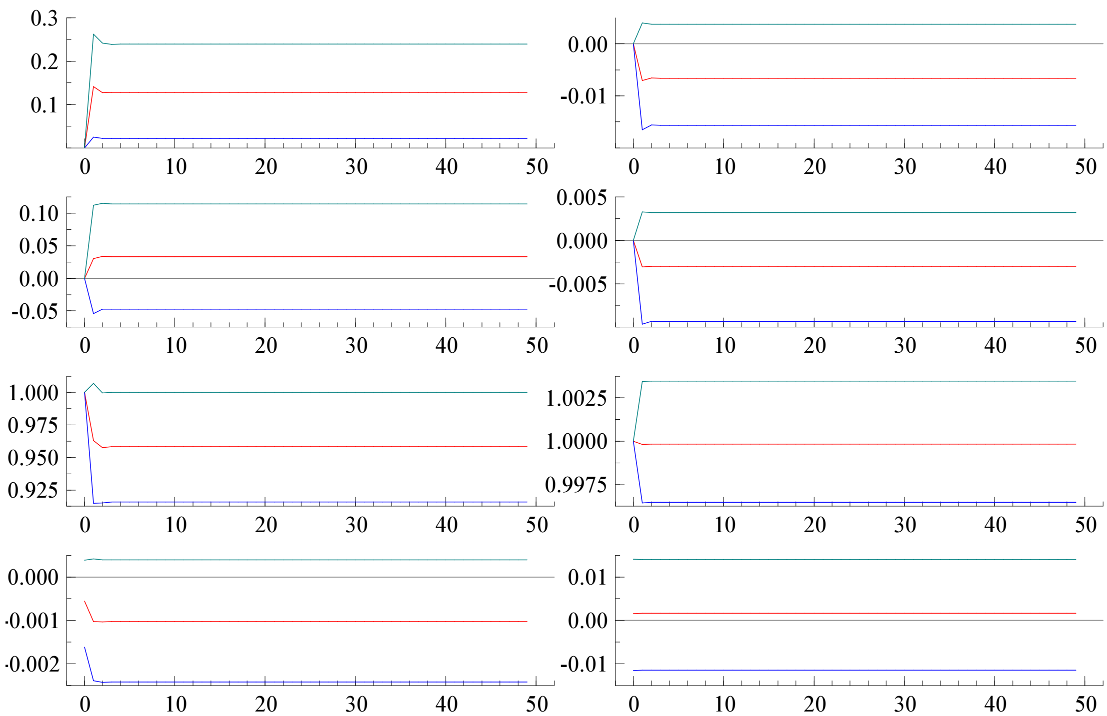
Responses to one unit shock of MOVE:



Notes: The first column is the responses in regime 1. The second column is the responses in regime 2. The order of variables is *VIX*, *MOVE*, *OIL* and *TED*.

Responses to one unit shock of OIL:

