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A behavioral explanation for the negative asymmetric return–volatility relation ☆

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Abstract

We examine the short-term dynamic relation between the S&P 500 (Nasdaq 100) index return and changes in implied volatility at both the daily and intraday level. Neither the leverage hypothesis nor the volatility feedback hypothesis adequately explains the results. Alternatively, we propose that the behavior of traders (from the representativeness, affect, and extrapolation bias concepts of behavioral finance) is consistent with our empirical results of a strong daily and intraday negative return–implied volatility relation. Moreover, both the presence and magnitude of the negative relation and the asymmetry between return and implied volatility are most closely associated with extreme changes in the index returns. We also show that the strength of the relation is consistent with the implied volatility skew.

JEL classification: G12

Keywords: Return–volatility relation; Behavioral finance; Leverage hypothesis; Volatility feedback hypothesis; VIX

1. Introduction

Empirical evidence shows a negative relation between realized daily and weekly market returns and volatility. More specifically, negative (positive) innovations to return are correlated with positive (negative) innovations to volatility, with a greater asymmetric effect when returns decline/volatility increases. Two documented theories attempt to explain this negative relation. Black (1976) postulates that negative shocks to returns increase financial leverage, making stocks riskier and therefore subsequently driving up volatility, labeled the leverage hypothesis. Poterba and Summers (1986) and Campbell and Hentschel (1992) present the volatility feedback hypothesis, where any innovations to volatility (especially positive ones) lead to a decrease in returns. The leverage hypothesis has few supporters (see e.g. Low, 2004), while the volatility feedback hypothesis involves a complicated economic process that passes through expectations and dividends to validate the negative relation and only (weakly) explains the longer-term return–volatility relation. More recently, Low (2004) suggests that a behavioral explanation could be the cause of the asymmetric effect of losses being associated with larger volatility changes than are gains, but he does not relate his results to behavioral concepts and only examines the leverage effect to test the overall relation.

We investigate the relation between daily and intraday changes using the new CBOE Volatility Index (the VIX) and the returns on the S&P 500 index, as well as the corresponding Nasdaq volatility (VXN) and index return. We focus on the short-term dynamics of the return–volatility

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relation, contrary to the majority of past studies that employ weekly and monthly data on realized volatility to examine this relation. Our aim is to provide a detailed analysis of the *short-term* relation between market returns and implied volatility in order to identify the characteristics of the strong negative and asymmetric correlation between these variables.

We add to the literature by providing intraday results for the return–volatility relation, determining the factors affecting the relation, comparing five different forms of the model, and linking specific behavioral explanations with the observed daily and intraday results. In particular, we show that the negative and asymmetric association of return to changes in implied volatility is consistent with behavioral explanations of this phenomenon, while the leverage and volatility feedback models do not explain our results. We also examine: (1) return quintiles to show how implied volatility reactions are associated with the size of return innovations and (2) different measures of implied volatility to investigate the influence of the implied volatility skew, as well as determining the importance of realized volatility.

The empirical aspects of our study include four major differences from previous research. First, we use both the new VIX and the new VXN to measure implied volatility, with the new measures being better metrics of market expectations since they include the entire strike price range of implied volatilities. Second, we compare results using the VIX (VXN) to those of the near-the-money implied volatility, as well as including 5-min realized volatility as an independent variable. This allows us to disentangle the effects of the implied volatility skew from near-the-money implied volatility to examine the characteristics of the return–volatility relation and to distinguish the importance of implied volatility from current volatility. Third, we quantify the volatility response to the magnitude of return innovations, unlike other studies that only test for the presence of an asymmetric response. Fourth, in addition to using daily data, we investigate the relation at the intraday frequency using data sampled at 30-min and 5-min intervals, which allows us to solidify our behavioral explanation.

Our main empirical findings can be summarized along three dimensions. First, consistent with earlier studies, we find a significant negative and asymmetric correlation between innovations in return and (implied) volatility for stock indexes. However, by using regression models similar to those of Bollerslev and Zhou (2006), the results are consistent with behavioral explanations of the relation, but not the leverage or volatility feedback explanations. The results also show the superiority of employing the new VIX (VXN) to examine the return–volatility relation compared to either the near-the-money implied volatility or the contemporaneous realized volatility.

Our second contribution is a detailed analysis of the relation between return and implied volatility through time, as well as for quintiles of returns and their associated volatility innovations. We find that the individual years show a consistently strong relation over the different periods, unlike the sample inconsistency reported by others. Moreover, the quintiles of return results show that the strongest support for the negative and asymmetric relation is associated with the extreme changes in returns and volatility. The main implication of this finding is that "tail" events are important determinants of the return–volatility relation, which subsequently relates to the shape of the return distribution.

Third, by comparing the results of two implied volatility measures, the new VIX that employs all strike prices and the near-the-money implied volatility of the market, we show the importance of the implied volatility skew in explaining the return–volatility asymmetry. This supports the inferences of Dennis et al. (2006), who suggest that the magnitude of the asymmetry might be related to the slope of the implied volatility function, although they do not calculate the IVF.

Taken as a whole, our research shows that there is more to the return–volatility relation than suggested by the established hypotheses. In particular, we show the lack of support for established leverage and volatility feedback theories concerning this relation, while the results are consistent with behavioral explanations. In addition, we examine the characteristics of the relation using different models, across samples, for different measures of volatility, and for the sign and size of the return innovations.

2. The relation between returns and volatility in equity markets

2.1. The leverage and volatility feedback hypotheses

The negative relation between returns and volatility is widely documented in the literature. As pointed out by Bollerslev et al. (2007), most studies show a negative correlation between current return shocks and future volatility, with some studies illustrating that negative news is associated with a larger increase in volatility than positive news. The two popular theories associated with the negative return–volatility relation are the leverage hypothesis and the volatility feedback hypothesis. The leverage hypothesis states that when the value of a firm falls, the value of its equity becomes a smaller percentage of the total firm's value. Since the equity of the firm bears the entire risk of the firm, the volatility of equity should subsequently increase. This theory has been associated with the observed negative return–volatility relation for so long that this relation is typically referred to as the leverage effect. However, Christie (1982) and Schwert (1989) argue that it is difficult to account for the return–volatility effect given realistic estimates of leverage.

The volatility feedback hypothesis postulates that positive shocks to volatility cause negative returns. Campbell and Hentschel (1992) show theoretically that if *expected* future stock returns increase when volatility increases, then current stock prices (and hence returns) will fall to adjust to this change in future expectations. Thus, an increase to volatility causes negative returns. The volatility feedback hypothesis relies on the existence of time-varying risk premiums as the link between changes in volatility and returns (Poterba and Summers, 1986). This model implies that returns are negatively skewed, causing a large negative change in expectations to be amplified by the model, while a large positive change in expectations will be dampened by the model. In fact, this model states that *any* shock in volatility will cause negative returns; only "no news" will reduce volatility. Although the Campbell and Hentschel (1992) model involves a somewhat complicated non-linear multiperiod adjustment through dividends and expected returns, this theory is often tested using linear regression models. Empirically, Campbell and Hentschel only find weak support for their volatility feedback hypothesis.

