# Asymmetric return-volatility relation around the clock: Quantile regression analysis

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Abstract

This study using almost 24-hour minute-by-minute data of e-mini S&P 500 index futures to measure realized volatility and examines return-realized volatility relation in daily frequency and intraday frequency of 15-mins interval for daytime and overnight trading periods. In daily frequency, we find significantly negative coefficients of contemporaneous and lagged returns on return-realized volatility relation, supporting volatility feedback and leverage effect. At intraday of 15-mins interval, our results show that a significantly positive return-volatility relation for positive returns, but a significantly negative relation for negative returns. Further, the estimated values of negative contemporaneous returns are more pronounced than the value of positive contemporaneous on volatility. Thus, we support prospect theory and loss aversion on the return-volatility relation at intraday frequency. Moreover, we associate U-shaped (inversed U-shaped) relation between contemporaneous positive (negative) return and volatility at 15-mins interval during active daytime trading period. Overall, our evidences of return-realized volatility relation provide more completely pictures and explanations of fundamental theory and behavioral theory.

Keywords: realized volatility, prospect theory, affect heuristic, volatility feedback effect, leverage effect.

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## 1. Introduction

The traditional asset pricing models postulate a positive relation between expected return and volatility. However, the ex-post realized return-volatility relation has found a negative relation, and the negative relation is more significantly when the realized return is negative. To solve the risk-volatility puzzle, two main theories of fundamental theory and behavioral theory propose different arguments. Fundamental theory focuses on risk-based perspective to explain the return-volatility relation and proposes two effects: leverage effect and volatility feedback effect. The explanation of **leverage effect** is that when a drop in the value of the stock (negative return) increases financial leverage, it makes the stock riskier and increase volatility. Thus, leverage effect suggests a negative correlation between lagged returns and current market volatility (Black, 1976). The **volatility feedback effect** postulates that volatility rests on a time-varying risk premium (French, Schwert and Stambaugh ,1987; Cambell and Hentschel, 1992; Bekaert and Wu, 2000). If volatility is priced, an anticipated increase in volatility would raise the required rate of return, in turn leading to immediate stock price decline and thus amplified the initial negative return. Thus, volatility feedback effect suggests the negative relation between contemporaneous returns and volatility. On the other hand, behavioral finance theory suggests investors' behavior bias, such as stereotypes, rules of thumb and representativeness, to explain the relation between return and volatility. A prominent behavioral theory is prospect theory proposed by Kahmenan and Tversky (1979) that investors are more sensitive to losses than to gains of the same magnitude (called loss aversion) and investors are risk-averse for gain and risk-seeking for losses. Accordingly, we hypothesize that investors are risk-averse when their investment experiences a rise in price, implying a positive relation between return and volatility; in contrast, for the price with a fall, investors become risk-seeking and infer a negative return-volatility relation. In addition, Slovic, Finucane, Peters and MacGregor (2002) suggest that most of our decisions are induced by an affective or emotional judgment. They propose that affect heuristic as having a quality of “goodness” or “badness” that can be thought of as feelings or a mental short-cut, leads investors to judge benefits and risks. Using available affective impression can be easier and more efficient than weighing the pros and cons of various reasons. Thus, people often use an “affective pool” (containing all the positive and negative tags associated with the representations) in the process of making judgments, and the perceived risk (benefit) would be very pronounced while the risk is very high (low). Therefore, based on prospect theory and affect heuristic, investors have different risk attitudes toward gains and losses and we expect the return-volatility relations for positive and negative returns are different and the relation would be more pronounced in high volatility quantiles.

Comparing the differences between fundamental and behavioral theory, the mechanisms of the risk-based explanation involve economic process to pass through the leverage changes and expected return varying and should be expected to work relative slowly. In contrast, the behavioral theories such as prospect theory and affect heuristic bias often take place immediately and might be observed in very short intraday period. Wang and Yang (2013) analyze the daily return and conditional volatility relation by GARCH-M model, taking into account the volatility feedback effect. Their results show that volatility feedback effect cancels out the risk premium effect in the expected return and indicate conditional volatility has little predictive power for the expected return. Agbeyegbe (2015) use daily frequency to examine return-volatility and support volatility feedback effect and leverage effect. Recently, some studies applying implied volatility (Hibbert et al, 2008; Badshah; 2013; Daigler et al., 2014; Talukdar et al., 2016) focused on short-term frequency data (daily or intraday) suggest the **behavioral theory** are more dominated than leverage and volatility feedback effects on the return-volatility relation. Given that time interval might reflect different displays for fundamental and behavioral theories, thus, this study would examine the return-volatility relation for daily and intraday frequency, respectively.

Reviewing previous studies related to risk-return relation, numerous studies have typically been examined by means of generalized autoregressive conditional heteroskedasticity in mean (GARCH-M) model on risk-return relation. However, due to the fact that the conditional volatility of stock market returns is not observable, different approaches and specification used by previous studies are largely responsible for the conflicting empirical evidences (Bali and Peng, 2006). To avoid model specification bias on the volatility measure, more and more studies employs model-free volatility to measure risk. Implied volatility and realized volatility are two model-free volatility measures and have figured prominently in the recent academic. Implied volatility provides ex ante risk-neutral expectations of future volatilities and has been used to examine the return-volatility relation in recent studies. For example, Low (2004) use implied volatility index to examine return-volatility relation and find the relation is asymmetric and nonlinear. Hibbert, Daigler and Dupoyet (2008) find a strong daily and intraday negative return-implied volatility relation. Badshah (2013) finds neither the leverage hypothesis nor the volatility feedback hypothesis effectively explain the asymmetric return-implied volatility relation, and suggests that the affect and representativeness heuristics play important role on the daily return-volatility relation. Daigler, Hibbert and Pavlova (2014) find that both the positive and negative contemporaneous returns of euro result in increased implied volatility in the upper quantiles, with the effect being strong for negative returns of the euro. Padungsaksawasdi and Daigler (2014) examine the return-implied volatility relation for commodities (gold, euro and oil) ETFs and find that relation is weaker than for stock indexes. Talukdar, Daigler and Parhizgari (2016) use three newly released indices to examine return-implied volatility relation and confirmed the new indices are important determinant to explain return-volatility relation. Lee, Liao and Tung (2017) examine VIX futures basis on S&P 500 index futures and show that the impact of VIX basis on subsequent S&P 500 futures significantly varies with return distribution.

Another model-free measure of realized volatility is computed by summing squared returns from high-frequency data over short time intervals during the trading day. The advantages of realized volatility is that it is an asymptotically unbiased estimator of the integrated variance (Adersen, Bollerslev and Diebold, 2003) and it can afford much more accurate ex post observations of actual volatility than the more traditional sample variances based on daily or coarser frequency data (Bollerslev, Gibson and Zhou, 2011). Although prior studies have used realized volatility to examine the return-volatility relation (Bollerslev and Zhou, 2006; Ghysels, Santa-Clara and Valkanov, 2005), they often use longer term measure of realized volatility, such as monthly (Bollerslev and

Zhou, 2006), but their evidences find the leverage and volatility feedback effects are weak on return-volatility relation. Bollerslev Litvinova and Tauchen 2006) show high-frequency data is much more precisely estimating the daily cross-correlation patterns in comparison with previously available estimates obtained from daily data alone and find that high frequency data may be used in more accurately assessing volatility asymmetries. Bollerslev, Gibson and Zhou (2011) propose that realized volatilities from daily returns or lower frequency data generally returns in biased and inefficient estimates, leading to unreliable statistical inference. Nowadays, high frequency financial returns data is available, but most of recent literatures based on high frequency intraday data often applying implied volatility to examine the volatility-return relation (Hibbert et al, 2008; Padungsaksawasdi and Daigler, 2014; Talukdar et al., 2016; Chiarella et al., 2016). Few studies use intraday realized volatility to examine the return-realized volatility. To fill the gap, this study sums minute-by-minute high-frequency squared returns at 15-mins and daily intervals as intraday volatility and daily volatility to provide more clear evidences among the above distinct explanations on return-volatility relation. In addition, to examine the asymmetric return-volatility relation between positive and negative returns, this study employs the quantile regression model (hereafter QRM) to examine the potential nonuniform return-volatility relation across volatility quantiles.

Furthermore, financial information accumulates globally around the clock. The daytime trading period of a stock market is typically half the length of the overnight non-trading period. Inevitably, not all price sensitive financial information becomes available during trading hours. Martens (2002) shows stock prices potentially have different dynamics during daytime trading hours compared to overnight non-trading hours. Tsiakas (2008) indicate there is clear misspecification if we assume that daytime and overnight information stem from the same data generating process, and this is especially true for volatility. Despite evidences on the increasing role of overnight non-trading hour information, there are little empirical researches of daytime and overnight returns-volatility relation. To shed light on daytime and overnight information playing role in the return-volatility relation, this study uses e-mini S&P 500 index futures, which is traded on GLOBEX almost 24 hours a day, linked to the largest stock market (U.S.) and has the highest liquidity in the world. Based on daytime trading of US market, we set daytime trading period is from 8:30 (14:30 GMT) to 16:00 (21:00 GMT)[1]. Other hours (from 0:00 GMT to 14:29 GMT) of a day is non-daytime trading period. In other words, to understand the return-volatility relation across daytime and overnight period might be different, we examine the return-volatility relation for daytime and overnight trading periods separately.

The goal of this study is using minute-by-minute data of e-mini S&P 500 index futures to calculate daily realized volatility and intraday realized volatility for daytime and overnight trading periods, respectively, to examine the asymmetric return-volatility relation. Our study contributes to the literatures in several ways. First, this study examines the return-volatility relation at daily and intraday frequencies respectively to provide more clearly pictures to explain leverage effect, volatility feedback effect or behavioral bias on the return-volatility puzzle. Second, to avoid model specification bias leads to inconsistent results, recently, a few studies employ volatility index (VIX) high frequency data to examine the return-volatility relation, but no work examines the return-volatility by high-frequency realized volatility. Extending the literatures, this study

[1] During the Daylight Savings Time, the trading hours will start at 13:30 GMT and end at 20:00 GMT.

applies another model-free volatility, which is calculated by minute-by-minute high frequency data. The ex-post realized volatility is more accurate than traditional sample variances based on daily or coarser frequency data. Third, in fact, negative and positive returns imply bad news and good news for investors and result in very different impacts on volatility. Moreover, based on affect heuristic, the impacts on volatility would change as volatility varying and the effect would be more pronounced for extreme volatility. Previous empirical studies often use ordinary least squares (OLS) mean regression to describe the average behavior of the central distribution on the return-volatility relation, except for few studies that support behavioral explanation on return-volatility relation (Hibbert et al, 2008; Badshah; 2013; Daigler et al., 2014; Talukdar et al., 2016). Therefore, this study uses qunatile regression model rather than a single measure of OLS to examine the asymmetric return-volatility relation. Fourth, most previous studies examining return-volatility relation focus on daytime trading periods, and limited studies consider the relation during overnight non-trading period. Extending the studies, we examine the asymmetric return-volatility relation across daytime and non-daytime trading periods by almost 24 hours of e-mini S&P 500 index futures.

Our analysis yields several findings. First, in daily frequency, our results show that the relation between contemporaneous return and volatility for both positive and negative return subsamples are significantly negative and the negative impact on volatility for negative return subsample is stronger than positive returns subsample, supporting volatility feedback effect. The coefficients of lagged return on volatility are also negative, supporting leverage effect. In other words, risk-based fundamental theory can explain the negative return-volatility relation in daily frequency. Second, at 15-mins interval frequency, the coefficients of contemporaneous returns are larger than lagged returns across all volatility quantiles. In addition, we find a significantly positive relation between contemporaneous positive return and volatility, but a significantly negative relation between contemporaneous negative return and volatility. Thus, the results of intraday return-volatility relation support the prospect theory developed by Kahneman and Tversky (1979), that investors lean toward risk aversion when their assets experience appreciation (gain), but lean toward risk seeking when their assets experience depreciation (loss). Third, the intraday results show that the negative contemporaneous returns have more pronounced effect than the positive contemporaneous on volatility returns. The asymmetric effect between positive and negative returns is consistent with loss aversion (Low, 2004). Fourth, very interesting, we find a U-shaped (inversed U-shaped) relation between contemporaneous positive (negative) return and volatility during daytime trading period. We associate the U-shaped (inversed U-shaped) relation between return and volatility across quantiles with affect heuristic, that investors use affect pool to produce 'net risk' or 'net benefit' to make decision rather than independent judgments of risk and benefit. In positive returns, risk averse investors have a diminishing sensitivity of risk aversion at low volatility quantiles owing to investors feel 'net benefit' while the risk is low (increased perceived benefit), but become an increasing sensitively of risk aversion at high volatility quantiles owing to investors feel 'net risk' while risk is high (decreased perceived benefit). Likewise, in negative returns, we find risk seeking investors have a diminishing sensitivity of risk seeking at low volatility with 'net benefit' and an increasing sensitivity of risk seeking at high volatility with 'net risk'. However, in inactive trading during overnight period, we find an increasing sensitively risk averse (risk seeking) in positive (negative) return when volatility moves from median to upper quantiles and the absolute value of negative return coefficients are larger than the positive return coefficients. Therefore, we infer that high trading volumes during daytime could provide more evidences of affect heuristic. Finally, different from positive and negative return subsample, we find a flat pattern on the return-volatility relation across varying volatility quantiles for full return. The “canceled-out” effect on the return-volatility relation across varying quantiles confirms that it is important to examine the asymmetric return-volatility relation for positive and negative returns separately.

