THREE ESSAYS ON MARKET ANOMALIES

AND EFFICIENT MARKET HYPOTHESIS

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ABSTRACT

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This dissertation consists of three distinct essays. The first essay investigates the risk interpretation of the investment premium by empirically examining the fundamental view versus the sentimental view. Overall, the results show that financial factors are the dominant driver of investment returns and they control the negative relation between investment and stock return.

In the second essay, I examine the impact of financial contagion resulting from four global financial crises based on analyses of the global value premium. Results show that equity markets become more integrated after financial crises that exhibit global effects but less integrated after crises that exhibit regional effects. Overall findings support the risk story of the global value premium.

The third essay examines the joint dynamics of volume and volatility in the junk bond market during the 2007-2008 financial crisis. Using trading volume information as a proxy for changes in the information set available to investors when financial crises occur, I investigate the impact of the subprime crisis on the informational efficiency of the junk bond market. The overall results show that the crisis does not have an impact on the market efficiency of the junk bond market.

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CHAPTER 1

INTRODUCTION

For many decades, there has been a battle between mainstream finance and behavioral finance, and the Efficient Market Hypothesis (EMH) is considered the main weapon in this battle. Fama (1970) defined efficiency in terms of the speed and completeness with which capital markets incorporate relevant information into security prices. This means that there are two main implications of the EMH: (1) security prices are rational in the sense that they reflect risk rather than sentiment, and (2) no one can systematically beat the market (Statman, 1999).

Based on these two implications, researchers have formulated two main groups of tests of the efficiency of financial markets. The first group of tests is based on testing the asset pricing models Fama(1991) states that *"market efficiency per se is not testable"*. This means that the EMH must be tested jointly with an asset pricing model such as the Capital Asset Pricing Model (CAPM). The EMH and CAPM are connected in the sense that the former implies the rationality of the prices of capital assets since capital markets allocate resources efficiently, and the latter describes the pricing mechanism of these capital assets. Therefore, the CAPM provides a mean for testing the EMH and at the same time serves to show that markets are efficient since the central prediction of CAPM is that market beta is sufficient to describe the cross sectional expected returns.

However, many empirical studies agree on the fact that there are other effects or anomalies that can describe expected returns. The list of these anomalies is large but I will mention only two of them – 'investment effect' and 'value effect'. Chen and Zhang (2010), for example, find that low-investment stocks earn higher expected returns than high-investment stock. In addition, Fama and French (1992) find security returns to be positively related to book-to-market. The problem with these anomalies is that they cannot be explained by the single-factor CAPM, and they are also inconsistent with the idea of the EMH since security prices did not appear to reflect all available information. In general, there are two common explanations for these effects – risk (rational) explanation and behavioral (irrational) explanation. According to the risk explanation, the capital asset prices are rational that reflect only utilitarian characteristics, such as risk. Therefore, the rational explanation interprets the effects as a risk premium for a state-variable risk. Alternatively, the behavioral explanation views the effects as anomalies rather than risk factors, since asset prices are irrational in the sense that they reflect value-expressive characteristics, such as sentiment. Like most hypotheses in finance and economics, the evidence on these two explanations is mixed.

The second group of the empirical tests of the EMH is the autocorrelation test of independence that measures the significance of any correlation in return overtime. In its weak form, the EMH says that security prices adjust rapidly to the arrival of new information and, therefore, the current price of security fully reflects all historical information. Those who believe that capital markets are efficient would not expect to profit by trading on the information contained in the security's return or trading history. One would expect insignificant correlations in return overtime if market is efficient.

The above two groups of tests of the EMH motivates my research interests in this dissertation. I raise three main research questions in three distinct essays that will contribute to the understanding of market anomalies and the efficiency of financial markets. The first essay "What Explains the Investment Puzzle: Fundamental Beta or Financial Beta?" examines the risk explanation versus the behavioral story of the investment effect. In particular, I empirically test two hypotheses. The first hypothesis tests the determinants of investment return, using Vector Auto Regression (VAR) model and impulse response (IRF) function. The findings show that the firm-level investment returns is attributed mainly to the variability in discount rate news. The second hypothesis examines the determinants of the negative relation between stock return and investment return using the beta decomposition approach. The results show that the value of the financial betas is greater than the value of fundamental betas for decile portfolios based on one-dimensional (two-dimensional) classification by investment return (size and investment return). Overall, the results show that financial factors are main driver of investment returns, and they are also the dominant driver of the negative relation between investment return and stock return.

In the second essay “Financial Crises and the Global Value Premium: Revisiting Fama-French”, I investigate the rational versus irrational explanation of the global value premium documented by Fama and French (1998), using international data from thirteen countries during four selected financial crises. The main idea of this essay is that if global value stocks are fundamentally riskier than global growth stocks, one would expect value stocks to perform more poorly than growth stocks during financial crises. This is because risk-averse investors rush to get rid of high-risk securities and replace them with low-risk liquid securities during the bad states of the economy. To this end, I propose a new international asset pricing model that is a composite of the asymmetric Sign GARCH model developed by Glosten, Jagannathan and Runkle (1993) (GJR-GARCH model) and the international version of the Fama and French model (1998). The results show that value stocks consistently perform more poorly than growth stocks during the four financial crises. These findings support the risk story for a global value premium.

The third essay “The Subprime Crisis and the Efficiency of the Junk Bond Market: Evidence from the Microstructure Theory” investigates the impact of the recent financial crisis on the Junk bond market, along three dimensions: First, I examine the impact of the subprime crisis on the high yield bond return volatility using GJR-GARCH model. Second, I investigate the trading volume impact of the crisis using censored regression model. Finally, I explore the impact of the financial crisis on the junk bond Market Efficiency using the volume-volatility relation. The overall results of VAR and 2SLS estimates show that the financial crisis does not have an impact on the efficiency of the junk bond market.

This dissertation consists of five chapters with one chapter per essay. Chapter two and three cover the first and the second essay, respectively. Both essays focus on the first group of the EMH tests (i.e., the risk interpretation of anomalies). Chapter four presents the third essay, which examines the second group of tests (i.e., independence tests). In each chapter, I review the relevant literature, identify the contributions of my study, cover the data and methods used, and then I present the results. Finally, I conclude my dissertation in chapter five.

CHAPTER 2

WHAT EXPLAINS INVESTMENT PUZZLE: FUNDAMENTAL BETA OR FINANCIAL BETA?

2.1 Introduction

Why do low-investment stocks earn higher expected returns than high-investment stocks? This appears to be a critical but difficult question that attracted the attention of scholars and investment professionals for many decades. The production-based models and the real option theory imply two explanations for such investment puzzle (i.e., negative relation between real investment and expected returns) – a fundamental story and a behavioral story. The fundamental story (or the cash flow channel) interprets the investment premium as a common risk factor of stock returns such that high-investment firms and low-investment firms are exposed to different cash flow risks. Controlling for discount rates, the higher the current investment, the lower the marginal productivity of capital under diminishing returns to scale, the lower the expected returns as firms exploit investment opportunities. Alternatively, the behavioral view (or the discount rate channel) reinterprets the high returns of low-investment firms as one of the stock return anomalies that are due to error by some investors. Specifically, changes in the investor sentiment affect the investment policy through changes in discount rates that investors apply to cash flows. Controlling for expected cash flows, the lower the discount rate, the higher the current investment, the lower the future returns.

Though the cash flow and discount rate channels may successfully describe variation in securities' expected return by their covariance with investment's return, but they never explain such variation. This leaves an open question: What real risks cause variations in investment returns that cause expected stock returns to vary? The literature based on the Q-theory of investment developed by Tobin (1969) emphasizes two determinants of the cyclical variability of investment – investment and financial variables. The investment return, therefore, may increase either because there is good news about future cash flows (investment channel), or because there is a decline in the cost of capital that investors apply to these cash flows (financial channel).

The two channels (i.e., fundamental and financial) that determine investment returns, as well as the two explanations of the investment puzzle (i.e., fundamental and behavioral), motivate my research interest. Specifically, my goal in this study is to test two hypotheses empirically. First, I empirically examine the determinants of the variability of investment returns. I use the vector autoregression (VAR) approach to break firm-level investment returns into fundamental (i.e., marginal productivity of capital 'MPK') and financial (i.e., cost of capital) components. Second, I examine the fundamental versus the behavioral story of the 'investment puzzle', by breaking the sensitivity of stock returns to the investment returns (i.e., investment beta) into two betas – fundamental (or cash flow) beta and financial (or discount rate) beta. The main idea of this study can be summarized in figure 2.1.

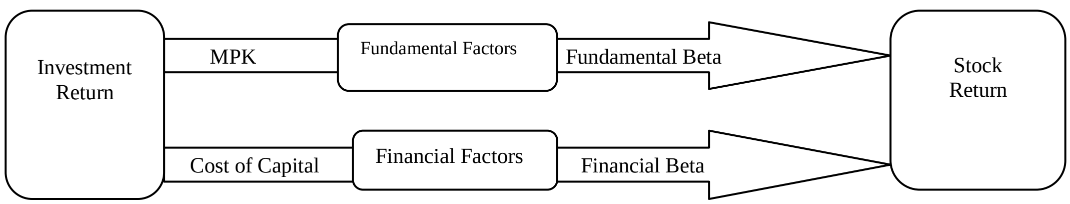

Figure 2.1 Investment Return – Stock Return Relation: Fundamental and Financial Factors

I believe this study contributes to the existing theoretical and empirical investment literature in two ways. First, my theoretical work in section three bridges a gap between the Tobin's q-theory of real investment and production based models to provide a model that can explain the real risks that determine the 'investment puzzle'. Specifically, I show theoretically that both the investment and financial channels that determine the optimal investment level from the Q-theory of investment literature are the same real risk factors that govern the negative relation between real investment and expected returns inspired by the production-based models and the real option theory. Second, to the best of my knowledge, this study is the first one that empirically investigates the determinants of the investment-return relation, by running a horse race between the cash flow and discount rate channel without the need to control one while examining the other. Thanks to the beta decomposition approach (e.g., Campbell and Vuolteenaho, 2004), I am able in section four to isolate the sensitivity of the stocks' expected return to the investment component (fundamental beta) from the financial component (financial beta) of investment returns[1].

The organization of the rest of this chapter is as follows: Section two presents study hypotheses and literature review. Section three develops a theoretical model. Section four presents the econometric methodology. Section five describes the data. Section six shows the empirical results.

2.2 Testable Hypotheses

My work is related to two strands of literature. The first one is based on the present value version of the Q-theory of investment that focuses on examining the determinants of the optimal investment level by separating the response of investment to shocks from fundamental factors than those from financial factors (e.g., Abel and Blanchard, 1986; Gilchrist and Himmelberg, 1995; and Love and Zicchino, 2006). The second strand includes the production-based models and the real option theory that predict two channels (i.e., cash flow and discount rate channels) that govern the investment-return relation (e.g., Li, Livdan, and Zhang 2009). In this study, I test two hypotheses inspired by these two strands of literature.

2.2.1 Hypothesis 1

The first hypothesis is that investment return is positively related to the marginal productivity of capital and negatively related to the discount rate. This hypothesis follows from the early literature on the determinants of the variability of manufacturing investment. Early research led by Franco Modigliani and Merton Miller (M&M) capital structure irrelevance proposition, emphasized that the financial structure of any firm will not affect its market value in perfect capital markets. This proposition provides the theoretical foundation for the neoclassical theory of investment that implies that firm's financial structure is irrelevant to investment decisions (i.e., classical dichotomy) since internal and external funds are

[1] The reason for such gap in literature is that valuation equation is used to be the workhorse for explaining the investment-return relation (i.e., investment is high when future marginal cash flow (numerator) is high or when the discount rate (denominator) is low). Fama and French (2006) show that tests based solely on the valuation equation cannot split between the cash flow effects and the discount rate effects.

perfect substitutes. This means that fundamental factors, measured by the expected present value of future profits, are the only determinants of the investment decisions.

The neoclassical theory of investment, however, does not provide a complete description of the determinants of the investment level, since M&M's perfect capital assumption is not satisfied in real life. There are many factors that make external finance more costly than internal finance such as agency costs, financial distress costs and transaction costs (Fazzari et al., 1988). With these frictions, classical dichotomy no longer holds and 'financial factors' can affect firm-level investment through the capital adjustment cost: the higher the investment costs, the lower the elasticity of the firm's investment with respect to changes in discount rate. These frictions are usually viewed as an evidence of financing constraints (e.g., Love and Zicchino, 2006).

An alternative approach to examining the investment determinants is the Q-theory of investment originated in Tobin and Brainard (1963) and Tobin (1969). According to the Tobin's q-theory, the firm's investment return (defined as the marginal rate at which a firm can transfer resources through time by increasing investment today and decreasing at a future date) should rise with its Q (defined as the ratio of market value of new additional investment goods to their replacement cost of capital). The present value version of the theory states that the marginal cost of investment equals the marginal benefits of investment defined as the present value of the expected future profit (e.g., Abel and Blanchard, 1986; and Shapiro, 1986). A more recent literature introduces financing constraints as a proxy for investment frictions into the Q-theory (e.g., Li and Zhang, 2010). Unlike the neoclassical theory of investment, therefore, the q-theory emphasizes the importance of financial factors (such as debt leverage, and dividend payments) and the investment factors as two determinants of investment.

2.2.2 Hypothesis 2

The second hypothesis in this study is that capital investment is negatively correlated with future equity returns through two channels – fundamental and financial channels. This hypothesis stems from two related strands of literature that explain the negative relation between current investment return and future stock return –production-based models and real option models – through cash flow channel and discount rate channel. The production-based models link market performance to aggregate investment, while the real option models link stock return to firm-specific investment.

Much of the work on the production-based models is built upon the q-theory, and Cochrane (1991) is the first one who reinterprets the q-theory of investment as a production-based model to show that investment return and stock return are equal. According to the q-theory, the discount rate channel controls for expected cash flows, and predicts that the lower the discount rate, the higher the current investment, the lower the future returns (e.g., Cochrane (1996); Li, Vassalou, and Xing (2006); and Liu, Whited, and Zhang (2009)). Alternatively, the cash flow channel says that, controlling for the discount rates, the higher the future marginal productivity, the higher the current investment, the lower the marginal productivity of capital under diminishing returns to scale, the lower the expected returns as the firms exploit investment opportunities (e.g., Li, Livdan, and Zhang (2009)).

More recently, the real option models have been developed which focus on the link between the firm-specific investment patterns and the cross section of stock returns. These models view the firm value as a sum of the value of the existing assets (measured by summing the present value of future cash flows from all ongoing projects) and the value of the growth options (measured by the present value of all future positive NPV projects). In the real option models, the cash flow channel holds project revenue risks constant and focuses on the numerator of the present value formula through decomposing the cash flow among revenues from the existing assets and growth options (e.g., Berk, Green and Naik (1999) and Gomes, Kogen, and Zhang (2003)). In contrast, the discount rate channel holds expected cash flow constant and focuses on the denominator of the valuation equation through examining the cross-sectional dispersion in new project betas (e.g., Carlson, Fisher and Giammarino (2004)).

An intuitive way to summarize this section is to say that hypothesis 2 complements hypothesis 1. In particular, hypothesis 1 explains variation in investment returns through two channels – cash flow and discount rate channel, and hypothesis 2 states that these two channels are responsible for describing variation in stock expected return by its covariance with investment return.

2.3 The Theoretical Model

In this section, I develop a model that serves as a mathematical formulation for the hypotheses developed in the previous section. In my model, I assume that there are heterogeneous firms in the economy indexed by 'i'. Each firm uses capital stock (K_{it}) and other costless inputs to produce homogenous output. The major production constraint facing the firm is capital accumulation, since the level of capital stock next period (K_{it+1}) depends on three factors: the current capital stock (K_{it}), investment level (I_{it}), and depreciation rate of existing capital (δ). The capital accumulation, therefore, can be represented mathematically as follows: $K_{it+1} = K_{it}(1-\delta) + I_{it}$. The firm's production function is Cobb-Douglas given by $f(K_{it}) = K_{it}^{\alpha}$ where $'\alpha'$ is the capital share. The production function exhibits diminishing returns to scale $(i.e., 0 < \alpha < 1)$, which means that more investments lead to lower marginal product of capital. Production is subject to aggregate productivity shocks (X_t) that serve as a source of systematic risk as well as firm-specific productivity shocks (Z_{it}) that act as a source of firm heterogeneity. Let $\pi(K_{it}, X_t, Z_{it})$ denote the firm's operating profits that is function of capital (k_{it}), aggregate shocks (X_t), and firm-specific shocks (Z_{it}), as follows:

$$\pi(K_{it}, X_t, Z_{it}) = e^{X_t + Z_{i,t}} f(K_{it}) = e^{X_t + Z_{it}} K_{it}^{\alpha} \qquad (1)$$

Firms' opportunity cost is reflected in the adjustment cost $\phi(I_{it}, K_{it})$ that represents the firms' foregone operating profit since they have to reduce sales to increase investment. Following the literature (e.g., Li, Livdan and Zhang, 2009; and Liu, Whited and Zhang, 2009), I assume that the adjustment cost function is quadratic in capital growth (I_{it}/K_{it}), as follows:

$$\phi(I_{it}, K_{it}) = \frac{\gamma}{2}\left(\frac{I_{it}}{K_{it}}\right)^2 K_{it} \qquad (2)$$

If the total cost of investment $(I_{it} + \phi(I_{it}, K_{it}))$ exceeds the existing capital level, firms will resort to issue stocks assuming that new equity is the only source of external financing. The firm's cash flow (FCF_{it}), therefore, equals the operating profits minus the total cost of investment:

$$FCF_{it} = \pi(K_{it}, X_t, Z_{it}) - I_{it} - \phi(I_{it}, K_{it}) \quad (3)$$

Since my focus is on investment, I assume that firms take operating profits as given and they choose the optimal capital investment to maximize its market value of equity (V_{it}) given by the discounted value of future free cash flows, subject to the capital accumulation condition. Based on the above framework, the firm's optimization problem can be stated as follows:

$$\left\{ \begin{array}{l} V_{it} = \max\limits_{(I_{it}, K_{it})} E\left[\sum\limits_{t=1}^{\infty} \beta_{t+1} (\pi(K_{it}, X_t, Z_{it}) - I_{it} - \phi(I_{it}, K_{it})) \right] \\ Subject \quad to: \quad K_{it+1} = K_{it}(1-\delta) + I_{it} \end{array} \right\} \qquad (4)$$

In this section, I will use the optimization problem as approximated by equation 4 to provide mathematical justification for my two testable hypotheses in this study. First, I solve equation 4 to decompose the real factors that cause variations in investment return into two channels - fundamental channel (marginal productivity of future capital) and financial channel (cost of capital). Second, I use these two channels to explain variations in equity return in response to variations in investment returns, as production-based models and real option models predict.

2.3.1 Mathematical Formulation of Hypothesis 1: Theoretical Determinants of Investment Return

By setting the Lagrangian multiplier for the firm's optimization problem (equation 4) and taking the first-order condition with respect to (K_{it+1}), I get 'q_{it}' (or what is called marginal q) that reflects the shadow price of capital, as follows:

$$q_{it} = \sum_{t=0}^{\infty} \beta_{t+1} \left[\frac{\partial \pi(K_{it+1}, X_{t+1}, Z_{it+1})}{\partial K_{it+1}} - \frac{\partial \phi(I_{it+1}, K_{it+1})}{\partial K_{it+1}} + (1-\delta) q_{it+1} \right] \qquad (5)$$

Equation 5 shows the relation between investment and the expected present value of marginal profits, as the Q-theory predicts (e.g., Abel and Blanchard, 1986, and Gilchrist and Himmelberg, 1995). The marginal product of capital is given by $\left(\partial \pi(K_{it+1}, X_{t+1}, Z_{it+1}) / \partial K_{it+1} = \alpha K_{it+1}^{\alpha-1}\right)$, the marginal reduction in adjustment costs generated by an extra unit of capital is given by $\left(\partial \phi(I_{t+1}, K_{it+1}) / \partial K_{it+1} = (\gamma/2 [I_{t+1}/K_{it+1}]^2)\right)$, and the marginal liquidation value of capital net of depreciation is given by $\left((1-\delta)q_{it+1}\right)$. For clarity, I define $L(K)=\left[\left(\alpha K_{it+1}^{\alpha-1}\right)+\gamma/2\left(I_{it+1}/K_{it+1}\right)^2\right]$, so that I can rewrite equation 5, as follows:

$$q_{it}=\sum_{t=0}^{\infty}\beta_{t+1}\left[\alpha K_{it+1}^{\alpha-1}+\frac{\gamma}{2}\left(\frac{I_{it+1}}{K_{it+1}}\right)^2+(1-\delta)q_{it+1}\right]=\sum_{t=0}^{\infty}\beta_{t+1}\left[L(K)+(1-\delta)q_{it+1}\right] \quad (6)$$

The optimality condition states that the shadow price of capital is equal to the discounted infinite stream of marginal products of depreciating capital at all future dates. In other words, equation 6 breaks the determinants of the cyclical variability of investment down into two components: discount rate risk (variations in the cost of capital $\left(\beta_{t+1}\right)$), and cash flow risk (variations in the marginal productivity of capital).