2.2. Empirical evidence on the return–volatility relation

Following the empirical discovery of the existence of a negative correlation between returns and volatility, there was burgeoning research into which of the two theories best explained this relation. Most studies only consider one of these theories, often use monthly data, and generate mixed empirical results. For example, Schwert (1989) examines the S&P 500 daily return–volatility relation, concluding that it is difficult for the leverage hypothesis to explain the observed associated negative relation, while Bollerslev et al. (2006) conclude that the magnitude of the impact of a decrease in prices on volatility is too large to be explained by financial leverage fluctuations alone, as also shown by Figlewski and Wang (2001), and others.[1] Glosten et al. (1993) and Engle and Ng (1993) use various GARCH models to find support for the volatility feedback hypothesis.[2]

The previous studies focus mainly on the negative contemporaneous relation, with little emphasis on its asymmetry. Bekaert and Wu (2000) and Wu (2001) do examine asymmetry. The former find that the volatility feedback hypothesis is more likely to generate an asymmetric response than would the leverage effect by using the Japanese stock market. Bekaert and Wu (2000) and Dennis et al. (2006) also distinguish between strong and weak forms of the asymmetric relation. The strong form relates to a negative relation of returns with volatility, while the weak form says the negative relation exists for returns and expected volatility, after controlling for the absolute return shock and volatility innovation. Our models examine the weak form of this relation, with implied volatility being used as a proxy for expected volatility (the later is supported by evidence from Dennis et al.).

The first empirical study of the relation between the VIX as a measure of implied volatility and the market return was that of Fleming et al. (1995). They employ the old VIX series (now the VXO) the S&P 100 (which only uses near-the-money options) along with leads and lags of the stock market returns. For the entire sample their model explains 40.8% of the changes in volatility when market crashes are excluded. Only the coefficient on the contemporaneous return was consistently significant (and negative), while the other variables were typically insignificant or marginally significant.

By defining fear as an accelerating increase in the VXO, Low (2004) characterizes the nature of the asymmetric risk–return relation as a form of loss aversion (Whaley, 2000, first defined the VIX as a "fear gauge"). Using daily data, Low uses a regression model to investigate the non-linear contemporaneous relation between percentage changes in the VXO and the S&P 100 returns. Low reports a higher R^2 for the downside-return partition than the upside-return partition (59% versus 46%). He also documents an increasing slope for the downside partition, which he describes as a "convex profile for extreme losses." Whereas Low (2004) finds support for financial leverage as an explanation for the asymmetry, the robustness checks confirm that this explanation is at best a weak one.

2.3. A behavioral explanation of the return–implied volatility relation

The leverage and volatility feedback hypotheses are based on fundamental factors of the firm. However, these explanations relate to a longer-term lagged effect between return and volatility, or vice versa. Moreover, Dennis et al. (2006) show that the return–volatility relation is only a market phenomenon, not a firm one.

Our study involves shorter-term (daily and intraday) frequencies using implied volatilities of market data. In order to explain such a short-term relation we employ behavioral concepts. Shefrin (2005, Chapter 18, 2007, Chapter 4) discusses a negative return–risk relation in terms of representativeness, affect, and extrapolation bias. Managers and investors judge the risk–return relation for stocks to be negative (based on survey results), as investors view high return and low risk to be representative of good investments. This concept can be extended to the market such that larger negative (positive) returns and larger (smaller) risk or volatility are viewed as related characteristics of market behavior. Related to 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. Such labels strongly affect people's decisions (see Finucane et al., 2000). Consequently, the common use of heuristics (rules of thumb or mental shortcuts) to make decisions is easily extended to market return and option implied volatility

[1] Andersen et al. (2001), Dennis et al. (2006), Kim and Kon (1994) and Tauchen et al. (1996) additionally demonstrate that the effect is more pronounced for market indexes than for individual stocks.

[2] Bollerslev and Zhou (2006) concentrate on showing the theoretical consistency between the positive *expected* return–volatility relation from the CAPM and the negative *empirical* contemporaneous return–volatility relation. However, they do show that implied volatility provides a statistically significant return–volatility relation for monthly observations, while realized volatility often does not.

decisions in a way that these "affect heuristics" (based on intuition and instinct), in combination with the representativeness of negative returns and high risk, cause the negative return–implied volatility relation.[3] This view is consistent with the common perception that investors and dealers of options bid up put prices (for downside protection) during market downturns due to the fear of additional future losses (see the price pressure argument of Bollen and Whaley, 2004). Finally, extrapolation bias, the extrapolation of past events to form a forecast, in combination with those who believe recent events are representative of the future, also explains why a negative (positive) return would cause traders to increase (decrease) put option premiums.

Option traders' perceptions of volatility are the key factor in determining the VIX. We postulate that market returns influence the fear and exuberance of investors such that negative returns create fears of additional declines in the market, while positive returns create the exuberance of potential additional increases in the market, i.e. the representativeness associated with momentum effects. Shefrin (1999) supports this view, as does the use of the new VIX/VXN measures of implied volatility, since these measures include the implied volatility skew. In addition, Bakshi and Madan (2006) use 100 years of daily Dow Jones Industrial Average prices to show that the probability of a daily stock market decline in excess of 5% is a non-negligible 0.25%, that crash arrival rates are higher than rally arrival rates, and finally that market crashes are significantly more severe than market rallies. Thus, it appears that investors possess a legitimate reason to fear potential severe market declines and consequently will react to evidence of a potential or ongoing decline.[4] Moreover, the "fear of a crash" causes the level of market implied volatility to increase more during market declines than it decreases during market advances. This is consistent with the negative skewness associated with the market return distribution. It is also consistent with the typical skew relation, where implied volatilities are larger for out-of-the-money puts but essentially flat for calls. Finally, Giot (2005) shows that there is a strong negative relation between contemporaneous changes in implied volatility and the underlying stock index for both the S&P 100 and the Nasdaq 100 indexes (the old VIX and VXN). Giot (2005) also finds that negative returns for the S&P 100 index are associated with much greater relative changes in the VXO than positive returns, supporting the behavioral contention that investors suffer from fear. Hypotheses described in Section 3 provide behavioral associations for the return–volatility relation outlined above.

