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Asymmetries of the intraday return-volatility relation

Ihsan Badshah [a,*], Bart Frijns [a], Johan Knif [b], Alireza Tourani-Rad [a]

[a] Department of Finance, Auckland University of Technology, Private Bag 92006, Auckland 1142, New Zealand
[b] Department of Finance and Statistics, Hanken School of Economics, P.O. BOX 287, Vaasa 65100, Finland

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ABSTRACT

This study investigates the asymmetry of the intraday return-volatility relation at different return horizons ranging from 1, 5, 10, 15, up to 60 min and compares the empirical results with results for the daily return horizon. Using data on the S&P 500 (SPX) and the VIX from September 25, 2003 to December 30, 2011 and a Quantile-Regression approach, we observe strong negative return-volatility relation over all return horizons. However, this negative relation is asymmetric in three different aspects. First, the effects of positive and negative returns on volatility are different and more pronounced for negative returns. Second, for both positive and negative returns, the effect is conditional on the distribution of volatility changes. The absolute effect is up to five times larger in the extreme tails of the distribution. Third, at the intraday level, there is evidence of both autocorrelation in volatility changes and cross-autocorrelation with returns. This lead-lag relation with returns is also very asymmetric and more pronounced in the tails of the distribution. These effects are, however, not observed at the daily return horizon.

1. Introduction

The relation between risk and return is a fundamental principle in finance and has extensively been examined in the past four decades (Markowitz & Blay, 2013). Moreover, the relation between volatility and equity returns has commonly been documented to be asymmetric. Returns and volatility are negatively related and this relation is more prominent for negative returns (Bekaert & Wu, 2000; Black, 1976; Christie, 1982; French, Schwert, & Stambaugh, 1987).

In this paper, we take a new look at the risk and return relation by examining the intra-daily effects of negative and positive stock index returns over various parts of the conditional volatility index (VIX) distribution. Our approach allows us to investigate the cases of extreme asymmetric volatility in more depth. As the level of volatility increases, e.g. during financial crises, it is expected that the negative asymmetric return-volatility relation will be significantly more pronounced in the extreme parts of the conditional VIX distribution than what traditional models, e.g., the Ordinary Least Squares (OLS), will predict. Our methodology, Quantile Regression analysis, allows modelling of the return-volatility relation with emphasis on different parts of the conditional volatility distribution, including the extreme tails. By using a combination of the robust Quantile Regression approach and a data set of varying high-frequency returns and VIX, our study is able to monitor the strong contemporaneous negative asymmetric return-volatility relation across the conditional VIX distribution. Well-known hypotheses put forward in the literature for this relation, such as the *leverage effect* and the *volatility feedback effect*, have not been able to completely characterize such a strong contemporaneous relation at stock index level. Additional investigation of the asymmetric relationship between equity returns and volatility is vital as it has important implications for asset pricing models, option pricing and risk management practices.

The use of high frequency data, which we believe is the first time used in the literature to investigate the relation between index return and implied volatility, has enabled us to reveal several aspects of this relation that are not discernable using daily data as in the existing literature. Overall, we observe that the strength of the asymmetric return-volatility relation increases with the return horizon and is strongest for daily returns. We further note that the asymmetry increases monotonically from the median to the tails of the distribution. As a consequence, OLS analysis will underestimate the asymmetry of this relation beyond the median. Moreover, results based on OLS reveals no asymmetry in the relation at higher frequencies, e.g., 1 m interval, whereas results using Quantile Regression shows that there is a strong asymmetric return-volatility relation in the tails of the conditional VIX

* Corresponding author.
E-mail addresses: ibadshah@aut.ac.nz (I. Badshah), bfrijns@aut.ac.nz (B. Frijns), jknif@hanken.fi (J. Knif), atourani@aut.ac.nz (A. Tourani-Rad).

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distribution. At higher frequencies lagged effects also become more pronounced. Finally, across all frequencies, we find that OLS analysis underestimates the stronger relation in the tails of the distribution.

The remainder of the paper is structured as follows. Section 2 briefly reviews the literature on the return-volatility relation. Section 3 discusses the data used in the study and Section 4 presents the methodology applied. Section 5 reports on the results and Section 6 finally summarizes and concludes.

2. The asymmetric return-volatility relation

2.1. The leverage and volatility feedback explanations

Black (1976) and Christie (1982) attribute the asymmetric return-volatility relation to the financial leverage of a firm. The hypothesis they put forward is *the leverage effect*: a decline in the value of the stock increases a firm's leverage, as a result the firm's debt/equity ratio increases, which increases firm's risk level. As the risk level increases, the volatility of the equity is also expected to increase. In contrast, French et al. (1987), Campbell and Hentschel (1992), and Bekaert and Wu (2000), attribute the asymmetric return-volatility relation to the volatility feedback effect.[1] The hypothesis they put forward is that if volatility is priced, an expected increase in volatility raises the expected returns on equity leading to an immediate stock price decline to reflect the increase in risk. It states that increases in volatility imply that required future returns will increase and, as a result, current stock prices decline. These firm's fundamental-based explanations for the asymmetric volatility fail to characterize the strong negative asymmetric return-volatility relation at stock index level at high frequencies such as daily or higher frequencies.[2]

There is an abundance of studies that examine the return-volatility relation. However, empirical studies on the asymmetric return-implied volatility relation are relatively recent and fewer in number (including Fleming, Ostdiek, & Whaley, 1995; Whaley, 2000; Low, 2004; Giot, 2005; Dennis, Mayhew, & Stivers, 2006; Hibbert, Daigler, & Dupoyet, 2008; Frijns, Tallau, & Tourani-Rad, 2010; Allen et al., 2012; Badshah, 2013; Agbeyegbe, 2016). Fleming et al. (1995) are the first to investigate the relation between S&P 100 (OEX) returns and VXO (the predecessor of VIX) changes, they document a strong negative contemporaneous relation between implied volatility changes and returns. However, they find other lags to be insignificant or marginally significant.[3] Low (2004) attempts to explain this strong negative contemporaneous asymmetric return-implied volatility relation between OEX returns and VXO changes by the behavioral theory of loss-aversion (Kahneman & Tversky, 1979), in which the impact of losses is higher than gains. He confirms the strong negative contemporaneous asymmetric return-implied volatility relation and finds the relation to be nonlinear, its shape can be best described as a downward sloping reclined S-curve. The negative (positive) returns have convex (concave) profiles. Convexity (concavity) implies accelerating increases (decreases) in the VXO. Hibbert et al. (2008) examine the negative asymmetric return- implied volatility relation between the SPX (NASDAQ-100 index, NDX) returns and changes in the VIX (VXN) at intraday and daily frequencies. They find a stronger negative asymmetric return-implied volatility relation contemporaneously than at lags, and conclude that explanations such as leverage and volatility feedback hypotheses cannot explain this strong relation as the effect of return on volatility, and vice versa, should involve longer lags at lower frequencies than at higher frequencies.[4] Dennis et al. (2006) provide evidence that the negative asymmetric return-implied volatility relation is a market-wide phenomenon rather than an individual stock-level characteristic. Badshah (2013), using Quantile Regression models, examines the asymmetric return-volatility relation at the daily frequency for several stock market indexes. He observes strong negative asymmetric return-volatility relation in the tails of the conditional volatility changes distribution, and finds that OLS underestimates (overestimates) this relation in the positive (negative) tail of the conditional volatility changes distribution.

In this paper, we explore the intraday asymmetric return-volatility relation at high frequencies using Quantile Regressions. Agbeyegbe (2016) examines the return implied volatility relation for the US stock market indices (Dow Jones 30, S&P 500, and NASDAQ100) using linear quantile regression and copula quantile regression methods, and finds that the return-volatility relation depends on the quantile being examined, and this relation is found to be of inverted U-shape.[5]

2.2. Investor heterogeneity and the return-volatility relation

The new VIX uses a cross-section of strike prices, and therefore captures market-wide investor sentiment (errors in investors' beliefs) of fear and exuberance. In the stock market, usually investors have different beliefs about fundamentals of a firm and as a result we observe different stock price forecasts. Differences in beliefs are usually higher in down-market than in up-market conditions.[6] Shefrin (2008), for example, through survey data, finds that investors have heterogeneous beliefs which play an important role in asset pricing. He shows that the expected returns in the US stock market are not uni-modal, but bimodal and fat-tailed. He attributes these clusters to the two types of extreme beliefs that manifest themselves in the tails of the distributions. The right-end tail of the distribution represents the extreme beliefs of optimistic investors and the left-end tail represents the extreme beliefs of pessimistic investors. The optimistic investors (pessimistic investors) overestimate (underestimate) expected returns and underestimate (overestimate) volatility. These survey results are consistent with the view that institutional investors, being pessimists, would buy out of the money (OTM) put options to hedge their underlying portfolios. This buying pressure for OTM put options increases their prices beyond the efficient level. This finding is consistent with Bollen and Whaley's (2004) and Han (2008) who find skewed volatilities across the strike prices are purely caused by the demand for OTM put options. Earlier, Jackwerth and Rubinstein (1996) observe a skew in the implied volatility across different strike prices, which they attribute to the fear of crashes. Shiller (2000) confirms this fear of crashes through survey results in which investors predict more than a 10% probability of market crash within the next six months.

Based on Shefrin's (2001, 2008) observations that investor heterogeneity leads to a bi-model and fat-tailed stock index return distribution, we note that OLS regression estimates (using the conditional mean function) only focuses on the central part of the distribution. OLS

[1] Poterba and Summers (1986), and French et al. (1987), argue that asymmetric volatility reflects the time varying risk premium that induces the volatility feedback effect.