In spite of the attractiveness of the q-theory, its empirical performance has not been satisfactory due to the difficulty in computing marginal q, since it requires computing the expectation of a present value of a stream of marginal profits as in equation 6. Therefore, I re-express the q-theory as a relation between returns, as in Cochrane (1991), instead of modeling it as a fundamental present value relation. By setting the first order derivative of the objective function in the firm's optimization problem in equation 4 with respect to $\left(I_{it+1}\right)$, I get:

$$q_{it}=1+\frac{\partial\phi\left(I_{it},K_{it}\right)}{\partial I_{it}}=1+\gamma\left(\frac{I_{it}}{K_{it}}\right) \quad (7)$$

The first-order condition says that a firm should invest up to the point where the expected present value of marginal benefits of investment 'q_{it}' should equal its marginal cost of investment $\left(1+\gamma\left(I_{it}/K_{it}\right)\right)$. Equivalently, investment returns $\left(R_{i,t+1}^{Investment}\right)$ can be defined as a ratio of the marginal benefit of investment (equation 6) to the marginal cost of investment (equation 7):

$$R_{i,t+1}^{Investment}=\frac{\text{Marginal Benefits of Investment}}{\text{Marginal Costs of Investment}}\equiv\frac{\alpha K_{it+1}^{\alpha-1}+\gamma/2\left(I_{it+1}/K_{it+1}\right)^2+(1-\delta)q_{it+1}}{1+\gamma\left(I_{it}/K_{it}\right)}\equiv\frac{L(K)+(1-\delta)q_{it+1}}{1+\gamma\left(I_{it}/K_{it}\right)} \quad (8)$$

Equation 8 implies that there are two major channels affecting investment returns: fundamental factors (numerator) that work through the marginal productivity of capital, and financial factors (denominator) that work through the investment adjustment costs. Taken together, equations 6 and 8 are analogous to stock price and return equations, respectively. Specifically, equation 6 measures the shadow price of capital as the present value of marginal products of depreciating capital, and equation 8 measures investment returns as a ratio of marginal benefits to marginal cost of investment. If I substitute $1+\gamma\left(I_{it}/K_{it}\right)=q_{it}$ from equation 7, I can approximate a relation between investment price $\left(q_{it}\right)$ and investment return $\left(R_{i,t+1}^{Investment}\right)$ as follows:

$$R_{i,t+1}^{Investment} \equiv \left\{\frac{L(K)}{q_{it}}\right\}+\left\{\frac{(1-\delta)q_{it+1}}{q_{it}}\right\} \qquad (9)$$

Equation 9 expresses the investment return as a sum of two ratios: the first ratio is proportional to the marginal productivity of capital (analogous to the dividend yield), and the second ratio is function of the investment growth (analogous to the capital yield). The major problem in computing investment returns, as in equation 9, is the assumption that returns are time-varying. Such assumption makes it much more difficult to work with present value relations because the shadow price of capital $\left(q_{it}\right)$and marginal productivity of capital $\left(L(K)\right)$ appear to grow exponentially over time rather than linearly like many other macroeconomic time series. This means that price-return becomes nonlinear (Campbell, Lo and MacKinlay 1997).

Following Campbell and Shiller (1988)[2], I achieve linearity by estimating a log-linear present value relation between capital prices and marginal productivity of capital, through two steps. First, I take the logarithm of equation 9 and define $\left(r_{i,t+1}^{Investment}\right)$ as the log investment return:

$$\begin{aligned} r_{i,t+1}^{Investment} &\equiv \log\left((1-\delta)q_{it+1}+L(K)_{t+1}\right)-\log q_{it} \\ &\equiv \log\left((1-\delta)q_{it+1}-\log\left(q_{it}\right)+\log\left(1+e^{\left[\log L(K)_{t+1}-\log(1-\delta)q_{it+1}\right]}\right)\right. \end{aligned} \qquad (10)$$

[2] Campbell and Shiller (1988) develop a log-linear present value relation between prices and dividends, based on an accounting framework: high prices must be followed by high future dividends, or low future returns or some combination of both. Analogous to their intuition, the log-linear present value relation between marginal productivity of capital and capital prices can also provide an accounting framework. Specifically, equation (6) says that high capital prices must be followed by high expected future marginal productivity$\left(L(K)\right)$, or low future returns$\left(\beta\right)$, or some combination of both.

Second, I achieve linearity between $(q_{i,t+1})$ and $(L(K)_{t+1})$ by using a first-order Taylor expansion to approximate $(r_{i,t+1}^{Investment})$ around its mean. If I substitute the first-order Taylor approximation $\left(f(x_{t+1}) \approx f(\bar{x}) + f'(\bar{x})(x_{t+1} - \bar{x})\right)$ into equation 10, I get:

$$r_{i,t+1}^{Investment} \approx k + (1-\rho)\log L(K)_{t+1} + \rho \log(1-\delta) q_{it+1} - \log q_{it} \qquad (11)$$

Where k and ρ are linearization parameters defined by $k \equiv -\log(\rho) - (1-\rho)\log(1/\rho - 1)$, and $\rho \equiv 1/\left(1 + e^{[\log L(K) - \log q]}\right)$. The log investment return is defined now as a weighted average of the marginal productivity of capital and the liquidation value net of depreciation. If I assume that $\lim_{j\to\infty} \rho^j \left((1-\delta) q_{it+1+j}\right) = 0$ and solve for log 'q_{it}', I can write capital prices as linear combination of expected marginal product of capital and returns, as follows:

$$\log(q_{it}) \equiv \frac{k}{1-\rho} + E_t\left[\sum_{j=0}^{\infty} \rho^j \left((1-\rho)\left(L(K)_{t+1+j}\right) - r_{i,t+1+j}^{Investment}\right)\right] \qquad (12)$$

Similar to Campbell (1991), I use the log-linear present value approach to write the investment returns as linear combination of revisions in expected marginal productivity of capital and returns. If I substitute equation 12 into equation 11, I get:

$$r_{t+1}^{Investment} - E_t\left[r_{t+1}^{Investment}\right] = (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \left(\Delta L(K)_{t+1+j}\right) - (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{t+1+j}^{Investment}$$

$$= N_{CF,t+1}^{\text{Investment}} - N_{DR,t+1}^{\text{Investment}} \qquad (13)$$

The merit of equation 13 is that it provides a mathematical justification for hypothesis 1, since it allows me to decompose the unexpected investment return $\left[r_{t+1}^{Investment} - E_t\left(r_{t+1}^{Investment}\right)\right]$ into two components – cash flow investment news '$N_{CF,t+1}^{Investment}$' (the unpredictable component of returns, since marginal q is unobservable) and discount rate investment news '$N_{DR,t+1}^{Investment}$' (the predictable or the expected investment returns).

2.3.2. Mathematical Formulation of Hypothesis 2: Theoretical Determinants of Investment Return-Stock Return Relation

In order to provide a mathematical formulation for hypothesis 1, as in equation 13, I use present value relations to distinguish between cash flow and discount rate channels that explain variations in investment returns, while controlling for stock return process. Now, I want to explain the variation in stock returns while holding investment return constant, in order to formulate hypothesis 2 mathematically. Following Cochrane (1991), I set investment return $\left(R_{i,t+1}^{Investment}\right)$, estimated by equation 8, equal to the stock return $\left(R_{i,t+1}^{Stock}\right)$ as follows:

$$R_{i,t+1}^{Stock} = R_{i,t+1}^{Investment} \equiv \frac{\alpha K_{it+1}^{\alpha-1} + \gamma/2\left(I_{it+1}/K_{it+1}\right)^2 + (1-\delta)q_{it+1}}{1+\gamma\left(I_{it}/K_{it}\right)} \quad (14)$$

If I take the derivative of $\left(R_{i,t+1}^{Stock}\right)$ in equation 14 with respect to $\left(I_{it}\right)$, as in Li, Livdan, and Zhang (2009), I get:

$$\frac{\partial R_{i,t+1}^{Stock}}{\partial I_{it}} = \left\{\left[\frac{\alpha(\alpha-1)K_{it+1}^{\alpha-2}}{1+\gamma\left(I_{it}/K_{it}\right)}\right] - \left[\frac{\gamma\left(\alpha K_{it+1}^{\alpha-1}\right)}{\left(1+\gamma(I_{it}/K_{it})\right)^2 K_{it}}\right]\right\} < 0 \qquad (15)$$

Equation 15 is the mathematical counterpart of hypothesis 2, since it says that there are two channels that drive the negative relation between stock returns and investment returns: cash flow channel (the first term) that works through diminishing returns to scale (since the first term will equal zero if the production function exhibits constant returns to scale $(i.e., \alpha = 1)$, and discount rate channel (the second term) that works through the adjustment costs. The cash flow channel says that the higher the future marginal productivity, the higher the current investment, the lower the marginal productivity of capital under diminishing returns to scale, the lower the expected returns as firms exploit investment opportunities. The discount rate channel predicts that the lower the discount rate, the higher the current investment, the lower the future returns.

2.4 The Empirical Model

In this section, I set up the empirical tests of the two hypotheses discussed in section two and formulated mathematically in section three. First, I examine hypothesis 1 empirically in order to split between the effects of the cash flows and the effects of the discount rate on the investment return. Next, I aggregate these two components of investment return in order to estimate a common factor that serves as a state variable that describe investment returns. These two aggregated channels allow me to test hypothesis 2 empirically by breaking investment beta (i.e., stock returns' sensitivity to the investment returns) into two betas – fundamental (or cash flow) beta and financial (or discount rate) beta.

2.4.1 Empirical Design for Testing Hypothesis 1: Impulse Response Function

Hypothesis 1 states that investment return is driven by two major factors: fundamental factors (that work through the marginal productivity of capital), and financial factors (that work through the investment adjustment costs). However, there are three major challenges in testing this hypothesis empirically. My first problem is the difficulty of measuring the fundamental channel, since marginal q is unobservable. In order to solve this problem, I use equation 13 as my framework to decompose the unexpected investment return into unpredictable (fundamental) and predictable (financial) components. In particular, I will focus on measuring the 'predictable financial factors', while leaving the 'unpredictable fundamental factors' in the error term of the investment return equation. In other words, I assume that the unpredictable fundamental channel equal the difference between actual and expected investment return, as in equation 13.

The second problem is finding an appropriate measure of the observable discount rate channel or the financial factors. I will use book-to-market and asset size to proxy for the discount rate and the financing constraints, respectively. The rationale for using the 'book-to-market' variable is that it serves as a state variable that describe the state of discount rate (systematic risk), while controlling for the expected cash flow (Berk, Green and Naik 1999). Zhang (2005) shows that value firms exhibit lower capital investment than growth firms since they have more unproductive capital stock. One might expect, therefore, that growth firms (low BEME) invest the most since a greater fraction of their value consists of growth options. Furthermore, growth firm invest the most since they have lower cost of capital and less risky compared to value firms. Since the least risky firms have the lowest cost of capital, one might expect again that growth firms invest the most. Additionally, I follow Gilchrist and Himmelberg (1995) and Li and Zhang (2010) in using 'asset size' as a firm-level proxy of financing constraints, since young and less well-known firms typically have small assets and consequently more financially constrained than well-known firms with big assets.

Third, it is difficult to isolate the response of investment returns to the cash flow channel (fundamental factors), and the discount rate channel (financial factors). In order to overcome this problem, I use the vector autoregressive approach to decompose investment return. Specifically, I assume that data are generated by the following first-order VAR model:

$$\begin{bmatrix} Z_{i,t+1} \\ X_{t+1} \end{bmatrix} = a + \Gamma \begin{bmatrix} Z_{i,t} \\ X_t \end{bmatrix} + u_{i,t+1} \quad (16)$$

According to the literature review discussed in section two, the negative relation between current investment return and future stock return is documented at the aggregate level (as predicted by the q-theory) and at the firm level (as predicted by the real option model). This led me to assume in section three in the model development that firm-level production is subject to firm-specific productivity shocks $\left(Z_{it}\right)$ and aggregate productivity shocks $\left(X_t\right)$. In order to reconcile both strands of literature, therefore, I include both firm-level and aggregate variables in the state vector. My vector of firm-level variables $\left(Z_{i,t+1}\right)$ includes three variables - investment growth rate (IGR), book-to-market (BEME), and asset size (ATQ). Investment growth rate is my main variable of interest, since I use it as a proxy for the investment returns. Cochrane (1991 and 1996) shows that investment returns, as calculated by equation 8, can be approximated by the investment growth rate without any misrepresentation of the model. In order to measure the expected component of the investment returns (i.e., the financial factors), I use book-to-market and asset size that serve as proxy for discount rate and financing constraints, respectively.

The rationale for including aggregate variables in the VAR model is to allow macroeconomic variables to affect firm-level investment returns. Since there is no feedback from firm-level variables to aggregate variables, I constrain the lower left corner of Γ matrix to zero. In this context, I use a four-aggregate variable vector $\left(X_{t+1}\right)$ that includes variables that have a common "business cycle" component that forecasts aggregate investment returns. Similar to Cochrane (1991 and 1996), these variables include aggregate investment growth rate, term premium (defined as the ten-year government bond return minus Treasury bill return), corporate premium (measured as the difference between corporate bond return and Treasury bill return), and the lagged real value weighted stock return.

After estimating the VAR model in equation 16, my next step is to use these parameter estimates to decompose investment returns into two components, as in equation 13. Since discount rate news reflect the predictable component of investment returns, the expected investment return news $\left(N_{DR,i,t+1}^{Investment}\right)$ can be expressed using the following function:

$$N_{DR,i,t+1}^{Investment} = e1'\lambda u_{i,t+1} \quad (17)$$

Where $\lambda \equiv \rho\Gamma\left(I-\rho\Gamma\right)^{-1}$, $e1'$ is a vector with the first element equal to one and the remaining elements equal to zero $\left(e1' \equiv [1 0 0 0 0 0 0]\right)$, $'\Gamma'$ is the estimated VAR transition matrix, and $'\rho'$ is set equal to 0.937. Equation 17 models the discount rate news as a linear function of the t+1 shock vector, so that the greater the ability of the VAR state variables (in the first row of the VAR matrix) to predict investment return, the higher the predictable component in investment return, and consequently, the greater the discount rate news.

Once I calculate discount rate news using equation 17, cash flow news $\left(N_{CF,i,t+1}^{Investment}\right)$ can be computed directly as residuals. Specifically, I can restate equation 13 to define cash flow news as the sum of unexpected investment return and expected (discount rate) news:

$$\because \text{Unexpected Investment Return} = r_{i,t+1}^{Investment} - E_t\left[r_{i,t+1}^{Investment}\right] = N_{CF,i,t+1}^{\text{Investment}} - N_{DR,i,t+1}^{\text{Investment}}$$

$$\begin{aligned}\therefore N_{CF,i,t+1}^{Investment} &= \text{Unexpected Investment Return} + \text{Expected Return}\left(\mathrm{N}_{\mathrm{DR,i,t+1}}^{Investment}\right)\\ &= e1'u_{i,t+1} + \mathrm{e}1'\lambda u_{i,t+1}\\ &= \left(e1' + e1'\lambda\right)u_{i,t+1} \qquad (18)\end{aligned}$$

Equation 18 says that if all of the firm-level and aggregate variables' coefficients in the first row of the estimated VAR transition matrix (Γ) have zero values (i.e., the investment returns are completely unpredictable), the expected return news $\left(N_{DR,i,t+1}^{Investment} = \lambda' u_{i,t+1}\right)$ will have zero value and the investment return will be driven only by the cash flow news $\left(N_{CF,i,t+1}^{Investment} = e1'u_{i,t+1}\right)$.

I use the above extracted news terms to empirically test the first hypothesis that examines how much of the variability in investment returns is due to variability in the marginal product of capital (proxied by the cash flow news in equation 18) and how much is due to variability in the cost of capital (proxied by the discount rate news in equation 17). To this end, I calculate the variance-covariance matrix for the cash flow news and discount rate news. The magnitude of the variance of the cash flow news relative to the discount rate news can tell us whether the fundamental or financial factors are the major driver of the firm-level investment returns.

The problem with the variance-covariance matrix, however, is that errors are unlikely to be diagonal. This means that it is difficult to shock one variable while holding other variables constant. Therefore, I use the impulse response function (IRF) to measure the response of investment return to a lagged unit impulse in financial variables, while holding the fundamental factors constant. One of the major drawbacks of using IRF is its sensitivity to variables ordering since the underlying assumption is that variables that appear earlier in the system have contemporaneous and lagged effect on variables that appear later in the ordering, while the variables that come later in the model have only lagged effect on the previous variables in the ordering. Love and Zicchino (2006), for example, adopt a particular ordering – the fundamental factor (proxied by sales-to-capital) followed by the financial factor (proxied by cash flow scaled by capital) and the investment level. The problem with adopting a particular ordering is that it is based on assumptions which might not be plausible, and, consequently, leads to major distortions in IRF. To overcome the problem of order dependence, I use the orthogonalized or the generalized IRF[3].

[3] Pesaran and Shin (1998) show that the orthogonalized or the generalized IRF are the same only when examining the impulse responses of the shocks to the first equation in VAR (the first equation in the VAR matrix as estimated by equation (16) is the one of our particular interest in this paper).

2.4.2 Empirical Design for Testing Hypothesis 2: Beta Decomposition Approach

There is a wealth of empirical evidence for the cross-sectional negative relation between stock and investment return. For example, Chen and Zhang (2010) develop a new three factor model $\left(r_i - r_f = \varphi + \beta_i^{Market} r^{Investment} + \beta_i^{Investment} r^{Investment} + \beta_i^{ROA} r^{ROA} + u_i\right)$ that says that excess return on a security is described by its sensitivity to three factors: the traditional market factor $\left(\beta_i^{Market}\right)$ in addition to two common factors formed on investment $\left(\beta_i^{Investment}\right)$ and return on assets $\left(\beta_i^{ROA}\right)$. In order to empirically test the second hypothesis, I need an econometric methodology in the manner of Campbell and Vuolteenaho (2004) who decompose market return into cash flow and discount rate news in order to break market beta $\left(\beta_i^{Market}\right)$ into cash flow (bad) and discount rate (good) betas. My goal is to decompose investment returns (rather than market returns) into cash flow and discount rate news in order to split investment beta $\left(\beta_i^{Investment}\right)$ (rather than market beta) into fundamental and financial betas. In order to estimate these two betas, I use a two-step procedure. First, I need to estimate a common factor that serves as a state variable that describe investment returns. Therefore, I approximate two equal weighted portfolios for discount rate news and cash flow news, in the manner of Vuolteenaho (2002), as follows:

$$N_{DR,t+1}^{Investment} \approx \frac{1}{n}\sum_{i=1}^{n} N_{DR,i,t+1}^{Investment} = \frac{1}{n}\sum_{i=1}^{n} \lambda u_{i,t+1} \qquad (19)$$

$$N_{CF,t+1}^{Investment} \approx \frac{1}{n}\sum_{i=1}^{n} N_{DR,i,t+1}^{Investment} = \frac{1}{n}\sum_{i=1}^{n} \left(e1' + \lambda\right) u_{i,t+1} \qquad (20)$$

$$N_{t+1}^{Investment} = N_{DR,t+1}^{Investment} + N_{CF,t+1}^{Investment} \qquad (21)$$

Second, these two approximated aggregated channels allow me to break investment beta $\left(\beta_i^{Investment}\right)$ (i.e., the sensitivity of stock returns to the investment returns) into two betas – discount rate (financial) beta and cash flow (fundamental) beta:

$$\text{Financial Beta}: \beta_{DR,i}^{Investment} \equiv \frac{Cov_t\left(r_{i,t+1}^{Stock}, -N_{DR,t+1}^{Investment}\right)}{Var\left(r_{t+1}^{Investment}\right)} \qquad (22)$$

$$\text{Fundamental Beta}: \beta_{CF,i}^{Investment} \equiv \frac{Cov_t\left(r_{i,t+1}^{Stock}, -N_{CF,t+1}^{Investment}\right)}{Var\left(r_{t+1}^{Investment}\right)} \qquad (23)$$

The cash flow investment beta $\left(\beta_{CF,i}^{Investment}\right)$ is defined as the covariance between stock returns and cash flow investment returns, and I call it fundamental beta because it measures the sensitivity of stock returns to the shocks from the fundamental marginal productivity of capital. In addition, the discount rate investment beta $\left(\beta_{DR,i}^{Investment}\right)$ is defined as the covariance between the stock returns and discount rate component of investment returns, and I call it financial beta since it measures the sensitivity of stock returns to financial factors.

These two betas are the ones of the interest since they are the empirical counterparts of both channels that derive the negative relation between investment return and stock return, as estimated by equation 15. In particular, fundamental beta reflects the cash flow channel (assuming a constant discount rate, the higher the current level of investment, the lower the marginal product of capital, the lower the expected stock returns) as predicted by Li, Livdan, and Zhang (2009). Alternatively, financial beta reflects the discount rate channel (assuming constant returns to scale, the lower the discount rate, the higher the current investment, the lower the future stock return). Past research had to control one channel in order to examine the other, but using beta decomposition approach allows me to run a horse race between both channels.

2.5 Data Description and Experimental Design

2.5.1 Basic Data

My data set consists of quarterly firm-level data as well as aggregate data from the first quarter in 1963 to the second quarter in 2011. I start my sample period in 1963 to make my results more comparable to those in literature. I obtain financial statement and balance sheet data from quarterly COMPUSTAT, and stock return data from the Center for Research in Security Prices (CRSP). I consider all domestic, primary stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ stock markets.

2.5.2 Data Requirements

To be included in the tests, a firm must meet two criteria that have been used in the literature: First, I exclude financial firms (i.e., firms in finance, insurance and real estate) such as closed-end funds, trusts, ADRs, and REITs, due to the difficulty of interpreting their capital investment – which is our major focus in this study. Since investment literature focuses mostly on manufacturing firm, I include only firms in the manufacturing sector defined as those with primary standard industrial classifications (SIC) between 2000 and 3999. Second, I include only firms whose fiscal year end in December in order to align the timing of firm-level and aggregate data across firms. Other studies, such as Vuolteenaho (2002), Liu, Whited and Zhang (2009), and Xing (2008), use this requirement and they find that it does not affect the representatives of the sample since the fiscal year of most firms ends in December.

2.5.3. Variables Definition

I use three firm-level variables – investment growth rate (IGR), Book-to-Market (BE/ME), and asset size (ATQ). 'IGR' is measured as the growth rate in the firm's capital expenditures $\left(I_t/I_{t-1}-1\right)$, where $\left(I_t\right)$ is defined as the sum of the firm's quarterly gross property, plant, and equipment (PPEGTQ) (investment in long-term assets) and the firm's quarterly inventories (INVTQ) (investment in the short-term assets). 'BE' is the quarterly book value of the equity defined as the sum of the COMPUSTAT book value of common equity (CEQQ) and balance sheet deferred taxes and investment tax credit (TXDITCQ) less the book value of preferred stock (PSTKQ). 'ME' is the market value of equity measured as the quarterly closing price of common equity (PRCCQ) multiplied by the number of quarterly common shares outstanding (CSHOQ). 'ATQ' is the quarterly book value of total assets.

In addition, I use four aggregate variables: aggregate real value weighted stock return (MKT), default premium (default), term premium (term), and Aggregate investment growth rate (AIGR). 'MKT' is the excess returns on the S&P composite index over the consumer price index inflation. 'Default' is calculated as the difference between Moody's seasoned yields on Baa and Aaa corporate bonds. 'Term' is defined as the difference between 10-year government bond return and three-month Treasury bill return. 'AIGR' is the quarterly change in the gross private domestic investment (GPDI).