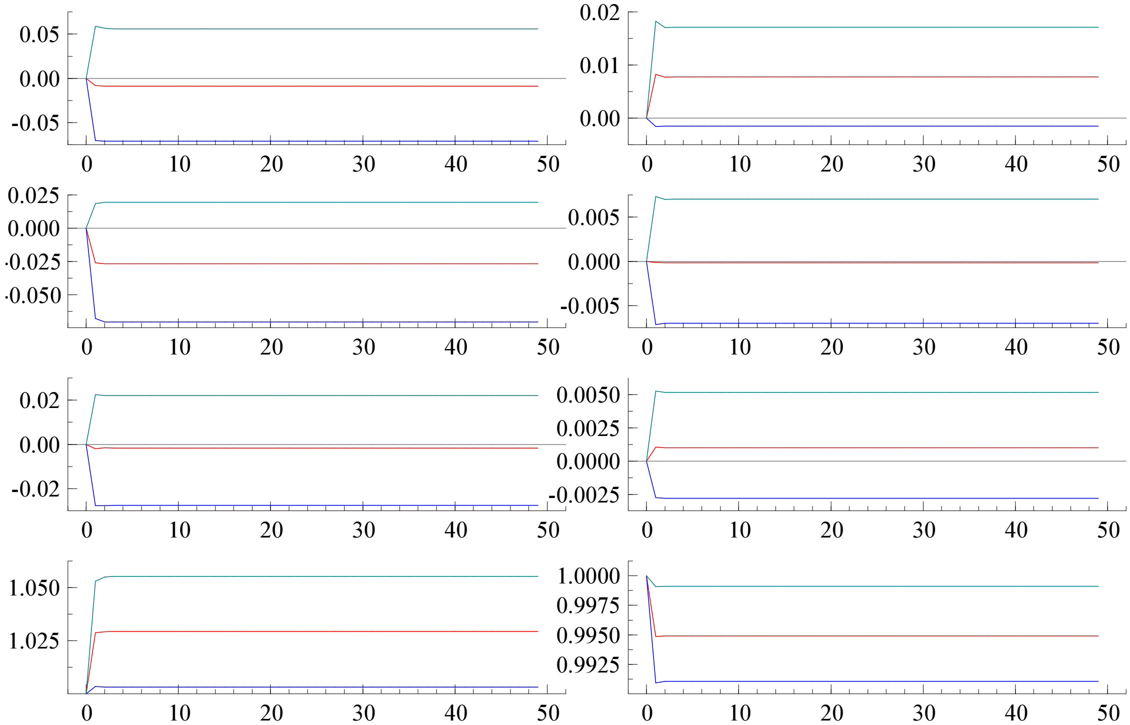
Regime 1 Regime 2



Notes: The first column is the responses in regime 1. The second column is the responses in regime 2. The order of variables is *VIX*, *MOVE*, *OIL* and *TED*.

Responses to one unit shock of *TED*:

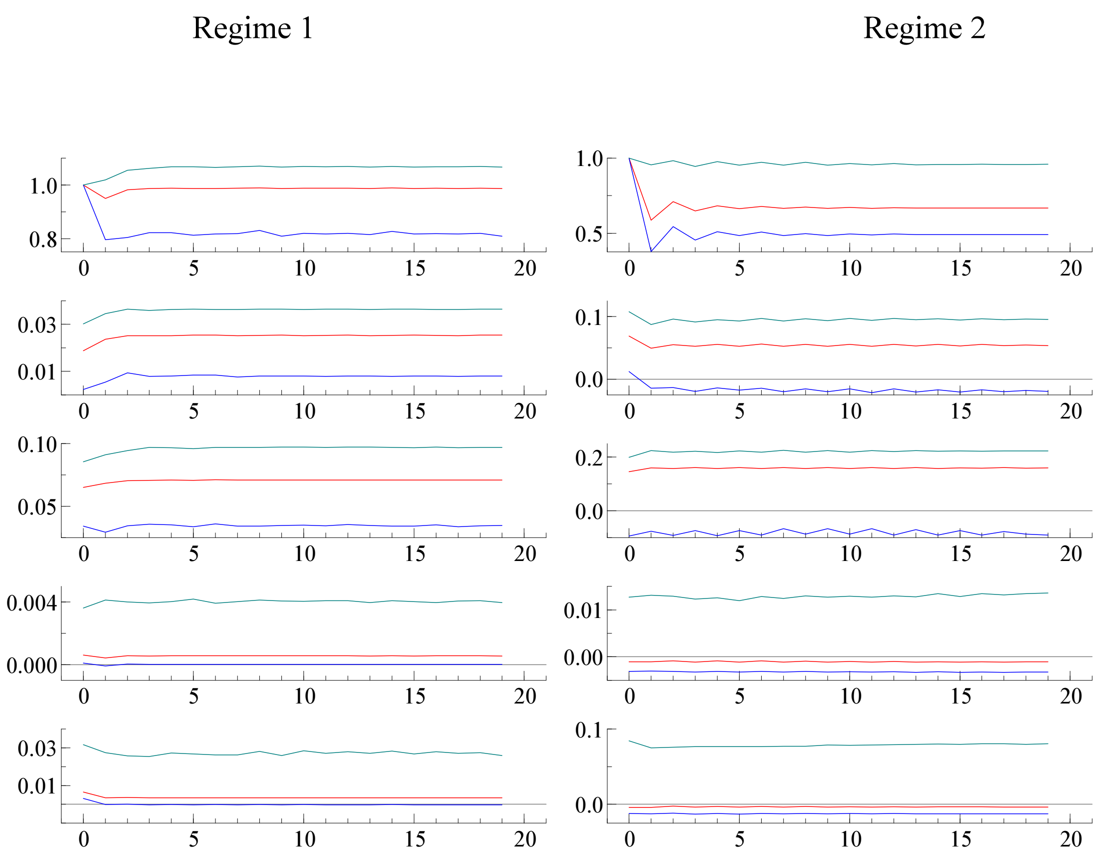
Regime 1 Regime 2



Notes: The first column is the responses in regime 1. The second column is the responses in regime 2. The order of variables is *VIX*, *MOVE*, *OIL* and *TED*.

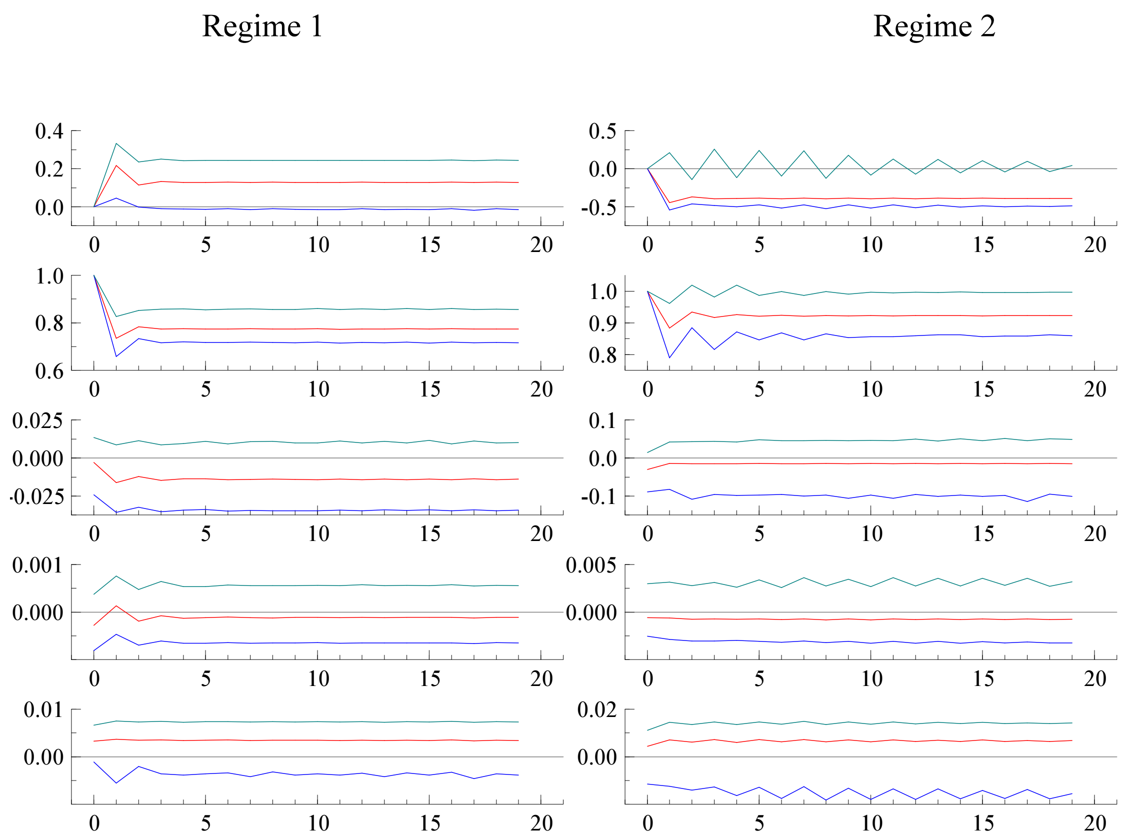
Figure 1.3 Monthly Impulse Response Function

Responses to one unit shock of *VIX*:



Notes: The first column is the responses in regime 1. The second column is the responses in regime 2. The order of variables is *VIX*, *MOVE*, *DFR*, *IP* and *OIL*.