3. Data and variable description

This analysis employs data from three sources. We obtain the daily values for the S&P 500 stock index, the Nasdaq 100 index, the new VIX and the new VXN from the Chicago Board Options Exchange (CBOE) Master Data Retrieval (MDR) file. The near-the-money implied volatilities on the S&P 500 options and the Nasdaq 100 options are provided by Historical Options Data. We obtain 5-min returns to calculate realized volatility and the 30- and 5-min VIX and return data for the intraday analysis of the return–volatility relation from Tradestation. The daily data for the new VIX covers the nine-year period from January 1998 to December 2006, a total of 2263 trading days. The (available) period for the corresponding VXN is from February, 2001 to December 2006, a total of 1485 trading days. Intraday data for the new VIX and VXN start September 22, 2003.

3.1. The VIX and VXN

The Chicago Board Options Exchange's (CBOE) VIX index is a market implied volatility determined from the bid and ask prices of the S&P 500 index options. The VIX is calculated from all available stock index option bid and ask prices in the tradable range of these options, providing an estimate of expected stock market volatility for the subsequent 30 calendar days. The original VIX, now disseminated under the new ticker symbol VXO, was introduced in 1993. It is based on the S&P 100 index, considers only near-the-money options, and is calculated using the implied volatilities obtained from the Black–Scholes option-pricing model. The (new) VIX was introduced in September 2003, is based on options on the S&P 500 index, uses options across the tradable range of all strike prices possessing both a bid and ask price, and is independent of any option-pricing model. These new features have increased the practical appeal of the VIX, since the S&P 500 is the core index of equities in the United States, the new calculation procedure provides a more robust measure of expected volatility, and it includes the option implied volatility skew.[5] We employ reconstructed values for the VIX back to 1998.

3.2. Intraday realized volatility

The 5-min realized volatility is the square root of the summed 5-min realized variance. Following Andersen

[3] The affect heuristic is used to find benefits and reduce risks. Benefits are a positive affect and risks a negative affect. Those who employ the affect heuristic, therefore, create a negative relation between benefits and risks. Thus, affect and representativeness reinforce one another in terms of risk and return.

[4] David and Veronesi (2002) arrive at a similar conclusion, but with a different explanation. Namely, when returns have a negative drift then investor uncertainty typically increases, increasing (perceived) volatility. Hence, when returns are negative, volatility changes are positive.

[5] In September 2003, the CBOE implemented a new CBOE NASDAQ Volatility Index (VXN) with a revised VXN price history back to February, 2001. The same formula and methodology used to calculate the VIX is used for the VXN, with the VXN using Nasdaq 100 index option prices.

et al. (2003), the 5-min realized variance series is constructed by accumulating the squared intraday 5-min returns, which are the logarithmic differences between the prices recorded at or immediately before the corresponding 5-min time stamps.

4. Methodology

Use of the VIX provides several advantages for examining the return–volatility relation compared to realized volatility. First, the VIX is based on market determined bid and ask option prices, which allows us to examine how traders and option dealers react to the return dynamics of the market. Second, use of the VIX avoids statistical estimation problems associated with realized measures of volatility.[6] Third, since the VIX is a (constant 30-day) forward-looking volatility measure, it is a proxy for expected volatility and changes in conditional stock market volatility (see Fleming et al., 1995). Finally, since the new VIX includes the entire range of available strike prices, it includes the effect of the implied volatility skew and the demand for out-of-the-money puts used for protection against potential losses (and hence is related to behavioral effects on the VIX).

4.1. Daily data

The first stage of our analysis employs five regression models to investigate the *daily* return–volatility relation. Model M1 is[7]

$$\text{M1}\quad \Delta\text{VIX}_t = \alpha_0 + \alpha_1 R_t + \alpha_2 R_{t-1} + \alpha_3 R_{t-2} + \alpha_4 R_{t-3} + \alpha_7 \Delta\text{VIX}_{t-1} + \alpha_8 \Delta\text{VIX}_{t-2} + \alpha_9 \Delta\text{VIX}_{t-3} + \alpha_{13} \Delta 5\text{min}_t + \varepsilon_t, \tag{1a}$$

where ΔVIX_t is the change in the VIX at time t, given by $\text{VIX}_t - \text{VIX}_{t-1}$,[8] R_t is the contemporaneous daily percentage change in the S&P 500 index, R_{t-1}, R_{t-2} and R_{t-3} are the one-, two- and three-day lag returns for the S&P 500, respectively, ΔVIX_{t-1},ΔVIX_{t-2} and ΔVIX_{t-3} are the one-, two- and three-day lag changes in the VIX, and $\Delta 5\text{min}_t$ is the contemporaneous daily change in the 5-min realized volatility. Determining the fit and importance of the contemporaneous return, whether lagged return and lagged ΔVIX variables are relevant, and including a measure of realized intraday volatility allows us to test Hypotheses I and II:

Hypothesis I. Contemporaneous return is the most important factor that determines changes in current implied volatility.

If Hypothesis I is true, then the behavioral explanation of the return–volatility relation is superior to the leverage or volatility feedback hypothesis, since the latter explanations involve lagged relations. Hypothesis I is also consistent with the representativeness and affect theories, as investors associate negative returns with periods of volatility.

Hypothesis II. Lagged returns and/or changes in past implied volatilities are important factors used by the market to determine changes in the current implied volatility.

If the lagged returns are insignificant then the leverage effect is suspect for daily data. If past changes in implied volatilities affect current changes in implied volatilities then trends in option time value changes occur. Past changes in implied volatilities affecting current changes in implied volatility is consistent with the extrapolation bias behavioral theory, as investors would expect volatility changes to maintain a trend in the near future.

Hypothesis III. A change in the contemporaneous realized intraday volatility is the most important variable in explaining the ΔVIX (i.e., it is a realized volatility-implied volatility relation, not a return–implied volatility relation). Alternatively:

Modified Hypothesis III. If changes in realized volatility do affect changes in implied volatility as a secondary factor, then current volatility as well as return influences option time values. This hypothesis supports a behavioral explanation as well, given that investors can translate current realized volatility increases into higher future realized volatility, which in turns would cause a higher current VIX.

Model M2 replaces the VIX with the near-the-money implied volatility measure (IV):

$$\text{M2}\quad \Delta\text{IV}_t = \alpha_0 + \alpha_1 R_t + \alpha_2 R_{t-1} + \alpha_3 R_{t-2} + \alpha_4 R_{t-3} + \alpha_7 \Delta\text{IV}_{t-1} + \alpha_8 \Delta\text{IV}_{t-2} + \alpha_9 \Delta\text{IV}_{t-3} + \alpha_{13} \Delta 5\text{min}_t + \varepsilon_t \tag{1b}$$

We can compare M2 to M1 to examine the importance of the volatility skew via Hypothesis IV:

Hypothesis IV. Using the complete range of strike prices to determine market implied volatilities provides a better explanation of the return–volatility relation than only employing near-the-money implied volatility, i.e. the VIX provides superior results to near-the-money implied volatility.