The remainder of this paper is organized as follows. Section 2 reviews different hypotheses and the literature on asymmetric return-volatility relation. Section 3 discusses the data and methodology on the realized volatility and quantile regression model in futures exchanges across different time zones. Section 4 presents and discusses empirical results. The final section is the conclusion.

## 2. Literatures and hypotheses

Although a long-standing principal in traditional finance is positive relation between expected return and volatility, in reality, the return-volatility relation is negative. The negative risk-return relation is contrast to the prediction of mainstream theory (i.e. CAPM), which is often referred to volatility puzzle. According to previous studies, we summarize the literatures based on traditional theories and behavioral theory on the negative return-volatility relation explanation.

### 2.1 Traditional theories for the return-volatility relation

Leverage effect and volatility feedback effect are two prominent traditional finance theories associated with the negative return-volatility relation. Both of them explain the asymmetric return-volatility relation is risk-based, but the main different is causality. The leverage effect claims that the causality relation runs from return to volatility, whereas the volatility feedback effect contends that the relation runs from volatility to return.

Black (1976) and Christie (1982) were among the first to present that leverage effect can explain the negative asymmetric return-volatility property. The explanation they put forth is that a drop in the value of the stock (negative return) increase financial leverage, which makes the stock riskier and increase volatility. Thus, the leverage effect predicts a negative relation between lagged returns and current market volatility. Other, French, Schwert and Stambaugh (1987), Campbell and Hentschel (1992) and Bekaert and Wu (2000, 2001) propose volatility feedback effect, they rest on a time-varying risk premium to explain the volatility asymmetry. If volatility is priced, an anticipated increase in volatility would raise the required rate of return, in turn leading to immediate stock price decline and thus amplified the initial negative return. Thus, we would find a negative relation between contemporaneous returns and volatility. Volatility is typically higher after stock market falls than after it rises, so stock returns are negatively correlated with future volatility. Further, Campbell and Hentschel (1992) mentioned that volatility feedback can explain the characteristics of asymmetry effect on return-volatility relation. Suppose if there is a large piece of good news, large piece of news tend to be followed by other large pieces of news (volatility is persistent), so this piece of news increase futures expected volatility. This in turn increases the required rate of return on stock and lowers the stock price, dampening the positive impact of the good news. In contrast, if a large piece of bad news, the stock price falls because higher volatility raises the required rate of return on stock, but now the volatility effect amplifies the negative impact of bad news. In other words, the negative relation between contemporaneous return and volatility for negative returns are stronger than for positive returns.

However, the mechanisms of the risk-based explanation involve economic process to pass through the financial leverage changes and time-varying risk premium. They might be expected to work themselves out relative slowly. Thus, we examine the return-volatility relation in daily frequency as follows:

*H1: According to risk-based explanation, a significant negative relation between lagged return and volatility, supporting leverage effect; a significant negative relation between contemporaneous return and volatility, supporting volatility feedback effect.*

*H2: The negative relation between contemporaneous return and volatility for negative returns is more pronounce than for positive returns, supporting asymmetry effect.*

2.2 behavioral theories for the return-volatility relation

Some researches related to behavioral finance theory has argued that financial markets are inefficient in the short-run, and there is the possibility of mispricing (Hirshleifer, 2001; Shefrin, 2008). Recently, more and more studies employ behavioral-based concepts to explain the return-volatility relation, such as Low (2004), Hibbert, Daigler and Dupoyet (2008), Badshan (2013), Daigler, Hibbert and Pavlova (2014), Padungsaksawasdi and Daigler (2014), Lee and Li (2016) and Talukdar, Daigler and Parhizgari (2016). Hibbert, Daigler and Dupoyet (2008) examine the return-implied volatility relation in daily and intraday frequencies and suggest that leverage effect and volatility feedback effect are not the primary explanations of the return-volatility relation and propose a behavioral explanation to explain their results. Badshah (2013) uses quartile regression to investigate short-term return-volatility relation, he finds neither the leverage hypothesis nor the volatility feedback hypothesis effectively explain the asymmetric return-volatility relation, and suggests that the affect and representativeness heuristics play important role on the short-term return-volatility relation. More recently, Talukdar, Daigler and Parhizgari (2016) indicate that behavioral theories explain the return-volatility relation better than the fundamental theories in high frequency data.

While standard finance theory assumes investors are risk aversion, the prospect theory proposed by Kahnemen and Tversky (1979) argues that investors have different risk attitudes toward gains and losses, measured with respect to a certain reference point. There is a phenomenon known as loss aversion, implying investors have a tendency to be less (more) willing to gamble with profits (losses). Investors are instinctively risk averse when they face a gain and become risk seeker when they face loss. Then, we hypothesize that the return-volatility relation is positive for risk-averse investor when the return is positive (gain). Oppositely, for stocks with a negative return, investors behave like a risk seeker and the return-volatility relation becomes negative. Some studies are consistent with the prospect theory. Fiegenbaum and Thomas (1988) and Fiegenbaum (1990) indicate that a negative association exists between risk and return for firms having return below their industry target levels (reference points) and a positive association exists for firm with return above the target. Also, they find the negative risk-return relation is generally steeper than the positive relation. Bali, Cakici and Whitelaw (2011) and Han and Kumar (2013) argue that the negative relation between risk and return comes from investors' strong tendency to gamble with stocks. More recently, Lee and Li (2016) examine the idiosyncratic risk-return relation by quantile regression and find that idiosyncratic risk is positively (negatively) associated with return at the high (low) quantiles of returns. Those findings are in line with the prospect theory that investors lean toward risk aversion (risk seeking) behavior when they encounter a profit (loss). In addition, the behavioral finance literatures posit a phenomenon known as 'loss aversion' (Kahnemen and Tversky, 1979), in which losses loom larger than gains. Loss aversion could translate into a greater responsiveness of downside price pressure on raising risk relative to the responsiveness of upside price pressure on lowering risk. Consistent with loss aversion, Low (2004) find that risk perception tends to increase when downside volatility increases more than upside volatility. Badshan (2013) find the return-volatility relation is asymmetric, that is, the negative returns have a higher impact than positive returns. Lee et al. (2017) show the impact of VIX basis on returns is stronger under bad market conditions than under good market condition. Given that investors' behavior often take place immediately and could be observed in very short time intervals. Thus, we examine the intraday return-volatility relation (i.e. at 15-min interval) on behavioral finance arguments.

*H3: According to prospect theory, investors are risk averse (risk seeker) when they face a gain (loss). When the price goes up (down), we expect a significant positive (negative) relation between contemporaneous return and volatility for risk averse (risk seeker).*

H4: *Based on loss aversion, we expect the impact of negative returns on the volatility is larger than positive returns, that is, the return-volatility relation is asymmetric.*

Furthermore, Shefrin (2008) suggests heterogeneous beliefs play an important role in asset pricing and discusses the negative return-volatility relation in terms of representativeness, affect and extrapolation bias. The representative heuristic refers to an overreliance on stereotypes and is a principle that underlines particular rules of thumb to make quick or otherwise irrational judgments (Tversky and Kahneman, 1974). Representativeness is the “affect” characteristic, where people form emotional associations with activities, with a positive affect label being considered good and a negative affect label being bad. Reality available affective impression can be easier and more efficient than weighting the pros and cons of various reasons. The affect heuristic is a mental shortcut that investors often use to judge benefits and risks (Finucane, Alhakami, Slovic and Johnson, 2000). The relation between perceived risk and perceived benefit was linked to individual’s general affective evaluation of a hazard. For example, if an activity was “liked”, people tended to judge its risk as low and its benefits as high. If the activity was “disliked”, the judgments were opposite—high risk and low benefit. That is, individuals make judgment by deliberating on what the net difference between risk and benefit rather than independent judgments of risk and benefit (Alhakami and Slovic, 1994). The common use of affect heuristics in making judgments is easily extended to stock market return and volatility decision. According to investors are used to making decision by ‘affect pool’, decreasing the overall affect pool by decreasing perceived benefit would lead to an increase in perceived risk. In contrast, increasing the affect pool by decreasing perceived risk would lead to an increase in perceived benefit. Thus, we expect the ‘net risk’ (or ‘net benefit’) should be more significant while the risk is high (low). In addition, based upon prospect theory, investors’ behaviors for positive and negative innovation reflect different impacts on returns. In positive returns (gain), we hypothesize that risk averse investors have a diminishing sensitivity of risk aversion at lower volatility owing to investors feel ‘net benefit’ while the risk is low (increased perceived benefit), but the sensitively of risk aversion becomes increasing at higher volatility owing to investors feel ‘net risk’ while risk is high (decreased perceived benefit). Likewise, in negative returns (loss), we expect risk seeking investors have a diminishing sensitivity of risk seeking at lower volatility with ‘net benefit’ and an increasing sensitivity of risk seeking at higher volatility with ‘net risk’. Thus, we posit following hypotheses:

*H5: Based on affect heuristic, investors get used to* make decisions by ‘affect pool’, *thus,* the ‘net risk’ (or ‘net benefit’) should be more significant when the risk is high (low). *While investors are risk averse, the positive relation between contemporaneous return and volatility is U-shaped; in contrast, while investors are risk seeker, the negative relation between contemporaneous return and volatility is inversed U-shaped.*

2.3 information flow across time zone

Financial information accumulates globally around the clock. However, the daytime trading period of a stock market is typically half the length of the overnight trading period. In recent years, a number of events may have changed the amount and role of financial information that becomes available during overnight trading hours. These include the increasing integration in global financial markets and the extension of trading hours in stock exchanges. International news might replace domestic news during overnight trading hours. Some studies describe the increasing role of overnight information and show that daytime and overnight volatilities are different. French and Roll (1986) suggests that hourly daytime volatility is substantially higher than hourly overnight volatility because daytime trading induces volatility by revealing price sensitive private information. But Tsiakas (2008) examine the predictive ability of information accumulated during overnight trading hours for a set of European and US stock indexes and indicates that would have a clear misspecification if we assume that daytime and overnight information stem from the same data generating process, especially for volatility.

However, until now, there are few papers examined the volatility transmission (Cai, Howorka, and Wongswan, 2008; Martinez and Tse, 2008) and volatility-volume relation (Kao and Fung, 2012) across daytime and overnight trading periods. Extending previous studies often examine the return-volatility relation mainly on daytime period, this study examine the return-volatility relation across daytime and overnight trading periods. Compared trading activities in daytime with overnight trading periods, trading activities in daytime period is more frequent than in overnight trading period. Gervais and Mingelgrin (2001) report that trading volume tends to influence excess return. Avramov, Chordia and Goyal (2006) proposed a trading-based explanation for the asymmetric effect in volatility and suggest that the volatility response to stock price changes is caused by trading activity. Thus, we use almost 24-hour trading data to examine the return-volatility relation in actively daytime period and inactively overnight period respectively. We infer that the frequency of trading activity across daytime and overnight trading periods might influence the return-volatility relation and hypothesize that the return-volatility relation in daytime trading period is more pronounce than in overnight trading period.

*H6: According to the different trading patterns between daytime and overnight trading periods, the return-volatility relation in daytime trading period would be different between daytime and overnight period.*

## 3. Data

### 3.1 Data description

This study uses minute by minute data of the E-mini S&P 500 index futures, which is the largest index futures contracts on the CME, to examine the return-volatility relation. The E-mini S&P 500 index traded on the CME via GLOBEX are almost 24 hours a day. The long trading hours enable us to compare the return-volatility relation across daytime and overnight trading periods.

<Insert Figure 1>

Figure 1 shows both local and Greenwich Mean Time (GMT) times of daytime regular trading for U.S. The regular trading hours based on US stock market is set as the American zone from 8:30 (14:30 GMT) to 16:00 (21:00 GMT).[2] The daytime trading period in U.S. is only about 6.5 hours, and other non-regular overnight trading periods still release information for other local market (i.e. Asian and Europe zones).

Figure 2 presents the mean of hourly trading volume in E-mini S&P 500 (ES) for 24 hours a day. It shows E-mini S&P 500 index futures trading volumes are high in United States daytime trading period but extremely low in overnight trading period. As our expectation, the S&P 500 index is the stock market index in U. S. The trading volume of the E-mini S&P 500 index futures in daytime of home exchange is higher since all information related to U.S. releases at business trading hours. Thus, compared to overnight period, we expect more investors' behaviors might be observed and reflected during the daytime period.

