Three Essays on Modeling Stock Returns: Empirical Analysis of the Residual Distribution, Risk-Return Relation, and Stock-Bond Dynamic Correlation

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Dedications

To my wife, who encouraged my doctoral study,

and my loved parents who have always supported me

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Abstract

Three Essays on Modeling Stock Returns: Empirical Analysis of the Residual Distribution, Risk-Return Relation, and Stock-Bond Dynamic Correlation.

Jiandong Li
Thomas C. Chiang Ph.D. (Supervisor)

This dissertation studies the following issues: the presence of non-normal distribution features and the significance of higher order moments, the tradeoff between risk and return, and the dynamic conditional correlation between stock returns and bond returns. These issues are structured into three essays.

Essay #1 tackles the non-normal features by employing the exponential generalized beta distribution of the second kind (EGB2) to model 30 Dow Jones industrial stock returns. The evidence suggests that the model with the EGB2 distribution assumption is capable of taking care of stock return characteristics, including fat tails, peakedness (leptokurtosis), skewness, clustered conditional variance, and leverage effect, therefore, is capable of making a good prediction on the happenings of extreme values. The goodness of fit statistic provides supporting evidence in favor of the EGB2 distribution in modeling stock returns. Evidence also suggests that the leverage effect is diminished when higher order moments are considered.

Essay #2 examines the risk-return relation by applying high frequency data of 30 Dow Jones industrial stocks. I find some supportive evidence in favor of the positive relation between the expected excess return and expected risk. However, this positive relation is not revealed for all 30 stocks using a standard weighted least squares regression (WLS) method. Using a quantile regression method, I find that the risk-return

relation evolves from negative to positive as the returns' quantile increases. This essay also finds interesting evidence that the intraday skewness coefficient explains a great deal of the variation in the excess returns.

Essay #3 mainly focuses on the analysis of the time-varying correlations between stock and bond returns using the asymmetric dynamic conditional correlation (ADCC) model (Cappiello *et al.,* 2004). The estimated coefficients show some volatile behavior and display some degree of persistence over time. Testing the asymmetric dynamic correlations by using a set of macroeconomic information, I find that the federal funds rate, the relative volatility between the stock and bond markets, the yield spread, and oil price shocks are the significant factors for the coefficients' time varying.

Chapter 1: Overview

1.1 Motivations

1.1.1 Essay #1 - The Significance of Higher Order Moments and Non-normal Distributions

Why should I be concerned about higher order moments and non-normal distributions in modeling stock returns? This is the central issue of essay #1. In illustrating the capital asset pricing model (CAPM), standard finance textbooks highlight only the first two moments: the mean and the variance. Despite the CAPM's contributions to academic research and its guidance for investment, its validity has been subject to criticism. In practice, investors do not behave as described by the mean-variance framework. In the literature, other factors, such as liquidity and skewness, are found to be priced in empirical studies (for example, Harvey and Siddque, 2000). The first essay aims to improve stock return modeling by including skewness and kurtosis in the test equation.

In his early research, Fama (1965) found that stock return series are characterized by non-normal distribution. Current research suggests that the non-normality is reflected in the non-zero skewness coefficient, the positive excess kurtosis, and the lower inter-percentile range around the median. Studying the higher order moments is meaningful for several reasons. First, from an econometrics point of view, Hansen (1994) notes that empirical specifications of asset pricing model are incomplete unless higher order moments are specified. Estimation and forecasting accuracy depends on the full specification of the distribution moments. Second, from the perspective of empirical finance studies, higher order moments have particular economic meaning. Johnson and Schill (2006) suggest that the Fama-French factors (SMB and HML) can be viewed as proxies for higher order co-skewness and co-kurtosis. Third, and more important, for portfolio management, higher order moments are considered additional risk instruments in constructing "new" portfolio theory, as argued by Jurczenko and Maillet (2002) and the papers cited therein. As a result, ignorance of higher order moments, which may be used to capture extreme values, in modeling financial data can lead to deceiving investment decisions.

One of the key reasons for the popularity of using the generalized autoregressive heteroskedasticity (GARCH) models in financial analysis is that it is capable of handling the second order moment, namely, the volatility clustering, in which large changes tend to follow large changes, and small changes tend to follow small changes. In either case, disturbances, positive or negative, become part of the information set being used to construct the variance forecast of the subsequent period's disturbance.

To tackle higher order moments, researchers have developed models based on GARCH-type models (see Engle, 1995). A further extension is to allow the asymmetric effect of the innovations being considered in modeling the conditional variance. Specifically, negative shocks have a greater impact on conditional volatility than positive shocks do.

Different approaches are considered to model higher order moments. The first one is to let the higher order moments be priced factors. For instance, Harvey and Siddique (2000) report that the co-skewness of portfolio returns is a determinant of expected returns. Patton (2004) shows that accounting for skewness improves performance of optimal asset allocation. Ranaldo and Favre (2003) discover that both co-skewness and co-kurtosis affect the risk-return characteristics in hedge funds.

The second approach is to model higher order moments using a similar method to model the conditional variance. Harvey and Siddique (1999) and Lambert and Laurent (2000) add an extra conditional skewness process based on a GARCH model. Brooks *et al*. (2005) follow the same approach to specify the conditional kurtosis autoregression.

The third approach is to use non-Gaussian distributions to replace the normal distribution assumption, as in Mandelbot (1963), Fama (1965), Officer (1972), Clark (1973), McCulloch (1985), Bollerslev (1987), Nelson (1991), Hansen (1994), Liu and Brorsen (1995) and Mittnik *et al*. (1998), among many others. Specifically, these studies propose the *t*-distribution, skewed *t*-distribution, general error distribution (GED, also known as the exponential power distribution), and α-stable Levy distributions.

Briefly speaking, the *t*-distribution is symmetric so that it inherently fails to address the issue of skewness. The GED is not flexible enough to allow for larger innovations. The α-stable distribution has theoretical appeal on account of the generalized central limit theorem; however, its moments are not defined for an order greater than α. In particular, the variance is not defined except for one special case: normal distribution; skewness and kurtosis are always indefinable. Finally, the skewed *t*-distribution used in Hansen (1994) is far from being parsimonious, and it is hard to interpret its parameters due to the transformations imposed.

Recognizing the weakness of the above distributions, it is necessary to have a model that encompasses the features of asymmetry, high peak, and fat tails. I find that the exponential generalized beta distribution of the second kind (EGB2) is able to meet the above diverse criteria. Current application of the EGB2 distribution is not satisfactory in that the goodness of fit test rejects the EGB2 distribution (Wang *et al.,* 2001). I shall use the EGB2 distribution in modeling stock returns and verify its validity. Put more precisely, I would like to construct a model that is capable of capturing general stock return features such as autocorrelation, volatility clustering, skewness, and fat tails.

1.1.2 Essay #2 - Relation between Return and Expected Risk

The risk-return trade-off plays a central role in the portfolio theory of financial economics. Since Merton's (1973) pioneer research on an intertemporal CAPM that postulates a positive relation between expected excess return and conditional variance, there has been a large amount of empirical research devoted to investigating this risk-return hypothesis. However, the results are conflicting. French *et al*. (1987), Baillie and DeGennaro (1990), Campbell and Hentschel (1992), Scruggs (1998), and Ghysels *et al*. (2005) find evidence in favor of the hypothesis for the positive relation. However, Campbell (1987), Breen *et al*. (1989), Nelson (1991), Glosten *et al*. (1993), and Lettau and Ludvigson (2002) do not find supportive evidence.

The research in this essay is motivated by the puzzle of inconclusive evidence when Merton's hypothesis is tested. To see how risk and return related on individual stocks, I test the relation between daily excess returns and expected risk on 30 Dow Jones Industrial Average (DJIA) stocks. The results are very interesting. I observe both a positive relation and a zero relation. One stock even shows a weak negative relation. In this essay, I use high frequency data to construct the daily variance and intraday skewness that appear to be able to control idiosyncratic risk.

As my research shows, the inconclusive results are based on the weighted least squares regression methodology that models the relationship between explanatory variables and the mean of the dependent variable. As a result, the estimation fails to highlight the impact of the extreme movements of the series under study. To address this issue, I employ the quantile regression, which is capable of examining the relation between explanatory variables and conditional quantiles of the dependent variables (Koenker, 2005; Chen, 2006). This essay shows that the risk-return relation evolves from negative to positive as the return's quantile increases.

1.1.3 Essay #3 - Dynamic Stock-Bond Return Relation

The study of the return correlation between stock market and bond market is one of the most significant topics in analyzing financial asset movements since the correlations between different assets are important inputs for asset allocation, portfolio selection, and risk management. In reviewing the current literature, however, two points are worth noting.

The first is the measurement of the two markets' returns. For the stock market, researchers often use the P/E ratio or dividend yields; for the bond market, some researchers use negative change of yield to maturity (YTM). These measures need to be redefined, since they are unable to cover a broad category of investment instruments. Thus, I use market index funds to proxy for returns in the two markets in studying the stock-bond market relation. In particular, this essay explores the stock-bond market return relation by investigating two Vanguard index funds.

The relationship between two asset returns is not without controversy. Both positive and negative correlations are found in the empirical studies, and they also offer good economic explanations. Papers by Keim and Stambaugh (1986), Campbell and Ammer (1993), and Kwan (1996) argue that both asset returns are subject to common economic fundamentals. Economic forces and contagion effect tend to move returns on both assets in the same direction. Thus, they support the argument for a positive correlation. However, the "flight to/from quality" argument presented by Gulko (2002), Connolly *et al*. (2005), and Baur and Lucey (2006) contends that there is a negative correlation. Hartmann *et al*. (2001) show that stock-bond contagion is about as frequent as flight to quality. The empirical analyses derived from the above arguments may be based on piecemeal regression results or confined to special sample periods.

In fact, the correlation coefficients may shift over time due to changing market conditions triggered by different external shocks. For this reason, it is more convincing to construct a time-varying model and search for appropriate economic factors that explain the dynamic relation. For this reason, this essay follows a two-step approach. In the first step, I employ the asymmetric dynamic conditional correlation (ADCC) model (Engle, 2002; Cappiello *et al.,* 2004) to generate time-varying correlations. In the second step, I search for a set of macro variables or indicators to explain the time-varying behavior of the correlation coefficient.

1.2 Contributions

The contributions of this dissertation can be summarized as follows.

For the first essay:

- I find that the EGB2 distribution is superior to alternative distributions such as normal distribution and *t*-distribution in handling skewness and kurtosis. The evidence applies to 30 individual stocks in the Dow Jones Industrial Average. The evidence is supported by the good of fit statistics for the EGB2 distribution.
- This study has significant implications for evaluating the probability that a big loss on stock returns will occur. This research provides a valuable instrument for risk management.
- Using the EGB2 distribution in modeling stock returns can alleviate the asymmetric effect (leverage effect). It suggests that the so-called leverage effect is, at least, partially attributable to the model's misspecification due to the imposition of a normal distribution.

For the second essay:

- I systematically test the risk-return relation by using high frequency data on stock returns. Standard regression results suggest that some stocks show a positive relation, that some stocks don't show any significant relation, and that one stock shows a weak negative relation.

- I resolve the puzzling relation between excess stock returns and risk by using quantile regression method. Estimated results indicate that the sign of the risk-return relation varies from low quantile to high quantile. At low quantile, the sign is negative; at high quantile, the sign is positive. The median quantile regression result is around zero. Quantile regression gives a full picture of the risk-return relation.
- While using intraday variance as a proxy for risk, I found that it is highly correlated with realized volatility.
- I find that the intraday skewness coefficient is a very powerful explanatory variable for explaining the variation in the stocks' excess return.

For the third essay:

- This study uses a rolling window method to measure the unconditional correlation and an asymmetric dynamic conditional correlation (ADCC) model to measure the dynamic correlation. The rolling correlation coefficients from 22 trading day window, from a bivariate BEKK method and from the ADCC method are close to each other.
- The average correlation coefficient over the sample is negative but close to zero.
- This study investigates the underlying economic factors that drive the correlation between two asset returns to change over time. I find that factors such as the federal funds rate, the relative return volatility between the stock and bond markets, the yield spread, and oil price shocks are highly significant.

1.3 Samples

The first essay uses daily returns on 30 Dow Jones Industrial Average stocks. The sample period is 1986-2005. In addition, returns on the Standard & Poor's 500 (S&P500) index are used to measure market return. Both daily returns on the S&P500 index and daily returns on 30 Dow Jones firms are taken from CRSP database. To calculate the excess returns, 3-month Treasury bill rate is used and is obtained from the Federal Reserve database.

The second essay uses the excess returns on the 30 stocks from the first essay plus some new variables generated from high frequency data. The 5-minute trading information of these 30 stocks is taken from the *Trade and Quotation* (TAQ) database. The sample period is 1998-2005, owing to the availability of high frequency data.

The third essay uses two index funds: VBMFX and VTSMX. VBMFX is Vanguard's Total Bond Market Index fund, which tracks Lehman Brothers' Aggregate Bond Index. VTSMX is Vanguard's Total Stock Market Index fund, which tracks the overall equity market index. The historical prices are taken from http://finance.yahoo.com. The sample period is 1996-2006. Besides these two index funds, oil prices are taken from the U.S. Department of Energy, and a variety of interest rates are taken from the Federal Reserve.

1.4 Dissertation Structure

This dissertation consists of 5 chapters. The three essays are divided among Chapters 2, 3 and 4; each chapter constitutes one essay. Chapter 5 contains an overall summary for the dissertation. To maintain the integrity of the dissertation, I have placed all references, tables, and figures at the end of the dissertation.

Chapter 2: Empirical Analysis of Asset Returns with Skewness, Kurtosis, and Outliers – Evidence from 30 Dow Jones Industrial Stocks

Abstract

This paper uses the exponential generalized beta distribution of the second kind (EGB2) to model returns on 30 Dow Jones industrial stocks. The model accounts for stock return characteristics including fat tails, peakedness (leptokurtosis), skewness, clustered conditional variance, and leverage effect. The evidence suggests that the error assumption based on the EGB2 distribution is capable of accounting for skewness, kurtosis, and peakedness and, therefore is capable of making a good prediction about extreme values. The goodness of fit statistic provides supporting evidence in favor of the EGB2 distribution in modeling stock returns. This paper also finds evidence that the leverage effect is diminished when higher moments are considered.

JEL classification: C16; C22; C46; G11

Keywords: Stock return modeling, Higher moments, EGB2 distribution, Risk management

2.1 Introduction

Focusing on economic rationales, financial economists have identified a set of fundamental variables to predict stock returns over time, including market risk, change in interest rate, inflation rate, real activities, default risk, term premium, dividend yields, and earning yields, among other variables. In the cross-section analysis, Fama and French (1993) further emphasize a size factor (SMB) and a value factor (HML). Depending on the frequency of the data being studied, the Monday effect or the January effect is usually added to the model to highlight calendar anomalies. The empirical evidence of statistical significance that justifies these variables is rather diverse. The mixed results have been attributed to variations in sample size, frequency, country, market, and/or model specification. As Avramov (2002) argues, the lack of consensus in choosing the “correct” variables may stem from model uncertainty, since equilibrium asset pricing theories are not explicit about which variables should be included in the predictive regression.

To deal with this uncertainty, researchers occasionally resort to a missing variable, a proxy for risk. It becomes more apparent as GARCH-type models show that financial data demonstrate some sort of volatility clustering phenomenon. Incorporating the conditional variance into the mean equation is definitely helpful in tying stock returns to volatility (see French *et al.,* 1987; Akgiray, 1989; Baillie and DeGennaro, 1990; and Bollerslev *et al.,* 1992, among others). However, the GARCH-type specification based on normal distribution cannot account for the presence of extreme values. Recent financial market developments show that significant daily loss occurs more frequently and volatility cannot reasonably be predicted from normal distribution. The popularity of using a normal distribution assumption lies in the fact that the statistical analysis of stock returns can be simplified, allowing the analyst to focus on the first two moments. This simplification, however, misses the information contained in higher moments.

Accounting for higher order moments is important in modeling stock return series for the following reasons. First, from an econometrics point of view, Hansen (1994) notes that empirical specifications of asset pricing model are incomplete unless higher order moments are specified. Estimation and forecasting accuracy depends on the full specification of the distribution moments. Many authors have found that higher order moments (and co-moments) can serve as explanatory variables for modeling stock returns (Harvey and Siddique, 2000; Patton, 2004; Ranaldo and Favre, 2003). Excluding information from higher order moments in modeling asset returns is bound to result in missing variable and misspecification problems.

Second, from the perspective of empirical finance studies, higher order moments have particular economic meaning. Johnson and Schill (2006) suggest that the Fama-French factors (SMB and HML) can be viewed as proxies for higher order co-skewness and co-kurtosis. They show that the Fama-French loadings generally become insignificant when higher order systematic co-moments are included in cross-sectional regressions of portfolio returns.

Third, for portfolio management, higher order moments are considered additional risk instruments in constructing "new" portfolio theory, as argued by Jurczenko and Maillet (2002) and the papers cited therein. Further, the underlying theory of stochastic dominance (Vinod, 2004) suggests that portfolio selection is determined not only by the conditional mean and variance but also by the skewness and kurtosis. The evidence provided by Harvey *et al*. (2006) and Cvitanic *et al*. (2005) substantiates the validity of the new portfolio theory. Moreover, in their recent studies, Andersen and Sornette (2001) and Malevergne and Sornette (2006) find that by incorporating higher order moments risk, it is possible to increase the expected return of the portfolio while lowering its risks. Similarly, in his study of the Hong Kong stock market, Tang (1998) finds that diversification reduces the standard deviation but worsens the negative skewness and fat tails. The evidence thus points to the fact that pricing risk based exclusively on the second moment may be very misleading. In light of this consideration, existing risk management techniques ought to be revised as well.

The significance of higher order moments has been revealed in a series of dramatic market events such as the market crash in 1987, the Asian crisis in 1997, and the financial collapse of

Long Term Capital Management (LTCM) and Orange County. To address excess risk, both financial institutions and regulators demand risk management techniques to deal with occurrences of extreme values. Although Value at Risk (VaR) has been used to predict the maximum loss of a portfolio over a target horizon in a given confidence interval, the standard VaR models based on normal distribution often underestimate the potential risk.

Three approaches have been developed to deal with higher order moments in the literature. The first approach is to treat higher order moments as explanatory variables in the stock return equation. The four-moment CAPM by Jurczenko and Maillet (2002) and Ranaldo and Favre (2003) is an example. The difficulty of this approach lies in how to generate the explanatory variables. It usually relies on higher frequency data or a rolling sample method. The second method is to apply a GARCH approach to higher conditional moments. Harvey and Siddique (1999) consider the conditional skewness, while Brooks *et al*. (2005) tackle the autoregressive conditional kurtosis. Although the two approaches are capable of extracting information from the higher order moments and useing them to explain the conditional mean, they have not completely resolved the fundamental issue that the dependent variable frequently violates the assumption of normal distribution.[1] This leads to the third approach: applying non-Gaussian distributions to model stock returns so that higher order moments are naturally incorporated. This paper falls into the third category.

The knowledge that stock returns do not follow a Gaussian distribution dates back to the papers by Mandelbrot (1963) and Fama (1965). Subsequent research includes Officer (1972), Clark (1973), McCulloch (1985), Bollerslev (1987), Nelson (1991), Hansen (1994), Liu and Brorsen (1995), and Mittnik *et al*. (1999), among many others. The studies in these papers

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[1] Both Harvey and Siddque (1999) and Brooks *et al*. (2005) use a *t*-distribution. As shown in this paper, a *t*-distribution has long tails but it is not fit for stock return data on its peakedness.

propose the *t*-distribution, skewed *t*-distribution, general error distribution (GED, also known as the exponential power distribution), and α-stable Levy distributions. Briefly speaking, the *t*-distribution is symmetric so that it inherently fails to address the issue of skewness. The GED is not flexible enough to allow for larger innovations. The stable distribution has theoretical appeal because of the generalized central limit theorem (CLT); however, its moments are not defined for an order greater than α. In particular, the variance is not defined except for one special case: normal distribution; skewness and kurtosis are always indefinable. Finally, the skewed *t*-distribution used in Hansen (1994) is far from being parsimonious, and it is hard to interpret its parameters because of the transformations imposed.

Recognizing the weakness of the above distributions, it is necessary to have a model that encompasses the features of asymmetry, high peak, and fat tails. I find that the exponential generalized beta distribution of the second kind (EGB2)[2] is able to meet the diverse criteria, which forms the research foundation of this paper.

Results emerging from this study show that the EGB2 distribution works very well in dealing with high order moments of individual stock returns. The evidence indicates that an AR(1)-GJR-GARCH(1,1) model based on the EGB2 distribution provides a unique specification in handling the stylized facts of stock return behavior: autocorrelation, conditional heteroskedasticity, the leverage effect, skewness, excess kurtosis, and peakedness.

This study contributes to the literature in the following ways. First, I find that the EGB2 distribution is superior to models based on normal distribution and *t*-distribution in handling skewness and kurtosis as evidenced by the goodness of fit statistics. Second, the prevalent risk

[2] There are different names for the EGB2 distribution in non-financial fields or in non-American journals; for example, generalized logistic distribution is used in Wu *et al*. (2000), *z*-distribution in Barndorff-Nielsen *et al*. (1982), the Burr type distribution in actuarial science in Hogg and Klugman (1983), and four parameter Kappa distribution in geology in Hosking (1994).

management tool: Value at Risk (VaR) can be updated via the EGB2 distribution. It informs investors that omitting higher moments "leads to a systematic underestimate of the true riskiness of a portfolio, where risk is measured as the likelihood of achieving a loss greater than some threshold" (Brooks *et al.,* 2005, page 400). Third, this paper systematically examines all 30 stocks in the Dow Jones industrial index. The individual stocks cover a broad range of assets and reveal a variety of fat tail characteristics. The model encompasses a rich spectrum of asset features that help to guide portfolio decisions. Fourth, I find that the asymmetric effect (the leverage effect) is diminished when the EGB2 distribution is applied. This implies that the so-called leverage effect is, at least, partially attributable to the model's misspecification because of the imposition of normal distribution on the return series.

The remainder of the chapter is organized as follows. Section 2.2 describes the methodology of the EGB2-GARCH model. Section 2.3 discusses the data. Section 2.4 presents the empirical results on the stock returns by applying different distributions. Section 2.5 reports the goodness of fit tests. Section 2.6 contains the probability evaluation using the EGB2 distribution. Section 2.7 contains conclusions.

2.2 The GARCH-Type Model Based on the EGB2 Distribution

2.2.1 General Specification

The AR(1)-GARCH(1,1)-GJR-EGB2 stock return model can be represented by a system given below:

$$r_t = \phi_0 + \phi_1 r_{m,t} + \phi_2 r_{t-1} + \delta D_{87} + \varepsilon_t \tag{2.1.a}$$

$$\varepsilon_t = \sqrt{h_t} z_t \tag{2.1.b}$$

$$h_t = w + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma\, I(\varepsilon_{t-1} < 0)\varepsilon_{t-1}^2 \tag{2.1.c}$$

$$\varepsilon_t \,|\, \Im_{\,t-1} \sim D(0, h_t, \lambda) \tag{2.1.d}$$

Equation (2.1.a) is the mean equation, where r_t is the individual stock's excess return (stock return minus the risk-free rate) at time t; ε_t is an error term. The inclusion of an AR(1) term in the mean equation accounts for autocorrelation arising from non-synchronous trading or slow price adjustments (Lo and MacKinlay, 1990; Amihud and Mendelson, 1987).[3] The market's equity premium (stock market return minus the risk-free rate), $r_{m,t}$, at time t is included in the equation to capture market risk as suggested by the CAPM. The dummy variable, D_{87}, takes the value of unity in the week of October 19, 1987, and 0 otherwise. The series, z_t, in equation (2.1.b) is a standardized error by conditional variance.

The conditional variance, h_t, is assumed to follow a GARCH(1,1) process; $w, \alpha, a\text{nd } \beta > 0$ to ensure a strictly positive conditional variance; ***I*** is an indicative function that takes the value of 1 only when the error term is negative. γ is used to capture the asymmetric effect of the extraordinary shock to the variance: bad news usually has a larger effect than does good news. In this study, I adopt the asymmetric GARCH approach suggested by Glosten, Jagannathan and Runkle (1993) for its simplicity and effectiveness. The distribution of ε_t is assumed to be a general specification conditional on the distribution captured by the parameter λ. For the normal distribution, the error follows that $\varepsilon_t \mid \Im_{t-1} \sim N(0, h_t)$. In a variant of a normal distribution, in this paper, I consider two alternatives: *t*- and EGB2 distributions.

2.2.2 Modeling Financial Time Series Based on Non-normal Distributions

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[3] Depending on the significance test of the AR(1) coefficient in the AR(1)-GARCH(1,1) model, the AR(1) term is then dropped for some stocks. The following stocks do not have an AR(1) variable: MSFT, HON, DD, GM, IBM, MO, CAT, BA, PFE, AA, DIS, MCD, JPM, and INTC. Stock PG, which is the only one that shows Q(30) is significant, adds an AR(4) variable to ensure that autocorrelation is removed. The rest of this paper follows this pattern. The recent literature suggests that the sign of the AR(1) coefficient, ϕ_2, can be used to detect feedback trading behavior (Sentana and Wadhwani, 1992; Antoniou *et al.,* 2005). My results show that the coefficient of AR(1) is negative.

Student's *t*-distribution is well known for its capacity to capture the fat-tail phenomenon. Bollerslev (1987), Bollerslev *et al*. (1994), and Hueng and Yau (2006) incorporated *t*-distribution into the GARCH model specification. The probability density function (pdf) of a normalized Student's *t*-distribution takes the form of:

$$t(x;\delta,\sigma,v)=\frac{\Gamma(\frac{v+1}{2})}{\Gamma(\frac{v}{2})\sigma\sqrt{\pi(v-2)}}\left[1+\frac{1}{v-2}(\frac{x-\delta}{\sigma})^{2}\right]^{-\frac{v+1}{2}} \tag{2.2}$$

where x is a random variable; v is the degree of freedom of the *t*-distribution (v>2); and Γ is the Gamma function. The excess kurtosis coefficient of *t*-distribution is given by $\frac{6}{v-4}$ for v>4. In light of system (2.1.a - 2.1.d), the only change is the error distribution, which is given by: $\varepsilon_t \mid \Im_{t-1} \sim t(0,h_t,v)$. From this perspective, both the coefficients and the degree of freedom of the *t*-distribution are estimated simultaneously by maximizing the following log-likelihood function:

$$\begin{aligned}\log L = T&\left[\log(\Gamma(\frac{v+1}{2})-\log(\Gamma(\frac{v}{2})-0.5\log(\pi(v-2))\right]\\ &-0.5\sum\left[\log(h_t)+(v+1)\log(1+\frac{\varepsilon_t^{\,2}}{h_t(v-2)})\right]\end{aligned} \tag{2.3}$$

Although the *t*-distribution is good at modeling fat tails for time data, its shortcoming is its built-in symmetrical nature. The distribution, however, is unable to take care of the skewness characteristic present in the financial time series. Thus, I turn to the exponential generalized beta distribution of the second kind (EGB2) developed by McDonald (1984; 1991) and McDonald and Xu (1995).

EGB2 is attractive because of its simplicity and the ease with which it can be used to estimate the parameters.[4] There is a closed-form density function for the EGB2 distribution; its higher order moments are finite and explicitly expressed by its parameters. Moreover, it is flexible and able to accommodate a wider range of data characteristics, such as thick tails and skewness, than commonly used normal and log-normal distributions.

The EGB2 distribution has the probability density function (pdf) given by:

$$EGB2(x;\delta,\sigma,p,q)=\frac{\left[e^{(\frac{x-\delta}{\sigma})}\right]^{p}}{|\sigma|\,B(p,q)\left[1+e^{(\frac{x-\delta}{\sigma})}\right]^{p+q}} \tag{2.4}$$

where x is a random variable; δ is a location parameter that affects the mean of the distribution; σ reflects the scale of the density function; p and q ($p > 0$ and $q > 0$) are shape parameters that together determine the skewness and kurtosis of the distribution of the excess return series; and ***B****(p, q)* is the beta function.[5] As suggested by McDonald (1991), the EGB2 is suitable to coefficient of skewness values between -2 and 2 and coefficient of excess kurtosis values up to 6.

[4] It is not my intention to exhaust all the non-Gaussian models in this study, which is infeasible. Rather, my strategy is to adopt a distribution rich enough to accommodate the features of financial data. To my knowledge, there are different types of flexible parametric distributions parallel to the EGB2 distribution to model both third and fourth moments in the literature. One family of such distributions is a skewed generalized *t*-distribution (SGT) (Thedossiou, 1998); Hueng and Yau, 2006). Special cases of SGT include a generalized *t*-distribution (McDonald and Newey, 1988), a skewed *t*-distribution (Hansen, 1994), and a skewed generalized error distribution (SGED) (Nelson, 1991). The skewness and excess kurtosis of SGT are in the range (-∞, ∞) and (1.8, ∞), respectively. Another family is the inverse hyperbolic sine distribution (IHS) (Johnson, 1949; Johnson *et al.,* 1994). The skewness and excess kurtosis of IHS is in the range (3, ∞) and (-∞, ∞). EGB2 has less coverage for skewness and excess kurtosis than SGT and IHS. However, it covers many skewness-kurtosis combinations encountered in practice and its performance is "impressive" in estimating the slope coefficient in a simulation (Hansen *et al.,* 2006). Other families of flexible distributions are also available in the literature. But there isn't any comparison with the EGB2 distribution.

[5] It should be noted that beta function here has nothing to do with the stock's beta.

The distribution is capable of accommodating fat-tails and skewed error features pertinent to stock return modeling.[6]

For the standardized EGB2 distribution with shape parameters p and q, the univariate GARCH-EGB2 log-likelihood function is:[7]

$$\begin{aligned}\log L = T\left\lfloor \log(\sqrt{\Omega}) - \log(B(p,q)) + p\Delta \right\rfloor \\ + \sum\left[p(\frac{\sqrt{\Omega}\varepsilon_t}{\sqrt{h_t}}) - 0.5\log(h_t) - (p+q)\log(1+\exp(\frac{\sqrt{\Omega}\varepsilon_t}{\sqrt{h_t}} + \Delta)) \right]\end{aligned} \tag{2.5}$$

where $\Delta = \psi(p) - \psi(q)$, $\Omega = \psi'(p) + \psi'(q)$ and ψ and ψ' represent digamma and trigamma functions, respectively.[8] The BFGS algorithm is used in RATS® to conduct the maximize likelihood estimation. The skewness and excess kurtosis for EGB2 distribution are given respectively by:

$$Skewness = g(p,q) = \frac{\psi''(p) - \psi''(q)}{(\psi'(p) + \psi'(q))^{1.5}} \tag{2.6}$$

$$Kurtosis = h(p,q) = \frac{\psi'''(p) + \psi'''(q)}{(\psi'(p) + \psi'(q))^{2}} \tag{2.7}$$

and ψ'' and ψ''' represent tetragamma and pentagamma functions.

Since the skewness and kurtosis coefficients are based on parameters p and q, the standard deviation of skewness and kurtosis coefficients can be drawn by using the standard delta method (see the appendix for details). By using these measures, I can judge if the EGB2 distribution correctly handles skewness and kurtosis.

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[6] Many distributions are nested in the EGB2 distribution. Wang *et al*. (2001) show that the EGB2 distribution is very powerful in modeling exchange rates that have fat tails and leptokurtosis features. The EGB2 converges to normal distribution as $p = q$ approaches infinity, to log-normal distribution when only p approaches infinity, to the Weibull distribution when p=1 and q approaches infinity, and to the standard logistic distribution when p=q=1. It is symmetric (called Gumbel distribution) for $p = q$. The EGB2 is positively (negatively) skewed as $p > q$ ($p < q$) for $\sigma>0$.

[7] This can be obtained in the appendix of Wang *et al*. (2001).

[8] The digamma function is the logarithmic derivative of the gamma function; the trigamma function is the derivative of the digamma function. See details in the appendix.

2.3 Data and Summary Statistics

In analyzing asset returns, movements in the Dow Jones Industrial Average (DJIA) are often considered one of the most important pieces of news that indicate the health of the financial market and investment performance. This paper uses the DJIA 30 stocks as the sample, which represents a group of well-established and diverse companies. The sample covers the period from October 29, 1986, through December 31, 2005. One of the reasons for using this period is its completeness. I can employ and assess information on all 30 stocks in the sample period.[9] This time period also captures the recent, very vigorous stock market while covering several major market crashes and financial crises.

Following the conventional approach, I use returns on the Standard & Poor's 500 (S&P500) index to measure the market return. Both the daily returns on S&P500 index and data on the 30 Dow Jones firms are taken from the CRSP database. The short-term interest rate is measured by the 3-month Treasury bill rate, which is taken from the Federal Reserve's website.[10] The daily risk-free rate is measured using the annual rate divided by 360. Excess stock returns are the difference between actual stock returns and the short-term interest rate.

Weekly data are used in order to be consistent with industrial practice. For example, Value Line, Bloomberg and Baseline all use weekly data to calculate the stock's beta. Daily stock

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[9] Trading data on stock C (Citi Group) starts on Oct 29, 1986. Within this period, only one stock has one missing value. Stock MO (Philips-Morris Co.) was not traded on May 25, 1994, due to "pending news which could affect the stock price". On May 25, 1994, Philip Morris's board was meeting to announce if the company would split its food and tobacco units. In this sample period, the most striking event is the market crash on October 19, 1987. This paper considers the 1987 market crash as an outlier in later parts. The week of the 9/11 terrorist attacks has only one day of trading information and is incorporated into next week.

[10] http://www.federalreserve.gov/releases/H15/data.htm#top. Treasury bill secondary market rates (serial: tbsm3m) are the averages of the bid rates quoted on a bank discount basis by a sample of primary dealers who report to the Federal Reserve Bank of New York. The rates reported are based on quotes at the official close of the U.S. government securities market for each business day. During this sample period, there are 47 observations that the S&P500 has trading information while the tbsm3m series has missing values. The lagged values of tbsm3m were taken for these 47 days.

returns are seldom used in the industry. It is also helpful to smooth out the volatility for a single-date outlier. An additional advantage of using weekly observations is that some calendar effects such as the Monday effect, can be avoided. Excess returns are measured on a weekly basis. Table 2.1 reports summarized statistics for weekly excess returns.

<Table 2.1>

Looking at Table 2.1, we see that six stocks have a positive value for the skewness coefficient and two are significant at the 1% level, while the remaining 24 stocks show negative values and 13 of them are significant at the 1% level.[11] A negative skewness coefficient means that there are more negative extreme values than positive extreme values in the sample period.[12] With respect to the excess kurtosis (kurtosis coefficient minus 3), all of the estimated values are statistically significant at the 1% level, suggesting a serious fat-tail problem. The range of the excess kurtosis coefficient is between 1.08 and 24.13. By checking the range of peakedness measured by the inter-quartile range (i.e. 0.75 fractile minus 0.25 fractile), we see that it lies between 1.01 and 1.26. This range is much lower than the referenced figure, 1.35, indicating the presence of a high peak in the probability density function for all of the stocks under investigation. Testing for dependency, Ljung-Box Q statistics show that 10 stocks are serially autocorrelated, and 27 of 30 stocks are autocorrelated in the squared term as shown by the Q^2 test. The latter suggests a volatility clustering phenomenon and is consistent with a GARCH-type

[11] The sign of the skewness coefficient is related to data frequency. The skewness of the weekly returns has nothing to do with the skewness of the daily returns. For example, the stock HON (index=2) shows significant positive skewness in its daily returns but significant negative skewness in its weekly returns.

[12] The skewness coefficient is the relation between the second order moment and the third order moment. It is calculated by: $\frac{T}{(T-1)(T-2)\sigma^3}\sum(x_i-\mu)^3$ where μ is the mean of the sample. The literature on positive and negative values of the distribution skewness is confusing. I follow the definition of the skewness by the distribution's moments (Kenney and Keeping, 1962).

specification. By inspecting the Jarque-Bera statistics, the normality for all 30 stocks is uniformly rejected.[13]

The preliminary statistical results from Table 2.1 clearly indicate that the popular normality assumption does not conform to the weekly returns. The individual stock returns often show positive excess kurtosis (fat tails), accompanied by skewness. The evidence of peakedness is not in agreement with the normal distribution either. Besides the non-Gaussian features, some weekly stock returns show autocorrelation and almost all of them feature volatility clustering.

2.4 Empirical Evidence

In this section, I estimate the system of equations from (2.1.a) through (2.1.d) and present evidence of the GARCH(1,1) model based on different distributions. I also analyze the impact of outliers on the EGB2 distribution.

2.4.1 GARCH(1,1) Model Based on the Normal Distribution

Table 2.2 reports the estimates of a GARCH(1,1) model based on the assumption that the error series follows a normal distribution, $\varepsilon_t \mid \Im_{t-1} \sim N(0, h_t)$.[14] Looking at the *t*-statistics, the null hypothesis of the absence of skewness is rejected at the 1% level for 11 out of 30 cases (4 positive and 7 negative), while the null hypothesis of the absence of excess kurtosis is rejected for all of the cases. Moreover, the Jarque-Bera tests show that all of the return residuals are rejected by assuming Gaussian distribution. Further checking into the measure of peakedness, the estimate values range from 1.06 to 1.30. All of these figures are lower than the reference point of

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[13] All the non-normality features are more remarkable in the daily data and less so in the monthly data. This is consistent with Brown and Warner (1985), who reported that the non-normal features tend to vanish in low frequency data, such as monthly observations. Even so, subject to the individual monthly stock returns, the Jarque-Bera test rejects the normality for 23 of 30 stocks at the 1% level.

[14] The standardized residuals are obtained by dividing the estimated regression residual by its conditional standard deviation. Standardizing the error term makes the distribution comparison feasible. Mean and variance are not reported in the table due to the use of normalization.

the standard normal distribution, 1.35, indicating that all of the returns are leptokurtic. It is apparent that assuming that residuals for the estimated financial data are normally distributed is invalid.