‘MKT’ data is downloaded directly from French’s website, while ‘default’, ‘term’, and ‘AIGR’ are obtained from the Federal Reserve Economic Data (FRED).

2.6 Empirical Results

Table 2.1 reports descriptive statistics that include means, standard deviations, minimums, and maximums for firm-level (Panel ‘A’) and aggregate variables (Panel ‘B’) used in the composite VAR as in equation 16. From Panel ‘A’, the investment growth rate has a mean of 0.26, and standard deviation of 95.76. The book-to-market ratio and quarterly asset size have a mean of -1.86 and 2885.52, respectively. From Panel ‘B’, the aggregate investment growth rate has a mean of 0.85 and a standard deviation of 4.18. The market premium, default premium, and term premium have a mean of 1.49, 1.08, and 1.88, respectively.

Table 2.1 Descriptive Statistics of the VAR Variables

Variable	N	Mean	St. Deviation	Min	Max
	Panel (A): Descriptive Statistics – Firm-level variables				
IGR	92598	0.2602	95.7560	-11320.00	16854.35
BE/ME	92598	-1.8642	720.2634	-169690.50	60133.97
ATQ	92598	2885.52	15543.16	0	479921.00
	Panel (B): Descriptive Statistics – Aggregate variables				
MKT	92598	1.4853	8.9487	8.9487	23.3200
Default	92598	1.0760	0.4961	0.5600	3.0200
Term	92598	1.8826	1.2356	-1.4300	3.8000
AIGR	92598	0.8513	4.1842	-15.3000	13.1000

Table 2.2 presents the parameter estimates of the composite VAR in equation 16, using all the forecasting variables that include firm-level variables $\left(Z_{i,t+1}\right)$ and aggregate variables$\left(X_{t+1}\right)$. The firm-level variables include the growth rate in the firm’s capital expenditures (IGR), book-to-market ratio (BEME), and the book value of total assets (ATQ). The aggregate variables include the aggregate real value weighted stock return (MKT), the default premium (default), the term premium (term), and the growth rate in the aggregate investment (AIGR). Each row of table 2.2 corresponds to a different equation of the composite VAR. The first row in the table is the one of major interest since it implies that two out of three firm-level variables have some ability to predict quarterly firm investment returns. In particular, investment returns are high when past one-quarter book-to-market ratio and asset size are high.

In addition, the coefficient of firm investment returns on the term premium is significant at 10%. This result is consistent with the findings of Cochrane (1991), and it means that term premium has a ‘business cycle’ component that can predict the investment returns at the firm-level.

Table 2.2 Composite VAR Parameter Estimates

	IGR_{t-1}	ATQ_{t-1}	$BEME_{t-1}$	MKT_{t-1}	$Default_{t-1}$	$Term_{t-1}$	$AIGR_{t-1}$	R^2
IGR_t	-0.01 (0.08)	0.01** (0.01)	0.02* (0.01)	0.00 (0.02)	-0.25 (0.33)	-0.31** (0.15)	-0.01 (0.04)	6.48%
ATQ_t	35.57** (15.99)	0.91*** (0.03)	-7.95*** (2.57)	0.35 (4.23)	142.53*** (63.62)	36.36 (29.28)	-10.24 (7.95)	74.96%
$BEME_t$	-0.34 (0.49)	-0.01 (0.01)	0.30*** (0.08)	-0.17 (0.13)	2.84 (1.98)	-0.05 (0.91)	-0.37 (0.24)	17.59%
MKT_t	-0.05 (0.32)	-0.01 (0.01)	-0.01 (0.05)	0.06 (0.08)	0.67 (1.30)	0.80 (0.60)	-0.16 (0.16)	1.37%
$Default_t$	-0.01 (0.01)	0.01*** (0.01)	0.01 (0.00)	-0.00 (0.00)	0.94*** (0.03)	-0.03 (0.01)	0.01 (0.00)	71.10%
$Term_t$	-0.01 (0.02)	0.01 (0.01)	0.02 (0.02)	-0.01* (0.00)	0.16 (0.10)	0.84*** (0.04)	-0.01 (0.01)	72.50%
$AIGR_t$	0.08 (0.15)	-0.01 (0.01)	-0.02 (0.02)	0.13*** (0.04)	-0.09 (0.61)	0.79*** (0.28)	0.29*** (0.07)	22.76%

Table 2.3 translates the VAR parameter estimates from table 2.2 into a function of $(e1'\lambda)$ where $e1' \equiv (1\ 0\ 0\ 0\ 0\ 0\ 0\ 0)$, $\lambda \equiv \rho\Gamma(I-\rho\Gamma)^{-1}$, $\rho \equiv 0.937$, and Γ is the estimated VAR matrix. The shock vector (u_i) from each equation in the VAR system is linearly modeled as a function of $(e1'\lambda)$ to decompose the firm-level investment returns into investment cash flow news $\left(N^{Investment}_{CF,i,t+1} = (e1' + e1'\lambda)u_{i,t+1}\right)$ and investment discount rate news $\left(N^{Investment}_{DR,i,t+1} = e1'\lambda u_{i,t+1}\right)$. I use these extracted news terms to empirically test the first hypothesis that examines how much of the variability in the investment returns is due to variability in the marginal product of capital (proxied by the cash flow news) and how much is due to variability in the cost of capital (proxied by the discount rate news). Panel (A) show the descriptive statistics of both news terms. The cash flow news has a mean of -0.82, and standard deviation of 4.85, while the discount rate news has a mean of -0.86 and standard deviation of 2.93. These preliminary results show that the standard deviation of the firm-level cash flow news is approximately twice the standard deviation of the discount rate news. Panel (B) shows the results of the

variance decomposition investment returns since it reports the covariance matrix of the news terms. The results show that the variance of the cash flow news is 23.53 and the variance of the discount rate news is 8.60. This means that 73% of the firm-level investment returns is attributed to variability in marginal productivity of capital and only 27% is attributed to variability in cost of capital.

Table 2.3 Variance Decomposition of Firm-level Investment Returns

Panel (A): Descriptive Statistics		
	$N_{DR,i,t+1}^{Investment}$	$N_{CF,i,t+1}^{Investment}$
Mean	-0.8616	-0.8205
Standard Deviation	2.9330	4.8508
Minimum	-17.0691	-34.4021
Maximum	6.0826	16.6046
Panel (B): The Covariance Matrix of the News Terms		
News Covariance	$N_{DR,i,t+1}^{Investment}$	$N_{CF,i,t+1}^{Investment}$
$N_{DR,i,t+1}^{Investment}$	8.6029	13.5912
$N_{CF,i,t+1}^{Investment}$	13.5912	23.5307

Although the above results from the variance decomposition might lead me to conclude that fundamental factors are the dominant determinant of investment, these results show suspect because the errors of the variance-covariance matrix are unlikely to be diagonal. Therefore, I proceed to the second empirical test of hypothesis one which is the orthogonal impulse response function. Table 2.4 presents the results of the orthogonal impulse response function that show the response of the system to an impulse, and figure 2.2 reports graphs of impulse responses for the VAR model with three variables estimated – IGR, N_{CF}, N_{DR}. The result of my particular interest is the response of investment return (IGR) to the fundamental and financial variables (i.e., IGR is the response while N_{CF} and N_{DR} are the impulses). In contrast to the results of the variance decomposition, I find that the impact of the lagged financial news on investment return is much larger than the impact of the lagged fundamental news. In particular, the long-run responses of IGR to an impulse in CF are -0.0615, -0.0153, -0.0181, -0.0177, -0.0165 for lag 1, 2, 3, 4, and 5 respectively, while the long-run responses of IGR to an impulse in DR are

-0.2101, -0.2051, -0.1871, -0.1687, -0.1510 for lag 1, 2, 3, 4, and 5 respectively. These results, therefore, indicate that discount rate news is the main driver of the firm-level investment returns.

Table 2.4 Orthogonal Impulse Response Function

Response\Impulse	Lag	CF	DR	IGR
CF	1	-0.0305 (0.5856)	0.7229 (0.5052)	0.2484 (1.3520)
	2	0.0737 (0.3904)	0.6263 (0.4263)	0.2271 (1.2230)
	3	0.0635 (0.3515)	0.5576 (0.3929)	0.2075 (1.0826)
	4	0.0566 (0.3147)	0.4958 (0.3582)	0.1871 (0.9623)
	5	0.0504 (0.2808)	0.4408 (0.3256)	0.1675 (0.8558)
DR	1	0.0257 (0.4656)	0.7760 (0.3806)	0.2019 (1.4608)
	2	0.0774 (0.4010)	0.6842 (0.3891)	0.2171 (1.3256)
	3	0.0687 (0.3725)	0.6100 (0.3846)	0.2123 (1.1814)
	4	0.0617 (0.3388)	0.5430 (0.3631)	0.1979 (1.0524)
	5	0.0551 (0.3048)	0.4830 (0.3362)	0.1802 (0.9367)
IGR	1	-0.0615 (0.2106)	-0.2101 (0.4017)	0.2019 (0.4658)
	2	-0.0153 (0.0337)	-0.2051 (0.1329)	0.0560 (0.3986)
	3	-0.0181 (0.0692)	-0.1871 (0.0734)	-0.0077 (0.3622)
	4	-0.0177 (0.0837)	-0.1687 (0.0890)	-0.0341 (0.3265)
	5	-0.0165 (0.0851)	-0.1510 (0.0979)	-0.0434 (0.2928)

Now, I turn to the empirical testing of the second hypothesis. To this end, I aggregate firm-level news series by forming two equal weighted portfolios for cash flow and discount rate news using formulas (19) and (20). After that, I sort the NYSE, AMEX, and NASDAQ stocks into five quintiles based on investment growth rate (IGR). The portfolio “LOW” is the lowest IGR portfolio (quintile 1) while the portfolio “HIGH” is the highest IGR portfolio (quintile 5). I then regress the returns of investment growth rate (IGR) sorted portfolios on the aggregated cash flow and discount rate news, in order to estimate the fundamental and financial beta, using equations (20) and (21), which add up to investment beta.

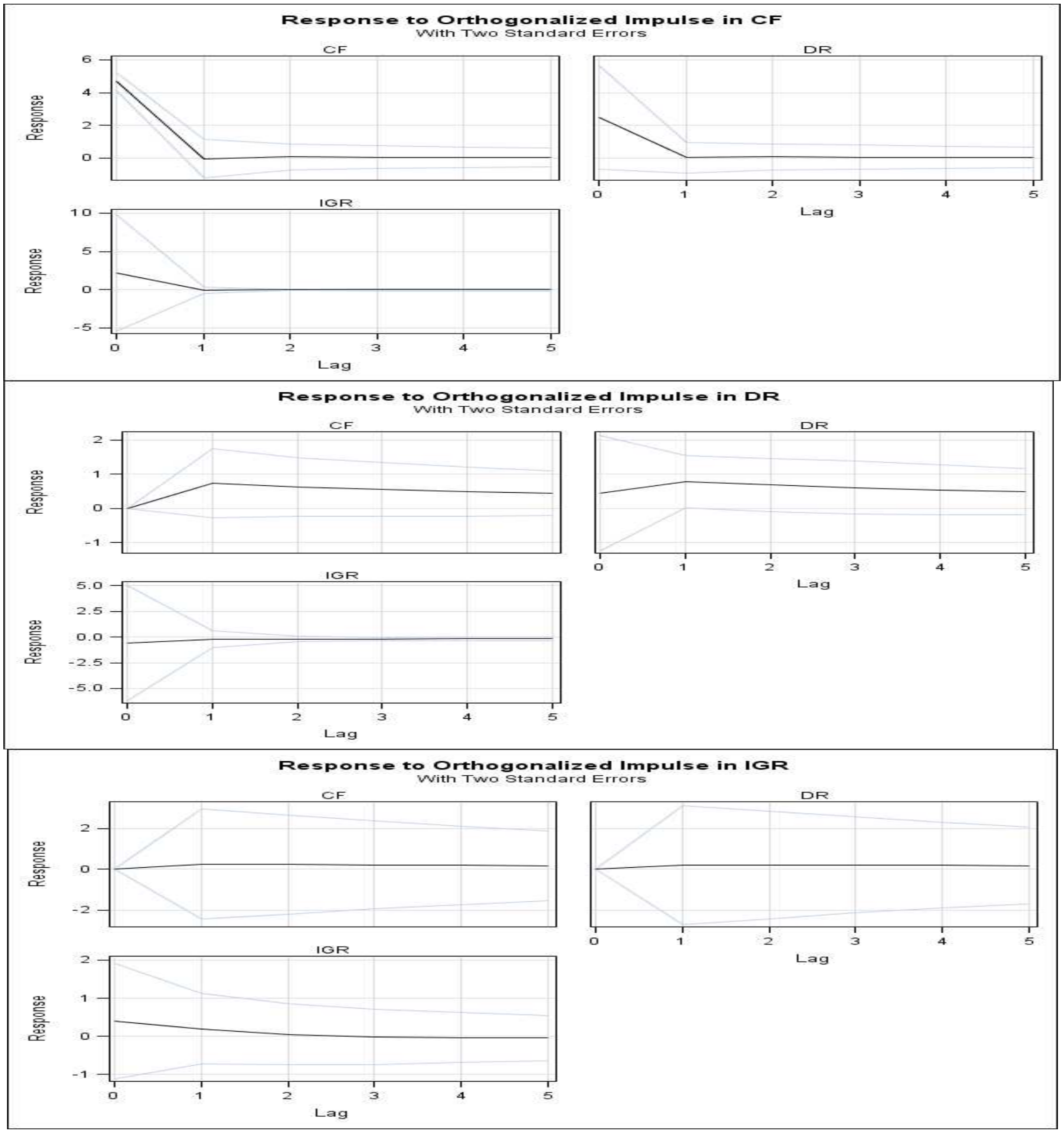

Figure 2.2 Impulse Responses for 5 lag VAR of IGR CF DR

Table 2.5 puts such procedure to work. In particular, Panel (A) reports the value of fundamental and financial betas for one-dimensional sorting by investment return proxied by IGR. Panel (B) shows the results of those estimated betas for two-dimensional sorting by IGR and size. Taken together, the results from both panels are consistent and show that the value of the financial betas is greater than the value of fundamental betas for all decile portfolios whether based on one-dimensional and two-dimensional classification. This means that financial factors rather than fundamental factors are the dominant driver of the negative relation between investment and stock return.

Table 2.5 Fundamental and Financial Betas for Decile Portfolios

Panel (A): One-Dimensional Sorting by Investment Growth Rate (IGR)					
	LOW	2	3	4	HIGH
Fundamenta l Beta : $\beta_{CF,i}^{Investment}$	-0.14772 (0.04183)	-0.10044 (0.02638)	0.16529 (0.11775)	0.77371 (0.98806)	0.00670 (0.01761)
Financial Beta : $\beta_{DR,i}^{Investment}$	0.31199 (0.05047)	1.31838 (0.04871)	0.76478 (0.01794)	0.33666 (0.04054)	1.18781 (0.02846)
Panel (B): Two-Dimensional Sorting by Investment Growth Rate (IGR) and Size (ATQ)					
Fundamenta l Beta : $\beta_{CF,i}^{Investment}$	LOW	2	3	4	HIGH
Small	-0.06692 (0.02292)	-0.21557 (0.11985)	-0.00907 0.00848	-0.00756 0.05655	0.00096 0.01030
2	-0.01217 (0.09470)	-2.76084 (1.23719)	0.35025 0.56244	-0.23083 0.49501	-0.02687 0.16659
3	0.07457 (1.19861)	-0.26303 (0.27965)	-0.45188 0.43491	0.27255 2.39302	-0.08907 0.09529
4	-0.000152 (0.00521)	0.82251 (0.60943)	0.35720 0.44032	0.07729 0.33695	1.51682 0.72185
Large	-0.02648 (0.06557)	-0.00130 (0.00505)	-0.47260 0.53269	-0.19448 0.67965	0.33866 0.60685
Financial Beta : $\beta_{DR,i}^{Investment}$	LOW	2	3	4	HIGH
Small	0.99645 (0.06943)	1.00918 (0.00600)	1.03531 0.00414	1.05704 0.00874	1.18341 0.02092
2	1.05882 (0.00919)	1.15174 (0.01114)	0.86616 0.00667	0.92090 0.00553	1.16572 0.01814
3	0.96569 (0.02577)	-0.26303 (0.27965)	0.40594 0.04997	0.08973 0.02492	0.21425 0.03294
4	0.92525 (0.03289)	0.94365 (0.02181)	0.95361 0.01683	0.91167 0.02445	0.83487 0.05281
Large	0.00201 (0.00574)	-0.04060 (0.01996)	0.09610 0.02811	0.31705 0.04348	0.36721 0.04212

CHAPTER 3

FINANCIAL CRISES AND THE GLOBAL VALUE PREMIUM: REVISITING FAMA-FRENCH

3.1 Introduction

Financial crises occur with recurring patterns as evidenced by at least one severe global financial crisis per recent decade – the 1987 stock market crash, the 1997 Asian financial crisis, and the 2007 credit meltdown. A common feature of the crises of the last few decades has been the rapid spread from one country to others in a process that has come to be known as “contagion”. Starting with the 1987 stock market crisis that began in Hong Kong, global stock markets plummeted one after another in Europe and in the United States. The 1997-1998 Asian crisis began in Thailand with the collapse of the Thai Baht and spread rapidly into neighboring countries. The 2007-2008 financial crisis that hit the world as a result of the implosion of the US mortgage market was followed by a series of collapses in major world markets. The surprising frequency has stimulated extensive research related to crises.

This study investigates effects of financial market crises from two perspectives – the global value premium and equity market integration. The primary purpose is to investigate whether or not the global value premium is a risk factor affecting equity market integration. When a financial crisis occurs in any region in the world with fears of contagion, risk-averse investors rush to quality and liquidity by trying to get rid of high-risk, illiquid securities and replacing them with low-risk liquid securities. Therefore, if global value stocks are fundamentally riskier than global growth stocks, one would expect value stocks to perform more poorly than growth stocks during financial crises (Lakonishok et al., 1994). The permanence of the effects evident during crises can be investigated by viewing pre-crisis and post-crisis relationships. The study makes contributions to both integration literature and asset pricing literature. It is the first attempt I found to investigate the impact of financial crises along two dimensions: global value premium and financial integration. Financial integration can be defined in terms of either a global market portfolio or Purchasing Power Parity (PPP). The global market portfolio argues that international markets are integrated if all financial assets yield the same risk-adjusted expected returns to investors the world over (assuming that investors do not hedge exchange rate risks and the single relevant source of risk is the market portfolio). According to PPP, two financial markets are integrated if securities are priced identically and the exchange risk premium is zero. My initial results indicate that countries share "distress risk factors" (proxied by the global value premium) during four crisis periods. The findings of distress risk motivate adding the global value premium as a third dimension for measuring financial market integration. According to the new measure, financial markets are integrated if value stocks underperform growth stocks in bad states of the world as proxied by financial crises.

This chapter proposes a new international asset pricing model that takes into account market risk, foreign exchange risk, value premium, time-varying risk premium, and leverage effect, well-known phenomena in the literature that refer to asymmetric responses of return volatility series to bad news and good news. The model is named GJR-GARCH-FF because it is a composite of the asymmetric Sign GARCH model developed by Glosten, Jagannathan and Runkle (1993) (GJR-GARCH model) and the international version of the Fama and French model (1998). The original FF model is based on two crucial assumptions – that purchasing power parity holds and that the price of risk is constant. The merit of my newly introduced model is that it relaxes these two assumptions by adding the exchange risk premium to the FF model and then incorporating it as the mean equation in the GJR-GARCH model. The results show that the new model provides an attractive representation of countries' returns since the average intercept of the model is significantly lower than the FF two factor model.

The remainder of the chapter is organized as follows: data and crisis periods are explained in section two, methodology is set forth in section three, empirical results are reported in section four, and robustness tests are in section five.

3.2 Data and Crisis Periods

Data from January 1975 to December 2007 for thirteen countries – Australia, Belgium, France, Germany, Hong Kong, Italy, Japan, Netherlands, Singapore, Sweden, Switzerland, the UK and the US – is used to test the risk explanation for the global value premium, before, after and within crisis periods, allowing for both long-run effects and shorter-run effects. Pre-crisis and post-crisis periods each require a long data span to provide an adequate number of meaningful observations. Thus, for the pre-crisis and post-crisis analysis, I can include only two crises – the international debt crisis in 1982-1983 and the Asian crisis in 1997-1998 – in order to ensure no overlapping observations. However, studying within crisis periods allows for inclusion of four crises: the international debt crisis in 1982-1983, the ERM crisis in 1992-1993, the Asian crisis in 1997-1998 and the September 11, 2001 attack.

Three important currencies—the British pound, German mark[4] and Japanese yen proxy for foreign exchange risk while the monthly market return is the value weighted average of returns for firms in each country. The return on one-month US Treasury Bills is used as the risk-free rate, because the analysis is from the perspective of a US investor. All of the exchange rate data is obtained from Compustat, while the returns on individual countries' portfolios, the global market portfolio, value and growth portfolio, and the risk-free rate are obtained from Kenneth French's homepage[5].

A challenge in examining financial crises is to identify the precise beginning and ending of a crisis, that is to pinpoint the source of the crisis (identify the major triggering event). According to the Federal Deposit Insurance Corporation (FDIC) (1997), the international debt crisis officially started on August 15, 1982 when Mexico declared its inability to pay its debt obligations. By the end of 1983, the crisis management efforts could be called successful, since Mexico had fulfilled its interest payments and the large international banks did not collapse. Therefore, I define the 'debt crisis period' from August 1982 to December 1983. According to the International Monetary Fund (1998), the Asian crisis began

[4] On January 1, 1999, the euro was adopted by eleven countries – including Germany – as their official currency. Therefore, I use DM during the first part of the period and I then use the Euro as a proxy for the DM during the latter part of the study.
[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

July 2, 1997 when the bank of Thailand devalued the baht by roughly 20%. On March, 1999, the Asian crisis had ended when the IMF approved a $1 billion increase in its emergency loan package for Indonesia, and the DJIA closed above the 10,000 level for the first time in its history. Therefore, I define the 'Asian crisis period' from July 1997 to March 1999. Table 3.1 shows the decomposition of the sample period of the study for each crisis.