[6] The use of statistical estimation of volatility, instead of employing the VIX, can create two types of errors, namely sampling errors and model misspecification errors. Implied volatility is not prone to these errors. First, implied volatility is obtained from option prices, as described by Eq. (1), rather than being a statistical estimate of latent volatility; therefore, the VIX avoids sampling error. Moreover, if the model is robust to small variations in its specifications then the model misspecification error will be small. Since the VIX is based on bid-ask quotes instead of transactions prices, it even avoids typical microstructure issues. Finally, implied volatility provides a forecast of future volatility, not an estimate of current volatility. Bollerslev and Zhou (2006) discuss various methodological issues regarding volatility in more detail.

[7] We outline the models in terms of the S&P 500 index and the VIX, with the understanding that the same models are also applied to the Nasdaq 100 and the VXN.

[8] This specification is consistent with the expression for the dynamics of stochastic volatility, dV, and is comparable to Fleming et al. (1995).

We compare the results of our model to the model used by Fleming et al. (1995),[9] labeled M3, and to the two models used by Low (2004), labeled M4 and M5. These three models are

$$\begin{aligned} \text{M3} \quad \Delta\text{VIX}_t &= \alpha_0 + \alpha_1 R_t + \alpha_2 R_{t-1} + \alpha_3 R_{t-2} \\ &\quad + \alpha_5 R_{t+1} + \alpha_6 R_{t+2} + \alpha_{14}|R_t| + \varepsilon_t \\ \text{M4} \quad \%\Delta\text{VIX}_t &= \alpha_0 + \alpha_1 R_t + \varepsilon_t \\ \text{M5} \quad \%\Delta\text{VIX}_t &= \alpha_0 + \alpha_1 R_t + \alpha_{15} R_t^2 + \varepsilon_t \end{aligned} \tag{1c}$$

The additional variables R_{t+1} and R_{t+2} in M3 are the one- and two-day lead returns for the S&P 500, respectively, $|R_t|$ is the absolute value of the contemporaneous return on the S&P 500, R_t^2 is the square of the contemporaneous return on the S&P 500, and $\%\ \Delta\text{VIX}_t$ is the percentage change in the VIX at time t. We perform separate regressions for each year in our sample as well as for the entire sample.

4.2. Intraday data

In the second stage of our analysis, we perform full sample and annual regressions using data sampled at 30-min and 5-min intervals, respectively. The 30-min and 5-min data span the period January 2004–December 2006.[10] Because data on the implied volatility (IV) variable is only available at the daily frequency, we omit model M2 in this stage of the analysis. Similarly, since the variable Δ5min is only available at daily frequencies, by construction, we employ $|R_t|$ in model M1. Otherwise the models are equivalent to those given in (1). If the lagged return variables in the intraday analysis are significant then:

Hypothesis V. Significant lagged values of the return variables provide additional support for causation from return to implied volatility, which is consistent with a behavioral relation between these variables.

4.3. The return–volatility asymmetry

We repeat the regression models in (1) in order to investigate asymmetry in the return–volatility relation by separating the daily contemporaneous returns into positive and negative changes (ΔR_t^+, ΔR_t^-). We also obtain positive and negative quintile results, which allow us to examine the sensitivity of the relation to the magnitude of the returns. Examining asymmetric and quintile results leads to Hypotheses VI–VIII.[11]

[9] We employ an updated version of their model where we replace the VXO which they use in their study with the new VIX, and we replace the return on the S&P 100 with the return on the S&P 500.

[10] We use this shorter sample since the new VIX methodology, which took effect in September 2003, has not been back-calculated for intraday data.

[11] Low (2004) presents a very limited examination of very extreme returns. His model is tested here for all quintiles using M5.

Hypothesis VI. Asymmetry exists for the return–implied volatility relation.

Hypothesis VII. The return–implied volatility relation is dominated by extreme return situations.

Hypothesis VIII. Asymmetric return–volatility relations are more pronounced at the extreme returns.

5. Daily results

5.1. Daily summary measures

Table 1 provides summary mean and standard deviation statistics for each variable for the daily data using the overall sample period (yearly results are available upon request). Over the sample period the change in the VIX is well behaved, with a mean of −0.005 and a standard deviation of 1.301. Both the mean of the VXN (31.037) and its standard deviation (14.977) are much larger than the corresponding VIX values, which is expected due to the greater volatility of the returns in the Nasdaq market. Examining the correlation matrix for the variables used in the daily analysis of the VIX, we find a large (and statistically significant) Pearson correlation coefficient of −0.80 between the contemporaneous S&P 500 returns and the changes in the VIX for the entire sample. This is significantly larger in magnitude than reported by Fleming et al. (1995), who report a correlation of −0.68, suggesting that the new formulation for the VIX is more directly associated with the contemporaneous return than is the old VIX (VXO). As expected, there is a large positive correlation coefficient of 0.58 between the ΔVIX and the ΔIV, but the magnitude of the correlation between the ΔIV and the contemporaneous return is only −0.47.[12] Similar to Bollerslev and Zhou's (2006) conclusion regarding previous research for the volatility hypothesis, the change in realized volatility (Δ5min) here has a much lower correlation with return than does the change in either of the implied volatility measures. *However*, the signs for Bollerslev and Zhou's longer-term return–implied volatility relation are positive, while the same daily contemporaneous relation here is negative (Bollerslev and Zhou allude to negative relations in the literature for *realized* volatility measures).

5.2. The relation between the S&P 500 returns and implied volatility for daily data

Table 2 provides the results for the five regression models described in (1) for the entire data set. Comparing the R^2s for various models shows that our model (M1) has the best fit, although the improvement over the Fleming

[12] We perform similar analysis using the Nasdaq 100 data; the results are qualitatively similar. These results are available from the authors upon request.

Table 1
Statistical properties of the daily data

	VIX_t/VXN_t	$\Delta VIX_t/\Delta VXN_t$	IV_t	ΔIV_t	R_t (%)	$\lvert R_t\rvert$ (%)	$(R_t)^2$ (%)	$\Delta 5min_t \times 10^3$
S&P 500 mean	21.040	−0.005	18.840	−0.018	0.017	0.837	0.013	−0.010
S&P 500 std. dev.	7.001	1.301	7.128	2.630	1.149	0.786	0.029	0.032
Nasdaq mean	31.037	−0.026	29.295	−0.033	−0.023	1.382	0.039	−0.093
Nasdaq std. dev.	14.977	1.327	15.125	2.513	1.965	1.396	0.086	0.040

The VIX_t and IV_t are the daily values of the CBOE Volatility Index and the near-the-money implied volatility (calculated from the Black–Scholes model), respectively. The contemporaneous return R_t is the daily return on the S&P 500 Index and $\Delta 5min_t$ is the daily change in the 5-min realized volatility. The equivalent data is presented for the Nasdaq 100 returns and the VXN.
The sample period for the S&P 500 extends from January 1998 to December 2006 (daily, yielding 2263 trading days) while the sample period for the Nasdaq extends from February 2001 to December 2006 (daily, yielding 1485 trading days).