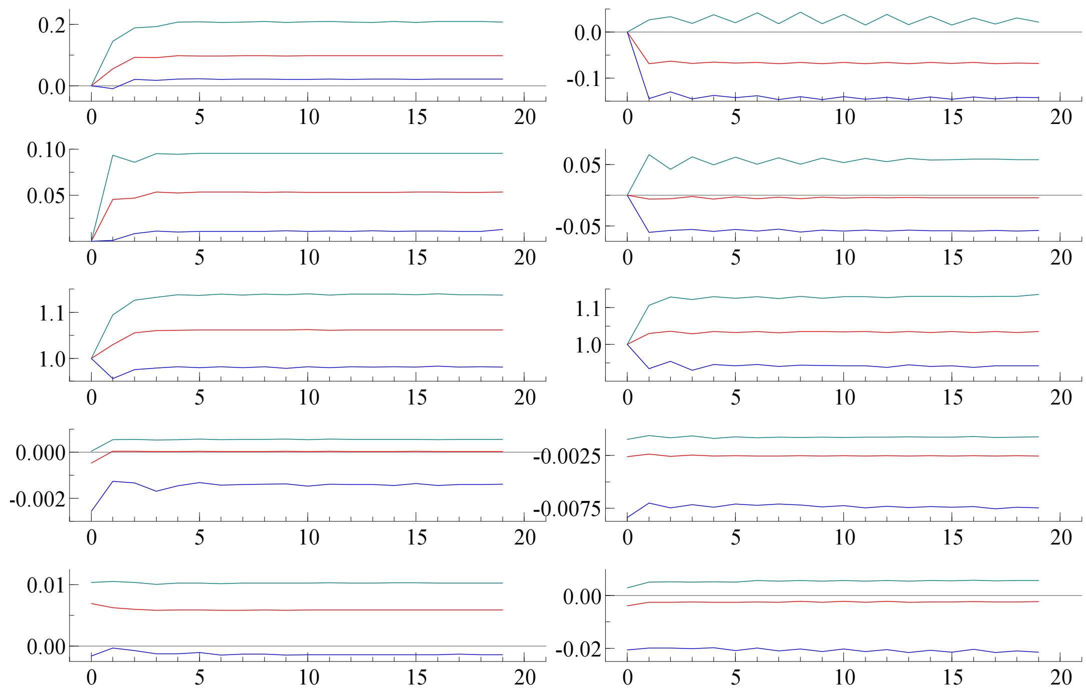
Responses to one unit shock of *MOVE*:



Notes: The first column is the responses in regime 1. The second column is the responses in regime 2. The order of variables is *VIX*, *MOVE*, *DFR*, *IP* and *OIL*.

Responses to one unit shock of *DFR*:

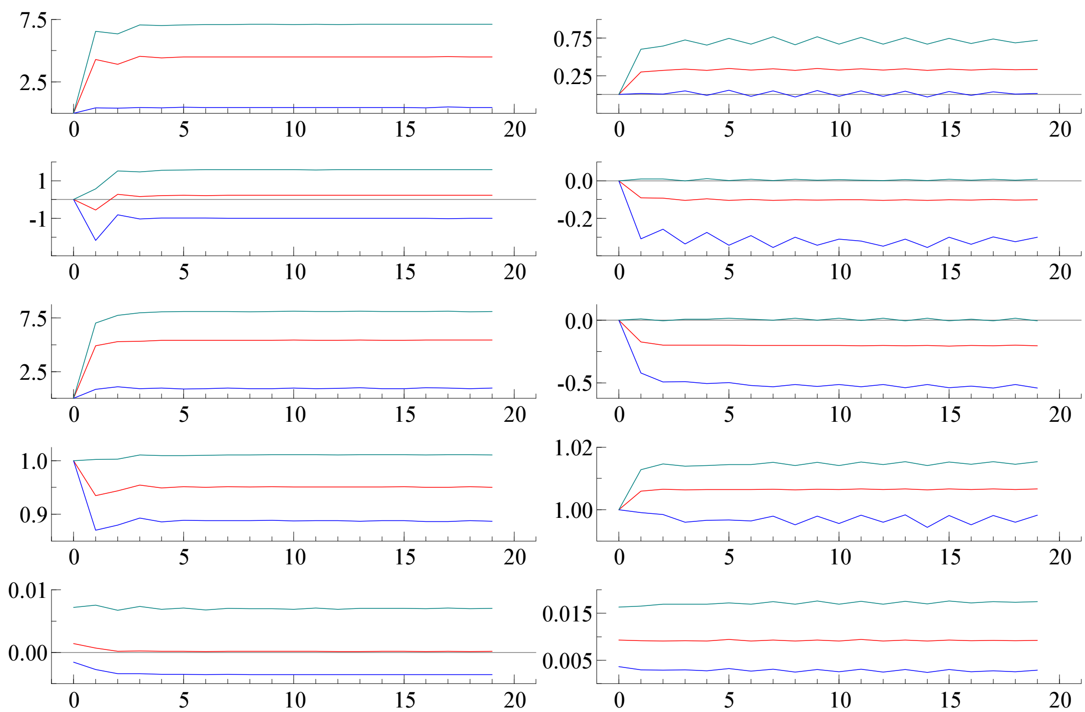
Regime 1 Regime 2



Notes: The first column is the responses in regime 1. The second column is the responses in regime 2. The order of variables is *VIX*, *MOVE*, *DFR*, *IP* and *OIL*.

Responses to one unit shock of *IP*:

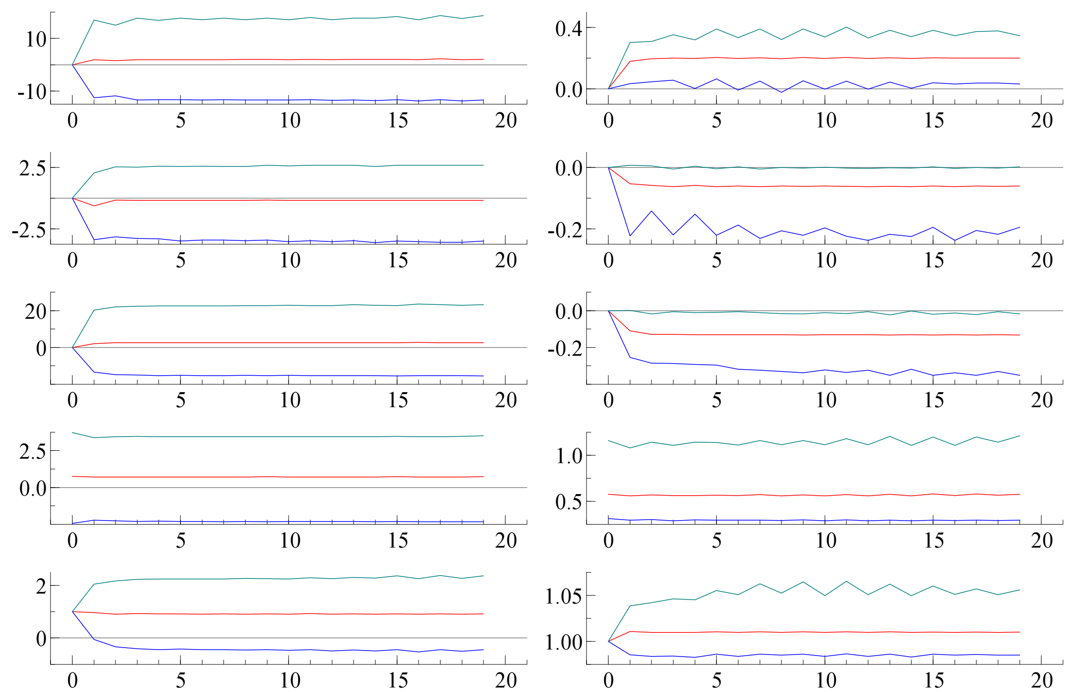
Regime 1 Regime 2



Notes: The first column is the responses in regime 1. The second column is the responses in regime 2. The order of variables is *VIX*, *MOVE*, *DFR*, *IP* and *OIL*.