[2] Schwert (1990) and Bollerslev, Litvinova, and Tauchen (2006), among others, argue that the asymmetry in volatility is too strong to be explained by the leverage effect. Also previous empirical studies show that the volatility feedback hypothesis is not always consistent. Furthermore, some studies find that there is not always a positive relation between current volatility and expected future returns (e.g., Breen, Glosten, & Jagannathan, 1989). However, other studies support the hypothesis (e.g., French et al., 1987; Campbell & Hentschel, 1992; Bali and Bali & Peng, 2006).

[3] Later Giot (2005) investigates the negative contemporaneous return-implied volatility relation in both SPX and NDX stock market indexes. He confirms the strong negative asymmetric contemporaneous return-volatility relation of Fleming et al. (1995).

[4] Other studies such as Bollerslev et al. (2006) examine the asymmetric return-volatility relationship for stock market index using intraday data; however, they use realized volatility instead. They conclude that the magnitude of the effect of price drop on volatility is too strong to be explained by financial leverage fluctuations. Bali and Bali and Peng (2006) also use intraday data in their study however their focus is not asymmetry rather they tests for risk-return trade in the intertemporal CAPM framework, they find significant and positive relationship between risk and return for each of the volatility measure such as realized, GARCH and implied volatility.

[5] Other studies who investigate return implied volatility relation using quantile regression methods, for example Agbeyegbe (2015) for Oil ETF, and Daigler et al. (2014) and Kaurijoki et al. (2015) for currencies.

[6] Li (2007), and Buraschi and Jiltsov (2006) highlight the role of heterogeneous beliefs in asset prices and options prices, respectively.

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Table 1
Descriptive statistics of the high frequency and daily
The intraday (1, 5, 10, 15, 60 min) and daily percentage continuously compounded returns of SPX stock market index and the daily percentage changes of VIX stock market volatility index.

	SPX(1 M)	SPX(5 M)	SPX(10 M)	SPX(15 M)	SPX(60 M)	SPX(Daily)	ΔVIX(1 M)	ΔVIX(5 M)	ΔVIX(10 M)	ΔVIX(15 M)	ΔVIX(60 M)	ΔVIX(Daily)
Mean	−0.00001	−0.00010	−0.00004	−0.00026	0.00075	0.00957	−0.00016	−0.00076	−0.00145	−0.00258	−0.00403	0.00174
Median	0.00000	0.00000	0.00150	0.00310	0.00700	0.05415	0.00000	0.00000	0.00000	0.00000	−0.02000	−0.07000
Maximum	1.4545	1.9990	3.3709	3.5723	4.94220	10.9572	2.7200	2.9900	3.8800	5.1900	5.52000	16.5400
Minimum	−1.8048	−2.6425	−2.3560	−2.7019	−4.63230	−9.4695	−2.9000	−2.9100	−3.6300	−4.9200	−5.67000	−17.3600
Std. Dev.	0.05084	0.11570	0.16077	0.19526	0.35879	1.34827	0.06154	0.14062	0.20314	0.26084	0.49045	1.92981
Skewness	−0.04459	−0.00217	0.25177	0.28827	0.68892	−0.30873	0.04917	0.14964	0.02619	0.29662	0.37738	0.57154
Kurtosis	36.6009	27.4520	23.9133	25.6492	30.68201	13.5128	134.4004	44.4036	35.6729	38.6380	23.35870	21.5306
JarqueBera	36,618,950.0	3,893,843.7	1,426,045.6	1,145,371.8	395,618.8	9981.1	560,000,000	11,164,740.1	3,478,668.3	2,834,687.6	213,748.8	31,022.1
Prob	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ρ_1	0.047***	0.004*	−0.008**	0.01**	−0.005	−0.121***	0.016***	0.103***	0.134***	0.131***	0.065***	−0.148***
ρ_2	0.004***	−0.015***	0.01***	0.017***	0.007	−0.050***	0.038***	0.07***	0.065***	0.05***	−0.042***	−0.078***
ρ_3	−0.002***	−0.001***	0.017***	0.007***	−0.030***	0.026***	0.022***	0.03***	0.031***	0.01***	−0.023***	−0.030***
ADF	−443.74***	−136.19***	−158.01***	−160.11***	−44.64***	−37.106***	−150.45***	−135.33***	−146.15***	−112.69***	−45.41***	−22.32***
No. Obs	778,417	156,300	78,207	53,551	12,360	2160	778,417	156,300	78,207	53,551	12,360	2160

Notes: This table reports the descriptive statistics for the percentage continuously compounded returns on S&P 500 stock index and for the percentage changes in the VIX volatility Index both sampled at different frequencies such as 1 min, 5 min, 10 min, 15 min, 60 min and daily. The autocorrelation coefficients ρ, the Jarque-Bera and the Augmented Dickey-Fuller (ADF) (an intercept is included in the test equation) test values are reported.
***, ** and * denote rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

models further assume that this is a good description for the entire conditional distribution of the dependent variable. Hence, this traditional approach ignores any deviations of the relation at the tails of the distribution and fails to account for the effect of unobserved investors' heterogeneity. However, through the use of Quantile Regressions, we can allow for the presence of heterogeneity in beliefs of investors and observe different responses in different parts of the conditional distribution of the dependent variable (Koenker & Bassett, 1978; Koenker & Hallock, 2001; Koenker, 2005).

3. Data

Intraday data for the SPX and the VIX are obtained from the Thomson Reuters Tick History database maintained by SIRCA.[7] Data are sampled for the period when both the new VIX index and intraday data are available. The resulting sample starts September 25, 2003 and ends December 30, 2011 covering a total of 2160 trading days. Intraday, both the SPX and the VIX are computed at a 15 s frequency. For the empirical analyses, data is sampled at various frequencies, namely 1-, 5-, 10-, 15-, 60-minutes. Besides the intraday samples, as a benchmark, data are also collected at a daily frequency. The various data frequencies are used to examine how the asymmetric return-volatility relation is affected by the sampling frequency. From the raw data, we compute percentage continuously compounded returns and first differences in the VIX.

Table 1 reports summary statistics for SPX returns and for first differences of the VIX. The sample size increases from 2160 observations at a daily frequency to 778,417 observations at a one-minute frequency. As expected, for returns on the SPX (first columns of Table 1), the average return, as well as the standard deviations of returns, increase as the sampling frequency decreases (going from 1 min to daily). Furthermore, the distributions of high frequency returns appear to be considerably more non-normal than the distribution of daily returns. This is confirmed by the Jarque-Bera statistics. At all sampling frequencies there is evidence of autocorrelation. Although statistically significant, the autocorrelation is relatively small in absolute terms. Finally, the ADF tests reject the null hypotheses of unit roots in the return series.

The second part of Table 1 reports summary statistics for the first difference in VIX (ΔVIX). As with the return data, mean changes and standard deviations increase as the sampling frequency decreases. Overall, ΔVIX is positively skewed and this skewness is higher at the daily frequency than at high intraday frequencies. On the other hand, kurtosis is considerably higher for high-frequency intraday data than for daily data indicating increasingly fatter tails with increasing sampling frequency. This again results in intraday ΔVIX being more non-normally distributed than for daily data, as evidenced by the Jarque-Bera statistics. As with return data, evidence of ΔVIX being autocorrelated is found. However, these autocorrelations are again small in absolute terms. The null hypotheses of the presence of a unit roots in ΔVIX are rejected.

4. Methodology

The Quantile Regression model (QRM) approach is utilized to assess the intraday asymmetric relation between returns on the SPX and ΔVIX. Quantile regressions allow us to investigate the asymmetric return-volatility relation across quantiles. With exceptions of Allen et al. (2012), Badshah (2013), Daigler, Hibbert, and Pavlova (2014), Kaurijoki, Nikkinen, and Aijo (2015), Agbeyegbe (2015, 2016), most of the studies have employed traditional regression models that focus on the average relation (at the mean of the distribution) between volatility changes and returns. This traditional approach might lead to a situation where important information about this relation is not correctly modelled if, for example, the relation is asymmetric or different in the tails of the conditional distribution. Focusing on the tails of this distribution is important as the tails represent extreme changes in VIX, typically observed during crisis periods. The approach of this study allows modelling of the return-volatility relation with a focus on different parts of the distribution of conditional changes in volatility, ΔVIX, including the extreme tails. Furthermore, the QRM requires weaker distributional assumptions, it provides a distributionally more robust method of modelling the conditional ΔVIX distribution and is, hence, less sensitive to extreme observations. With implied volatility changes it is often the case that the distributions are skewed and leptokurtic. Agbeyegbe (2016) uses quantile regression and copula quantile regression methods to examine the return-implied volatility relationship for the US stock market indices, and finds strong negative return-implied volatility relationship which is of inverted U-shape. Alexander (2008) uses quantile regression methods and observe similar findings for FTSE 100 index, i.e. the relation is of inverted U-shape. Similarly, Allen et al. (2012) uses quantile regression methods (both linear and non-linear) for both the US and European stock market indices, and find strong asymmetry in the return-volatility relation. Agbeyegbe (2015) is the first to use quantile regression and copula quantile regression methods to examine the return

[7] Securities Industry Research Centre of Asia-Pacific.