Table 3.1 Sample Period Description

Crisis	Pre-Crisis Period	Crisis Period	Post-Crisis Period
International Debt Crisis	Aug 1979 – July 1982	Aug 1982 – Dec 1983	Jan 1984 – Dec 1986
Asian Crisis	July 1994 – June 1997	July 1997– Mar 1999	April 1999 – Mar 2002

3.3 Methodology

The goal is to test whether the global value premium is a risk premium rather than a behavioral factor and whether the international equity markets become more integrated after financial crises.

3.3.1 Supporting Rationale

Two primary approaches for measuring financial market integration are market beta and purchasing power parity (PPP). The more popular is beta as measured by the CAPM that assumes investors do not hedge against exchange rate risks and the single relevant source of risk is the market portfolio. However, studies differ in terms of the definition of the market portfolio as to whether it is a global, local or hybrid portfolio. The global CAPM (the integration model) is based on the logic that the international markets are perfectly integrated, such that all financial assets yield the same risk-adjusted expected returns to investors the world over. In this case, the global portfolio risk is the only risk considered. The domestic CAPM (the segmentation model) assumes that the local market is perfectly segmented from the world market and, therefore, the capital markets may demonstrate substantially different risk-return trade-offs. In this case, the local market portfolio will be the source of risk and should replace the returns for the global index in the CAPM formulation. Many studies find evidence of market segmentation (e.g., You et al., 2006; Bruner et al., 2008; Koedijk et al., 2002; Harris et al., 2003).

A more realistic approach than the two above versions is a two-factor Hybrid CAPM (Mid-Segmentation Model) that assumes capital markets are neither perfectly integrated nor perfectly segmented, so that global and domestic risk factors should be priced separately. This approach was originally launched by Erunza and Losq (1985) and Erunza, Losq, and Padmanabhan (1992), and empirically supported by Bruner et al. (2008). Finally, the Fama-French two factor model (1998) is an alternative version of CAPM that says that international returns are explained by the value premium and the global market premium. They empirically test their model and find that for thirteen countries the model fits the data well.

Rather than being defined in terms of the market portfolio, financial integration can also be defined in terms of PPP based on the 'Law of One Price'. The idea behind PPP is simple: once converted to a common currency at current exchange rates, national prices should be equal. According to PPP, therefore, two financial markets are integrated if securities are priced identically and the exchange risk premium is zero. Any deviations from PPP cause national investors to perceive different exchange rate adjusted returns from the same security and thus the exchange risk premium should be considered. Solnik (1983) was the first to explore this issue by arguing that CAPM should contain an exchange risk premium in addition to the market risk premium when PPP is violated. Wu (2008) finds that the international version of the FF model does not fit the data well, and he documents that the international CAPM with exchange risk is the best international model for forecasting compared to the CAPM and the FF model.

3.3.2. Model Development

The cited literature reveals two primary weaknesses in modeling the first and second moments. First: there is no clear-cut determination of the best international asset pricing model in explaining international returns. Asset pricing models that use beta as an integration measure differ in many regards such as whether to include the home country or the global index as the mean-variance efficient portfolio in the regression; whether to include exchange rate risk as an additional source of risk; and whether to incorporate the value premium as captured by Fama and French (1998) in the CAPM regression. Second: a common weakness in studies that apply CAPM in the international setting is that they are based on the constant price of risk (CRP) assumption inherent in CAPM. However, a time-varying risk premium on equities is widely documented in the literature. This means that investors' expectations about future security returns are conditional on all available information, and that modeling integration of financial markets without taking into account this time variation will yield imprecise results. Therefore, the CRP assumption should be relaxed to allow the price of market risk to vary over time.

In light of these two methodological observations in the international CAPM literature, I propose a new model that takes into account market risk, foreign exchange rate risk, the value premium, and a time-varying risk premium. In particular, the FF two factor model assumes that there is no deviation from PPP and the price of risk is constant. This study relaxes these two assumptions. To this end, I add two modifications to the original FF two-factor model: first, I assume that PPP does not hold by adding the foreign exchange risk premium as another risk factor in addition to the market risk premium and the value premium. Second, in order to relax the constant risk price (CRP) assumption, I incorporate the new model as the mean equation in the asymmetric GJR-GARCH model. Although conditional heteroskedasticity models appear to be among the best that are currently available, there is a major drawback of using first generation of GARCH models because they are said to be symmetrical, due to the quadratic specification used for the conditional variance (i.e., the error term is squared). Therefore, volatility will be a function only of the innovation's magnitude, since the lagged shock will have the same effect on the present volatility whether the lagged shock is positive or negative (i.e., neutral impact). This symmetrical nature of the traditional GARCH models makes them not well suited for capturing a well-known phenomenon of asymmetric volatility in stock returns series or what is called asymmetric or leverage effects (e.g., French, Schwert and Stambaugh, 1987; Glosten, Jagannathan and Runkle, 1993). The asymmetric volatility phenomenon (AVP) is a market dynamic that shows that periods of crisis (when residual is negative) cause the level of market volatility to increase more than in periods of relative calm (when residual is positive). To handle the asymmetries in the conditional variance, I use the asymmetric Sign-GARCH model of Glosten, Jagannathan and Runkle (1993) (GJR-GARCH model) that allows for different reactions of volatility to the sign of past innovations. I call the newly created model GJR-GARCH-FF, because it is a composite of both the GJR-GARCH model with the FF model. Mathematically, it can be represented as follows:

$$
\begin{aligned}
& r_{i,t} - r_{f,t} = \beta_0 + \beta_1 (r_{g,t} - r_{f,t}) + \beta_2 (H - L) \\
& \qquad + \beta_3 (Pound) + \beta_4 (Mark) + \beta_5 (Yen) + \varepsilon_{i,t} \\
& \varepsilon_{\mathrm{i,t}} \left| (\varepsilon_{\mathrm{i,t-1}}, \varepsilon_{i,t-2}, ...) \sim (0, \sigma^2_{i,t}) \right. \\
& \sigma^2_{i,t} = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \varepsilon^2_{i,t-1} + \sum_{i=1}^{p} \delta_1 \sigma^2_{i,t-1} + \sum_{i=1}^{r} \lambda_1 S_{i,t-1} \varepsilon^2_{i,t-1} \\
& \text{Where} \ : S_{i,t-1} = \begin{Bmatrix} 1, \text{ if } \ \varepsilon_{\mathrm{i,t-1}} < 0 \\ 0, \text{ otherwise} \end{Bmatrix}
\end{aligned} \tag{1}
$$

The model consists of two equations: the mean equation and the variance equation. In the mean equation, the excess monthly market return for a country is computed by subtracting the risk-free rate (r_f) from the monthly market return for that country $(r_{c,t})$. The excess return of a country is a function of three risk factors: global market risk premium $(r_{g,t} - r_f)$ where $(r_{g,t})$ is the return on the global equity market portfolio, the value premium (H–L) measured by the return difference between the high and low BE/ME portfolio for each country, representing the international version of the distress factor in the FF two-factor model, and the exchange risk premium proxied by three selected important currencies that are the British Pound, German Mark, and Japanese Yen, with the US dollar as the reference currency. The intercept (β_0) examines to what extent the new model can explain international returns, the (β_1) coefficient measures integration, the (β_2) coefficient explores the risk explanation of the global value premium, and the (β_3), (β_4) and (β_5) coefficients are exchange risk premiums and are used as control variables. Following Fama and French (1998), I do not include size premium (small minus big- the difference between the returns on diversified portfolios of small and big stocks) because the data for the twelve countries (other than US) is from Morgan Stanley's Capital International (MSCI) which primarily includes large firms that represents 80 percent of a market's invested wealth. It is clear from the above formulation that the mean equation is the international Fama and French two-factor model with currency risk. By incorporating such equation into the GJR-GARCH model, the new model becomes the time-varying empirical counterpart to the FF model (with currency risk).

The variance equation expresses the current volatility (measured by variance $(\sigma^2_{i,t})$) as a function of four factors: the mean volatility (a), news about volatility from the previous period measured as the lag of the squared residual from the mean equation $(\varepsilon^2_{i,t-1})$ (the ARCH term), the last period's variance $(\sigma^2_{i,t-1})$ (the GARCH term) to control for volatility clustering, and the asymmetric volatility term $(S_{i,t-1}\varepsilon^2_{i,t-1})$ to account for the leverage effect. A model with 'q' lags of $(\varepsilon^2_{i,t-1})$, 'p' lags of $(\sigma^2_{i,t-1})$ and 'r' lags of $(S_{i,t-1}\varepsilon^2_{i,t-1})$ is labeled GJR (p, q, r), and I determine the lag structure in the conditional variance equation based on Akaike (AIC) and Bayesian (BIC) information criteria. The central feature of the above specification is that the dummy variable (S) allows the conditional variance to differ on crash days, since the effect of lagged shock on current volatility now is a function of its magnitude and its sign rather than its magnitude only, as in the original GARCH models. Specifically, volatility is affected by one term (α_i) when the residual is negative (i.e., good news), while it is affected by two terms $(\alpha_i + \lambda_i)$ when the residual is negative (i.e., bad news).

3.4 Empirical Results

3.4.1 FF Model versus GJR-GARCH-FF Model

My goal in this section is to evaluate the ability of the GJR-GARCH-FF model to explain international returns. To this end, I perform three different tests. As a preliminary test, I use the standard GJR-GARCH (p, q, r) model (under the restriction that $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0)$ to model the monthly excess return for individual countries. I test several GARCH (p) terms, ARCH (q), and asymmetric (r) terms and find that the most appropriate model is GJR-GARCH (3, 1, 1):

$$r_{i,t} - r_{f,t} = \beta_0 + \varepsilon_{i,t}; \qquad \varepsilon_{\mathrm{i,t}} \left| (\varepsilon_{\mathrm{i,t-1}}, \varepsilon_{i,t-2}, \ldots\ldots\ldots) \right. \sim N(0, \sigma^2_{i,t})$$

$$\sigma^2_{i,t} = \alpha_0 + \alpha_1\, \varepsilon^2_{i,t-1} + \delta_1\, \sigma^2_{i,t-1} + \delta_2 \sigma^2_{i,t-2} + \delta_3 \sigma^2_{i,t-3} + \lambda_1\, S_{i,t-1}\varepsilon^2_{i,t-1}$$

$$\text{Where } : S_{i,t-1} = \begin{Bmatrix} 1, \text{if } \ \varepsilon_{\mathrm{i,t-1}} < 0 \\ 0, \text{otherwise} \end{Bmatrix} \tag{2}$$

Table 3.2 sets forth results of estimating equation 2 and shows that most of the estimated coefficients of the ARCH term (α_1) and the three GARCH terms $(\delta_1, \delta_2, \delta_3)$ are highly significant at 1% for almost all of the countries. Moreover, the asymmetry parameters are statistical significant for most of the countries, indicating the presence of the leverage effect. This indicates that GJR-GARCH is an acceptable representation of international returns and shows the existence of changing conditional variance in return series in international markets.

In the second test, the following three international asset pricing models are investigated relative to my model in order to examine which model best describes international returns data:

One factor global CAPM: $r_{i,t} - r_{f,t} = \beta_0 + \beta_1\left(\mathrm{r}_{\mathrm{g,t}} - r_{f,t}\right) + \varepsilon_{\mathrm{i,t}}$ (3)

Global CAPM with foreign exchange risk:

$$r_{i,t} - r_{f,t} = \beta_0 + \beta_1\left(\mathrm{r}_{\mathrm{g,t}} - r_{f,t}\right) + \beta_2\left(Pound\right) + \beta_3\left(Mark\right) + \beta_4\left(Yen\right) + \varepsilon_{\mathrm{i,t}} \quad (4)$$

Fama-French two factor model: $r_{i,t} - r_{f,t} = \beta_0 + \beta_1\left(r_{\mathrm{g,t}} - r_{f,t}\right) + \beta_2\left(H - L\right) + \varepsilon_{\mathrm{i,t}}$ (5)

Table 3.3 sets forth the intercepts obtained from each model. They should be insignificantly different from zero if the model fits the data well. The average intercept of the GJR–GARCH–FF model is lower than that of the other three models. Specifically, the average intercept of the GJR-GARCH-FF model is lower in magnitude and significance than the intercept of the one factor global CAPM and the global CAPM with foreign exchange risk. More importantly, the average mean in the GJR-GARCH-FF model is lower than the FF model in nine out of thirteen countries, particularly important because three of these nine countries are G5 countries – USA, France, and Italy.

Additional evidence comes from Table 3.4 that presents results of the remaining estimated coefficients of the mean equation ($\beta_1, \beta_2, \beta_3, \beta_4, and\ \beta_5$) in the GJR-GARCH-FF model. The FF two-factor model and the GJR-GARCH-FF model produce similar market and value slopes with similar levels of significance. This indicates that adding the exchange risk premium and the conditional volatility equation yields better results in describing international returns.

Table 3.2 Maximum Likelihood Estimates of GJR-GARCH (3, 1, 1) Model – Without Risk Factors
(Entire Sample Period: January 1975 – December 2007)

Country Name	α_1	δ_1	δ_2	δ_3	λ_1
Australia	0.0404*** (0.0114)	2.3619*** (0.0404)	-2.2783*** (0.0706)	0.8838*** (0.0417)	-0.0356*** (0.0110)
Belgium	0.1913*** (0.0506)	0.0942** (0.0446)	-0.0830** (0.0448)	0.7013*** (0.0826)	0.0703 (0.0693)
France	0.0426*** (0.0184)	2.0433*** (0.0443)	-1.8961*** (0.0770)	0.7690*** (0.0498)	0.0630** (0.0259)
Germany	0.1621** (0.0688)	0.2898 (0.2432)	0.4931* (0.2876)	-0.0511 (0.3052)	-0.0107 (0.0674)
Hong Kong	0.2192*** (0.0662)	0.5077*** (0.1672)	0.8461*** (0.0373)	-0.5112*** (0.1542)	-0.1616*** (0.0595)
Italy	0.0177*** (0.0002)	-0.7249*** (0.0107)	1.0052*** (0.0017)	0.7341*** (0.1086)	0.0035 (0.0077)
Japan	0.03112* (0.0192)	1.1706*** (0.0375)	-1.1580** (0.0525)	0.8761*** (0.0453)	0.0768** (0.0309)
Netherlands	-0.0379 (0.0255)	0.7928*** (0.0800)	-0.8175*** (0.1008)	0.6258*** (0.0898)	0.1665*** (0.0555)
Singapore	0.0844*** (0.0177)	0.8196*** (0.0261)	0.8737*** (0.0261)	-0.7652*** (0.0143)	-0.0597*** (0.0186)
Sweden	0.1602*** (0.0552)	0.7983*** (0.0995)	-0.7519*** (0.1049)	0.5746*** (0.1133)	0.0931 (0.0791)
Switzerland	0.3084*** (0.0938)	-0.3907*** (0.1207)	0.6247*** (0.0701)	0.3168** (0.1677)	-0.1953** (0.0852)
UK	0.0788*** (0.0247)	1.7593*** (0.046262)	-1.6134*** (0.0951)	0.7090*** (0.0550)	0.0400 (0.0288)
USA	-0.0620 (0.0637)	0.0852 (0.1927)	0.3766** (0.1690)	0.1134 (0.1802)	0.3508*** (0.1300)

*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level.

Table 3.3 Comparison of Different International Asset Pricing Models:

Country Name	One Factor Global CAPM	Global CAPM with FX Risk	FF Model	GJR-GARCH-FF Model
Australia	0.328853 (0.282700)	0.321424 (0.286223)	0.120349 (0.286348)	0.0780 (0.25665)
Belgium	0.405651** (0.206155)	0.394714* (0.207974)	0.356302* (0.211370)	0.3583* (0.1942)
France	0.228604 (0.240311)	0.185902 (0.240505)	0.319353 (0.245871)	0.1062 (0.1509)
Germany	0.271052 (0.208022)	0.268132 (0.205090)	0.183952 (0.212662)	0.2472 (0.1981)
Hong Kong	0.677500* (0.376465)	0.640320* (0.380580)	0.523385 (0.384936)	0.3869 (0.3411)
Italy	0.116628 (0.313361)	0.170572 (0.317154)	0.059972 (0.321484)	0.0329 (0.2709)
Japan	-0.246033 (0.165586)	-0.296351* (0.157472)	-0.199058 (0.169678)	-0.2254 (0.1673)
Netherlands	0.432684* (0.175061)	0.456496*** (0.173707)	0.408708** (0.179660)	0.2165 (0.1616)
Singapore	0.323239 (0.308772)	0.259758 (0.308973)	0.044425 (0.310601)	0.1539 (0.2690)
Sweden	0.442448* (0.265767)	0.421945 (0.265129)	0.464788* (0.272828)	0.3766 (0.2439)
Switzerland	0.342963* (0.723976)	0.339132* (0.193750)	0.291839 (0.197005)	0.1671 (0.1895)
UK	0.361359* (0.217785)	0.442408** (0.190551)	0.309597 (0.223299)	0.0661 (0.1289)
USA	0.336955* (0.183803)	0.292019 (0.181723)	0.340052* (0.188718)	0.2332 (0.1799)

*Significant at 10% level, **Significant at 5% level

The final diagnostic test is the ARCH LM Test, which is a Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) in the residuals since ignoring ARCH effects may result in a loss of efficiency. To test the null hypothesis that there is no ARCH up to order q in the residuals, a regression of the squared residuals (ε_t^2) on constant and lagged squared residuals up to order q is run, as follows:

$$\varepsilon_t^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s \, \varepsilon_{t-s}^2 \right) + \mu_t$$

This particular specification of heteroskedasticity is motivated by the observation that in many financial time series, the magnitude of residuals appears to be related to the magnitude of recent residuals.

Table 3.4 Maximum Likelihood Estimates of the GJR-GARCH-FF (3, 1, 1) Model:
(Entire Sample Period: January 1975 – December 2007)

Country Name	β_1	β_2	β_3	β_4	β_5
Australia	0.9643***	0.3035***	-13.2677	12.1657	-8.4258
	(0.0475)	(0.0874)	(14.9505)	(9.4389)	(10.0956)
Belgium	0.7842***	0.1209**	11.4240	4.4949	-7.1480
	(0.0354)	(0.0605)	(8.8093)	(2.9505)	(6.2745)
France	1.0488***	-0.0085	-15.8766	12.7131***	-18.6552***
	(0.0369)	(0.0487)	(10.6198)	(2.2681)	(6.4500)
Germany	0.8841***	0.1217**	-2.7082	14.4222***	-18.0845**
	(0.0394)	(0.0605)	(8.2640)	(2.0880)	(7.2382)
Hong Kong	0.9744***	0.1623	-2.7809	-9.9128	8.6519
	(0.0684)	(0.1124)	(16.6076)	(15.0074)	(15.6419)
Italy	0.9720***	0.0887	-0.7660	2.9652	-4.0444
	(0.0645)	(0.0882)	(13.1864)	(9.6852)	(10.7835)
Japan	1.1148***	-0.0484	-26.408***	-6.0782*	32.1272***
	(0.0302)	(0.0486)	(9.2015)	(3.4905)	(6.5921)
Netherlands	0.8727***	0.0550	1.9586	-4.0104	-20.3498***
	(0.0339)	(0.0428)	(6.6565)	(3.6234)	(5.9884)
Singapore	0.7769***	0.4051***	-11.3974	-8.1434	7.9714
	(0.0535)	(0.1007)	(15.1652)	(13.2926)	(10.9933)
Sweden	0.9607***	0.0879	-24.3429*	13.6049	-25.6233***
	(0.0521)	(0.0786)	(12.7325)	(11.4274)	(10.0470)
Switzerland	0.6878***	0.1009*	6.6354	5.4241**	-0.5114
	(0.0336)	(0.0619)	(8.6565)	(2.7425)	(7.0024)
UK	0.8400***	0.1142***	38.8402***	1.2024	-13.7862**
	(0.0307)	(0.0411)	(8.9922)	(5.1374)	(5.4624)
USA	0.6063***	-0.0324	-21.8383**	5.2890	-22.2785***
	(0.0345)	(0.0404))	(10.5614)	(8.4082)	(8.4195)

*Significant at 10% level, **Significant at 5% level

If the variance equation is correctly specified, there should be no ARCH remaining in the standardized residuals. Table 3.5 reports the results of the F-statistics for the Lagrange Multiplier test. The values of

LM are insignificant for all countries (except France). This result leads to the rejection of the null hypothesis (i.e., the residuals are homoscedastictic), meaning that the variance equation in the GJR-GARCH model has been correctly formulated.

Table 3.5 ARCH-LM Test of the GJR-GARCH-FF model

Country Name	ARCH-LM				
	Lag (1)	Lag (2)	Lag (3)	Lag (4)	Lag (5)
Australia	0.0032 (0.0510)	-0.0126 (0.0509)	0.0264 (0.0508)	0.0930 (0.0555)	0.0036 (0.0557)
Belgium	-0.0250 (0.0509)	0.0297 (0.0512)	-0.0148 (0.0512)	-0.0280 (0.0511)	0.0261 (0.0511)
France	0.1184* (0.0510)	0.0576 (0.0514)	-0.0443 (0.0514)	0.0324 (0.0514)	0.0072 (0.0510)
Germany	-0.0511 (0.0508)	0.0423 (0.0508)	0.0382 (0.0508)	-0.0364 (0.0507)	0.0299 (0.0508)
Hong Kong	-0.0398 (0.0508)	0.0266 (0.0508)	0.0191 (0.0506)	-0.0265 (0.0506)	0.1024 (0.0505)
Italy	0.0415 (0.0511)	0.0071 (0.0512)	0.0085 (0.0511)	-0.0029 (0.0512)	0.0081 (0.0511)
Japan	0.0008 (0.0506)	-0.0016 (0.0506)	0.0009 (0.0505)	0.0752 (0.0505)	0.0276 (0.0506)
Netherlands	-0.0013 (0.0508)	-0.0251 (0.0508)	0.0312 (0.0507)	0.0572 (0.0507)	-0.0040 (0.0508)
Singapore	-0.0007 (0.0510)	-0.0213 (0.0510)	-0.0288 (0.0510)	0.0436 (0.0513)	0.0008 (0.0514)
Sweden	-0.0085 (0.0507)	0.0397 (0.0507)	-0.0039 (0.0509)	-0.0146 (0.0509)	-0.0411 (0.0509)
Switzerland	0.0305 (0.0516)	0.0192 (0.0516)	0.0547 (0.0515)	-0.0175 (0.0516)	0.0303 (0.0514)
UK	0.0351 (0.0510)	0.0074 (0.0510)	0.0060 (0.0514)	0.0078 (0.0514)	-0.0422 (0.0514)
USA	-0.0288 (0.0508)	0.0780 (0.0507)	-0.0017 (0.0509)	0.0213 (0.0508)	0.0082 (0.0508)

3.4.2 Fundamental Riskiness of the Global Value Premium

Following the approach of Lakonishok et al. (1994) where a fear of market breakdown causes risk-averse investors to rush to quality and liquidity, I examine the performance of global value strategies (high BE/ME – low BE/ME) for the thirteen countries in the sample during financial crises. The rationale is that if value stocks are fundamentally riskier than glamour stocks, then risk-averse investors should replace risky value stocks with less risky glamour stocks during economic recessions when the marginal utility of consumption is especially high[6]. Therefore, one would expect the global premium coefficient (β_2) from equation (1) during crisis period to be lower than that of pre-crisis and post crisis period.