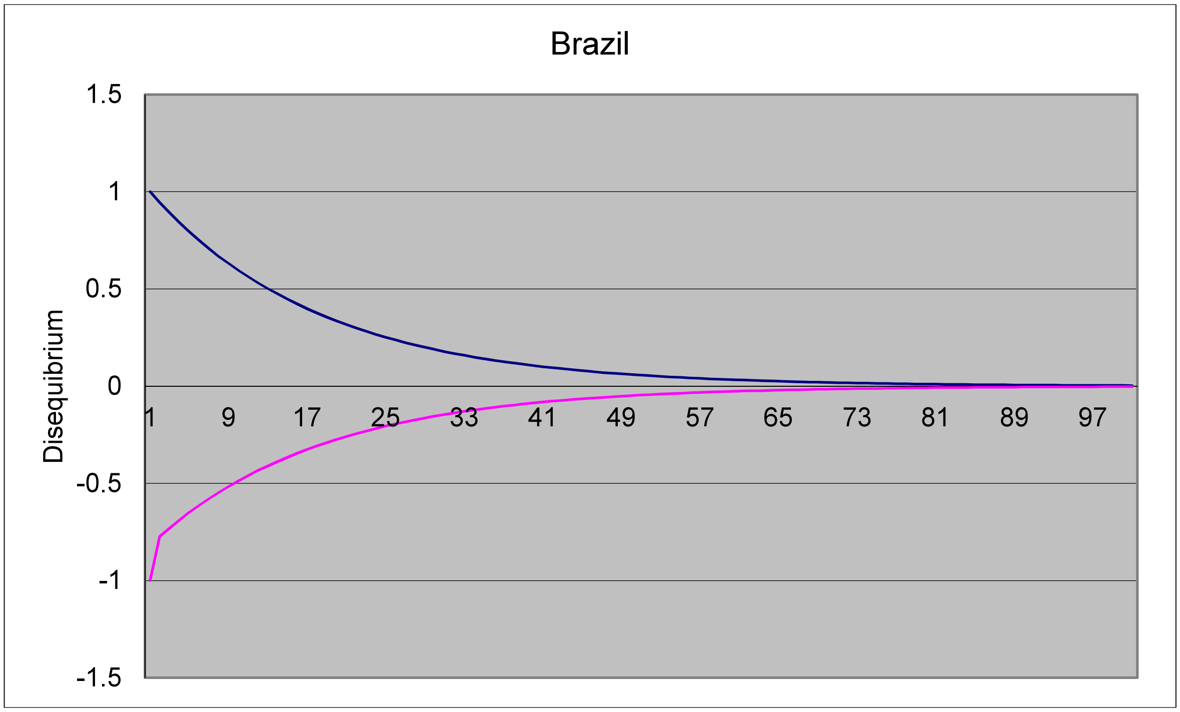
Responses to one unit shock of *OIL*:

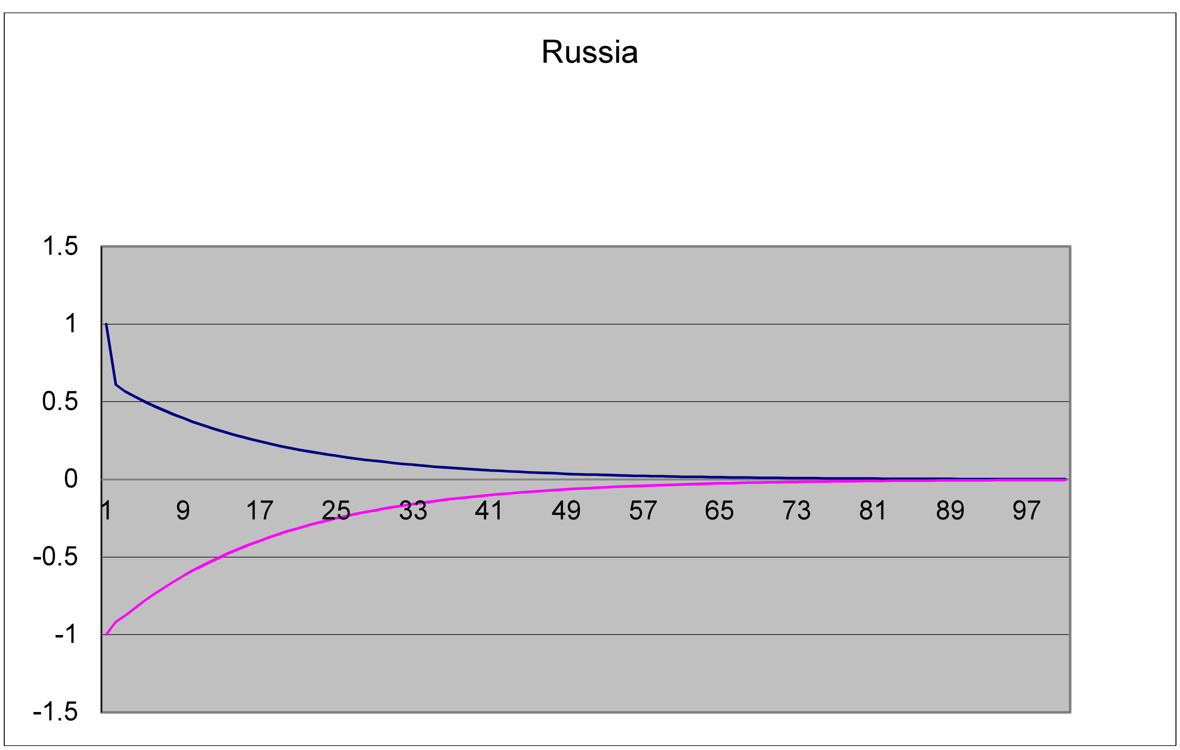
Regime 1 Regime 2

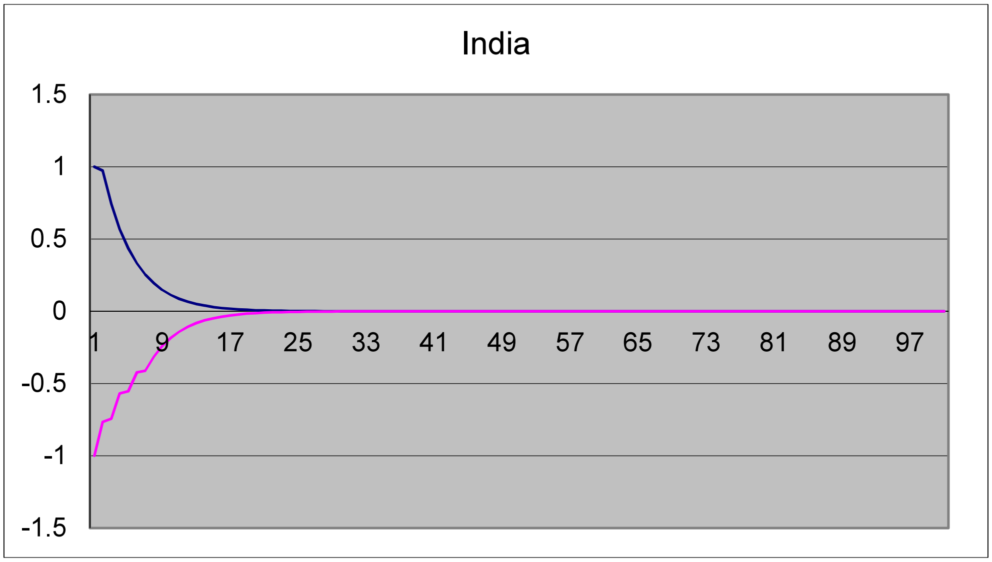


Notes: The first column is the responses in regime 1. The second column is the responses in regime 2. The order of variables is *VIX*, *MOVE*, *DFR*, *IP* and *OIL*.