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Table 2
Quantile regression results: Response variable intraday (1 min) ΔVIX1.

q	Intercept	R_t^+	R_t^-	R_{t-1}^+	R_{t-2}^+	R_{t-3}^+	R_{t-1}^-	R_{t-2}^-	R_{t-3}^-	ΔVIX_{t-1}	ΔVIX_{t-2}	ΔVIX_{t-3}	R^2(%)
0.05	−0.014***	−1.255***	−0.230***	−0.558***	−0.248***	−0.184***	−0.026***	0.075***	0.099***	−0.129***	−0.016***	0.004	40.3
	(−64.85)	(−152.89)	(−47.54)	(−69.92)	(−31.36)	(−26.12)	(−4.08)	(11.11)	(14.24)	(−36.33)	(−4.78)	(1.47)	
0.10	−0.010***	−1.076***	−0.280***	−0.433***	−0.168***	−0.122***	−0.073***	0.023***	0.045***	−0.122***	−0.013***	0.003	35.6
	(−91.84)	(−207.67)	(−81.86)	(−91.21)	(−43.15)	(−31.82)	(−20.25)	(6.20)	(11.12)	(−47.55)	(−5.76)	(1.47)	
0.15	−0.008***	−0.965***	−0.323***	−0.365***	−0.135***	−0.096***	−0.105***	−0.0009	0.025***	−0.121***	−0.014***	0.002	32.2
	(−86.84)	(−221.68)	(−101.29)	(−84.36)	(−46.24)	(−31.38)	(−33.38)	(−0.29)	(8.47)	(−54.34)	(−8.27)	(1.26)	
0.20	−0.006***	−0.885***	−0.357***	−0.323***	−0.115***	−0.081***	−0.126***	−0.012***	0.011***	−0.122***	−0.014***	0.001	29.2
	(−77.26)	(−237.19)	(−125.32)	(−95.77)	(−44.57)	(−32.20)	(−42.08)	(−4.64)	(4.15)	(−62.51)	(−8.06)	(1.023)	
0.25	−0.004***	−0.819***	−0.388***	−0.297***	−0.100***	−0.067***	−0.139***	−0.025***	0.002	−0.122***	−0.015***	0.002*	27.5
	(−70.14)	(−247.69)	(−175.13)	(−94.60)	(−44.67)	(−25.83)	(−54.37)	(−10.37)	(1.19)	(−64.46)	(−10.24)	(1.78)	
Median	−0.0002***	−0.580***	−0.566***	−0.197***	−0.058***	−0.027***	−0.205***	−0.063***	−0.031***	−0.119***	−0.017***	0.004***	21.5
	(−5.37)	(−275.71)	(−279.91)	(−79.77)	(−31.50)	(−14.65)	(−81.55)	(−32.67)	(−18.89)	(−61.96)	(−16.26)	(4.11)	
0.75	0.004***	−0.396***	−0.805***	−0.124***	−0.021***	0.006**	−0.301***	−0.109***	−0.069***	−0.115***	−0.016***	0.005***	27.5
	(53.02)	(−151.54)	(−291.19)	(−46.28)	(−8.46)	(2.87)	(−89.83)	(−43.08)	(−28.64)	(−49.13)	(−11.09)	(5.04)	
0.80	0.005***	−0.365***	−0.870***	−0.109***	−0.011***	0.016***	−0.333***	−0.123***	−0.083***	−0.115***	−0.016***	0.005***	29.4
	(61.56)	(−129.03)	(−269.14)	(−37.84)	(−4.18)	(6.16)	(−83.60)	(−42.66)	(−28.27)	(−47.11)	(−9.69)	(3.95)	
0.85	0.007***	−0.332***	−0.950***	−0.088***	0.004	0.030***	−0.377***	−0.140***	−0.100***	−0.114***	−0.014***	0.006***	32.5
	(80.13)	(−118.81)	(−273.23)	(−26.55)	(1.21)	(10.44)	(−91.86)	(−41.80)	(−29.90)	(−43.02)	(−8.83)	(4.29)	
0.90	0.009***	−0.292***	−1.059***	−0.054***	0.025***	0.052***	−0.440***	−0.174***	−0.126***	−0.113***	−0.013***	0.008***	35.8
	(82.40)	(−74.61)	(−225.26)	(−11.42)	(6.35)	(14.04)	(−76.01)	(−33.36)	(−33.45)	(−33.58)	(−6.40)	(3.99)	
0.95	0.013***	−0.250***	−1.213***	0.006	0.077***	0.109***	−0.573***	−0.252***	−0.195***	−0.120***	−0.014***	0.013***	40.4
	(73.24)	(−44.45)	(−174.93)	(0.80)	(10.53)	(15.71)	(−60.59)	(−37.98)	(−26.95)	(−25.49)	(−4.36)	(3.80)	
OLS	−0.0003*	−0.705***	−0.674***	−0.279***	−0.100***	−0.044***	−0.317***	−0.098***	−0.045***	−0.160***	−0.021***	0.007	37.6
	(−1.52)	(−79.34)	(−59.99)	(−27.14)	(−12.18)	(−5.45)	(−35.13)	(−11.43)	(−5.37)	(−16.23)	(−2.94)	(1.18)	
Quantile slope equality test results: Only significant results of asymmetry are reported.													
		0.2–0.4***	0.2–0.4***	0.2–0.4***	0.2–0.4***	0.2–0.4***	0.2–0.4***	0.2–0.4***	0.2–0.4***				
		0.4–0.5***	0.4–0.5***	0.4–0.5***	0.4–0.5***	0.4–0.5***	0.4–0.5***	0.4–0.5***	0.4–0.5***				
		0.5–0.6***	0.5–0.6***	0.5–0.6***	0.5–0.6***	0.5–0.6***	0.5–0.6***	0.5–0.6***	0.5–0.6***				
		0.6–0.8***	0.6–0.8***	0.6–0.8***	0.6–0.8***	0.6–0.8***	0.6–0.8***	0.6–0.8***	0.6–0.8***	0.6–0.8*			

Notes: The MRM and QRM specification 2 and 3 respectively are estimated for the asymmetric return-volatility relation between changes in the VIX and SPX return. In both specification 2 and 3, we control for financial/economic crises effects by including dummy variables for eight crisis days (not reported). In the context of QRM, the standard errors are obtained using the bootstrap method; therefore, robust t-statistics (in parentheses) are computed for each of the quantile estimates. The MRM specification 2 is estimated with Newey and West (1987) correction for heteroscedasticity and autocorrelation.
***, **, and * denote rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

volatility relation between the Oil VIX and Oil ETF where he finds a similar inverted U-shaped relationship for the Oil market. Daigler et al. (2014) use quantile regression method to study the return and implied volatility relationship for currency market, namely between the Euro VIX and Euro ETF returns. They find a weaker return implied volatility relationship for Euro in comparisons to the equity markets. Another study of interest that uses quantile regression for currencies is that of Kaurijoki et al. (2015).They investigate the return implied volatility relationship for high and low yielding currencies. Interestingly, they find the return volatility relationship for high yielding currencies somehow similar to that of stock markets but opposite for the low yielding currencies.

We build on the previous literature by applying quantile regression methods to a varying return horizons (i.e. 1, 5, 10, 15, 60 min, and daily) to monitor the asymmetry in return volatility relationship across the return horizons and quantiles of the volatility changes distribution, which will provide a more completed picture of the asymmetric return volatility relationship.

Before specifying the QRM model for the intraday asymmetric return-volatility relation, a standard benchmark mean regression model (MRM) similar to that of Low (2004), Giot (2005), and Hibbert et al. (2008) is specified. For the analysis, ΔVIX_{it} is defined as the percentage changes in VIX of frequency i where $i = 1, 5, 10, 15, 60$ min, and daily. R_{it} is the percentage continuously compounded return of the S&P500 index of frequency i where $i = 1, 5, 10, 15,$ 60 min, and daily. For assessing asymmetry, we define positive and negative returns as:

$$R_{it}^+ = \begin{cases} R_{it} \text{ if } R_{it}>0 \\ 0 \text{ if } R_{it}<0 \end{cases} \text{ and } R_{it}^- = \begin{cases} R_{it} \text{ if } R_{it}<0 \\ 0 \text{ if } R_{it}>0. \end{cases} \tag{1}$$

The benchmark Mean-Regression model (MRM) for the intraday asymmetric return-volatility relation has the following form:

$$\Delta VIX_{it} = \alpha + \sum\nolimits_{L=1}^{3} \beta_{iL} \Delta VIX_{it-L} + \sum\nolimits_{L=0}^{3} \gamma_{iL} R_{it-L}^+ + \sum\nolimits_{L=0}^{3} \delta_{iL} R_{it-L}^- + \varphi_i \text{dummies} + u_t, \tag{2}$$

Where α is the intercept, β_{iL} are the coefficients for the lagged ΔVIX for return horizon i, where $L = 1$ *to* 3. The terms γ_{iL} are the coefficients for the positive returns and δ_{iL} are the coefficients for the negative returns on the SPX index for frequency i, in both cases lags run from $L = 1$ *to* 3. We follow Agbeyegbe (2015) to control for economic/financial crises in our specification. Specifically, we identify those days in which SPX has realized significant drops (i.e. 6% or greater in day) during our sample period from September 25, 2003 to December 31, 2011; in total, being eight days over the entire sample period. Those eight crises days are represented by dummy variables for all six frequencies (i.e. 1, 5, 10, 15, 60 min, and daily).[8, 9]

The residuals u_t are assumed to be independently and identically distributed (*i.i.d.*) with zero mean. Consequently, the MRM assumes that the effects of both types of returns are constant across different sizes of ΔVIX_{it}. Hence, this traditional approach might neglect important information across quantiles of the ΔVIX distribution if the effect is not constant. The QRM approach is able to monitor the effect across the ΔVIX distribution.[10]

[8] This approach is also consistent with Bali, Demirtas, and Levy (2009) who show that these extreme events can be used to predict future expected returns at the market level.

[9] These eight days on which SPX has witnessed 6% or more decline are on the following dates: October 15, 2008 (−9%); December 1, 2008 (−8.9%); September 29, 2008 (−8.8%); October 9, 2008 (−7.6%); November 20, 2008 (−6.7%); August 8, 2011 (−6.6%); November 19, 2008 (−6.1%); and October 22, 2008 (−6.0%).