<Insert Figure 2 here>

The leverage and volatility feedback effects on return-volatility relation are thought of as applying at coarser time interval. We focus on daily return-volatility relation to examine these two risk-based explanations. Meanwhile, given that the return-volatility relation across daytime and overnight trading periods vary considerably in trading volumes, the return-volatility relation in daily frequency would disregard the details of the intraday activities in a day. Also, behavioral bias often deems to be observed in very short time interval. To this end, we investigate the intraday return-volatility relation at 15-mins intervals across daytime and overnight trading periods to provide more complete

[2] During the Daylight Savings Time, the trading hours will start at 13:30 GMT and end at 20:00 GMT.

evidences to explain return-volatility relation.

Table 1 presents descriptive statistics of the realized return and realized volatility of E-mini S&P 500 (ES) futures for daily frequency and intraday15-mins interval for daytime and overnight periods. In daily frequency, the mean of ES realized return (RET) is 0.0004 and with a standard deviation of 0.01. The mean value of ES realized volatility (RV) is 0.0092, which is close to standard deviation of realized return. At intraday, the mean of return in daytime (0.006) and in overnight (0.007) are similar, but the standard deviation of RET in overnight is 1.298, which is much larger than in 0.001 in daytime. Similarly, we find the mean of realized volatility (RV) in daytime (1.188E-3) is higher than RV in overnight (0.798E-3) trading period. These results shows that the RET and RV between daytime and overnight periods are very different and the daytime trading market are more volatile.

<Insert Table 1 here>

## 3.2 Methodology

### 3.2.1 Volatility measures

We use minute by minute data to construct the realized variance in daily frequency and intraday at 15-mins interval respectively.

$$RV_t^2 = \sum_{i=1}^{N} (\log P_{t+i/N_j} - \log P_{t+(i-1)/N_j})^2 \tag{1}$$

For daily realized variance, the N is the 1-mins observations at date t. For the intraday realized variance at 15-mins interval, the N is the 1-mins observations in each 15 minutes. The realized standard deviation is the square root of realized variance. In this study, we use realized standard deviation proxy for realized volatility (RV).

### 3.2.2 Quantile Regression

In OLS, the mean equation, which explains how the mean of response (or dependent) variable changes with the vector of covariates (or independent variables), describes the relation at the mean of the response variable's distribution between response variable and the covariance. We briefly discuss a simple linear regression model as follows:

$$y_t = \alpha + \beta x_t + \varepsilon_t \tag{2}$$

where the parameters $\alpha$ and $\beta$ are constants and y is the independent variable, x is the dependent variable, $\varepsilon$ is the error term and subscript t is for time periods t. The conditions mean we can write $E(y|x) = \alpha + \beta x_t$. Assume the y and x are bivariate normal will assure that the distribution function $F(y|x)$ is normal. The OLS estimates are then the solution to the optimization problem

$$\min_{\alpha\beta} \sum_t (y_t - \alpha - \beta x_t)^2 \tag{3}$$

When the join distribution of x and y is not bivariate normal, we need more than conditional mean and conditional variance to specify the conditional distribution of the dependent variable. Shefrin (2001, 2008) suggests that investor's heterogeneity leads to a multimodal and fat-tailed stock index return distribution. To account for investors' heterogeneity in futures markets, we use quantiles regression framework. The quantile regression model proposed by Koenker and Bassett (1978) has some advantages over

OLS: (i) it does not assume any specific distribution about the error of the model; (ii) it produces robust estimates even when the errors are skewed and leptokurtic; and (iii) it accounts for any omitted variable bias.

The linear quantile regression is stated in terms of optimization problem. Let $q \in (0, 1)$ and $q^{th}$ quantile of the error term be defined as $F_{\varepsilon}^{-1}$, where the error has a distribution function given as $F_{\varepsilon}$. The simple linear quantile regression model is then given as

$$F^{-1}(q|x) = \alpha + \beta x_t + F_{\varepsilon}^{-1}(q) \tag{4}$$

where $F_{\varepsilon}^{-1}(q)$ is the conditional quantile of the dependent variable in the general case.

More generally, let $y_1, y_2, \ldots, y_T$ be a random sample on the regression process with $u_t = y_t - x_t\beta$ having distribution function F and $x_1, x_2, \ldots, x_T$ be a sequence of K-vectors of a known design matrix, the q-th quantile regression will be any solution to the following problem:

$$\min_{\beta \in R^k} \left(\sum_{t \in \tau_q} q|y_t - x_t\beta| + \sum_{t \in \tau_{1-q}} (1-q)|y_t - x_t\beta|\right) \tag{5}$$

with $\tau_q = \{t : y_t \geq x_t\beta\}$ and $\tau_{1-q}$ is the complement.

### 3.2.3 QRM for the return-volatility relation

With respect that investors' heterogeneous beliefs and affect heuristic characteristic might cause the asymmetric return-volatility relation varying across the entire distribution of the dependent variable (realized volatility), we examine the return-volatility relation by quantile regression (QR) model developed by Koenker and Basset (1978). Hibbert et al.

(2008) find that regressions by quantile show that the extreme changes are most strongly associated with return-implied volatility relation. Badshan (2013) find the asymmetry monotonically increases when moving from the median quantile to the uppermost quantile, suggesting affect heuristic plays a crucial role in short-term asymmetric relation. Daigler, Hibbert and Pavlova (2014) find that both positive and negative contemporaneous return of the euro result in increased volatility in the extreme quantiles of the conditional distribution. Referring to Hibbet et al. (2008), Badshah (2013) and Daigler et al. (2014), we first specify a mean regression model (OLS), which is considered to be a benchmark model to examine the return-volatility relation in the analysis. Different from Hibbet et al. (2008), Badshan (2013) and Daigler et al. (2014) using VIXs proxy for volatility, we apply realized volatility (RV) to examine the return-volatility relation in QR model.

$$RV_t = \alpha_0 + \alpha_1 RV_{t-1} + \alpha_2 RV_{t-2} + \alpha_3 RV_{t-3} + \alpha_4 RET_t + \alpha_5 RET_{t-1} + \alpha_6 RET_{t-2} + \alpha_7 RET_{t-3} + \varepsilon_t \quad (6)$$

$RV_t$ is realized standard deviation proxy for realized volatility. $RET_t$ is contemporaneous realized return. To address investors' heterogeneous beliefs and affect heuristic characteristic might cause the asymmetric return-volatility relation across quantiles of volatility changes, we adopt quantile regression model (QRM) to re-examine the model of Equation (6). The qth quantile regression model has following form:

$$RV_t = \delta_0^q + \delta_1^q RV_{t-1} + \delta_2^q RV_{t-2} + \delta_3^q RV_{t-3} + \delta_4^q RET_t + \delta_5^q RET_{t-1} + \delta_6^q RET_{t-2} + \delta_7^q RET_{t-3} + \varepsilon_t \quad (7)$$

The main feature of quantile-regression framework is that the effects of the variables that are captured by $\alpha_i^q$ vary for each qth quantile within the range of q$\in$(0,1).

According to prospect theory and loss aversion in behavioral theory, investors have different risk attitudes toward gains and losses (Kahnemen and Tversky, 1979; Lee and Li, 2016) and risk perception tends to increase when downside volatility increases more than upside volatility (Low, 2004; Chen and Ghysels, 2010; Badshan, 2013). To account for the possibility of asymmetry effect of positive return (gain) and negative returns (loss) on volatility, we separate return into positive return ($R^+$) and negative returns ($R^-$) as follows:

$$RET_t^+ = \{ \begin{matrix} RET_t \; if \; RET_t > 0 \\ 0 \quad if \; RET_t < 0 \end{matrix} \qquad \text{and} \qquad RET_t^- = \{ \begin{matrix} RET_t \; if \; RET_t < 0 \\ 0 \quad if \; RET_t > 0 \end{matrix} \tag{8}$$

Then, we examine the return-volatility relation for positive and negative returns in QR model respectively. The qth quantile regression model for *positive return* has form in Equation (9) and *negative return* in Equation (10).

$$RV_t = \beta_0^q + \beta_1^q RV_{t-1} + \beta_2^q RV_{t-2} + \beta_3^q RV_{t-3} + \beta_4^q RET_t^+ + \beta_5^q RET_{t-1}^+ + \beta_5^q RET_{t-2}^+ + \beta_6^q RET_{t-3}^+ + \varepsilon_t \quad \textbf{(9)}$$

$$RV_t = \gamma_0^q + \gamma_1^q RV_{t-1} + \gamma_2^q RV_{t-2} + \gamma_3^q RV_{t-3} + \gamma_4^q RET_t^- + \lambda_5^q RET_{t-1}^- + \gamma_5^q RET_{t-2}^- + \gamma_6^q RET_{t-3}^- + \varepsilon_t \quad (10)$$

4. Empirical results

We attempt to achieve three goals in the empirical analysis. First, given that investors' behavioral bias might observed in very short periods, but the leverage effect and volatility feedback effect work out relative slowly. We examine the daily and intraday return-volatility relation respectively. Second, given that negative and positive returns imply bad news (loss) and good news (gain) for investors, then investors have different reactions or risk attitudes on volatility. To address the asymmetry effect on return-volatility relation, we separate contemporaneous return into positive and negative returns. Third, the frequency of trading activities at daytime differs widely at overnight period. To take into account whether actively trading influences the return-volatility relation, this study examines the intraday return-volatility relation for daytime and overnight trading periods separately.

### 4.1 Daily return-volatility relation

Table 2 presents the daily results of the OLS and QRM regressions for E-mini S&P 500 index. To save space, we report the important upper, median and lower QRM estimators in the Table 2. The OLS results are shown at the bottom of the table that is estimated with heteroskedasticisty-consistent standard errors. We report the results of full sample in the Panel A, contemporaneous positive returns in the Panels B and contemporaneous negative returns B and C.

Panel A shows that the coefficients of contemporaneous return ($RET_t$) are significantly negative and the value of $RET_t$ are quite similar (range from -0.083 and -0.091) across quantiles. The significant negative relation between contemporaneous return and volatility is consistent with Hibbert et al (2008). However, Hibbert et al (2008) and Badhah (2013) applying implied volatility find that the coefficients of lagged returns ($RET_{t-1}$) are not significant as contemporaneous return, thus they indicate that leverage effect is not very convincing for daily data.  Different from them, we find the impacts of lagged return ($RET_{t-1}$) on realized volatility (RV) are also significantly negative across quantiles. The absolute values of $RET_{t-1}$ on the realized volatility across volatility quantiles (range between -0.065 and -0.087) are slight lower than the absolute values of $RET_t$. At the bottom of the table, we also find the OLS estimates of contemporaneous and lagged return have significant negative relation on RV. Thus, in the preliminary results of Panel A, the significantly negative relation between contemporaneous return and volatility supports volatility feedback effect and the significantly negative relation between lagged return and volatility is in consistent with leverage effect. These results confirmed that the risk-based explanations of our hypothesis 1(*H1).*

Panel B shows the results for contemporaneous positive return ($RET_t^+$) subsample. Similar with Panel A, we find the coefficients of $RET_t^+$ are significantly negative on RV, except for the lowest quantiles (0.05, 0.1) and the highest quantile (0.95). The coefficients of $RET_{t-1}^+$ are also significantly negative. In Panel C of contemporaneous negative returns ($RET_t^-$) subsample, we also find that the coefficients of $RET_t^+$ and $RET_{t-1}^+$ are significantly negative with realized volatility for all quantiles. Thus, these evidences support volatility feedback and leverage effects (H1) regardless of positive or negative returns. In addition, we note that lagged realized volatility (RVS) has highly significant positive effects on current realized volatility up to 3 lags for ES in Panels A, B and C of the Table 2. The significant positive effects on current realized volatility show the volatility is persistent.

To examine the asymmetry effect of return-volatility relation, we compare the returns estimates between positive and negative returns subsamples in Panel B and Panel C of Table 2. Our results show that the negative relation between contemporaneous return and volatility for negative returns is stronger and more significant than positive returns, supporting the *H2*. The results confirm Campbell and Hentschel (1992) argument that volatility feedback effect can explain the asymmetric return-volatility relation in daily frequency. That is, price increases caused by good news, and volatility persistent increase futures expected volatility and make a higher required rate of return on stock, which would dampen the positive impact of the good news. Oppositely, bad news induces price declines and the volatility persistent effect amplifies the negative impact of bad news. The OLS estimates at the bottom of the table also confirmed that negative return-volatility relation is more pronounce for negative returns ($RET^{-}$) than for positive return ($RET^{+}$). The findings are different from previous analysis of Hibbert et al (2008) and Badhah (2013) that they examine return-volatility relation for implied volatility and find only contemporaneous returns are significantly negative, whereas the lagged returns coefficients are mostly insignificant.