<Table 2.2>

2.4.2 GARCH(1,1) Model Based on the Student's *t*-Distribution

Estimating the model by using a *t*-distribution indicates that the excess kurtosis has been substantially removed from the estimated residuals. As shown in Table 2.3, 29 stocks show that the coefficients of excess kurtosis are insignificant. This demonstrates the effectiveness of a *t*-distribution in modeling the excess kurtosis. However, the problem of skewness has not been resolved at all. The evidence shows that 18 out of 30 stocks are significant at the 5% level or higher. There are 4 significant positive and 8 significant negative skewness coefficients in the standardized residuals at the 1% level.[15]

Another problem emerging from this model is the insufficient peakedness of the distribution. The range of the estimated degree of freedom is (3.9-11.1), which corresponds to the range of peakedness (1.53-1.39). Note that the actual peakedness measurement from Table 2.3 is in the range of (1.02-1.29), indicating the presence of leptokurtosis. The *t*-distribution is worse than the normal distribution in modeling the peakedness. (Please refer to Figure 2.1.)

<Table 2.3><Figure 2.1>

2.4.3 GARCH(1,1) Model Based on the EGB2 Distribution

To advance the study, I re-estimate the GARCH(1,1) model by employing the EGB2 distribution. Table 2.4 reports the comparable statistics based on the standardized residuals from

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[15] To deal with the skewness, a number of skewed *t*-distributions have been proposed (Thedossiou, 1998); Hueng and Yau, 2006). One obvious drawback of a skewed *t*-distribution in my study is the outcome of its peakedness measurement, which displays platykurtosis (flat-topped density). This appears to be the opposite of the leptokurtic stock returns. For this reason, I do not report results from a GARCH model based on a skewed *t*-distribution in order to focus on the EGB2 distribution.

GARCH(1,1) cum EGB2 distribution: $\varepsilon_t \mid \Im_{t-1} \sim EGB2(0, h_t, p, q)$. The results show that the skewness problem for most cases has been alleviated by using the EGB2 distribution. The evidence indicates that only 5 stocks show the presence of skewness. Turning to the statistics of excess kurtosis, I find that the EGB2 distribution works well for some stocks' kurtosis but not for all of them. The evidence in Table 2.4 indicates that 9 stocks still show excess kurtosis.

Table 2.4 also contains the range of *p*, (0.334-1.776), and of *q*, (0.348-1.669). The reported *p* and *q* values suggest that the residuals' distributions are far from the normal distribution that requires that values for both *p* and *q* approach infinity. Based on the estimated shape parameters, the expected peakedness for the 30 stocks is in the range of (1.07-1.26). The peakedness obtained from residuals of the mean equation is in the range of (1.06-1.30), conforming to the existence of a high peak implied by the EGB2 distribution.

With respect to the beta coefficients, I find that the estimated values are highly significant, ranging from 0.69 to 1.32. The evidence suggests that the market risk is still one of the most influential factors for predicting individual stocks. It is of interest to compare the beta values and the associated standard errors across different distributions. As may be seen from Figure 2.2, where the figures are mainly reproduced from Table 2.2 to Table 2.4, I find no significant difference among them for the estimated betas. This is not surprising since the estimations of the betas are obtained from the average effect based on the whole probability space. My finding is consistent with the results from Nelson (1991) and Hansen (1994).

<Table 2.4><Figure 2.2>

Inspecting the lagged individual stock return variable, I find that about half of them have a negative sign and are statistically significant, indicating that a mean reversion process is present in the weekly data. Turning to the 1987 market crash dummy, the testing results show that 20 out of 30 stocks are significant at the 5% level, although the signs are mixed. The diverse movements signify the profound impact of an influential observation. Consistent with most financial data, with a few exceptions, the coefficients of the GARCH equation for each stock are found to be highly significant.

One of most striking results emerging from the estimations is that while testing the leverage effect, only 4 stocks are found to be statistically significant at the 5% level. The number of stocks that show asymmetric effects has been reduced dramatically, as compared with the statistics reported in Table 2.2, where 15 stocks show a significant asymmetric effect. It can be argued that the so-called asymmetric effect may result from the fact that the empirical analysis was built on a misleading assumption by imposing a normal distribution on financial data.

A disturbing fact in Table 2.4 is that three stocks show a kurtosis coefficient greater than 6, which is beyond the scope of the EGB2 distribution. Despite this shortcoming and the above-mentioned 9 stocks that have significant kurtosis, I find a significant improvement compared with the model that assumes a normal distribution or a *t*-distribution. The predicted skewness and excess kurtosis of the EGB2 distribution are much closer to the observed skewness and kurtosis. Thus, the EGB2 distribution has a good fit, although the results are not perfect.[16] Finally, I check the independence for both return level and return squares. I find that in only three cases can the null hypothesis be rejected by either Q test or Q^2 test at the 5% level, but none at the 1% level. In general, the models are adequate.

2.4.4 The Impact of Outliers

Theoretically, the EGB2 distribution is feasible for coefficients of skewness in a range of (-2, 2) and the coefficients of excess kurtosis in a range of (0, 6). However, the statistics in Table 2.4

[16] Some refinement of the model is contained in the following section.

do not fall in these desired ranges. Two possible reasons might contribute to this problem. First, the residual series was contaminated by the presence of outliers. As pointed out by Peña *et al*. (2001), an outlier can have very serious effects on the properties of the observed time series and it can affect the estimated residuals and the parameter values. Second, the mean equation and/or the variance equation may be mis-specified, although an asymmetric effect has been considered.[17] To address this issue, I further investigate the stock return series on which outliers might more seriously impinge.

Investigating the 9 stocks with excess kurtosis, I find a common phenomenon: multiple outliers are present. This means that a 1987 market crash dummy is incapable of accommodating multiple extreme values in the data series. For instance, stock UTX (index =10) has an extreme value of -38% in the week of the 9/11 terrorist attacks in 2001. To address the issue, I identify the outliers and use intervention analysis, as in the study by Box and Tiao (1975), and the extension of the analysis in Tsay *et al*. (2000) and Peña *et al*. (2001). Table 2.5 reports the statistics of the residual analysis for these 9 stocks by adding different dummies in the mean equation. This result is rather encouraging as seen by the evidence that it reduces the significance of the kurtosis coefficient. It reveals that the kurtosis problem is somehow related to the failure to take into account extraordinary events that disturb the data structure, rather than the failure of the EGB2 distribution. It is evident that after removing the effect of outliers in a given time series, the EGB2 distribution is capable of addressing the financial data with skewness and kurtosis in an appropriate range.[18]

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[17] Engle *et al.* (1987) suggest putting a conditional volatility variable in the mean equation, which is called a GARCH-M model. However, the expected sign of the conditional variance variable is uncertain, according to literature surveys. There is another reason that it is not finally adopted. I cannot find the significance of the conditional volatility variable.

[18] Longin (1996) proposes the use of a Frechet distribution, which is able to highlight those extreme price movements. However, his model is not for whole return distribution but only for extreme values.

<Table 2.5>

2.5 Distributional Fit Test

Previous sections emphasized estimates of parameters pertinent to modeling the skewness and kurtosis of the standardized residuals by applying non-Gaussian distributions. As part of the modeling process, model checking in terms of goodness of fit is also important. Table 2.6 and Figure 2.3 compare a GARCH(1,1) model based on three distributions: normal, Student's *t*, and EGB2. The reported log-likelihood function values (negative) clearly show that the EGB2 distribution outperforms the rival distributions: the normal distribution and the *t*-distribution. However, as noted by Boothe and Glassman (1987), making non-nested distribution comparisons based on log-likelihood values can lead to spurious conclusions.[19] Consequently, I calculate the goodness of fit test statistics[20] to compare differences between the observed distribution of standardized residuals and the theoretical distribution based on estimated shape parameters following Snedecor and Cochran (1989).

The null hypothesis tested by the goodness of fit test statistic is that the observed and predicted distribution functions are identical. The test statistic is calculated by:

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \tag{2.8}$$

where O_i is the observed count of actual standardized residuals in the i^{th} data class (interval), E_i is the expected count derived from the estimated values for the distribution parameters, and k is the number of data intervals used in distributional comparisons. This test statistic has an asymptotic

[19] Normal distribution is a special case of the EGB2 distribution. Likelihood Ratio Test suggests that there is significant improvement in the fit of the EGB2 distribution than that of the normal distribution.

[20] The chi-square test is an alternative to the Anderson-Darling and Kolmogorov-Smirnov goodness of fit tests. The chi-square test and Anderson-Darling test make use of the specific distribution in calculating critical values. This has the advantage of allowing a more sensitive test and the disadvantage that critical values must be calculated for each distribution.

chi-squared distribution with degrees of freedom equal to the number of intervals minus the number of estimated distribution parameters minus one. For the EGB2 distribution, 2 parameters are estimated; for the Student's t distribution, one parameter is estimated; for the normal distribution, no parameter is required, since the error term has been standardized.

Table 2.6 reports the results of the χ^2 test for three distributions used in the GARCH(1,1) model. The test power is maximized by choosing a data class equiprobably (equal probability). The rule of thumb of a χ^2 test is to choose the number of groups starting at $2T^{0.4}$. [21] The test results show that the null hypothesis is rejected by 12 stocks on the normal distribution at the 1% level, 28 stocks on the *t*-distribution, and only 3 stocks on the EGB2 distribution. Furthermore, the χ^2 test statistic also shows that the EGB2 distribution yields lower absolute values. We can conclude that the residuals in the model based on the EGB2 distribution deviate the least from the theoretical distribution. The evidence suggests that the Student's *t*-distribution is able to solve the kurtosis problem, but it could not fit the whole error distributions due to peakedness. Putting the evidence together, it is clear that the EGB2 distribution is superior to the *t*-distribution and normal distribution in my empirical analysis.

<Table 2.6><Figure 2.3>

2.6 Implication of the EGB2 Distribution

One of the main objectives of analyzing financial data for risk management purposes is to provide an answer to the question: how do we evaluate the probability of extreme values by using statistical distributions? According to normal distribution, the 1987 market crash with

[21] My sample contains 999 observations; 40 intervals are used. Each group (data class) has 25 observations theoretically. The degrees of freedom are 37, 38 and 39 for the EGB2 distribution, *t*-distribution, and normal distribution, respectively. (The chi-squared critical values are given in the notes to Table 2.6.)

more than -17σ (daily data) would have never happened. However, recent market crashes indicate that big market swings or significant declines in asset prices happen more frequently than expected. Although VaR is one of the most prevalent risk measures used under normal conditions, it cannot deal with extreme values, since extreme values are *not* normal. From this perspective, the EGB2 distribution provides a management tool for calculating risk.

Table 2.7 reports the probability of the semi-volatility of shocks. Here, I concentrate on the probability of the error term having negative shocks. From this table, I see that the predicted probability for extreme values (beyond -2σ) is greater than that of the normal distribution. For instance, probabilities of -5σ and -7σ shocks for MSFT (index =1) are 4.9E-5 and 8.4E-7 and are much greater than 2.8E-7 and 1.3E-12 based on the normal distribution.

Yet, the probabilities for the EGB2 distribution under a moderate range (within ±2σ) are less than that of the normal distribution. This is an alternative way to tell the peakedness and fat tails of portfolio returns. Notice that the crossing point between the EGB2 distribution and the normal distribution is in the neighborhood of ±2σ, where the probabilities of both distributions are about the same value. This feature implies that a VaR at the 95% confidence level based on the normal distribution is by chance consistent with reality. However, beyond this critical level, the VaR method based on the normal distribution leads to underestimated forecasts of losses. Nevertheless, the EGB2 distribution in this regard provides a broader spectrum of risk information for guiding risk management.

<Table 2.7>

2.7 Conclusion

In this paper, I present empirical evidence on the stock return equation based on market risk, time series pattern, and asymmetric conditional variance for the 30 Dow Jones stocks. Special attention is given to the issue of skewness, kurtosis, and outlier effects. Although I find no significant difference over the estimated betas and the corresponding standard errors of the distributions, the evidence shows that the exponential generalized beta distribution of the second kind (EGB2) is superior to the Student's *t*-distribution and normal distribution in dealing with data that demonstrate skewness and excess kurtosis simultaneously. The superiority of the EBG2 distribution in modeling financial data is not only due to its flexibility but also to its closed-form density function for the distribution. Its higher order moments are finite and explicitly expressed by its parameters. Thus, the EGB2 model provides a useful tool for forecasting variances involving extreme values. As a result, this model can be practically used for risk management.

Consistent with the finding in the literature, the asymmetric effects are highly significant in the standard GJR-GARCH specification by assuming normal distributions. However, incorporating the heavy tail information into the distributions reduces the asymmetric effects. My study confirms that the EGB2 distribution has the capacity to deal with the asymmetric effects. Since the excess kurtosis is often caused by outliers, my finding suggests that removing the contamination of outliers from the residuals enhances the performance of the EGB2 distribution. In short, the GJR-GARCH-type model based on the EGB2 distribution provides a richer framework for modeling stock return volatility. It accommodates several special stock return features, including fat tail, skewness, peakedness, autocorrelation, volatility clustering, and the leverage effect. As a result, this model is effective for empirical estimation and is suitable to risk management.

Appendix 1 to Chapter 2: Moments of the EGB2 Distribution

The pdf of the EGB2 distribution[22] is:

$$EGB2(x;\delta,\sigma,p,q) = f(x) = \frac{\left[e^{(\frac{x-\delta}{\sigma})}\right]^p}{|\sigma| B(p,q)\left[1+e^{(\frac{x-\delta}{\sigma})}\right]^{p+q}}$$

The first order moment is:

$$mean = \int_{-\infty}^{\infty} f(x)xdx = \int_{-\infty}^{\infty} \frac{\left[e^{(\frac{x-\delta}{\sigma})}\right]^p}{|\sigma| B(p,q)\left[1+e^{(\frac{x-\delta}{\sigma})}\right]^{p+q}} xdx$$

Let $z = \dfrac{x-\delta}{\sigma}$, then

$$mean = \int_{-\infty}^{\infty} \frac{\left[e^z\right]^p}{|\sigma| B(p,q)\left[1+e^z\right]^{p+q}} (\delta+\sigma z)\sigma dz$$

Let $A = \dfrac{\left[e^z\right]^p}{\left[1+e^z\right]^{p+q}}$ for convenience, then

$$mean = \frac{\delta}{B(p,q)} \int_{-\infty}^{\infty} Adz + \frac{\sigma}{B(p,q)} \int_{-\infty}^{\infty} Azdz$$

We know $B(p,q) = \int_{-\infty}^{\infty} Adz$ from the identity function of the B(*p, q*) so that

[22] The quantile function of the EGB2 distribution is exactly the regularized incomplete beta function.

$$mean = \delta + \frac{\sigma}{B(p,q)} \int_{-\infty}^{\infty} Azdz$$

Taking first order difference of B(*p, q*) with respect to *p* we get

$$\frac{d}{dp} B(p,q) = \int_{-\infty}^{\infty} \frac{d}{dp}(A)dz$$

Since we have:

$$\frac{d}{dp}(A) = \frac{d}{dp}\left(\frac{\left[e^{z}\right]^{p}}{\left[1+e^{z}\right]^{p+q}}\right) = Az - A\ln(1+e^{z})$$

$$\frac{d}{dq}(A) = \frac{d}{dq}\left(\frac{\left[e^{z}\right]^{p}}{\left[1+e^{z}\right]^{p+q}}\right) = -A\ln(1+e^{z})$$

So:

$$\frac{d}{dp} B(p,q) = \int_{-\infty}^{\infty} \left[Az - A\ln(1+e^{z})\right]dz = \int_{-\infty}^{\infty} Azdz + \int_{-\infty}^{\infty} \frac{d}{dq}(A)dz = \int_{-\infty}^{\infty} Azdz + \frac{d}{dq} B(p,q)$$

So:

$$\int_{-\infty}^{\infty} Azdz = \frac{d}{dp} B(p,q) - \frac{d}{dq} B(p,q) = B(p,q)\left[\Psi(p) - \Psi(q)\right]$$

where Ψ is the digamma function. Finally, we get the mean equation:

$$mean = \delta + \sigma\left[\Psi(p) - \Psi(q)\right]$$

Following the above part, the second order central moment is:

$$Var = \int_{-\infty}^{\infty} f(x)(x - mean)^2 dx = \int_{-\infty}^{\infty} \frac{\left[e^{(\frac{x-\delta}{\sigma})}\right]^{p}}{|\,\sigma\,|\, B(p,q)\left[1+e^{(\frac{x-\delta}{\sigma})}\right]^{p+q}} \left(x - \delta - \sigma\left(\Psi(p) - \Psi(q)\right)\right)^2 dx$$

Same as before, let $z = \dfrac{x-\delta}{\sigma}$, $A = \dfrac{\left[e^z\right]^p}{\left[1+e^z\right]^{p+q}}$ then

$$Var = \frac{\sigma^2}{B(p,q)} \int_{-\infty}^{\infty} A\left(z - \left(\Psi(p) - \Psi(q)\right)\right)^2 dz$$

$$\begin{aligned}
Var &= \frac{\sigma^2}{B(p,q)} \left\{ \int_{-\infty}^{\infty} Az^2 dz - \int_{-\infty}^{\infty} 2Az\left(\Psi(p) - \Psi(q)\right)dz + \int_{-\infty}^{\infty} A\left(\Psi(p) - \Psi(q)\right)^2 dz \right\} \\
&= \frac{\sigma^2}{B(p,q)} \left\{ \int_{-\infty}^{\infty} Az^2 dz - 2\left(\Psi(p) - \Psi(q)\right)\int_{-\infty}^{\infty} Azdz + \left(\Psi(p) - \Psi(q)\right)^2 \int_{-\infty}^{\infty} Adz \right\} \\
&= \frac{\sigma^2}{B(p,q)} \left\{ \int_{-\infty}^{\infty} Az^2 dz - B(p,q)\left(\Psi(p) - \Psi(q)\right)^2 \right\} \\
&= \sigma^2 \left\{ \frac{1}{B(p,q)} \int_{-\infty}^{\infty} Az^2 dz - \left(\Psi(p) - \Psi(q)\right)^2 \right\}
\end{aligned}$$

We calculate the following second order differences first:

$$\frac{d^2}{dp^2}(A) = A(z - \ln(1+e^z))^2$$

$$\frac{d^2}{dq^2}(A) = A(\ln(1+e^z))^2$$

$$\begin{aligned}
\frac{d^2}{dpdq}(A) &= -A(\ln(1+e^z))(z - \ln(1+e^z)) \\
&= -Az(\ln(1+e^z)) + A(\ln(1+e^z))^2
\end{aligned}$$

Now take the second order differences of B(*p, q*):

$$
\begin{aligned}
\frac{d^2}{dp^2}B(p,q) &= \int_{-\infty}^{\infty}\frac{d^2}{dp^2}(A)dz \\
&= \int_{-\infty}^{\infty} A(z-\ln(1+e^z))^2\,dz \\
&= \int_{-\infty}^{\infty} Az^2dz - 2\int_{-\infty}^{\infty} Az\ln(1+e^z)dz + \int_{-\infty}^{\infty} A(\ln(1+e^z))^2\,dz \\
&= \int_{-\infty}^{\infty} Az^2dz + 2\left[\frac{d^2}{dpdq}B(p,q) - \frac{d^2}{dq^2}B(p,q)\right] + \frac{d^2}{dq^2}B(p,q) \\
&= \int_{-\infty}^{\infty} Az^2dz + 2\frac{d^2}{dpdq}B(p,q) - \frac{d^2}{dq^2}B(p,q)
\end{aligned}
$$

So:

$$
\int_{-\infty}^{\infty} Az^2dz = \frac{d^2}{dp^2}B(p,q) - 2\frac{d^2}{dpdq}B(p,q) + \frac{d^2}{dq^2}B(p,q)
$$

Therefore:

$$
\begin{aligned}
Var &= \sigma^2\left\{\frac{1}{B(p,q)}\left\{\frac{d^2}{dp^2}B(p,q) - 2\frac{d^2}{dpdq}B(p,q) + \frac{d^2}{dq^2}B(p,q)\right\} - \left(\Psi(p)-\Psi(q)\right)^2\right\} \\
&= \sigma^2\left\{\left\{\begin{matrix} \left[\left(\Psi(p)-\Psi(p+q)\right)^2 + \left(\Psi'(p)-\Psi'(p+q)\right)\right] \\ -2\left[\left(\Psi(p)-\Psi(p+q)\right)\left(\Psi(q)-\Psi(p+q)\right) - \Psi'(p+q)\right] \\ +\left[\left(\Psi(q)-\Psi(p+q)\right)^2 + \left(\Psi'(q)-\Psi'(p+q)\right)\right] \end{matrix}\right\} - \left(\Psi(p)-\Psi(q)\right)^2\right\} \\
&= \sigma^2\left\{\left\{\left(\Psi(p)-\Psi(q)\right)^2 + \left(\Psi'(p)+\Psi'(q)\right)\right\} - \left(\Psi(p)-\Psi(q)\right)^2\right\} \\
&= \sigma^2\left(\Psi'(p)+\Psi'(q)\right)
\end{aligned}
$$

where Ψ’ is the trigamma function.

In the same vein as the above two moment calculation but with higher order differences, we get the next two central moments as:

$$
\begin{aligned}
The3rdMoment &= \sigma^3\left(\Psi''(p)-\Psi''(q)\right) \\
The4thMoment &= \sigma^4\left(\Psi'''(p)+\Psi'''(q)\right)
\end{aligned}
$$

where Ψ’’ and Ψ’’’ are the tetragamma function and pentagamma function respectively.

Appendix 2 to Chapter 2: Delta Method and Standard Errors of the Skewness and Kurtosis Coefficients of the EGB2 Distribution

The delta method, in its essence, expands a function of a random variable about its mean, usually with a one-step Taylor approximation, and then takes the variance. For example, if we want to approximate the variance of *G(X)* where *X* is a random variable with mean μ and *G(X)* is differentiable, we can try

$$G(x) \approx G(\mu) + (x - \mu)G'(\mu)$$

so that

$$Var(G(x)) \approx G'(\mu)^2 Var(x)$$

where *G'() = dG/dX*. This is a good approximation only if X has a high probability of being close enough to its mean so that the Taylor approximation is still good.

The n^{th} central moments of the EGB2 distribution is given by:

$$The\ n^{th}\ Moment = \sigma^n \left(\psi^{n-1}(p) + (-1)^n \psi^{n-1}(q)\right)$$

where ψ^n is an n^{th} order polygamma function. Correspondingly, the skewness coefficient is given by:

$$Skewness = g(p,q) = \frac{\psi''(p) - \psi''(q)}{(\psi'(p) + \psi'(q))^{1.5}}$$

The variance of the skewness coefficient by the delta method is given by:

$$Var(Skewness) = g_p^{'}(p,q)^2 \operatorname{var}(p) + g_q^{'}(p,q)^2 \operatorname{var}(q) + 2g_p^{'}(p,q)g_q^{'}(p,q)\operatorname{cov}(p,q)$$

where

$$g_p^{'}(p,q) = \frac{\psi'''(p)(\psi'(p) + \psi'(q)) - 1.5\psi''(p)(\psi''(p) - \psi''(q))}{(\psi'(p) + \psi'(q))^{2.5}}$$

$$g_q'(p,q) = \frac{-\psi'''(q)(\psi'(p)+\psi'(q)) - 1.5\psi''(q)(\psi''(p)-\psi''(q))}{(\psi'(p)+\psi'(q))^{2.5}}$$

Similarly, the excess kurtosis coefficient is given by:

$$Kurtosis = h(p,q) = \frac{\psi'''(p)+\psi'''(q)}{(\psi'(p)+\psi'(q))^2}$$

The variance of the kurtosis coefficient by the delta method is given by:

$$Var(Kurtosis) = h_p'(p,q)^2 \operatorname{var}(p) + h_q'(p,q)^2 \operatorname{var}(q) + 2h_p'(p,q)h_q'(p,q)\operatorname{cov}(p,q)$$

where

$$h_p'(p,q) = \frac{\psi''''(p)(\psi'(p)+\psi'(q)) - 2\psi''(p)(\psi'''(p)+\psi'''(q))}{(\psi'(p)+\psi'(q))^3}$$

$$h_q'(p,q) = \frac{\psi''''(q)(\psi'(p)+\psi'(q)) - 2\psi''(q)(\psi'''(p)+\psi'''(q))}{(\psi'(p)+\psi'(q))^3}$$

Note: This appendix refers to Wang *et al*. (2001). However, there are typos and errors in that paper. The standard deviation formula for skewness used by Wang *et al.* (2001) is incorrect (see $g_q'(p,q)$ equation at http://www.econ.queensu.ca/jae/2001-v16.4/wang-fawson-barrett-mcdonald/Appendix4_delta_derivations.pdf). Therefore, I provide such an appendix. Accordingly, as I reviewed and replicated that paper using the data supplied by *the Journal of Applied Econometrics*, the EGB2 distribution did not remove the skewness problem completely as shown in their table 2.3. In addition, there is a computational error in the JPY series, so that its kurtosis has not been resolved either.

Appendix 3 to Chapter 2: Beta Function and Polygamma Functions

The beta function is defined as a definite integral:

$$\mathrm{B}(p,q) = \int_0^1 u^{p-1}(1-u)^{q-1}\,du$$

let $x \equiv \sqrt{u}$, so $u = x^2$ and $du = 2x dx$, and

$$\mathrm{B}(p,q) = 2\int_0^1 x^{2p-1}(1-x^2)^{q-1}\,dx$$

let $u \equiv x^2/(1-x^2)$, so

$$B(p,q)=\int_0^{\infty}\frac{u^{p-1}}{(1+u)^{(p+q)}}du$$

let $u \equiv e^z$ then we get what is used in the EGB2 distribution:

$$B(p,q)=\int_{-\infty}^{\infty}\frac{e^{zp}}{(1+e^z)^{(p+q)}}dz$$

By changing to a polar coordinate, we can get the important relation between the beta function and the gamma function:

$$B(p,q)=\frac{\Gamma(p)\Gamma(q)}{\Gamma(p+q)}$$

Taking the first order difference of B(*p, q*) with respect to *p*, we get:

$$\frac{d}{dp}B(p,q)=B(p,q)\left[\Psi(p)-\Psi(p+q)\right]$$

where Ψ is the digamma function. According to the beta function's symmetry, we get:

$$\frac{d}{dq}B(p,q)=B(p,q)\left[\Psi(q)-\Psi(p+q)\right]$$

The gamma function can be defined as a definite integral for $R[z]>0$

$$\Gamma(z)=\int_0^{\infty}t^{z-1}e^{-t}dt$$

The digamma function is the logarithmic derivative of the gamma function.

$$\Psi(z)=\frac{d}{dz}\ln(\Gamma(z))=\frac{\Gamma'(z)}{\Gamma(z)}$$

Taking the first order normal derivative of the digamma, we get trigamma; taking the first order derivative of the trigamma, we get tetragamma, and so on. The polygamma function is the nth normal derivative of the logarithmic derivative of Γ(z).

$$\Psi^{n}(z) = \frac{d^{n+1}}{dz^{n+1}} \ln(\Gamma(z))$$

which, for $n > 0$ can be written as

$$\Psi^{n}(z) = (-1)^{n+1} n! \sum_{k=0}^{\infty} \frac{1}{(z+k)^{n+1}}$$

which is used to calculate polygamma functions in this paper.

Chapter 3: Empirical Evidence on the Risk-Return Relation Based on the Quantile Regression

Abstract

This paper examines the risk-return relation by applying high frequency data from 30 Dow Jones industrial stocks. I find some supportive evidence in favor of the positive relation between the mean of the excess returns and expected risk. However, such a positive relation is not revealed on all sample stocks. By using a quantile regression, I find that the risk-return relation evolves from negative to positive as the return's quantile increases. Quantile regression gives a uniform picture on the risk-return relation for all 30 stocks. In this paper I also document that the intraday skewness coefficient explains a great deal of the variation in the excess returns.

JEL classification: C14; C33; G12; C22

Keywords: Risk-return tradeoff; High frequency data; Intraday skewness coefficient; Quantile regression

3.1 Introduction

The risk-return trade-off plays a central role in the portfolio theory of financial economics. Merton's (1973) pioneer research on the intertemporal CAPM postulates a positive relation between expected excess returns and conditional variance. Following Merton's theoretical prediction, there are voluminous studies devoted to investigating this risk-return hypothesis. French *et al*. (1987), Baillie and DeGennaro (1990), Campbell and Hentschel (1992), Campbell (1993), Scruggs (1998), and Ghysels *et al*. (2005) find a positive but mostly insignificant relation.

However, Campbell (1987), Breen *et al*. (1989), Nelson (1991), Glosten *et al*. (1993), and Lettau and Ludvigson (2002) report a negative relation.

Other research papers, such as Turner *et al*. (1989), Backus and Gregory (1993), Gennotte and Marsh (1993), Whitelaw (1994), and Harvey (2001), argue that the contemporaneous relation between expected returns and volatility is nonstationary and that the relation can be increasing, decreasing, flat, or nonmonotonic. They suggest that the sign of the test relation is conditioned on the methods (models and exogenous variables) being used. For instance, Koopman and Uspensky (1999) find evidence of a weak negative relationship with a stochastic-variance-in-mean model, but a weak positive relationship with an ARCH-based volatility-in-mean model. Harrison and Zhang (1999) report that the return-risk relationship is positive at long horizons. However, they find no significant correlation at short horizons. Brandt and Kang (2004) argue that the conditional correlation between the mean and volatility is negative, and the unconditional correlation is positive. Thus, the empirical evidence on the risk-return trade-off is inconclusive.

The risk-return relation studies have been circumscribed in using market index such as Standard & Poor's 500 since the portfolio theory states that individual stocks' risk contains idiosyncratic risk that can be diversified off. However, two reasons make the risk-return relation study on individual stocks meaningful. First, the capital asset pricing model (CAPM) is built on several restricted assumptions, including that all investors are homogenous and rational, the capital market is perfect, variance is an adequate measurement of risk, and the S&P500 is an index to proxy the market portfolio. These assumptions are not solid and leave the CAPM impractical. In practice, investors are trading individual stocks. The relation between the individual stocks' returns and variance deserves further attention. Second, the lack of attention on individual stocks with respect to the risk-return relation may result from the ignorance of the idiosyncratic risk. After I use a control variable for the idiosyncratic risk in the regression model, the relation between individual excess returns and risk is similar to that of aggregate market approach. Since the literature on risk-return trade-off using Standard & Poor’s 500 is inconclusive, the individual stocks’ risk-return trade-off study will provide us with a broader spectrum of asset analysis and enrich our understanding of investor behaviors.

In this paper, I use Dow Jones industrial 30 stocks to examine risk-return relation. I employ intra-day data and the risk is measured using intraday variance. This approach is appealing because using high frequency data allows me to derive the trading behavior presenting in daily activity, including market reaction to instant news, order placing, and program trading. This activity and information may not be predicted by the aggregated daily, weekly, and monthly data in constructing conditional variance.

Owing to this more effective information content, I find direct evidence that there is a positive relation between the expected daily excess stock return and its expected standard deviation. However, the positive relation between the excess return and expected risk is revealed only in part of my sample stocks. Some stocks in my sample are inclined to show a non-significant relation. One even shows a weak negative relation.

To explain this phenomenon, I use a quantile regression method to illustrate the full picture of the relation between excess returns and expected risk. Instead of modeling the expected value of the excess returns, a quantile regression models the whole distribution of excess returns. The quantile regression is superior to the least squares regression in the following two respects. First, the results derived from least squares regression methods lack robustness, producing either a positive or a negative relation that may change due to extreme values. Stock return series is notoriously known having many extreme values. The information on fat tails or unexpected variations has been exaggerated by employing the least squares regression method in the test equation. Second, the quantile regression covers the entire spectrum of dependent variable. It shows the changing of the impact of the explanatory variables on the dependent variable. This information has been left out using the least squares regression method, since it gives only one average value.

Results from quantile regressions show that the risk-return relation evolves from negative to positive as the return's quantile increases. Generally, I find evidence that with quantiles below the median, the excess return is negatively related to the expected risk; however, for quantiles above the median, I find that the excess return is positively related to the expected risk. In the median regression, the relation between excess return and expected risk is usually not significantly different from zero.

This paper contributes to the literature in several respects. First, this paper finds a way to study individual stocks' risk-return relation. Unexpected intraday volatility and intraday skewness coefficient work as control variables in the regression model. They both are powerful in explaining the variation in excess returns. Unexpected intraday volatility is the difference between actual intraday volatility and its expected part by ARMA process. The actual intraday volatility and the intraday skewness coefficient are calculated based on 5-minute returns' information.

The rationales of using unexpected volatility and intraday skewness coefficient as a way of controlling idiosyncratic risk come from the efficient market hypothesis (EMH). In many empirical studies, news variables such as earning announcements or changes in analysts' grading are used to explain the variation in the individual stocks' returns. The news variables represent the idiosyncratic risk. According to the EMH, any news will be quickly incorporated in the 5-minute return series. As a result, news has an impact on the unexpected intraday volatility and intraday skewness coefficient. In reverse, the unexpected intraday volatility and intraday skewness coefficient will reflect the news shock effect (idiosyncratic risk[23]), both in the scale and the sign. My evidence shows that the unexpected intraday volatility and the intraday skewness coefficient explain much bigger part of the variation in the excess returns than does the expected risk variable.

Second, the hypothesis that excess return is positively related to expected risk is tested using 30 Dow Jones industrial stocks. The findings provide concrete evidence of the relation between return and risk for large, diverse stocks. My results show that almost half of my sample stocks show a positive relation, while another half stocks show a zero relation.

Third, by using quantile regression analysis, this paper provides a full spectrum investigation of the relation between excess return and expected risk. I demonstrate that the sign varies from low quantiles to high quantiles, and the result for the median quantile is consistent with that of the conventional regression procedure, which is based on mean values. My results are consistent and robust across all 30 stocks under investigation.

The rest of the chapter is organized as follows: section 3.2 describes the model, the sample data, and variable measurements. Section 3.3 presents the empirical evidence on the risk-return relation using traditional least squares regression. Section 3.4 introduces quantile regression and presents results. Section 3.5 offers conclusions.

[23] An argument against my approach is that the news that moves market definitely affects individual stocks' intraday skewness coefficient as well. This is true. The intraday skewness coefficient reflects the news impact including broad market news and firm level news. However, since news that affects the market needs to be controlled in the regression as well, this paper only emphasizes its capability to control idiosyncratic risk in the individual stocks' regression.

3.2 Model, Sample Data Description, and Variable Measurements

3.2.1 Model

Market rationality suggests that investors will make a portfolio decision based on the choice of expected return and expected volatility. The hypothesis in Merton's notion is that there will be a positive relation between excess stock return and a predictable volatility component. In addition to the risk compensation factor, the literature suggests that news variables, such as unexpected changes in economic indicators, changes in Federal Reserve policy, earning and profit announcements, litigation, natural disasters, and the breakout of war, also play significant roles in determining excess return. Instead of collecting news variables for each stock, it can be assumed that unexpected news and its impact on economic agents' decision will be reflected in unexpected volatility (French *et al.,* 1987). The regression model can be written as:

$$r_t = \delta_0 + \delta_1 \sigma_t^e + \delta_2 \sigma_t^u + \varepsilon_t \qquad (3.1.a)$$

With the availability of high frequency data, I introduce a new variable, the intraday skewness coefficient of the stock's 5-minute returns, to reflect the news' impact on trading activity. To incorporate the information and to adjust for first order autocorrelation of stock returns, I write the following regression:

$$r_t = \delta_0 + \delta_1 \sigma_t^e + \delta_2 \sigma_t^u + \delta_3 Skew_t + \delta_4 r_{t-1} + \varepsilon_t \qquad (3.1.b)$$

where the dependent variable is stocks' excess return ($r = r_{raw} - r_f$) at day *t*; the regressors are expected volatility measured by the expected intraday standard deviation,[24] unexpected volatility measured by the unexpected intraday standard deviation, and the intraday skewness coefficient.

[24] Using a variance other than the standard deviation to proxy expected risk in regressions leads to a very similar conclusion. Results are not reported here.

$\delta_1>0$ is expected to verify the hypothesis that there is a trade-off between excess return and expected risk.

The unexpected volatility variable is essentially uncorrelated with the expected volatility variable. Including it in the regression doesn't affect the estimates of the expected volatility variable coefficient. But it helps to explain more variation in the excess return, thereby reducing the standard errors, which leads to more reliable estimates for the expected volatility variable. $\delta_2<0$ is expected according to the literature. I also include an AR(1) process to ameliorate autocorrelation in the daily return series, but I cannot predict the sign of δ_4 in the regression..

Using intraday skewness besides unexpected volatility variable as a control variable for idiosyncratic risk is based on the efficient market hypothesis (EMH). There are studies that explore the relation between returns and news such as a company's earnings, M&A activity announcements, and changes in analyst's grading. It is impossible to list all the firm level news variables, which implies the inevitable existence of the idiosyncratic risk for individual stocks in the regression. However, according to the EMH, the market is efficient; investors will react to any news quickly. So, all news will affect the 5-minute return series and, sequentially the skewness coefficient of the 5-minute return series. Should the news be good, there is a tendency toward a positive skewness coefficient; should the news be bad, there is a tendency toward a negative skewness coefficient. Any types of news will leave footstep on the intraday skewness coefficient. Therefore, I use the intraday skewness coefficient to reflect the idiosyncratic risk. $\delta_3>0$ is expected in the regression. In addition, using the skewness coefficient avoids the model uncertainty problem (Avramov, 2002) because of the EMH, by which no news won't affect the intraday skewness coefficient.

The time series property analysis of the intraday skewness shows that the intraday skewness is a martingale process. Since intraday skewness is unpredictable, it is qualified to work as a control variable for innovations in the daily interval series. There are some skewness variables in the finance literature. It is noteworthy that the intraday skewness coefficient variable doesn't describe daily returns' skewness. Rather, it describes 5-minute returns' skewness within a day. [25]

3.2.2 Sample Data

The data set consists of 5-minute trading information on the 30 component stocks of Dow Jones Industrial Average (DJIA) index during 1998-2005. The data source is the *Trade and Quotation* (TAQ) database, which provides continuously recorded information on the trade and quotations of securities. The data are manually checked and cleaned up for stock splits and dividend transaction within a day.[26] The 30 DJIA stocks are the blue chip stocks, which are very liquid in the market and consist of different industry sectors.