[10] Meligkotsidou, Vrontos, and Vrontos (2009) provide a useful discussion on the advantages of the QRM over the MRM.

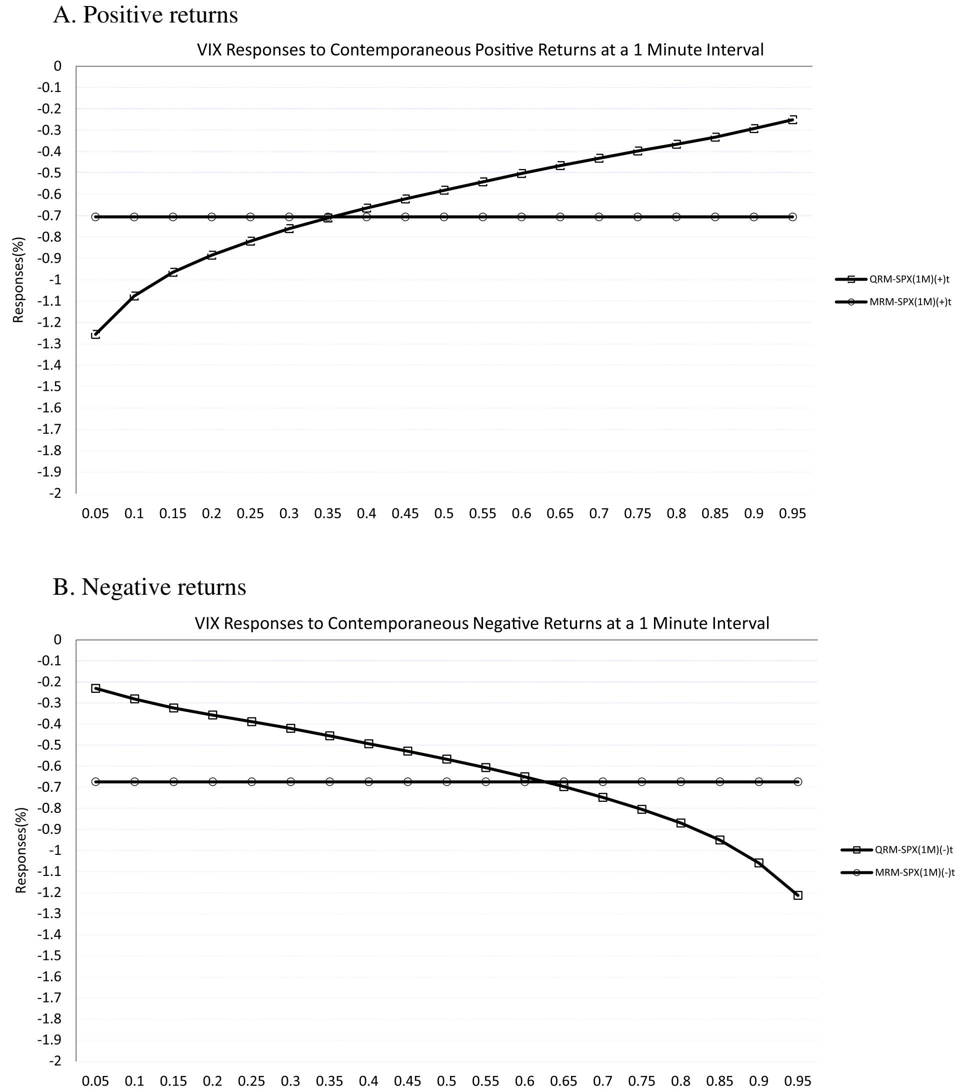

Fig. 1. Asymmetric relation between changes in VIX and returns on the S&P500 at a 1 min frequency. Panel A. Positive returns Panel B. Negative returns

Similar to the MRM, the qth QRM for examining the asymmetric return-volatility relation has the following form:

$$\Delta VIX_{it} = \alpha^{(q)} + \sum_{L=1}^{3}\beta_{iL}^{(q)}\Delta VIX_{it-L} + \sum_{L=0}^{3}\gamma_{iL}^{(q)}R_{it-L}^{+} + \sum_{L=0}^{3}\delta_{iL}^{(q)}R_{it-L}^{-} + \varphi_i^{(q)}\text{dummies} + u_t, \quad (3)$$

where $\alpha^{(q)}$ is the intercept, and $\beta_i^{(q)}$ are the coefficients for the lagged ΔVIX for return horizon i. The parameters $\gamma_{iL}^{(q)}$are the coefficients for positive returns and $\delta_{iL}^{(q)}$are the coefficients for negative returns on the SPX index for frequency i, where the lag L runs from 0 to 3 in both cases. Similar to Eq. (2), we control for economic/financial crises in Eq. (3) by including dummy variables for the eight crises days. The residuals, u_t, are assumed to be independent and derived from the error distribution $\Phi_q(u_t)$ with the qth quantile equal to zero. The main feature of the QRM is that the conditional effects of the changes in the explanatory variables, that are measured by $\beta_{iL}^{(q)}$, $\gamma_{iL}^{(q)}$, and $\delta_{iL}^{(q)}$ are functions of the quantile parameter q, $q \in (0,1)$. We estimate the QRM in (3) using the method proposed by Koenker and Bassett (1978).[11]

[11] See Koenker (2005) for mathematical details on the quantile models and their estimation techniques.

By applying the QRM to our data, the following empirical hypotheses can be tested:

Hypothesis 1. Contemporaneous negative and positive returns are the sole drivers of changes in the implied volatility.

Hypothesis 2. Past returns or past changes in implied volatilities are important determinants of changes in current implied volatility.

Hypothesis 3. The return-volatility relation is asymmetric, that is, implied volatility reacts differently to negative and positive returns.

Hypothesis 4. The relation between return and volatility is asymmetric and more pronounced in the extreme tails of the ΔVIX distribution.

Hypothesis 5. The asymmetric volatility remains the same across frequencies, i.e. 1, 5, 10, 15, 60 min, and daily.

5. Results

This section presents the empirical results for the Quantile Regression analysis as well as their comparisons to the traditional OLS results. We first report our results for the highest (1-minute) frequency and

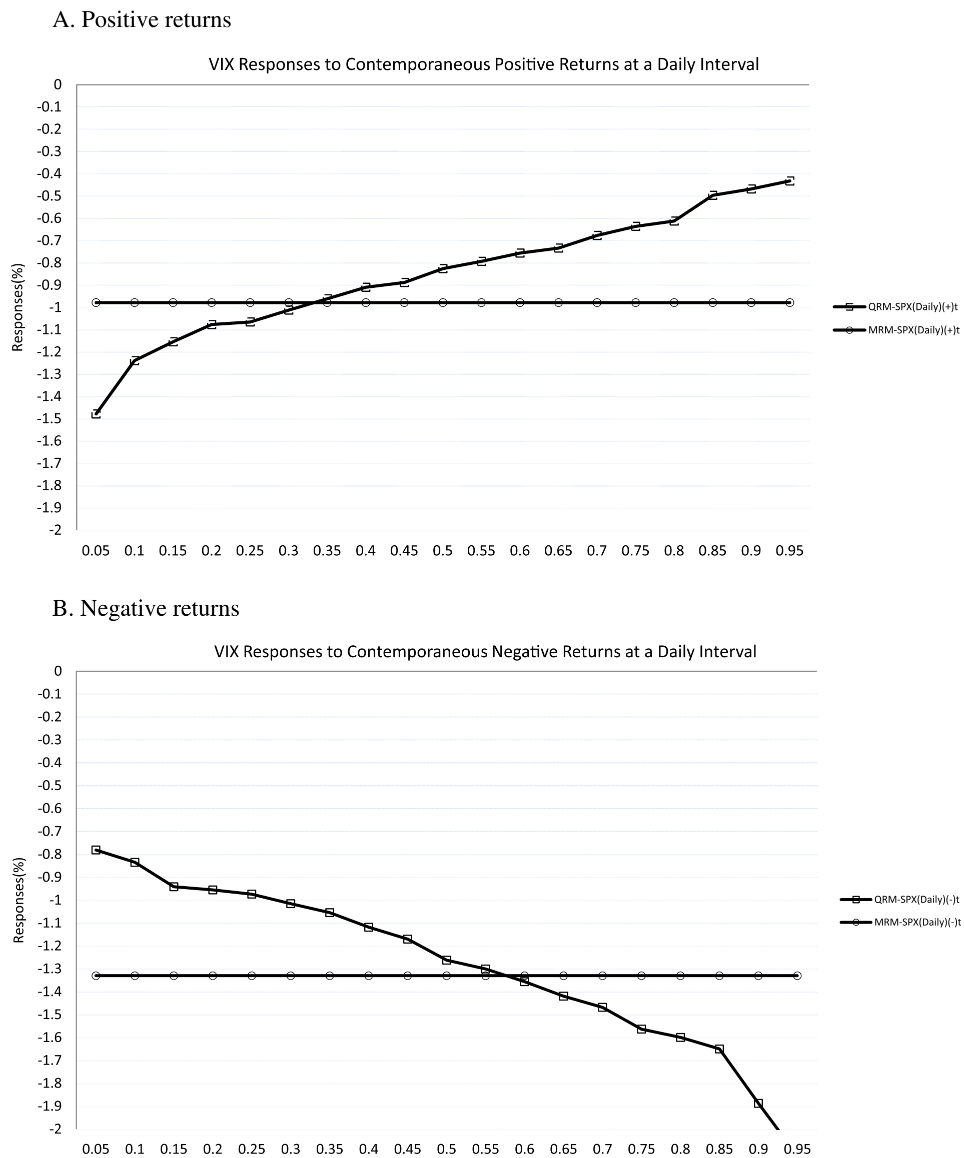

Fig. 2. Asymmetric relation between changes in VIX and returns on the S&P500 at a daily frequency. Panel A. Positive returns Panel B. Negative returns

subsequently we show how the data aggregation alters the relation between returns and volatility.