<Insert Table 2>

To clearly quantify the asymmetric return-volatility relation, we report the daily quantile regression plot for full, positive and negative contemporaneous returns in up, middle and down subplot of the Figure 3. The quantiles of the volatility distribution are represented on the x-axis, with the lower quantiles to the left and the upper quantiles to the right of the plot. The coefficients of returns are given on the y-axis. Figure 3 shows that full, positive and negative contemporaneous returns have negative impact in realized volatility. Same as the results of Table 2 and consistent with previous studies (Hibbert et al (2008), Badhah (2013) and Daigler et al (2014)), the negative returns are associated with higher volatility than positive returns, supporting asymmetry effect of return-volatility relation between good (positive returns) and bad news (negative returns) of H2. As we observe the changing patterns of returns estimates across volatility quantile, the figures show that the values of return estimates are quite flat across all volatility quantiles, especially for full returns. But only in down subplot of the Figure 3 for negative returns, we find the absolute values of $RET^{-}$ becomes larger in upper volatility quantiles (i.e. $q>0.8$). The results are some different with Low (2004), Badhah (2013) and Daigler et al (2014) that they find the return-implied volatility relation is monotonic increase from median quantile up to uppermost quantiles for both positive and negative returns and inferring behavioral argument of loss aversion to explain the asymmetric effect. In other words, our study provides evidences to support traditional risk-based explanations of volatility feedback and leverage effect, rather than behavioral theory in the daily return-realized volatility relation.

<Insert Figure 3>

Summarize our above findings of daily return-volatility relation for realized volatility. While we employ ex-post realized volatility to examine return-volatility relation, our results show that both of contemporaneous returns and lagged returns are significant negative in realized volatility, supporting fundamental explanations of volatility feedback and leverage effect for the daily return-volatility relation. Comparing the relation between contemporaneous return and volatility for positive and negative returns, we find the estimates of negative returns are higher and more significant than positive returns, confirming asymmetric return-volatility relation through volatility feedback effect proposed by Campbell and Hentschel (1992).

4.2 Intraday return-volatility relation across daytime and overnight trading periods

Daily data often impose some limitations, because they disregard the details of the activities that occur throughout the day. As we have seen that the trading volumes across daytime and overnight trading periods are very different in Figure 2 and investors' behavioral bias often could be observed in very short term interval. Therefore, in this section, we examine intraday return-volatility relation at 15-mins interval across daytime and overnight trading periods respectively. The quantile regression results of various time zones are reported in Table 3. We report the results of full sample of contemporaneous return in the Panel A of Table 3. To explore asymmetry of return-volatility relation, we saperate contemporaneous return into positive and negative return subsamples, we report two subsamples results at Panels B and C of Table 3. The OLS results are also shown at the bottom of each table estimated with heteroskedasticisty-consistent standard errors.

Panel A of Table 3 shows the results of the full sample for return-volatility relation for overnight and daytime trading periods respectively. We find the estimated coefficients of contemporaneous returns ($RET_t$) and lagged return ($RET_{t-1}$) are negative for both of overnight and daytime trading periods, which are similar with the results of daily frequency (at Panel A of Table 2), but the significant level of $RET_t$ becomes weak and the absolute values are quite minial, especially for overnight trading periods. In overnight trading period, the negative estimates of $RET_t$ (range from -0.009 to -0.017) are only statistically significant at 1% level in upper quantiles ($q \geq 0.5$) and the estimate of OLS at the bottom line is insignificant.  In daytime trading period, the negative estimates of

$RET_t$ (range from -0.023 to -0.031) are significantly, except for the lowest quantiles (q≤0.01). The coefficients of contemporaneous returns are insignificant or marginally contributes imply that the volatility feedback effect cannot explain the return-volatility relation well in very short-term.

We report the positive returns subsample of return-volatility relation in the Panel B of Table 3. The contemporaneous coefficients of returns ($RET_t^+$) are significantly positive at 1% confidence level across all quantiles and the estimate values of $RET_t^+$ increase for both of overnight (range from 0.170 to 0.322) and daytime (range from 0.146 to 0.228) periods monotonically from median quantile (q=0.5) to uppermost quantile (q=0.95). A comparison of contemporaneous positive coefficients ($RET_t^+$) and lagged ones ($RET_{t-1}^+$), we find that the values of contemporaneous positive returns are much larger than lagged positive returns. Conversely, in Panel C of Table 3 for negative return subsample, we find the estimated coefficients of contemporaneous return ($RET_t^-$) is significantly negative and the absolute value of $RET_t^-$ are larger than lagged returns across all quantile for both of overnight and daytime periods. The negative coefficient of $RET_t^-$ implies investors lean toward risk seeking when their assets experience depreciation (loss). Similar results are also shown in OLS model. The coefficients of contemporaneous for positive and negative returns support the prospect theory developed by Kahneman and Tversky (1979) that investors have an irrational tendency to be less (more) willing to gamble with profits (losses). The findings of Panel B and C of Table 3 confirm H3 that when investors face a gain (positive returns), they become risk averse. Then, there is a significant positive relation between contemporaneous return and volatility. When investors face a loss (negative returns), they become risk seeker. Thus, the relation between contemporaneous return and volatility change to negative.

Comparing the magnitudes of positive ($RET_t^+$) and negative ($RET_t^-$) contemporaneous return estimates in Panels B and C of Table 4, the result shows that the absolute values of $RET_t^-$ are larger than the value of $RET_t^+$ across overnight and daytime periods. The asymmetric effect between positive and negative returns supports the H4 of loss aversion that investors are more sensitive to losses than to gain of the same magnitude. The results are also consistent with Low (2004),Badshan (2013) and Lee and Li (2016), they suggest that that risk perception tends to increase when downside volatility increase more than upside volatility.

<Insert Panel A, B, C of Table 3>

To provide concise comparisons for : (1) the estimates of ORM for $\mathrm{RET_t}^+$ and $\mathrm{RET_t}^-$; (2) the differences of return-volatility relation across overnight and daytime trading periods. We construct the quantile estimates of contemporaneous returns in overnight trading periods in Figure 4. Figure 5 is plotted daytime trading period. Panel A, B and C are report the plots for full return (RET), positive return ($RET_t^+$) and negative returns ($RET_t^-$), respectively.

In the Panel A of Figures 4 for overnight trading period, we find a flat pattern of the return-volatility relation across volatility quantiles distribution, meaning that the realized volatility (RV) response to return presents similar across their quantiles. However, different from Panel A of full return sample, we find a very different asymmetric return-volatility relation for positive and negative returns in Panel B and C. Panel B shows an increasing positive slope in the relation between positive return and realized volatility, implying investors are in risk-averse domain in positive return subsample. More clearly, the asymmetry return-volatility relation is most pronounced from the median quantile up to the uppermost quantile (q=0.95). In contrast, Panel C shows a negative slope in the return-volatility relation, indicating risk-seeker domain in negative return subsample. Also, the asymmetry return-volatility relation is most pronounced at upper quantiles of the distribution, which is pronouced from the median quantile up to the uppermost quantile (q=0.95). The stronger asymmetry effect in the upper quantiles are in line with Hibbert et a. (2008), Badshah (2013) and Daigler et al. (2014). But results in Hibbert et a. (2008) and Badshah (2013) using VIX volatility as volatility show a significant negative contemporaneous relation throughout the conditional distribution, implying positive returns decrease VIX volatility, whereas negative returns increase VIX. Compared with them, our empirical results using realized volatility show that both positive return and negative return increase volatility in the upper quantiles, which is consistent with Chen and Ghysels (2010) suggest that very good news (usually high positive return) and bad news (negative returns) increase volatility and Daigler et al. (2014) euro currency and find both positive and negative returns increase volatility in upper quantiles. In addition, it is noticeable that a significant negative estimates between contemporaneous return and volatility in Panel A and the absolute value of RET is very minimal and the pattern is quite flat across various quantiles. We confer that the result is caused by a net ‘cancel-out’ effect caused from positive and negative return. Because the negative coefficients of $RET_t^-$ (see Panel B of Table 3) are larger than the positive coefficients of $RET_t^+$ (see Panel C of Table 3), the net effect is negative and quite small.

These results confirm that investors have heterogeneous beliefs (Shefrin, 2008) and have different risk attitudes toward gains and losses (Kahnemen and Tversky, 1979). Thus, examining positive and negative returns subsample separately could provide more evidences of asymmetric effect between return and volatility to describe the loss aversion of investor behaviors.

<Insert Figure 4>

Figure 5 show the return-volatility relation for daytime trading period. In the Panel A of Figure 5, we find a flat pattern across varying quantiles for full returns and present a cancel-out effect, which is similar with Panel A of Figure 4. But very interesting, we find the return-volatility relation across volatility quantiles becomes a U-shape for positive return subsample in the Panel B of Figure 5, and an 'inversed U-shape' for negative return samples in the Panel C of Figure 5. The results are consistent with Agbeyegbe (2015) that he finds an inverted U-shaped curve for the asymmetric return-implied volatility relationship. However, he does not explain the implication behind the inverted U-shaped relation between return and volatility across quantiles. In this study, we associate the U-shaped relation between return and volatility based on affect heuristic demonstrated by Finucane et al. (2000).

According to the affect heuristic, investor use 'affective pool' (containing all the positive and negative tags associated with the representations consciously or unconsciously) to make decision. The role of affect in judgment produce 'net riskiness' or 'net benefit' judgment rather than independent judgments of risk and benefit. Therefore, in positive return subsample, given that investors lean toward risk aversion, we find a diminishing sensitivity of risk aversion at lower volatility quantile (i.e. 0.05 to 0.5) because the information at lower volatility quantile should lead to an inference that the perceived benefit is high. The more favorable affective impression might let investors require lower risk premium to hold assets. After the volatility increases above kink (such as at higher volatility quantile from 0.55 to 0.95), decreasing favorability by increasing perceived risk would lead investor to require higher risk premium. Conversely, in negative return subsample of NK, given that investors lean toward risk seeking (implying high volatility with low return because investors tend to hold on assets at loss region for loss aversion), a diminishing sensitivity of risk seeking at lower volatility quantile because perceived benefit larger than perceived risk at lower volatility quantile, that might alleviate risk seeking effect. While perceived risk dominate investors' affect at upper volatility quantile (i.e. above 0.5 quantile), investors' loss aversion at risk-seeking region becomes strong and results in an increasing sensitivity of risk seeking. In other words, the results of Figure 5 provide evidences to validate the *affect heuristic* of H5.

<Insert Figure 5>

Moreover, to investigate the different return-volatility relation between overnight and daytime trading periods, we compare the results of Figure 4 and Figure 5. We find the volatility responses to contemporaneous positive and negative returns are most pronounced from the median quantiles up to the uppermost quantile (q=0.95) for overnight and daytime periods, but the diminishing sensitivity of risk averse (seeker) at lower volatility quantiles (q<0.5) for positive (negative) returns only observe in daytime trading period. The results support our hypothesize (H6) that the return-volatility relation in daytime trading period would be different between daytime and overnight period. *The findings of* (inversed) *U-shape* for (negative) positive returns in daytime period infer that active trading volumes could provide more evidences of investor behaviors (affect heuristic) than in overnight periods.

Summary of the intraday return-volatility results across overnight and daytime trading periods, we find that prospect theory and affect heuristic explain the return-volatility relation in very short-term interval (i.e. 15-mins interval) more appropriate than volatility feedback effect. The intraday results are different from our previous daily frequency results at section 4.1. These results are consistent with Daigler et al. (2014) and Talukdar et al. (2016) that the behavioral theories are more supported, particular under the high frequency data, than the fundamental theories in explaining return-volatility relation. In addition, a comparison of the quantile varying result with the traditional OLS estimates, the result indicates that OLS estimate which simply capture the mean effect, provide an incomplete picture about the relation between return and volatility in the extremely (upper or lower) quantiles. Thus, the quantile regression model provides more robust estimates on the return-volatility relation.

## 5. Conclusion

In this study, we use realized volatility to examine the asymmetric return-volatility relations by quantile regression model. We work at daily and intraday frequencies to provide more concise evidences for fundamental theory and behavioral theory on the return-volatility relation. To shed light on trading volumes are very different between overnight and daytime periods might influence the return-volatility relation, the E-mini S&P 500 index futures on the using GLOBEX is used in this study.

We find that the daily contemporaneous and lagged returns have significantly negative relation on the realized volatility, supporting volatility feedback and leverage effect. However, different results are found at intraday of 15-min interval. The results show a significantly positive relation between contemporaneous positive return and volatility but a significantly negative relation between contemporaneous negative return and volatility, supporting prospect theory that investors have different risk attitudes on positive and negative returns. These findings confirm that behavioral theory supports the return-volatility relation in very short-term interval, but fundamental theories of volatility feedback and leverage effect are appropriately in daily frequency.

Furthermore, in intraday return-volatility relation, our result shows that the estimates of negative returns are higher and more pronounced than the estimates of positive returns. The asymmetric return-volatility relation is consistent with loss aversion, which investors are more sensitive to losses than to gain. In addition, we employ qunatile regression to examine the asymmetric return-volatility relation across various volatility distribution, we find both positive and negative return have monotonically increasing volatilities and the asymmetry effect is most pronounced from the median quantile up to the uppermost quantile (q=0.95). Moreover, we find the U-shaped (inversed U-shaped) relation between contemporaneous positive (negative) return and volatility during active daytime trading and associate affect heuristic to explain the U-shaped (inversed U-shaped) relation between return and volatility across quantiles. According to these empirical findings, we suggest that it is important to examine return-volatility using quantile regression for positive and negative returns separately. Prior studies use OLS estimate would understate or overstate the return-volatility relation in the tail volatility quantiles regression.