Figure 2.1: Asymmetric Adjustment Path



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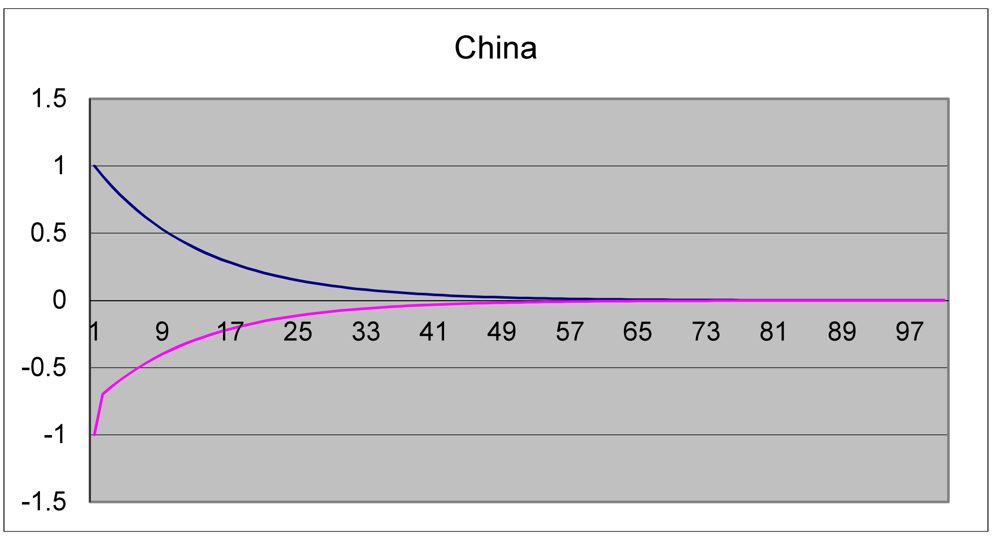
97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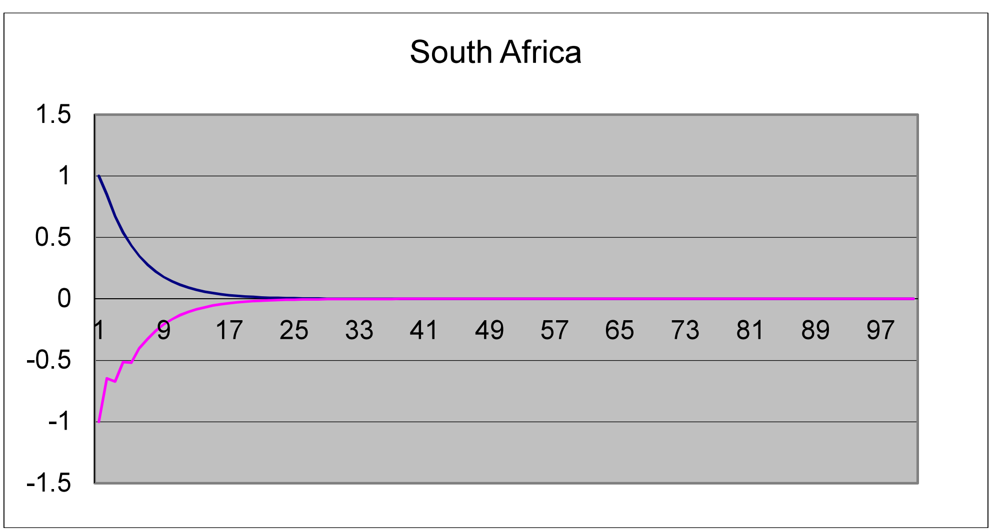
81
89
97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