5.1. The intraday asymmetric relation between SPX returns and VIX changes

Table 2 reports the results for the MRM in Equation (2) and the QRM in Eq. (3) for the intraday (1 min) asymmetric relation between VIX changes and SPX returns. The model contains 11 covariates[12] and an intercept.[13] In the context of the QRM, for each of the 12 coefficients, 19 quantile-regression coefficient estimates for each q in the set $q = \{0.05, 0.1, \ldots, 0.9, 0.95\}$ are obtained. The estimates of the benchmark MRM are reported in the 12th row of Table 2.

The contemporaneous positive and negative return covariates, with their 19 Quantile-Regression estimates, are plotted in Fig. 1 as a dashed curve with squares. The VIX responses to positive (negative) returns are plotted in the Panel A (Panel B) of Fig. 1.[14] In each plot the x-axis shows the quantile parameter (or q), and the y-axis indicates the covariate effect as a percentage. For each covariate, the estimates can be interpreted as the conditional effect of a percentage-point change of the covariate on volatility changes, holding other covariates constant. For the MRM, the constant OLS estimates are shown in both plots as solid, straight lines with circles over the different quantiles. Noticeably, QRM estimates of the contemporaneous effect of positive returns in Panel A are more negative than the corresponding OLS estimates for quantile values lower than 0.35. On the other hand, the QRM estimates are less negative for all quantiles larger than 0.35. Furthermore, the variation in the positive return-volatility relation is considerable over the range of quantiles. The coefficient for contemporaneous positive returns varies from -1.262 at the lower end of the distribution up to -0.248 at the upper end. The lower panel of Table 2 confirms that the variations in the estimated coefficients are statistically significant. Table 2 also shows that the autocorrelation structure of the ΔVIX is robust over the different quantiles. For cross-autocorrelations with SPX returns,

[12] In both models (MRM, and QRM), we control for financial/economic crises effects by including eight dummy variables, please see Section 4 for detail.

[13] It is interesting to compare intraday QRM and MRM estimates with the daily QRM and MRM estimates as most of the previous studies document the daily asymmetric return-volatility relation. In order to facilitate these comparisons daily QRM and MRM estimates are presented for the same sample in Table 3. A corresponding graphical representation is given in Fig. 2.

[14] The conventional 95% confidence level is used for the quantile-regression estimates.

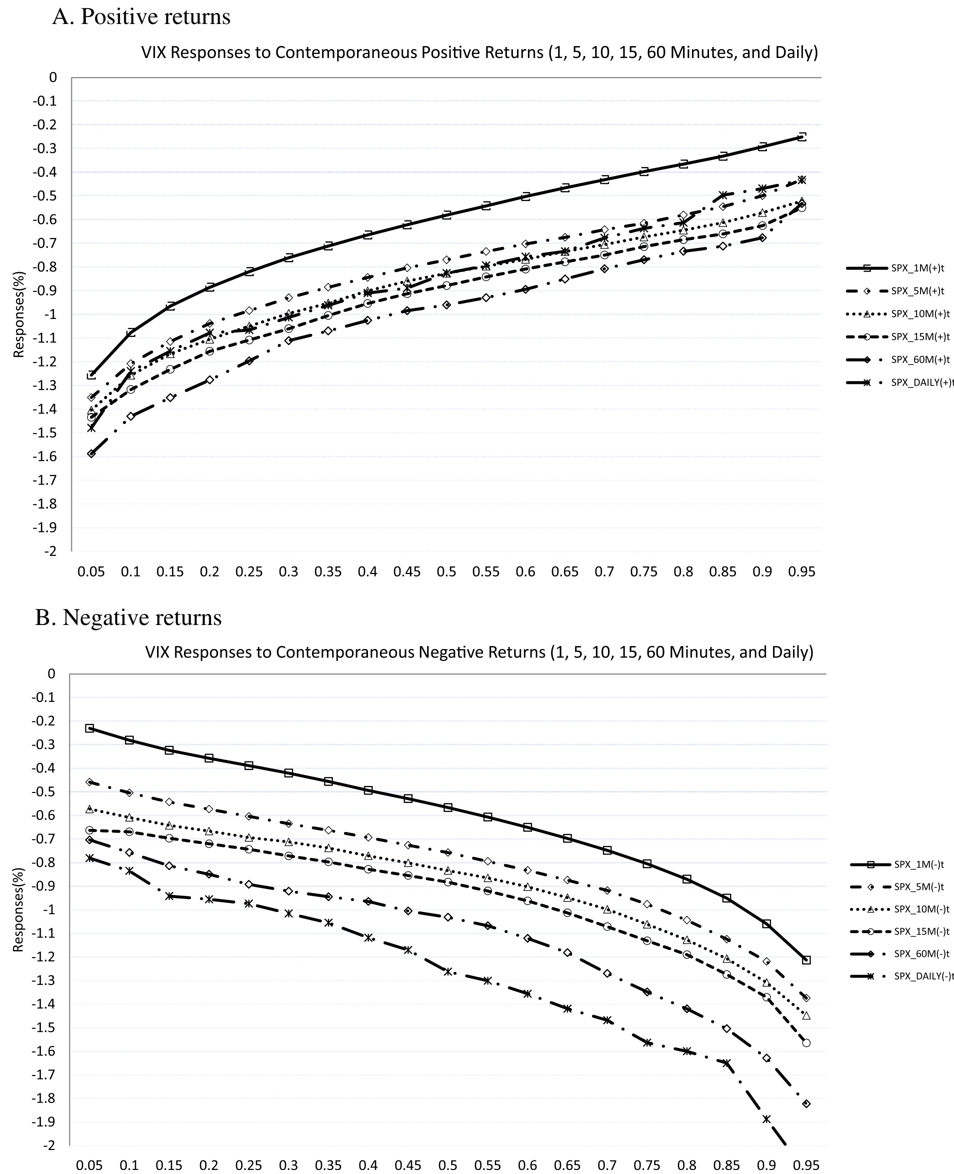

Fig. 3. QRM estimates across quantiles: Response variable ΔVIX at 1, 5, 10, 15, 60 min and a daily frequency. Panel A. Positive returns Panel B. Negative returns

however, the significant negative cross-autocorrelations tend to decrease and even become significantly positive with increasing lag-length in the upper part of the distribution. This result is consistent with the view that negative returns increase future volatility and positive returns decrease future volatility. Here again, the OLS estimates are not representative for describing the cross-autocorrelations between positive returns and volatility.

The plot for the contemporaneous effect of negative returns on ΔVIX in Panel B of Fig. 1 shows a mirror image of the results for positive returns. The QRM estimates of the contemporaneous effect of negative returns in Panel B are less negative than the corresponding the OLS estimates for quantile values lower than 0.65. On the other hand, the QRM estimates are more negative for all quantiles larger than 0.65. Furthermore, the variation in the negative return-volatility relation is also considerable over the range of quantiles. The coefficients for contemporaneous negative returns vary from −0.228 at the lower end of the distribution down to −1.218 at the upper end. The lower panel of Table 2 also confirms that the variations in the estimated coefficient are statistically significant. For cross-autocorrelations with negative SPX returns, the significant negative cross-autocorrelations tend to decrease and become significantly positive with increasing lag-length in the lower part of the distribution. Here, again, the OLS estimates are not representative for describing the cross-autocorrelations between negative returns and volatility.

The empirical results presented in Table 2 and Fig. 1 support Hypothesis 4 that the return-volatility relation has different asymmetries across different sizes of volatility changes, and these asymmetries are more pronounced in the tails of the conditional distribution. As a consequence, OLS, which determines the relation at the mean, is unable to capture the intraday asymmetric return-volatility conditional relation at the different parts of the ΔVIX distribution.

The estimated coefficients of covariates R_t^+ and R_t^- presented in Columns 3 and 4 of Table 2, respectively, represent the contemporaneous intraday return-volatility relation. If these coefficients are compared with the coefficients of corresponding lagged covariates, it becomes apparent that both contemporaneous and even lagged returns are important for determining changes in the VIX. The coefficients are statistically significant at the 1% level across all quantiles. The empirical results on the significant impact of lagged covariates at this high frequency have not been reported in the literature. On the other hand, when comparing the magnitudes of the coefficients, it is apparent that even at the 1-minute frequency the contemporaneous returns seem to be more important