In conclusion, our results provide a more complete picture on the return-volatility relation. Our empirical results also point out that return-volatility relation has a sight different pattern across volatility quantiles for overnight and daytime periods because high trading volumes make the affect heuristic more pronounced. Those findings raise some new awareness that investors have different risk attitude toward upside and downside volatility, more sensitive to losses than to gain, and affect heuristic make the U-shaped (inversed U-shaped) return-volatility relation for positive (negative) returns. Those findings can provide useful information for modeling the return-volatility relation and for future research.

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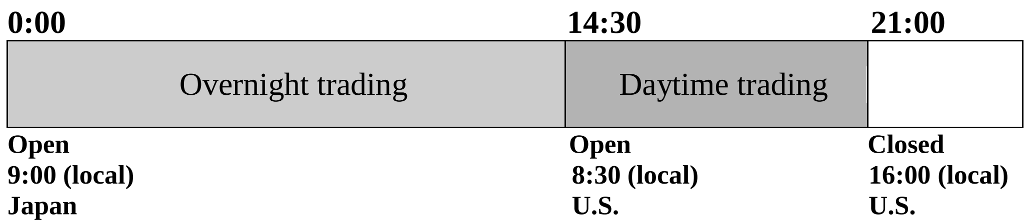
Figure 1. Timeline of Greenwich Mean Time (GMT) in U.S.



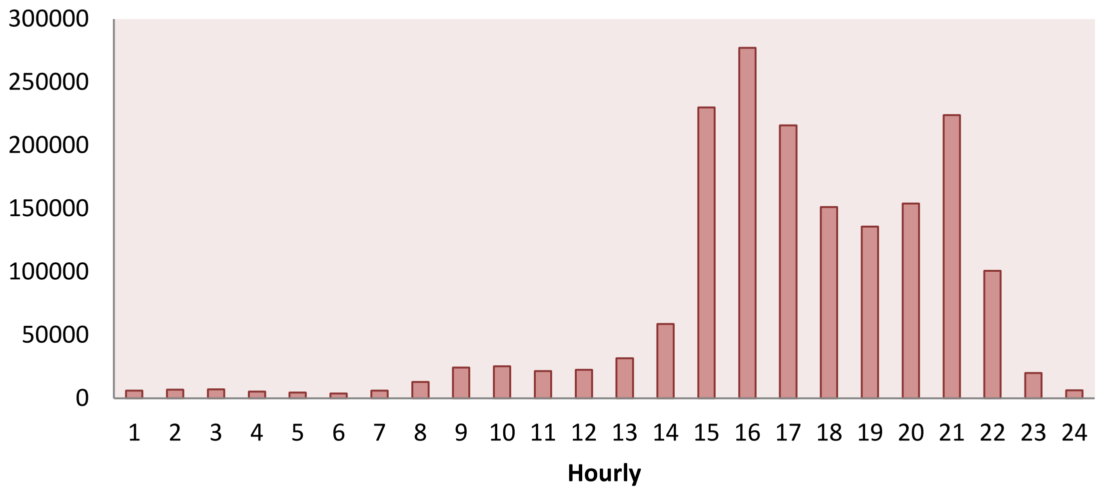




Figure 2 the mean of trading volume at each hour of **E-mini S&P 500 index** futures in CME from 4/12/2010 to 12/31/2015.

Table 1 Descriptive Statistics of **daily** and **intraday** frequencies for E-mini S&P index futures

| | daily | | Intraday (at 15-min interval) | | | |
|---|---|---|---|---|---|---|
| | full day | | Overnight trading | | Daytime trading | |
| | RET | RV | RET | RV | RET | RV |
| Mean | 0.0004 | 0.0092 | 0.006 [a] | 0.798 [a] | 0.007 [a] | 1.188 [a] |
| Median | 0.0008 | 0.0080 | 0.000 [a] | 0.640 [a] | 0.000 [a] | 1.026 [a] |
| Maximum | 0.0625 | 0.0520 | 24.554 [a] | 23.008 [a] | 17.593 [a] | 30.196 [a] |
| Minimum | -0.0589 | 0.0019 | -25.335 [a] | 0.000 [a] | -28.493 [a] | 0.000 [a] |
| Std. Dev. | 0.0100 | 0.0047 | 0.001 | 0.001 | 1.2980 | 0.7920 |
| Skewness | -0.3566 | 2.9649 | -0.131 | 5.649 | -0.110 | 4.0578 |
| Kurtosis | 7.529 | 18.211 | 43.928 | 96.119 | 20.928 | 69.854 |
| Observations | 1428 | 1428 | 85581 | 85581 | 38793 | 38793 |

"**a**" presents the value at $\times 10^{-3}$

Table 2 Quantile regression results for daily return-volatility relation (Cont.)

| Quantiles | intercept | $RV_{t-1}$ | $RV_{t-2}$ | $RV_{t-3}$ | $RET_t$ | $RET_{t-1}$ | $RET_{t-2}$ | $RET_{t-3}$ | Adj $R^2$ (%) |
|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Full sample** | | | | | | | | | |
| 0.05 | **0.002** | **0.311** | **0.118** | **0.103** | **-0.088** | **-0.065** | **-0.037** | -0.011 | 28.14 |
| | **(4.66)** | **(4.35)** | **(2.32)** | **(2.99)** | **(-2.19)** | **(-4.26)** | **(-2.69)** | (-0.72) | |
| 0.1 | **0.001** | **0.411** | **0.103** | **0.120** | **-0.090** | **-0.071** | **-0.018** | -0.009 | 34.76 |
| | **(5.99)** | **(7.83)** | **(2.30)** | **(3.47)** | **(-7.07)** | **(-6.80)** | **(-1.61)** | (-0.84) | |
| 0.15 | **0.001** | **0.433** | **0.134** | **0.105** | **-0.090** | **-0.070** | **-0.016** | -0.010 | 38.70 |
| | **(9.32)** | **(9.91)** | **(3.06)** | **(4.43)** | **(-9.66)** | **(-6.89)** | **(-1.81)** | (-1.60) | |
| 0.2 | **0.001** | **0.432** | **0.194** | **0.079** | **-0.091** | **-0.073** | **-0.018** | -0.016 | 41.42 |
| | **(6.94)** | **(8.35)** | **(4.12)** | **(2.87)** | **(-10.91)** | **(-6.50)** | **(-2.10)** | (-1.99) | |
| 0.25 | **0.001** | **0.452** | **0.205** | **0.078** | **-0.090** | **-0.076** | **-0.021** | -0.016 | 43.69 |
| | **(8.08)** | **(12.25)** | **(4.72)** | **(3.06)** | **(-11.66)** | **(-10.20)** | **(-2.62)** | (-1.97) | |
| 0.5 | **0.001** | **0.475** | **0.254** | **0.123** | **-0.090** | **-0.079** | -0.013 | -0.007 | 51.64 |
| | **(5.61)** | **(10.63)** | **(5.99)** | **(3.10)** | **(-12.63)** | **(-10.08)** | (-1.48) | (-0.86) | |
| 0.75 | **0.001** | **0.565** | **0.243** | **0.167** | **-0.085** | **-0.083** | -0.007 | -0.008 | 57.87 |
| | **(6.50)** | **(21.34)** | **(4.06)** | **(3.29)** | **(-10.67)** | **(-10.27)** | (-0.67) | (-0.94) | |
| 0.8 | **0.001** | **0.572** | **0.276** | **0.160** | **-0.083** | **-0.079** | 0.001 | -0.005 | 59.00 |
| | **(4.65)** | **(14.73)** | **(4.41)** | **(3.24)** | **(-9.72)** | **(-8.00)** | (0.08) | (-0.44) | |
| 0.85 | **0.001** | **0.660** | **0.234** | **0.162** | **-0.083** | **-0.070** | 0.010 | -0.013 | 60.13 |
| | **(5.87)** | **(10.10)** | **(4.41)** | **(3.33)** | **(-9.72)** | **(-6.81)** | (0.80) | (-1.37) | |
| 0.9 | **0.001** | **0.640** | **0.269** | **0.218** | **-0.092** | **-0.082** | 0.010 | -0.015 | 61.63 |
| | **(3.43)** | **(5.50)** | **(2.54)** | **(3.08)** | **(-8.56)** | **(-4.31)** | (0.73) | (-0.76) | |
| 0.95 | **0.001** | **0.690** | **0.310** | **0.213** | **-0.083** | **-0.087** | 0.018 | -0.003 | 63.32 |
| | **(2.45)** | **(6.80)** | **(5.12)** | **(3.55)** | **(-9.18)** | **(-4.17)** | (0.72) | (-0.13) | |
| OLS | **0.001** | **0.508** | **0.241** | **0.107** | **-0.093** | **-0.098** | -0.012 | -0.01 | 74.37 |
| | **(6.57)** | **(11.6)** | **(4.45)** | **(2.75)** | **(-6.43)** | **(-5.77)** | (-1.28) | (-1.08) | |

Table 2 Quantile regression results for daily return-volatility relation (Cont.)

| Quantiles | intercept | $RV_{t-1}$ | $RV_{t-2}$ | $RV_{t-3}$ | $RET_t$ | $RET_{t-1}$ | $RET_{t-2}$ | $RET_{t-3}$ | Adj $R^2$ (%) |
|---|---|---|---|---|---|---|---|---|---|
| **Panel B: Positive return subsample** | | | | | | | | | |
| 0.05 | **0.002** | **0.330** | **0.080** | **0.117** | 0.031 | **-0.043** | -0.038 | -0.015 | 24.95 |
| | **(8.67)** | **(5.34)** | **(1.95)** | **(3.95)** | (1.05) | **(-2.06)** | (-1.99) | (-0.86) | |
| 0.1 | **0.001** | **0.449** | **0.120** | **0.093** | -0.035 | **-0.074** | -0.030 | -0.013 | 29.86 |
| | **(5.90)** | **(8.20)** | **(1.95)** | **(2.13)** | (-1.25) | **(-3.67)** | (-1.64) | (-0.73) | |
| 0.15 | **0.001** | **0.492** | **0.145** | 0.066 | **-0.055** | **-0.083** | -0.019 | -0.005 | 33.30 |
| | **(6.78)** | **(10.95)** | **(2.74)** | (1.83) | **(-2.42)** | **(-3.98)** | (-1.07) | (-0.38) | |
| 0.2 | **0.001** | **0.539** | **0.158** | 0.063 | **-0.062** | **-0.085** | -0.012 | -0.014 | 35.94 |
| | **(4.99)** | **(9.69)** | **(2.94)** | (1.69) | **(-2.99)** | **(-4.21)** | (-0.73) | (-1.05) | |
| 0.25 | **0.001** | **0.563** | **0.190** | 0.072 | **-0.072** | **-0.093** | -0.020 | -0.010 | 38.40 |
| | **(4.16)** | **(11.63)** | **(3.25)** | (1.63) | **(-4.05)** | **(-5.33)** | (-1.32) | (-0.77) | |
| 0.5 | **0.001** | **0.606** | **0.234** | **0.089** | **-0.088** | **-0.094** | 0.001 | -0.006 | 46.94 |
| | **(5.59)** | **(11.60)** | **(7.68)** | **(2.59)** | **(-6.75)** | **(-5.93)** | (0.04) | (-0.51) | |
| 0.75 | **0.001** | **0.719** | **0.200** | **0.133** | **-0.069** | **-0.093** | 0.025 | 0.000 | 53.92 |
| | **(4.41)** | **(21.66)** | **(5.62)** | **(2.72)** | **(-4.65)** | **(-4.96)** | (1.39) | (0.02) | |
| 0.8 | **0.001** | **0.727** | **0.204** | **0.175** | **-0.063** | **-0.099** | 0.016 | -0.020 | 55.38 |
| | **(5.33)** | **(15.43)** | **(5.47)** | **(3.63)** | **(-3.66)** | **(-5.29)** | (0.88) | (-1.16) | |
| 0.85 | **0.001** | **0.722** | **0.263** | **0.148** | **-0.059** | **-0.097** | 0.013 | -0.029 | 56.75 |
| | **(6.37)** | **(11.21)** | **(5.24)** | **(3.11)** | **(-4.23)** | **(-5.56)** | (0.69) | (-1.83) | |
| 0.9 | **0.001** | **0.754** | **0.277** | **0.136** | **-0.070** | **-0.068** | 0.025 | -0.008 | 58.31 |
| | **(3.53)** | **(11.34)** | **(4.90)** | **(2.29)** | **(-3.57)** | **(-2.49)** | (0.96) | (-0.27) | |
| 0.95 | **0.001** | **0.896** | **0.242** | **0.176** | -0.025 | **-0.093** | 0.003 | 0.045 | 60.31 |
| | **(1.72)** | **(7.44)** | **(2.82)** | **(2.00)** | (-1.21) | **(-2.70)** | (0.09) | (1.68) | |
| OLS | **0.001** | **0.656** | **0.199** | 0.072 | **-0.055** | **-0.103** | -0.005 | -0.003 | 69.22 |
| | **(5.38)** | **(12.61)** | **(3.24)** | (1.55) | **(-2.33)** | **(-5.87)** | (-0.38) | (-0.18) | |