Table 2
Regression results for daily changes in the VIX and near-the-money implied volatility

	R^2 (%)	Intercept	R_t	R_{t-1}	R_{t-2}	R_{t-3}	R_{t+1}	ΔVIX_{t-1}	ΔVIX_{t-2}	ΔVIX_{t-3}	ΔIV_{t-1}	ΔIV_{t-2}	$\Delta 5min_t$	$\lvert R_t\rvert$	R_t^2
M1	66.2	0.008	−88.289*	−1.123	1.062	1.898		−0.071*	−0.065*	−0.048*			3.745*		
		(0.49)	(−61.98)	(−0.48)	(0.46)	(0.82)		(−3.43)	(−3.16)	(−2.32)			(7.36)		
M2	40.6	0.009	−102.827*	−47.888*	−10.649*	24.042*					−0.51*	−0.172*	5.787*		
		(0.21)	(−26.87)	(−10.89)	(−2.40)	(5.56)					(−24.34)	(−7.64)	(4.23)		
M3	65.3	−0.081*	−90.532*	4.496*	8.194*		−3.608*							10.485*	
		(−3.38)	(−64.28)	(3.17)	(5.75)		(−2.56)							(5.01)	
M4	57.1	0.002*	−3.609*												
		(2.34)	(−54.86)												
M5	57.5	0.000	−3.613*												12.288*
		(0.18)	(−55.16)												(4.67)

In this table we compare the results of our two models, M1 and M2, to those of Fleming et al. (1995) M3, and Low (2004) M4 and M5:

$M1\quad \Delta VIX_t = \alpha_0 + \alpha_1 R_t + \alpha_2 R_{t-1} + \alpha_3 R_{t-2} + \alpha_4 R_{t-3} + \alpha_7 \Delta VIX_{t-1} + \alpha_8 \Delta VIX_{t-2} + \alpha_9 \Delta VIX_{t-3} + \alpha_{13} \Delta 5min_t + \varepsilon_t$

$M2\quad \Delta IV_t = \alpha_0 + \alpha_1 R_t + \alpha_2 R_{t-1} + \alpha_3 R_{t-2} + \alpha_4 R_{t-3} + \alpha_{10} \Delta IV_{t-1} + \alpha_{11} \Delta IV_{t-2} + \alpha_{12} \Delta IV_{t-2} + \alpha_{13} \Delta 5min_t + \varepsilon_t$

$M3\quad \Delta VIX_t = \alpha_0 + \alpha_1 R_t + \alpha_2 R_{t-1} + \alpha_3 R_{t-2} + \alpha_5 R_{t+1} + \alpha_6 R_{t+2} + \alpha_{14} \lvert R_t\rvert + \varepsilon_t$

$M4\quad \%\Delta VIX_t = \alpha_0 + \alpha_1 R_t + \varepsilon_t$

$M5\quad \%\Delta VIX_t = \alpha_0 + \alpha_1 R_t + \alpha_{15} R_t^2 + \varepsilon_t$

where ΔVIX_t and ΔIV_t are the changes in the VIX and IV from the close on day t minus the close on day $t-1$. R_t is the return in the S&P 500 index from day $t-1$ to day t; R_{t-1}, R_{t-2} and R_{t-3} are the one-, two- and three-day lagged returns in the index, respectively; R_{t+1} is the one-day lead return and $\Delta 5min_t$ is the change in the 5-min volatility from day $t-1$ to day t. t-statistics are given in brackets; asterisks (*) show significance at the 1% level. All results accept the hypothesis of no autocorrelation at the one percent significance level according to the Durbin–Watson statistics (not displayed). Variables that are not significant in any model are suppressed.

et al. (1995) model updated for the new VIX is marginal (which is logical since the variables are similar in nature). The increase in R^2s over the two models employed by Low (2004), i.e. M4 and M5, is almost 10% in each case. Examining the regression results from M1 shows that our Hypothesis I is verified, namely that the contemporaneous returns are significantly negative and are the most important determinant of current implied volatility, and thus supporting the representativeness and affect behavioral theories. Note that lagged changes in the VIX and the contemporaneous 5-min volatility are also significant, albeit much less important. Hence, Hypothesis II (the significance of past implied volatilities) is valid. This finding supports the extrapolation bias behavioral explanation, with investors projecting these realized volatility increases to temporarily continue into the future, which also would increase the VIX. And since lagged returns are not significant in M1, the leverage effect explanation is not very convincing for daily data.

Table 2 also shows that Hypothesis III is not true (realized volatility is not the most important variable affecting implied volatility changes), but that the Modified Hypothesis III is true, i.e. realized volatility is a significant variable. This result also supports extrapolation bias, as noted in conjunction with Hypothesis II. Thus, the relation between return and volatility is not a simple one. In addition, the results of model M3 show that when only returns (leads, lags, and contemporaneous) and the absolute return (as a measure of volatility) are used to explain changes in the VIX, then the lagged returns are significant, albeit of the incorrect sign. However, when the lagged values of changes in the VIX are included in model M1, then the lagged returns are no longer significant. Of the two lead return variables included in model M3, only the one-day lead is significant. Consequently, while M1 and M3 possess essentially equivalent R^2s, the composition of the significant variables suggests that M1 is a more consistent model in explaining the economic factors affecting implied volatility.

Comparison of models M1 and M2 shows that using the VIX provides a superior fit for the data compared to the near-the-money IV model, namely 66.2% versus 40.6%. In addition, while the lagged returns are not significant in model M1, they are significant in M2. These results provide evidence that the near-the-money implied volatility model does not adequately capture the return–volatility dynamics of the data, rather the VIX model M1 (which includes all strike prices of the underlying options, and hence the skew) possesses a superior relation with the S&P 500 returns, validating our Hypothesis IV posited earlier.

5.3. The relation between volatility and the nasdaq 100 returns for daily data

The full-sample daily results for the Nasdaq 100 returns with the VXN are qualitatively similar to those found for the S&P 500-VIX relation (not presented here for space considerations; available upon request). The main difference is the substantially lower R^2 for all of the models using the VXN. This finding is consistent with Giot's (2005) contention for the S&P 100 index that during market periods of higher volatility option traders are less aggressive in reacting to negative returns. This conclusion can be applied to the Nasdaq results, since the Nasdaq is inherently more volatile than the S&P 500. In addition, the significance of the variables is lower for the VXN and (unlike the VIX) the first lag of the return is negative and marginally significant for the VXN.