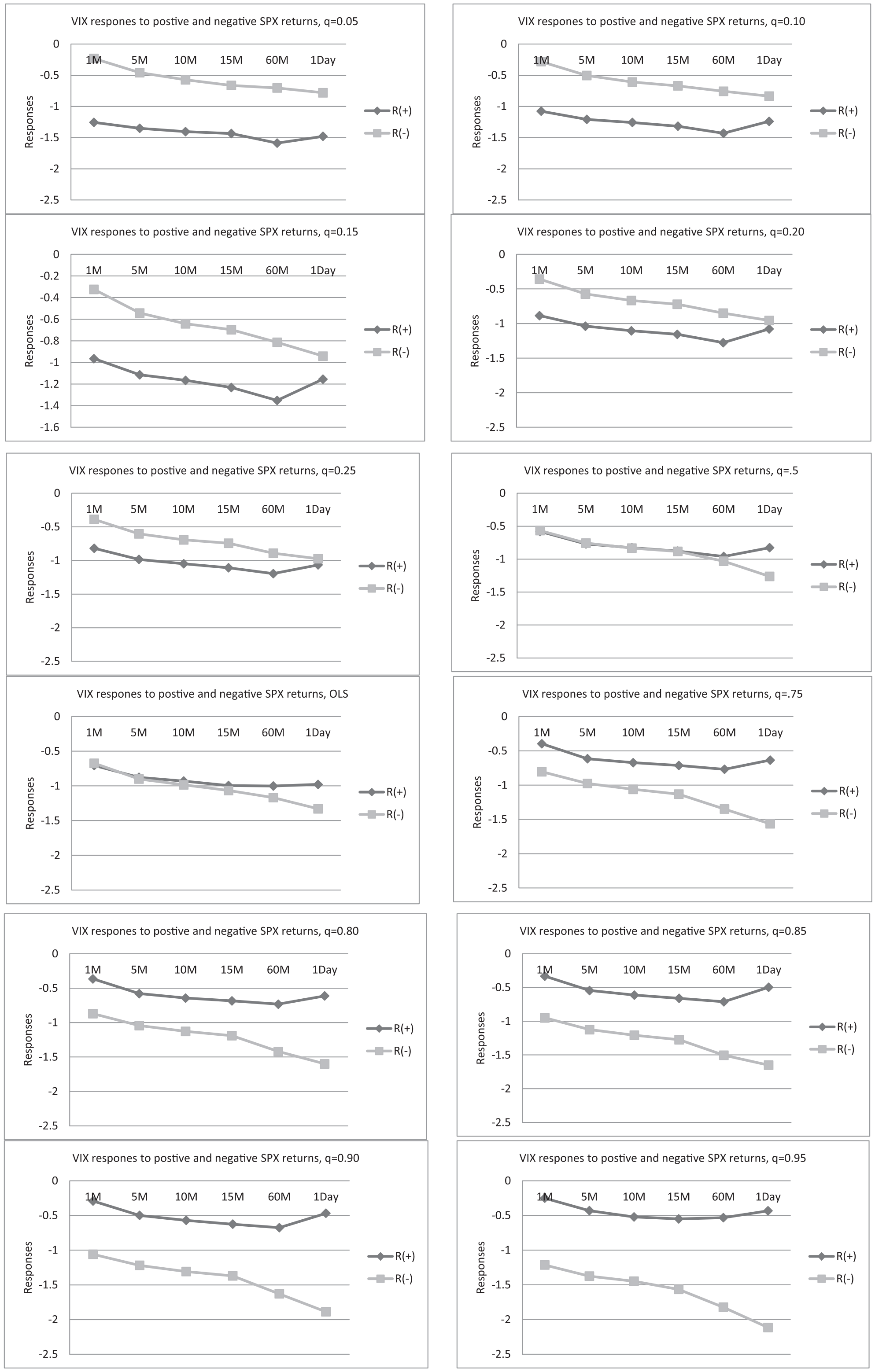

Fig. 4. QRM estimates: VIX response comparision across time intervals (1,5,10,15,60 min and day) at each quantile.

in determining the changes in volatility than the lagged covariates. Thus, these results do not fully support Hypothesis 1 that contemporaneous returns are the sole source of changes in implied volatility. This hypothesis would imply that fundamental explanations for the return-volatility relation, such as the leverage and volatility feedback, cannot explain the intraday dynamic return-volatility relation. However, a significant, up to three-minute lagged, effect cannot fully be regarded as evidence of leverage and volatility feedback as these explanations relate to a longer-term lagged effect between return and volatility, or vice versa.

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Table 3
Quantile regression results: Response variable daily ΔVIXD.

q	Intercept	R_t^+	R_t^-	R_{t-1}^+	R_{t-2}^+	R_{t-3}^+	R_{t-1}^-	R_{t-2}^-	R_{t-3}^-	ΔVIX_{t-1}	ΔVIX_{t-2}	ΔVIX_{t-3}	R^2(%)
0.05	−0.181	−1.478	−0.781	−0.341	−0.216	−0.318	0.390	0.374	0.327	−0.062	−0.065	−0.067	58.4
	(−0.003)	(−0.05)	(−0.01)	(−0.01)	(−0.002)	(−0.007)	(0.007)	(0.006)	(0.003)	(−0.002)	(−0.002)	(−0.002)	
0.10	−0.160	−1.239	−0.835	−0.202	−0.146	−0.198	0.296	0.360	0.227	−0.061	−0.024	−0.024	53.7
	(−0.05)	(−0.57)	(−0.14)	(−0.08)	(−0.02)	(−0.07)	(0.04)	(0.06)	(0.03)	(−0.03)	(−0.009)	(−0.01)	
0.15	−0.105	−1.154***	−0.941**	−0.180	−0.178	−0.210	0.167	0.335	0.218	−0.077	−0.020	−0.030	50.6
	(−0.59)	(−8.22)	(−2.14)	(−1.32)	(−0.46)	(−1.10)	(0.36)	(0.64)	(0.68)	(−0.57)	(−0.07)	(−0.25)	
0.20	−0.054	−1.077***	−0.955***	−0.160**	−0.175	−0.163*	0.168	0.276	0.206	−0.059	−0.024	−0.030	48.4
	(−0.67)	(−16.84)	(−5.96)	(−2.08)	(−1.12)	(−1.86)	(1.33)	(1.51)	(1.59)	(−0.91)	(−0.20)	(−0.50)	
0.25	−0.036	−1.06***	−0.973***	−0.123*	−0.153	−0.128*	0.133	0.239*	0.180	−0.048	−0.042	−0.025	46.8
	(−0.48)	(−16.30)	(−4.78)	(−1.87)	(−1.24)	(−1.84)	(0.94)	(1.71)	(1.51)	(−0.74)	(−0.39)	(−0.69)	
Median	0.021	−0.826***	−1.262***	−0.103*	0.005	0.016	0.096	0.115	0.117	−0.047	−0.025	0.017	44.9
	(0.37)	(−15.21)	(−9.39)	(−1.84)	(0.08)	(0.34)	(0.92)	(0.99)	(1.44)	(−1.04)	(−0.44)	(0.48)	
0.75	0.121**	−0.636***	−1.563***	−0.018	0.046	0.026	0.038	0.062	0.050	−0.042	0.014	0.009	52.1
	(2.64)	(−11.27)	(−15.49)	(−0.31)	(0.71)	(0.46)	(0.45)	(0.82)	(0.74)	(−1.14)	(0.34)	(0.26)	
0.80	0.145	−0.612***	−1.599***	0.010	0.099	0.082	0.008	0.048	0.068	−0.039	0.020	0.035	54.5
	(0.70)	(−3.81)	(−3.23)	(0.07)	(0.33)	(0.43)	(0.01)	(0.12)	(0.21)	(−0.31)	(0.08)	(0.30)	
0.85	0.174***	−0.496***	−1.650***	0.061	0.138**	0.106*	0.043	−0.019	0.055	0.001	0.045	0.036	57.8
	(3.98)	(−8.09)	(−17.17)	(1.17)	(2.04)	(1.80)	(0.49)	(−0.23)	(0.67)	(0.04)	(0.87)	(1.13)	
0.90	0.270	−0.468	−1.887***	0.074	0.195	0.121	0.115	0.003	0.005	0.054	0.047	0.050	62.0
	(0.72)	(−1.14)	(−2.61)	(0.15)	(0.25)	(0.31)	(0.13)	(0.004)	(0.009)	(0.23)	(0.10)	(0.16)	
0.95	0.378***	−0.432***	−2.11***	0.102	0.289	0.080	0.002	0.105	−0.181	0.058	0.135	−0.038	68.1
	(2.63)	(−4.43)	(−10.83)	(0.93)	(0.60)	(0.70)	(0.001)	(0.65)	(−0.63)	(0.81)	(1.41)	(−0.27)	
OLS	0.064*	−0.978***	−1.330***	−0.105**	−0.060	−0.107*	0.015	0.111	0.089	−0.088*	−0.000	−0.054	74.6
	(1.78)	(−11.48)	(−21.82)	(−1.64)	(−1.12)	(−1.68)	(0.16)	(1.37)	(1.35)	(−1.78)	(−0.001)	(−1.18)	
Quantile slope equality test results: Only significant results of asymmetry are reported.													
		0.2–0.4*				0.2–0.4*							
		0.4–0.5*											

Notes: The MRM and QRM specification 2 and 3 respectively are estimated for the asymmetric return-volatility relation between changes in the VIX and SPX return. In both specification 2 and 3, we control for financial/economic crises effects by including dummy variables for eight crisis days (not reported). In the context of QRM, the standard errors are obtained using the bootstrap method; therefore, robust t-statistics (in parentheses) are computed for each of the quantile estimates. The MRM specification 2 is estimated with Newey and West (1987) correction for heteroscedasticity and autocorrelation.
***, **, and * denote rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

It is further evident from the absolute differences in the estimated coefficients of covariates R_t^+ and R_t^- in Columns 3 and 4 of Table 2, respectively, that there are asymmetric effects for all quantile-regression estimates. Wald tests are applied to test whether the difference between the coefficients $\gamma_t^{(q)}$ and $\delta_t^{(q)}$ in (3) is statistically significant. The null hypothesis (i.e., the coefficients for contemporaneous positive and negative returns are equal) for the Wald test is rejected for each of the quantile regressions.[15] These results imply that there exists an asymmetric return-volatility relation. As a consequence, these empirical results support Hypothesis 3: the return-volatility relation is asymmetric, that is, implied volatility reacts differently to negative and positive returns.