Table 3.6 reports results of the estimated coefficients of the global value premium (β_2) from equation (1) for pre-crisis, crisis, and post-crisis periods for the international debt crisis. Although several of the world's largest banks faced the prospect of major loan defaults as a consequence of the crisis, the fear of a widespread banking collapse in creditor countries was concentrated primarily in the USA and Japan[7]. It is easy to understand, therefore, that Japan is the only country in table 3.6 whose global premium coefficient is lower during crisis period than during pre-crisis and post-crisis periods.

[6] A striking example that supports the rationale of such an approach is the collapse of Long-Term Capital Management (LTCM). In January 1998, the spread between high-yield corporate bonds and US treasuries was 4 percentage points. LTCM believed that such spread was excessively wide as a consequence of the Asian crisis, and that this spread would narrow when the crisis ended. Consequently, LTCM engaged in 'market neutral arbitrage' by longing high-yielding, less liquid bonds and shorting low-yielding, more liquid bonds. By August 1998, the crisis continued and fear spread over the world because of the collapse of the Russian market. Consequently, the spread between US B-rated bonds and high-rated corporate bonds rose from 2 percentage points before the crisis to 5.7 percentage points. This wide spread led to the collapse of the LTCM by September 1998 (Edwards, 1999).

[7] The US banks' exposure was the highest because the major debtors were concentrated in Latin America. The largest Latin American countries (Mexico, Brazil, Venezuela, and Argentina) owed the eight largest US banks $37 billion that constituted 147% of their capital and reserves at the end of 1983. The size of such debt coupled with the overexposure (lending in excess of capital assets) gave rise to a fear of financial collapse to the largest American banks such as Citibank, Bank of America, Chase Manhattan, and Morgan Guaranty (FDIC, 1997). The Japanese banks also had a similar rate of debt exposure. the exposure level of the Bank of Tokyo (that handled $753 million as the leading international bank in forming syndicate loans by 1981 in Mexico) was 83% of its capital, and the exposure of Long-Term Credit Bank of Japan and Mitsui Bank was 53.6% and 28.3%, respectively (Katada, 2001).

In particular, the (β_2) coefficient is positive for Japan during the pre-crisis period (0.3290) and turned negative during the crisis period (– 0.3371). In addition, the estimated global premium coefficient for the US during the crisis period was negative (–0.1010) before turning positive after the crisis (0.0448).

Table 3.6 Global Value Premium Coefficient Estimates of GJR-GARCH-FF Model: International Debt Crisis (1982-83)

Country Name	Pre-Crisis Period: (Aug 1979 – July 1982)	Crisis Period: (Aug 1982 – Dec 1983)	Post-Crisis Period (Jan 1984 – Dec 1986)
	$\beta_{2,before}$	$\beta_{2,crisis}$	$\beta_{2,after}$
Australia	-0.4453* (0.2621)	-0.0813 (0.6037)	-0.2510 (0.4317)
Belgium	-0.5381 (0.5294)	-0.1569 (0.8401)	0.0155 (0.2979)
France	-0.7886** (0.3969)	0.6853 (0.6592)	-0.1085 (0.3112)
Germany	0.2683 (0.2054)	0.1199 (1.0788)	0.5183 (0.3172)
Hong Kong	-0.2520 (0.6464)	2.4366* (1.3502)	-0.1873 (0.6179)
Italy	-0.0442 (0.7555)	0.1242 (0.9172)	1.1072** (0.4665)
Japan	0.3290 (0.2533)	-0.3371 (0.4127)	-0.0728 (0.2117)
Netherlands	-0.7365** (0.3645)	0.4856 (0.8571)	-0.1452 (0.2397)
Singapore	0.6844 (0.5894)	1.6578** (0.4698)	0.4164** (0.2322)
Sweden	-0.2599 (0.4127)	0.3164 (1.7647)	-0.0732 (0.3203)
Switzerland	-0.0473 (0.3105)	0.2666 (0.7027)	0.3016 (0.2157)
UK	-0.2452 (0.4686)	-0.0155 (0.3465)	-0.0789 (0.5196)
USA	-0.2296 (0.3489)	-0.1010 (0.5670)	0.0448 (0.1820)

*Significant at 10% level, **Significant at 5% level.

Table 3.7 sets forth the values of the (β_2) coefficient estimates before, during, and after the Asian crisis. The Asian crisis began as a currency crisis where the Asian countries were subject to a series of speculative currency attacks starting with Thai baht, followed by Malaysian ringgit and Singapore dollar. These events raised fears of worldwide economic meltdown due to contagion effects. Such fear is in line with the results in table 3.7 that indicate that (β_2) coefficients during the crisis period are lower than those during the pre-crisis period for nine out of thirteen countries. The results from Tables 3.6 and 3.7 support the risk explanation of the global risk premium, although the results are weak since most of the estimated coefficients are insignificant.

Table 3.7 Global Value Premium Coefficient Estimates of GJR-GARCH-FF Model: Asian Crisis (1997-99)

Country Name	Pre-Crisis Period: (July 1994-June 1997)	Crisis Period: (July 1997- Mar 1999)	Post-Crisis Period (April 1999 – Mar 2002)
	$\beta_{2,before}$	$\beta_{2,crisis}$	$\beta_{2,after}$
Australia	0.1805 (0.4098)	0.1108 (0.4847)	0.3172** (0.1339)
Belgium	0.4891*** (0.3244)	-0.5747* (0.3172)	0.3030* (0.1872)
France	0.4811 (0.4432)	-0.0526 (0.2416)	0.0456 (0.0741)
Germany	0.8470** (0.4286)	-0.1182 (0.3106)	-0.1212 (0.1306)
Hong Kong	0.5641 (1.0583)	-0.4689 (0.8817)	-0.0110 (0.1842)
Italy	0.9196 (0.9246)	-0.0107 (0.4164)	-0.2834** (0.1229)
Japan	-0.8629*** (0.3077)	-0.0874 (0.4965)	-0.1214*** (0.1030)
Netherlands	0.7653** (0.3350)	-0.4296 (0.3171)	0.1409** (0.0830)
Singapore	1.8167*** (0.4452)	-0.2188 (0.7141)	0.2307 (0.3108)
Sweden	0.3529 (0.7445)	0.4417 (0.4403)	-0.3953 (0.3260)
Switzerland	-0.9893** (0.4824)	-0.1612 (0.2379)	0.1940** (0.1079)
UK	0.2333 (0.2988)	0.1233 (0.1884)	0.0853* (0.0503)
USA	0.1535 (0.4239)	0.1593 (0.4444)	0.0118 (0.1581)

*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level.

3.4.3 Financial Crises and Integration

This section investigates the impact of financial crises – via contagion – on the integration of international financial markets. By comparing the coefficients from regressing each country's portfolio return on the global market premium (β_1) from equation (1) for each of the pre-crisis, crisis, and post-crisis periods, I can measure the impact of the financial crises on the integration of financial markets.

Table 3.8 presents the values of (β_1) from equation (1) covering the three sub-periods of the international debt crisis. Comparison of results from the pre-crisis period and crisis period reveals that the size of (β_1) is greater in the pre-crisis period for ten out of thirteen countries – Australia, France, Hong Kong, Italy, Netherlands, Singapore, Sweden, Switzerland, the UK, and the USA. Surprisingly, Hong Kong and Australia were positively correlated with the global market portfolio before the crisis but become negatively correlated during the crisis. Comparison of the (β_1) coefficient from the pre-crisis

Table 3.8 Global Market Portfolio Coefficient Estimates of GJR-GARCH-FF Model: International Debt Crisis (1982-83)

Country Name	Pre-Crisis Period: (Aug 1979 – July 1982)	Crisis Period: (Aug 1982 – Dec 1983)	Post-Crisis Period (Jan 1984 – Dec 1986)
	$\beta_{1,before}$	$\beta_{1,crisis}$	$\beta_{1,after}$
Australia	1.1118*** (0.1645)	-0.8127** (0.6037)	0.9756*** (0.2682)
Belgium	0.7081*** (0.1977)	1.2394** (0.5000)	0.7800*** (0.2083)
France	1.4178*** (0.1582)	0.3092*** (0.2866)	0.8442*** (0.1412)
Germany	0.6757*** (0.1207)	0.9942** (0.5261)	0.8924*** (0.2111)
Hong Kong	1.7771*** (0.3810)	-0.0610 (0.9762)	0.4731 (0.4257)
Italy	0.8516** (0.3708)	-0.1291 (0.3584)	0.8011*** (0.2779)
Japan	0.8794** (0.1042)	1.5407*** (0.2443)	1.2304*** (0.1254)
Netherlands	0.9569*** (0.2528)	0.7272 (0.6111)	0.8119*** (0.1915)
Singapore	0.9028*** (0.3008)	0.7586 (0.5511)	0.3864** (0.1693)
Sweden	0.5523* (0.2107)	0.2716 (1.1124)	0.6633*** (0.1918)
Switzerland	0.9842*** (0.1539)	0.8704** (0.4140)	0.6158*** (0.1450)
UK	1.1464*** (0.2078)	0.6680*** (0.2245)	0.7515*** (0.2333)
USA	0.6064*** (0.1236)	0.4640 (0.3973)	0.2636 (0.1943)

period and the post-crisis period leads to similar conclusions. Except for Belgium, Germany, Japan, and Sweden, the β_1 coefficient (β_1) is higher in the pre-crisis period than the post crisis-period. Thus, it appears that international financial markets became less integrated after the debt crisis.

Table 3.9 sets forth the values of (β_1) coefficient for the Asian crisis. Its contents are contradictory to those in Table 3.8 since twelve out of thirteen countries became more integrated (reveal greater (β_1) coefficients) during the Asian crisis relative to the pre-crisis period. Comparison of the pre-crisis period and the post crisis period confirms the results since (β_1) coefficients estimated using the post crisis period are higher than those calculated in the pre-crisis period for all of the sample countries except Japan. Thus international financial markets became more integrated after the Asian crisis.

Table 3.9 Global Market Portfolio Coefficient Estimates of GJR-GARCH-FF Model: Asian Crisis (1997-99)

Country Name	Pre-Crisis Period: (July 1994-June 1997)	Crisis Period: (July 1997- Mar 1999)	Post-Crisis Period (April 1999 – Mar 2002)
	$\beta_{1,before}$	$\beta_{1,crisis}$	$\beta_{1,after}$
Australia	0.8989*** (0.1553)	0.9518*** (0.2587)	1.0722*** (0.1907)
Belgium	0.4622*** (0.1150)	0.7729*** (0.2746)	0.6847*** (0.1642)
France	0.7650*** (0.2547)	1.2847*** (0.2119)	1.3981*** (0.1167)
Germany	0.4787*** (0.1880)	1.1914*** (0.1613)	1.1999*** (0.1302)
Hong Kong	0.9859*** (0.2522)	1.0754** (0.5796)	1.1230*** (0.1627)
Italy	0.6643** (0.3455)	1.3755*** (0.3069)	0.9783*** (0.1523)
Japan	1.5024*** (0.1284)	0.9548** (0.5770)	1.1388*** (0.1487)
Netherlands	0.7934*** (0.1282)	1.1156*** (0.2226)	1.0179*** (0.0728)
Singapore	0.4034** (0.2047)	1.1090 (0.7783)	0.8577*** (0.2638)
Sweden	0.6191** (0.3642)	1.5156*** (0.2108)	1.7028*** (0.2346)
Switzerland	0.5049** (0.2189)	0.7889*** (0.2141)	0.5832*** (0.1156)
UK	0.6108*** (0.1374)	0.7577*** (0.1011)	0.7841*** (0.0573)
USA	0.4899*** (0.1415)	0.9140*** (0.2371)	0.9726*** (0.1816)

For the selected sample period, the above results indicate that if the international debt crisis is considered regional while the Asian crisis is considered global, effects of crises are dependent upon the geographic impact of the individual crisis. In other words, financial crises with regional effects (such as the less developed debt crisis that affected primarily Latin American countries) decrease financial integration, while crises with global effects (such as the Asian crisis) increase integration. This new evidence raises the issue of appropriate economic explanation. I believe the international debt crisis reflects intra-regional contagion effects, while the Asian crisis reflects global herding behavior[8].

During regional crises (such as the international debt crisis), investors pay little attention to international news and focus primarily on regional news. In particular, when Mexico declared its inability to pay its debt obligations in 1982, intra-regional contagion took place since difficulties in interest payments were evident in most of the Latin American countries (e.g., Argentina, Brazil, Bolivia, Ecuador and Venezuela). Consequently, investors began to withdraw their investments from the Latin American market for safer markets. As a result, the Latin American countries adopted restrictive capital controls for self-protection, further segmenting their markets. This implies an increase in gains from global market portfolio diversification, since the Latin American countries become less integrated with the world.

In contrast to regional crises, global crises (such as the Asian crisis) affect the remainder of the world. Investors' decisions are affected not only by their local countries' situation, but also by other countries' markets. This is evident in the Asian crisis when the Asian markets, with their vast global capital flows, rode out their crises with increased cooperation not only with each other but with the remainder of the world. As the Asian crisis continued and the global stock markets plummeted one after another in Europe and in the United State and fear spread over the world, the herding behavior prevails (i.e., investors start to follow the crowd leading to a uniform behavior among international investors). This leads to a higher integration among international markets and, consequently, to lower diversification benefits since equity markets are exposed to common systematic risk.

[8] Chiang et al. (2007) differentiates between 'contagion' and 'herding' in the sense that the former reflects the spread of one shock from one market to another, while the latter describes the mechanism of a behavioral convergence among investors' sentiments.

3.5 Robustness Tests: Short-term Effects (Within Crisis Period Analysis)

A common problem in empirical research of financial crises is that results might be affected by the choice of window length. That is, my choice of duration of three years before and three years after the crises may have an impact on the results. Therefore, I need another test that is not sensitive to period duration to verify whether my period definition affects the central results. Therefore, I report month-by-month returns on the highest BE/ME (value) relative to the lowest BE/ME (growth) portfolios for four crises: the Latin American debt crisis (1982-1983), the European Monetary System (ERM) crisis (1992-1993), the Asian crisis (1998-1999), and the September 11, 2001 attack. If global value stocks are fundamentally riskier, one would expect a negative return for the value strategies during financial crises.

3.5.1 International Debt Crisis

As mentioned earlier, US and Japanese banks' exposure was the greatest and they faced the prospect of major loan defaults and failure as a consequence of the crisis. Table 3.10 reveals that monthly returns on the US value strategy are negative in the three months following August 1982, the starting month of the crisis. In addition, the average value premium during the entire crisis period (August 1982 – December 1983) in the USA and Japan is zero and -0.68%, respectively. The value premium of -1.15 for Hong Kong may relate to Hong Kong's close relationship to Japan. Although the European banks had less exposure to third world lending than did the U.S. and Japanese banks, the value strategy in August and September of 1982 yielded negative returns in the UK, Germany, and Italy where the major European banks are located.

3.5.2 ERM Crisis[9]

Table 3.11 shows the month-by-month returns of the value strategy during the ERM crisis from September, 1992 until December, 1993, and reflects the fear of investors during the period.

[9] The ERM crisis of 1992-1993 is a crisis of the exchange rate system. A primary reason for the crisis is the difference in economic strength of members of ERM. Germany witnessed a strong economy and was concerned about domestic inflation and raised its interest rate to 8.7%. The UK and Italy, however, were suffering from recession and severe budget deficits, forcing them to adopt stimulative policies by reducing interest rates. Such contradiction dramatically widened the interest rate differentials between Germany and other ERM members.

Table 3.10 Month-by-Month Returns during the International Debt Crisis Period
(August 1982 – December 1983): Value – Growth

	Australia	Belgium	France	Germany	HK	Italy	Japan	Neth.	Sing.	Sweden	Switz.	UK	USA	Australia
08/82	-1.46	-1.58	1.65	-0.24	6.93	-4.58	-0.73	-6.31	1.59	2.68	0.29	-4.18	1.1	-1.46
09/82	-1.09	-0.39	-2.97	-4.55	6.04	-5.86	-1.92	6.21	12.15	-4.07	-0.64	-12.65	-1.55	-1.09
10/82	-2.84	3.2	5.27	-4.94	-1.19	-3.83	-2.34	5.56	9.61	-7.99	0.79	9.49	-3.52	-2.84
11/82	-0.95	-2.76	3	-3.47	2.6	2.77	-2.22	5.96	-0.49	-16.97	-5.31	0.79	-3.55	-0.95
12/82	0.96	0.92	4.23	5.69	5.25	-5.51	2.76	-7.07	-0.95	-0.59	1.46	1.89	0.11	0.96
01/83	-5.26	2.75	9.87	0.97	-2.64	-7.99	3.16	-8.21	11.61	15.48	4.44	8.76	1.79	-5.26
02/83	3.89	3.7	-3.55	4.02	4.97	9.65	4.82	12.94	3.24	-0.89	1.58	3.3	-1.62	3.89
03/83	2.44	1.54	-1.26	5.7	-8.18	19.62	-2.61	-3.96	2.45	-1.48	0.8	3.94	0.67	2.44
04/83	5.44	-4.43	7.55	-1.1	-1.54	-2.13	-3.44	-7.02	-2.74	-10.46	4.71	1.42	1.07	5.44
05/83	-2.17	2.44	4.07	-4.39	-8.81	-2.33	-6.34	6.93	0.17	-1.61	-4.1	1.41	-0.87	-2.17
06/83	1.89	-3.31	3.5	0.72	0.45	-7.83	-4.04	0.74	-1.2	5.69	1.72	3.62	-4.79	1.89
07/83	6.61	5.85	-6.42	4.69	-3.56	2.02	-4.76	2.18	-1.23	3.33	2.74	2.23	4.41	6.61
08/83	4.48	1.61	15.83	0.42	-8.15	2.56	2.6	-3.84	-2.93	6.35	-2.74	3.55	5.81	4.48
09/83	7.52	5.16	-8.62	2.36	-7.46	1.59	0.42	-1.45	4.15	0.33	2.51	-0.12	-1.38	7.52
10/83	1.89	5.19	-1.29	1.58	-6.15	-4.44	2.36	3.12	-2.51	0.45	5.64	2.25	3.65	1.89
11/83	3.65	-8.37	0.46	2.62	-0.98	6.54	-2.71	1.62	-0.6	2.24	-3.84	3.4	-1.4	3.65
12/83	-3.45	8.59	-0.03	-2.11	2.82	4.28	3.42	-1.19	-1.36	6.61	-2.28	6.92	0.12	-3.45
Average	1.27	1.18	1.84	0.47	-1.15	0.27	-0.68	0.37	1.82	-0.05	0.46	2.12	0.00	1.27

For September 1992, Italy earned the highest negative return (-9.98%) followed by Sweden with a return of -9.20% for the value strategy, reflecting speculation against the Italian Lira. On September 11, 1992 the Italian Lira was the first victim of the crisis as it was subject to severe speculative attacks. On September 17, the Lira was withdrawn from the ERM after it fell below its ERM floor. The speculative attacks turned to Sweden's currency, forcing the Riksbank to raise its lending rate on September 8 to 24% and then 75% the next day (Sevilla, 1995).

In contrast to the Italian Lira, the French Franc remained a strong currency. However, it was subject to massive speculative sales in July-August 1993, but by the end of 1993 it returned to levels close to those prevailing before the crisis. These facts are in line with the results in table 3.11 that indicate that French data reveals a positive return for the first two months of the crisis, but the return on the value premium turns negative from August 1993 until November 1993, the same period as the Franc devaluation due to massive speculative sales in July-August 1993.

Giavazzi and Giovannini (1989) point out that the US dollar tends to be weak in foreign exchange markets when the EMS is unstable. The ERM crisis mirrored such regularity, since the US dollar reached its lowest value in September 2, 1992 which is the official starting month of the crisis (Edison and Kole, 1995). As table 3.11 shows, it seems that fear spread from the European countries at that time to the US because the value strategy in the US yields negative return during the early stage (September – November 1992) and the final stage (August – November 1993) of the ERM crisis.