Table 3.1 provides general daily excess return information and related statistics for the 30 stocks under investigation.[27] In the whole sample period, most stocks show a positive value. The distribution of the daily return is typical: it has fat tails and usually a non-zero skewness coefficient. The normality is rejected for all 30 stocks using a Jarque-Bera (JB) test. Portmanteau Q test of order 10 indicates autocorrelation and a Lagrange multiplier (LM) test of order 10 indicates heteroskedasticity in the daily return series.

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[25] There are traditionally three ways to address stock returns' skewness. 1) Use co-skewness as a risk factor to explain return variation. 2) Similar to GARCH-type modeling, use an autoregressive process to describe skewness. 3) Use non-Gaussian distributions to model stock returns. The rationale for the above approaches is that skewness is a risk factor, and investors prefer positive skewness.

[26] The sample contains 8 years of data (2013 day observations, 156,040 5-minute observations) for 30 stocks. However, stock XOM has 1 year less data than the other stocks; stock VZ has 2 years less. Overall, there are a total of 237 stock-years. In addition, stocks WMT and SBC have several missing values in the 5-minute trading data series.

[27] The excess stock return is the difference between the actual stock return and the short-term interest rate. The risk free rate is measured by the 3-month Treasury bill secondary market rate, which is retrieved from the Federal Reserve's website: http://www.federalreserve.gov/releases/H15/data.htm#top (serial: tbsm3m). The daily risk free rate is measured by using the annual rate divided by 360.

<Table 3.1>

Now I investigate the 5-minute return series. Overall, the 5-minute return series severely deviates from the normal distribution. Taking stock HD's 5-minute return series in 1998 as an example, I find that the majority (71.73%) of 5-minute returns are within ±0.002. There are 21.88% and 5.49% 5-minute return observations in the range of ±(0.002-0.005) and ±(0.005-0.01), respectively. The 5-minute returns beyond ±0.01% are 0.90%. Figure 3.1 shows a histogram of stock HD's 5-minute return in 1998, in which the high peakedness is remarkable.

Figure 3.1 also contains a probability density function (pdf) of the normal distribution with the same mean and variance as those of the 5-minute return's distribution. By comparison, the center pdf value of the 5-minute return is 0.50, while the corresponding normal distribution value is just less than 0.36. In addition, there is a slight negative skewness in the 5-minute returns. The whole sample (8 years) of 5-minute return series' distribution shows more severe fat and long tails. The descriptive statistics and normality test for the 5-minute return are not reported to save space.

<Figure 3.1>

3.2.3 Intraday Variance, Intraday Skewness, and Volatility Decomposition

The stocks' daily volatility is measured by using the intraday variance method. It is defined as the variance of the 5-minute returns within that day:

$$\sigma^2_{intraday,t} = c_1 \sum_{i=1}^{78} (r_{i,t} - \mu)^2 \tag{3.2}$$

where c_1 is an adjusting constant for freedom (equal to 78/77=1.012987); r_{it} is the 5-minute return on day t. μ is the estimated mean value of 5-minute returns. I rely on 5-minute equally spaced returns for all of my calculations. The market operates from 9:30 a.m. EST to 4:00 p.m. EST generally so that there are 78 observations on each trading day.

Compared with the realized volatility measurement [28] (Bollerslev and Wright, 2001; Anderson *et al.,* 2003) that is common in research using high frequency data, the intraday variance measurement takes into consideration the mean value of 5-minute returns. As shown in Figure 3.1, the mean value, the standard deviation, and the number of observations for 5-minute returns is 7.7E-6, 0.27%, and 19526 respectively, indicating that it is reasonable to assume a zero mean value. So both intraday variance and realized volatility measurements are almost linearly related. (Pearson's correlation coefficient between two measurements is always greater than 0.995 for all 30 stocks.) The results of the analysis in the following sections are not changed if I switch the intraday variance to realized volatility.

However, I advocate the intraday approach in this paper because it fits the framework of the intraday moment statistics. There are natural breaks in the high frequency (HF) data (market opens and closes). The 5-minute returns typically have big price movements at the beginning of the trading day and somehow slow down around lunch hours. I should take that information into account. If I analyze HF data without considering such breaks, I lose information. The realized volatility method (Anderson *et al.,* 2003) considers the break, but it can also be used in a period not within a day. That is its disadvantage in defining daily variance. The method of the intraday variance is more scalable, as becomes clear when I define intraday skewness.

---

[28] The daily return realized volatility is the summation of squared one-period returns (for example, 5-minute returns) from t_0 to t_1 (t_0 and t_1 are the two ends of the day). Other related volatility measurements include the summation of squared one-period returns plus products of adjacent returns due to non-synchronous trading (French *et al.,* 1987), and MIDAS measurement by Ghysels *et al*. (2005), which puts different weights on past daily returns when calculating monthly variance. The scheme of the weights is estimated spontaneously with the mean equation.
Other volatility measurements include implied volatility from the Black-Scholes option pricing model and other stochastic volatility models. Implied volatility is not accurate because of the "smile" and "smirk" phenomenon for options at different strike prices. Different from GARCH-type models, stochastic volatility models let variance follow a stochastic process.

I have 78 observations of 5-minute returns so that I will have intraday skewness and intraday kurtosis. This paper will show that the intraday skewness coefficient is important to explain the variation in daily returns. It is defined as:

$$Skew_t = c_2 \frac{\sum_{i=1}^{78} (r_{i,t} - \mu)^3}{\sigma_{intraday,t}^3} \tag{3.3}$$

where c_2 is an adjusting constant for freedom (equal to 78/(77*76)=0.013329); $r_{i,t}$ is the 5-minute return on day t. μ is the estimated mean value of 5-minute returns within day t. $\sigma_{intraday}$ is the square root of the intraday variance as defined in the equation (3.2).

Market rationality suggests that rational traders usually explicitly incorporate expected risk into excess returns. It follows that unexpected volatility may produce a surprise impact on the test equation. Therefore, I decompose the volatility into expected and unexpected components. The expected volatility is derived from optimal forecast of an ARIMA process (The method is described in French *et al.,* 1987.) The unexpected component of volatility is obtained by subtracting expected variance from actual variance.

Table 3.2 summarizes the descriptive statistics for three variables: expected volatility, unexpected volatility, and the intraday skewness coefficient. It also contains Pearson's correlation coefficients for these three variables. I find that they have a very low correlation to each other, so that including them together in the regression won't cause a multicollinearity problem.

<Table 3.2>

Figure 3.2 gives an example of these intraday moment variables for stock HD. It has three panels. Panel A depicts the intraday standard deviation; Panel B is its decomposition of predicted volatility and unexpected volatility. I find the predicted value tracks the actual standard deviation

closely but in a smoother fashion. Panel C gives the intraday skewness coefficient in the sample period.

<Figure 3.2>

3.3 Empirical Results

The regression results of equation (3.1.a) and equation (3.1.b) using weighted least squares (WLS) are shown in Table 3.3. The weights are just the inverse of the intraday standard deviation. WLS is adopted to correct heteroskedasticity. Table 3.3 also contains a simple regression where only the expected volatility variable exists in the right side of the equation.

<Table 3.3>

From Table 3.3, I find that the expected volatility is significantly positive at traditional significance levels for 15 stocks in the simple regression. Six stocks show significance at the 1% level; an additional 4 stocks show significance at the 5% level; and an additional 5 stocks show significance at the 10% level. A total 15 stocks out of 30 support the hypothesis that excess returns are positively related to expected volatility. However, there is one count-evidence in my sample. Stock PG (index=11) shows that there is a significant negative relation between excess returns and expected risk at the 5% level. The rest of the 14 stocks generally show positive signs (except that stock DIS, index=19 and stock MCD, index=21, show a negative sign) but no significance.

In the multiple regression of equation (3.1.a), nineteen out of 30 stocks show significant support for the hypothesis that there is a positive relation. In addition, the rest of the stocks support a zero relation. The stock PG shows a negative but insignificant coefficient because of the inclusion of the control variable: unexpected volatility. Only stock PG (index=11) and stock

MCD (index=21) out of 30 stocks show a negative coefficient of the expected risk variable in the regression model (3.1.a). In the multiple regression of equation (3.1.b), the estimates of the expected risk variable are very similar to those of the regression of equation (3.1.a). I can conclude that I find a positive relation between excess returns and expected risk for big capitalized stocks overall.

Turning to other explanatory variables, I find that excess returns are negatively related to unexpected volatility. Twenty-seven out of 30 stocks show negative significance on the unexpected volatility variable. The rest of the 3 stocks show no significance. That there is a negative relation between excess returns and unpredicted volatility is indirect evidence that supports the risk-return trade-off.[29]

I see from Table 3.3 that the intraday skewness coefficient variable has a very high t-value. This is the case for all 30 stocks. This indicates that the excess return is strongly positively related to the intraday skewness coefficient.[30] Comparing the adjusted R^2 of three regression models, I find that the intraday skewness coefficient variable explains a bigger portion of the variation in excess returns than do other variables. The average adjusted R^2 of the regression model (3.1.b) among these 30 stocks is 8.53% while the adjusted R^2 of the model without the intraday skewness variable is 2.54%.

The adjusted R^2 of the model that contains only the expected risk variable is mere 0.15%, and the maximum among 30 stocks is 0.94%. The small adjusted R^2 of the regression model tells one

[29] When I do an ARMA process for the standard deviation, I find that the standard deviation generally follows a positive coefficient moving average process. When the unexpected standard deviation increases, all predicted standard deviations will be revised upward for all future time periods. If the hypothesis that the risk premium is positively related to the predicted standard deviation is true, then the discount rate for future cash flows increases. If the cash flows are unaffected, the current stock price will be reduced. Thus, I observe a negative relation between excess returns and the unexpected standard deviation (French *et al.,* 1987).

[30] I also regress the daily stock return on the daily market return and the stock's intraday skewness coefficient. The intraday skewness coefficient is still very significant for all 30 stocks. That indicates that the intraday skewness coefficient contains shocks to the individual stock. (Results are not reported here.)

thing: the expected risk really explains very little about excess returns, even though almost two third of the sample stocks show a significant coefficient in the regression equation. This result strengthens the claim that investors consider some other risk measure to be more important than the standard deviation of portfolio returns (Baillie and DeGennaro, 1990). Comparing with the explanatory power of the skewness variable, I conclude that the intraday skewness coefficient works as a good control variable. It reflects overall impact from individual stocks' news shocks. Since it explains the variation in excess returns incrementally, the model has smaller standard errors of the regression. Adding such a variable in the regression is where my model is different from the models used in French *et al*. (1987), Campbell (1987), and Ghysels *et al*. (2005).

There might be a missing variable problem in equation (3.1.b). Nonetheless, since I already included the *ex ante* part risk and innovation part risk, I can expect that any missing variables will mainly affect the coefficients of the innovation part risk variables and the coefficient of the expected volatility variable will be affected only marginally. Moreover, any missing variables will affect the intraday skewness coefficient according to the efficient market hypothesis (EMH). Including the intraday skewness coefficient in the regression partially solves the missing variable problem.

The AR(1) variable is significant for 13 out of the 30 stocks. The signs, however, are mixed. The residual checks reveal that problems of autocorrelation still exist in the residual series from adopting only one lag dependent variable. However, accurate identification of the ARMA process for all 30 stocks makes the model more complicated and distracts from the focus on the risk-return relation. The existence of the autocorrelation can be understood as the result of a mis-specification problem (Greene, 2003). As mentioned before, the mis-specification problem should affect the expected volatility variable only marginally, since I include the unexpected volatility variable and the intraday skewness coefficient variable in the regression.

Since I have 30 stocks in the sample, panel data analysis is feasible. However, the Hausman test for random effects and the *F* Test for fixed effects point out that a pooled regression is best. On the bottom of Table 3.3, I report the pooled regression results, which indicate that there is a significant positive relation between excess returns and expected volatility. The adjusted R^2 is 6.54%. Still, the skewness variable explains the most part. The adjusted R^2 of the model that doesn't include the skewness variable is 1.33%, while the expected standard deviation alone only contributes 0.08%.

Now, I can conclude that there is evidence to support a positive relationship between excess returns and expected risk for big capitalized stocks at the daily level.[31] Stock PG shows a negative relation in the whole sample but it becomes insignificant after controlling unexpected risk. The pooled regression also supports a positive relation. The unanswered question is why some stocks support an argument that excess returns statistically have nothing to do with expected risk.

3.4 Quantile Regression on the Relation Between Returns and Risk

In the previous section, I find evidence of a positive relation between excess returns and expected risk, measured by the intraday standard deviation; I also find evidence that there is no relation between excess returns and expected risk. This conflicting conclusion doesn't change with model specification selection (WLS or the GARCH-type model) or with sample selection

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[31] I also apply a GARCH-M model (Engle *et al.,* 1987) to solidify my conclusion about the relation between excess returns and expected risk. The major results are not changed. Results are not reported here.

(either in the whole sample or in the sub-samples). This section tries to answer the question: why isn't positive relation with significance revealed in some stocks?

The source of the problem is that employing the weighted least squares (WLS) method focuses on the mean as a measure of location. Information about the tails of a distribution is lost. In addition, WLS is sensitive to extreme outliers that can significantly distort the results. To address this issue, it is informative to focus on different segments of the data and investigate the underlying functional relation. For this reason, I re-examine the equation (3.1.b) using a quantile regression.

Unlike the WLS regression, which models the relation between explanatory variables and the mean of the dependent variable, the quantile regression models the relation between explanatory variables and the conditional quantiles of the dependent variables (Koenker 2005; Chen, 2006). In a specific case of the quantile regression, the median regression models the 0.5 quantile (or the 50^{th} percentile) of the dependent variable.[32]

A quantile regression is more appropriate when extreme values are present. It has two advantages: (1) it can be used in various distributions especially skewed distributions; (2) if the extreme values change, the quantile regression coefficient doesn't change its value and standard error. This is especially true for stock returns that present fat tails and skew distribution (see Table 3.1). The existence of the fat tails seriously affects the inference of the least squares regression. For example, stock PG has an astounding extreme value of daily returns of -31% in my sample period. This explains why stock PG reveals a negative relation between risk and return using only one explanatory variable in the regression. The daily return of -31% is, of

[32] Quantiles are a set of 'cut points' that divide a sample of data into groups containing (as far as possible) equal numbers of observations. Specifically, Percentiles are values that divide a sample of data into one hundred groups containing equal numbers of observations. For example, 50% of the data values lie below the median. I call the median the 50^{th} percentile or 0.5 quantile.

course, an influential outlier in the least squares regression analysis. Similarly, those stocks don't show significance on the expected risk variable because there are too many extreme values. However, I cannot just remove outliers from my analysis because of the lack of publicly accepted criteria for selecting outliers.

As stated earlier, I estimate β through WLS regression by minimizing the weighted square of deviations from the conditional mean of the sample as follows:

$$\hat{\beta}_{OLS} = \arg\min \sum_{i=1}^{n} w_i (y_i - x'\beta)^2 \tag{3.4.a}$$

where $x'\beta$ is the conditional mean of the sample of the dependent variable given x; w_i is the weighting factor. Analogously, I can obtain a quantile regression estimate by minimizing weighted deviations from the conditional quantile:

$$\hat{\beta}_{quantile,\tau} = \arg\min \sum_{i=1}^{n} \rho_\tau (y_i - x'\beta) \tag{3.4.b}$$

where $x'\beta$ is the conditional τ^{th} quantile of the sample of the dependent variable given x (Koenker, 2005). ρ_τ is a weighting factor called a check function (Yu *et al.,* 2003), which can be shown in Figure 3.3. It has the form:

$$\rho_\tau(u) = \begin{cases} \tau\, u & \mathrm{u} \geq 0 \\ (\tau - 1)u & \mathrm{u} < 0 \end{cases} \tag{3.4.c}$$

When τ =0.5, ρ_τ becomes the absolute value function and the quantile regression becomes the median regression. In other words, estimation here is based on a weighted sum (with weights depending on the quantile values) of absolute values of residuals. The quantile regression is solvable if the quantile is expressed as linear functions of the parameters.[33]

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[33] This paper uses a SAS® QuantReg procedure to conduct the quantile regression for equation (3.1.b). The QuantReg procedure is experimental and is available in http://support.sas.com/techsup/ (Chen, 2006).

<Figure 3.3>

Figure 3.4 depicts the coefficient of the expected volatility variable with a range of quantiles from 0.05 to 0.95 for three stocks (PG, KO, and UTX) running the regression model (3.1.b).[34] The charts clearly show that the coefficient of the quantile regression (in red) is an upward function of the quantiles (of the excess returns). The relation between excess returns and expected risk evolves from negative to positive as the quantile increases. At lower quantiles (less than 0.50), the excess return is negatively related to expected risk; at higher quantiles, the excess return is positively related to expected risk; at the median, the excess return is not correlated with expected risk generally. Correspondingly, the *t*-value is usually insignificant for the median regression. There are 4 stocks show significant coefficients, and 2 stocks show significant negative coefficients at the median regression.

If I focus on the below-median quantiles --- for example, when I consider the value at risk (VaR) using a 0.05 quantile --- the coefficient is negative. It implies that given other conditioning variables, the higher the expected risk, the lower the quantile of the excess returns. In other words, under more volatile market conditions, the excess return is more likely to have a big loss. In contrast, when I focus on the above-median quantiles, the coefficient is positive. The economic meaning is that the higher the risk the higher the gain. This is actually the interpretation of the risk-return trade-off. But, I add into this trade-off a dimension of quantiles.

<Figure 3.4>

The charts also show the WLS regression results. For stocks KO and PG, the coefficients are both insignificant; for stock UTX, the coefficient is 5% significantly positive. As stated earlier, the WLS regression focuses on the mean of the dependent variable (excess return). The mean of

[34] Stock PG is the only stock that has a negative coefficient in the WLS regression. Stock KO has the worst Sharpe ratio and stock UTX has the highest Sharpe ratio among the 30 stocks. Therefore, I present these 3 stocks. Needless to say, other stocks have similar results.

the return is an important input for portfolio management. However, the relation is very fragile, depending on the extreme values in the sample selection. Moreover, the WLS regression has only one estimate; it provides very limited information about the risk-return relation, as shown by the quantile regression. A collection of conditional quantile regressions provides a much more complete statistical analysis of the stochastic relationships among variables and a more robust result against possible outliers.

Figure 3.4 also shows the coefficients for the other two explanatory variables. Just like that of the expected standard deviation, the coefficient of the unexpected standard deviation moves upward as the quantile increases, and evolving from the negative zone to the positive zone. I find that the coefficients are in the range (-20, 10). At quantiles lower than 0.7 or so, the coefficients are negative; at quantiles higher than 0.75 or so, the coefficients are positive. However, I generally find a negative coefficient in the WLS regression.

Turning to the intraday skewness variable, I find that the coefficients are quite constant in the whole spectrum of quantiles. The coefficients are always positive no matter what quantile is used. This strengthens my conclusion that the intraday skewness coefficient is positively related to excess returns. In addition, the WLS regression estimates are greater than those of the quantile regression.

Table 3.4 reports the coefficients for all 30 stocks at 5 different quantiles (0.05, 0.25, 0.5, 0.75, and 0.95). Among all 30 stocks, the coefficient for the median is statistically zero (except for 6 stocks: MSFT, PFE, JNJ, and C with positive significance, and stocks DD and CAT with negative significance). This implies that there is no correlation between the median of excess returns and expected risk generally.

<Table 3.4>

Figure 3.5 gives an example in which only the expected standard deviation is included in the regression. I compare the predicted value of excess returns at two quantiles (0.25, 0.75) and at the mean level using WLS. The stock is HD, and the WLS predicted value line is different from a horizontal line at the 10% significance level (t-value of the slope is 1.76). The predicted value line for the 25th percentile is downward and the predicted value line for the 75th percentile is upward. More importantly, Figure 3.5 shows the scatter plot between risk and return variables. It has a cone or comet shape with a horizontal axis. As risk increases, return has a bigger range. This scatter plot explains the quantile regression results very easily.

Figure 3.6 is another way to show that the relation between excess returns and expected risk varies in 11 quantiles (0.01, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and 0.99). It is easy to see that the relation evolves from negative to positive as the quantile increases.

<Figure 3.5><Figure 3.6>

3.5 Conclusion

This paper systematically investigates the risk-return relation by exploring the information derived from high frequency data. I adopt an ARIMA process to forecast expected risk proxied by the expected intraday standard deviation. I find that the daily excess returns are positively related to expected risk in some stocks, but there is no significant relation between excess returns and expected risk for other stocks. There is one case of a weak negative relation. The pooled regression indicates that there is a positive relation overall among the 30 stocks. I find that excess returns are negatively related to unexpected volatility for almost all 30 stocks, which is indirect evidence of a positive risk-return relation.

I use a quantile regression to investigate why some stocks show a risk-return trade-off while other stocks show a zero correlation between excess returns and expected risk. My analysis is one of a few studies that apply high frequency data and quantile regression to study the risk-return relation. I find that the extreme values are the reason for the variation in the relationship between return and risk. More importantly, I show that the WLS regression results are not so rich as those from the quantile regression. As the quantile of interest increases, the relation between excess returns and expected risk evolves from negative to positive. At the median, the relation is generally a zero relation.

My analysis of risk-return relation makes use of an important variable: intraday skewness coefficient. I find that a positive relation between excess returns and the intraday skewness coefficient always exists. The intraday skewness coefficient is a useful explanatory variable for the variation in the daily returns. According to the efficient market hypothesis, the intraday skewness coefficient is used as a control variable in the regression models. In particular, it explains a much bigger part than the unexpected risk variable does, leaving only a small part of the variation to be explained by expected risk. The fact that expected volatility explains very little of the variation in excess returns is the primary reason why empirical studies often find mixed results about the risk-return relation.

Chapter 4: The Dynamic Correlation between Stock and Bond Returns

Abstract

To analyze the correlation between stock and bond markets, this paper uses the asymmetric dynamic conditional correlation (ADCC) model proposed by Cappiello *et al*. (2004) to examine two market index funds. The correlations between the two markets are very volatile, although the average correlation coefficient over the sample is negative. Testing the dynamic correlations by using a set of macroeconomic information, the evidence shows that relative volatility between stock and bond markets, the yield spread, oil price shocks, and the federal funds rate are the significant factors.

JEL Classification: E42, E44, G12, G18

Keywords: Stock-bond market correlation, Dynamic Conditional Correlation, Monetary policy

4.1 Introduction

The investigation of the correlation between returns on the stock and bond markets is one of the most significant topics in analyzing financial return series because the empirical correlations between different assets provide inputs for guiding asset allocation, portfolio selection, and risk management. There are good reasons for the many studies that analyze these two asset returns, since these two types of assets constitute the major categories in the daily investment menu. A standard investment textbook suggests that holding diverse assets in a portfolio is a good investment strategy. Since the returns on bonds provide investors with fixed incomes while returns on stocks are the reward for investing in risky assets, holding combined assets in the investment portfolio allows investors to reduce risk. Owing to their inherent difference in hedging risk, stocks and bonds are considered to be substitutes in a general equilibrium framework (Tobin, 1982). However, the wealth effect suggests that stocks and bonds are complements, especially during boom periods. These ambiguous relationships lead to uncertainty about the sign of the correlation between stock returns and bond returns.

The study of the stock-bond correlation has been popularized recently by the so-called Fed model. The Fed model is based on the idea that investors view stocks and bonds as competing assets in their portfolio.[35] It states that whenever a yield differential is created, investors will reallocate assets from lower return investments to higher return ones. Thus, equilibrium is achieved as earnings yields (E/P) equal bond yields. This idea seems to provide practitioners a parity condition for arbitrage between stock and bond investments. However, this model is oversimplified, and its implications can be misleading. Because of this shortcoming, reassessment of the Fed model has provoked a substantial amount of research on the relation between stock and bond returns.

This essay examines the aggregate correlation between returns of these two assets. This paper enhances current knowledge of the stock-bond market correlation in the following respects. First, I use returns on the total bond market index fund to proxy for the bond market's returns, instead of using yield to maturity (YTM) of the long-term bond. For the stock market, I use returns on the total stock market index fund to proxy for the stock market's returns, rather than using

[35] The Fed model describes the stock-bond market relation (Yardeni 1997; Abbott 2000). This model states that the stock's P/E ratio should be the reciprocal of the bond market's yield to maturity. In other words, there is a negative relationship between the stock market's P/E ratio and bond yields.

changes in P/E ratios. This approach provides a direct and more comprehensive measure of the broad category assets in the two markets.

Second, I provide different methods to generate unconditional correlations and conditional correlations. This paper uses a rolling window to measure unconditional correlation and a BEKK-GARCH model (Engle and Kroner, 1995) and an asymmetric dynamic conditional correlation (ADCC) model to generate dynamic correlations, as proposed by Engle (2002) and extended by Cappiello *et al*. (2004). The conditional correlation is superior to unconditional correlation in that the estimated coefficients are conditional on econometric refinement.

Third, in addition to exploring the correlation between the two markets, I also explain the dynamic movements of the conditional correlations by using macro factors. This paper provides insights that explain the time-varying correlations. Specifically, evidence shows that the relative volatility between the stock and bond markets, the yield spread in the bond market, oil price shocks, and the federal funds rate are the significant factors. Higher relative volatility in the stock market, higher yield spread, and oil price shocks will lead to a negative correlation between returns in the two markets; a higher federal funds rate will lead to a positive stock-bond correlation. In sum, this study not only pioneers research to explain the dynamic conditional correlation,[36] but also provides financial implications for practitioners on dynamic asset allocation reacting to changes in the state variables.

This chapter is structured as follows. Section 4.2 provides a literature review of studies on the stock-bond market return correlation. Section 4.3 describes the sample data. Section 4.4

[36] There are some proposals on the Internet that try to explain the conditional correlations. Such proposals include, for example, Urga and Cajigas (2006) and Baele *et al*. (2006). This paper has been independently developed by the author. Regarding unconditional correlations, there are some explanations such as uncertainty about expected inflation, unexpected inflation, and the real interest rate (Li, 2002) and stock market volatility (Connolly *et al.,* 2005).

estimates different correlation models. Section 4.5 investigates the factors that influence dynamic correlation coefficients. Section 4.6 contains concluding remarks.

4.2 Literature Review

4.2.1. Definition

Studies on the relation between the stock and bond returns are complex and voluminous. The topics in the literature are often differentiated from each other by varying definitions of assets returns (Shiller and Beltratti; 1992), lead and lag relation (Downing *et al.,* 2006),[37] econometric methods, sample periods (Lander *et al.,* 1997), and markets/countries under study (Durre and Giot, 2005), among others.

The prevalent approach developed from the Fed model in testing the return correlation usually uses the E/P ratio to measure stock returns and the yield on the 10-year government bond to measure bond returns.[38] Using the E/P ratio as a measure of stock returns obviously is oversimplified if I compare it with a constant dividend growth model as in equation (4.1.a). It states that stock price is the present value of future cash flows by using variables of risk free rate, the risk premium, δ, and dividend growth rate, *g*. Similarly, I can derive the price of bonds represented in equation (4.1.b). In expression:

$$p_s = \frac{D(1+g)}{r_f + \delta_s - g} \tag{4.1.a}$$

$$p_b = \frac{C}{r_f + \delta_b} \tag{4.1.b}$$

[37] This paper focuses on the contemporaneous correlation between the two markets' returns. By using a VAR model, I cannot find any leading and/or lagging relation between the two return series.

[38] Besides using the P/E ratio and the bond yield, Shiller and Beltratti (1992) use forecasted values of discount rates and dividend growth rates to infer "theoretical" prices of stocks and bonds. They find that the theoretical correlation between returns on stocks and long-term bonds is a mere 0.06.

where the subscript s indicates stock; the subscript b indicates bond; p stands for price; D (dividend) and C (coupon) stand for future cash flows per period for stocks and bonds, respectively; r_f is the risk free rate; δ represents the risk premium; and g represents the expected growth rate. To derive the Fed model, we need to assume that g=0 (no dividend growth), $\delta_s = \delta_b$ (no risk premium difference between stocks and bonds), and $D = E$ (all the earnings are paid out as dividends). The above assumptions are, of course, too strong to set the Fed model on solid ground. [39]

Using (4.1.1) and (4.1.b) allows us to write the constant correlation coefficient between stock return and bond return as:

$$\rho_{sb} = \frac{Cov(r_s, r_b)}{\sqrt{\sigma_s^2 \cdot \sigma_b^2}} \tag{4.1.c}$$

where r stands for returns; σ stands for the returns' standard deviation. With the help of these equations, I can find different scenarios about the sign of the correlation coefficient as follows.

4.2.2. Relation Between Stock Returns and Bond Returns

Theoretically, it is has been argued that stock and bond returns are positively correlated. Basically, stock and bond markets are exposed to common macroeconomic conditions. When economic prospects are good, optimistic investors tend to purchase stocks, even though the bond

[39] The Fed model has been criticized by Estrada (2006) from both a theoretic viewpoint and on the basis of empirical tests. First, the required return for stock is in real term while the required return for bond is expressed in nominal term (Modigliani, 1997). Second, since stocks and bonds have different risk levels, it is implausible to assume that both risk premiums are equal. Third, the Fed model is absolutely groundless when the interest rate is very low, and one cannot judge equilibrium from the model, since neither P/E ratio nor interest rate can serve as a benchmark for one another. Fourth, the phenomenon of the co-movement of the P/E ratio and the reciprocal of the interest rate is valid only in the period 1968-2005 for U.S. markets. It is invalid in the longer period from 1871 to 2005 in U.S. markets.
However, Ritter (2002) argues that it is a conceptual mistake to think stocks are riskier than bonds. Contrary to the prevailing notion of a 7% risk premium, there is only a 1% risk premium between stocks and bonds if considering the holding period (stock returns show mean reversion), inflation, and geometric average method. By and large, Ritter (2002) thinks that the Fed model has practical validity.

coupon rates are high. Experience in the late 1990s suggests that the wealth effect may be a dominant factor that encourages investors to hold both types of assets. Empirical studies by Keim and Stambaugh (1986), Campbell and Ammer (1993), and Kwan (1996) provide some supportive evidence.

The literature also suggests a negative correlation between returns on the two assets. This occurs when the stock market is in a down period or during a market crash. In the latter case, the stock risk premium δ_s and the bond premium δ_b diverge. In fact, when the stock market falls, investors may become more risk-averse. Under this circumstance, bonds become more attractive to investors, and investors move funds to the bond market from the stock market, a phenomenon called "flight to quality" (Hartmann *et al.,* 2001). On the other hand, when the stock market rallies (that is, investors become less risk-averse), investors are induced to go back to those high returns, a phenomenon called "flight from quality." The correlation between stock returns and bond returns is therefore negative due to these two "flights." Empirically, this phenomenon is supported by Gulko (2002), Connolly *et al*. (2005) and Baur and Lucey (2006).

Besides investors' different perspectives on the market, regulators play a role as well in the stock-bond relation. When the economy is overheating, the Federal Reserve may change its targeted rate in an attempt to slow down the economy. The Fed may raise its interest rate, an action that drags down bond prices. However, market momentum and the expectations of increasing profits may continually drive stock prices upward. From this perspective, it is likely to be the case that the stock returns and bond returns are negatively correlated.

Putting the above-mentioned arguments together, it is not clear whether stock returns are positively or negatively correlated with bond returns or even if there is any correlation. Some researchers, such as Alexander *et al*. (2000), have tried to reconcile the issue of the correlation's mixed signs. They find a significant positive correlation between daily stock returns and high yield bond returns at the individual firm level. They also detect a negative co-movement around wealth-transferring events. Thus, the sign issue is unsettled. This paper is devoted to examining the correlations between returns on the stock and bond markets and inquiring whether the sign is time-varying.

With respect to the methodology in the correlation studies, the traditional approach relies on a simple regression analysis or takes an unconditional correlation based on a specific sample period. In light of the recent advancement of time-series analysis, Scheicher (2003) uses a bivariate GARCH model to estimate the conditional correlation of stock returns and spread changes at the firm level. He finds a weak linkage between the stock market and the corporate bond market. DeGoeij and Marquering (2004) also apply a multivariate GARCH model to examine the stock-bond relation by using BEW estimation method.[40] My paper further advances the econometric techniques by using both BEKK and asymmetric dynamic conditional correlation (ADCC) models. The representation of ADCC model not only has econometric appeal in modeling time-varying correlations, but also better specifies the dynamic process with risk- averse behavior.

4.3 Data

To provide a direct and consistent measure for stock market returns and bond market returns, this essay employs data provided by Vanguard: Vanguard Total Bond Market Index Fund (VBMFX) and Vanguard Total Stock Market Index Fund (VTSMX).[41] VBMFX was incepted on

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[40] Of course, GARCH-type models are not always used to study the time-varying correlation. For example, Pelletier (2006) adopts a regime-switching approach, where the transitions between regimes are modeled by a Markov chain.

[41] The information about the two funds is taken from http://flagship.vanguard.com.

12/11/1986; it is the earliest fund to track Lehman Brothers' Aggregate Bond Index. The Lehman Aggregate Bond Index comprises government securities (Treasury and agency), mortgage-backed securities, asset-backed securities, corporate securities, and international dollar-denominated issues to simulate the universe of bonds in the market (market capitalized weighted). All are investment grade.[42] Municipal bonds and Treasury inflation protected issues are excluded. The maturities of the bonds in the index are more than one year. The average weighted maturity is around 7 years (intermediate-term bond).

VTSMX is Vanguard's Total Stock Market Index fund that tracks the overall equity market index. It tracks the Dow Jones Wilshire 5000 composite index through 4/22/2005, and the MSCI U.S. Broad market index thereafter. VTSMX was incepted in 4/27/1992 and is a blend of value and growth stocks of large capitalized firms.

The two funds' data are obtained from historical prices at http://finance.yahoo.com. The VBMFX series begins on 6/4/1990 and the VTSMX series begins on 6/20/1996; the data sample ends on 12/29/2006. To construct a balanced dataset, I truncate the VBMFX series and set 6/20/1996 as the starting point. Figure 4.1 gives a visual comparison of these series. It can be seen that VBMFX is less volatile than VTSMX. The VBMFX series shows gradual upward movement while the VTSMX series shows remarkable ups and downs. Both index funds show non-stationarity and are characterized by an increasing time trend during this sample period. The correlation coefficient of these two funds is 0.558 for the whole sample period.

<Figure 4.1>

Dividing the sample according to the bull-bear market (VTSMX series), I find that the whole sample consists of two bull markets (6/20/1996-3/24/2000 and 10/9/2002-12/29/2006) and one

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[42] Basically, this paper researches the relation between stocks and investment grade bonds. Regarding speculative grade bonds, Blume *et al*. (1991) show that low grade bonds behave like both bonds and stocks.

bear market (3/25/2000-10/8/2002). The unconditional correlation coefficients for the three periods are 0.91, -0.93, and 0.94, respectively.

Table 4.1 contains statistical descriptions of these series including the unconditional correlation coefficient between these two funds. An augmented Dickey-Fuller test (ADF) indicates that both fund series are not stationary. That implies that correlation is not the appropriate statistic to describe the two fund series. According to Engle and Granger's (1987) method, the residual from a single equation is not stationary, suggesting the absence of a co-integration relation between these two fund series. Using Stock and Watson's (1988) approach, there is more than one common trend in the VAR system, further confirming the absence of co-integration. (Co-integration test results are not reported here).

Taking log-difference and looking at the returns of the two index funds, I find that both return series are stationary as shown by the ADF test. Pearson's correlation coefficient is -0.088 for the whole sample period. The return correlation coefficients in the sub-samples are 0.09 (6/20/1996-3/24-2000), -0.22 (3/24/2000-10/9/2002), and -0.15 (10/9/2002-12/29/2006), respectively.[43] By comparing the correlation coefficient of the two fund series, although they are positively correlated in bull markets (as shown by the 0.91 in the first period 3/24/2000-10/9/2002 and 0.94 in the third periods 10/9/2002-12/29/2006), the return correlation coefficients move in opposite direction (0.09 vs. -0.15). This is evidence that measuring correlation using index levels and index returns can give different pictures of the relation between the stock and bond markets.

<Table 4.1>

[43] The Pearson's correlation coefficient between VTSMX return and 20 year bond minus YTM change is -0.108 in the whole sample, 0.12, -0.26, and -0.20 in the three sub-samples. These numbers are close to the correlation coefficients between two index fund returns but are not the same.

4.4 Correlation Coefficients Between Stock and Bond Markets

4.4.1 Rolling Correlation

The simple calculation of correlation coefficients in the above section indicates that the correlation coefficient changes dramatically across different sample periods. This leads us to believe that a constant correlation coefficient is misleading, since it fails to reflect on-going market conditions in response to external shocks. A simple method to derive a time-varying correlation coefficient is to use a rolling correlation coefficient for returns on these two funds.

There are two approaches for constructing a rolling correlation coefficient. One is to use a rolling fixed window, that is, using a fixed window size (number of observations in the window) and rolling the window ahead along the timeline. Thus, I use 22, 250 and 1250 trading days as window sizes, which correspond approximately to 1 month (see, for example, Connolly *et al.,* 2005), 1 year, and 5 years of observations. The second method is to expand the window. This method assumes that the starting point is fixed (6/20/1996); the correlation coefficients are calculated as the number of observations increases over time. Specifically, I define:

$$\rho_{sb,tm} = \frac{Cov(\bar{r}_{s,tm}, \bar{r}_{b,tm})}{\sqrt{\sigma^2_{s,tm} \cdot \sigma^2_{b,tm}}} \tag{4.1.d}$$

where $\rho_{sb,tm}$ is the correlation coefficient by using a rolling estimate; $\bar{r}_{s,tm}$ and $\bar{r}_{b,tm}$ are stock and bond returns at time t with the window length of m days; and $\sigma^2_{s,tm}$ and $\sigma^2_{b,tm}$ are the corresponding variances.

Table 4.2 reports rolling correlations between the two return series for various measures. I shall discuss different correlation coefficients at a later point.

<Table 4.2>

4.4.2 GARCH-BEKK Estimation

The rolling correlation coefficient is appealing, since it is easy to construct and simple to understand. The main drawback of this approach is that it gives an equal weight to all of the sample points under a fixed window. However, within each window length, structural changes with different degrees of volatility are often found. Moreover, the choice of window length may be arbitrary. Thus, it is necessary to construct the time-varying correlation coefficient, which is able to weight the variance conditional on empirical regularity. The generalized autoregressive heteroskedasticity (GARCH) type models can achieve this goal.