Each individual row of Table 2 (i.e., for each specific q-value) shows that the impact of negative and positive SPX returns on VIX changes are different and highly asymmetric. The changing nature of the quantile estimates provides an interesting picture of how changes in volatility depend on the contemporaneous and lagged covariates.[16] The absolute value of R_t^- monotonically increases when moving from a lower quantile to an upper quantile; i.e., the marginal effect of negative returns is larger in the upper quantiles. For example, the absolute effect is over 5 times higher for $q = 0.95$ than for $q = 0.05$. This situation is reversed for positive returns.[17] Thus, these asymmetric responses across the quantiles of the conditional distribution of implied volatility changes confirm Hypothesis 4: the relation between return and volatility is asymmetric and more pronounced in the extreme tails of the ΔVIX distribution.

[15] The OLS regression estimates are close to the $q = 0.5$ (median)-Quantile Regression estimates.

[16] The equality of the coefficients across quantiles is tested using the Wald test.

[17] This tests the equality of quantile slope coefficients of each variable across quantiles, hence testing the null hypothesis that the coefficients of a particular covariate across quantile are the same. The test results are reported in the lower panel of Table 2 that rejects the null hypothesis of the equality of the coefficients (the contemporaneous and lagged negative and positive returns) across quantiles.

As most of the previous studies have focused on the asymmetric return-volatility relation at a daily frequency, it is important to compare the high frequency (1-minute interval) results of this study with corresponding results at the daily frequency. Empirical results for the daily return horizon are presented in Table 3.

There are three major differences in results for the 1-minute and the daily interval. First, the relation between return and volatility is much more pronounced at the daily level than at the 1-minute level. The absolute values of the coefficients of R_t^+ and R_t^- are higher at the daily level across all quantiles. This is also evident from the OLS regressions. Second, the coefficients of lagged covariates (negative and positive returns and lagged volatility) are mostly significant at the intraday 1-minute level. However, at the daily level autocorrelation in ΔVIX almost completely disappears and the cross-autocorrelation with returns is significant only for q-values lower than 0.05. This observation indicates that the effect of negative return shocks on volatility is persistent whereas the effect of positive return shocks is not at the daily level. Third, in comparison to the 1-minute level the R-squared values are higher for the daily level across all q-values.

5.2. Comparisons of the intraday asymmetric return-volatility relations across sampling frequency

In this section, the robustness of the empirical results on the short-term asymmetric return-volatility relations is investigated over different intraday return horizons. The return horizons are 1, 5, 10, 15, 60 min, and daily. The results for the QRM estimates of model (3) are reported in Table 4. The results for all six time-intervals are grouped according to each q-value. The estimates of the MRM in (2) are reported in the last four rows of Table 4. Additionally, the two positive and negative return covariates with their 19 quantile-regression estimates are graphed in Fig. 3 for each intraday time-interval, where $q = \{0.05, 0.1, \ldots, 0.9, 0.95\}$. The ΔVIX_i, (i = 1, 5, 10, 15, 60, and daily) responses to positive (negative) returns are plotted in the upper (lower) panel of Fig. 3. Generally, the graphs confirm the robustness of the results across the different intraday return horizons. The intraday return-volatility relation is highly asymmetric across the conditional distribution of volatility changes. Furthermore, the response to negative returns (in the lower panel) seems to be a monotonically decreasing function of the return horizon. However, for positive returns (in the upper panel) the relation to the return horizon is less clear. Still the 1-minute interval has the lowest absolute values across all q-values.

To analyze the asymmetry, Fig. 4 compares ΔVIX responses to negative and positive returns across the six time intervals for each q-value separately. These results demonstrate that the asymmetry, interpreted as the vertical distance between the two lines of the graphs of Fig. 4, is a decreasing function of the length of the return horizon and, hence, is lowest at the daily return horizon for q-values below the median. On the other hand, for q-values from median and above the asymmetry is an increasing function of the return horizon and is most pronounced

Table 4
Quantile regressions results: Response comparison across time intervals (1,5,10,15,60 min and day) at each quantile.