Table 2 Quantile regression results for daily return-volatility relation

| Quantiles | intercept | $RV_{t-1}$ | $RV_{t-2}$ | $RV_{t-3}$ | $RET_t$ | $RET_{t-1}$ | $RET_{t-2}$ | $RET_{t-3}$ | Adj $R^2$ (%) |
|---|---|---|---|---|---|---|---|---|---|
| **Panel C: Negative return subsample** | | | | | | | | | |
| 0.05 | **0.002** | **0.255** | **0.104** | 0.077 | **-0.170** | **-0.118** | **-0.042** | -0.009 | 33.20 |
| | **(4.91)** | **(4.76)** | **(2.59)** | (1.71) | **(-11.04)** | **(-5.51)** | **(-2.09)** | (-0.40) | |
| 0.1 | **0.002** | **0.333** | **0.117** | 0.051 | **-0.160** | **-0.106** | **-0.035** | -0.018 | 38.14 |
| | **(7.89)** | **(8.40)** | **(1.92)** | (1.10) | **(-10.29)** | **(-7.16)** | **(-2.17)** | (-0.74) | |
| 0.15 | **0.001** | **0.325** | **0.153** | **0.078** | **-0.164** | **-0.103** | **-0.027** | -0.018 | 41.28 |
| | **(9.52)** | **(8.34)** | **(3.32)** | **(3.19)** | **(-15.89)** | **(-7.76)** | **(-2.32)** | (-1.17) | |
| 0.2 | **0.002** | **0.311** | **0.181** | **0.074** | **-0.164** | **-0.118** | **-0.024** | -0.020 | 43.66 |
| | **(11.03)** | **(8.20)** | **(4.37)** | **(3.63)** | **(-17.01)** | **(-9.60)** | **(-2.20)** | (-1.72) | |
| 0.25 | **0.002** | **0.363** | **0.171** | **0.053** | **-0.163** | **-0.114** | -0.023 | -0.023 | 45.45 |
| | **(8.39)** | **(7.01)** | **(4.25)** | **(2.17)** | **(-15.04)** | **(-9.49)** | (-1.80) | (-1.78) | |
| 0.5 | **0.001** | **0.412** | **0.199** | **0.109** | **-0.157** | **-0.124** | -0.017 | -0.015 | 52.76 |
| | **(7.79)** | **(10.82)** | **(6.69)** | **(3.66)** | **(-15.43)** | **(-7.95)** | (-1.21) | (-1.27) | |
| 0.75 | **0.001** | **0.493** | **0.218** | **0.138** | **-0.163** | **-0.132** | -0.012 | -0.011 | 59.20 |
| | **(5.29)** | **(9.44)** | **(7.09)** | **(3.08)** | **(-12.09)** | **(-7.95)** | (-0.86) | (-0.68) | |
| 0.8 | **0.001** | **0.505** | **0.249** | **0.127** | **-0.167** | **-0.127** | 0.006 | -0.019 | 60.40 |
| | **(5.44)** | **(14.39)** | **(4.57)** | **(2.85)** | **(-9.73)** | **(-5.80)** | (0.44) | (-0.86) | |
| 0.85 | **0.001** | **0.509** | **0.243** | **0.170** | **-0.189** | **-0.153** | 0.016 | -0.016 | 61.82 |
| | **(5.67)** | **(7.20)** | **(3.46)** | **(3.30)** | **(-10.99)** | **(-6.39)** | (0.84) | (-0.89) | |
| 0.9 | **0.001** | **0.536** | **0.290** | **0.140** | **-0.184** | **-0.145** | 0.034 | -0.012 | 63.77 |
| | **(6.01)** | **(7.37)** | **(3.82)** | **(2.79)** | **(-10.42)** | **(-3.79)** | (1.25) | (-0.48) | |
| 0.95 | **0.001** | **0.607** | **0.303** | **0.146** | **-0.219** | **-0.208** | 0.032 | -0.001 | 65.96 |
| | **(2.74)** | **(6.50)** | **(4.33)** | **(2.50)** | **(-3.90)** | **(-5.82)** | (1.19) | (-0.01) | |
| OLS | **0.002** | **0.397** | **0.203** | **0.082** | **-0.194** | **-0.168** | -0.018 | -0.025 | 77.30 |
| | **(7.21)** | **(8.83)** | **(4.00)** | **(2.24)** | **(-8.11)** | **(-5.66)** | (-0.95) | (-1.46) | |

Table 5 Quantile regression results of intraday return-volatility relation at 15-mins interval for overnight and daytime trading periods **(Cont)**

| **Overnight trading period** | | | | | | | | | | **daytime trading period** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Quantiles | intercept | $RV_{t-1}$ | $RV_{t-2}$ | $RV_{t-3}$ | $RET_t$ | $RET_{t-1}$ | $RET_{t-2}$ | $RET_{t-3}$ | Adj $R^2$(%) | intercept | $RV_{t-1}$ | $RV_{t-2}$ | $RV_{t-3}$ | $RET_t$ | $RET_{t-1}$ | $RET_{t-2}$ | $RET_{t-3}$ | Adj $R^2$(%) |
| **Panel A: Full return** | | | | | | | | | | | | | | | | | | |
| 0.05 | **0.000** | **0.256** | **0.059** | **0.035** | 0.004 | **-0.007** | 0.001 | 0.001 | 16.69% | **-0.000** | **0.372** | **-0.087** | **0.159** | -0.008 | -0.013 | -0.008 | **-0.012** | 10.58 |
| | **(50.16)** | **(46.76)** | **(11.00)** | **(7.43)** | (0.34) | **(-2.36)** | (0.58) | (0.28) | | **(-2.86)** | **(26.85)** | **(-4.76)** | **(17.52)** | (-0.20) | (-1.38) | (-1.13) | **(-2.01)** | |
| 0.1 | **0.000** | **0.316** | **0.083** | **0.045** | 0.001 | **-0.008** | -0.004 | 0.000 | 20.91% | **0.000** | **0.382** | **0.052** | **0.126** | -0.021 | **-0.019** | **-0.013** | **-0.006** | 17.39 |
| | **(53.57)** | **(74.59)** | **(21.81)** | **(12.27)** | (0.09) | **(-2.97)** | (-1.96) | (-0.21) | | **(5.47)** | **(54.45)** | **(8.31)** | **(18.32)** | (-1.79) | **(-5.18)** | **(-3.58)** | **(-2.03)** | |
| 0.15 | **0.000** | **0.346** | **0.106** | **0.055** | 0.000 | **-0.011** | **-0.005** | 0.000 | 23.86% | **0.000** | **0.394** | **0.105** | **0.113** | **-0.023** | **-0.021** | **-0.011** | **-0.005** | 21.75 |
| | **(55.85)** | **(75.93)** | **(19.87)** | **(15.95)** | (-0.01) | **(-4.98)** | **(-2.65)** | (-0.07) | | **(10.07)** | **(51.44)** | **(11.57)** | **(16.60)** | **(-2.79)** | **(-7.07)** | **(-3.31)** | **(-2.00)** | |
| 0.2 | **0.000** | **0.375** | **0.120** | **0.063** | -0.006 | **-0.013** | **-0.007** | -0.001 | 26.17% | **0.000** | **0.414** | **0.133** | **0.103** | **-0.026** | **-0.022** | **-0.012** | -0.004 | 24.84 |
| | **(51.86)** | **(77.58)** | **(33.24)** | **(21.88)** | (-1.24) | **(-5.95)** | **(-3.83)** | (-0.38) | | **(17.72)** | **(60.48)** | **(18.55)** | **(19.91)** | **(-4.68)** | **(-8.02)** | **(-4.85)** | (-1.79) | |
| 0.25 | **0.000** | **0.398** | **0.137** | **0.066** | -0.006 | **-0.013** | **-0.008** | -0.001 | 28.13% | **0.000** | **0.434** | **0.149** | **0.104** | **-0.026** | **-0.024** | **-0.012** | **-0.006** | 27.25 |
| | **(50.06)** | **(74.91)** | **(27.62)** | **(19.49)** | (-1.38) | **(-5.64)** | **(-3.90)** | (-0.51) | | **(18.22)** | **(65.25)** | **(21.87)** | **(19.22)** | **(-6.02)** | **(-8.87)** | **(-4.81)** | **(-2.93)** | |
| 0.5 | **0.000** | **0.489** | **0.197** | **0.095** | **-0.009** | **-0.017** | **-0.008** | 0.000 | 35.72% | **0.000** | **0.499** | **0.204** | **0.112** | **-0.025** | **-0.026** | **-0.009** | **-0.006** | 34.35 |
| | **(50.75)** | **(75.99)** | **(34.71)** | **(20.96)** | **(-3.46)** | **(-7.85)** | **(-4.18)** | (-0.25) | | **(28.87)** | **(69.77)** | **(30.67)** | **(18.77)** | **(-8.36)** | **(-10.59)** | **(-3.82)** | **(-2.90)** | |
| 0.75 | **0.000** | **0.601** | **0.276** | **0.132** | **-0.011** | **-0.020** | **-0.008** | -0.002 | 42.47% | **0.000** | **0.557** | **0.253** | **0.139** | **-0.027** | **-0.033** | **-0.016** | **-0.007** | 37.88 |
| | **(32.57)** | **(81.72)** | **(32.71)** | **(18.16)** | **(-4.37)** | **(-8.23)** | **(-2.95)** | (-0.60) | | **(31.09)** | **(70.23)** | **(30.61)** | **(17.93)** | **(-10.66)** | **(-11.74)** | **(-5.31)** | **(-2.26)** | |
| 0.8 | **0.000** | **0.631** | **0.294** | **0.145** | **-0.011** | **-0.021** | -0.005 | -0.001 | 43.83% | **0.000** | **0.565** | **0.265** | **0.144** | **-0.029** | **-0.035** | **-0.017** | **-0.009** | 38.21 |
| | **(33.64)** | **(62.79)** | **(29.42)** | **(15.93)** | **(-4.89)** | **(-7.80)** | (-1.51) | (-0.25) | | **(35.43)** | **(61.48)** | **(29.76)** | **(16.90)** | **(-11.03)** | **(-11.77)** | **(-5.22)** | **(-2.77)** | |
| 0.85 | **0.000** | **0.670** | **0.316** | **0.165** | **-0.013** | **-0.022** | -0.006 | 0.002 | 45.09% | **0.000** | **0.555** | **0.279** | **0.155** | **-0.030** | **-0.039** | **-0.019** | **-0.008** | 38.32 |
| | **(28.62)** | **(71.00)** | **(30.38)** | **(17.05)** | **(-5.53)** | **(-7.39)** | (-1.63) | (0.42) | | **(30.93)** | **(65.66)** | **(33.53)** | **(18.08)** | **(-11.99)** | **(-11.22)** | **(-5.01)** | **(-2.00)** | |
| 0.9 | **0.000** | **0.721** | **0.361** | **0.190** | **-0.013** | **-0.022** | -0.004 | 0.005 | 46.20% | **0.000** | **0.529** | **0.301** | **0.187** | **-0.024** | **-0.040** | **-0.024** | -0.011 | 38.00 |
| | **(20.29)** | **(48.84)** | **(20.89)** | **(12.09)** | **(-5.48)** | **(-4.66)** | (-0.79) | (0.96) | | **(33.66)** | **(35.20)** | **(23.02)** | **(12.86)** | **(-7.01)** | **(-6.40)** | **(-4.21)** | (-1.72) | |
| 0.95 | **0.000** | **0.839** | **0.419** | **0.256** | **-0.017** | **-0.029** | -0.013 | 0.012 | 47.05% | **0.001** | **0.472** | **0.345** | **0.225** | **-0.031** | **-0.045** | **-0.034** | -0.006 | 37.23 |
| | **(14.49)** | **(31.91)** | **(17.65)** | **(8.53)** | **(-5.00)** | **(-4.35)** | (-1.43) | (1.29) | | **(41.91)** | **(45.73)** | **(25.15)** | **(10.61)** | **(-9.11)** | **(-10.22)** | **(-4.34)** | (-0.68) | |
| OLS | **0.000** | **0.491** | **0.196** | **0.101** | -0.014 | **-0.023** | -0.010 | 0.004 | 50.98% | **0.000** | **0.479** | **0.186** | **0.124** | **-0.020** | **-0.037** | **-0.019** | **-0.009** | 51.80 |
| | **(22.50)** | **(43.44)** | **(22.16)** | **(13.03)** | (-1.38) | **(-4.36)** | (-1.94) | (0.84) | | **(22.30)** | **(28.67)** | **(12.43)** | **(14.14)** | **(-2.96)** | **(-3.34)** | **(-3.40)** | **(-2.50)** | |