5.4. Annual regressions using daily data

Table 3 provides the results for the individual years for the models in equation (1) for the VIX and the VXN series. Panel A shows the R^2s and combined return slopes (of the contemporaneous and significant lagged returns) for each VIX model.[13] Panel B provides the same results for the VXN. As with the full sample results, model M1 is consistently superior to the other models in terms of its R^2s (and is substantially better than previous studies, such as Fleming et al., 1995).[14] The R^2 values for model M2 for the S&P 500 (near-the-money implied volatilities) are substantially larger than those from Dennis et al. (2006); our model M1 possesses R^2s that are substantially larger than those for M2. These results confirm the usefulness of employing the new VIX, as well as the importance of using the entire range of strike prices to examine this relation. None of the individual lagged returns (not shown here for space reasons; available upon request) are significant for M1 for the VIX, but are significant and *positive* for six of the nine years for M3, providing additional support for the superiority of model M1.[15]

[13] This is similar to the procedure used by Fleming et al. (1995).

[14] M1 and M3 possess similar R^2 values, with Model M3 for VXN having a marginally larger R^2 for several years.

[15] Moreover, only five lagged dependent variable coefficients are significant for model M1, while thirteen are significant for model M2. The realized contemporaneous volatility measures are consistently significant for models M1, M3, and M5, but are only significant for three years for model M2. In addition, all of the years accept the hypothesis of no autocorrelation at the one percent significance level according to the Durbin–Watson test, with the exception of 1999.

5.5. Conclusions concerning the daily results

Based on these results we conclude that the leverage hypothesis is not consistent with our daily return–volatility results, since the lagged return effects are weak and relatively unimportant. In other words, the leverage theory suggests that the primary relation should exist from returns to volatility over a long lag time, not contemporaneously, as shown here. However, the significance of the effect of lagged volatility changes supports the behavioral extrapolation bias. Finally, the realized volatility variable is significant for just over half of the years, showing the relative importance of return over realized volatility to explain the changes in implied volatility, which is consistent with the behavioral explanation (e.g. representativeness) being a viable explanation for the return–implied volatility relation.

6. Intraday results

6.1. Analysis using intraday data

Summary statistics for 5- and 30-min interval data on the VIX/VXN are omitted for space considerations. Both the means and standard deviations are stable over the sample period and are approximately equal to one-tenth of the equivalent daily values for the 5-min data. The correlation matrix for the intraday variables are consistent with the daily data, although the large sample size causes some correlations to be significant at very low correlation values. Surprisingly, a highly significantly negative Pearson correlation coefficient of −0.64 exists between the change in the VIX and the contemporaneous return for the 5-min data, although this value is somewhat smaller than the daily and the 30-min correlation. Finally, the correlation between the changes in the VIX and the lagged and lead returns are either insignificant or marginally significant for the 5-min interval.

6.2. The relation between the VIX and the S&P 500 returns using intraday data

In Table 4 we provide results for our regression models using VIX intraday data.[16] Panel A shows the results for the 30-min time interval and panel B provides the results for the 5-min interval. The fit of the regressions are remarkably high for intraday time intervals, with model M1 possessing an R^2 of 57.9% for the 30-min data and 42.3% for the 5-min data. Unlike the results for the daily data, the fit of the different models are quite similar, with the R^2 difference between models at

[16] Model 2 is not examined due to the lack of intraday near-the-money implied volatilities.

Table 3
Annual regression results for daily changes in the VIX and the VXN

Year	M1		M2		M3		M4		M5	
	R^2 (%)	Comb. Return	R^2 (%)	Comb. Return	R^2 (%)	Comb. Return	R^2 (%)	Comb. Return	R^2 (%)	Comb. Return
Panel A – Changes in the VIX										
1998	78.2	−117.260	41.0	−107.329	75.3	−108.372	66.7	−4.129	67.1	−4.185
1999	69.6	−96.380	46.9	−130.385	69.6	−72.062	63.9	−3.975	64.0	−3.958
2000	65.9	−70.814	50.3	−120.606	64.7	−61.670	60.8	−3.048	60.9	−3.044
2001	69.1	−91.137	52.0	−145.962	69.8	−91.764	67.1	−3.342	69.9	−3.319
2002	73.4	−87.783	66.7	−104.287	72.1	−89.263	66.4	−2.876	68.9	−2.980
2003	47.3	−55.816	41.5	−61.162	47.9	−48.150	40.7	−2.305	43.1	−2.381
2004	60.2	−87.951	47.7	−90.925	61.2	−87.448	57.8	−5.339	60.4	−5.329
2005	70.6	−89.663	61.0	−89.176	70.8	−77.760	68.2	−6.802	70.1	−6.819
2006	67.3	−108.358	61.2	−111.062	66.4	−92.986	66.9	−7.784	68.3	−7.952
Panel B – Changes in the VXN										
2001	37.7	−29.146	30.6	−74.889	38.3	−36.801	35.5	−0.689	39.6	−0.686
2002	43.9	−51.604	35.9	−77.174	43.5	−48.778	41.2	−0.888	41.4	−0.902
2003	28.4	−16.014	26.1	−10.831	28.6	−20.054	22.4	−0.941	24.1	−0.990
2004	54.4	−54.154	26.9	−95.723	54.8	−62.275	51.3	−2.404	51.3	−2.405
2005	45.4	−49.040	40.8	−68.119	42.5	−50.734	40.6	−3.033	40.8	−3.033
2006	49.8	−61.654	40.7	−70.965	47.6	−62.728	45.6	−3.378	47.5	−3.432

This table presents the annual results for the five regression models as described in the text and previous tables. Panel A provides summary results for changes in the VIX and Panel B provides the corresponding results for the VXN. The R^2 and combined return coefficients, which are the sums of the contemporaneous and significant lagged return coefficients, are reported for each of the models.