Variable	q	Intercept	R_t^+	R_t^-	R_{t-1}^+	R_{t-2}^+	R_{t-3}^+	R_{t-1}^-	R_{t-2}^-	R_{t-3}^-	ΔVIX_{t-1}	ΔVIX_{t-2}	ΔVIX_{t-3}	R^2(%)
ΔVIX1	0.05	−0.014***	−1.255***	−0.230***	−0.558***	−0.248***	−0.184***	−0.026***	0.075***	0.099***	−0.129***	−0.016***	0.004	40.3
ΔVIX5	0.05	−0.023***	−1.350***	−0.458***	−0.525***	−0.291***	−0.220***	0.002	0.108***	0.142***	−0.056***	0.018**	0.011	49.4
ΔVIX10	0.05	−0.034***	−1.403***	−0.572***	−0.462***	−0.321***	−0.258***	−0.010	0.142***	0.215***	−0.013	−0.001	0.013	51.7
ΔVIX15	0.05	−0.046***	−1.434***	−0.662***	−0.476***	−0.301***	−0.230***	0.042	0.233***	0.230***	0.009	−0.001	0.008	51.6
ΔVIX60	0.05	−0.109**	−1.587***	−0.703***	−0.313***	−0.149	−0.174	0.087	0.379***	0.263	−0.036	0.002	−0.005	53.2
ΔVIXD	0.05	−0.181	−1.478	−0.781	−0.341	−0.216	−0.318	0.390	0.374	0.327	−0.062	−0.065	−0.067	58.4
ΔVIX1	0.10	−0.010***	−1.076***	−0.280***	−0.433***	−0.168***	−0.122***	−0.073***	0.023***	0.045***	−0.122***	−0.013***	0.003	35.6
ΔVIX5	0.10	−0.015***	−1.207***	−0.504***	−0.391***	−0.196***	−0.146***	−0.045***	0.051***	0.097***	−0.041***	0.017***	0.020***	45.5
ΔVIX10	0.10	−0.022***	−1.256***	−0.608***	−0.377***	−0.227***	−0.155***	−0.039***	0.067***	0.136***	−0.015	−0.001	0.014	47.8
ΔVIX15	0.10	−0.030***	−1.316***	−0.669***	−0.389***	−0.208***	−0.126***	−0.021	0.131***	0.162***	0.001	0.008	0.020**	47.9
ΔVIX60	0.10	−0.076***	−1.429***	−0.757***	−0.223***	−0.084	−0.142	0.101	0.201***	0.202**	−0.002	−0.020	−0.007	49.5
ΔVIXD	0.10	−0.160	−1.239	−0.835	−0.202	−0.146	−0.198	0.296	0.360	0.227	−0.061	−0.024	−0.024	53.7
ΔVIX1	0.15	−0.008***	−0.965***	−0.323***	−0.365***	−0.135***	−0.096***	−0.105***	−0.0009	0.025***	−0.121***	−0.014***	0.002	32.2
ΔVIX5	0.15	−0.012***	−1.114***	−0.542***	−0.321***	−0.157***	−0.113***	−0.070***	0.019***	0.066***	−0.042***	0.014***	0.020***	42.9
ΔVIX10	0.15	−0.016***	−1.166***	−0.642***	−0.327***	−0.177***	−0.124***	−0.054***	0.033***	0.089***	−0.016**	0.001	0.009	45.3
ΔVIX15	0.15	−0.021***	−1.231***	−0.696***	−0.328***	−0.167***	−0.108***	−0.053***	0.088***	0.121***	−0.001	0.009	0.012	45.4
ΔVIX60	0.15	−0.058***	−1.351***	−0.813***	−0.190***	−0.062*	−0.068	0.060	0.192***	0.176***	−0.003	−0.008	0.002	46.7
ΔVIXD	0.15	−0.105	−1.154***	−0.941**	−0.180	−0.178	−0.210	0.167	0.335	0.218	−0.077	−0.020	−0.030	50.6
ΔVIX1	0.20	−0.006***	−0.885***	−0.357***	−0.323***	−0.115***	−0.081***	−0.126***	−0.012***	0.011***	−0.122***	−0.014***	0.001	29.2
ΔVIX5	0.20	−0.009***	−1.038***	−0.572***	−0.277***	−0.127***	−0.087***	−0.084***	0.004	0.046***	−0.041***	0.012***	0.021***	40.9
ΔVIX10	0.20	−0.013***	−1.105***	−0.666***	−0.282***	−0.139***	−0.088***	−0.073***	0.015*	0.066***	−0.017***	0.005	0.010*	43.4
ΔVIX15	0.20	−0.016***	−1.155***	−0.720***	−0.270***	−0.126***	−0.080***	−0.058***	0.069***	0.097***	0.001	0.013**	0.016**	43.6
ΔVIX60	0.20	−0.045***	−1.276***	−0.849***	−0.145***	−0.057	−0.055	0.033	0.167***	0.142**	0.002	−0.004	−0.000	44.6
ΔVIXD	0.20	−0.054	−1.077***	−0.955***	−0.160**	−0.175	−0.163*	0.168	0.276	0.206	−0.059	−0.024	−0.030	48.4
ΔVIX1	0.50	−0.0002***	−0.580***	−0.566***	−0.197***	−0.058***	−0.027***	−0.205***	−0.063***	−0.031***	−0.119***	−0.017***	0.004***	21.5
ΔVIX5	0.50	−0.0009***	−0.769***	−0.757***	−0.151***	−0.048***	−0.016***	−0.161***	−0.051***	−0.008**	−0.041***	0.010***	0.022***	35.7
ΔVIX10	0.50	−0.001***	−0.826***	−0.833***	−0.141***	−0.040***	−0.006	−0.153***	−0.024***	−0.004	−0.015***	0.018***	0.016***	39.0
ΔVIX15	0.50	−0.002***	−0.878***	−0.882***	−0.129***	−0.025***	0.0007	−0.142***	−0.010	0.016**	0.005	0.021***	0.017***	39.5
ΔVIX60	0.50	−0.011*	−0.959***	−1.031***	−0.036**	0.042**	0.027	−0.057**	0.052*	0.074***	0.013	0.011	0.013	40.6
ΔVIXD	0.50	0.021	−0.826***	−1.262***	−0.103*	0.005	0.016	0.096	0.115	0.117	−0.047	−0.025	0.017	44.9
ΔVIX1	0.80	0.005***	−0.365***	−0.870***	−0.109***	−0.011***	0.016***	−0.333***	−0.123***	−0.083***	−0.115***	−0.016***	0.005***	29.4
ΔVIX5	0.80	0.007***	−0.579***	−1.043***	−0.065***	0.004	0.032***	−0.296***	−0.120***	−0.061***	−0.036***	0.016***	0.029***	41.2
ΔVIX10	0.80	0.009***	−0.644***	−1.127***	−0.045***	0.033***	0.042***	−0.290***	−0.095***	−0.053***	0.003	0.027***	0.024***	41.1
ΔVIX15	0.80	0.011***	−0.684***	−1.190***	−0.023**	0.058***	0.055***	−0.285***	−0.087***	−0.038***	0.020**	0.032***	0.021***	44.9
ΔVIX60	0.80	0.024*	−0.733***	−1.420***	0.067**	0.122***	0.093***	−0.190***	0.005	0.020	0.026	0.027	0.019	47.6
ΔVIXD	0.80	0.145	−0.612***	−1.599***	0.010	0.099	0.082	0.008	0.048	0.068	−0.039	0.020	0.035	54.5
ΔVIX1	0.85	0.007***	−0.332***	−0.950***	−0.088***	0.004	0.030***	−0.377***	−0.140***	−0.100***	−0.114***	−0.014***	0.006***	32.5
ΔVIX5	0.85	0.010***	−0.545***	−1.124***	−0.042***	0.026***	0.048***	−0.349***	−0.151***	−0.078***	−0.034***	0.025***	0.031***	43.3
ΔVIX10	0.85	0.013***	−0.612***	−1.207***	−0.024**	0.057***	0.063***	−0.339***	−0.119***	−0.071***	0.005	0.032***	0.027***	46.1
ΔVIX15	0.85	0.015***	−0.660***	−1.274***	0.004	0.091***	0.077***	−0.329***	−0.106***	−0.071***	0.020**	0.038***	0.018**	46.8
ΔVIX60	0.85	0.035***	−0.711***	−1.504***	0.137***	0.159***	0.123***	−0.195***	−0.030	0.016	0.049**	0.024	0.031*	50.0
ΔVIXD	0.85	0.174***	−0.496***	−1.650***	0.061	0.138**	0.106*	0.043	−0.019	0.055	0.001	0.045	0.036	57.8
ΔVIX1	0.90	0.009***	−0.292***	−1.059***	−0.054***	0.025***	0.052***	−0.440***	−0.174***	−0.126***	−0.113***	−0.013***	0.008***	35.8
ΔVIX5	0.90	0.013***	−0.498***	−1.218***	−0.007	0.057***	0.078***	−0.419***	−0.201***	−0.111***	−0.032***	0.029***	0.032***	46.1
ΔVIX10	0.90	0.018***	−0.570***	−1.308***	0.009	0.094***	0.099***	−0.399***	−0.167***	−0.094***	0.009	0.030***	0.032***	48.7
ΔVIX15	0.90	0.022***	−0.625***	−1.370***	0.027	0.139***	0.106***	−0.396***	−0.130***	−0.118***	0.016	0.041***	0.013	49.3
ΔVIX60	0.90	0.051*	−0.676***	−1.628**	0.172***	0.231***	0.190**	−0.231***	−0.060	−0.010	0.056	0.039	0.040	53.3
ΔVIXD	0.90	0.270	−0.468	−1.887***	0.074	0.195	0.121	0.115	0.003	0.005	0.054	0.047	0.050	62.0
ΔVIX1	0.95	0.013***	−0.250***	−1.213***	0.006	0.077***	0.109***	−0.573***	−0.252***	−0.195***	−0.120***	−0.014***	0.013***	40.4
ΔVIX5	0.95	0.019***	−0.430***	−1.374***	0.049***	0.120***	0.135***	−0.542***	−0.287***	−0.189***	−0.040***	0.035***	0.035***	49.9
ΔVIX10	0.95	0.028***	−0.521***	−1.448***	0.081***	0.154***	0.164***	−0.551***	−0.241***	−0.163***	0.012	0.030**	0.033***	52.2
ΔVIX15	0.95	0.036***	−0.549***	−1.564***	0.084*	0.229***	0.160***	−0.559***	−0.209***	−0.159***	0.0003	0.055**	0.014	52.8
ΔVIX60	0.95	0.065	−0.531***	−1.822***	0.213	0.273	0.237	−0.412	−0.158	−0.134	0.053	0.018	0.028	58.1
ΔVIXD	0.95	0.378***	−0.432***	−2.11***	0.102	0.289	0.080	0.002	0.105	−0.181	0.058	0.135	−0.038	68.1
ΔVIX1	OLS	−0.0003*	−0.705***	−0.674***	−0.279***	−0.100***	−0.044***	−0.317***	−0.098***	−0.045***	−0.160***	−0.021***	0.007	37.6
ΔVIX5	OLS	−0.0007	−0.876***	−0.900***	−0.224***	−0.064***	−0.041***	−0.223***	−0.069***	−0.009	−0.046***	0.038***	0.020**	56.5
ΔVIX10	OLS	−0.001	−0.929***	−0.984***	−0.190***	−0.092***	−0.052***	−0.210***	−0.059***	−0.0006	0.006	0.002	0.006	60.6
ΔVIX15	OLS	−0.004**	−0.994***	−1.066***	−0.191***	−0.026	−0.025	−0.203***	−0.013	0.021	0.007	0.030**	0.001	62.4
ΔVIX60	OLS	−0.024***	−1.001***	−1.167***	−0.053	0.040	0.033	−0.093**	0.021	0.056	0.014	−0.025	0.014	64.6
ΔVIXD	OLS	0.064*	−0.978***	−1.330***	−0.105**	−0.060	−0.107*	0.015	0.111	0.089	−0.088*	−0.000	−0.054	74.6

Notes: The MRM and QRM specification 2 and 3 respectively are estimated for the asymmetric return-volatility relation for each of the volatility index separately. In both specification 2 and 3, we control for financial/economic crises effects by including dummy variables for eight crisis days (not reported). In the context of QRM, the standard errors are obtained using the bootstrap method; therefore, robust t-statistics (in parentheses) are computed for each of the quantile estimates. The MRM specification 2 is estimated with Newey and West (1987) correction for heteroscedasticity and autocorrelation. ***, **, and * denote rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

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at the daily return horizon. This observed conditional asymmetric behavior of the return-volatility relation has not been so far documented in the literature. As a consequence of this finding, Hypothesis 5, stating that the asymmetry in the return-volatility relation is robust across different intraday return horizons is not supported. This could be due to option market investors changing their position (or rebalance their portfolios) slowly.[18]

Comparing the estimated contemporaneous coefficients of covariates R_t^+ and R_t^- in columns 4 and 5 of Table 4 with those of the corresponding lagged covariates, it is evident that contemporaneous negative and positive returns are the most important factors among the covariates that determine changes in the volatility index. This pattern is robust for different q-values for each of the time intervals. The contemporaneous covariates are robustly statistically significant at the 1% level. The lagged covariates are also significant, especially at shorter return horizons. Thus, these results do not fully support Hypothesis 1 that contemporaneous returns are the sole source of changes implied volatility. This hypothesis would imply that fundamental explanations for the return-volatility relation, such as the leverage and volatility feedback, cannot explain the intraday dynamic return-volatility relation. However, the longest lag for a significant autocorrelation or cross-autocorrelation appears at three lags. This time span is also very short for drawing conclusions regarding fundamental-based explanations such as leverage and volatility feedback.

Table 4 further shows that the absolute values of the coefficients for R_t^+ are consistently higher than the corresponding coefficients for R_t^-. These results validate Hypothesis 3. Furthermore, according to each row of Table 4 (i.e., each quantile of the estimates), the absolute value of R_t^- monotonically increases when moving from lower to higher q-values, i.e., the marginal effect of negative returns is much larger in the upper quantiles. The situation is reversed for positive returns. Again, these results support Hypothesis 4.

6. Conclusions

This paper examines the intraday asymmetric relation between return and volatility by analyzing the relation at different parts of the conditional distribution of volatility changes. The S&P 500 index and the VIX index are sampled at different frequencies, ranging from 1, 5, 10, 15, 60 min, to one day, over the period September 25, 2003 to December 30, 2011. The results indicate that the relation between return and volatility is not robust across the different parts of the distribution of volatility changes. These results are consistent for all sampling frequencies considered. The effects of return shocks are more pronounced in the tails of the conditional distribution of volatility changes. Furthermore, the asymmetry between effects of positive and negative return shocks is varying over different quantiles of the distribution of volatility changes. Finally, at the intraday level, our study finds statistically significant autocorrelation and cross-autocorrelation patterns for the implied volatility changes that are not observed at the daily level.

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[18] Bollen and Whaley (2004) empirically show that higher implied volatility is purely induced by net-buying pressure of put options. As risk-averse investors who always hedge their underlying portfolio by taking positions in index puts, and due to limits to arbitrage, market makers want compensation for the induced risk, hence they increase option prices which ultimately increases implied volatility (as both have a monotonic relationship).

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