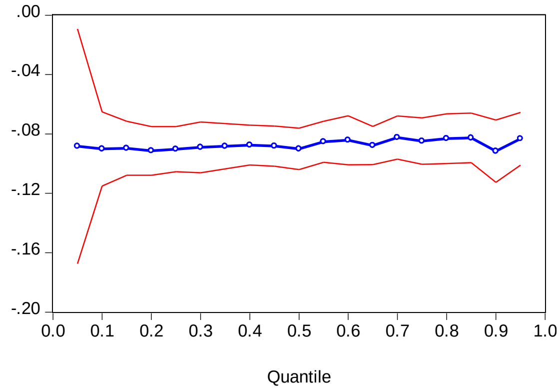
Table 5 Quantile regression results of intraday return-volatility relation at 15-mins interval for overnight and daytime trading periods **(Cont)**

| **Overnight trading period** | | | | | | | | | | **daytime trading period** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Quantiles | intercept | $RV_{t-1}$ | $RV_{t-2}$ | $RV_{t-3}$ | $RET_t^+$ | $RET_{t-1}^+$ | $RET_{t-2}^+$ | $RET_{t-3}^+$ | Adj $R^2$(%) | intercept | $RV_{t-1}$ | $RV_{t-2}$ | $RV_{t-3}$ | $RET_t^+$ | $RET_{t-1}^+$ | $RET_{t-2}^+$ | $RET_{t-3}^+$ | Adj $R^2$(%) |
| **Panel B: Positive return** | | | | | | | | | | | | | | | | | | |
| 0.05 | **0.000** | **0.218** | **0.048** | **0.028** | **0.208** | **0.011** | **0.010** | **0.009** | 20.40% | -0.000 | **0.248** | **-0.061** | **0.137** | **0.319** | -0.006 | **-0.017** | **-0.038** | 17.37 |
| | **(53.64)** | **(50.55)** | **(9.74)** | **(17.48)** | **(33.82)** | **(2.65)** | **(2.00)** | **(2.61)** | | (-0.47) | **(24.34)** | **(-5.07)** | **(18.07)** | **(48.97)** | (-0.62) | **(-2.95)** | **(-5.64)** | |
| 0.1 | **0.000** | **0.276** | **0.075** | **0.035** | **0.190** | **0.010** | 0.004 | 0.002 | 24.02% | **0.000** | **0.337** | **0.048** | **0.116** | **0.203** | -0.007 | -0.014 | **-0.028** | 20.64 |
| | **(53.05)** | **(51.95)** | **(15.39)** | **(9.96)** | **(41.56)** | **(2.45)** | (1.17) | (0.74) | | **(5.60)** | **(44.27)** | **(5.98)** | **(15.54)** | **(30.70)** | (-1.08) | (-1.87) | **(-3.84)** | |
| 0.15 | **0.000** | **0.313** | **0.090** | **0.046** | **0.181** | **0.009** | 0.001 | 0.003 | 26.66% | **0.000** | **0.364** | **0.087** | **0.103** | **0.171** | **-0.010** | **-0.013** | **-0.014** | 24.18 |
| | **(58.51)** | **(67.17)** | **(27.06)** | **(15.04)** | **(46.59)** | **(2.94)** | (0.20) | (1.09) | | **(13.29)** | **(48.58)** | **(11.81)** | **(18.18)** | **(32.74)** | **(-2.12)** | **(-2.92)** | **(-3.81)** | |
| 0.2 | **0.000** | **0.339** | **0.107** | **0.053** | **0.177** | **0.009** | -0.002 | 0.002 | 28.77% | **0.000** | **0.390** | **0.119** | **0.096** | **0.150** | **-0.013** | **-0.013** | **-0.012** | 26.80 |
| | **(57.02)** | **(68.04)** | **(22.10)** | **(14.41)** | **(46.10)** | **(2.59)** | (-0.59) | (0.68) | | **(15.80)** | **(55.80)** | **(17.35)** | **(16.19)** | **(30.95)** | **(-2.67)** | **(-3.28)** | **(-2.71)** | |
| 0.25 | **0.000** | **0.360** | **0.121** | **0.060** | **0.172** | **0.009** | -0.001 | 0.001 | 30.59% | **0.000** | **0.411** | **0.139** | **0.096** | **0.139** | **-0.015** | **-0.012** | **-0.007** | 28.89 |
| | **(53.90)** | **(64.81)** | **(24.54)** | **(15.92)** | **(45.12)** | **(2.71)** | (-0.43) | (0.37) | | **(18.20)** | **(58.15)** | **(19.87)** | **(16.22)** | **(30.50)** | **(-3.80)** | **(-2.53)** | **(-1.90)** | |
| 0.5 | **0.000** | **0.451** | **0.181** | **0.088** | **0.170** | 0.006 | -0.001 | -0.001 | 37.82% | **0.000** | **0.490** | **0.189** | **0.114** | **0.125** | **-0.024** | **-0.009** | **-0.008** | 35.48 |
| | **(53.01)** | **(69.78)** | **(29.76)** | **(17.75)** | **(47.53)** | (1.82) | (-0.30) | (-0.31) | | **(25.94)** | **(71.10)** | **(26.29)** | **(17.29)** | **(30.38)** | **(-5.40)** | **(-2.25)** | **(-2.38)** | |
| 0.75 | **0.000** | **0.567** | **0.247** | **0.122** | **0.195** | 0.000 | 0.002 | 0.001 | 44.59% | **0.000** | **0.544** | **0.254** | **0.127** | **0.146** | **-0.033** | **-0.021** | **-0.011** | 39.01 |
| | **(42.42)** | **(74.33)** | **(35.37)** | **(15.34)** | **(40.86)** | (-0.02) | (0.47) | (0.26) | | **(31.29)** | **(56.43)** | **(28.19)** | **(14.50)** | **(28.12)** | **(-6.49)** | **(-3.91)** | **(-2.05)** | |
| 0.8 | **0.000** | **0.602** | **0.268** | **0.130** | **0.209** | 0.000 | 0.004 | 0.000 | 46.02% | **0.000** | **0.556** | **0.268** | **0.134** | **0.156** | **-0.042** | **-0.027** | **-0.013** | 39.44 |
| | **(34.78)** | **(64.80)** | **(24.75)** | **(16.58)** | **(39.80)** | (-0.04) | (0.64) | (0.02) | | **(30.05)** | **(58.73)** | **(31.63)** | **(16.64)** | **(33.52)** | **(-7.61)** | **(-4.97)** | **(-2.35)** | |
| 0.85 | **0.000** | **0.636** | **0.292** | **0.144** | **0.227** | -0.003 | 0.001 | 0.001 | 47.47% | **0.000** | **0.559** | **0.284** | **0.145** | **0.171** | **-0.052** | **-0.030** | **-0.014** | 39.67 |
| | **(28.07)** | **(54.38)** | **(22.99)** | **(13.97)** | **(45.40)** | (-0.59) | (0.24) | (0.14) | | **(29.35)** | **(55.55)** | **(24.57)** | **(10.94)** | **(23.38)** | **(-8.83)** | **(-4.51)** | **(-2.20)** | |
| 0.9 | **0.000** | **0.691** | **0.315** | **0.172** | **0.252** | -0.008 | 0.004 | 0.001 | 48.85% | **0.000** | **0.539** | **0.308** | **0.163** | **0.193** | **-0.058** | **-0.039** | **-0.012** | 39.73 |
| | **(23.99)** | **(53.50)** | **(20.01)** | **(12.80)** | **(60.73)** | (-1.10) | (0.47) | (0.10) | | **(36.20)** | **(64.92)** | **(34.45)** | **(17.20)** | **(19.15)** | **(-7.18)** | **(-5.14)** | **(-1.59)** | |
| 0.95 | **0.000** | **0.803** | **0.402** | **0.212** | **0.322** | -0.039 | -0.012 | 0.002 | 50.16% | **0.001** | **0.509** | **0.332** | **0.203** | **0.228** | **-0.066** | **-0.048** | **-0.003** | 39.31 |
| | **(12.72)** | **(38.62)** | **(14.90)** | **(9.97)** | **(39.59)** | (-3.47) | (-0.92) | (0.10) | | **(40.64)** | **(44.89)** | **(25.23)** | **(11.64)** | **(18.76)** | **(-6.96)** | **(-2.83)** | **(-0.28)** | |
| OLS | **0.000** | **0.450** | **0.170** | **0.085** | **0.248** | -0.004 | 0.000 | 0.006 | 55.72% | **0.000** | **0.467** | **0.183** | **0.112** | **0.183** | **-0.034** | **-0.031** | **-0.018** | 57.85 |
| | **(23.60)** | **(36.58)** | **(18.67)** | **(11.54)** | **(16.87)** | (-0.48) | (0.00) | (0.89) | | **(22.67)** | **(26.15)** | **(13.01)** | **(10.06)** | **(13.31)** | **(-4.24)** | **(-3.46)** | **(-2.69)** | |

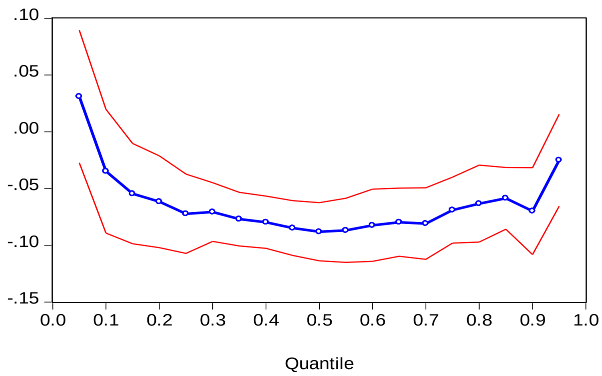
Table 5 Quantile regression results of intraday return-volatility relation at 15-mins interval for overnight and daytime trading periods