Table 4
Regression results for intraday changes in the VIX

	R^2 (%)	Intercept	R_t	R_{t-1}	R_{t-2}	R_{t-3}	R_{t+1}	ΔVIX_{t-1}	ΔVIX_{t-2}	ΔVIX_{t-3}	$\lvert R_t \rvert$	$(R_t)^2$
Panel A: S&P 500 30-min data												
M1	57.9	−0.007*	−88.888*	−9.475*	−0.994	−0.956		−0.005	0.015	−0.001	7.649*	
		(−3.75)	(−110.45)	(−7.71)	(−0.81)	(−0.78)		(−0.43)	(1.39)	(−0.06)	(6.83)	
M3	57.9	−0.008*	−88.877*	−9.076*	−2.253*		−0.717				7.779*	
		(−3.81)	(−110.41)	(−11.29)	(−2.80)		(−0.89)				(6.95)	
M4	56.8	0.000*	−6.032*									
		(2.17)	(−108.97)									
M5	57.2	−0.000	−6.084*									113.907*
		(−1.37)	(−109.93)									(9.61)
Panel B: S&P 500 5-min data												
M1	42.3	−0.004*	−75.104*	−14.311*	−6.239*	−3.786*		−0.115*	−0.029*	−0.010*	8.358*	
		(−10.72)	(−208.63)	(−30.54)	(−13.23)	(−8.05)		(−28.52)	(−7.18)	(−2.54)	(17.37)	
M3	41.5	−0.004*	−74.942*	−5.682*	−3.435*		−1.113*				8.217*	
		(−10.57)	(−206.74)	(−15.73)	(−9.51)		(−3.08)				(16.96)	
M4	39.0	0.000	−5.077*									
		(1.61)	(−197.44)									
M5	39.5	0.000*	−5.153*									190.640*
		(−3.40)	(−199.21)									(21.26)

This table gives the results of the following four regression models using data sampled at 30-min and 5-min intervals:

M1 $\Delta VIX_t = \alpha_0 + \alpha_1 R_t + \alpha_2 R_{t-1} + \alpha_3 R_{t-2} + \alpha_4 R_{t-3} + \alpha_7 \Delta VIX_{t-1} + \alpha_8 \Delta VIX_{t-2} + \alpha_9 \Delta VIX_{t-3} + \alpha_{13}|R_t| + \varepsilon_t$

M3 $\Delta VIX_t = \alpha_0 + \alpha_1 R_t + \alpha_2 R_{t-1} + \alpha_3 R_{t-2} + \alpha_5 R_{t+1} + \alpha_6 R_{t+2} + \alpha_{14}|R_t| + \varepsilon_t$

M4 $\%\Delta VIX_t = \alpha_0 + \alpha_1 R_t + \varepsilon_t$

M5 $\%\Delta VIX_t = \alpha_0 + \alpha_1 R_t + \alpha_{14} R_t^2 + \varepsilon_t$

where ΔVIX_t and ΔIV_t are the change in the VIX and near-the-money IV between the close at time t minus the close at time $t-1$. R_t is the return on the S&P 500 index from time $t-1$ to time t; R_{t-1}, R_{t-2} and R_{t-3} are the one-, two- and three-time lagged returns in the index, respectively and R_{t+1} is the one-time lead return. Panel A shows the results for observations at 30-min time intervals and Panel B provides the results for observations at 5-min time intervals. t-statistics are given in brackets; asterisks (*) show significance at the 1% level.

the 30-min frequency being 1.1% and at the 5-min frequency being 3.3%.[17] The significance of the three return lags and the ΔVIX lags shows that recent intraday returns and volatilities affect changes in the current VIX values, and that a five- to 15-min persistence in the direction of the VIX exists. Overall, these intraday results provide support for the return to VIX causation

[17] In addition, the fit of M1 for the intraday data is superior to Low's (2004) *daily* results.

direction for the return–volatility relation, which is consistent with our Hypothesis V.

The results from the intraday data provide strong evidence that any return–volatility hypothesis restricted to a long lead time between the causation factor and the effect variable, such as needed by the leverage and volatility feedback models, does not explain these strong intraday results. Thus, there is more to the return–volatility relation than is explained by the classic hypotheses. Moreover, the results support behavioral theories such as representativeness, affect, and extrapolation bias, where only very short periods or time intervals are needed for the observed relations to take place. Finally, these results shed doubt on the importance of time-varying risk premiums as a key factor in the return–volatility relation, since time-varying risk premiums are not associated with such short time intervals.

6.3. The relation between the VXN and the Nasdaq 100 returns using intraday data

Results using intraday data for the VXN and Nasdaq 100 have been omitted for space considerations and are available upon request. The results are qualitatively similar to those for the VIX and are consistent with the daily results using the VXN. Somewhat surprisingly, the coefficient of the contemporaneous return for the VXN is only about two-thirds of the coefficient for the VIX. However, this finding is consistent with Giot (2005), who argues that option traders are less aggressive in reacting to negative returns during market periods of higher volatility, causing the co-movements between returns and volatility to be muted. In addition, comparison of the results for M1 across the VIX and VXN shows that the magnitude of the coefficient of the contemporaneous return decreases as the sampling frequency increases for the VIX, while the magnitude of the coefficient of the contemporaneous return for the VXN is larger at the intraday intervals than at the daily interval.

6.4. Annual regressions using intraday data

The VIX (VXN) results for the S&P 500 (Nasdaq100) return–volatility regressions using the individual yearly data for both the 30-min and 5-min time intervals (not shown here) show that the results are consistent across the years, with almost equivalent R^2 values to the overall sample in Table 4, and therefore the results for the overall sample are not affected by aggregating the data. However, comparing the daily results to the 30- and 5-min results shows that the lagged returns and the lagged changes in the dependent variable become more significant as the frequency is increased. This suggests that adjustments in the bid-ask spreads of some option strikes lag changes in the market intraday return, i.e. not all option strikes react instantaneously to market innovations in return. In addition, except for the squared return measure included in M5, the realized volatility is insignificant for the higher frequencies. Consequently, there is a small but significant "spillover" effect across intraday time intervals, but actual realized volatility is not an important factor in the return–volatility relation measured by the intraday annual samples.

6.5. Conclusions concerning the intraday results

The intraday results provide strong evidence that is counter to the implications of both extant theories, i.e. the leverage hypothesis and the volatility feedback hypothesis. Specifically, the leverage effect is inconsistent with an intraday relation, and volatility feedback should possess a greater significance of the realized volatility measures at the higher intraday frequencies.

7. Return–volatility asymmetry

Panels A and B of Table 5 show the results of the five regression models for the VIX when returns are segregated into positive and negative daily changes (the VXN results are similar in nature but possess lower R^2s and lower significance values for the variables than the VIX results). Comparison of the Panel A and Panel B R^2 values shows that a better fit is achieved in the negative return partition for both markets. The coefficients for the contemporaneous return and some of the lagged return coefficients are negative and significant for both the positive and negative return samples for all models in both panels. However, both the magnitude and significance of the contemporaneous return coefficients are consistently greater for the negative returns, supporting Hypothesis VI. For example, the magnitudes (t-statistics) for the VIX model M1 is -80.544 (-29.19) for positive returns and -97.039 (-30.80) for negative returns. However, the asymmetry effect is less pronounced for the VIX (M1) than for near-the-money implied volatility (M2), although M2 has significantly lower R^2s. More generally, these daily asymmetry results show that the lagged returns (associated with the leverage effect by Bollerslev and Zhou, 2006) are not significant in model M1 and are significant only for the *near*-the-money implied volatility model M2. Moreover, lagged ΔVIX and ΔIV variables are more important than lagged return values. These results provide additional evidence against the leverage hypothesis.