There are two representations of a multivariate GARCH model. DeGoeij and Marquering (2004) apply a GARCH-BEW model (Bollerslev *et al.,* 1988) to examine the stock-bond relation. However, the BEW representation has three shortcomings. The most noticeable one is that it cannot ensure the positive definiteness of the covariance matrix. Another one is that the covariance is independent of conditional variances. This conflicts with the fact that correlation tends to increase as variability increases. Third, it could lead to over-parameterization. These shortcomings can be overcome by another representation: GARCH-BEKK, which is described in Engle and Kroner (1995).

The BEKK model in GARCH(1,1) can be written as:

$$\begin{cases} r_t = \mu_t + \varepsilon_t \\ \varepsilon_t | \Im_{t-1} \sim N(0, H_t) \end{cases} \tag{4.2.a}$$

where r_t is the asset return vector; μ_t is the mean vector of returns; ε_t is an error term vector, which follows conditional multi-normal distribution with zero mean but with heteroskedasticity; $\Im_{t-1}$ is the information set available at *t-1*; H_t is the conditional variance/covariance matrix. In an expansion form for representing stock and bond returns, the variables are expressed as:

$$r_t = \begin{bmatrix} r_s \\ r_b \end{bmatrix}_t, \ \mu_t = \begin{bmatrix} \mu_s \\ \mu_b \end{bmatrix}_t, \ \varepsilon_t = \begin{bmatrix} \varepsilon_s \\ \varepsilon_b \end{bmatrix}_t, \text{ and } H_t = \begin{bmatrix} h_{ss} & h_{sb} \\ h_{sb} & h_{bb} \end{bmatrix}_t$$

The covariance matrix H_t is modeled directly as a GARCH(1,1) process. I can write H_t in the form:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B \quad (4.2.b)$$

where C, A, B are 2x2 matrices and C is a low triangular matrix. The conditional correlation coefficient is then defined as:

$$\rho_{BEKK,t} = \frac{h_{sb,t}}{\sqrt{h_{ss,t}}\sqrt{h_{bb,t}}} \quad (4.2.c)$$

4.4.3. GARCH-DCC Estimation

The BEKK method in modeling a multivariate GARCH approach often involves computational complexity, especially when the variables involved get larger. Engle (2002) proposes a dynamic conditional correlation coefficient (DCC) model by parameterizing the conditional correlation directly. In particular, the procedure is divided into two steps. The first step is to estimate a series of univariate GARCH estimates, and the second step is to calculate correlation coefficients. Thus, parameters to be estimated in the correlation process are independent of the number of series to be correlated. It follows that very large correlation matrices can be estimated. In addition, the DCC method provides a mechanism to correct the heteroskedasticity problem, since the residuals of the returns are standardized by the conditional standard deviation based on a GARCH(1,1) process.

While Engle's (2002) paper has a computational advantage, it ignores the asymmetric effect of news impact on asset returns.[44] The follow-up paper by Cappiello *et al*. (2004) fills in this gap. To provide an updated research method, the research procedure in this essay shall follow Cappiello *et al*. (2004) by incorporating the GJR-type asymmetric effect. The model thus is labeled as an ADCC in GARCH(1,1) process.

In particular, in the first stage, I specify two asset returns in a univariate asymmetric GARCH(1,1) process as follows:

$$\begin{aligned} r_{i,t} &= \mu_i + \varepsilon_{i,t} \\ \eta_{i,t} &= \max[0, -\varepsilon_{i,t}] \\ \varepsilon_i &\sim N(0, H_i) \\ h_{i,t} &= c_i + a_i * \varepsilon_{i,t-1}{}^2 + b_i * h_{i,t-1} + d_i \eta_{i,t-1}^2 \end{aligned} \qquad i = \text{s, b} \qquad (4.3.\text{a})$$

where r is the return and h is the conditional variance; subscript s and b stand for stock and bond, respectively; ε is an error term following heteroskedastic normal distribution.

In the second stage, I model the correlation coefficients based on the residuals that have been normalized from the first stage as follows:

$$\begin{aligned} & z_{s,t} = \frac{\varepsilon_{s,t}}{\sqrt{h_{s,t}}}, z_{b,t} = \frac{\varepsilon_{b,t}}{\sqrt{h_{b,t}}} \\ & z_s \sim N(0, q_s), z_b \sim N(0, q_b) \\ & \lambda_{s,t} = \max[0, -z_{s,t}], \lambda_{b,t} = \max[0, -z_{b,t}] \\ & q_{sb,t} = (1 - \alpha - \beta - g)\overline{\rho}_{sb} + \alpha z_{s,t-1} z_{b,t-1} + \beta q_{sb,t-1} + g \lambda_{s,t-1} \lambda_{b,t-1} \end{aligned} \qquad (4.3.\text{b})$$

[44] Different ways have been suggested for specifying asymmetric effects. The first one is to allow the conditional variance to respond differently to positive and negative innovations. The second type is to allow shocks to enter the variance equation non-linearly. The last type is to allow re-centering of "new impact curve" so that the point of no change in the variance is not necessarily centered at zero. Hentschell (1995) provides an overview of the three types of asymmetric effect.

where z is the normalized residual; q is the conditional variance for the normalized residual; and $\bar{\rho}_{sb}$ is the unconditional correlation coefficients between the two return series. Then, the dynamic conditional correlation coefficient between the two markets is defined as:

$$\rho_{DCC,t} = \frac{q_{sb,t}}{\sqrt{q_{s,t}}\sqrt{q_{b,t}}} \tag{4.3.c}$$

4.4.4. Estimated Results

Table 4.3 reports the estimates of $\rho_{BEKK,t}$ and $\rho_{ADCC,t}$ from equations (4.2.c) and (4.3.c), respectively. Both estimations are conducted in RATS® program. As may be seen from the reported statistics on the lagged conditional variance and the lagged shock terms, most of these coefficients are statistically significant, indicating that the GARCH-type model is relevant. However, one special feature emerging from the ADCC model is the estimates of asymmetric coefficients. The evidence suggests that the b_s asymmetric effect for the VTSMX return series is significant; however, b_b, the similar coefficient for the VBMFX return series is not. This finding is consistent with the results in Cappiello *et al*. (2004) in that the equity market shows a remarkable asymmetric effect, while there is little supportive evidence for an asymmetric effect in the bond market.

<Table 4.3>

To show the special feature associated with different models, the correlation coefficients are incorporated into Table 4.2 for comparison. Table 4.2 now contains the correlation coefficients from the rolling methods, the GARCH-BEKK method, and the GARCH-ADCC method. For the rolling methods, the derived correlation coefficients apparently depend on the window length. The longer the window length the smoother the coefficient will be. However, a longer window length will lead to fewer results. It also suggests that the rolling window leads to more volatile coefficients than does the expanding window.

In addition, some short-period rolling window coefficients have a unit root. An ADF test indicates that the rolling correlation coefficient with a window length of 1-year is not stationary (p-value is 0.148), while the correlation coefficients for a window length of 22 days and 5 years are stationary (p-value is zero).

The correlation coefficients from the BEKK and ADCC methods are close to the rolling correlation coefficients with 22 trading days. But the rolling correlation coefficient with 22 trading days has a bigger standard deviation. Another difference is that conditional correlation coefficients have more observation values than do rolling correlation coefficients. To visualize the movements and comparison of the estimated coefficients, Figure 4.2 depicts five estimated correlation coefficient series, including rolling coefficients from a moving window with 22 days and 250 days, a rolling coefficient from an expanding window, BEKK, and ADCC. With the exception of the one derived from the expanding window method, the other four coefficient series display very similar patterns, positing some common turning points.

If I focus on the ADCC series, the correlation between returns in the two markets is positive at the beginning of the sample; then it falls to negative; and there is positive movement in the middle followed by negative movement. The negative movement drags the correlation into a negative regime for most of the time at the end of the sample period. However, overall, I do observe that the correlation coefficients display some degree of persistence.

<Figure 4.2>

Since estimated coefficients show both positive and negative relations, I am unable to clearly claim that the relation is positive or negative. For the rolling window coefficient with 22 trading days, the average correlation coefficient is -0.03; for the rolling window coefficient with 250 trading days, the average correlation coefficient is -0.08; for the ADCC coefficient, the average coefficient is -0.02. Considering the standard deviation of 0.37, 0.22, and 0.25, respectively, the average coefficients are all statistically different from zero. To get more insight on the estimated coefficients, Figure 4.3 shows a histogram of all ADCC coefficients. Basically, the correlation coefficients between the stock and bond markets are quite symmetrical and span a big range, swinging between the positive zone and the negative zone. The average correlation coefficient over the entire sample is negative but close to zero.

<Figure 4.3>

4.5 Explaining Correlation Coefficients

The question that needs to be answered now is: what factors might contribute to making the correlation coefficients time-varying? Some researchers (David and Veronesi, 2004) suggest that state variables that are able to proxy future uncertainty, such as real interest rates, the inflation rate, and earning growth, should be considered. In this study, I examine the significance of the relative conditional volatility of the stock and bond markets, the yield spread, oil price shocks and federal funds rate (expected inflation rate) to explain the time-varying correlations between returns on the stock and bond markets. The regression model is written as:[45]

$$\rho_{ADCC,t} = \phi_0 + \phi_1 VR_{s,b,t} + \phi_2 SPREAD_t + \phi_3 D_{oil,t} + \phi_4 FFR_t + v_t \quad (4.4)$$

where ρ is the asymmetric dynamic conditional correlation between the stock and bond markets; $VR_{s,b}$ is the variance ratio computed by the conditional volatility of the stock market divided by the conditional volatility of the bond market; *SPREAD* is the difference between the YTM of

[45] Since the paper is using daily data, other macroeconomic variables such as economic growth and real interest rates are not available. This might lead to a mis-specification problem.

long-term and short-term bonds, which reflects the expected change in future yield as implied by the expectations hypothesis. However, this spread may also reflect changes in the expected inflation rate as argued by Mishkin (1990); $D_{oil,t}$ is an oil dummy variable that takes a value of 1 if there is a 5% price jump/reduction on those days and zero otherwise.[46] This variable captures the impact from the oil market; *FFR* is the federal funds rate, which captures the impact from the money market; it also represents the stance of the Federal Reserve's monetary policy. In addition, as popularized by Fama (1975), the federal funds rate could also serve as a proxy for inflation expectations. The estimates of equation (4.4) are reported in Panel A, Table 4.4.

<Table 4.4>

The asymmetric dynamic conditional correlation coefficients between the stock and bond markets are negatively related to the relative volatility of the stock and bond markets.[47] The negative correlation suggests that a greater uncertainty in the stock market will reduce the correlation between these two markets. Note that the source of uncertainty associated with the stock returns does not have to originate from economic fundamentals *per se*. It could be a spillover from a shock in the bond market. My evidence suggests that as long as there is an external shock that creates a greater variance in the stock market relative to the bond market, the correlation of returns on the two assets will decline. This can be seen in Figure 4.4: the low values of the ADCC correlation coefficients are often associated with the higher conditional variances in the stock market. This phenomenon is consistent with the notion of a "flight to quality".

[46] I am using Spot Prices for Crude Oil and Petroleum Products from U.S. Department of Energy.
[47] Connolly *et al*. (2005) report that a negative relation between the uncertainty measures of stock market and the future correlation of stock and bond returns. However, they use 22 trading day rolling correlation instead of conditional correlation. Their bond return is measured from 10-year bond return.

The asymmetric dynamic conditional correlation coefficients between the stock and bond markets are also negatively correlated with the term structure spread. Since the *SPREAD* is calculated as the difference between the 20-year bond return and the 10-year bond return,[48] a rise in the yield spread signifies that the future interest rate is anticipated to be higher, putting selling pressure on stock market investors. This market reaction can lead to stock return volatility. Note that stock return volatility could also come through the channel of a change in inflation rate expectations, since a larger yield spread may also mean higher inflation expectations, as suggested by Mishkin (1990). The impact on the correlation coefficient can be further exacerbated if stock market prices are more sensitive to the yield spread than bond prices, a situation will create a wedge in the covariance term.

An oil price shock affects the correlation between the stock and the bond markets negatively. This implies that on days when there are shocks, the ways that stock prices and bond prices react to the shocks and their speeds in adjusting to the new equilibrium are somewhat different, so that the coefficient is reduced.

The evidence from the federal funds rate (*FFR*) is seen to have a positive effect on the correlation coefficient. This finding is consistent with the scenario that both stock and bond market returns are affected in the same directions by the prevailing liquidity, both in high *FFR* periods and in low *FFR* periods. My interpretation of this positive relation is that during periods with a high *FFR*, which are usually associated with a booming economy, the “wealth effect” generates positive returns for both the stock and the bond markets. However, low *FFR* periods are more likely associated with an economy in recession. Correspondingly, I observe that both bond returns and stock returns are relatively low. As may be seen in Figure 4.4, the federal funds

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[48] I don’t use very short-term bond returns such as the 3 month T-bill returns because those returns are very highly correlated with another independent variable, the federal funds rate. Both bond return series are obtained from the Federal Reserve Board.

rate has patterns similar to those seen in the rolling correlation coefficient and the asymmetric dynamic conditional correlation coefficient.

To provide a robustness check, I also estimate equation (4.4) using other measures of correlation coefficients, including $\rho_{sb,22}$ (22-day rolling correlation coefficient), $\rho_{sb,250}$ (250-day rolling correlation coefficient), and $\rho_{sb,BEKK}$ (BEKK correlation coefficient). The evidence in Panel A shows that both signs and statistical significances are similar. In fact, the explanatory power in terms of R^2 is even higher; it increases from 0.36 to 0.65.

I further estimate the models by replacing the oil shock dummy variable with the conditional variance of oil returns obtained by running a GARCH(1,1) model on the oil price change. With one exception--- the case of $\rho_{sb,250}$ ---I find no change in the estimated results.

<Figure 4.4>

The regression analysis stresses the marginal effect of each variable on the correlation coefficient. However, if interest focuses mainly on the signs of the coefficient, it would be appropriate to use a standard logistic regression to investigate the relationship between the dependent variable dichotomous outcomes (positive, negative) and a set of explanatory variables. I run a logistic regression and the results are shown in Table 4.5. The model is:

$$P(\rho_{ADCC} > 0) = \frac{1}{1 + e^{-(\phi_0 + \phi_1 VR_{s,b,t} + \phi_2 SPREAD_t + \phi_3 D_{oil,t} + \phi_4 FFR_t + v_t)}} \qquad (4.5)$$

where the dependent variable is the probability that the correlation coefficient is positive. The independent variables are the same as those in the OLS regression equation (4.4). The results are consistent with OLS regression results and suggest that higher stock market volatility, higher inflation expectations, and oil price shocks will make the stock-bond correlation negative, while the federal funds rate makes the correlation positive.

<Table 4.5>

Generally, the regression results show that the correlation coefficient varies over time because of macroeconomic state variables. When there is more risk in the equity market and the oil market, or when additional expected risk is reflected in the term structure, a “flight to quality” phenomenon prevails; the correlation coefficient has a propensity to be negative. When there is no change in the risk profile of the asset markets, both the equity and bond markets move together. Common economic factors reflected in the money market and in monetary policy will lead to positive correlation coefficients.

4.6 Conclusion

The relationship between the stock and the bond markets is an important factor in asset allocation and risk management. The extant literature shows no consensus on the direction of the correlation. This paper investigates the correlation between the U.S. stock and bond markets using two index fund proxies and a more advanced econometric model---the asymmetric dynamic conditional correlation (ADCC) model---to measure the time-varying correlation coefficients.

Results show that all types of correlation coefficient depend on the sample periods under investigation. The rolling correlation coefficient depends also on the chosen window size. All types of correlation coefficients are time-varying and very volatile, swinging between positive regime and negative regime. It is therefore inappropriate to claim the sign of the stock-bond return correlation without indication of the sample period. My sample period (1996-2006) observes an average negative stock-bond correlation although it is very close to zero.

The asymmetric dynamic conditional correlation between stock and bond market returns depends on a few key economic factors. My evidence concludes that the correlation is negatively correlated with stock market volatility, the yield spread, and oil price shocks; however, the correlation is positively correlated with the level of the federal funds rate. In my study, the “flight to/from quality,” inflation concerns, and common macroeconomic conditions all play a role in determining the signs of the correlation coefficient of the stock and bond markets.

Chapter 5: Summary

This dissertation concentrates on three aspects of modeling stock returns: the error term distribution, the risk-return relation when high frequency data are applied, and the asymmetric dynamic conditional correlation of stock-bond returns.

In chapter 2 (essay #1), I adopt the exponential generalized beta of the second distribution (EGB2) as the error term's distribution. An AR(1)-GARCH-GJR model effectively reduces the problems of the error term including autocorrelation, volatility clustering, skewness, and fat tails. The goodness of fit test proves that the empirical application of the EGB2 distribution is superior to the normal distribution and *t*-distribution. In addition, I find that the EGB2 distribution can be helpful when using value at risk (VaR) method and is significant in explaining the asymmetric effect (the leverage effect). It implies that the so-called leverage effect is at least partially attributable to the model's mis-specification due to the imposition of a normal distribution on the return series.

In chapter 3 (essay #2), high frequency data are used to construct daily variance variables. Using a conventional regression model to examine the risk-return relation at the daily level is inconclusive. I find evidence of a positive risk-return relation. I also find evidence that there isn't any relation between expected returns and risk. To analyze the issue, I employ a quantile regression to investigate the possibility of a risk-return trade-off. The evidence shows that as the quantile increases, the relation between excess returns and expected risk evolves from negative to positive. Another finding derived from this study is that the daily returns are positively related to intraday skewness. Using intraday skewness as an input variable for the daily excess return equation increases the explanatory power significantly.

In chapter 4 (essay #3), I explore the correlation between stock market returns and bond market returns. Using the ADCC model to derive the asymmetric dynamic conditional correlation between the stock market and bond markets reveals a time-varying character. The dynamic conditional correlation depends on stock market volatility, the yield spread, and oil price shocks. This set of variables has a negative relation with the conditional correlation. My study also finds that the conditional correlation is positively correlated with the level of the federal funds rate.

In sum, this dissertation provides a pioneer approach to the above three areas of empirical research on stock returns. By using cutting-edge econometric techniques and high frequency data, this dissertation advances our knowledge by presenting new evidence that describes the market behavior in the modern economic environment.

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Appendix of Tables

Table 2.1 Descriptive Statistics of Weekly Excess Returns: 1986-2005

index	company name	ticker	nobs	mean	variance	skewness	kurtosis	peakedness	Jarque-Bera	Q(30)	$Q^2(30)$
1	Microsoft Corp.	MSFT	999	0.00623	0.00243	0.1054	1.7434	1.1322	128.3609	40.0341	210.3496
						[1.36]	[11.25]***		0***	0.1	0***
2	Honeywell International	HON	999	0.00234	0.00189	-0.7458	10.4318	1.0107	4622.3848	66.6923	138.3476
						[-9.62]***	[67.30]***		0***	0***	0***
3	Coca-Cola Co.	KO	999	0.00264	0.00122	-0.2049	1.5426	1.0786	106.0431	35.541	222.6358
						[-2.64]***	[9.95] ***		0***	0.22	0***
4	E.I. DuPont de Nemours	DD	999	0.00186	0.00141	-0.1613	1.4728	1.0986	94.6198	51.4363	278.872
						[-2.08]**	[9.50] ***		0***	0.01***	0***
5	Exxon Mobil Corp.	XOM	999	0.00253	7.84E-04	-0.1485	1.3036	1.1647	74.4108	119.402	208.3203
						[-1.92]*	[8.41] ***		0***	0***	0***
6	General Electric Co.	GE	999	0.00297	0.00119	-0.1052	3.2818	1.1407	450.1587	50.5722	197.9357
						[-1.36]	[21.17] ***		0***	0.01**	0***
7	General Motors Corp.	GM	999	8.57E-04	0.00176	-0.1895	2.192	1.1856	205.9881	35.2411	26.7299
						[-2.45]**	[14.14] ***		0***	0.23	0.64
8	International Business	IBM	999	0.00168	0.00159	0.0399	2.3767	1.0927	235.388	40.55	198.6334
						[0.51]	[15.33] ***		0***	0.09*	0***
9	Altria Group Inc.	MO	999	0.00361	0.00157	-0.3389	3.9432	1.0472	666.3313	37.7432	79.336
						[-4.37]***	[25.44] ***		0***	0.16	0***
10	United Technologies	UTX	999	0.00296	0.00147	-1.4454	12.8243	1.0301	7193.6328	76.4998	43.2729
						[-18.6]***	[82.74] ***		0***	0***	0.06*
11	Procter & Gamble Co.	PG	999	0.00304	0.00125	-2.09	24.1258	1.055	24955.353	99.2438	45.9705
						[-26.9]***	[155.6] ***		0***	0***	0.03**
12	Caterpillar Inc.	CAT	999	0.00319	0.00187	0.1223	3.4189	1.1005	489.0329	49.6413	63.4811
						[1.58]	[22.06] ***		0***	0.01**	0***
13	Boeing Co.	BA	999	0.00243	0.00175	-0.9363	8.9094	1.0939	3450.0172	26.1619	85.6471
						[-12.0]***	[57.48] ***		0***	0.67	0***
14	Pfizer Inc.	PFE	999	0.00292	0.00151	-0.2471	1.6742	1.2616	126.8375	46.246	95.4955
						[-3.19]***	[10.80] ***		0***	0.03**	0***
15	Johnson & Johnson	JNJ	999	0.00299	0.00109	-0.0269	2.3118	1.18	222.5903	51.99	123.6244
						[-0.35]	[14.92] ***		0***	0.01**	0***
16	3M Co.	MMM	999	0.00229	9.87E-04	-0.0023	2.3585	1.0821	231.5415	43.9957	202.3982
						[-0.03]	[15.22] ***		0***	0.05**	0***
17	Merck & Co. Inc.	MRK	999	0.00238	0.00145	-0.3045	2.4453	1.1817	264.3375	34.283	58.3937
						[-3.93]***	[15.78] ***		0***	0.27	0***
18	Alcoa Inc.	AA	999	0.00279	0.00208	-0.4607	6.0484	1.1334	1558.134	56.6534	73.5826
						[-5.95]***	[39.02] ***		0***	0***	0***
19	Walt Disney Co.	DIS	999	0.00246	0.00166	-0.2527	2.9907	1.2043	382.9379	38.326	77.1463
						[-3.26]***	[19.30] ***		0***	0.14	0***
20	Hewlett-Packard Co.	HPQ	999	0.00322	0.00285	-0.1841	2.1588	1.1304	199.6392	51.4856	186.6745
						[-2.38]**	[13.93] ***		0***	0.01***	0***

Table 2.1 (Continued)

index	company name	ticker	nobs	mean	variance	skewness	kurtosis	peakedness	Jarque-Bera	Q(30)	Q2(30)
21	McDonald's Corp.	MCD	999	0.0022	0.00123	-0.0701	1.085	1.2158	49.8201	36.5428	140.4038
						[-0.90]	[7.00] ***		0***	0.19	0***
22	JPMorgan Chase & Co.	JPM	999	0.00252	0.00239	-0.0532	1.9238	1.079	154.5247	42.948	353.6849
						[-0.69]	[12.41] ***		0***	0.06*	0***
23	Wal-Mart Stores Inc.	WMT	999	0.00324	0.00161	0.0414	1.3849	1.1689	80.1245	47.2936	333.5604
						[0.53]	[8.94] ***		0***	0.02**	0***
24	American Express Co.	AXP	999	0.00284	0.0018	-0.2135	2.7292	1.2052	317.6268	45.6515	148.3075
						[-2.75]***	[17.61] ***		0***	0.03**	0***
25	Intel Corp.	INTC	999	0.0055	0.00342	-0.632	3.8506	1.2007	683.6673	29.5866	87.1171
						[-8.15]***	[24.84] ***		0***	0.49	0***
26	Verizon Communications	VZ	999	0.00152	0.00116	0.1909	1.8996	1.2103	156.263	55.9734	254.7223
						[2.46]**	[12.26] ***		0***	0***	0***
27	AT&T	T	999	0.00196	0.00133	0.2295	3.1149	1.1904	412.6303	51.7092	300.738
						[2.96]***	[20.10] ***		0***	0.01***	0***
28	Home Depot Inc.	HD	999	0.00539	0.0023	-0.4238	4.5083	1.1297	875.9315	36.4251	165.8335
						[-5.47]***	[29.09] ***		0***	0.19	0***
29	American International	AIG	999	0.00278	0.00139	0.3886	2.8457	1.2107	362.2258	44.6777	112.3984
						[5.01]***	[18.36] ***		0***	0.04**	0***
30	Citigroup Inc.	C	999	0.00422	0.00208	0.1921	2.9292	1.1439	363.2863	42.9245	93.5565
						[2.48]**	[18.90] ***		0***	0.06*	0***
31	S&P500 (Market)		999	0.00133	4.62E-04	-0.5292	2.8903	1.173	394.3576	58.9947	238.3201
						[-6.83]***	[18.65]***		0***	0***	0***

Note: The 30 stocks are sorted by permanent CRSP number. nobs is the number of observations. The last row Market is measured by the S&P500. Numbers below coefficients are t-values (with brackets). Numbers below tests are p-values. *** indicates 1% significance, ** 5%, * 10%. The standard deviations of skewness and excess kurtosis coefficients are given approximately by $(6/T)^{0.5}$ and $(24/T)^{0.5}$, respectively. The peakedness is measured by $f_{0.75}$-$f_{0.25}$, the distance between the values of the standardized variable at which the cumulative distribution function equals 0.75 and the value at which the cumulative distribution function equals 0.25. The reference value of the standard normal distribution is 1.35. A number of peakedness less than 1.35 means there is high peak in the probability density function. A normality test is conducted by the Jarque-Bera statistic. An independence test is conducted by a Ljung-Box Q test up to the order of 30. The Q^2 test up to the order of 30 is to show volatility clustering.

Table 2.2 Statistics of the Standardized Errors on the GARCH(1,1)-Normal Distribution: Weekly Data, 1986-2005

index	skewness	kurtosis	peakedness	JB	Q(30)	$Q^2(30)$	ϕ_0	ϕ_1	ϕ_2	δ	w	α	β	γ
1	0.325 [4.19] ***	1.7464 [11.25] ***	1.2393	144.3966 0***	33.8396 0.29	23.6315 0.79	0.0038 [3.26]***	1.1478 [19.60]***	 [NA]	-0.1035 [-1.92]*	0.000012 [1.46]	0.043 [3.75]***	0.947 [68.46]***	0.0064 [0.30]
2	-0.1386 [-1.79]*	3.7809 [24.36] ***	1.1149	597.6384 0***	40.1232 0.1	18.262 0.95	0.0002 [0.20]	1.1546 [23.30]***	 [NA]	0.1514 [4.72]***	0.000007 [2.01]**	0.0251 [2.73]***	0.9483 [110.4]***	0.0475 [2.47]**
3	-0.0996 [-1.28]	1.7435 [11.23] ***	1.1815	128.0553 0***	34.0617 0.28	19.7525 0.92	0.0019 [2.29]**	0.9433 [21.38]***	-0.043 [-1.69]*	0.1308 [5.26]***	0.000024 [2.00]**	0.0772 [3.29]***	0.89 [25.35]***	0.0115 [0.35]
4	0.1178 [1.52]	0.8954 [5.77] ***	1.1559	35.6498 0***	30.6938 0.43	34.7945 0.25	0.0007 [0.84]	1.0984 [28.66]***	 [NA]	0.0174 [0.63]	0.000008 [1.90]*	0.0523 [3.13]***	0.9403 [69.26]***	-0.0022 [-0.10]
5	0.1453 [1.87]*	0.9415 [6.06] ***	1.2957	40.3688 0***	36.0064 0.21	18.1299 0.96	0.0021 [3.51]***	0.6815 [24.05]***	-0.172 [-7.18]***	0.1284 [0.00]	0.000004 [8.01]***	0.0407 [32.48]***	0.968 [857.7]***	-0.0334 [-14.1]***
6	0.2082 [2.68]***	1.2395 [7.99] ***	1.226	71.1013 0***	44.0888 0.05**	28.2673 0.56	0.0015 [2.50]**	1.1891 [39.18]***	-0.0662 [-3.05]***	0.0525 [2.91]***	0.000005 [2.10]**	0.0284 [3.24]***	0.9557 [90.24]***	0.0097 [0.52]
7	0.0232 [0.30]	1.7674 [11.39] ***	1.191	129.9834 0***	37.1809 0.17	19.0182 0.94	-0.0006 [-0.58]	1.0286 [22.84]***	 [NA]	0.0042 [0.14]	0.000024 [1.77]*	0.008 [0.81]	0.9443 [49.51]***	0.0652 [3.10]***
8	-0.2299 [-2.96]***	2.4445 [15.75] ***	1.0648	257.2865 0***	34.2906 0.27	28.8303 0.53	-0.0008 [-0.87]	0.9271 [20.08]***	 [NA]	0.0206 [0.93]	0.00001 [1.99]**	0.0217 [2.10]**	0.9296 [66.45]***	0.0956 [3.41]***
9	-0.6695 [-8.63]***	4.1205 [26.54] ***	1.0558	780.568 0***	22.7618 0.82	23.094 0.81	0.0027 [2.87]***	0.8083 [15.71]***	 [NA]	-0.0296 [-1.09]	0.000011 [3.62]***	-0.007 [-0.92]	6 0.9666 [127.9]***	0.0615 [5.18]***
10	-0.4853 [-6.25]***	3.8586 [24.86] ***	1.1821	658.2901 0***	36.9234 0.18	9.2842 1	0.0019 [2.31]**	1.0402 [25.05]***	-0.0725 [-2.97]***	-0.1718 [-5.12]***	0.000002 [1.07]	0.0439 [3.93]***	0.9599 [158.7]***	-0.0111 [-0.67]
11	-0.4783 [-6.16]***	3.587 [23.08] ***	1.13	573.0948 0***	46.8546 0.03**	31.4136 0.4	0.0014 [1.84]*	0.8322 [21.56]***	-0.0987 [-4.11]***	0.1153 [3.54]***	0.000029 [2.84]***	0.0764 [2.69]***	0.8365 [26.21]***	0.14 [3.42]***
12	0.2028 [2.61]***	3.7273 [24.01] ***	1.1323	584.5448 0***	33.3369 0.31	16.408 0.98	0.0022 [1.94]*	1.0168 [18.30]***	 [NA]	-0.1516 [-4.42]***	0.000016 [2.66]***	0.0019 [0.27]	0.9663 [113.5]***	0.042 [3.56]***
13	-0.0969 [-1.25]	1.7346 [11.17] ***	1.1864	126.6834 0***	26.0719 0.67	44.0327 0.05**	0.0018 [1.90]*	0.9425 [17.05]***	 [NA]	0.0029 [0.09]	0.000011 [2.00]**	0.0143 [1.45]	0.9523 [98.07]***	0.0491 [2.37]**
14	-0.2625 [-3.38]***	1.7829 [11.49] ***	1.2095	143.6545 0***	41.7312 0.08*	32.5686 0.34	0.0014 [1.39]	0.9127 [17.52]***	 [NA]	-0.0347 [-1.20]	0.00005 [2.77]***	0.0189 [1.17]	0.9101 [36.57]***	0.0545 [2.38]**
15	0.0521 [0.67]	1.0313 [6.64] ***	1.2023	44.682 0***	39.197 0.12	23.4614 0.8	0.0021 [2.59]***	0.827 [18.58]***	-0.0929 [-3.50]***	0.0214 [0.55]	0.000028 [2.48]**	0.0157 [0.82]	0.9135 [34.30]***	0.0717 [2.76]***
16	0.1481 [1.91]*	1.6954 [10.92] ***	1.1093	123.1715 0***	32.113 0.36	43.3573 0.05**	0.0011 [1.59]	0.8627 [23.05]***	-0.0839 [-3.39]***	-0.0368 [-1.22]	0.000003 [1.50]	0.0095 [1.04]	0.9704 [117.5]***	0.031 [2.37]**
17	-0.5395 [-6.95]***	5.5791 [35.94] ***	1.1373	1342.749 0***	35.2725 0.23	13.3108 1	0.002 [2.04]**	0.8975 [19.70]***	-0.0696 [-2.47]**	-0.0272 [-0.94]	0.000014 [2.54]**	-0.0052 [-0.65]	0.9651 [106.2]***	0.0536 [3.74]***
18	0.1916 [2.47]**	1.3209 [8.51] ***	1.2232	78.6646 0***	48.917 0.02**	37.3444 0.17	0.0008 [0.76]	1.129 [19.86]***	 [NA]	-0.2635 [-4.00]***	0.00002 [2.14]**	0.0399 [2.99]***	0.9382 [66.10]***	0.0151 [0.68]
19	0.0434 [0.56]	1.8057 [11.63] ***	1.1739	135.8917 0***	31.3465 0.4	34.4645 0.26	0.0011 [1.10]	1.12 [22.25]***	 [NA]	-0.0509 [-1.75]*	0.000009 [2.01]**	0.0236 [1.99]**	0.9627 [111.4]***	0.0111 [0.64]
20	-0.0463 [-0.60]	2.9953 [19.30] ***	1.1578	373.4356 0***	37.8005 0.15	31.4578 0.39	0.0017 [1.31]	1.3192 [19.80]***	-0.0634 [-2.53]**	-0.1321 [-3.67]***	0.000019 [1.86]*	0.0214 [2.25]**	0.9659 [108.9]***	0.0053 [0.34]

Table 2.2 (Continued)

index	skewness	kurtosis	peakedness	JB	Q(30)	$Q^2(30)$	ϕ_0	ϕ_1	ϕ_2	δ	w	α	β	γ
21	0.0039 [0.05]	1.413 [9.10] ***	1.2017	83.0282 0***	34.6267 0.26	27.0469 0.62	0.0009 [0.97]	0.8581 [17.25]***	[NA]	0.1522 [5.58]***	0.000013 [2.41]**	0.0158 [1.39]	0.9529 [80.21]***	0.0344 [1.79]*
22	-0.1535 [-1.98]**	1.5692 [10.11] ***	1.1886	106.3135 0***	38.6063 0.13	25.3614 0.71	-0.0001 [-0.13]	1.28 [26.27]***	[NA]	-0.0775 [-1.74]*	0.000003 [0.75]	0.0212 [1.61]	0.9427 [81.87]***	0.0764 [3.51]***
23	0.11 [1.42]	1.0494 [6.76] ***	1.2199	47.807 0***	33.1966 0.31	20.3827 0.91	0.0017 [2.15]**	1.1453 [24.08]***	-0.0764 [-2.97]***	0.0414 [0.94]	0.000013 [2.02]**	0.0357 [2.86]***	0.9436 [67.03]***	0.0147 [0.85]
24	-0.0935 [-1.20]	1.2285 [7.91] ***	1.2377	64.2169 0***	38.8477 0.13	28.2932 0.55	0.0008 [0.92]	1.3293 [33.18]***	-0.0455 [-2.12]**	0.0361 [1.25]	0.000004 [1.37]	0.0123 [1.13]	0.9607 [139.4]***	0.0468 [2.26]**
25	-0.1157 [-1.49]	1.1022 [7.10] ***	1.1877	52.7396 0***	39.102 0.12	18.3382 0.95	0.0034 [2.43]**	1.4716 [22.73]***	[NA]	-0.3448 [-19.6]***	0.000139 [1.63]	0.0918 [2.58]***	0.8552 [15.05]***	-0.0131 [-0.38]
26	0.1525 [1.97]**	1.4721 [9.48] ***	1.1727	93.9842 0***	18.7153 0.95	25.0171 0.72	0.0004 [0.43]	0.7143 [16.06]***	-0.1018 [-3.38]***	0.114 [4.37]***	0.00002 [2.31]**	0.0151 [1.02]	0.915 [42.86]***	0.1031 [2.93]***
27	0.1414 [1.82]*	1.7771 [11.45] ***	1.1934	134.6485 0***	28.2358 0.56	46.9571 0.03**	0.0011 [1.25]	0.8291 [18.36]***	-0.0536 [-1.94]*	0.1442 [5.09]***	0.000005 [1.48]	0.0527 [3.83]***	0.9445 [96.88]***	-0.0015 [-0.08]
28	-0.24 [-3.09]***	1.7515 [11.28] ***	1.2185	137.1534 0***	35.0204 0.24	49.3694 0.01**	0.0039 [3.83]***	1.328 [24.83]***	-0.0679 [-2.93]***	-0.1298 [-3.15]***	0.000022 [2.29]**	0.0583 [3.74]***	0.9209 [65.73]***	0.0117 [0.62]
29	0.1677 [2.16]**	2.281 [14.69] ***	1.1977	221.0298 0***	21.721 0.86	34.2298 0.27	0.0018 [2.19]**	1.1269 [24.40]***	-0.0865 [-3.53]***	0.0229 [0.72]	0.000022 [2.33]**	0.0359 [2.68]***	0.9123 [36.49]***	0.0516 [1.60]
30	0.741 [9.55]***	7.2363 [46.62] ***	1.1258	2268.791 0***	32.4082 0.35	15.2051 0.99	0.0024 [2.44]**	1.4348 [29.36]***	-0.0655 [-2.77]***	-0.0534 [-1.36]	0.000096 [2.43]**	0.0605 [2.01]**	0.837 [15.74]***	0.0388 [0.90]

Note: The 30 stocks are sorted by permanent CRSP number. Numbers below coefficients are t-values (with brackets). Numbers below tests are p-values. *** indicates 1% significance, ** 5%, * 10%. The standard deviations of skewness and excess kurtosis coefficients are given approximately by $(6/T)^{0.5}$ and $(24/T)^{0.5}$, respectively. The peakedness is measured by $f_{0.75}$-$f_{0.25}$, the distance between the values of standardized variable at which the cumulative distribution function equals 0.75 and the value at which the cumulative distribution function equals 0.25. The reference value of the standard normal distribution is 1.35. A number of peakedness less than 1.35 means there is high peak in the probability density function. A normality test is conducted by the Jarque-Bera (JB) statistics. An independence test is conducted by a Ljung-Box Q test up to the order of 30. The Q^2 test up to the order of 30 is to show volatility clustering. The model is:

(2.1.a) $r_t = \phi_0 + \phi_1 r_{m,t} + \phi_2 r_{t-1} + \delta D_{87} + \varepsilon_{it}$

(2.1.b) $\varepsilon_t = \sqrt{h_t} z_t$

(2.1.c) $h_t = w + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma\, I(\varepsilon_{t-1} < 0)\varepsilon_{t-1}^2$

(2.1.d) $\varepsilon_t \mid \Im_{t-1} \sim N(0, h_t)$. The following stocks do not have an AR(1) variable: MSFT, HON, DD, GM, IBM, MO, CAT, BA, PFE, AA, DIS, MCD, JPM, INTC.