| **Overnight trading period** | | | | | | | | | | **daytime trading period** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Quantiles | intercept | $RV_{t-1}$ | $RV_{t-2}$ | $RV_{t-3}$ | $RET_t^+$ | $RET_{t-1}^+$ | $RET_{t-2}^+$ | $RET_{t-3}^+$ | Adj $R^2$(%) | intercept | $RV_{t-1}$ | $RV_{t-2}$ | $RV_{t-3}$ | $RET_t^+$ | $RET_{t-1}^+$ | $RET_{t-2}^+$ | $RET_{t-3}^+$ | Adj $R^2$(%) |
| **Panel C: Negative return** | | | | | | | | | | | | | | | | | | |
| 0.05 | **0.000** | **0.211** | **0.052** | **0.034** | **-0.210** | **-0.029** | -0.005 | 0.002 | 20.34% | -0.000 | **0.266** | **-0.087** | **0.140** | **-0.324** | -0.012 | 0.001 | 0.020 | 17.76 |
| | **(51.77)** | **(43.56)** | **(13.97)** | **(13.44)** | **(-38.10)** | **(-5.32)** | (-1.21) | (0.49) | | (-1.08) | **(17.15)** | **(-7.48)** | **(15.25)** | **(-45.03)** | (-0.80) | (0.10) | (1.82) | |
| 0.1 | **0.000** | **0.266** | **0.068** | **0.042** | **-0.195** | **-0.036** | **-0.014** | -0.004 | 24.17% | **0.000** | **0.315** | **0.029** | **0.114** | **-0.228** | **-0.038** | -0.013 | 0.005 | 21.67 |
| | **(57.10)** | **(54.27)** | **(16.50)** | **(15.45)** | **(-45.33)** | **(-9.42)** | **(-4.72)** | (-1.04) | | **(7.34)** | **(32.22)** | **(3.07)** | **(17.10)** | **(-42.66)** | **(-6.09)** | (-1.83) | (1.00) | |
| 0.15 | **0.000** | **0.301** | **0.083** | **0.052** | **-0.185** | **-0.042** | **-0.015** | -0.006 | 26.92% | **0.000** | **0.342** | **0.077** | **0.098** | **-0.203** | **-0.034** | **-0.016** | -0.001 | 25.39 |
| | **(60.96)** | **(78.08)** | **(20.43)** | **(15.54)** | **(-44.90)** | **(-13.60)** | **(-4.68)** | (-1.68) | | **(14.57)** | **(44.83)** | **(9.07)** | **(14.41)** | **(-46.24)** | **(-7.27)** | **(-3.03)** | (-0.13) | |
| 0.2 | **0.000** | **0.324** | **0.103** | **0.056** | **-0.185** | **-0.045** | **-0.014** | -0.005 | 29.14% | **0.000** | **0.357** | **0.106** | **0.096** | **-0.195** | **-0.037** | **-0.019** | -0.006 | 28.21 |
| | **(60.33)** | **(68.13)** | **(19.82)** | **(15.25)** | **(-63.35)** | **(-15.09)** | **(-4.16)** | (-1.80) | | **(16.54)** | **(44.59)** | **(13.98)** | **(15.65)** | **(-39.77)** | **(-7.95)** | **(-3.94)** | (-1.44) | |
| 0.25 | **0.000** | **0.349** | **0.117** | **0.060** | **-0.185** | **-0.047** | **-0.017** | -0.003 | 31.05% | **0.000** | **0.374** | **0.125** | **0.096** | **-0.187** | **-0.041** | **-0.020** | -0.003 | 30.43 |
| | **(58.61)** | **(75.34)** | **(25.90)** | **(18.68)** | **(-51.55)** | **(-16.21)** | **(-5.37)** | (-1.03) | | **(24.98)** | **(50.28)** | **(17.44)** | **(18.04)** | **(-43.91)** | **(-8.66)** | **(-5.10)** | (-1.04) | |
| 0.5 | **0.000** | **0.432** | **0.175** | **0.080** | **-0.197** | **-0.054** | **-0.021** | -0.004 | 38.58% | **0.000** | **0.440** | **0.180** | **0.103** | **-0.185** | **-0.050** | **-0.019** | -0.006 | 37.44 |
| | **(53.40)** | **(82.47)** | **(28.17)** | **(17.89)** | **(-48.23)** | **(-15.58)** | **(-6.57)** | (-1.38) | | **(31.18)** | **(65.61)** | **(31.88)** | **(17.25)** | **(-44.98)** | **(-13.12)** | **(-4.77)** | (-1.47) | |
| 0.75 | **0.000** | **0.529** | **0.239** | **0.119** | **-0.233** | **-0.061** | **-0.019** | -0.002 | 45.62% | **0.000** | **0.485** | **0.216** | **0.133** | **-0.219** | **-0.061** | **-0.021** | -0.009 | 41.43 |
| | **(41.39)** | **(70.73)** | **(28.40)** | **(15.34)** | **(-58.26)** | **(-13.87)** | **(-3.91)** | (-0.44) | | **(30.15)** | **(57.75)** | **(26.75)** | **(17.24)** | **(-36.92)** | **(-10.27)** | **(-3.91)** | (-1.79) | |
| 0.8 | **0.000** | **0.559** | **0.258** | **0.128** | **-0.245** | **-0.060** | **-0.019** | -0.005 | 47.07% | **0.000** | **0.493** | **0.229** | **0.138** | **-0.229** | **-0.063** | **-0.026** | -0.010 | 41.99 |
| | **(27.94)** | **(62.37)** | **(22.26)** | **(12.43)** | **(-65.04)** | **(-11.55)** | **(-2.83)** | (-0.84) | | **(39.85)** | **(56.98)** | **(28.42)** | **(19.28)** | **(-47.75)** | **(-11.83)** | **(-5.46)** | (-1.89) | |
| 0.85 | **0.000** | **0.587** | **0.288** | **0.142** | **-0.267** | **-0.059** | **-0.019** | -0.001 | 48.60% | **0.000** | **0.490** | **0.246** | **0.148** | **-0.253** | **-0.065** | **-0.026** | -0.009 | 42.36 |
| | **(32.21)** | **(53.43)** | **(26.20)** | **(14.00)** | **(-58.87)** | **(-9.56)** | **(-2.80)** | (-0.21) | | **(29.47)** | **(48.04)** | **(27.99)** | **(15.77)** | **(-83.63)** | **(-8.67)** | **(-4.03)** | (-1.35) | |
| 0.9 | **0.000** | **0.643** | **0.323** | **0.161** | **-0.298** | **-0.055** | -0.018 | 0.008 | 50.10% | **0.000** | **0.468** | **0.274** | **0.164** | **-0.282** | **-0.068** | **-0.026** | -0.008 | 42.51 |
| | **(21.00)** | **(47.63)** | **(20.49)** | **(11.39)** | **(-46.00)** | **(-6.55)** | (-1.92) | (0.83) | | **(37.48)** | **(57.97)** | **(27.82)** | **(18.41)** | **(-51.94)** | **(-10.53)** | **(-2.93)** | (-1.04) | |
| 0.95 | **0.000** | **0.717** | **0.378** | **0.242** | **-0.371** | **-0.058** | -0.015 | 0.022 | 51.65% | **0.001** | **0.414** | **0.312** | **0.210** | **-0.328** | **-0.082** | **-0.030** | -0.004 | 42.21 |
| | **(14.22)** | **(29.39)** | **(14.03)** | **(9.48)** | **(-43.53)** | **(-5.93)** | (-1.79) | (1.87) | | **(36.08)** | **(39.68)** | **(18.85)** | **(9.76)** | **(-29.01)** | **(-7.11)** | **(-2.42)** | (-0.28) | |
| OLS | **0.000** | **0.411** | **0.168** | **0.088** | **-0.277** | **-0.060** | -0.023 | 2.63E-05 | 57.38% | **0.000** | **0.409** | **0.158** | **0.111** | **-0.225** | **-0.073** | **-0.023** | -0.005 | 56.84 |
| | **(25.07)** | **(31.74)** | **(20.12)** | **(12.18)** | **(-22.04)** | **(-5.84)** | (-2.36) | (0.004) | | **(23.44)** | **(38.30)** | **(8.64)** | **(14.22)** | **(-37.73)** | **(-2.89)** | **(-2.22)** | (-0.78) | |

Panel A: full return (RET)




Panel B: positive return ($RET^{+}$)




Panel C: negative returns ($RET^{-}$)

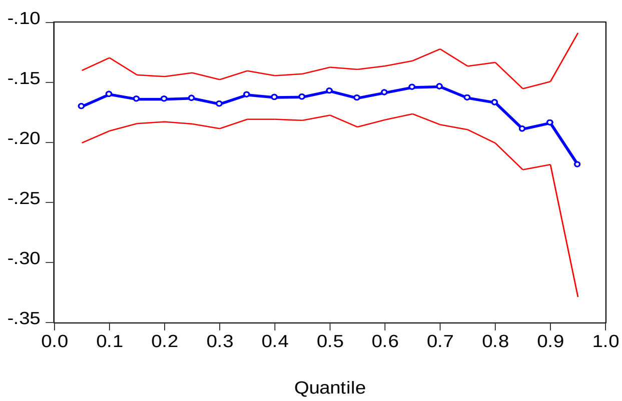



Figure 3 Quantile regression plot of the return and realized volatility relation at daily frequency. The quantiles of the volatility distributions are on the *x*-asix with lower quantiles at the left and the coefficients of daily contemporaneous returns are on the *y*-axix. The dark blue line shows the actual estiamtes and the red lines show the 95% confidence limits.

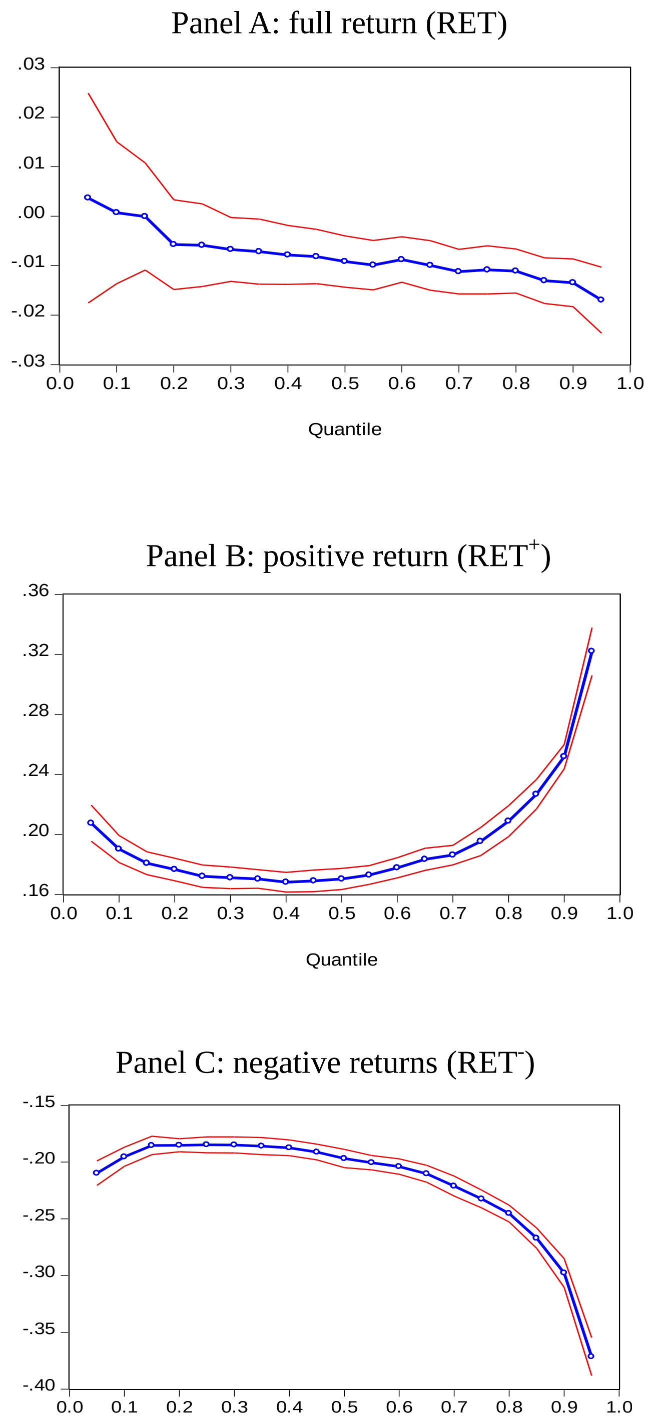



Figure 4 Quantile regression plot of the intraday return-volatility relation at 15-mins interval **in overnight trading period**. The quantiles of the volatility distribution are on the *x*-asix with lower quantiles at the left and the coefficients of contemporaneous returns are on the *y*-axix. The dark blue line shows the actual estimates and the red lines show the 95% confidence limits.

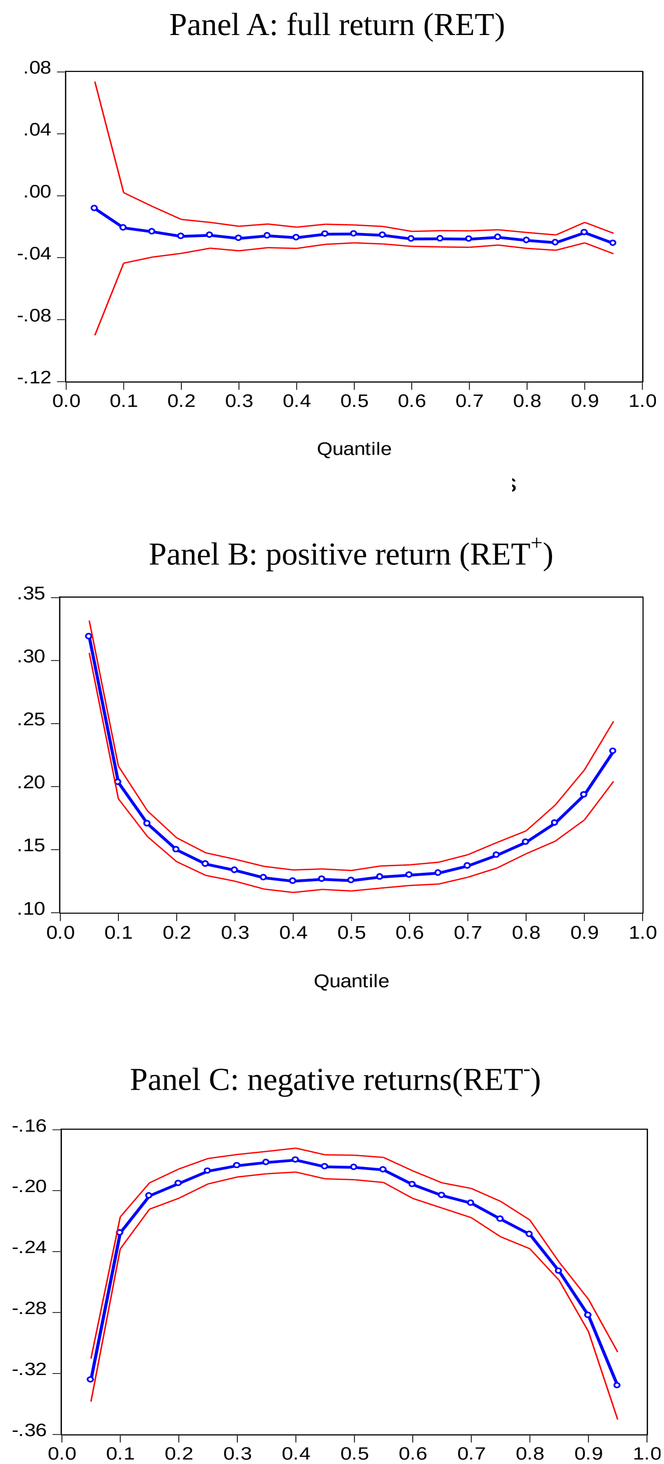



Figure 5 Quantile regression plot of the intraday return-volatility relation at 15-mins interval **in daytime trading period**. The quantiles of the volatility distribution are on the *x*-asix with lower quantiles and the left and the coefficients of contemporaneous return are on the *y*-axix. The dark line shows the actual estimates and the red lines show the 95% confidence limits.