3.5.3 Asian Crisis

Although data from the international debt crisis and the ERM crisis supports the risk story of the value premium, the strongest supporting evidence is from the Asian Crisis. Table 3.12 presents the monthly returns of the value strategy relative to the growth strategy during the Asian crisis, mirroring the chronological events. The table indicates a negative return on the value premium in July 1997 (the starting month of the crisis) for nine out of thirteen countries, and in October 1997 for Hong Kong (when the Hong Kong dollar came under attack and the Hong Kong stock index lost roughly 30% of its value (Kaminsky and Schmukler, 1999)). Also, the November return for the same strategy in Japan is -5.65%,

Table 3.11 Month-by-Month Returns during the ERM Crisis
(September 1992 – December 1993): Value – Growth

	Australia	Belgium	France	Germany	HK	Italy	Japan	Neth.	Sing.	Sweden	Switz.	UK	USA
09/92	3.48	0.43	1.13	-4.61	5.74	-9.98	-1.13	-5.08	-0.76	-9.2	-8.81	0.13	-0.43
10/92	6.48	-5.07	1.65	-3.1	-2.91	2.13	3.48	-16.93	-2.99	-14.94	-2.77	2.4	-1.67
11/92	6.28	-2.77	-2.08	0.54	2.2	2.22	1.33	0.59	2.03	15.38	-8.87	0.09	-0.36
12/92	-6.82	5.87	3.27	2.84	-7.16	1.97	1.38	-1.6	0.22	-6.54	-4.88	5.55	2.76
01/93	1.31	2.55	0.75	3.04	2.22	0.92	-1.29	8.78	-4.63	15.09	15.81	2.84	6.37
02/93	-2.31	6.51	4.04	-0.62	1.53	12.46	-2.39	-11.8	8.9	-5.13	5.22	4.42	5.28
03/93	1.66	2.81	-4.91	0.16	1.38	-0.03	6.06	11.76	0.17	-3.87	1.17	5.17	1.07
04/93	5.06	-1.34	1.25	-1.83	2.21	-0.54	3.07	2.78	7.34	-5.78	1.21	1.84	3.6
05/93	2.47	-0.02	0.35	-0.7	-2.73	-8.18	-2.69	7.82	-2.2	4.36	-2.23	-0.62	-3.29
06/93	1.45	-1.4	3.71	5.4	4.88	0.7	-2.61	3.05	-3.88	-1.39	-3.32	2.31	4.02
07/93	6.89	4.53	5.11	-1	-7.58	3.44	3.12	7.59	2.59	7.67	9.62	2.6	3.62
08/93	3.12	4.66	-1.67	1.62	-8.43	-1.19	0.79	4.46	-5.4	-0.34	-3.15	-1.11	-0.39
09/93	3.07	1.66	-2.72	0.84	-1.22	-7.35	-0.6	0.96	8.93	-17.15	-5.91	2.66	-0.19
10/93	-3.3	1.54	-1.04	0.19	4.15	-1.55	3.31	-2.79	0.21	12.41	-1.55	-1.84	-1.91
11/93	-2.6	2.65	-2.35	-0.32	5.57	2.98	-1.81	-1.34	-6.47	15.98	0.4	1.41	-1.4
12/93	-4.84	-0.33	0.02	5.34	13.48	5.57	7.2	-0.47	29.4	7.21	4.5	2.02	0.9
Average	1.34	1.39	0.41	0.49	0.83	0.22	1.08	0.49	2.09	0.86	-0.22	1.87	1.12

reflecting the collapse of Hokkaido Takushoku Bank Ltd which was one of the biggest Japanese banks at that time. On January, 1998 another catastrophic financial event occurred – the collapse of the Peregrine Investment Holdings, the then largest private investment bank in Asia. Peregrine was based in Hong Kong, and this might explain the extremely poor performance of value stocks relative to growth stocks on January 1998 for Hong Kong (-21.86%) and Singapore (-27.83%). Table 3.12 data for June 1998 is in line with the crash of the Russian stock market because of Russia's inability to pay its debts. Final evidence comes from the collapse of the LTCM in September 1998 that raised fears of the breakdown of the entire international banking system. This is again consistent with the negative return on the US (-2.49%) and especially the Japanese (-3.62%) value premium. Overall, ten out of thirteen countries had average negative returns on the value strategy over July 1997 to March 1999. The results from tables 3.10 and 3.12 are in line with the results from tables 3.6 and 3.7, and they support the risk explanation of the global risk premium.

3.5.4 September 11, 2001 Attack

The last crisis examined is the terrorist attack on the US on September 11, 2001. Unlike the previous three examined crises that covered more than 12 months, the analysis of the September 11, 2011 crisis covers only a few months. This gives a more clear-cut explanation of the global value premium. The figures in Table 3.13 reflect the performance of the value strategy relative to the growth strategy surrounding the attack period (April 2001– February 2002). The most striking observation is that the value stocks underperformed the growth stocks on September 2001 for ten of thirteen countries. In particular, the return on the value strategy on September 2001 was negative for these ten countries.

Table 3.12 Month-by-Month Returns during the Asian Crisis
(July 1997 – March 1999): Value – Growth

	Australia	Belgium	France	Germany	HK	Italy	Japan	Neth.	Sing.	Sweden	Switz.	UK	USA
07/97	2.59	-4.54	5.81	-5.57	-12.73	-3.16	-7.69	-0.13	-1.21	-1.34	0.42	2.32	-1.38
08/97	1.68	6.69	4.64	2.59	12.24	0.31	0.33	1.27	24.23	2.04	7.8	3.59	3.03
09/97	5.26	-3.36	7.52	-4.14	-8.78	1.86	-7.74	4.34	-13.98	-2.24	-2.83	-4.91	0.56
10/97	2.92	-1.16	5.1	-0.74	-9.73	7.84	2.00	-6.64	-10.04	-0.88	-4.09	1.83	0.99
11/97	6.61	0.84	-4.4	4.28	5.62	-8.18	-5.65	-4.75	-12.69	-2.59	-0.41	0.62	-1.53
12/97	-1.34	-2.71	2.2	-2.28	3.32	1.8	-5.92	-0.22	-2.55	0.88	-4.33	-3.76	3
01/98	-2.23	-3.73	-1.75	-13.7	-21.86	11.02	21.46	1.83	-27.83	-3.26	-0.82	-5.33	-3.2
02/98	-8.83	1.87	-1.78	8.01	24.92	11.08	4.66	-2.86	27.56	-1.29	-4.48	0.37	-0.48
03/98	2.13	3.56	9.5	5.13	-2.84	14.53	-2.76	1.61	15.01	3.78	18.62	5.33	2.49
04/98	4.15	4.98	-0.74	4.67	-6.07	-8.67	-6.06	0.67	-7.98	-1.01	6.66	-0.07	-0.59
05/98	-4.31	-1.02	3.83	-5.48	-11.75	-0.02	1.31	-7.07	-5.3	0.32	0.01	3.94	3.26
06/98	9.98	-9.33	-5.92	-5.67	-14.99	-6.53	3.87	-1.3	-3.97	-8.81	-4.71	-3.53	-3.45
07/98	-9.57	-6.29	-3.89	1.32	-10.65	-7.2	-3.01	-0.18	-17.92	-2.7	3.53	0.29	-3.48
08/98	-6.67	3.68	-9.72	6.86	10.22	-9.02	-2.62	-6.78	-25.86	-2.33	-14.09	-6.38	2.51
09/98	-0.04	-6.91	-3.93	15.27	-6.89	-4.11	-3.26	-15.6	7.86	-2.05	2.97	7.29	-2.49
10/98	2.94	1.88	-1.33	-8.76	37.74	3.43	9.2	0.67	59.6	-0.15	-2.3	-8.64	-3.71
11/98	-6.37	-0.37	-4.59	-4.87	10.7	-0.3	0.77	-7.21	12.39	-13.6	6.06	0.85	-3.02
12/98	-5.35	-8.89	-9.54	7.95	-2.3	-0.01	-1.69	-4.08	-5.33	-2.74	-5.82	-8.1	-5.73
01/99	-8.68	-1.15	-0.7	-2.78	-15.08	-9.93	2.77	-7.1	7.73	4.17	-5.77	-4.41	-6.5
02/99	7.37	5.69	4.46	5.48	3.03	-5.3	-2.4	4.92	-0.86	-1.75	1.87	6.15	1.49
03/99	-0.64	11.57	2.12	9.65	4.91	4.79	2.01	9.84	12.98	5.47	9.28	3.9	-3.54
Average	-0.40	-0.41	-0.15	0.82	-0.52	-0.28	-0.02	-1.85	1.51	-1.43	0.36	-0.41	-1.04

Table 3.13 Month-by-Month Returns around the September 11, 2001 Attack:
(April 2001 – February 2002): Value – Growth

	Australia	Belgium	France	Germany	HK	Italy	Japan	Neth.	Sing.	Sweden	Switz.	UK	USA
04/01	-1.26	6.97	-6.56	-8.17	-10.24	-1.15	5.31	12.06	4.16	-10.62	2.39	2	-3.95
05/01	2.09	4.24	9.31	1.1	0.73	13.21	2.83	-10.37	8.36	4.12	-4.42	-7.62	3.74
06/01	9.46	-10.82	1.14	-0.19	2.99	-3.41	6.26	-24.53	2.94	2.65	1.56	-5.88	0.75
07/01	3.4	-0.74	2.85	4.85	5.41	2.67	4.04	-5.58	-0.6	2.97	-1.04	-1.22	2.54
08/01	-0.59	-1.6	9.16	-4.79	2.68	11.32	8.77	-15.8	-4.34	8.91	1.95	-0.1	1.5
09/01	-1.26	-9.15	-7.51	-6.79	-12.9	-10.1	-6.48	-4.85	5.27	3.42	-16.52	4.09	-0.87
10/01	3.45	17.48	-1.57	5.29	6.74	-11.8	-4.3	18.63	4.92	-3.75	4.13	3.12	-5.58
11/01	1.21	9.33	0.38	4.58	3.53	-0.27	-3.2	7.4	-3.69	-6.18	1.78	8.09	1.49
12/01	2.21	9	0.19	0.71	13.95	-2.38	1.53	4.27	-1.53	3.95	-1.78	0.23	1.7
01/02	-4.91	-0.84	-6.49	-7.19	-4.78	5.8	3.48	1.74	8.98	4.98	4.02	-8.05	0.44
02/02	-4.3	9.17	-0.32	0.12	-2.65	-8.88	1.18	-0.67	0.83	10.86	-3.33	-6.51	0.85

CHAPTER 4

THE SUBPRIME CRISIS AND THE EFFICIENCY OF THE JUNK BOND MARKET: EVIDENCE FROM THE MICROSTRUCTURE THEORY

4.1 Introduction

Financial crises occur frequently as evidenced by at least one severe global financial crisis per recent decade – the 1987 stock market crash, the 1997 Asian financial crisis, and the 2007 credit meltdown. The recurring occurrence of financial crises during the last few decades motivated three strands of literature on financial crises. One strand investigates crisis transmission in terms of how financial crises lead to comovements among the international stock markets (e.g., Gerlach et al., 2006). The second strand examines the reasons behind the occurrence of financial crises (e.g., Summers, 2000). The third category focuses on the relation between crises and market efficiency (e.g., Lim et al., 2008).

My research interests in this study fall in the latter category. After the onset of the 2007-2008 financial crisis, there has been a debate in the finance circles on the role of the efficient market hypothesis (EMH) in the occurrences of financial crises. On one hand, financial crises can be viewed as an evidence of the failure of the efficient market hypothesis, since market should have predicted the crisis if it is efficient. On the other hand, others defend the EMH based on the argument that bubbles were present in the economic history before the evolution of the market efficiency concept in 1970s, such as the 1637 Dutch tulip, the Railway Mania in the 1840s, and the Florida Land bubble in 1926 (e.g., Ball 2009). This debate motivates my research question in this study. In particular, my goal is to better understand this debate by examining the impact of the recent financial crisis on the market efficiency of the high-yield (Junk) corporate bond market, an issue that is understudied in the literature.

The contribution of this study is twofold. First, to the best of my knowledge, this study fills a gap in the literature since it is the first one that examines the impact of financial crises on the informational efficiency of financial markets using data from the fixed income market. The importance of investigating the junk bond market stems from the unique association between trading in the high-yield corporate bond market and financial crises. Risk-averse investors rush for quality and liquidity during the bad states of economy. As a result, they tend to replace risky securities with less risky securities during financial crises. A striking example that supports the association between crises and trading in junk bonds is the collapse of Long-Term Capital Management (LTCM). When the fear spread all over the world in August 1998 because of the Asian crisis, the spread between US B-rated bonds and high-rated corporate bonds rose from 2 percentage points before the crisis to 5.7 percentage points. The second contribution is the empirical methodology that I propose in this study. My objective is to examine the impact of the financial crisis on market efficiency within the context of the market microstructure theory (price-volume models). However, the empirical examination of the volume-volatility relation suffers from three major methodological problems – truncation of volume data[10], heteroskedasticity of return data, and endogenity between volume and return variables. I propose a three-step procedure that is free from these three problems. First, I examine the reaction of the average daily trading volume of the junk bonds to the financial crisis, using the censored regression model that is well suited for truncated data. Second, I investigate the impact the crisis had on the junk bond return volatility, using asymmetric Sign-GARCH model of Glosten, Jagannathan and Runkle (1993) (GJR-GARCH model) to account for the leverage effect, a well-known phenomenon in the literature which refers to the asymmetric response of the return volatility series to bad and good news. Finally, I use the fitted values of volume and volatility from the estimated censored regression model and GJR-GARCH, respectively, to estimate the volume-volatility relation using two-stage least square (2SLS) methodology. By comparing the estimated volume coefficients before and during the crisis, I can examine the impact of the crisis on the market efficiency of the junk bond market. If lagged volume has no power in forecasting volatility during the crisis, but had such predictive power before the crisis, this would suggest that the crisis increased the efficiency of the junk bond market, and vice versa.

[10] The problem with using TRACE data is that trade size information is not reported completely, since the volume information reported by TRACE for junk bonds is truncated at one million dollars (1MM+). As a result, bond trading volume data is censored and has a truncated distribution.

The rest of the chapter is organized as follows: literature review is discussed in section two. Section three presents methodology. Section four discusses data. Section five presents empirical results.

4.2 Literature Review

My work links three strands of literature – financial crises, market microstructure, and market efficiency. Figure 4.1 shows my intuition for linking the three strands of literature.

Figure 4.1 The Linkage among the three Strands of the Literature

The market microstructure theory examines how information is incorporated into security market prices through trading activities. The bid-ask spread models and price-volume models are among the major categories of literature on the market microstructure theory[11]. I use the former models to link microstructure models to financial crises literature, while I use the latter models to connect microstructure theory to the efficient market hypothesis.

4.2.1 Trading and Financial Crises

The quoted bid-ask spread includes three-components: order processing costs, inventory control, and adverse selection. I can understand the role of trading volume information in financial markets from the adverse selection component that is designed to compensate 'uninformed' market participants for the risk of trading with better 'informed' investors. The adverse selection theory introduces two components of trading volume information – informational and liquidity components. Equilibrium in financial market looks like a game between informed traders and liquidity suppliers (Kyle, 1985). Under 'informational trading' view, information is the primary motive for trading in financial securities, and any increase in trading volume is a signal of informational trading that means that there is new information reached the market. In most of the time, 'uniformed' traders as a group will lose money by trading against the informed investors' private information. Consequently, uniformed investors will widen the bid-ask spread

[11] Other categories include price formation models, market structure models, non-stock market microstructure models, and optimal security market regulation models.

to make some money (Easely and O'hara, 1992). Alternatively, the primary trading motive for 'liquidity or non-informational trading' is demand for liquidity (Harris and Raviv, 1993).

In a normal market, investors are interested mainly in gathering fundamental information such as future investment opportunities and dividends. As financial markets shift from normal environment to crash environment, investors' trading motive also shifts from informational trading to liquidity trading. One of the major troubling aspects of financial crashes is the drying up of supply (Bookstaber, 1999). This can be seen during the 1987 equity market crash, the 1991 junk bond crisis, the LTCM collapse, and the 2008 subprime crisis, since illiquidity was an extremely key feature in all of these crises (Ball, 2009). In addition, Dick-Nielsen et al. (2011) find that illiquidity in corporate bond market had little contribution to the corporate bond spread before the subprime crisis, but the lack of liquidity was the key factor in widening the spreads during the crisis period compared to the credit risk component of the spread.

4.2.2 Price-Volume Models and Efficient Market Hypothesis

One of the major categories of the market microstructure theory is price-volume models, inspired by the market axiom that says *"it makes volume to make prices move"*. The literature on price-volume relation can be categorized into information theories (such as the sequential information arrival hypothesis 'SEQ'), and noise theories (such as the dispersion of beliefs theory). The main assumption of SEQ models (e.g. Copeland, 1976; Jennings et al., 1981; and Jennings and Barry, 1983) is the gradual arrival of new information to the market. Such sequential flow of information resulting from asymmetric information among investors leads to a bi-directional causality between trading volume and return volatility of securities.

The Dispersion of Beliefs Theory represents another strand of literature that examines the implication of noise trading models (e.g., Delong et al., 1990) for the volume-volatility relation. The theory assumes that traders' behavior in the market is heterogeneous, given that such disagreement among traders can arise either because traders simply interpret commonly known data differently (Harris and Raviv, 1993) or because they have different private information (Shalen, 1993). The key prediction of the dispersion of beliefs theory is that current trading volume data can predict future return volatility.

This evidence is in line with the technical approach to investment, since technicians expect a gradual price adjustment to reflect gradual flow of information that causes trends in security price movements.

This philosophy is in sharp contrast to the EMH that contends that past performance has no influence on future performance. In its weak form, the EMH implies that security prices adjust rapidly to the arrival of new information and the current security price fully reflects all historical information. If market is efficient, therefore, it should not be possible to profit by trading on the information contained in the asset's price history.

4.2.3 Financial Crises and Efficient Market Hypothesis

After the onset of the subprime crisis, the EMH has come under attack based on the claim that it is responsible for the occurrence of the housing bubble because if market is efficient, it should have predicted the crisis. Moreover, people believe in the validity of market efficiency and, consequently, do not verify the fair value of securities since the market price reflects all available information.

Theoretically, it is difficult to examine the above argument, because one of the major limitations of the EMH is that it assumes continuous trading and, consequently, ignores liquidity trading (Ball, 2009). However, several studies (e.g., Chen et al., 2007) find that liquidity is priced in corporate yield spreads. As I mentioned earlier, investors' trading motive shifts from informational trading to liquidity trading as the financial market shifts from normal environment to crisis environment. This limitation might explain the lack of theoretical research on the impact of financial crises on the efficiency of financial markets. Given such gap in the theoretical literature, few studies empirically examined the impact of financial crises on market efficiency and the evidence is mixed. For example, Hoque et al. (2007) examine the impact of the Asian financial crisis on the market efficiency of eight Asian markets, using variance ratio tests for the pre-crisis and post-crisis periods. Their findings show that the Asian crisis does not significantly affect the market efficiency of six Asian markets. On the other hand, Lim et al. (2008) use a rolling bi-correlation test statistic as a proxy for market efficiency and they find that the Asian crisis adversely affect the market efficiency of the same eight Asian markets.

4.3 Methodology

My goal is to investigate the impact of the subprime financial crisis on the junk bond market, along three dimensions. First, I investigate the trading volume impact of the financial crisis. Second, I examine the impact of the crisis on the junk bond return volatility. Finally, I explore the impact of the crisis on the Junk bond Market Efficiency.

4.3.1 Modeling Trading Volume: Censored Regression

In modeling the determinants of junk bond trading volume, it is important to bear in mind the limitations of TRACE data set that the pooled OLS regression might suffer. The problem with using TRACE data is that trade size information is not reported completely, since volume information reported by TRACE for junk bonds is truncated at one million dollars (1MM+). As a result, bond volume data (my dependent variable) is censored and has a truncated distribution. Therefore, using OLS to estimate the impact of independent variables on trading volume will produce biased parameter estimates, since one of the OLS assumptions (i.e., the independence between OLS errors and explanatory variables) is violated.

To handle this truncation problem, I use a limited dependent variable approach that is the censored regression model since it is specifically suited for estimation where the dependent variable is only partially observed over some range. The censored regression models use MLE estimation to produce unbiased estimates when the dependent variable is truncated, and can be driven from an underlying latent variable model, as follows:

$$VB_{it}^{*} = \alpha_{it} \mathrm{X}_{\mathrm{it}} + \xi_{it} \qquad (1)$$

Where (X_{it}) is a vector of the determinants of trading volume of junk bonds, such as bond age, price volatility, equity volume, equity return, market return, autocorrelation in volume, and VIX CBOE. The literature promotes these variables as the key determinants of trading in junk bond market (e.g., Alexander et al., 2000; and Hotchkiss and Jostava, 2007)[12]. (VB_{it}^{*}) is an unobserved (latent) variable, but I only observe (VB_{it}) which is an indicator function as follows:

[12] Other volume determinants that have been used in the literature include bond rating and issue size.

$$VB = \begin{cases} VB_{it}^{*} & \text{if } v_{it}^{*} < 1 \text{ million} \\ 1 \text{ million} & \text{if } v_{it}^{*} > 1 \text{ million} \end{cases} \qquad (2)$$

In this case, the data is right censored or top coded. This means that I know the actual value of a variable only up to a certain threshold (i.e., 1 million), but for values greater than this threshold I know only that the variable is at least as the threshold. The indicator function in equation (2) is of particular interest because large trades (with par value size above $1million) are typically institutional trades[13] carried out by well-informed institutional traders with high bargaining power, given that the junk bond market is largely institutional.

4.3.2 Modeling Return Volatility: GJR-GARCH

After examining the impact of financial crisis on the trading volume of high yield corporate bond market, the next step is to investigate the volatility impact of the crisis. The evidence of the excess volatility of corporate bonds documented by Bao and Pan (2010) show that OLS assumptions are violated. The common practice to capture the heteroskedasticity of return volatility is to use the autoregressive conditional heteroskedasticity (ARCH) and generalized ARCH (GARCH) models proposed originally by Engle (1982) and Bollerslev (1986) respectively. The first generation of the GARCH model have allowed the magnitude of volatility to be predicted from past news and lagged conditional variance, as:

$$r_{it} = \mu + \varepsilon_{it}, \quad \varepsilon_{i,t} \sim (0, \sigma_{it}^{2}) \qquad (3)$$

$$\sigma_{it}^{2} = \beta_{o} + \beta_{1}\, \varepsilon_{it-1}^{2} + \beta_{2}\, \sigma_{it-1}^{2} \qquad (4)$$

Although it appears from literature that conditional heteroskedasticity models are among the best that are currently available, there is a major drawback of using the first generation of GARCH models in examining financial crises. The GARCH models are said to be symmetrical, due to the quadratic specification used for the conditional variance (i.e., the error term is squared). Therefore, volatility will be a function only of the innovation’s magnitude, since the lagged shock will have the same effect on the present volatility whether the lagged shock is positive or negative (i.e., neutral impact).

This symmetrical nature of the traditional GARCH model makes them not well suited for capturing a well-known phenomenon in the literature which is the asymmetric volatility in stock returns series or what is called asymmetric or leverage effect (e.g., French et al. 1987). The asymmetric volatility phenomenon (AVP) is a market dynamic that shows that periods of crash environment (when residual is negative) cause the level of market volatility to increase more than in periods of relative calm (when residual is positive).