Stock PG is the only one to have an AR(4) variable in the mean equation to ensure that autocorrelation is removed.

Table 2.3 Statistics of the Standardized Errors on the GARCH(1,1)-t Distribution: Weekly Data, 1986-2005

index	skewness	kurtosis	peakedness	Q(30)	$Q^2(30)$	ϕ_0	ϕ_1	ϕ_2	δ	w	α	β	γ	v
1	0.343 [4.42]***	1.7838 [-0.53]	1.2436 (1.44)	33.2195 0.31	23.0715 0.81	0.0025 [2.37]**	1.1206 [20.40]***	[NA]	-0.1049 [-2.37]**	1.1E-05 [1.04]	0.0476 [3.09]***	0.942 [44.63]***	0.0103 [0.37]	6.4635
2	-0.2319 [-2.99]***	4.7297 [-0.50]	1.1348 (1.48)	40.0766 0.1	21.0042 0.89	0 [-0.00]	1.0971 [23.66]***	[NA]	0.1458 [7.48]***	1.9E-05 [2.36]**	0.0298 [2.30]**	0.939 [62.86]***	0.0277 [1.21]	4.5243
3	-0.1337 [-1.72]*	1.994 [-0.17]	1.1909 (1.44)	33.3153 0.31	20.5154 0.9	0.0019 [2.49]**	0.9345 [23.49]***	-0.0596 [-2.41]**	0.1281 [6.46]***	9E-06 [0.99]	0.0687 [3.12]***	0.9273 [28.16]***	-0.0097 [-0.30]	6.7609
4	0.1218 [1.57]	0.9512 [-1.02]	1.1426 (1.44)	30.255 0.45	33.7479 0.29	0.0004 [0.55]	1.0819 [27.61]***	[NA]	0.016 [0.84]	9E-06 [1.60]	0.0598 [2.55]**	0.929 [49.02]***	0.0065 [0.22]	6.7749
5	0.1278 [1.65]*	1.0005 [0.44]	1.2934 (1.39)	34.3873 0.27	16.7991 0.97	0.002 [3.09]***	0.6895 [22.69]***	-0.1679 [-6.81]***	0.1297 [0.00]	6E-06 [5.48]***	0.0501 [20.20]**	0.9537 [425.1]***	-0.0284 [-6.14]***	11.1396
6	0.2187 [2.82]***	1.3807 [0.14]	1.2375 (1.41)	45.1364 0.04**	27.5533 0.59	0.0012 [2.04]**	1.1779 [38.69]***	-0.061 [-3.49]***	0.0524 [2.98]***	4E-06 [1.49]	0.0295 [2.43]**	0.9515 [79.40]***	0.0224 [0.97]	8.6249
7	0.0013 [0.02]	2.0779 [-0.39]	1.1981 (1.44)	36.1023 0.2	18.2453 0.95	-0.001 [-1.01]	1.0089 [21.65]***	[NA]	0.0026 [0.10]	1.1E-05 [1.23]	0.0154 [1.31]	0.9586 [78.94]***	0.0433 [2.03]**	6.2797
8	-0.2701 [-3.48]***	2.8559 NA	1.0195 (1.53)	34.8834 0.25	28.569 0.54	-0.001 [-1.20]	0.9383 [24.54]***	[NA]	0.0218 [1.35]	5E-06 [1.06]	0.0297 [2.05]**	0.9489 [72.36]***	0.0491 [1.89]*	3.9057
9	-0.706 [-9.10]***	4.5322 [-0.12]	1.0486 (1.48)	22.5016 0.84	21.7429 0.86	0.0035 [3.79]***	0.804 [16.44]***	[NA]	-0.0309 [-1.61]	1.4E-05 [2.07]**	0.0176 [0.81]	0.9518 [57.86]***	0.0397 [1.75]*	4.0701
10	-0.8208 [-10.5]***	6.9991 [2.28]**	1.1804 (1.45)	33.9934 0.28	7.8299 1	0.0021 [2.69]***	1.0041 [26.12]***	-0.0877 [-3.61]***	-0.1768 [-7.95]***	1.5E-05 [1.58]	0.0539 [2.17]**	0.9273 [31.36]***	0.001 [0.04]	5.9383
11	-0.8627 [-11.1]***	8.5655 [0.88]	1.1322 (1.45)	48.1859 0.02**	21.2743 0.88	0.0022 [3.01]***	0.8264 [21.67]***	-0.1159 [-4.51]***	0.1119 [5.75]***	0.000015 [2.88]***	0.0492 [2.69]***	0.9235 [61.63]***	0.0176 [0.65]	5.1337
12	0.1705 [2.20]**	4.2164 [-0.53]	1.1414 (1.48)	34.2222 0.27	14.6933 0.99	0.0017 [1.69]*	1.0317 [21.07]***	[NA]	-0.1496 [-5.66]***	1.4E-05 [1.48]	0.0201 [1.34]	0.9592 [65.73]***	0.0231 [1.30]	4.8239
13	-0.1782 [-2.30]**	2.0983 [-0.25]	1.1979 (1.44)	26.1595 0.67	46.3158 0.03**	0.0015 [1.50]	0.9043 [18.78]***	[NA]	-0.0005 [-0.02]	1.9E-05 [2.23]**	0.0132 [1.03]	0.9502 [72.45]***	0.0414 [1.70]*	6.4902
14	-0.2855 [-3.68]***	2.0056 [-0.52]	1.1918 (1.44)	40.2125 0.1	30.7673 0.43	0.0018 [1.94]*	0.92 [20.01]***	[NA]	-0.0344 [-1.64]*	2.9E-05 [1.81]*	0.03 [1.56]	0.9247 [36.67]***	0.044 [1.55]	6.1476
15	0.0652 [0.84]	1.0808 [-0.94]	1.1834 (1.44)	39.0689 0.12	25.1389 0.72	0.0018 [2.34]**	0.8325 [21.67]***	-0.0783 [-3.08]***	0.0243 [0.98]	2.3E-05 [2.06]**	0.0226 [1.02]	0.9211 [32.82]***	0.059 [2.15]**	6.828
16	0.1556 [2.00]**	1.6957 [-0.86]	1.0909 (1.48)	32.1196 0.36	42.3807 0.07*	0.0011 [1.60]	0.8569 [24.26]***	-0.0758 [-3.35]***	-0.0366 [-2.23]**	4E-06 [1.47]	0.0121 [0.79]	0.9688 [106.0]***	0.0277 [1.81]*	4.863
17	-0.8697 [-11.2]***	10.312 [2.80]***	1.1498 (1.45)	31.9551 0.37	7.3149 1	0.0019 [2.16]**	0.9572 [21.44]***	-0.0651 [-2.47]**	-0.0208 [-0.96]	2.6E-05 [2.27]**	0.0285 [1.57]	0.9234 [44.28]***	0.0484 [1.69]*	5.5646
18	0.1839 [2.37]**	1.3727 [-0.43]	1.2229 (1.42)	49.1214 0.02**	37.5822 0.16	0.0004 [0.43]	1.1146 [22.39]***	[NA]	-0.2645 [-7.62]***	1.6E-05 [1.50]	0.0326 [2.23]**	0.9427 [58.66]***	0.0282 [1.14]	7.4977
19	0.0404 [0.52]	1.8821 [-0.69]	1.1772 (1.45)	30.5184 0.44	31.6679 0.38	0.0011 [1.19]	1.1197 [26.38]***	[NA]	-0.0509 [-2.38]**	1.2E-05 [1.57]	0.0295 [1.90]*	0.9512 [62.59]***	0.0162 [0.70]	5.9915
20	-0.0672 [-0.87]	3.2296 [-0.69]	1.1420 (1.48)	37.5776 0.16	30.4423 0.44	0.0017 [1.39]	1.2807 [22.11]***	-0.0657 [-2.79]***	-0.1361 [-4.78]***	1.6E-05 [1.42]	0.0294 [2.29]**	0.9602 [85.02]***	0.0057 [0.28]	4.8937
21	-0.0207 [-0.27]	1.6059 [-0.55]	1.2007 (1.44)	34.3777 0.27	27.0955 0.62	0.0005 [0.55]	0.865 [20.89]***	[NA]	0.1532 [6.54]***	9E-06 [1.51]	0.0179 [1.39]	0.955 [73.68]***	0.0394 [1.61]	6.6886
22	-0.1468 [-1.89]*	1.6039 [-0.72]	1.1651 (1.44)	38.9648 0.13	25.0082 0.72	0.0001 [0.12]	1.3264 [27.83]***	[NA]	-0.0731 [-2.56]**	4E-06 [0.81]	0.0217 [1.28]	0.9422 [63.96]***	0.0748 [2.90]***	6.3138
23	0.1166 [1.50]	1.0596 [-0.71]	1.2152 (1.42)	33.3934 0.31	21.1235 0.88	0.0014 [1.71]*	1.1359 [26.23]***	-0.0768 [-3.28]***	0.0406 [1.28]	1.3E-05 [1.30]	0.0379 [2.49]**	0.9393 [46.50]***	0.0202 [0.92]	7.765

Table 2.3 (Continued)

index	skewness	kurtosis	peakedness	Q(30)	Q2(30)	ϕ_0	ϕ_1	ϕ_2	δ	w	α	β	γ	v
24	-0.1277 [-1.65]*	1.3495 [-0.10]	1.2377 (1.41)	37.6296 0.16	28.6486 0.54	0.0006 [0.71]	1.3136 [30.37]***	-0.0494 [-1.99]**	0.0342 [1.35]	8E-06 [1.59]	0.0138 [0.98]	0.952 [82.43]***	0.0545 [2.10]**	8.2353
25	-0.1312 [-1.69]*	1.2702 [-0.82]	1.1790 (1.44)	39.0144 0.13	28.3397 0.55	0.0038 [2.90]***	1.45 [20.87]***	 [NA]	-0.2712 [-7.00]***	9E-06 [0.53]	0.0514 [16.39]**	0.9609 [60.67]***	-0.0311 [-1.56]	6.8554
26	0.2108 [2.72]***	1.9665 [-0.67]	1.1407 (1.45)	19.1298 0.94	26.7937 0.63	0.0002 [0.23]	0.7986 [19.30]***	-0.0871 [-3.28]***	0.1231 [5.48]***	1.9E-05 [1.94]*	0.0515 [2.05]**	0.8996 [36.66]***	0.0672 [1.60]	5.8863
27	0.1706 [2.20]**	1.9752 [-0.48]	1.1781 (1.44)	27.9549 0.57	46.7514 0.03**	0.0009 [1.20]	0.8697 [20.74]***	-0.05 [-1.97]**	0.1487 [6.38]***	8E-06 [1.51]	0.0621 [3.27]***	0.9383 [68.32]***	-0.015 [-0.51]	6.2806
28	-0.2452 [-3.16]***	1.9163 [-0.16]	1.2308 (1.44)	34.7149 0.25	53.8793 0***	0.004 [3.78]***	1.2955 [24.05]***	-0.067 [-2.83]***	-0.1331 [-4.47]***	2.5E-05 [1.94]*	0.0515 [3.10]***	0.9275 [54.01]***	0.0041 [0.18]	6.8976
29	0.1626 [2.10]**	2.4257 [0.33]	1.1944 (1.44)	21.4156 0.87	31.1321 0.41	0.0012 [1.55]	1.1447 [26.33]***	-0.0772 [-3.46]***	0.0254 [1.07]	0.00002 [1.84]*	0.0403 [2.29]**	0.9188 [33.77]***	0.0332 [1.10]	6.849
30	0.7595 [9.79]***	10.0335 [1.90]*	1.1622 (1.45)	31.9395 0.37	10.6979 1	0.0016 [1.85]*	1.406 [30.66]***	-0.0759 [-3.58]***	-0.0565 [-1.87]*	1.1E-05 [1.16]	0.0189 [1.82]*	0.9579 [59.90]***	0.0278 [1.27]	5.316

Note: The 30 stocks are sorted by permanent CRSP number. Numbers below coefficients are t-values (with brackets). Numbers below tests are p-values. *** indicates 1% significance, ** 5%, * 10%. The standard deviation of skewness coefficients is given approximately by $(6/T)^{0.5}$. The excess kurtosis coefficient of the *t*-distribution is given by $\frac{6}{v-4}$ for $v>4$. Its standard deviation is obtained from the delta method. The peakedness is measured by $f_{0.75}$-$f_{0.25}$, the distance between the values of standardized variable at which the cumulative distribution function equals 0.75 and the value at which the cumulative distribution function equals 0.25. The reference value of the standard normal distribution is 1.35. The reference value for the estimated *t*-distribution is reported below actual peakedness (with parenthesis), which is in the range (1.39, 1.53). A number of peakedness less than reference value means there is a high peak in the probability density function. A normality test is omitted since the assumption is Student's *t*-distribution. An independence test is conducted by a Ljung-Box Q test up to the order of 30. The Q^2 test up to the order of 30 is to show volatility clustering. The model is:

(2.1.a) $r_t = \phi_0 + \phi_1 r_{m,t} + \phi_2 r_{t-1} + \delta D_{87} + \varepsilon_{it}$

(2.1.b) $\varepsilon_t = \sqrt{h_t} z_t$

(2.1.c) $h_t = w + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma\, I(\varepsilon_{t-1} < 0)\varepsilon_{t-1}^2$

(2.1.d) $\varepsilon_t \mid \Im_{t-1} \sim t(0, h_t, v)$.

The following stocks do not have an AR(1) variable: MSFT, HON, DD, GM, IBM, MO, CAT, BA, PFE, AA, DIS, MCD, JPM, INTC.
Stock PG is the only one to have an AR(4) variable in the mean equation to ensure that autocorrelation is removed.

Table 2.4 Statistics of the Standardized Errors on the GARCH(1,1)-EGB2 Estimates: Weekly Data, 1986-2005

index	skewness	kurtosis	peakedness	Q(30)	$Q^2(30)$	ϕ_0	ϕ_1	ϕ_2	δ	w	α	β	γ	p	q
1	0.3412	1.7765	1.2455	33.4102	22.9306	0.0034	1.1176		-0.101	1.1E-05	0.0473	0.9435	0.0045	1.0233	0.7971
	[0.43]	[1.18]	(1.20)	0.31	0.82	[3.23]***	[21.84]***	[NA]	[-2.27]**	[1.08]	[3.23]***	[45.21]***	[0.17]		
2	-0.2048	4.4376	1.1664	40.0458	19.8209	0	1.1021		0.1467	1.4E-05	0.0269	0.9437	0.029	0.5436	0.5274
	[-1.87]*	[9.86]***	(1.13)	0.1	0.92	[-0.01]	[26.13]***	[NA]	[7.30]***	[2.67]***	[2.49]**	[79.79]***	[1.50]		
3	-0.1272	1.9475	1.1934	33.3921	20.4258	0.002	0.9353	-0.056	0.1291	1.1E-05	0.0694	0.9241	-0.0101	0.8898	0.8338
	[-1.65]*	[1.70]*	(1.19)	0.31	0.9	[2.94]***	[21.09]***	[-2.19]**	[6.63]***	[0.97]	[2.89]**	[23.65]***	[-0.29]		
4	0.1248	0.953	1.1425	30.344	33.8905	0.0008	1.0782		0.0169	9E-06	0.0642	0.9277	-0.0007	0.7613	0.6589
	[-0.49]	[-1.75]*	(1.17)	0.45	0.29	[0.95]	[28.14]***	[NA]	[0.91]	[1.45]	[2.61]***	[44.76]***	[-0.02]		
5	0.1341	0.9897	1.2981	34.7639	17.1257	0.0021	0.6903	-0.1673	0.1301	5E-06	0.0481	0.9584	-0.0317	1.776	1.6686
	[0.72]	[1.18]	(1.26)	0.25	0.97	[2.95]***	[19.25]***	[-6.31]***	[6.99]***	[1.00]	[2.81]***	[32.60]***	[-1.26]		
6	0.2233	1.3534	1.2350	45.1204	27.1924	0.0014	1.1795	-0.0632	0.0532	4E-06	0.032	0.9529	0.0141	1.378	1.1263
	[0.28]	[1.06]	(1.23)	0.04**	0.61	[2.13]**	[39.92]***	[-3.10]***	[3.53]***	[1.49]	[2.42]**	[81.42]***	[0.58]		
7	0.0048	1.9897	1.2069	36.3661	18.4223	-0.0007	1.0121		0.0036	1.3E-05	0.0136	0.956	0.0463	0.8337	0.7498
	[-0.98]	[1.52]	(1.18)	0.2	0.95	[-0.65]	[21.31]***	[NA]	[0.15]	[1.33]	[1.28]	[69.88]***	[2.16]**		
8	-0.257	2.7399	1.0606	34.8276	28.5692	-0.0012	0.9455		0.0223	6E-06	0.0262	0.944	0.056	0.3342	0.3477
	[-1.22]	[1.48]	(1.08)	0.25	0.54	[-1.35]	[23.95]***	[NA]	[1.61]	[1.24]	[1.96]**	[64.61]***	[2.13]**		
9	-0.6971	4.3728	1.0869	22.6857	21.929	0.0026	0.8023		-0.0322	1.3E-05	0.0054	0.9573	0.0486	0.3736	0.4322
	[-3.07]***	[7.39]***	(1.09)	0.83	0.86	[2.64]***	[18.33]***	[NA]	[-1.97]**	[2.46]**	[0.35]	[71.58]***	[2.73]***		
10	-0.7098	5.8553	1.1884	34.6538	8.0929	0.0017	1.009	-0.087	-0.1769	0.00001	0.0458	0.9423	-0.003	0.6849	0.7425
	[-4.88]***	[12.84]***	(1.17)	0.26	1	[2.23]**	[27.68]***	[-3.83]***	[-8.36]***	[1.72]*	[2.60]***	[54.62]***	[-0.13]		
11	-0.6741	6.0631	1.1326	46.4982	26.043	0.0017	0.8242	-0.1203	0.11	1.9E-05	0.0518	0.9004	0.0504	0.5305	0.6015
	[-3.52]***	[12.84]***	(1.14)	0.03**	0.67	[2.32]**	[22.70]***	[-4.71]***	[6.16]***	[2.44]**	[2.32]**	[34.82]***	[1.31]		
12	0.1834	4.1096	1.1571	34.3886	15.0915	0.0024	1.0259		-0.1484	1.6E-05	0.017	0.9585	0.0245	0.609	0.5251
	[-0.26]	[7.69]***	(1.14)	0.27	0.99	[2.18]**	[20.40]***	[NA]	[-6.07]***	[1.68]*	[1.22]	[64.75]***	[1.45]		
13	-0.1586	2.0019	1.2016	26.1503	45.7982	0.0016	0.912		0.0008	1.7E-05	0.0128	0.9503	0.0442	0.866	0.8183
	[-1.67]*	[2.05]**	(1.19)	0.67	0.03**	[1.70]*	[17.47]***	[NA]	[0.03]	[2.22]**	[1.00]	[74.53]***	[1.84]*		
14	-0.2815	1.9679	1.2027	40.3874	30.9281	0.0013	0.9224		-0.0352	3.2E-05	0.0276	0.9212	0.0483	0.748	0.8582
	[-0.80]	[1.47]	(1.18)	0.1	0.42	[1.38]	[18.75]***	[NA]	[-1.67]*	[2.04]**	[1.52]	[37.57]***	[1.63]		
15	0.0796	1.0827	1.1947	39.075	24.6498	0.0021	0.8394	-0.0769	0.0268	2.4E-05	0.0306	0.9128	0.0564	0.8794	0.7645
	[-0.74]	[-1.16]	(1.19)	0.12	0.74	[2.53]**	[21.19]***	[-3.00]***	[1.03]	[2.08]**	[1.14]	[30.49]***	[1.92]*		
16	0.1496	1.703	1.1076	32.4643	43.0084	0.0011	0.8548	-0.074	-0.0368	3E-06	0.0089	0.9711	0.0299	0.4835	0.4921
	[1.29]	[-1.12]	(1.12)	0.35	0.06*	[1.57]	[25.54]***	[-3.22]***	[-2.62]***	[1.42]	[0.82]	[105.5]***	[1.88]*		
17	-0.799	9.2326	1.1596	32.7319	8.4127	0.0019	0.9539	-0.0652	-0.021	2.4E-05	0.0206	0.9335	0.0452	0.5532	0.5478
	[-5.64]***	[21.66]***	(1.14)	0.33	1	[2.01]**	[23.75]***	[-2.52]**	[-1.07]	[2.20]**	[1.25]	[46.75]***	[1.68]*		
18	0.2006	1.3321	1.2287	49.0945	38.2149	0.0009	1.1161		-0.262	1.9E-05	0.0349	0.9417	0.0183	1.1292	0.9509
	[0.15]	[0.43]	(1.21)	0.02**	0.14	[0.87]	[20.81]***	[NA]	[-8.05]***	[1.67]*	[2.31]**	[56.20]***	[0.72]		
19	0.0419	1.8661	1.1842	30.6913	32.2694	0.0012	1.1209		-0.0504	1.1E-05	0.0287	0.9535	0.014	0.7224	0.6921
	[-0.11]	[0.85]	(1.17)	0.43	0.36	[1.26]	[25.84]***	[NA]	[-2.66]***	[1.59]	[1.67]*	[69.68]***	[0.55]		
20	-0.0622	3.1716	1.1715	37.46	30.6583	0.0017	1.277	-0.0667	-0.1363	1.7E-05	0.0261	0.9614	0.0057	0.6121	0.5983
	[-0.66]	[5.14]***	(1.15)	0.16	0.43	[1.30]	[20.89]***	[-2.69]***	[-5.28]***	[1.62]	[2.14]**	[96.11]***	[0.30]		
21	-0.0083	1.5496	1.2055	34.3959	27.1835	0.0008	0.8637		0.1543	9E-06	0.0194	0.9549	0.0332	0.8679	0.7485
	[-1.47]	[0.21]	(1.18)	0.27	0.61	[0.88]	[21.01]***	[NA]	[7.51]***	[1.66]*	[1.45]	[75.20]***	[1.57]		
22	-0.1528	1.6012	1.1773	38.8848	24.9758	-0.0001	1.322		-0.0747	4E-06	0.0197	0.9422	0.0788	0.7846	0.8586
	[-0.31]	[0.50]	(1.19)	0.13	0.73	[-0.12]	[29.64]***	[NA]	[-2.45]**	[0.75]	[1.24]	[66.75]***	[2.76]***		
23	0.122	1.0602	1.2103	33.3633	21.3757	0.0018	1.135	-0.0739	0.043	1.5E-05	0.0397	0.936	0.0198	1.0471	0.879
	[-0.53]	[-0.68]	(1.20)	0.31	0.88	[1.98]**	[26.40]***	[-2.96]***	[1.47]	[1.63]	[2.48]**	[47.76]***	[0.88]		

Table 2.4 (Continued)

index	skewness	kurtosis	peakedness	Q(30)	Q2(30)	ϕ_0	ϕ_1	ϕ_2	δ	w	α	β	γ	p	q
24	-0.1166 [-1.86]*	1.321 [0.48]	1.2361 (1.22)	37.8084 0.15	28.7249 0.53	0.0007 [0.84]	1.3141 [33.10]***	-0.0483 [-2.29]**	0.0357 [1.45]	7E-06 [1.36]	0.0151 [1.07]	0.9543 [86.97]***	0.0485 [1.84]*	1.1216	0.9945
25	-0.1305 [0.30]	1.2595 [-0.52]	1.1869 (1.19)	39.0536 0.12	28.8414 0.53	0.0032 [2.37]**	1.4509 [23.06]***	[NA]	-0.2732 [-6.75]***	8E-06 [0.44]	0.0493 [2.99]***	0.9632 [50.58]***	-0.0312 [-1.42]	0.7835	0.9016
26	0.2048 [0.99]	1.9035 [1.20]	1.1586 (1.17)	19.1195 0.94	26.5286 0.65	0.0004 [0.44]	0.7923 [20.62]***	-0.0884 [-3.31]***	0.1229 [6.16]***	1.8E-05 [1.86]*	0.0454 [1.99]**	0.9039 [37.62]***	0.0669 [1.67]*	0.7541	0.7163
27	0.1627 [1.19]	1.9351 [1.01]	1.1779 (1.17)	27.9691 0.57	46.5729 0.03**	0.001 [1.09]	0.873 [19.65]***	-0.0499 [-1.82]*	0.149 [6.82]***	7E-06 [1.51]	0.0595 [3.19]***	0.9396 [69.05]***	-0.0114 [-0.40]	0.724	0.7236
28	-0.2448 [-1.27]	1.873 [2.01]**	1.2342 (1.20)	34.7132 0.25	52.5435 0.01**	0.0037 [3.47]***	1.3029 [26.02]***	-0.0683 [-2.77]***	-0.1334 [-4.64]***	2.4E-05 [1.86]*	0.0531 [3.16]***	0.9257 [51.93]***	0.0055 [0.25]	0.8967	0.9744
29	0.1727 [-0.21]	2.3833 [3.43]***	1.2032 (1.20)	21.5452 0.87	32.2833 0.35	0.0016 [1.90]*	1.1419 [27.31]***	-0.0754 [-3.26]***	0.0273 [1.04]	2.2E-05 [1.91]*	0.0409 [2.28]**	0.9138 [30.42]***	0.0348 [1.10]	0.9941	0.8369
30	0.754 [3.64]***	9.3273 [29.70]***	1.1708 (1.15)	33.0307 0.32	11.0894 1	0.0023 [2.43]**	1.4123 [31.60]***	-0.0674 [-3.11]***	-0.0517 [-2.13]**	1.9E-05 [1.17]	0.0271 [1.67]*	0.9441 [34.58]***	0.02 [0.86]	0.6879	0.5446

Note: The 30 stocks are sorted by permanent CRSP number. Numbers below coefficients are t-values (with brackets). Numbers below Q test and Q^2 test are p-values. *** indicates 1% significance, ** 5%, * 10%. The predicted higher moments are given by the formula: $Skewness = \frac{\psi''(p)-\psi''(q)}{(\psi'(p)+\psi'(q))^{1.5}}$, $Kurtosis = \frac{\psi'''(p)+\psi'''(q)}{(\psi'(p)+\psi'(q))^{2}}$.

Their standard deviations are obtained using the delta method. The peakedness is measured by $f_{0.75}$-$f_{0.25}$, the distance between the values of standardized variable at which the cumulative distribution function equals 0.75 and the value at which the cumulative distribution function equals 0.25. The reference value of the standard normal distribution is 1.35. A number of peakedness less than 1.35 means there is a high peak in the probability density function. The reference value of the EGB2 distribution is reported below peakedness with parenthesis and is in the range of (1.07, 1.26). A normality test is omitted since the assumption is the EGB2 distribution. An independence test is conducted by a Ljung-Box Q test up to the order of 30. The Q^2 test up to the order of 30 is to show volatility clustering. The estimated model is:

(2.1.a) $r_t = \phi_0 + \phi_1 r_{m,t} + \phi_2 r_{t-1} + \delta D_{87} + \varepsilon_{it}$

(2.1.b) $\varepsilon_t = \sqrt{h_t}\, z_t$

(2.1.c) $h_t = w + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma\, I(\varepsilon_{t-1} < 0)\varepsilon_{t-1}^2$

(2.1.d) $\varepsilon_t \mid \Im_{t-1} \sim EGB2(0, h_t, p, q)$

The following stocks do not have an AR(1) variable: MSFT, HON, DD, GM, IBM, MO, CAT, BA, PFE, AA, DIS, MCD, JPM, INTC.
Stock PG is the only one to have an AR(4) variable in the mean equation to ensure that autocorrelation is removed.

Table 2.5 Statistics of the 9 Stocks' Standardized Errors on the GARCH(1,1)-EGB2 Estimates: Weekly Data, 1986-2005

index	ticker	skewness	kurtosis	peakedness	Q(30)	$Q^2(30)$	ϕ_0	ϕ_1	ϕ_2	w	α	β	γ	p	q	N
2	HON	0.1578 [-0.20]	2.3953 [3.25]***	1.2182 (1.19)	50.5229 0.01**	30.1429 0.46	0.0006 [0.77]	1.0566 [27.88]***	[NA]	1.3E-05 [1.93]*	0.0408 [2.20]**	0.935 [55.37]***	0.0211 [0.80]	0.9103	0.7813	10
9	MO	-0.5069 [-2.07]**	2.7862 [2.28]**	1.1174 (1.12)	22.8401 0.82	27.9385 0.57	0.0027 [2.88]***	0.8159 [18.11]***	[NA]	1.3E-05 [1.76]*	0.0407 [2.24]**	0.9407 [58.26]***	0.0142 [0.64]	0.4568	0.5192	3
10	UTX	-0.1411 [-1.02]	1.2787 [-0.19]	1.2052 (1.20)	32.3131 0.35	29.7857 0.48	0.0021 [2.64]***	0.9843 [25.53]***	-0.0853 [-4.20]***	1.1E-05 [1.65]*	0.0414 [2.03]**	0.9334 [42.05]***	0.0221 [0.92]	0.8765	0.8795	2
11	PG	-0.0746 [0.13]	1.5127 [-0.66]	1.1577 (1.16)	44.1755 0.05*	25.669 0.69	0.0021 [2.57]***	0.7953 [22.15]***	-0.1211 [-4.74]***	1.7E-05 [1.92]*	0.0561 [2.20]**	0.8984 [31.66]***	0.0527 [1.45]	0.6161	0.6576	1
12	CAT	0.2477 [0.32]	2.0579 [1.17]	1.1768 (1.16)	32.5068 0.34	19.5369 0.93	0.0022 [2.07]**	1.0234 [21.42]***	[NA]	1.7E-05 [1.50]	0.0198 [1.07]	0.9527 [47.31]***	0.0284 [1.44]	0.7285	0.6271	3
17	MRK	-0.0976 [-1.09]	1.905 [0.43]	1.1634 (1.15)	34.2624 0.27	29.7861 0.48	0.002 [2.13]**	0.9621 [22.28]***	-0.0609 [-2.49]**	0.00002 [2.34]**	0.0183 [1.17]	0.9364 [53.32]***	0.0532 [2.28]**	0.6352	0.6109	1
20	HPQ	0.0938 [0.21]	1.8507 [1.33]	1.2149 (1.19)	38.0405 0.15	51.1062 0.01**	0.0019 [1.71]*	1.2568 [22.32]***	-0.0687 [-3.00]***	1.3E-05 [1.44]	0.0219 [1.71]*	0.9602 [87.05]***	0.0199 [0.96]	0.8271	0.7859	9
29	AIG	0.0815 [-0.81]	1.777 [2.09]**	1.232 (1.22)	20.983 0.89	28.3133 0.55	0.0016 [2.08]**	1.1323 [30.66]***	-0.0779 [-3.69]***	2.1E-05 [1.88]*	0.0434 [2.31]**	0.9149 [31.32]***	0.0283 [0.95]	1.2246	1.0228	2
30	C	0.2551 [-0.65]	1.3999 [-0.22]	1.1966 (1.19)	30.3054 0.45	29.5047 0.49	0.0024 [2.43]**	1.4095 [32.79]***	-0.0761 [-3.62]***	1.1E-05 [1.18]	0.0374 [2.24]**	0.9496 [50.63]***	0.002 [0.09]	1.0202	0.7612	3

Note: The 9 stocks have significant excess coefficients in Table 2.4. Numbers below coefficients are t-values (with brackets). Numbers below tests are p-values. *** indicates 1% significance, ** 5%, * 10%. The predicted higher moments are given by the formula: $Skewness = \frac{\psi''(p)-\psi''(q)}{(\psi'(p)+\psi'(q))^{1.5}}$, $Kurtosis = \frac{\psi'''(p)+\psi'''(q)}{(\psi'(p)+\psi'(q))^{2}}$. Their standard deviations are obtained using the delta method. The peakedness is measured by $f_{0.75}$-$f_{0.25}$, the distance between the values of standardized variable at which the cumulative distribution function equals 0.75 and the value at which the cumulative distribution function equals 0.25. The reference value of the standard normal distribution is 1.35. A number of peakedness less than 1.35 means there is high peak in the probability density function. The reference value of the EGB2 distribution is reported below peakedness with parenthesis and is in the range of (1.12, 1.22). A normality test is omitted since the assumption is the EGB2 distribution. An independence test is conducted by a Ljung-Box Q test up to order 30. The Q^2 test of order of 30 is to show volatility clustering. The model is:

(2.1.a) $r_t = \phi_0 + \phi_1 r_{m,t} + \phi_2 r_{t-1} + \Delta_n D_{extreme} + \varepsilon_{it}$

(2.1.b) $\varepsilon_t = \sqrt{h_t} z_t$

(2.1.c) $h_t = w + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma\, I(\varepsilon_{t-1} < 0)\varepsilon_{t-1}^2$

(2.1.d) $\varepsilon_t \mid \Im_{t-1} \sim EGB2(0, h_t, p, q)$

N in the table represents the number of dummies in the mean equation (at most 10). Those dummies represent the extreme values in the individual stock's return series.
The following stocks do not have an AR(1) variable: MSFT, HON, DD, GM, IBM, MO, CAT, BA, PFE, AA, DIS, MCD, JPM, INTC.
Stock PG is the only one to have an AR(4) variable in the mean equation to ensure that autocorrelation is removed.

Table 2.6 Fitness Comparisons among Alternative Distributions

Index	ticker	Likelihood (-lnL)			Chi Square Test Statistic		
		Normal	t	EGB2	Normal	t	EGB2
1	MSFT	2727.663	2405.698	1836.975	56.32**	70***	38.6
2	HON	2939.66	2655.106	2078.661	77.76***	129.92***	60.12***
3	KO	3070.488	2747.057	2175.794	45.6	89.76***	30.2
4	DD	3080.986	2748.706	2180.607	50.32	70.88***	41.04
5	XOM	3286.659	2949.103	2378.235	46.24	49.6*	38
6	GE	3330.797	2998.795	2428.805	33.36	54.72**	23.32
7	GM	2851.589	2529.761	1958.933	40.56	78.32***	36.4
8	IBM	2940.611	2646.765	2076.628	87.84***	151.04***	128.68***
9	MO	2870.27	2589.11	2016.484	76.56***	138.72***	49*
10	UTX	3086.131	2777.7	2204.927	56.24**	86.4***	42.64
11	PG	3099.136	2798.107	2226.256	77.6***	106.4***	47.92
12	CAT	2808.847	2515.001	1941.912	71.04***	110.88***	50.52*
13	BA	2869.513	2546.216	1974.935	54.72**	77.36***	44.12
14	PFE	2906.508	2585.459	2014.814	66***	84.08***	31.2
15	JNJ	3094.648	2764.042	2194.88	68.72***	86.72***	53**
16	MMM	3213.133	2899.268	2330.127	69.92***	99.68***	54.88**
17	MRK	2921.886	2622.322	2049.385	54.88**	91.52***	54.68**
18	AA	2820.431	2491.263	1921.461	43.92	69.84***	34
19	DIS	2947.914	2628.138	2057.377	45.84	76.56***	47.64
20	HPQ	2640.579	2341.888	1768.097	68.56***	117.92***	67.28***
21	MCD	3021.621	2694.789	2125.111	65.36***	117.12***	45.52
22	JPM	2851.61	2527.93	1957.228	54.72**	78.32***	48.72*
23	WMT	2993.255	2660.808	2091.682	48.64	64.48***	36.68
24	AXP	3013.207	2681.583	2111.124	42.32	72.8***	40.72
25	INTC	2560.727	2232.273	1663.033	58.8**	63.04***	26.32
26	VZ	3055.394	2733.302	2162.317	64.4***	106.32***	50.28*
27	T	3023.173	2700.77	2129.957	51.84*	85.84***	45.16
28	HD	2838.915	2515.001	1943.85	50.24	77.92***	42.24
29	AIG	3097.629	2777.491	2206.573	56**	63.28***	39.72
30	C	2918.77	2633.718	2060.1	75.44***	91.04***	39.76

Note: This table compares the GARCH(1,1) model based on three distributions: Normal, Student's *t* (t), and EGB2 based on a negative logarithm of the likelihood function value (Left) and the χ^2 goodness of fit test statistic value (Right). The quantiles are computed via 40 intervals. The degree of freedom (d.f.) is 37 for EGB2, 38 for *t*-distribution, 39 for normal distribution. The chi square critical values at 1%, 5% and 10% levels are 59.89, 52.19, and 48.36, respectively with d.f. being 37; 61.16, 53.39, and 49.51 with d.f. being 38; 62.43, 54.57, and 50.66 with d.f. being 39. *** indicates 1% significance, ** 5%, * 10%.
Results show that the EGB2 distribution has the lowest negative log-likelihood function value. Results also show that 12 stocks reject the normal distribution assumption; 28 stocks reject the Student's *t* distribution; only 3 stocks reject the EGB2 distribution at the 1% significance level.