In order to handle the asymmetries in the conditional variance, I use the asymmetric Sign-GARCH model of Glosten, Jagannathan and Runkle (1993) (GJR-GARCH model) that allows for different reactions of volatility to the sign of past innovations. The GJR-GARCH model can be formulated as follows:

$$r_{i,t} = \mu + \varepsilon_{i,t}; \quad \varepsilon_{i,t} \sim (0, \sigma^2_{i,t}) \tag{5}$$

$$\sigma^2_{it} = \beta_0 + \beta_1 \varepsilon^2_{i,t-1} + \beta_2 \sigma^2_{i,t-1} + \beta_3 S_{t-1}\varepsilon^2_{i,t-1} \tag{6}$$

$$\text{Where } : S_{i,t-1} = \begin{Bmatrix} 1, \text{ if } \varepsilon_{\text{i,t-1}} < 0 \\ 0, \text{ otherwise} \end{Bmatrix} \tag{7}$$

Like any traditional GARCH model, the above model consists of two equations. The mean equation specifies returns as a constant plus an error term that has a mean of zero and a variance of (σ^2_{it}).

The variance equation expresses the current volatility (measured by variance (σ^2_{it})) as a function of four factors: the mean volatility (a), news about volatility from the previous period measured as the lag of the squared residual from the mean equation (ε^2_{it-1}) (the ARCH term), the last period's variance (σ^2_{it-1}) (the GARCH term) to control for volatility clustering, and the asymmetric volatility term $(S_{t-1}\varepsilon^2_{it-1})$ to account for the leverage effect. A model with 'q' lags of (ε^2_{it-1}), 'p' lags of (σ^2_{it-1}) and 'r' lags of $(S_{t-1}\varepsilon^2_{it-1})$ is labeled GJR (p, q, r), and I determine the lag structure in the conditional variance equation based on Akaike (AIC) and Bayesian (BIC) information criteria. The central feature of the above

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[13] Institutional trades are defined as trade with par value size above $100,000.

specification is that the dummy variable (S) allows the conditional variance to differ on crash days, since the effect of lagged shock on current volatility now is a function of its magnitude and its sign rather than its magnitude only, as in the original GARCH models. In particular, volatility is affected by one term (β_1) when the residual is negative (i.e., good news), while it is affected by two terms $(\beta_1 + \beta_3)$ when the residual is negative (i.e., bad news).

4.3.3 Modeling Volume-Volatility relation (EMH Test): VAR and 2SLS

After modeling volume and volatility, I turn now to the relation of particular interest in this study that is examining the impact of the global financial crisis on the informational efficiency of the junk bond market within the context of the volatility-volume relation. In undertaking this exercise, it is important to account for endogenity problem (since the SEQ hypothesis implies that there is a bidirectional causal relation between trading volume and return volatility). In order to handle such endogenity problem, I use vector autoregression (VAR) and two-stage least squares (2SLS).

4.3.3.1 Vector Autoregressive (VAR) Model

The VAR system treats all the variables in the model as endogenous variables. Therefore, the relation between bond return volatility and trading volume can be examined by estimating the following vector autoregressive (VAR) system:

$$\hat{\sigma}^2_{i,t} = \alpha_0 + \sum_{i=1}^{I} \alpha_i \hat{\sigma}^2_{i,t-1} + \sum_{j=1}^{J} \beta_j VB_{i,t-j} + \varepsilon_t \qquad (8)$$

$$VB_{i,t} = \lambda_0 + \sum_{i=1}^{I} \lambda_i VB_{i,t-1} + \sum_{j=1}^{J} \delta_j \hat{\sigma}^2_{it-j} + e_t \qquad (9)$$

Where $(\hat{\sigma}^2_{it})$ represents the fitted values of volatility from equations (6); (VB_{it}) is the average daily bond volume; (α_i) and (λ_i) are the coefficients for the lagged regressor of the dependent variable; (β_j) and (δ_j) are the coefficients for the lagged explanatory variable. I estimate such VAR system for two subsamples – before and during the financial crisis. I am interested mainly in the value of the estimated (β_j) since any evidence of volatility predictability contradicts the implications of the EMH.

4.3.3.2 Two Stage-Least Square (2SLS) Model

Another way to account for endogenity (or simultaneity) bias and still get unbiased estimates is to estimate a simultaneous equation model using two stage least square (2SLS). The first step is to use the seven determinants of bond trading volume (i.e., bond age, price volatility, equity volume, equity return, market return, lagged bond trading volume, and VIX) as instruments to predict the endogenous bond trading volume (VB_{it}), as follows:

$$\begin{aligned} VB_{it} &= \alpha_0 + \alpha_1 (Age)_{it} + \alpha_2 (pricevol)_{it} + \alpha_3 (VE)_{it} + \\ &\quad \alpha_4 (RE)_{it} + \alpha_5 (RM)_{it} + \alpha_6 (VB)_{it-1} + \alpha_7 (VIX)_{it} + \xi_{it} \end{aligned} \qquad (10)$$

The next step is to run simple regression between fitted values of volatility $(\hat{\sigma}_{i,t-1})$ from equation (6) and lagged fitted values of volume $(\hat{VB}_{i,t-1})$ from equation (10), as follows:

$$\hat{\sigma}^2_{it} = \theta_0 + \theta_1 \hat{VB}_{i,t-1} + \varepsilon_{\text{it}} \qquad (11)$$

As a robustness test, I use alternative 2SLS specification. Instead of running a simple regression between the fitted values of volatility and volume, I incorporate the lagged fitted trading volume series $(\hat{VB}_{i,t-1})$ into the GJR-GARCH model directly to examine the effect of bond trading volume on bond return volatility, as follows:

$$r_{i,t} = \mu + \varepsilon_{i,t}; \quad \varepsilon_{i,t} \sim (0, \sigma^2_{i,t}) \qquad (12)$$

$$\sigma^2_{it} = \beta_0 + \beta_1 \varepsilon^2_{i,t-1} + \beta_2 \sigma^2_{i,t-1} + \beta_3 S_{t-1}\varepsilon^2_{i,t-1} + \beta_4 \hat{\text{VB}}_{\text{i,t-1}} \qquad (13)$$

$$\text{Where } : S_{i,t-1} = \begin{cases} 1, \text{ if } \varepsilon_{\text{i,t-1}} < 0 \\ 0, \text{ otherwise} \end{cases} \qquad (14)$$

<u>4.4 Data and Variables Measurement</u>

4.4.1 Data Requirements and Sample

The bond market in general is less transparent than equity and futures market in terms of the availability of basic information on trading activity. This led the SEC to encourage the National Association of Securities Dealers (NASD) in April 1994 to initiate the fixed income pricing system (FIPS) that is an electronic quotation system for the junk bonds as a source of trading volume in corporate bonds. In July 2002, FINRA, formerly NASD, launched another source of data that is TRACE (Transaction Reporting and Compliance Engine) to increase transparency in the corporate bond markets.

My data set is obtained from TRACE and consists of hourly prices and hourly trading volume for 19 junk bonds. Table 4.1 summarizes the major bond characteristics of these sample bonds. To be included in the sample, a bond must meet two criteria: First, the bond has to be actively traded in terms of number of trades so that they were included in TRACE 50 during 2008[14]. Second, the bond must be publicly traded since I am using data from the equity market.

4.4.2 Sample Period

My sample runs from July 2005 till July 2009. In order to address the impact of the subprime crisis on the US high yield corporate bond market, I further subdivide the sample into two subsamples – pre crisis and crisis period. Based on the above analysis of the chronology of the subprime crisis, I divide the sample period into two sub-periods:

(1) Pre-Crisis Period: from May 15, 2006 to July 17, 2007[15].

(2) Crisis Period: from July 18, 2007 to September 15, 2008[16].

My definition of the crisis period is similar to Santos (2011) and Longstaff (2010). I subdivide the crisis period into two phases to ensure a fair comparison, such that each period has roughly equal number of observations.

[14] TRACE 50 bonds are chosen by the NASD advisory committee and updated continuously overtime such that small trading volume were replaced with more active bonds.

[15] The first indications of a credit crunch appeared on July 17, 2007 when the credit spreads soar as a result of Bear Sterns announcement that two if its hedge funds with subprime exposure has released losses of $1.5 billion (more than 90% of their value). Two weeks later after the announcement, on July 31 2007, these two hedge funds filed for Chapter 15 bankruptcy.

[16] September 2008 is considered a historic month and a new phase of the crisis since it witnessed the bankruptcy of Lehman Brothers that is considered the largest bankruptcy filing in the US history. Lehman’s bankruptcy in September 2008 led to profound effects on the equity and bond market. On September 15 2008 – the day the Lehman Brothers filed for bankruptcy, the DJIA witnessed the largest drop in a single day since the September 11, 2001 attack (-4.4%). Also, the price volatility of investment grade bonds reached unprecedented levels during September 2008 (Longstaff, 2010; Cox and Glapa, 2009).

Table 4.1 Sample Description: Top Publicly Traded Junk Bonds by Number of Trades in 2008

Symbol	Issuer Name	Offering Dates	Coupon	Maturity	Rating	Trades	Total Observations
WM.IE	WASHINGTON MUTUAL, INC.	10/27/2003	4.000	1/15/2009	D	18,497	1222
WM.HE	WASHINGTON MUTUAL, INC.	3/30/2000	8.250	4/1/2010	D	10,774	654
GM.GM	GENERAL MOTORS CORPORATION	1/4/2001	7.200	1/15/2011	C	10,551	1740
GM.HB	GENERAL MOTORS CORPORATION	6/26/2003	8.375	7/15/2033	C	10,248	1489
F.GY	FORD MOTOR COMPANY	7/9/1999	7.450	7/16/2031	CC	6,887	2137
WM.IL	WASHINGTON MUTUAL, INC.	12/13/2004	4.200	1/15/2010	D	6,152	899
RAD.GA	Rite Aid Corporation	8/13/1993	6.875	8/15/2013	CCC	5,381	1481
GT.GF	GOODYEAR TIRE & RUBBER COMPANY	8/10/2001	7.857	8/15/2011	B	4,959	1504
LEH.HF	LEHMAN BROTHERS	8/14/1997	7.200	8/15/2009	CCC	4,905	1222
GM.HC	GENERAL MOTORS CORPORATION	2/23/2001	8.250	7/15/2023	C	4,807	1487
LEH.GZJ	LEHMAN BROTHERS	1/9/2007	5.250	2/6/2012	CCC	4,571	424
GM.HA	GENERAL MOTORS CORPORATION	6/26/2003	7.125	7/15/2013	C	4,380	1489
LEH.HQ	LEHMAN BROTHERS	10/27/1999	7.875	11/1/2009	CCC	4,318	1219
LEH.TZ	LEHMAN BROTHERS	2/18/2004	3.600	3/13/2009	CCC	4,079	978

Table 4.1 – *Continued*

WM.HV	WASHINGTON MUTUAL BANK	1/13/2001	6.875	6/15/2011	D	4,002	1030
CHK.HE	CHESAPEAKE ENERGY CORP	12/22/2005	6.500	8/15/2017	BB	3,789	1215
LEH.XS	LEHMAN BROTHERS	1/4/2005	4.250	1/27/2010	CCC	3,727	893
SFD.GG	SMITHFIELD FOODS, INC.	10/7/2004	7.000	8/1/2011	B	3,571	1352
DJTE.GA	TRUMP ENTERTAIN. RESORTS INC	3/30/2005	8.500	6/1/2015	D	3,453	839

4.4.3 Variables Measurement

The volume-volatility relation has been studied from different perspectives such as volume measure, volatility measure, time frequency and financial instruments used. Table 4.2 presents a survey of the measurement issues related to the previous research on volume – volatility relation.

4.4.3.1 Bond Return

My transaction data consists of hourly prices and hourly trading volume for bonds. Following Downing et al. (2009), I use the average daily price to calculate the daily bond return. My measure for log daily return is defined as follows:

$$r_{it} = \ln\left(\frac{\mathrm{P_{it}} + \mathrm{AI_{it}}}{\mathrm{P_{it-1}} + \mathrm{AI_{it-1}}}\right) \qquad (12)$$

Where $\mathrm{P_{it}}$ is the average daily clean price (i.e., not adjusted for accrued interests ($\mathrm{AI_{it}}$)). The reason for focusing on returns rather than on prices is that returns are stationary.

4.4.3.2 Bond Trading Volume and its Determinants

As I mentioned in section three, I use censored regression model to examine the impact of the global crisis on trading in junk bond market. My dependent variable in the censored regression is the bond average daily trading volume (VB_{it}), and I follow Alexander et al. (2000) by measuring volume as the natural log of the number of bonds traded per day. Following literature (e.g., Hotchkiss and Jostava, 2007), I use seven different determinants of trading volume: bond age, price volatility, equity volume, equity return, market return, autocorrelation in volume, and VIX. Age of the bond is measured by the number of years since the bond was issued. In order to calculate the bond age, I make use of the bond issuer and bond characteristics information from the Fixed Income Security Database (FISD). Price volatility is the absolute price return. Moreover, I include lagged bond trading volume to account for the autocorrelation in trading volume. Finally, I obtain the VIX index closing price from CBOE.

Table 4.2 Volume and Volatility Measurement Issues: Survey

Article	Trading Measure	Volatility Measure	Price Definition	Time Frequency	The financial instrument used
Ying (1966)	Turnover	-----------	Composite index	Daily	Common stock
Clark (1973)	Trading volume	Squared price change	Individual contracts	Daily	Future contracts
Epps and Epps (1975)	Trading volume	Price change	Individual stocks	Transactions	Common stock & bonds
Morgan (1976)	Turnover	Variance	Individual stocks	Monthly & 4-day interval	Common stock
Hanna (1978)	Trading volume	Price change	Individual stocks	Monthly	Bonds
Rogalski (1978)	Trading volume	Price change	Individual stocks	Monthly	Common stock & options
Tauchen and Pitts (1983)	Trading volume	Variance	Individual stocks	Daily	Common stock & future contracts
Grammatikos and Saunders (1986)	Trading volume	Standard deviation	Individual contracts	Daily	Future contracts
Jain and Joh (1988)	Turnover	Price change	Composite index	hourly	Common stock
Smirlock and Starks (1988)	No. of transactions	Absolute price change	Individual stocks	Transaction	Common stock
Lamoureux and Lastrapes (1990)	Trading volume	GARCH	Individual stocks	Daily	Common stock
Gallant et al. (1992)	Log trading volume	Log price change	Composite index	Daily	Common stock
Arrif and Lee (1993)	Trading volume	Price change	Individual stocks	weekly	Common stock
Foster and Viswanathan (1993)	Turnover	Variance	Individual stocks	Half hour	Common stock
Conrad et al. (1994)	No. of transactions	------------	Individual stocks	Weekly	Common stock

Table 4.2 – *Continued*

Hiemstra and Jones (1994)	Trading volume	EGARCH	Composite index	Daily	Common stock
Martikanien et al. (1994)	Trading volume	Log price change	Composite index	Daily	Common stock
Anderson (1996)	Log trading volume	Squared price change	Individual stocks	Daily	Common stock
Chan et al. (1996)	Trading volume	Squared price change	Individual stocks	Every 65 minutes	Common stock
Chang et al. (1997)	Trading volume	Absolute volatility value	Individual contracts	Daily	Future contracts
Smith et al. (1997)	Trading volume & no. of transactions	Absolute price change	Individual stocks	Every 15 minutes	Common stock
Brooks (1998)	Proportion of shares traded	Squared price change	Composite index	Daily	Common stock
Hsu (1998)	Trading volume	GARCH	Individual stocks	Daily	Common stock
Diagler and Wiley (1999)	Trading volume	Conditional variance	Individual contracts	Daily	Future contracts
Chordia and Swaminathan (2000)	Turnover	-------------	Individual stocks	Daily	Common stock
Lee and Swaminathan (2000)	Turnover	------------	Individual stocks	monthly	Common stock
Safvenblad (2000)	Trading volume	-------------	Individual stocks	Daily	Common stock
Gervais et al. (2001)	Trading volume	-------------	Individual stocks	Daily & weekly	Common stock
Parisi and Acevedo (2001)	Trading volume	--------------	Individual stocks	Weekly	Common stock
Lee et al. (2002)	Trading volume	GARCH	Composite index	Daily	Common stock
Downing and Zhang (2004)	No. of transactions	The difference between high & low divided by average price	Individual stocks	Weekly	Bonds

4.5 Empirical Results

Table 4.3 shows descriptive statistics for the sample bonds' volume and returns before and during crisis period, and table 4.4 presents the estimated coefficients of equation (10). In general, volume results suggest that heavily traded bonds are associated with high contemporaneous equity volume and high lagged bond volume. This supports the literature that shows that stocks and bonds react to the firm-specific information (e.g., Hotchkiss and Ronen, 2002). The positive significant coefficients on lagged bond volume show that there is positive autocorrelation in Junk bond trading. These findings are consistent with the evidence in Hotchkiss and Jostava (2007).

Table 4.3 Summary Statistics for Return and Volume before and during the Crisis Period

	Trading Volume Statistics				Bond Return Statistics			
	Before Crisis Period		During Crisis Period		Before Crisis Period		During Crisis Period	
Bond	Mean	SD	Mean	SD	Mean	SD	Mean	SD
WM.IE	11.47	1.56	11.25	0.96	-0.00	0.02	-0.02	0.02
WM.HE	11.03	1.94	10.91	1.23	-0.00	0.04	-0.00	0.03
GM.GM	11.44	0.77	11.81	0.81	-0.00	0.04	-0.00	0.03
GM.HB	12.61	0.61	12.55	0.64	-0.00	0.04	-0.00	0.05
F.GY	12.37	0.64	12.39	0.73	-0.00	0.04	-0.00	0.04
WM.IL	11.67	1.63	11.11	1.39	-0.00	0.03	-0.00	0.03
RAD.GA	10.65	1.14	10.41	1.08	-0.00	0.06	0.00	0.05
GT.GF	11.16	0.85	10.77	0.95	0.00	0.02	-0.00	0.03
LEH.HF	9.87	1.20	10.09	1.05	0.00	0.02	-0.00	0.06
GM.HC	11.59	0.85	11.58	1.06	-0.00	0.04	-0.00	0.05
LEH.GZJ	12.93	1.43	11.73	1.38	-0.00	0.02	-0.00	0.05
GM.HA	11.72	1.01	11.72	1.01	-0.00	0.03	-0.00	0.04
LEH.HQ	10.17	1.23	10.34	1.26	-0.00	0.11	0.06	0.25
LEH.TZ	11.95	1.78	11.25	1.39	0.00	0.01	-0.00	0.07
WM.HV	11.85	1.96	11.24	1.46	-0.00	0.03	-0.00	0.03
CHK.HE	12.33	1.52	11.10	1.36	0.00	0.02	-0.00	0.03
LEH.XS	12.43	1.70	11.69	1.54	0.00	0.02	-0.00	0.05
SFD.GG	11.67	1.65	11.32	1.33	0.00	0.02	-0.00	0.03
DJTE.GA	12.86	1.11	12.88	1.14	-0.00	0.04	-0.00	0.04

Figure 4.1 plots the closing price of CBOE VIX bond during the sample period. From the figure, it is clear that there is a remarkable increase in volatility during the crisis in general and during the collapse of Lehman Brothers in September 2008 in particular. Table 4.4 shows a negative and strong significant relation between trading in junk bonds and the closing price of VIX. This evidence is in line with my argument that risk-averse investors rush for quality and liquidity during bad states of economy and, consequently, they tend to replace risky securities with less risky securities during financial crises.

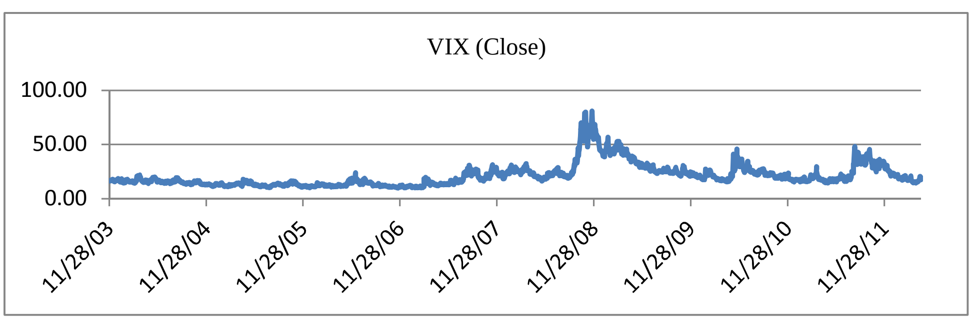

Figure 4.2 Closing Price of CBOE VIX

Table 4.4 Determinants of Trading Volume (Entire Sample Period): Censored Regression Model

Bond	Age	Volatility	VE	RE	RM	AC	VIX
WM.IE	-0.00*** (0.00)	-2.33 (1.61)	0.76*** (0.03)	-0.18 (0.90)	0.21 (4.94)	0.18 (0.03)	-0.06*** (0.01)
WM.HE	-0.01*** (0.00)	0.57 (2.09)	0.85*** (0.06)	0.19 (1.17)	1.31 (7.56)	0.20*** (0.04)	-0.11*** (0.02)
GM.GM	-0.00** (0.00)	-0.22 (0.60)	0.55*** (0.02)	1.69*** (0.59)	-1.12 (1.78)	0.35*** (0.02)	0.00** (0.00)
GM.HB	-0.00*** (0.00)	-0.28 (0.36)	0.38*** (0.02)	-0.43 (0.43)	1.94 (1.43)	0.58*** (0.02)	0.00* (0.00)
F.GY	-0.00*** (0.00)	0.49 (0.43)	0.52 (0.02)	-0.55 (0.61)	3.77** (1.47)	0.46*** (0.02)	0.00*** (0.00)
WM.IL	-0.00*** (0.00)	1.56 (1.87)	0.75*** (0.03)	-0.48 (1.05)	8.60 (6.24)	0.17*** (0.03)	-0.06*** (0.02)
RAD.GA	0.00*** (0.00)	0.88 (0.85)	0.63*** (0.03)	-0.78 (0.79)	3.85 (2.65)	0.21*** (0.02)	-0.00 (0.00)
GT.GF	-0.00*** (0.00)	0.27 (0.80)	1.46*** (0.05)	-0.50** (0.89)	0.20 (2.31)	0.22*** (0.02)	-0.01*** (0.00)
LEH.HF	-0.00*** (0.00)	1.88* (1.08)	0.83*** (0.03)	2.31*** (0.91)	-8.22* (4.50)	0.15*** (0.03)	-0.07*** (0.01)
GM.HC	0.00*** (0.00)	-0.25 (0.52)	0.60*** (0.02)	0.99 (0.62)	2.25 (2.02)	0.29*** (0.02)	0.01** (0.00)
LEH.GZJ	-0.01*** (0.00)	1.70 (1.69)	0.79*** (0.05)	0.46 (1.21)	-2.27 (7.07)	0.14*** (0.05)	-0.06*** (0.02)
GM.HA	0.00*** (0.00)	0.12 (0.58)	0.51*** (0.02)	0.06 (0.60)	-0.81 (1.97)	0.38*** (0.02)	0.00*** (0.00)
LEH.HQ	-0.00*** (0.00)	-0.72** (0.31)	0.83*** (0.03)	0.40 (0.93)	-1.77 (4.95)	0.12*** (0.03)	-0.06*** (0.01)
LEH.TZ	-0.00*** (0.00)	-1.27 (1.58)	0.88*** (0.03)	0.31 (1.41)	5.13 (7.55)	0.11*** (0.03)	-0.09*** (0.02)
WM.HV	-0.00*** (0.00)	-0.52 (1.37)	0.88*** (0.04)	-0.60 (1.16)	3.93 (6.52)	0.18*** (0.03)	-0.12*** (0.01)
CHK.HE	-0.00*** (0.00)	-0.78 (1.34)	0.60*** (0.02)	-0.22 (1.37)	-1.08 (3.06)	0.26*** (0.03)	-0.02*** (0.00)
LEH.XS	-0.00*** (0.00)	-1.71 (1.91)	0.83*** (0.04)	-0.71 (1.42)	5.36 (7.40)	0.16*** (0.03)	-0.06*** (0.02)
SFD.GG	-0.00*** (0.00)	0.39 (1.28)	0.77*** (0.03)	0.38 (1.26)	-3.87 (2.91)	0.21*** (0.03)	-0.01*** (0.03)
DJTE.GA	-0.00** (0.00)	0.16 (0.28)	0.59*** (0.03)	-1.16 (0.81)	6.28** (2.97)	0.45*** (0.03)	-0.00 (0.01)

*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level.

Table 4.5 sets out the results of the estimated parameters of the GJR-GARCH model for the two sub-periods – before and during the financial crisis. Before the crisis, most of the estimated ARCH, GARCH and the asymmetry (GJR) parameters are small and not statistically significantly different from zero. During the crisis, most of the ARCH and GARCH estimates are statistically significant at 1% level.

The magnitude of the ARCH term increases during the crisis period, and this proves that the volatility dynamics become more ‘reactive’. Moreover, the magnitude of the asymmetry parameters becomes large and highly statistical significant at 1% level, indicating the presence of the leverage effect during the financial crisis. It seems, therefore, that the GJR-GARCH model provides a better description of volatility dynamics during the crisis period compared to the before crisis period.

Table 4.5 Estimates of Volatility before and during the Crisis Period: GJR-GARCH Estimates

	During Crisis Period				Crisis Period			
	β_0	β_1	β_2	β_3	β_0	β_1	β_2	β_3
WM.IE	0.00 (0.00)	0.04 (2.35)	0.58 (0.37)	-0.05 (2.35)	0.00** (0.00)	4.81*** (0.88)	0.18*** (0.03)	4.83*** (1.10)
WM.HE	0.00 (0.00)	0.04 (0.55)	0.58* (0.34)	-0.06 (0.55)	0.00 (0.00)	-0.01*** (0.00)	0.99*** (0.00)	0.01*** (0.00)
GM.GM	0.00 (0.00)	0.02 (0.21)	0.58 (0.42)	-0.03 (0.21)	0.00 (0.41)	0.84*** (0.16)	-0.05 (0.43)	-0.84*** (0.16)
GM.HB	0.00 (0.00)	0.04** (0.02)	0.59 (0.41)	-0.05** (0.02)	0.00 (0.00)	0.08* (0.04)	0.59 (0.56)	-0.08*** (0.03)
F.GY	0.00 (0.00)	0.03*** (0.00)	0.59 (0.39)	-0.05*** (0.00)	0.00 (0.00)	-0.12*** (0.01)	1.00*** (0.00)	0.12*** (0.01)
WM.IL	0.00 (0.00)	0.05 (0.22)	0.94*** (0.01)	-0.06 (0.21)	0.00** (0.00)	4.02*** (0.45)	0.21*** (0.02)	2.56*** (0.68)
RAD.GA	0.00 (0.00)	-0.07*** (0.01)	0.98*** (0.00)	0.06*** (0.01)	0.00 (0.00)	0.45* (0.27)	0.75*** (0.10)	-0.45* (0.27)
GT.GF	0.00 (0.00)	0.04 (0.36)	0.82*** (0.13)	-0.05 (0.35)	0.00 (0.00)	0.03*** (0.00)	0.89*** (0.01)	-0.04*** (0.00)
LEH.HF	0.00 (0.00)	-0.97*** (1.33)	-0.02 (0.02)	1.67 (1.06)	0.00 (0.00)	11.09*** (0.91)	-0.00* (0.00)	-9.49*** (1.43)
GM.HC	0.00 (0.00)	0.03 (1.48)	0.59 (0.47)	-0.04 (1.48)	0.00 (0.00)	-0.03 (0.38)	0.70* (0.36)	0.02 (0.38)
LEH.GZJ	0.00 (0.00)	0.05 (0.32)	0.58 (0.62)	-0.06 (0.34)	0.00 (0.00)	7.46*** (0.37)	-0.01 (0.01)	-6.92*** (0.43)
GM.HA	0.00 (0.00)	0.02*** (0.00)	0.93*** (0.01)	-0.02*** (0.00)	0.00 (0.00)	-0.06*** (0.00)	1.02*** (0.00)	0.05*** (0.00)
LEH.HQ	0.00 (0.00)	0.87 (0.85)	-0.02 (0.03)	-1.24 (0.86)	0.00 (0.00)	0.58* (0.55)	-0.01 (0.69)	-1.53 (1.63)
LEH.TZ	0.00 (0.00)	0.04 (0.27)	0.57 (0.37)	-0.05 (0.26)	0.00 (0.00)	-0.15 (0.11)	0.54*** (0.01)	6.81*** (0.43)
WM.HV	0.00 (0.00)	0.04 (0.22)	0.57 (0.38)	-0.06 (0.22)	0.00 (0.00)	47.73*** (2.93)	0.02*** (0.00)	-46.61*** (2.96)
40CHK.HE	0.00 (0.00)	-0.08*** (0.00)	1.01*** (0.00)	0.08*** (0.00)	0.00 (0.00)	0.04*** (0.00)	0.58* (0.32)	-0.05*** (0.00)
LEH.XS	0.00 (0.00)	0.04 (0.87)	0.89*** (0.04)	-0.05 (0.87)	0.00 (0.00)	-0.40** (0.20)	-0.22** (0.08)	10.25** (4.05)
SFD.GG	0.00 (0.00)	0.03 (0.22)	0.94 (0.01)	-0.04 (0.20)	0.00 (0.00)	-0.02*** (0.00)	0.93*** (0.01)	0.00*** (0.00)
DJTE.GA	0.00 (0.00)	0.02 (0.49)	0.89*** (0.01)	-0.03 (4.89)	0.00 (0.00)	0.17 (0.13)	0.58 (0.42)	-0.18 (0.13)

After examining the impact of the financial crisis on the trading volume and return volatility of the junk bond market, I turn to VAR and 2SLS estimates to examine the impact of the recent financial crisis on the efficiency of the junk bond market, through examining bi-directional relation between volume and volatility. Table 4.6 presents the results from the two VAR specifications running from volume to volatility and from volatility to volume, as implied by equations (11) and (12), respectively. In each of these two specifications, the lagged dependent regressor estimated coefficients are not statistically different from zero in both sub-periods. These results indicate that historical trading volume data does not have any impact on the junk bond return volatility whether before or during crisis period.

Table 4.7 sets out the results of estimating the volume-volatility relation using 2SLS as an alternative methodological procedure to solve the endogenity problem. Panel (A) and (B) show the results the estimated volume coefficient from equation (11) and (13), respectively. The results from both panels are consistent. Unlike the results from the VAR estimates, the estimated 2SLS parameters support the notion that trading volume data has some predictability power of the bond return volatility. In particular, most of the lagged volume coefficients, with some exceptions, are positive and highly significant at 1% level. This gives some evidence that greater trading on the prior day increases the return volatility. The magnitudes of the lagged volume coefficients, however, are small indicating that there are other factors that help in predicting bond return volatility. Moreover, the magnitude and significance of the lagged volume regressor are similar in both subsample periods. This proves that the crisis does not have an impact on the informational efficiency of the junk bond market, at least from the price-volume relation perspective.

Table 4.6 Estimates of Volume-Volatility relation before and during the Crisis Period: VAR Model Results

	Crisis Period				During Crisis Period			
	β_1	β_2	δ_1	δ_2	β_1	β_2	δ_1	δ_2
WM.IE	4.06E-05 (8.4E-05)	6.27E-05 (8.4E-05)	100.17** (50.68)	-32.29 (50.96)	-1.11E-05 (0.00)	-4.00E-05 (0.00)	19.76 (20.16)	-35.94 (-1.7)
WM.HE	-1.57E-06 (5.7E-06)	-2.55E-06 (5.7E-06)	884.6670 (933.485)	-573.36 (934.92)	-6.84E-06 (7.2E-06)	5.35E-06 (7.1E-06)	-450.69 (563.96)	-284.72 (561.95)
GM.GM	-0.01 (0.00)	-0.01 (0.00)	-0.25 (0.57)	0.35 (0.57)	0.01 (0.00)	-0.01 (0.01)	0.22 (0.35)	0.01 (0.35)
GM.HB	3.15E-06 (3.7E-06)	-6.19E-07 (3.7E-06)	-592.79 (1100)	664.66 (1098)	3.35E-06 (5.6E-06)	3.76E-06 (5.6E-06)	-375.93 (582.57)	468.52 (583.73)
F.GY	8.14E-06** (4.7E-06)	-4.88E-06 (4.8E-06)	377.9976 (860.87)	-1287 (857.9)	-8.84E-07 (5.6E-06)	4.11E-06 (5.6E-06)	519.96 (574.462)	596.75 (577.834)
WM.IL	0.01 (0.00)	0.01 (0.00)	1.15 (2.96)	1.07 (2.96)	0.00 (0.00)	0.00 (0.00)	-1.78 (1.61)	0.05 (1.61)
RAD.GA	-1.37E-05 (9.8E-05)	-0.01 (9.8E-05)	-0.86 (35.00)	-7.14 (35.00)	-0.00 (0.00)	8.78E-05 (0.00)	35.19** (14.82)	-18.23 (14.96)
GT.GF	5.23E-07 (4.4E-06)	9.46E-07 (4.4E-06)	-359.29 (779.508)	499.68 (781.66)	5.23E-07 (4.4E-06)	9.46E-07 (4.4E-06)	-359.29 (779.5)	499.68 (781.6)
LEH.HF	0.01** (0.00)	-0.00 (0.00)	-11.98 (11.43)	-4.54 (11.43)	0.00 (0.00)	-0.00 (0.00)	-2.95 (2.59)	0.84 (2.61)
GM.HC	-3.14E-06 (2.17E-06)	-4.16E-06 (2.7E-06)	-1737.9 (1490)	-585.00 (1492.17)	3.07E-06 (3.9E-06)	-4.06E-06 (3.8E-06)	75.88 (879.68)	-903.12 (880.78)
LEH.GZJ	0.00 (0.00)	0.00 (0.00)	-12.90 (11.15)	19.69** (11.16)	-0.00 (0.00)	0.00 (0.00)	10.96** (4.48)	-5.21 (4.57)
GM.HA	-4.05E-06 (0.00)	0.00 (0.00)	0.28 (3.51)	-1.09 (3.51)	-0.00 (0.00)	0.00 (0.00)	0.48 (2.10)	2.69 (2.10)
LEH.HQ	7.32E-05 (0.00)	-0.00 (0.00)	-20.86 (35.09)	-2.06 (35.09)	-0.00 (0.00)	0.00 (0.00)	-3.21 (3.15)	4.04 (3.12)
LEH.TZ	-0.00 (0.00)	-0.00 (0.00)	-5.69** (2.86)	6.75** (2.86)	0.00 (0.00)	0.00 (0.00)	0.47* (1.86)	1.25 (2.03)
WM.HV	-0.00 (0.00)	-0.00 (0.00)	-0.91 (0.65)	-0.47 (0.65)	-0.00 (0.00)	-0.00 (0.00)	-0.15 (1.67)	-0.06 (1.67)
CHK.HE	2.14E-06 (2.5E-06)	-3.77E-06 (2.5E-06)	-291.21 (1474.48)	174.32 (1474.52)	2.05E-05** (8.4E-06)	-1.84E-06 (8.5E-06)	93.63 (410.42)	35.25 (48.58)
LEH.XS	0.00 (0.00)	0.00 (0.00)	9.79 (8.05)	-3.07 (8.07)	-0.00 (0.00)	0.00 (0.00)	3.99 (5.96)	5.97 (6.11)
SFD.GG	6.59E-07 (3.0E-06)	-1.50E-06 (3.0E-06)	-58.71 (1308.33)	-321.10 (1308.67)	-3.61E-06 (4.8E-06)	-3.60E-06 (4.8E-06)	-27.74 (790.37)	-108.85 (788.88)
DJTE.GA	-2.69E-05 (0.00)	-0.00 (0.00)	2.57 (15.93)	13.43 (15.93)	0.00 (0.00)	-0.00 (0.00)	1.99 (3.87)	1.07 (3.86)

*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level.

Table 4.7 Estimates of Volume-Volatility relation before and during the Crisis Period: 2SLS Model Results

	Panel (A)		Panel (B)	
	Before Crisis	During Crisis	Before Crisis	During Crisis
WM.IE	6.71E-05*** (0.00)	7.34E-05 (1.24E-05)	-1.08E-05 (2.60E-05)	0.01*** (2.08E-06)
WM.HE	0.0002*** (1.39E-06)	0.0002*** (1.07E-06)	-1.82E-05 (0.00)	-5.60E-05*** (3.31E-06)
GM.GM	0.0009** (0.00)	0.0009 (0.00)	-4.72E-05*** (1.36E-05)	-1.57E-05 (0.00)
GM.HB	0.0003*** (6.75E-07)	0.0002*** (7.57E-07)	-1.90E-05 (0.00)	-4.33E-05 (0.00)
F.GY	0.0002*** (5.05E-07)	0.0002*** (5.99E-07)	8.30E-06 (0.00)	-9.16E-05*** (9.72E-07)
WM.IL	0.0004** (0.00)	0.0002** (0.00)	-1.42E-05*** (1.50E-07)	0.00*** (1.92E-06)
RAD.GA	0.0002*** (1.57E-05)	0.0004*** (4.33E-05)	-9.30E-05*** (1.69E-05)	-0.00*** (1.70E-08)
GT.GF	6.72E-05*** (1.18E-06)	7.34E-05*** (1.24E-06)	-1.87E-05 (3.20E-05)	2.24E-05 (3.66E-
LEH.HF	0.0001*** (4.86E-05)	0.0002*** (5.30E-05)	0.00** (0.00)	-0.00*** (5.56E-05)
GM.HC	0.0003*** (7.28E-07)	0.0003*** (8.79E-07)	-2.01E-05 (0.00)	-1.40E-05 (0.00)
LEH.GZJ	0.0001** (8.53E-05)	0.0004*** (9.17E-05)	-1.48E-06 (0.00)	0.00*** (3.00E-05)
GM.HA	0.0002*** (8.36E-05)	0.0003*** (0.00)	-1.89E-05 (1.75E-05)	0.00*** (2.06E-05)
LEH.HQ	0.0002*** (3.58E-05)	0.0027*** (0.00)	-0.00** (0.00)	-0.00 (0.00)
LEH.TZ	0.0005** (0.00)	0.0007*** (0.00)	-2.52E-06 (7.59E-06)	-6.78E-05*** (1.06E-05)
WM.HV	0.0006** (0.00)	0.0005** (0.00)	-3.92E-05 (3.08E-05)	3.86E-05*** (7.40E-06)
CHK.HE	7.47E-05*** (7.89E-07)	7.89E-05*** (7.55E-07)	-2.11E-05** (8.45E-06)	-4.68E-05 (8.23E-05)
LEH.XS	0.0001** (6.64E-05)	0.0002** (8.01E-05)	-1.13E-05 (1.31E-05)	-0.01*** (1.05E-05)
SFD.GG	9.51E-05*** (9.79E-07)	9.26E-05*** (1.23E-06)	-1.38E-05 (0.00)	-6.83E-06 (8.20E-05)
DJTE.GA	0.0001*** (1.85E-05)	0.0004*** (7.67E-05)	-0.00*** (1.91E-05)	-1.22E-05 (0.00)

*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level

CHAPTER 5

CONCLUSION

For many decades, the Efficient Market Hypothesis (EMH) is considered the main weapon in the battle between mainstream finance and behavioral finance. Researchers have formulated two main groups of tests of the efficiency of financial markets. The first group of tests is based on investigating the risk versus the behavioral explanation of effects or market anomalies that can describe expected returns, and they are inconsistent with the idea of the EMH since security prices did not appear to reflect all available information. The second group of the empirical tests of the EMH is the autocorrelation test of independence that measures the significance of any correlation in return overtime. Those who believe that capital markets are efficient would expect insignificant correlations in return overtime. My work in chapter two and three is related to the first group of the EMH tests by examining the risk interpretation of investment premium and global value premium respectively, and chapter four focuses on the second group of tests (i.e., independence tests) by investigating the market efficiency of the junk bond market during the subprime crisis within the context of the price-volume relation.

Chapter two investigates the theoretical and empirical explanation for the investment effect (i.e., low-investment stocks earn higher expected returns than high-investment stocks). To this end, I empirically investigate two hypotheses. The first hypothesis investigates whether the marginal productivity of capital (fundamental factors) or the cost of capital (financial factors) is the main driver of the variability of firm-level investment returns. The second hypothesis examines the fundamental versus the behavioral explanation for the negative relation between stock returns and investment returns. The estimation of the orthogonal impulse response function gives direct empirical test of the first hypothesis, while I use the beta decomposition approach to test the second hypothesis. I conclude from the findings that (1) most of the firm-level investment returns are attributed to the variability in discount rate news compared to the variability in cash flow news, and (2) the value of the financial betas is greater than the value of fundamental betas for decile portfolios based on one-dimensional (two-dimensional) classification by investment return (size and investment return). Overall, I conclude that financial factors are main driver of investment returns, and they are also the dominant driver of the negative relation between investment and stock return.

Chapter three investigates the impact of financial crises along two dimensions: the global value premium and financial market integration. For risk aversion effects of the crises on the global value premium, the estimated coefficients of regressing the monthly excess return for the country's portfolio on the dollar global value premium during the Asian crisis period are lower than those during the pre-crisis period for nine of the thirteen countries in my sample. In addition, the month-to-month performance of value stocks relative to growth stocks is examined. Results show that value stocks consistently perform more poorly than growth stocks during four selected financial crises – the international debt crisis, the ERM crisis, the Asian crisis, and the terrorist attack on September 11, 2001. These findings support the risk story for a global value premium, because they indicate that international investors tend to rush to quality and liquidity by getting rid of high risk (high BE/ME) stocks and replacing them with low risk (low BE/ME) stocks during financial crises.

For the effects of the financial crises on the integration of financial markets, investigation of the impact of the international debt crisis (1982-1983) and the Asian crisis (1997-1998) indicates that international financial markets became less integrated during and after the Latin American debt crisis relative to before the crisis, while financial markets became more integrated during and after the Asian crisis relative to the period before the crisis. Therefore, financial crises with regional effects (such as the less developed debt crisis in 1982-1983 that affected primarily Latin American countries) decrease financial integration, while crises with global effects (such as the Asian crisis in 1997 and 1998) increase integration. This suggests that the Latin American countries adopted restrictive capital controls for self-protection, further segmenting their markets. However, the Asian markets, with their vast global capital flows, rode out their crises with increased cooperation not only with each other but with the remainder of the world. In summary, I conclude that (1) the proposed GJR-GARCH-FF model is superior to popular existing models for explaining international returns data, (2) the global value premium is a risk factor and not an anomaly, (3) value premiums change as a result of financial market crises, and (4) the global value premium contributes to measuring integration.

Chapter four examines the impact of the subprime crisis on the market efficiency of the junk bond market. The result of such examination reveals three main conclusions: (1) the estimates of the GJR-GARCH model provides a better description of volatility dynamics during the crisis period compared to the before crisis period, indicating the presence of leverage effect. (2) The results of VAR and 2SLS estimates show that crisis does not have an impact on the efficiency of the junk bond market. (3) It seems that my empirical three-step procedure gives better results than previous studies. Instead of using VAR to account for endogenity problem in the volume-volatility relation, I use the fitted values of volume and volatility from censored regression and GJR-GARCH to run 2SLS model. The results from VAR (2SLS) estimation show that volume is insignificant (significant) predictor of bond return volatility.

Findings in the three essays open directions for further research. First, my theoretical model in the first essay bridges a historical gap in the literature between Tobin's q-theory of real investment and production-based models, by providing a theoretical model that links the two theories. Such theoretical model open directions for more empirical testing in the future research. Second, identifying links between the global value premium and integration in the second essay allows creation of new and better methodologies to incorporate the global value premium. In addition, the results support use of the new GJR-GARCH-FF model in future studies because the average intercept of the GJR-GARCH-FF model is lower than that of competing models. Therefore, incorporating cross-sectional asset pricing models (e.g., CAPM; Fama-French three factor model, 1996; Carhart four-factor model, 1997) as the mean equation in GARCH models could yield improved empirical results. Finally, the three-step empirical procedure, proposed in the third essay, may open directions for future research on the volume-volatility relation. The overall results support use of the new procedure to overcome truncation and endogenity problem.

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