Table 2.7 The Probability of Negative Extreme Shocks in the Error Term

Stock \ Shocks		-7σ	-6σ	-5σ	-4σ	-3σ	-2σ	-1σ
1	MSFT	8.41E-07	6.42E-06	4.90E-05	0.000373	0.002832	0.021062	0.137138
2	HON	7.31E-06	3.76E-05	0.000193	0.000984	0.005031	0.025703	0.12933
3	KO	3.42E-06	2.03E-05	0.00012	0.000708	0.004177	0.024489	0.135087
4	DD	2.83E-06	1.73E-05	0.000105	0.000642	0.003902	0.023582	0.134136
5	XOM	1.05E-06	8.00E-06	6.07E-05	0.000459	0.003429	0.024407	0.143861
6	GE	4.52E-07	3.96E-06	3.47E-05	0.000303	0.002615	0.021451	0.141932
7	GM	3.30E-06	1.96E-05	0.000117	0.000693	0.004112	0.024242	0.134684
8	IBM	1.83E-05	8.05E-05	0.000352	0.001534	0.006686	0.029148	0.126866
9	MO	2.35E-05	9.97E-05	0.00042	0.001761	0.007391	0.031013	0.129726
10	UTX	1.17E-05	5.64E-05	0.000269	0.001287	0.006139	0.029219	0.135227
11	PG	1.53E-05	7.00E-05	0.000318	0.00144	0.006526	0.029553	0.132183
12	CAT	5.00E-06	2.74E-05	0.00015	0.000818	0.004465	0.024337	0.129658
13	BA	3.28E-06	1.97E-05	0.000118	0.000708	0.004233	0.025055	0.137264
14	PFE	9.08E-06	4.58E-05	0.00023	0.001154	0.00578	0.028808	0.137298
15	JNJ	1.90E-06	1.25E-05	8.18E-05	0.000536	0.003512	0.022751	0.135477
16	MMM	1.07E-05	5.16E-05	0.000248	0.001193	0.005729	0.027508	0.130414
17	MRK	9.13E-06	4.53E-05	0.000224	0.001105	0.005452	0.026874	0.130475
18	AA	2.66E-06	1.66E-05	0.000103	0.00064	0.00397	0.024331	0.137113
19	DIS	4.92E-06	2.74E-05	0.000152	0.000842	0.004664	0.025708	0.134949
20	HPQ	7.93E-06	4.05E-05	0.000206	0.001045	0.005301	0.02685	0.132606
21	MCD	2.13E-06	1.36E-05	8.67E-05	0.000552	0.003515	0.022249	0.132611
22	JPM	5.72E-06	3.12E-05	0.00017	0.00092	0.004991	0.026883	0.136911
23	WMT	1.21E-06	8.74E-06	6.28E-05	0.000451	0.003228	0.022585	0.138697
24	AXP	1.09E-06	8.05E-06	5.92E-05	0.000435	0.003184	0.022668	0.139658
25	INTC	1.14E-05	5.56E-05	0.000269	0.0013	0.006275	0.030129	0.138371
26	VZ	3.65E-06	2.13E-05	0.000124	0.00072	0.004185	0.024206	0.133382
27	T	6.62E-06	3.50E-05	0.000184	0.000964	0.005062	0.026487	0.133843
28	HD	6.65E-06	3.56E-05	0.00019	0.00101	0.005372	0.028274	0.139248
29	AIG	1.35E-06	9.52E-06	6.69E-05	0.000469	0.003282	0.022544	0.137761
30	C	1.91E-06	1.24E-05	7.97E-05	0.000514	0.003315	0.021299	0.13028
if normal		1.28E-12	9.87E-10	2.87E-07	3.17E-05	0.00135	0.02275	0.158655

Note: The probability is calculated based on estimated *p* and *q* values of the EGB2 distribution. It tells how often the error terms have negative extreme values. The probability values based on the normal distribution are the same for all 30 stocks. Results show the EGB2 distribution will forecast a much higher probability for extreme values' happening than does the normal distribution.

Table 3.1 Descriptive Statistics of DJIA Stock Daily Excess Returns, 1998-2005

index	company name	ticker	nobs	mean	std	skew	kurt	min	max	JB	Q(10)	LM(10)
1	Microsoft Corp.	MSFT	2013	0.000503	0.023546	0.130445	5.681048	-0.15613	0.195482	2696.455***	161.863***	94.73237***
2	Honeywell International Inc.	HON	2013	0.000278	0.024783	0.25227	13.19121	-0.17799	0.28206	14537.3***	81.94801***	61.06852***
3	Coca-Cola Co.	KO	2013	-0.00012	0.017234	-0.00469	4.074388	-0.10494	0.096384	1383.452***	271.4599***	150.8816***
4	E.I. DuPont de Nemours & Co.	DD	2013	5.51E-05	0.019716	0.207581	2.792277	-0.11054	0.098654	663.7593***	175.1704***	95.4759***
5	Exxon Mobil Corp.	XOM	1531	0.000371	0.015818	0.19371	3.805517	-0.08465	0.110382	925.4711***	291.5026***	145.0795***
6	General Electric Co.	GE	2013	0.000355	0.019413	0.213081	3.467643	-0.1068	0.124536	1017.041***	370.5333***	183.5689***
7	General Motors Corp.	GM	2013	-0.00014	0.022664	0.176485	4.54178	-0.13976	0.181053	1729.746***	88.78324***	60.32376***
8	International Business Machines	IBM	2013	0.000393	0.021594	0.156433	6.457098	-0.15559	0.131517	3484.735***	110.4***	70.82625***
9	Altria Group Inc.	MO	2013	0.000584	0.021229	0.069473	6.877293	-0.13847	0.162509	3945.569***	132.7556***	91.72635***
10	United Technologies Corp.	UTX	2013	0.000732	0.020507	-1.29541	19.41357	-0.28255	0.098252	32007.13***	87.53195***	78.23402***
11	Procter & Gamble Co.	PG	2013	0.000344	0.018081	-2.73268	48.15209	-0.31395	0.095081	195987.9***	20.9732**	17.73081*
12	Caterpillar Inc.	CAT	2013	0.000679	0.021667	0.098367	2.335853	-0.12175	0.108331	457.4485***	92.65071***	67.92374***
13	Boeing Co.	BA	2013	0.000393	0.022071	-0.39714	5.790625	-0.17632	0.099714	2848.446***	126.2502***	94.25249***
14	Pfizer Inc.	PFE	2013	0.000156	0.020485	-0.10403	2.479312	-0.11152	0.097034	515.4123***	224.2497***	116.9226***
15	Johnson & Johnson	JNJ	2013	0.000395	0.015801	-0.3584	7.408399	-0.1585	0.082077	4619.942***	181.1015***	115.4939***
16	3M Co.	MMM	2013	0.000456	0.016788	0.394831	2.940267	-0.06709	0.11055	772.2771***	145.9565***	97.78238***
17	Merck & Co. Inc.	MRK	2013	1.66E-06	0.019815	-1.17774	19.5089	-0.26785	0.130258	32219.25***	3.541215	3.302876
18	Alcoa Inc.	AA	2013	0.000548	0.023844	0.417723	2.621266	-0.11013	0.140446	630.6***	162.2479***	109.6327***
19	Walt Disney Co.	DIS	2013	7.66E-05	0.023469	0.064115	6.084492	-0.1837	0.152465	3088.089***	95.56756***	65.65652***
20	Hewlett-Packard Co.	HPQ	2013	0.000472	0.029646	0.223947	5.125707	-0.18708	0.208993	2206.958***	55.42822***	43.79064***
21	McDonald's Corp.	MCD	2013	0.000322	0.019548	0.11199	3.851494	-0.12822	0.10847	1240.316***	104.7887***	89.8757***
22	JPMorgan Chase & Co.	JPM	2013	0.000397	0.024764	0.363823	4.946213	-0.18112	0.160312	2083.708***	411.7909***	202.5261***
23	Wal-Mart Stores Inc.	WMT	2008	0.000577	0.020747	0.264275	2.41056	-0.09765	0.094187	505.8914***	389.8928***	182.9029***
24	American Express Co.	AXP	2013	0.000546	0.022854	0.082029	2.794868	-0.13603	0.127566	652.7848***	723.6375***	315.889***
25	Intel Corp.	INTC	2013	0.000601	0.031007	-0.11323	4.421846	-0.2205	0.201123	1633.945***	217.8026***	120.7392***
26	Verizon Communications Inc.	VZ	1383	-0.0001	0.019139	0.110876	4.432338	-0.11851	0.092669	1124.538***	228.9461***	114.3922***
27	AT&T	T	1989	9.1E-05	0.021337	0.065333	2.427628	-0.12677	0.092203	486.1663***	185.7254***	102.4186***
28	Home Depot Inc.	HD	2013	0.000641	0.024684	-0.66873	11.58655	-0.28752	0.12879	11348.27***	43.41298***	31.49115***
29	American International Group	AIG	2013	0.000403	0.020112	0.237391	2.839079	-0.10439	0.110157	690.1758***	381.5119***	170.7491***
30	Citigroup Inc.	C	2013	0.000582	0.02269	0.326174	5.776039	-0.15735	0.183246	2817.178***	351.7571***	182.4678***

Note: The components of the DJIA have changed over time. This list is valid as of the end of 2005. The 30 stocks are sorted by Permanent CRSP #. Among the 30 stocks only MSFT and INTC are primarily listed on NASDAQ; the rest are mainly listed on the NYSE.
The columns in order are the number of observations, the average value, the standard deviation of the daily return, the skewness coefficient, the kurtosis coefficient, minimum value, maximum value, Jarque-Bera normality test statistic, Portmanteau Q test of order 10, Lagrange multiplier test of order 10.
*** indicates 1% significance, ** 5%, * 10%.

Table 3.2 Descriptive Statistics about Three Explanatory Variables

index	ticker	Expected risk (σ^e)				Unexpected risk (σ^u)					Intraday Skewness Coefficient (Skew)					Pearson's Correlation Coefficients		
		mean	std	min	max	mean	std	t-value	min	max	mean	std	t-value	min	max	σ^e & σ^u	σ^e & skew	σ^u & skew
1	MSFT	0.0020	0.0008	0.0007	0.0052	-5E-07	0.0006	[-0.04]	-0.0020	0.0089	0.0333	0.6772	[2.21]**	-8.6734	5.6269	-0.0123	0.0308	0.0530
2	HON	0.0022	0.0007	0.0010	0.0056	1E-05	0.0007	[0.76]	-0.0027	0.0087	0.0858	0.8869	[4.34]***	-4.3901	8.4084	0.0145	-0.0403	0.0749
3	KO	0.0017	0.0006	0.0007	0.0041	-8E-07	0.0004	[-0.09]	-0.0016	0.0033	0.0250	0.7216	[1.55]	-5.1095	7.2110	-0.0014	-0.0009	0.0289
4	DD	0.0020	0.0007	0.0008	0.0044	-8E-06	0.0005	[-0.75]	-0.0016	0.0032	0.0330	0.7715	[1.92]*	-4.6719	7.2566	-0.0119	0.0388	0.0574
5	XOM	0.0015	0.0005	0.0006	0.0044	-4E-06	0.0004	[-0.43]	-0.0019	0.0035	0.0316	0.7230	[1.71]*	-4.7911	6.3369	0.0099	0.0152	0.0162
6	GE	0.0018	0.0007	0.0006	0.0051	-8E-07	0.0005	[-0.07]	-0.0020	0.0049	0.0503	0.6682	[3.38]***	-5.5313	4.6513	0.0036	0.0087	0.0484
7	GM	0.0019	0.0005	0.0010	0.0045	7E-06	0.0006	[0.51]	-0.0016	0.0048	0.0270	0.9474	[1.28]	-5.1953	6.0990	0.0138	-0.0106	0.0745
8	IBM	0.0018	0.0007	0.0006	0.0054	-1E-06	0.0005	[-0.10]	-0.0020	0.0064	0.1109	0.7340	[6.78]***	-6.5633	5.4968	0.0007	0.0004	0.1138
9	MO	0.0019	0.0007	0.0006	0.0053	2E-06	0.0007	[0.11]	-0.0027	0.0098	0.0733	0.9283	[3.54]***	-7.0750	7.7434	-0.0188	-0.0041	0.1350
10	UTX	0.0019	0.0007	0.0008	0.0054	6E-07	0.0005	[0.05]	-0.0021	0.0068	0.0266	0.8097	[1.47]	-6.7797	5.8471	-0.0037	0.0395	0.0452
11	PG	0.0016	0.0007	0.0006	0.0048	-7E-06	0.0005	[-0.68]	-0.0017	0.0075	0.0529	0.7690	[3.09]***	-5.9366	5.6044	-0.0005	-0.0139	0.0788
12	CAT	0.0020	0.0006	0.0009	0.0047	-2E-06	0.0005	[-0.14]	-0.0016	0.0039	0.0270	0.8106	[1.50]	-5.2645	5.7806	0.0005	0.0356	-0.0064
13	BA	0.0021	0.0007	0.0008	0.0054	-2E-06	0.0006	[-0.18]	-0.0016	0.0039	0.0685	0.8154	[3.77]***	-6.6058	5.0535	-0.0031	-0.0276	-0.0020
14	PFE	0.0019	0.0006	0.0008	0.0045	-4E-06	0.0006	[-0.34]	-0.0015	0.0073	0.0080	0.9101	[0.39]	-6.8670	7.0577	-0.0094	0.0181	-0.0611
15	JNJ	0.0015	0.0005	0.0007	0.0046	-1E-06	0.0004	[-0.11]	-0.0020	0.0041	0.0454	0.8545	[2.38]**	-7.5074	8.3439	0.0009	-0.0111	0.0318
16	MMM	0.0017	0.0006	0.0007	0.0041	-2E-06	0.0005	[-0.20]	-0.0016	0.0042	0.0753	0.7644	[4.42]***	-3.8780	6.3716	-0.0005	0.0663	-0.0133
17	MRK	0.0017	0.0005	0.0009	0.0045	5E-06	0.0006	[0.44]	-0.0017	0.0061	0.0175	0.9055	[0.86]	-8.1441	7.4488	0.0108	0.0384	-0.0427
18	AA	0.0021	0.0006	0.0011	0.0048	3E-06	0.0005	[0.26]	-0.0015	0.0031	0.0228	0.8240	[1.24]	-6.2952	5.9209	0.0112	0.0550	-0.0175
19	DIS	0.0022	0.0008	0.0009	0.0059	1E-05	0.0006	[0.84]	-0.0023	0.0095	0.0015	0.8556	[0.08]	-7.1292	8.2087	-0.0084	-0.0414	-0.0283
20	HPQ	0.0026	0.0009	0.0010	0.0065	6E-06	0.0008	[0.31]	-0.0036	0.0103	0.0372	0.8318	[2.00]**	-6.8651	5.5095	0.0022	0.0195	0.0727
21	MCD	0.0020	0.0006	0.0010	0.0040	6E-06	0.0006	[0.46]	-0.0017	0.0049	0.0641	0.7468	[3.85]***	-6.8217	4.0675	0.0035	-0.0519	-0.0428
22	JPM	0.0021	0.0009	0.0007	0.0083	6E-07	0.0007	[0.04]	-0.0033	0.0082	0.0315	0.7313	[1.93]*	-5.5299	5.0003	0.0171	0.0351	0.0273
23	WMT	0.0020	0.0008	0.0007	0.0044	-6E-06	0.0005	[-0.49]	-0.0020	0.0045	-0.0059	0.8576	[-0.31]	-6.4003	8.2325	-0.0044	-0.0487	0.0492
24	AXP	0.0020	0.0009	0.0006	0.0057	1E-05	0.0007	[0.82]	-0.0021	0.0130	0.0620	0.8292	[3.35]***	-8.7706	6.8086	-0.0132	-0.0022	-0.0635
25	INTC	0.0026	0.0010	0.0010	0.0066	7E-06	0.0006	[0.49]	-0.0028	0.0043	0.0076	0.6174	[0.56]	-3.9138	3.8880	0.0074	0.0427	0.0197
26	VZ	0.0019	0.0008	0.0007	0.0054	-2E-05	0.0005	[-1.39]	-0.0018	0.0048	-0.0106	0.9376	[-0.42]	-8.0829	7.5522	-0.0511	0.0266	-0.0077
27	SBC	0.0021	0.0008	0.0008	0.0057	9E-06	0.0005	[0.71]	-0.0024	0.0039	0.0303	0.7655	[1.76]*	-5.2140	6.1872	-0.0004	-0.0168	-0.0454
28	HD	0.0021	0.0008	0.0009	0.0059	4E-06	0.0006	[0.28]	-0.0024	0.0084	-0.0005	0.8232	[-0.03]	-6.8957	7.0865	0.0266	-0.0137	-0.0011
29	AIG	0.0018	0.0006	0.0008	0.0056	2E-06	0.0005	[0.17]	-0.0014	0.0054	0.0373	0.8143	[2.06]**	-6.6749	7.2282	0.0013	0.0349	-0.0203
30	C	0.0021	0.0010	0.0007	0.0076	6E-07	0.0007	[0.04]	-0.0029	0.0070	0.0357	0.7967	[2.01]**	-5.5697	7.4403	0.0036	0.0036	0.0456

Note: This table describes the mean, standard deviation, minimum and maximum of the three explanatory variables: expected standard deviation, unexpected standard deviation, and intraday skewness coefficient. T-value tests if the mean is statistically different from zero. *** indicates 1% significance, ** 5%, * 10%. Unexpected standard deviation has a zero mean according to its construction.
The table also reports the Pearson's correlation coefficients among three variables. The three variables have very small correlation coefficients among them.

Table 3.3 Regression Results of Excess Returns on Expected Volatility

		Simple regression			Multiple regression (3.1.a)				Multiple regression (3.1.b)					
Index	ticker	δ_0	δ_1	R_a^2	δ_0	δ_1	δ_2	R_a^2	δ_0	δ_1	δ_2	δ_3	δ_4	R_a^2
1	MSFT	-0.003	1.268	0.09%	-0.003	1.305	-2.041	0.46%	-0.002	0.869	-1.976	0.005	-0.011	2.49%
		[-1.53]	[1.70]*		[-1.40]	[1.75]*	[-2.89]***		[-1.00]	[1.18]	[-2.79]***	[6.57]***	[-0.51]	
2	HON	-0.003	1.048	0.02%	-0.004	2.081	-8.824	8.05%	-0.005	2.443	-9.29	0.007	0.045	13.27%
		[-1.52]	[1.19]		[-1.75]*	[2.45]**	[-13.28]***		[-2.48]**	[2.96]***	[-14.15]***	[10.98]***	[2.01]**	
3	KO	-0.002	0.673	-0.01%	-0.002	0.837	-3.549	0.73%	-0.002	0.744	-3.337	0.005	0.042	4.00%
		[-1.16]	[0.92]		[-1.13]	[1.15]	[-3.99]***		[-1.11]	[1.04]	[-3.74]***	[8.22]***	[1.86]*	
4	DD	-0.003	1.16	0.08%	-0.003	1.301	-3.299	0.71%	-0.002	1.003	-3.842	0.006	0.012	4.81%
		[-1.62]	[1.60]		[-1.60]	[1.80]*	[-3.71]***		[-1.39]	[1.42]	[-4.39]***	[9.39]***	[0.53]	
5	XOM	-0.002	0.946	0.04%	-0.002	1.544	-7.548	3.79%	-0.002	1.415	-8.233	0.004	-0.071	7.35%
		[-1.37]	[1.24]		[-1.66]*	[2.05]**	[-7.79]***		[-1.63]	[1.92]*	[-8.46]***	[7.30]***	[-2.77]***	
6	GE	-0.004	2.082	0.39%	-0.005	2.565	-4.298	2.08%	-0.005	2.512	-5.236	0.006	-0.056	6.02%
		[-2.89]***	[2.99]***		[-3.14]***	[3.69]***	[-5.96]***		[-3.33]***	[3.69]***	[-7.11]***	[8.92]***	[-2.45]**	
7	GM	-0.001	0.274	-0.05%	-0.001	0.18	0.935	-0.03%	-0.002	0.725	-0.233	0.007	-0.045	8.03%
		[-0.36]	[0.27]		[-0.35]	[0.18]	[1.14]		[-0.97]	[0.74]	[-0.29]	[13.12]***	[-2.05]**	
8	IBM	-0.004	1.9	0.23%	-0.004	2.056	-1.609	0.35%	-0.004	1.686	-5.184	0.011	-0.071	9.85%
		[-2.06]**	[2.36]**		[-2.12]**	[2.54]**	[-1.87]*		[-2.33]**	[2.19]**	[-6.08]***	[14.27]***	[-3.17]***	
9	MO	-0.001	0.418	-0.04%	-0.001	0.542	-1.108	0.16%	-0.002	0.776	-2.257	0.008	0.045	10.18%
		[-0.47]	[0.50]		[-0.45]	[0.64]	[-2.24]**		[-1.08]	[0.97]	[-4.74]***	[14.96]***	[2.00]**	
10	UTX	-0.003	1.504	0.13%	-0.003	2.305	-9.887	7.85%	-0.002	1.605	-12.005	0.009	-0.09	18.25%
		[-1.80]*	[1.90]*		[-2.01]**	[3.02]***	[-13.01]***		[-1.29]	[2.23]**	[-16.34]***	[15.66]***	[-4.11]***	
11	PG	0.002	-1.653	0.16%	0.001	-0.299	-11.049	9.95%	0.001	-0.525	-13.192	0.006	-0.077	13.77%
		[1.35]	[-2.07]**		[0.69]	[-0.39]	[-14.81]***		[0.89]	[-0.70]	[-17.2]***	[8.83]***	[-3.31]***	
12	CAT	-0.002	0.865	0.01%	-0.002	0.948	-1.513	0.10%	0	0.353	-1.69	0.008	-0.007	7.08%
		[-0.79]	[1.05]		[-0.79]	[1.15]	[-1.70]*		[-0.23]	[0.44]	[-1.96]**	[12.34]***	[-0.32]	
13	BA	-0.001	0.373	-0.04%	-0.001	0.888	-7.397	3.51%	-0.002	1.022	-7.244	0.009	0.021	11.63%
		[-0.55]	[0.43]		[-0.62]	[1.05]	[-8.66]***		[-1.09]	[1.26]	[-8.77]***	[13.59]***	[0.97]	
14	PFE	-0.005	2.022	0.22%	-0.004	2.263	-8.038	6.59%	-0.004	2.037	-7.517	0.004	0.038	9.11%
		[-2.60]***	[2.32]**		[-2.26]**	[2.69]***	[-11.75]***		[-2.06]**	[2.45]**	[-11.07]***	[7.48]***	[1.71]*	
15	JNJ	-0.003	2.105	0.35%	-0.004	2.759	-6.835	4.14%	-0.004	2.772	-6.766	0.004	0.049	8.06%
		[-2.50]**	[2.83]***		[-2.77]***	[3.77]***	[-8.96]***		[-3.01]***	[3.86]***	[-8.90]***	[9.23]***	[2.14]**	
16	MMM	-0.003	1.906	0.28%	-0.003	1.921	-0.253	0.23%	-0.002	0.768	0.22	0.008	0.016	10.93%
		[-1.99]**	[2.57]***		[-1.99]**	[2.59]***	[-0.34]		[-1.12]	[1.09]	[0.31]	[15.54]***	[0.71]	
17	MRK	-0.009	4.472	0.94%	-0.009	4.711	-4.117	2.67%	-0.007	3.776	-3.554	0.007	0.015	11.79%
		[-4.57]***	[4.48]***		[-4.44]***	[4.75]***	[-6.07]***		[-3.81]***	[3.99]***	[-5.47]***	[14.43]***	[0.63]	

Table 3.3 (Continued)

		Simple regression			Multiple regression (3.1.a)				Multiple regression (3.1.b)					
Index	ticker	δ_0	δ_1	R_a^2	δ_0	δ_1	δ_2	R_a^2	δ_0	δ_1	δ_2	δ_3	δ_4	R_a^2
18	AA	-0.003	1.578	0.12%	-0.003	1.756	-3.791	0.77%	-0.002	1.232	-3.819	0.007	0.004	5.11%
		[-1.53]	[1.82]*		[-1.50]	[2.03]**	[-3.78]***		[-1.05]	[1.45]	[-3.87]***	[9.68]***	[0.18]	
19	DIS	-0.001	-0.021	-0.05%	-0.001	0.711	-6.185	3.91%	-0.002	0.963	-5.775	0.005	-0.021	6.42%
		[-0.27]	[-0.03]		[-0.61]	[0.94]	[-9.15]***		[-0.94]	[1.28]	[-8.59]***	[7.37]***	[-0.92]	
20	HPQ	-0.001	0.436	-0.03%	-0.001	0.399	0.328	-0.07%	0	-0.09	-1.431	0.014	0.008	11.41%
		[-0.47]	[0.55]		[-0.46]	[0.50]	[0.50]		[-0.03]	[-0.12]	[-2.28]**	[16.18]***	[0.35]	
21	MCD	0.001	-0.528	-0.03%	0.001	-0.225	-3.53	1.25%	0	0.086	-2.885	0.005	-0.017	4.90%
		[0.49]	[-0.59]		[0.47]	[-0.25]	[-5.2]***		[-0.05]	[0.10]	[-4.28]***	[8.87]***	[-0.75]	
22	JPM	-0.002	0.644	-0.01%	-0.003	1.414	-4.006	1.53%	-0.003	1.179	-4.589	0.01	-0.062	7.95%
		[-0.93]	[0.93]		[-1.52]	[2.01]**	[-5.68]***		[-1.47]	[1.73]*	[-6.70]***	[11.39]***	[-2.89]***	
23	WMT	-0.003	1.455	0.17%	-0.003	1.789	-4.646	1.91%	-0.004	2.101	-5.199	0.006	0.004	6.65%
		[-1.77]*	[2.08]**		[-1.84]*	[2.57]***	[-6.05]***		[-2.23]**	[3.09]***	[-6.82]***	[10.18]***	[0.18]	
24	AXP	-0.003	1.255	0.12%	-0.003	1.297	-2.503	1.08%	-0.002	0.736	-0.803	0.007	0.014	6.76%
		[-1.76]*	[1.86]*		[-1.47]	[1.93]*	[-4.52]***		[-1.14]	[1.13]	[-1.42]	[11.15]***	[0.64]	
25	INTC	-0.005	1.558	0.18%	-0.005	1.787	-4.16	0.87%	-0.004	1.391	-5.106	0.011	-0.066	4.74%
		[-1.97]**	[2.16]**		[-1.99]**	[2.47]**	[-3.88]***		[-1.56]	[1.96]**	[-4.77]***	[8.43]***	[-2.98]***	
26	VZ	-0.002	0.894	0.04%	-0.002	0.898	-6.903	4.15%	-0.001	0.761	-6.356	0.005	-0.019	8.85%
		[-1.45]	[1.24]		[-0.98]	[1.27]	[-7.75]***		[-0.86]	[1.10]	[-7.19]***	[8.44]***	[-0.71]	
27	SBC	-0.002	0.575	-0.01%	-0.002	0.872	-4.59	1.46%	-0.003	1.105	-4.183	0.008	-0.01	7.52%
		[-1.09]	[0.87]		[-1.10]	[1.33]	[-5.54]***		[-1.60]	[1.74]*	[-5.14]***	[11.48]***	[-0.44]	
28	HD	-0.003	1.383	0.10%	-0.004	1.935	-3.549	1.04%	-0.003	1.675	-3.734	0.01	0	8.70%
		[-1.72]*	[1.76]*		[-2.07]**	[2.44]**	[-4.46]***		[-1.79]*	[2.20]**	[-4.69]***	[13.06]***	[0.01]	
29	AIG	-0.006	2.864	0.56%	-0.006	3.339	-6.154	3.63%	-0.005	2.886	-5.524	0.008	0.007	11.25%
		[-3.34]***	[3.51]***		[-3.41]***	[4.15]***	[-8.06]***		[-3.25]***	[3.73]***	[-7.26]***	[13.2]***	[0.34]	
30	C	-0.006	2.348	0.69%	-0.007	3.039	-4.52	3.29%	-0.006	2.813	-5.29	0.008	0.001	9.01%
		[-3.55]***	[3.86]***		[-4.07]***	[5.01]***	[-7.41]***		[-3.97]***	[4.78]***	[-8.74]***	[11.32]***	[0.03]	
Pooled Regression		-0.00129	0.83255	0.08%	-0.00129	0.83722	-4.24792	1.33%	-0.00148	0.81649	-4.49782	0.00616	-0.0132	6.54%
		[-5.21]***	[7.09]***		[-5.26]***	[7.17]***	[-27.32]***		[-6.17]***	[7.19]***	[-29.52]***	[57.32]***	[-3.30]***	

Note: The regression models are $r_t = \delta_0 + \delta_1\sigma_t^e + \varepsilon_t$ (left panel), $r_t = \delta_0 + \delta_1\sigma_t^e + \delta_2\sigma_t^u + \varepsilon_t$ (middle panel), and $r_t = \delta_0 + \delta_1\sigma_t^e + \delta_2\sigma_t^u + \delta_3 Skew_t + \delta_4 r_{t-1} + \varepsilon_t$ (right panel). The three explanatory variables are: expected standard deviation (σ^e), unexpected standard deviation (σ^u), and intraday skewness coefficient (*Skew*). The numbers inside brackets are t-values. The adjusted R^2 is reported for each regression model. The last two rows report pooled regression results of all 30 stocks. *** indicates 1% significance, ** 5%, * 10%. In the left panel, 15 stocks show positive significances of the σ^e; and 1 stock (index=11) shows negative significance. In the middle panel, 19 stocks show positive significances of the σ^e; the rest are all insignificant. In the right panel, 15 stocks show positive significances of the σ^e; the rest are all insignificant.

Table 3.4 Estimates of Quantile Regression at 5 Different Quantiles

ticker	quantile	NAME	δ_0	δ_1	δ_2	δ_3	δ_4
MSFT	0.05	Estimate	0.006	-18.688	-14.153	0.005	-0.084
	0.05	t-value	[3.54]***	[-17.69]***	[-5.01]***	[3.51]***	[-1.54]
	0.25	Estimate	0	-6.397	-7.851	0.006	-0.037
	0.25	t-value	[0.01]	[-8.80]***	[-5.10]***	[4.89]***	[-1.26]
	0.5	Estimate	-0.002	1.149	-5.119	0.008	-0.023
	0.5	t-value	[-2.05]**	[1.70]*	[-4.63]***	[10.24]***	[-1.03]
	0.75	Estimate	-0.005	9.221	-2.755	0.007	-0.029
	0.75	t-value	[-4.01]***	[12.01]***	[-1.88]*	[8.00]***	[-0.82]
	0.95	Estimate	-0.006	20.247	3.472	0.006	0.071
	0.95	t-value	[-2.88]***	[17.24]***	[2.19]**	[5.33]***	[1.95]*
HON	0.05	Estimate	0.005	-17.494	-15.504	0.005	0.064
	0.05	t-value	[1.77]*	[-12.41]***	[-14.02]***	[4.39]***	[1.74]*
	0.25	Estimate	-0.001	-5.883	-9.703	0.004	0.019
	0.25	t-value	[-0.72]	[-7.55]***	[-8.22]***	[6.34]***	[0.55]
	0.5	Estimate	0	-0.312	-4.252	0.005	-0.014
	0.5	t-value	[-0.27]	[-0.38]	[-3.67]***	[10.01]***	[-0.54]
	0.75	Estimate	-0.004	7.958	0.529	0.005	-0.04
	0.75	t-value	[-1.62]	[6.22]***	[0.37]	[6.30]***	[-1.19]
	0.95	Estimate	-0.005	19.077	8.901	0.005	0.08
	0.95	t-value	[-1.59]	[12.32]***	[3.46]***	[3.33]***	[2.32]**
KO	0.05	Estimate	0.004	-16.69	-16.05	0.003	0.054
	0.05	t-value	[1.92]*	[-13.35]***	[-10.46]***	[5.21]***	[1.19]
	0.25	Estimate	0.001	-6.468	-6.597	0.002	0.04
	0.25	t-value	[0.56]	[-8.78]***	[-5.45]***	[3.79]***	[1.36]
	0.5	Estimate	0	-0.311	-1.682	0.003	0.017
	0.5	t-value	[-0.01]	[-0.35]	[-1.34]	[4.26]***	[0.64]
	0.75	Estimate	-0.002	6.87	2.561	0.004	0
	0.75	t-value	[-1.49]	[8.31]***	[1.68]*	[5.16]***	[0.01]
	0.95	Estimate	-0.001	15.494	6.217	0.003	0.026
	0.95	t-value	[-0.32]	[9.20]***	[2.49]**	[2.63]***	[0.41]
DD	0.05	Estimate	-0.002	-12.83	-17.536	0.005	-0.039
	0.05	t-value	[-0.95]	[-10.84]***	[-9.13]***	[4.47]***	[-0.90]
	0.25	Estimate	0.001	-6.518	-6.518	0.005	0.031
	0.25	t-value	[0.87]	[-9.63]***	[-5.85]***	[8.37]***	[1.34]
	0.5	Estimate	0.002	-1.649	-2.724	0.005	-0.017
	0.5	t-value	[1.04]	[-1.88]*	[-1.78]*	[7.57]***	[-0.55]
	0.75	Estimate	0	5.598	2.018	0.005	-0.014
	0.75	t-value	[-0.06]	[6.05]***	[1.34]	[11.69]***	[-0.57]
	0.95	Estimate	-0.005	18.18	10.156	0.004	-0.031
	0.95	t-value	[-2.72]***	[16.80]***	[5.14]***	[5.11]***	[-0.59]
XOM	0.05	Estimate	-0.001	-13.794	-17.656	0.004	-0.06
	0.05	t-value	[-0.28]	[-6.59]***	[-7.01]***	[3.77]***	[-0.91]
	0.25	Estimate	0	-5.851	-15.092	0.003	-0.088
	0.25	t-value	[0.11]	[-5.16]***	[-9.27]***	[5.48]***	[-2.58]***
	0.5	Estimate	0.001	-0.601	-10.186	0.004	-0.097
	0.5	t-value	[0.72]	[-0.61]	[-8.47]***	[5.95]***	[-3.67]***
	0.75	Estimate	0.001	5.325	-7.274	0.004	-0.096
	0.75	t-value	[0.63]	[4.79]***	[-3.83]***	[4.60]***	[-2.29]**
	0.95	Estimate	0.002	14.446	7.963	0.002	-0.067
	0.95	t-value	[0.70]	[8.55]***	[2.85]***	[1.89]*	[-0.95]

Table 3.4 (Continued)

ticker	quantile	NAME	δ_0	δ_1	δ_2	δ_3	δ_4
GE	0.05	Estimate	0	-14.142	-15.75	0.003	0.032
	0.05	t-value	[-0.09]	[-13.93]***	[-8.33]***	[3.31]***	[0.73]
	0.25	Estimate	-0.001	-5.708	-9.259	0.004	0.068
	0.25	t-value	[-1.39]	[-9.73]***	[-8.26]***	[7.48]***	[2.08]**
	0.5	Estimate	-0.002	0.672	-6.68	0.005	-0.019
	0.5	t-value	[-1.45]	[0.99]	[-4.56]***	[5.79]***	[-0.64]
	0.75	Estimate	0	6.347	-1.852	0.007	-0.068
	0.75	t-value	[-0.06]	[7.77]***	[-1.40]	[10.54]***	[-1.90]*
	0.95	Estimate	-0.002	17.261	3.777	0.004	-0.074
	0.95	t-value	[-0.81]	[10.66]***	[1.48]	[3.58]***	[-1.13]
GM	0.05	Estimate	0.005	-19.328	-16.834	0.005	-0.052
	0.05	t-value	[1.58]	[-10.61]***	[-8.35]***	[4.38]***	[-1.55]
	0.25	Estimate	0.004	-9.095	-7.241	0.005	-0.065
	0.25	t-value	[1.95]*	[-8.35]***	[-5.59]***	[9.77]***	[-2.76]***
	0.5	Estimate	0.003	-1.665	-1.832	0.007	-0.053
	0.5	t-value	[1.30]	[-1.49]	[-1.77]*	[12.30]***	[-2.06]**
	0.75	Estimate	-0.001	7.323	5.361	0.007	-0.053
	0.75	t-value	[-0.46]	[5.32]***	[3.27]***	[13.25]***	[-1.53]
	0.95	Estimate	-0.001	17.241	14.596	0.009	0.05
	0.95	t-value	[-0.26]	[8.13]***	[7.14]***	[8.17]***	[0.91]
IBM	0.05	Estimate	-0.001	-15.51	-19.369	0.004	-0.038
	0.05	t-value	[-0.31]	[-10.61]***	[-11.4]***	[4.27]***	[-0.57]
	0.25	Estimate	-0.002	-6.002	-11.485	0.006	-0.057
	0.25	t-value	[-1.97]**	[-10.63]***	[-7.33]***	[8.58]***	[-2.35]**
	0.5	Estimate	-0.002	0.698	-3.645	0.006	-0.042
	0.5	t-value	[-1.62]	[1.00]	[-2.30]**	[9.18]***	[-1.69]*
	0.75	Estimate	-0.004	8.709	2.127	0.006	-0.034
	0.75	t-value	[-3.41]***	[10.97]***	[1.18]	[9.40]***	[-0.91]
	0.95	Estimate	-0.004	18.682	7.157	0.006	0.054
	0.95	t-value	[-1.52]	[11.82]***	[2.37]**	[4.10]***	[1.10]
MO	0.05	Estimate	0.001	-14.638	-19.031	0.004	-0.036
	0.05	t-value	[0.32]	[-13.63]***	[-11.04]***	[3.82]***	[-0.83]
	0.25	Estimate	0	-6.256	-11.265	0.004	0.031
	0.25	t-value	[0.27]	[-8.82]***	[-11.3]***	[7.11]***	[1.00]
	0.5	Estimate	-0.001	-0.004	-5.569	0.004	-0.019
	0.5	t-value	[-0.53]	[0.00]	[-3.88]***	[6.42]***	[-0.65]
	0.75	Estimate	0	6.455	1.452	0.004	-0.029
	0.75	t-value	[-0.35]	[7.58]***	[1.11]	[6.82]***	[-1.09]
	0.95	Estimate	-0.001	16.119	12.429	0.004	-0.051
	0.95	t-value	[-0.27]	[9.89]***	[6.38]***	[3.22]***	[-0.90]
UTX	0.05	Estimate	-0.002	-12.218	-18.216	0.006	-0.048
	0.05	t-value	[-1.62]	[-13.69]***	[-9.78]***	[8.87]***	[-1.16]
	0.25	Estimate	-0.001	-5.436	-10.446	0.006	-0.085
	0.25	t-value	[-0.50]	[-5.54]***	[-10.25]***	[10.77]***	[-2.73]***
	0.5	Estimate	-0.001	0.207	-6.825	0.006	-0.108
	0.5	t-value	[-0.34]	[0.24]	[-3.77]***	[9.89]***	[-3.5]***
	0.75	Estimate	-0.003	8.601	1.548	0.006	-0.034
	0.75	t-value	[-2.19]**	[9.41]***	[0.79]	[8.55]***	[-1.29]
	0.95	Estimate	-0.001	15.742	8.582	0.007	-0.06
	0.95	t-value	[-0.29]	[10.20]***	[3.28]***	[7.72]***	[-1.27]

Table 3.4 (Continued)

ticker	quantile	NAME	δ_0	δ_1	δ_2	δ_3	δ_4
PG	0.05	Estimate	-0.001	-12.907	-20.482	0.004	-0.009
	0.05	t-value	[-0.97]	[-17.11]***	[-9.60]***	[6.72]***	[-0.23]
	0.25	Estimate	0	-5.969	-12.439	0.004	-0.027
	0.25	t-value	[-0.32]	[-9.34]***	[-10.68]***	[6.94]***	[-0.89]
	0.5	Estimate	0	0.018	-5.228	0.003	-0.053
	0.5	t-value	[-0.13]	[0.02]	[-3.28]***	[5.90]***	[-1.50]
	0.75	Estimate	-0.001	6.579	1.025	0.004	-0.088
	0.75	t-value	[-0.69]	[7.65]***	[0.55]	[5.85]***	[-2.36]**
	0.95	Estimate	-0.001	15.838	13.303	0.003	-0.139
	0.95	t-value	[-0.77]	[17.81]***	[6.35]***	[4.99]***	[-3.34]***
CAT	0.05	Estimate	-0.004	-13.472	-20.971	0.005	0.032
	0.05	t-value	[-1.66]*	[-10.13]***	[-12.3]***	[5.38]***	[0.66]
	0.25	Estimate	0.001	-6.161	-8.091	0.006	-0.034
	0.25	t-value	[0.29]	[-5.61]***	[-5.75]***	[9.38]***	[-1.00]
	0.5	Estimate	0.004	-1.996	-2.314	0.007	-0.016
	0.5	t-value	[1.73]*	[-1.80]*	[-1.87]*	[11.26]***	[-0.67]
	0.75	Estimate	0.006	3.127	4.793	0.008	0
	0.75	t-value	[3.18]***	[3.07]***	[2.85]***	[9.37]***	[0.02]
	0.95	Estimate	0.001	16.313	13.63	0.008	0.045
	0.95	t-value	[0.28]	[8.76]***	[6.43]***	[4.46]***	[0.82]
BA	0.05	Estimate	-0.003	-12.865	-20.059	0.005	-0.075
	0.05	t-value	[-1.77]*	[-14.44]***	[-14.23]***	[5.42]***	[-2.62]***
	0.25	Estimate	-0.002	-5.125	-8.863	0.006	-0.067
	0.25	t-value	[-1.36]	[-6.60]***	[-7.02]***	[12.65]***	[-2.85]***
	0.5	Estimate	0	-0.511	-2.857	0.007	-0.048
	0.5	t-value	[0.18]	[-0.55]	[-2.45]**	[10.63]***	[-1.36]
	0.75	Estimate	0.001	5.506	2.336	0.007	-0.028
	0.75	t-value	[0.48]	[4.74]***	[1.40]	[8.27]***	[-0.86]
	0.95	Estimate	0.002	15.443	18.295	0.005	0.048
	0.95	t-value	[0.87]	[11.97]***	[9.96]***	[4.81]***	[0.91]
PFE	0.05	Estimate	0	-15.316	-18.417	0.003	0.005
	0.05	t-value	[0.2]	[-11.62]***	[-8.94]***	[3.00]***	[0.08]
	0.25	Estimate	-0.003	-4.534	-11.687	0.004	0.024
	0.25	t-value	[-2.18]**	[-5.42]***	[-11.68]***	[7.97]***	[1.29]
	0.5	Estimate	-0.004	1.504	-7.207	0.004	0.014
	0.5	t-value	[-2.76]***	[1.98]**	[-4.39]***	[6.75]***	[0.44]
	0.75	Estimate	-0.003	7.979	0.121	0.005	0.065
	0.75	t-value	[-1.50]	[6.98]***	[0.08]	[6.97]***	[1.62]
	0.95	Estimate	0	15.842	11.538	0.007	0.019
	0.95	t-value	[-0.07]	[11.21]***	[5.97]***	[5.40]***	[0.62]
JNJ	0.05	Estimate	-0.001	-13.064	-13.953	0.003	0.078
	0.05	t-value	[-0.68]	[-10.46]***	[-7.80]***	[4.09]***	[1.82]*
	0.25	Estimate	0	-5.568	-7.244	0.003	0.022
	0.25	t-value	[-0.42]	[-7.46]***	[-7.81]***	[9.18]***	[0.86]
	0.5	Estimate	-0.004	2.348	-2.389	0.004	-0.011
	0.5	t-value	[-2.73]***	[2.41]**	[-1.91]*	[7.25]***	[-0.33]
	0.75	Estimate	-0.002	7.378	3.134	0.004	0.036
	0.75	t-value	[-1.61]	[7.34]***	[1.76]*	[7.18]***	[0.89]
	0.95	Estimate	0	16.112	11.968	0.005	0.029
	0.95	t-value	[-0.09]	[15.24]***	[5.32]***	[4.53]***	[0.76]

Table 3.4 (Continued)

ticker	quantile	NAME	δ_0	δ_1	δ_2	δ_3	δ_4
MMM	0.05	Estimate	-0.002	-12.621	-15.64	0.004	-0.013
	0.05	t-value	[-1.01]	[-8.97]***	[-6.61]***	[6.05]***	[-0.27]
	0.25	Estimate	0	-5.731	-6.014	0.006	-0.041
	0.25	t-value	[-0.40]	[-7.18]***	[-6.62]***	[10.49]***	[-1.72]*
	0.5	Estimate	-0.001	0.075	-1.725	0.006	-0.055
	0.5	t-value	[-0.63]	[0.10]	[-1.39]	[9.79]***	[-1.77]*
	0.75	Estimate	-0.001	6.619	6.617	0.006	-0.033
	0.75	t-value	[-0.59]	[6.47]***	[4.13]***	[7.70]***	[-1.01]
	0.95	Estimate	0.002	14.08	18.222	0.005	0.038
	0.95	t-value	[0.89]	[8.21]***	[6.80]***	[4.70]***	[0.60]
MRK	0.05	Estimate	-0.003	-12.786	-19.587	0.005	0.017
	0.05	t-value	[-1.03]	[-7.32]***	[-9.65]***	[5.11]***	[0.56]
	0.25	Estimate	0	-6.634	-9.737	0.005	-0.005
	0.25	t-value	[0.05]	[-5.93]***	[-10.46]***	[10.99]***	[-0.13]
	0.5	Estimate	-0.003	1.617	-4.157	0.005	0.041
	0.5	t-value	[-1.32]	[1.13]	[-2.79]***	[7.20]***	[1.28]
	0.75	Estimate	-0.006	9.61	2.468	0.005	-0.003
	0.75	t-value	[-4.61]***	[13.49]***	[2.16]**	[9.14]***	[-0.09]
	0.95	Estimate	0	16.469	15.44	0.006	0.066
	0.95	t-value	[-0.07]	[7.27]***	[6.77]***	[7.96]***	[1.64]
AA	0.05	Estimate	-0.003	-13.733	-15.805	0.007	-0.031
	0.05	t-value	[-0.74]	[-7.98]***	[-7.86]***	[5.14]***	[-0.6]
	0.25	Estimate	0.001	-7.104	-9.116	0.006	0.003
	0.25	t-value	[0.27]	[-7.26]***	[-8.18]***	[8.87]***	[0.12]
	0.5	Estimate	0	-0.317	-2.603	0.006	-0.019
	0.5	t-value	[-0.20]	[-0.33]	[-2.18]**	[10.05]***	[-0.66]
	0.75	Estimate	-0.003	7.977	4.179	0.007	-0.032
	0.75	t-value	[-1.25]	[6.94]***	[2.38]**	[9.38]***	[-0.89]
	0.95	Estimate	0	17.283	20.12	0.006	0.021
	0.95	t-value	[0.07]	[6.32]***	[6.79]***	[5.58]***	[0.36]
DIS	0.05	Estimate	-0.003	-12.989	-13.934	0.005	0.049
	0.05	t-value	[-1.35]	[-12.89]***	[-7.92]***	[5.82]***	[1.02]
	0.25	Estimate	0.001	-6.605	-7.448	0.004	0.012
	0.25	t-value	[0.41]	[-8.46]***	[-6.43]***	[6.21]***	[0.35]
	0.5	Estimate	0	-0.249	-3.663	0.005	-0.027
	0.5	t-value	[-0.19]	[-0.32]	[-2.66]***	[6.34]***	[-0.76]
	0.75	Estimate	-0.002	6.908	1.664	0.005	0.003
	0.75	t-value	[-1.29]	[9.27]***	[1.25]	[7.80]***	[0.10]
	0.95	Estimate	0.001	14.982	14.101	0.005	-0.016
	0.95	t-value	[0.37]	[10.59]***	[5.66]***	[4.16]***	[-0.37]
HPQ	0.05	Estimate	0.003	-16.481	-17.153	0.006	-0.032
	0.05	t-value	[0.87]	[-10.92]***	[-8.32]***	[3.92]***	[-0.9]
	0.25	Estimate	0.001	-6.964	-8.946	0.007	-0.053
	0.25	t-value	[0.37]	[-8.39]***	[-7.09]***	[8.55]***	[-1.75]*
	0.5	Estimate	-0.001	0.112	-3.116	0.008	-0.056
	0.5	t-value	[-0.33]	[0.12]	[-2.15]**	[8.54]***	[-2.23]**
	0.75	Estimate	0.001	5.795	2.063	0.009	-0.021
	0.75	t-value	[0.26]	[6.12]***	[1.30]	[9.07]***	[-0.63]
	0.95	Estimate	-0.001	17.653	13.814	0.008	-0.007
	0.95	t-value	[-0.43]	[12.6]***	[8.86]***	[8.77]***	[-0.15]

Table 3.4 (Continued)

ticker	quantile	NAME	δ_0	δ_1	δ_2	δ_3	δ_4
MCD	0.05	Estimate	0	-13.445	-13.089	0.004	-0.012
	0.05	t-value	[-0.14]	[-9.77]***	[-6.87]***	[2.85]***	[-0.24]
	0.25	Estimate	0	-5.988	-8.262	0.005	0.007
	0.25	t-value	[-0.01]	[-6.41]***	[-6.97]***	[9.22]***	[0.29]
	0.5	Estimate	0.002	-1.292	-2.65	0.004	-0.006
	0.5	t-value	[0.93]	[-1.24]	[-2.46]**	[9.37]***	[-0.20]
	0.75	Estimate	0.002	4.244	4.448	0.005	0.007
	0.75	t-value	[1.14]	[4.14]***	[3.03]***	[6.14]***	[0.20]
	0.95	Estimate	0.004	13.023	16.252	0.006	0.064
	0.95	t-value	[1.14]	[6.76]***	[7.37]***	[4.22]***	[1.26]
JPM	0.05	Estimate	0	-16.088	-12.613	0.004	-0.04
	0.05	t-value	[0.12]	[-12.01]***	[-5.46]***	[5.02]***	[-0.79]
	0.25	Estimate	0.002	-7.779	-10.088	0.004	-0.018
	0.25	t-value	[0.99]	[-9.08]***	[-5.49]***	[4.10]***	[-0.54]
	0.5	Estimate	0	-0.495	-5.029	0.004	-0.016
	0.5	t-value	[0.45]	[-1.08]	[-4.39]***	[6.09]***	[-0.77]
	0.75	Estimate	-0.001	6.745	-0.816	0.006	-0.056
	0.75	t-value	[-0.44]	[7.29]***	[-0.50]	[7.89]***	[-1.92]*
	0.95	Estimate	-0.004	20.07	9.709	0.006	0.114
	0.95	t-value	[-1.18]	[10.45]***	[3.26]***	[3.91]***	[1.76]*
WMT	0.05	Estimate	-0.002	-13.531	-14.377	0.004	0.067
	0.05	t-value	[-1.11]	[-14.24]***	[-6.29]***	[6.63]***	[1.59]
	0.25	Estimate	-0.001	-5.679	-8.31	0.004	0.018
	0.25	t-value	[-0.72]	[-8.30]***	[-7.67]***	[8.39]***	[0.55]
	0.5	Estimate	-0.002	1.004	-4.307	0.004	-0.043
	0.5	t-value	[-1.45]	[1.22]	[-4.00]***	[5.72]***	[-1.45]
	0.75	Estimate	-0.003	7.874	-2.717	0.004	-0.058
	0.75	t-value	[-2.26]**	[9.35]***	[-1.75]*	[6.92]***	[-1.67]*
	0.95	Estimate	-0.004	18.678	5.863	0.006	-0.12
	0.95	t-value	[-1.71]*	[12.54]***	[2.26]**	[4.60]***	[-1.95]*
AXP	0.05	Estimate	-0.003	-13.054	-15.385	0.004	0.021
	0.05	t-value	[-1.80]*	[-14.03]***	[-8.19]***	[6.30]***	[0.47]
	0.25	Estimate	0	-6.709	-10.043	0.006	-0.012
	0.25	t-value	[-0.49]	[-13.99]***	[-7.49]***	[9.29]***	[-0.50]
	0.5	Estimate	-0.001	0.226	-4.902	0.007	-0.036
	0.5	t-value	[-1.23]	[0.37]	[-2.67]***	[8.45]***	[-1.07]
	0.75	Estimate	-0.002	7.783	1.246	0.006	-0.044
	0.75	t-value	[-2.07]**	[12.54]***	[0.88]	[8.17]***	[-1.42]
	0.95	Estimate	-0.003	17.743	5.407	0.004	-0.015
	0.95	t-value	[-1.22]	[14.55]***	[2.43]**	[3.49]***	[-0.23]
INTC	0.05	Estimate	0.004	-17.355	-13.077	0.006	-0.002
	0.05	t-value	[1.18]	[-13.96]***	[-3.53]***	[4.13]***	[-0.03]
	0.25	Estimate	0	-7.024	-9.127	0.008	-0.022
	0.25	t-value	[0.10]	[-7.71]***	[-5.44]***	[6.48]***	[-0.66]
	0.5	Estimate	-0.001	0.294	-7.398	0.009	-0.036
	0.5	t-value	[-0.41]	[0.27]	[-3.89]***	[9.00]***	[-1.06]
	0.75	Estimate	-0.003	8.641	-4.555	0.009	-0.07
	0.75	t-value	[-1.65]*	[10.47]***	[-3.33]***	[10.31]***	[-2.95]***
	0.95	Estimate	0	17.719	-0.727	0.007	-0.109
	0.95	t-value	[0.00]	[12.62]***	[-0.48]	[3.85]***	[-2.01]**

Table 3.4 (continued)

ticker	quantile	NAME	δ_0	δ_1	δ_2	δ_3	δ_4
VZ	0.05	Estimate	-0.001	-13.227	-14.912	0.004	-0.164
	0.05	t-value	[-0.41]	[-13.25]***	[-11.8]***	[3.57]***	[-4.13]***
	0.25	Estimate	0.001	-6.874	-8.383	0.003	-0.019
	0.25	t-value	[0.35]	[-6.68]***	[-6.28]***	[5.18]***	[-0.48]
	0.5	Estimate	-0.002	1.02	-3.349	0.004	-0.054
	0.5	t-value	[-1.53]	[1.16]	[-2.93]***	[5.05]***	[-1.32]
	0.75	Estimate	-0.004	7.855	-1.357	0.005	-0.018
	0.75	t-value	[-2.87]***	[8.46]***	[-0.89]	[6.51]***	[-0.38]
	0.95	Estimate	-0.002	15.429	8.152	0.004	0.001
	0.95	t-value	[-0.87]	[9.71]***	[3.23]***	[4.05]***	[0.01]
SBC	0.05	Estimate	0	-14.25	-18.825	0.003	-0.086
	0.05	t-value	[0.12]	[-9.83]***	[-11.3]***	[2.25]**	[-2.01]**
	0.25	Estimate	0	-6.275	-11.431	0.005	-0.106
	0.25	t-value	[-0.12]	[-9.53]***	[-7.59]***	[8.60]***	[-3.63]***
	0.5	Estimate	0	-0.194	-4.081	0.006	-0.072
	0.5	t-value	[-0.37]	[-0.36]	[-4.07]***	[8.27]***	[-2.21]**
	0.75	Estimate	-0.001	6.292	3.336	0.006	-0.041
	0.75	t-value	[-0.55]	[7.16]***	[2.31]**	[7.92]***	[-1.63]
	0.95	Estimate	0	15.893	13.346	0.006	0.053
	0.95	t-value	[-0.13]	[10.36]***	[5.59]***	[8.59]***	[1.01]
HD	0.05	Estimate	0.002	-15.311	-16.232	0.005	0.003
	0.05	t-value	[0.76]	[-13.46]***	[-9.63]***	[4.94]***	[0.06]
	0.25	Estimate	0.001	-7.027	-11.393	0.006	-0.026
	0.25	t-value	[0.75]	[-7.57]***	[-8.26]***	[9.47]***	[-0.79]
	0.5	Estimate	-0.002	0.463	-6.744	0.007	0.013
	0.5	t-value	[-0.89]	[0.51]	[-4.64]***	[9.06]***	[0.52]
	0.75	Estimate	-0.004	8.79	-0.391	0.006	-0.01
	0.75	t-value	[-2.36]**	[9.70]***	[-0.18]	[7.76]***	[-0.37]
	0.95	Estimate	-0.004	18.767	11.346	0.006	0.04
	0.95	t-value	[-1.43]	[12.36]***	[3.54]***	[6.07]***	[1.48]
AIG	0.05	Estimate	0.001	-15.258	-18.004	0.005	-0.003
	0.05	t-value	[0.81]	[-15.09]***	[-22.36]***	[4.88]***	[-0.09]
	0.25	Estimate	0	-6.72	-10.173	0.005	-0.017
	0.25	t-value	[0.09]	[-8.10]***	[-8.07]***	[7.86]***	[-0.60]
	0.5	Estimate	-0.001	0.247	-3.831	0.006	-0.004
	0.5	t-value	[-0.76]	[0.24]	[-2.98]***	[9.43]***	[-0.17]
	0.75	Estimate	-0.004	8.229	3.402	0.006	0.05
	0.75	t-value	[-2.20]**	[7.90]***	[2.19]**	[10.77]***	[1.55]
	0.95	Estimate	-0.006	19.681	10.439	0.005	0.087
	0.95	t-value	[-2.42]**	[14.72]***	[4.47]***	[6.64]***	[1.61]
C	0.05	Estimate	0.001	-14.471	-16.136	0.003	0.029
	0.05	t-value	[0.70]	[-18.83]***	[-8.47]***	[5.19]***	[0.64]
	0.25	Estimate	-0.001	-5.629	-12.305	0.004	0.028
	0.25	t-value	[-1.12]	[-10.01]***	[-7.31]***	[7.49]***	[0.83]
	0.5	Estimate	-0.002	1.033	-7.199	0.005	-0.063
	0.5	t-value	[-1.94]*	[1.90]*	[-5.27]***	[8.57]***	[-1.92]*
	0.75	Estimate	-0.002	7.262	-3.359	0.005	-0.061
	0.75	t-value	[-1.99]**	[10.60]***	[-3.20]***	[5.89]***	[-2.11]**
	0.95	Estimate	-0.002	16.563	1.98	0.004	-0.024
	0.95	t-value	[-1.05]	[15.37]***	[0.91]	[4.63]***	[-0.37]

Note: The regression model is $r_t = \delta_0 + \delta_1\sigma_t^e + \delta_2\sigma_t^u + \delta_3 Skew_t + \delta_4 r_{t-1} + \varepsilon_t$. This table reports the coefficient estimates and t-values of four independent variables: expected risk, unexpected risk, intraday skewness coefficient and one period lag of dependent variable, for 0.05, 0.25, 0.5, 0.75, and 0.95 quantiles. *** indicates 1% significance, ** 5%, * 10%.

Table 4.1 Description of Variables: Daily Data, 1996-2006

Variables	vbmfx	vtsmx	r_vbmfx	r_vtsmx
N	2652	2652	2651	2651
MIN	5.18	12.56	-0.0134	-0.06955
MAX	9.98	34.31	0.01227	0.052765
MEAN	7.658428	23.99302	0.000245	0.000351
STD	1.400248	4.860356	0.002731	0.011226
Correlation coefficient	0.56		-0.09	
ADF test p-value	0.83	0.59	0.00	0.00
6/20/1996-3/24-2000 correlation coefficient (950 observations)	0.91		0.09	
3/24/2000- 10/9/2002 correlation coefficient (638 observations)	-0.93		-0.22	
10/9/2002-12/29/2006 correlation coefficient (1064 observations)	0.94		-0.15	

Note: r_vbmfx is the return on VBMFX fund; r_vtsmx is the return on VTSMX fund. The augmented Dickey Fuller (ADF) test has the order of AR=3. ADF test indicates that both fund series have unit root. However, the returns on the two funds are stationary.

Table 4.2 Description of Correlation Coefficients Between Two Returns

	rolling (22 trading days)		rolling (1 year)		rolling (5 years)		BEKK	ADCC
	moving window	expanding window	moving window	expanding window	moving window	expanding window		
N	2630	2630	2402	2402	1402	1402	2651	2651
MIN	-0.8043821	-0.1094712	-0.56829	-0.1094712	-0.2553353	-0.1094712	-0.7585	-0.60521
MAX	0.8217056	0.5932804	0.461269	0.4612691	0.0174841	0.0178548	0.553369	0.619481
MEAN	-0.0272538	0.0502171	-0.08414	0.0050264	-0.1645929	-0.0766577	-0.03266	-0.02019
STD	0.3698957	0.1923168	0.220371	0.1293768	0.0728973	0.0399980	0.254185	0.2537
ADF test p-value	0.00	0.06	0.148	0.00	0.00	0.00	0.00	0.00

Note: The table reports the rolling correlation, BEKK correlation, ADCC correlation between two market index fund returns.
The last row reports the augmented Dickey-Fuller (ADF) test statistic with an AR order of 3.

Table 4.3 Estimates of the GARCH(1,1) Models

Panel A: BEKK method

Variable	Coefficient	Std Error	t-Stat
μ_s	0.00071	0.000169	[4.20]***
μ_b	0.000254	5.24E-05	[4.84]***
VAR(1,1)	0.949115	0.005936	[159.88]***
VAR(2,1)	0.026989	0.018586	[1.45]
VAR(1,2)	0.005513	0.001587	[3.47]***
VAR(2,2)	0.98128	0.004433	[221.36]***
VBR(1,1)	0.305132	0.017762	[17.18]***
VBR(2,1)	-0.06524	0.054799	[-1.19]
VBR(1,2)	-0.02177	0.004468	[-4.87]***
VBR(2,2)	0.139299	0.012732	[10.94]***
VCR(1,1)	0.001045	0.000191	[5.48]***
VCR(2,1)	-0.00028	0.000323	[-0.87]
VCR(1,2)	0	0	[0.00]
VCR(2,2)	0.000296	6.97E-05	[4.24]***

Panel B: ADCC method

Variable	Coefficient	Std Error	t-stat
μ_s	3.05E-04	1.66E-04	[1.84]*
c_s	1.95E-06	4.35E-07	[4.48]***
a_s	-0.00988	0.00824	[-1.20]
b_s	0.91227	0.01218	[74.89]***
d_s	0.16234	0.01814	[8.95]***
μ_b	2.53E-04	5.83E-05	[4.34]***
c_b	3.45E-06	1.43E-06	[2.42]**
a_b	0.06475	0.03066	[2.11]**
b_b	0.47294	0.20148	[2.35]**
d_b	0.00156	0.03997	[0.04]
α	0.04583	0.00889	[5.15]***
β	0.93698	0.01255	[74.67]***
g	0.00132	0.00582	[0.23]

Note: The BEKK is estimated by following representations:

$$\begin{cases} R_t = \mu_t + \varepsilon_t \\ \varepsilon_t \left| \Psi_{t-1} \sim N(0, H_t) \right. \end{cases} \tag{4.2.a}$$

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B \tag{4.2.b}$$

where C, A, B are 2x2 matrices and C is a lower triangular matrix.

The ADCC is estimated by two separate steps. The model is as follows:

$$\begin{aligned} r_{i,t} &= \mu_i + \varepsilon_{i,t} \\ \eta_{i,t} &= \max[0, -\varepsilon_{i,t}] \qquad i = \text{stock, bond} \\ \varepsilon_i &\sim N(0, H_i) \end{aligned} \tag{4.3.a}$$

$$h_{i,t} = c_i + a_i * \varepsilon_{i,t-1}^{\;2} + b_i * h_{i,t-1} + d_i \eta_{i,t-1}^{\;2}$$

$$\begin{aligned} z_{s,t} &= \frac{\varepsilon_{s,t}}{\sqrt{h_{s,t}}}, z_{b,t} = \frac{\varepsilon_{b,t}}{\sqrt{h_{b,t}}} \\ z_s &\sim N(0, q_s), z_b \sim N(0, q_b) \\ \lambda_{s,t} &= \max[0, -z_{s,t}], \lambda_{b,t} = \max[0, -z_{b,t}] \\ q_{sb,t} &= (1 - \alpha - \beta - g)\overline{\rho}_{sb} + \alpha z_{s,t-1} z_{b,t-1} + \beta q_{sb,t-1} + g \lambda_{s,t-1} \lambda_{b,t-1} \end{aligned} \tag{4.3.b}$$

The numbers with brackets are t-values. *** indicates 1% significance, ** 5%, * 10%.

Table 4.4 Estimates of the Time-Varying Correlation Coefficients

Panel A

Independent Variable	Dependent variable $\rho_{sb,22}$ (22 trading days)	$\rho_{sb,250}$ (250 trading days)	$\rho_{sb,BEKK}$	$\rho_{sb,ADCC}$
ϕ_0	0.020382	0.01742	0.111915	0.040493
	[0.52]	[10.42]***	[5.11]***	[1.56]
ϕ_1	-0.01024	0.000185	-0.00935	-0.00682
	[-25.15]***	[-1.76]*	[-40.21]***	[-25.35]***
ϕ_2	-0.19289	0.0175	-0.17188	-0.18919
	[-4.90]***	[-32.39]***	[-7.82]***	[-7.27]***
ϕ_3	-0.07371	0.012927	-0.04209	-0.05812
	[-2.57]***	[-2.32]**	[-2.59]***	[-3.06]***
ϕ_4	6.006169	0.256221	2.25785	4.082628
	[10.60]***	[5.33]***	[7.01]***	[10.89]***
Adjusted R^2	0.3127	0.6493	0.5252	0.3598

Panel B

Independent Variable	Dependent variable $\rho_{sb,22}$ (22 trading days)	$\rho_{sb,250}$ (250 trading days)	$\rho_{sb,BEKK}$	$\rho_{sb,ADCC}$
ϕ_0	0.198207	0.368446	0.042163	0.194159
	[3.89]***	[16.50]***	[5.23]***	[5.85]***
ϕ_1	-0.00893	-0.00037	-0.0017	-0.00591
	[-21.84]***	[-2.08]**	[-26.30]***	[-22.19]***
ϕ_2	-0.33326	-0.69911	-0.05247	-0.30661
	[-7.38]***	[-35.31]***	[-7.34]***	[-10.42]***
ϕ_3	-0.05184	-0.06851	-0.00909	-0.04664
	[-4.23]***	[-12.75]***	[-4.69]***	[-5.84]***
ϕ_4	2.873807	-0.38265	0.444501	1.517535
	[4.46]***	[-1.35]	[4.36]***	[3.62]***
Adjusted R^2	0.3167	0.6710	0.3608	0.3673

Note: The dependent variables are the correlation coefficients between stock and bond markets from different methods. The model is: $\rho_t = \phi_0 + \phi_1 VR_{s,b,t} + \phi_2 SPREAD_t + \phi_3 D_{oil,t} + \phi_4 FFR_t + \nu_t$. $VR_{s,b}$ is the variance ratio computed by the conditional volatility of the stock market divided by the conditional volatility of the bond market; *SPREAD* is the difference between the yields of long-term bond and short-term bond; $D_{oil,t}$ is an oil dummy variable that takes value of 1 on days when there is a 5% price jump/reduction and zero otherwise; *FFR* is the federal funds rate.

In Panel B, the Oil dummy variable is replaced with the conditional variance of the oil returns.

The t-values are below the parameters (with brackets). *** indicates 1% significance, ** 5%, * 10%.

Table 4.5 Logistic Regression of the Sign of the ADCCs

	Dependent variable: probability of correlation coefficient to be positive			
Independent variable	Coefficient	Std Error	Wald_Chi	Significance
Intercept	0.181792	0.293783	0.382907	0.536051
Variance Ratio	-0.0738	0.005161	204.4783	2.2E-46***
Spread	-1.17986	0.303126	15.14994	9.93E-05***
Oil dummy	-0.39441	0.231787	2.895497	0.088827*
Federal Funds Rate	36.82053	4.348869	71.68486	2.52E-17***

Note: The model is $P(\rho_{ADCC} > 0) = \dfrac{1}{1 + e^{-(\phi_0 + \phi_1 VR_{s,b,t} + \phi_2 SPREAD_t + \phi_3 D_{oil,t} + \phi_4 FFR_t + v_t)}}$. $VR_{s,b}$ is the variance ratio that is computed by conditional volatility of stock market divided by conditional volatility of bond market; *SPREAD* is the difference of the YTM of long-term bond and short-term bond; $D_{oil,t}$ is an oil dummy variable which takes value of 1 on days when there is a 5% price jump/down and zero otherwise; *FFR* is the federal funds rate.

The test is a Wald chi square test. *** indicates 1% significance, ** 5%, * 10%.

Appendix of Figures

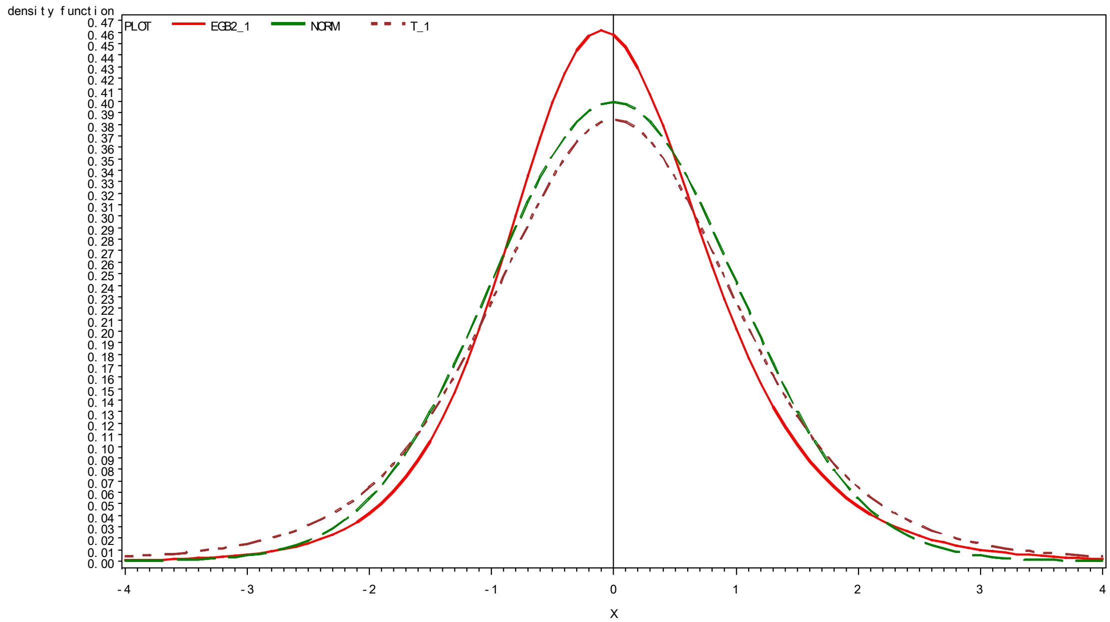
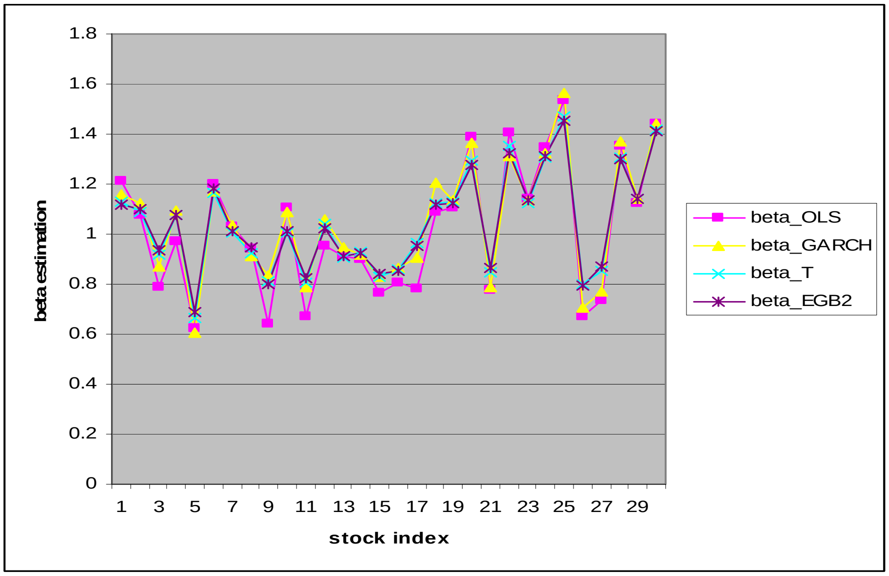


Figure 2.1 Comparisons of Probability Density Function of Three Distributions

Note: This chart compares the probability density function (pdf) of three distributions. The solid line is the EGB2 distribution; dashed line the normal distribution; and dash-dot line is the Student's *t*-distribution. Distribution estimated parameters are from stock MSFT (index=1): p=1.0233; q=0.7971; v=6.4635.



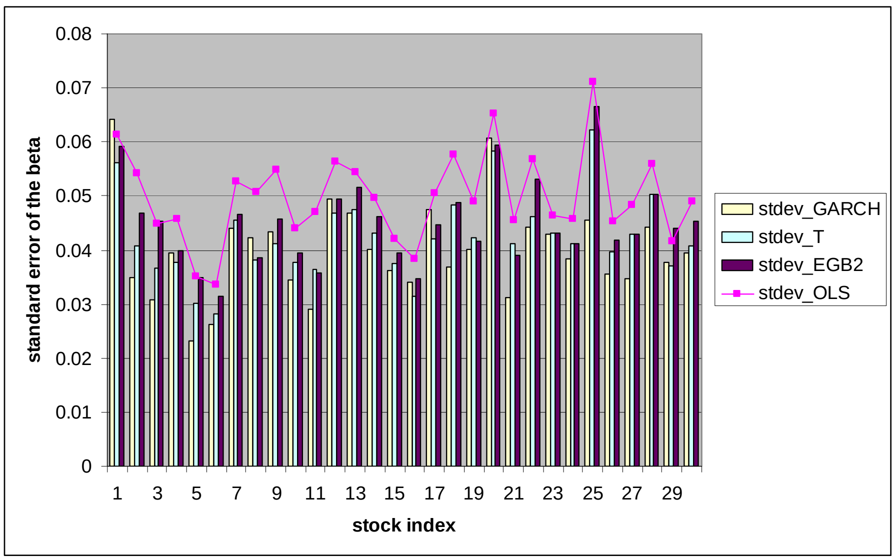


Figure 2.2 Comparisons of the Beta Estimation in Different Models.

Note: The upper figure contains the plots of beta coefficients. The lower figure presents the corresponding standard deviations of the beta coefficients.

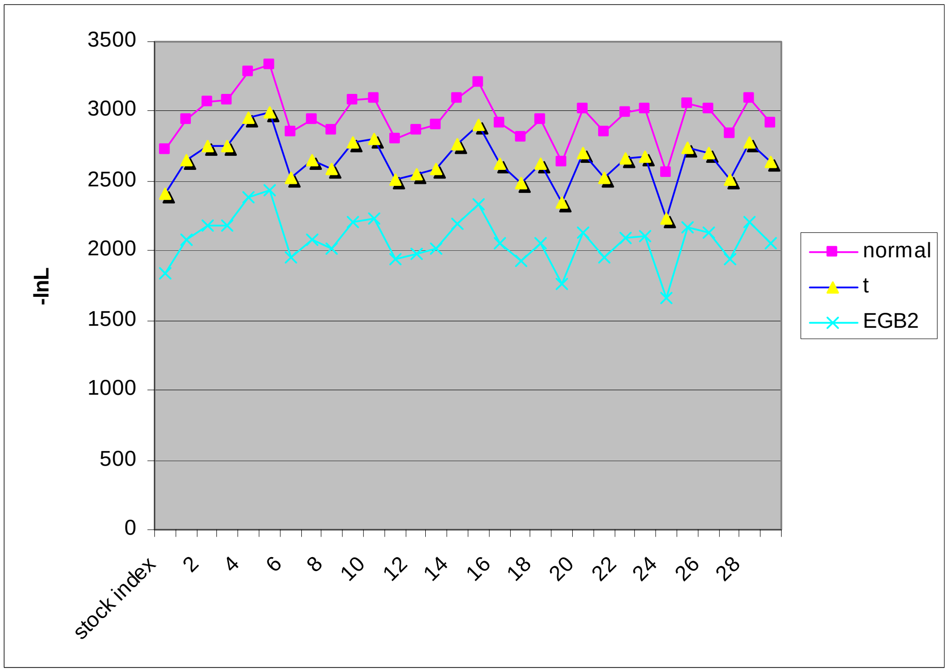


Figure 2.3 Comparisons of Log-Likelihood Function Values in Different Models

Note: The figure plots the negative logarithm value of the likelihood function. The greater the likelihood function value, the better the fit of the model is. So, roughly speaking, the EGB2 distribution is superior to the normal distribution and the Student's *t* distribution according to the figure.

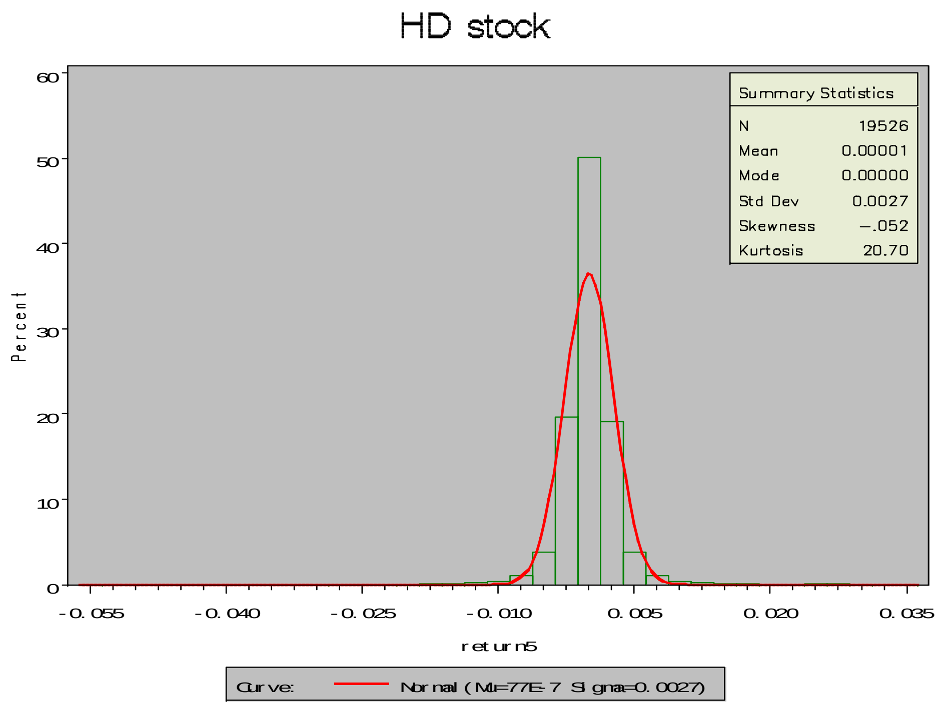


Figure 3.1 Comparison of the 5-Minute Return Histogram and Corresponding Normal Distribution

Note: This is the distribution of the 5-minute return in 1998 for stock HD.

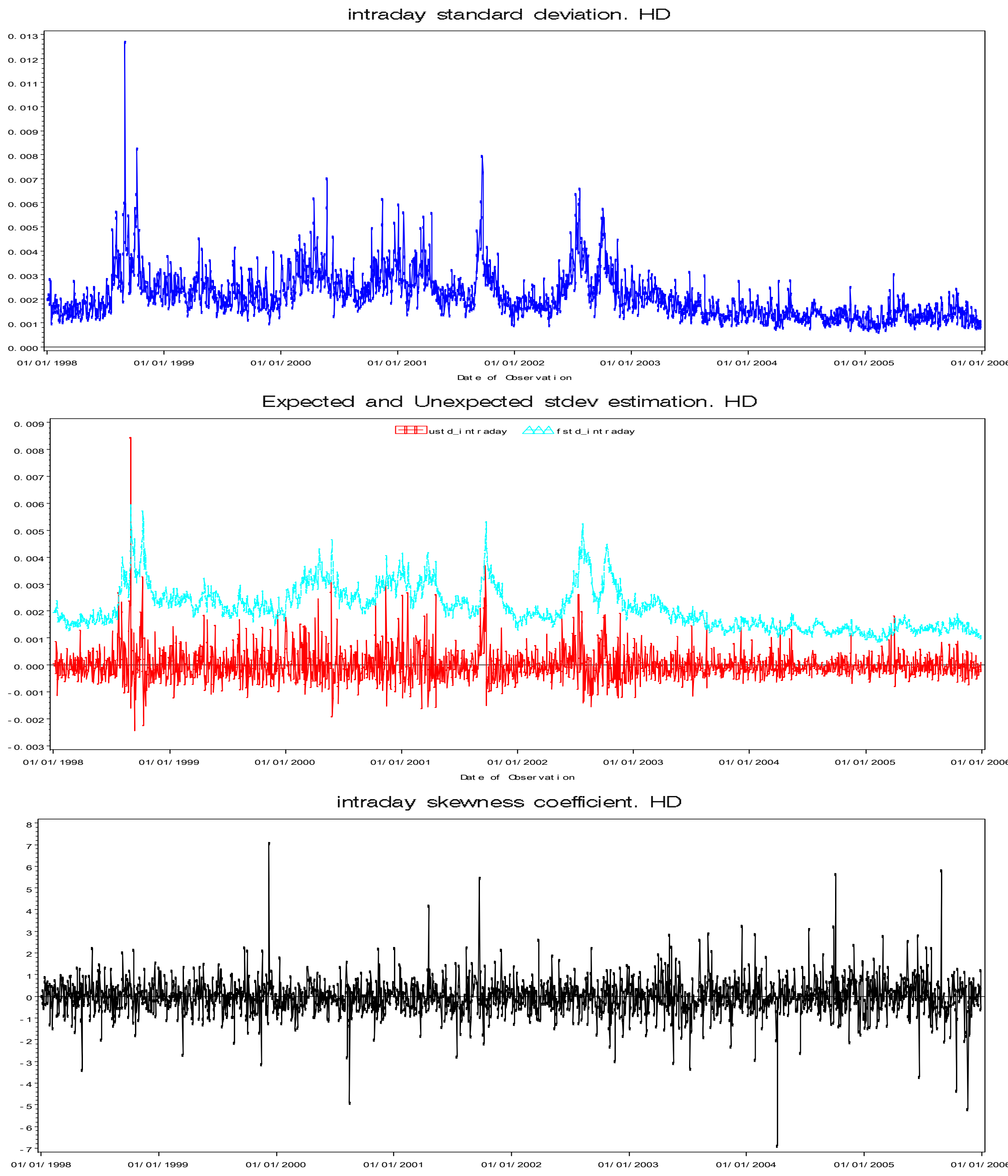


Figure 3.2 Example of Intraday Moment Variables

Note: These charts are for stock HD (index=28). The top one is the intraday standard deviation. The middle one is the decomposition of the intraday standard deviation. The red is the unexpected intraday standard deviation, and the cyan is the expected intraday standard deviation. The bottom one is the intraday skewness coefficient variable.

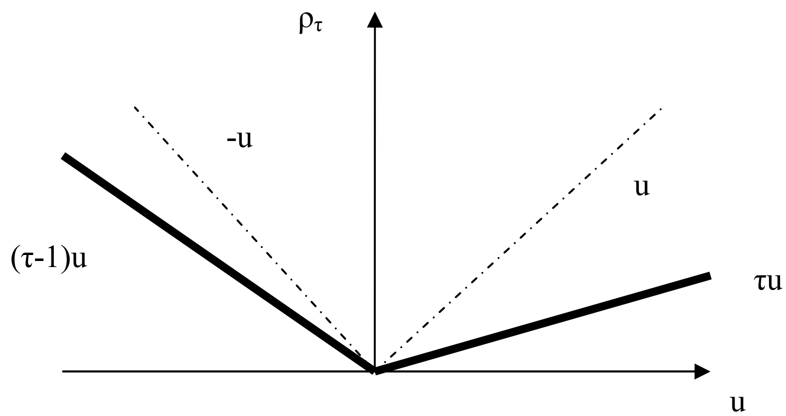
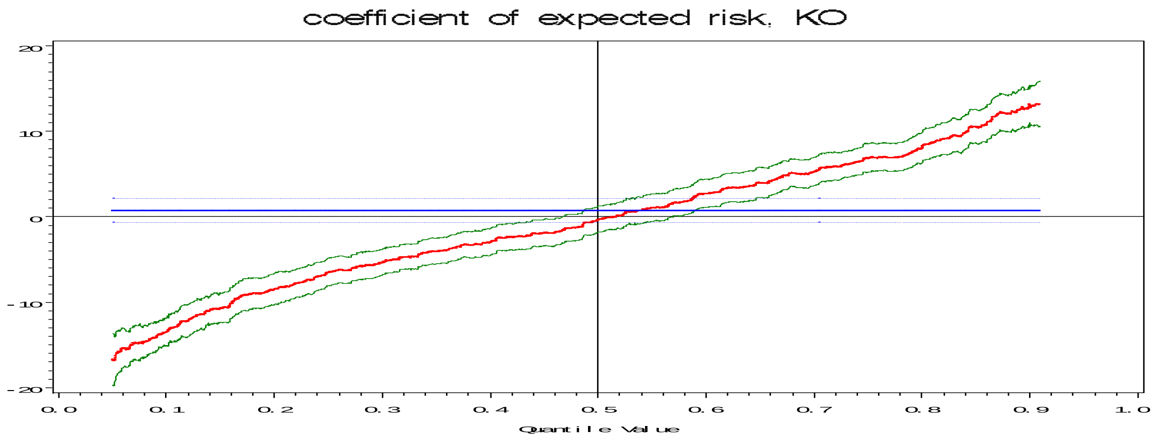
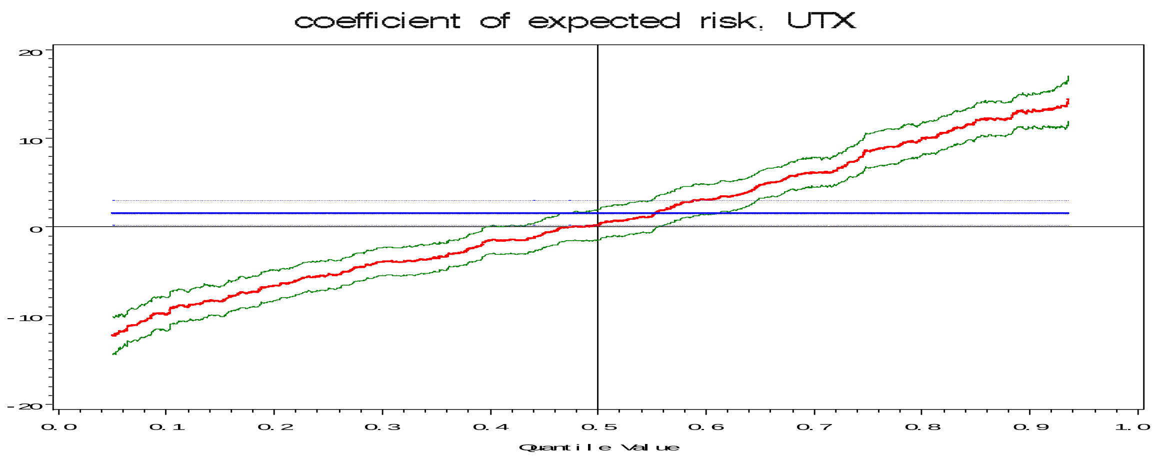


Figure 3.3 Quantile Regression ρ Function

Note: This is the check function ρ_τ in the quantile regression. $\rho_\tau(u) = \begin{cases} \tau u & u \geq 0 \\ (\tau - 1)u & u < 0 \end{cases}$


coefficient of expected risk, KO
20
10
0
-10
-20
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Quantile Value


coefficient of expected risk, UTX
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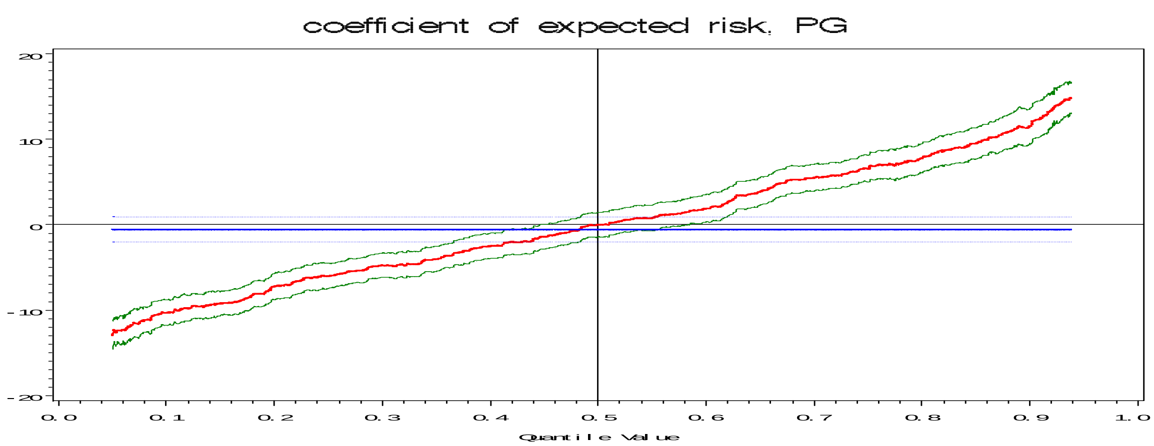
10
0
-10
-20
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Quantile Value


coefficient of expected risk, PG
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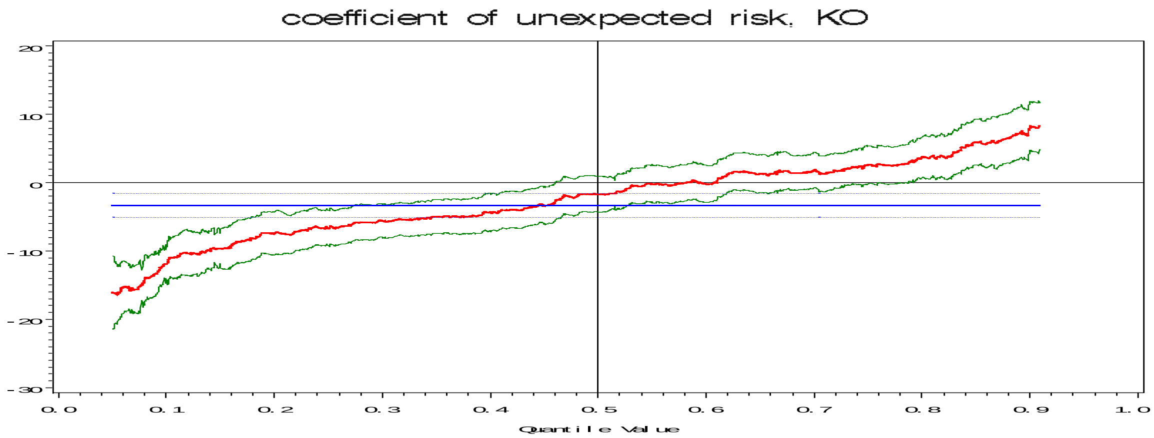
10
0
-10
-20
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Quantile Value


coefficient of unexpected risk, KO
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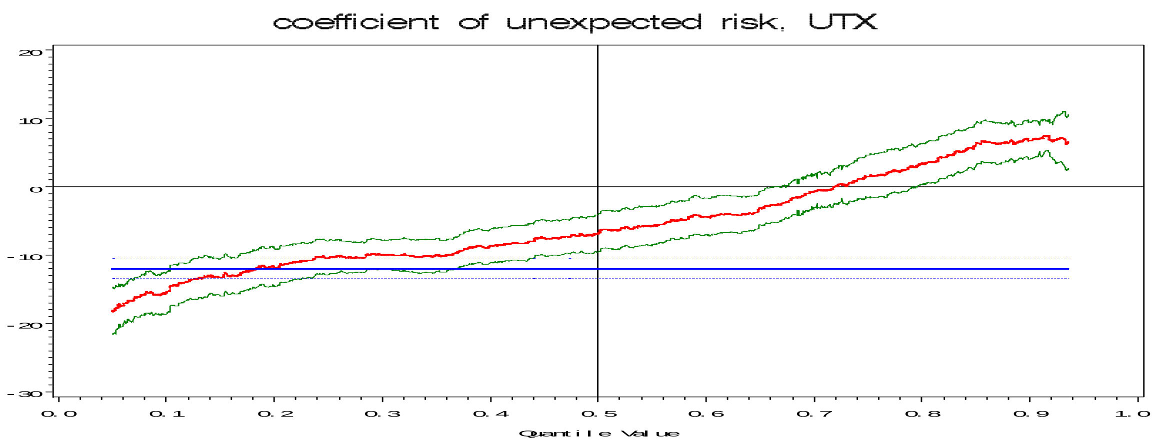
0.6
0.7
0.8
0.9
1.0
Quantile Value


coefficient of unexpected risk, UTX
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-10
-20
-30
0.0
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0.3
0.4
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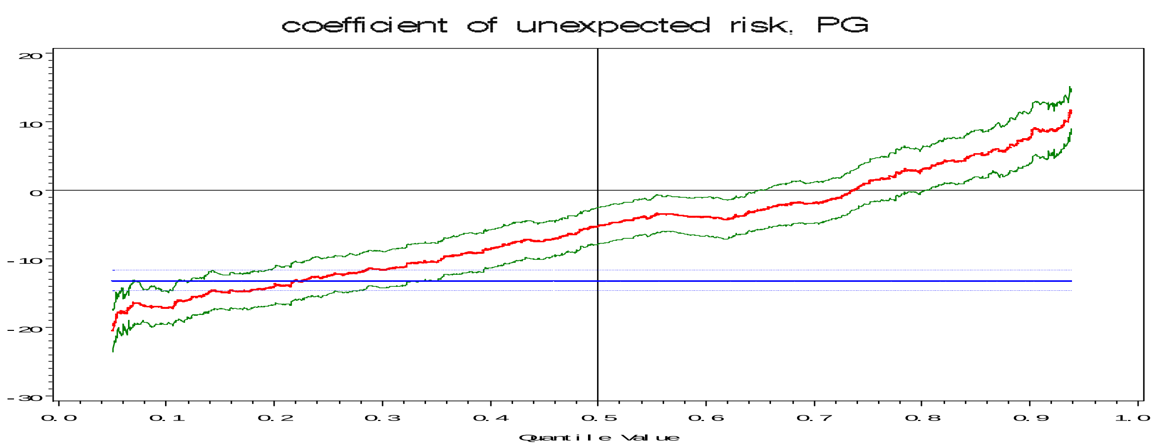
0.6
0.7
0.8
0.9
1.0
Quantile Value


coefficient of unexpected risk, PG
20
10
0
-10
-20
-30
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Quantile Value

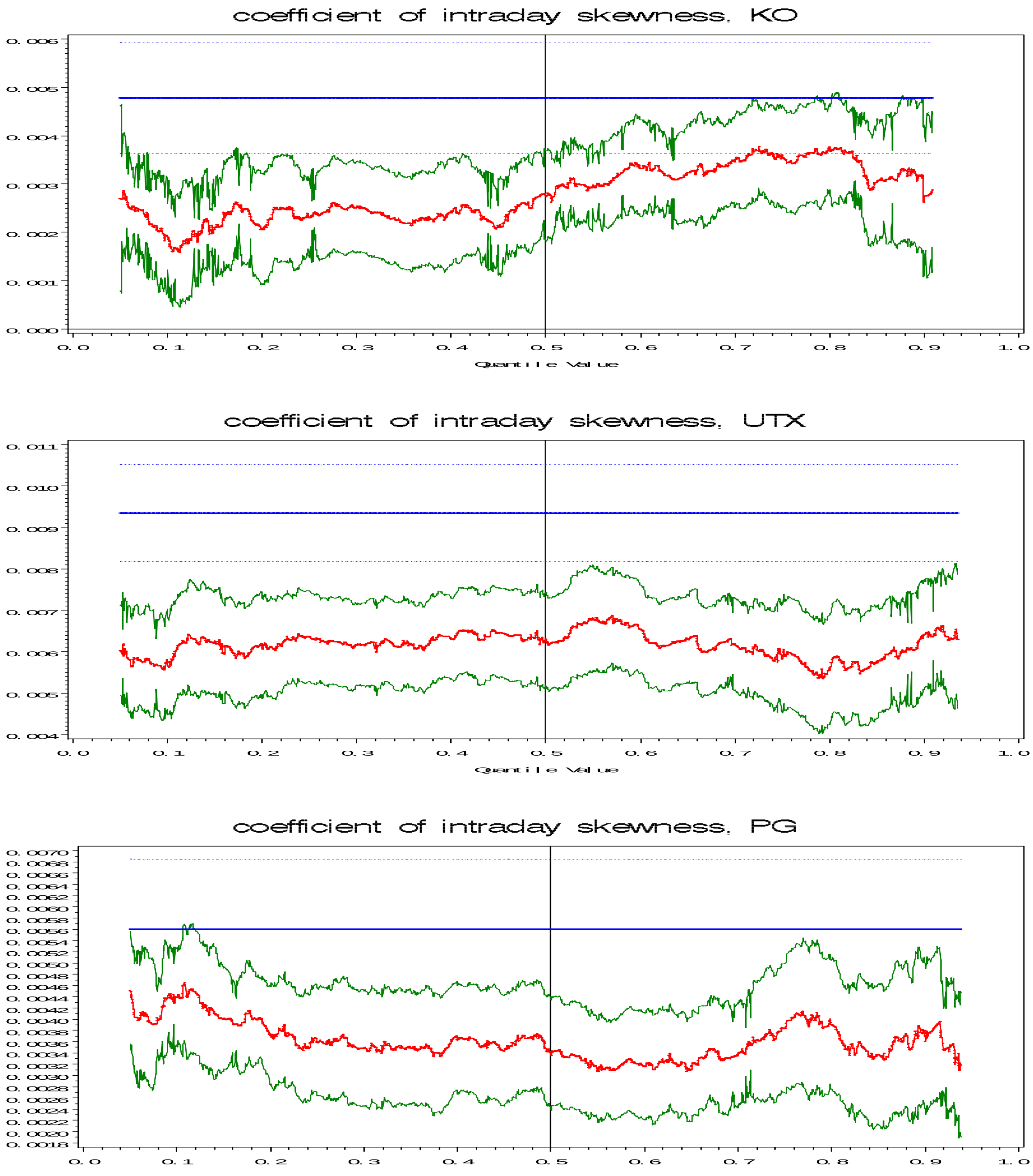


Figure 3.4 Comparison of WLS Regression and Quantile Regression

Note: The charts show the coefficient of the expected standard deviation, the unexpected standard deviation, and the intraday skewness variable (in red) in the quantile regression. The green lines are 95% confidence limits. The blue lines represent coefficient estimation and confidence limits from the WLS regression.
The charts are for stock PG, which shows a negative relation between excess returns and expected risk, for stock KO, which has the worst Sharpe ratio, and for stock UTX, which has the highest Sharpe ratio.

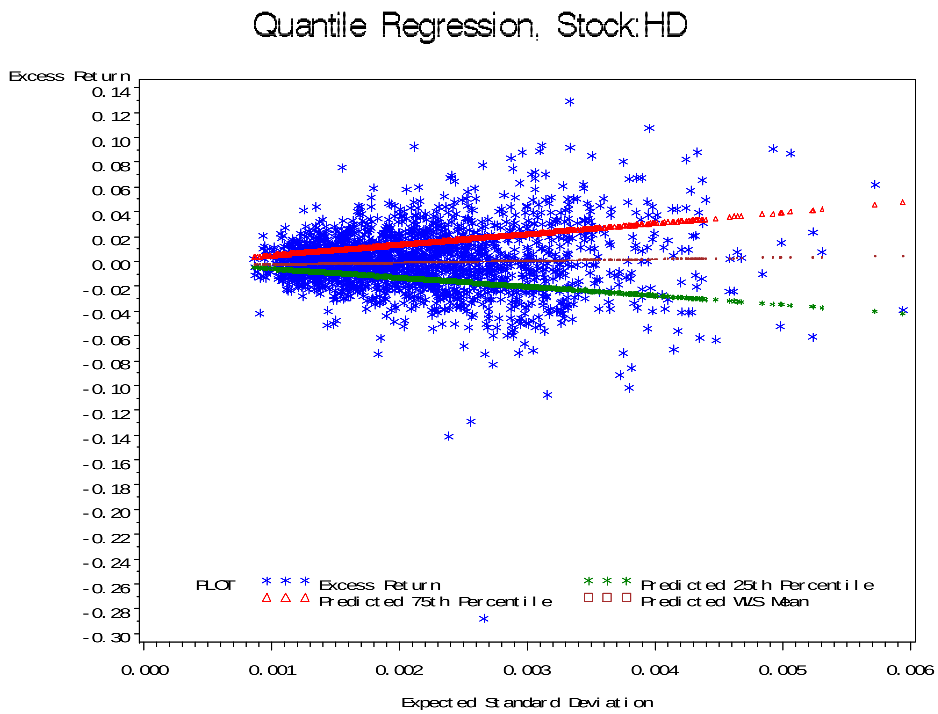


Figure 3.5 Comparison of the Predicted Value Line by Using WLS Regression and Quantile Regression

Note: The blue stars represent the scatter plot of expected risk and excess returns.
The bold lines (red and green) represent predicted lines from quantile regressions (25th and 75th quantiles).
The thin line (brown) represents the predicted value line from WLS regression.
The regression model is: $r_t = \delta_0 + \delta_1 \sigma_t^e + \varepsilon_t$

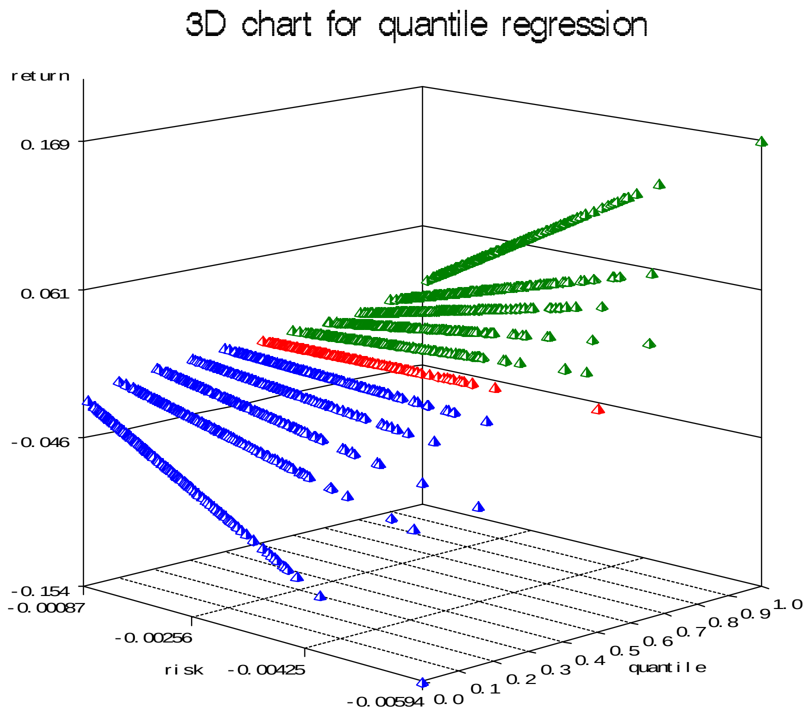


Figure 3.6 3-D Chart for Relation Between Excess Returns and Expected Risk Varying with Return Quantiles

Note: The regression model is: $r_t = \delta_0 + \delta_1 \sigma_t^e + \varepsilon_t$. The chart shows the predicted lines at different quantiles: 0.01, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and 0.99.
The vertical axis is the excess return; the two horizontal axises are expected risk and return's quantile. The central line (in red) is that of the median regression (0.5 quantile). The low quantile predicted lines are downward (in blue). The high quantile predicted lines are upward (in green).
Each regression has 2013 observations; for the reason of the memory size, each predicted line only contains one tenth observations.

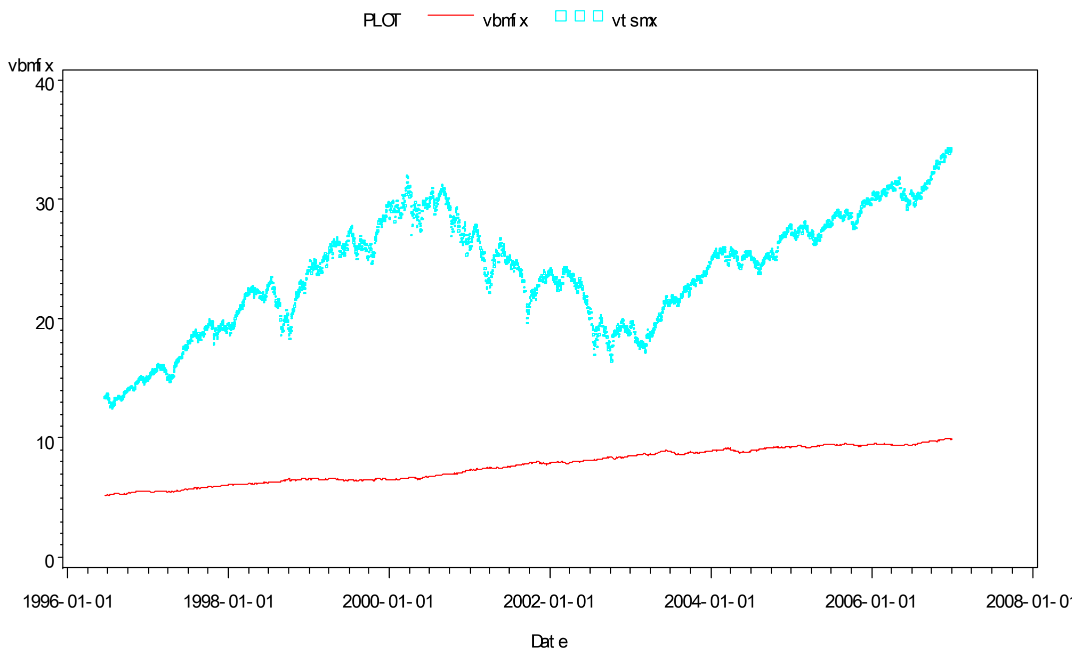


Figure 4.1 Two Market Index Funds Series

Note: This chart shows the level of the two funds: VBMFX and VTSMX. The more volatile one is the stock index fund VTSMX; the less volatile one is the bond index fund VBMFX. The sample period is 6/20/1996-12/29/2006.

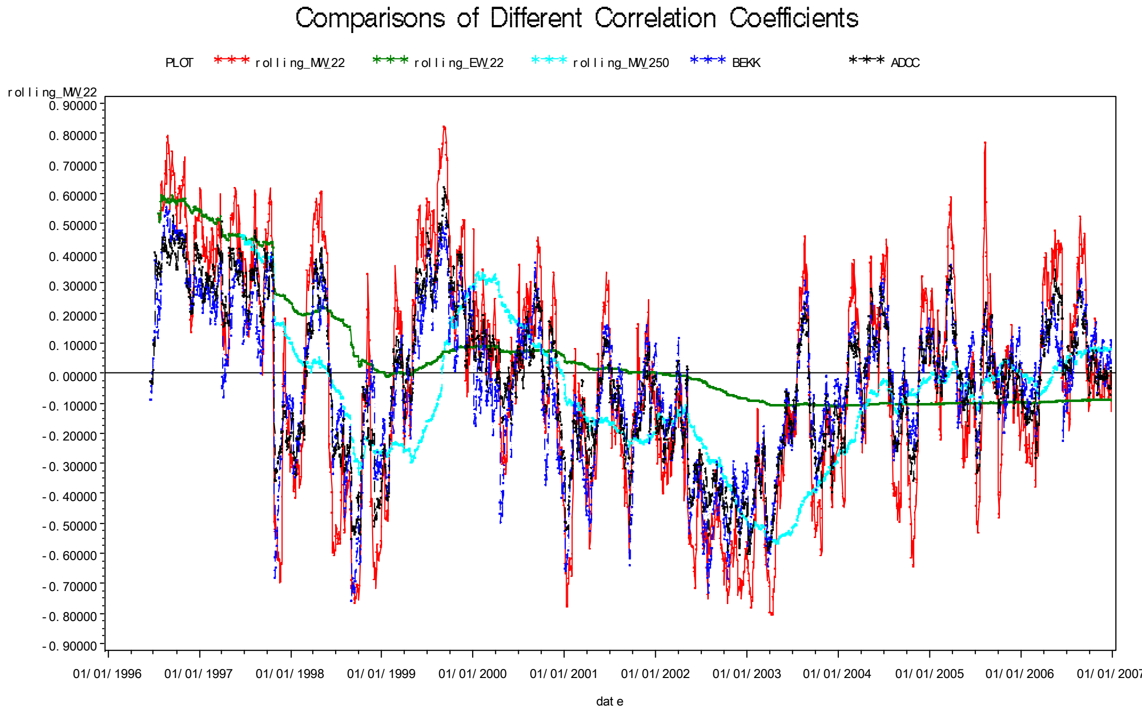


Figure 4.2 Comparisons of Different Correlation Coefficients

Note: This figure depicts five correlation coefficients. The red line represents a moving window (22 trading days); the cyan represents a moving window (250 trading days); the green represents an expanding window; the blue represents the BEKK coefficient; and the black represents the ADCC coefficient.

The correlation coefficient of a moving window of 22 trading days is similar to the BEKK and ADCC coefficients.

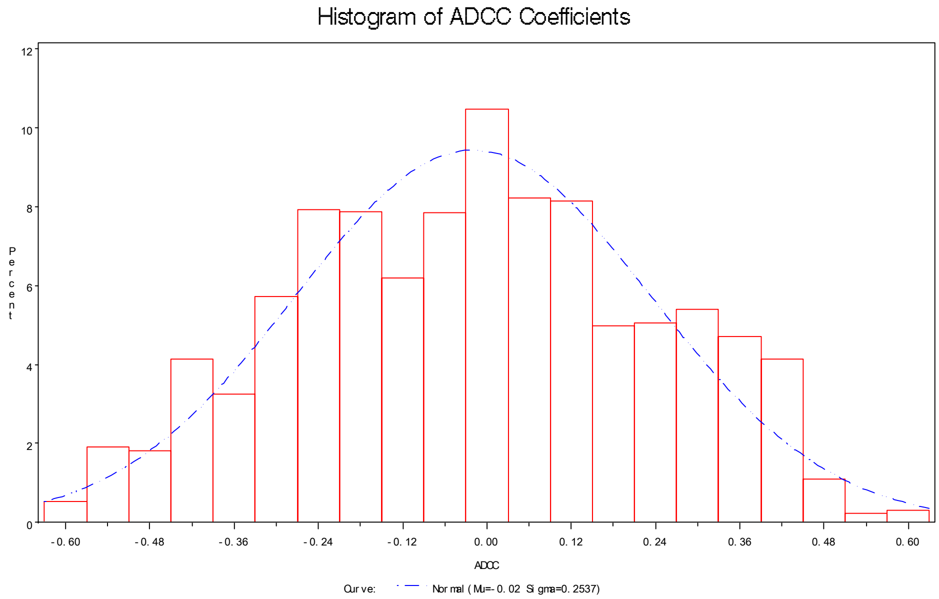
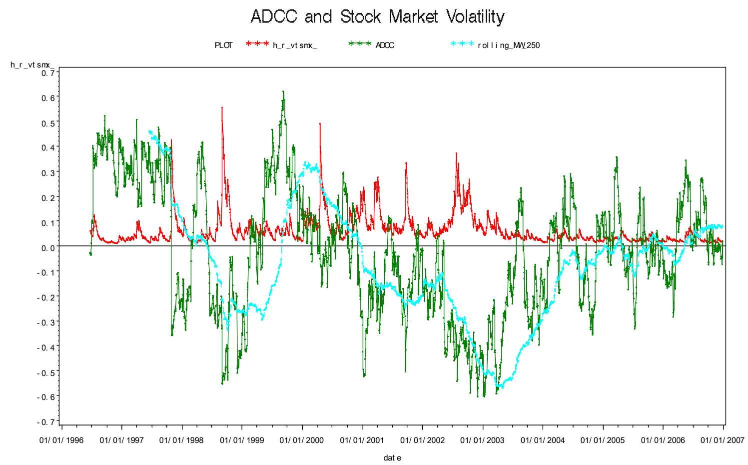


Figure 4.3 Histogram of ADCC Correlation Coefficients

Note: This chart is the histogram of the ADCC correlation coefficients. The mean value of the ADCC correlation coefficients is -0.02. The standard deviation of the ADCC correlation coefficients is 0.25. The observations of the ADCC is 2651.



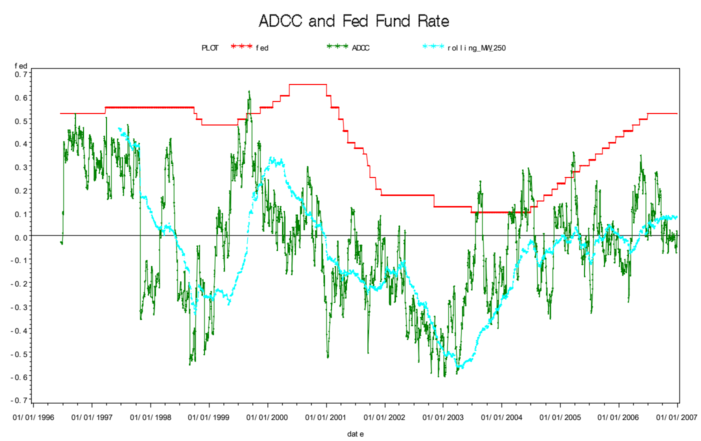


Figure 4.4 Stock-Bond Correlation Coefficient, Stock Market Conditional Variance, and Federal Funds Rate

Note: The green line is the ADCC coefficient; the cyan is a rolling correlation coefficient of 250 trading days. In the top chart, the red line is the stock market conditional variance. The negative values of the ADCC coefficients are often associated with stock market's volatility peaks. In the bottom chart, the red line is the federal funds rate. The federal funds rate shows a similar pattern as does the rolling correlation coefficient of 250 trading days. The federal funds rate is rescaled.

Curriculum Vitae

Contacting Email: jiandongli@hotmail.com

EDUCATION

LeBow College of Business, Drexel University, Philadelphia, PA 2007
Ph.D. in Finance

Kelley School of Business, Indiana University, Bloomington, IN 2002
Master of Business Administration, concentration in Finance and Information System

Tsinghua University, Beijing, China
Master of Engineering, concentration in Automotive Engineering 1996
Bachelor of Engineering, concentration in Automotive Engineering 1993

AREAS OF INTEREST

Time Series Analysis of Financial Data; Econometric Modeling and Forecasting;

Risk Management; Financial Markets and Institutions; Behavioral Finance

TEACHING EXPERIENCE

"FIN 698: SAS Programming in Financial Research," 2006

"FIN 301: Essentials of Corporate Finance," 2005

PROFESSIONAL EXPERIENCE

International Heritage Trading LLP, Indianapolis, IN June 2002-2003
Securities Trader, NASD series 7

Carl Schenck AG Beijing Office, Beijing August 1998-June 2000
Sales Manager

China International Science Center, Beijing June 1996-July 1998
Project Manager

CONFERENCE PRESENTATIONS

"Determinants of Stock Return Volatility: A Perspective of Belief Trading" in EFA 42nd Annual Meeting in 2006

"Determinants of Stock Return Volatility: A Perspective of Belief Trading" & "Time-varying Betas and Trading Volume" in MFA 55th Annual Meeting in 2006

"Empirical Analysis of Asset Returns with Skewness, Kurtosis, and Outliers: Evidence from 30 Dow Jones Industrial Stocks" in FMA Annual Meeting in 2007