Results for the return quintiles of the positive and negative sub-samples for the S&P 500 are provided in Table 6. The largest positive and negative returns have the best fit, confirming hypothesis VII that the return–implied volatility relation is strongly associated with the extreme returns. For example, the fifth negative return quintile possesses an R^2 of 38.8% for model M1, which is substantially higher than the quintile with the next best fit, the third (14.2%). Further inspection of the quintile results shows that only half of the contemporaneous return coefficients are significant, mostly the largest return quintiles, providing additional evidence of the validity of Hypothesis VII.

Table 5
Regression results for daily changes in the VIX and implied volatility for (a) positive and (b) negative contemporaneous returns

	R^2 (%)	Intercept	R_t	R_{t-1}	R_{t-2}	R_{t-3}	R_{t+1}	ΔVIX_{t-1}	ΔVIX_{t-2}	ΔVIX_{t-3}	ΔIV_{t-1}	ΔIV_{t-2}	ΔIV_{t-3}	$\Delta 5\text{min}_t$	$(R_t)^2$
Panel A: Positive returns															
M1	48.7	−0.046	−80.544*	1.05	4.279	−0.542		−0.102*	−0.066*	−0.112*				2.726*	
		(−1.46)	(−29.19)	(0.33)	(1.36)	(−0.17)		(−3.56)	(−2.35)	(−3.92)				(3.93)	
M2	34.8	−0.102	−82.224*	−57.307*	−14.442*	25.170*					−0.570*	−0.282*	−0.190*	6.125*	
		(−1.01)	(−9.27)	(−8.60)	(−2.02)	(3.51)					(−20.45)	(−8.56)	(−4.88)	(2.72)	
M3	46.1	−0.066*	−80.112*	9.592*	11.406*		−6.606*								
		(−2.11)	(−28.59)	(−5.15)	(−5.89)		(−3.22)								
M4	29.2	−0.010*	−2.663*												
		(−6.95)	(−22.02)												
M5	30.8	−0.004*	−4.001*												−28.715*
		(−2.24)	(−14.09)												(−3.46)
Panel B: Negative returns															
M1	51.8	−0.080*	−97.039*	−1.942	−0.554	3.607		−0.031	−0.062*	0.007				4.051*	
		(−2.25)	(−30.80)	(−0.55)	(−0.16)	(1.08)		(−1.05)	(−2.09)	(0.23)				(5.38)	
M2	40.7	−0.294*	−134.740*	−23.994*	0.991	17.111*					−0.360*	−0.002	0.042*	3.902*	
		(−4.19)	(−21.79)	(−4.39)	(0.19)	(3.68)					(−10.95)	(−0.07)	(2.13)	(2.64)	
M3	50.3	−0.087*	−100.810*	−1.412	4.946*		−1.597								
		(−2.41)	(−32.38)	(−0.66)	(2.36)		(−0.82)								
M4	35.4	0.006*	−3.589*												
		(3.38)	(−24.39)												
M5	36.2	0.002	−4.528*												41.446*
		(0.78)	(−14.70)												(5.20)

This table reports results of the following five regression models:

$M1$ $\Delta\text{VIX}_t = \alpha_0 + \alpha_1 R_t + \alpha_2 R_{t-1} + \alpha_3 R_{t-2} + \alpha_4 R_{t-3} + \alpha_7 \Delta\text{VIX}_{t-1} + \alpha_8 \Delta\text{VIX}_{t-2} + \alpha_9 \Delta\text{VIX}_{t-3} + \alpha_{13}\Delta 5\text{min}_t + \varepsilon_t$

$M2$ $\Delta\text{IV}_t = \alpha_0 + \alpha_1 R_t + \alpha_2 R_{t-1} + \alpha_3 R_{t-2} + \alpha_4 R_{t-3} + \alpha_{10}\Delta\text{IV}_{t-1} + \alpha_{11}\Delta\text{IV}_{t-2} + \alpha_{12}\Delta\text{IV}_{t-2} + \alpha_{13}\Delta 5\text{min}_t + \varepsilon_t$

$M3$ $\Delta\text{VIX}_t = \alpha_0 + \alpha_1 R_t + \alpha_2 R_{t-1} + \alpha_3 R_{t-2} + \alpha_5 R_{t+1} + \alpha_6 R_{t+2} + \alpha_{14}|R_t| + \varepsilon_t$

$M4$ $\%\Delta\text{VIX}_t = \alpha_0 + \alpha_1 R_t + \varepsilon_t$

$M5$ $\%\Delta\text{VIX}_t = \alpha_0 + \alpha_1 R_t + \alpha_{15} R_t^2 + \varepsilon_t$

where ΔVIX_t and ΔIV_t are the change in the VIX and near-the-money IV from the close on day t minus the close on day $t-1$. R_t is the return in the S&P 500 index from day $t-1$ to day t; R_{t-1}, R_{t-2} and R_{t-3} are the one-, two- and three-day lagged returns in the index, respectively; R_{t+1} is the one-day lead return and $\Delta 5\text{min}_t$ is the change in the 5-min volatility from day $t-1$ to day t. Panel A provides the results using only observations for which R_t is positive, while Panel B gives the results for the negative values of R_t. There are 1177 observations for which R_t is positive and 1086 for which R_t is negative. t-statistics are given in brackets; asterisks (*) show significance at the 1% level. Variables that are not significant in any model are suppressed.

Table 6
Summary regression results for daily changes in the VIX for positive and negative return quintiles

	R^2 (%)	Intercept	R_t	R_{t-1}	R_{t-2}	R_{t-3}	ΔVIX_{t-1}	ΔVIX_{t-2}	ΔVIX_{t-3}	$\Delta 5min_t$
Panel A: Positive return quintiles										
First	7.0	−0.023	−120.216*	−0.965	11.856	−3.480	−0.028	0.006	−0.038	1.507
		(−0.35)	(−2.29)	(−0.18)	(1.98)	(−0.63)	(−0.52)	(0.12)	(−0.76)	(1.09)
Second	11.1	−0.046	−78.354	−2.156	2.685	6.049	−0.171*	−0.036	0.001	1.714
		(−0.28)	(−1.59)	(−0.39)	(0.42)	(0.95)	(−2.98)	(−0.59)	(0.01)	(1.10)
Third	11.2	−0.102	−62.844	−6.502	−15.209*	−10.126	−0.127*	−0.153*	−0.173*	2.461
		(−0.36)	(−1.36)	(−0.99)	(−2.38)	(−1.72)	(−2.15)	(−2.79)	(−3.04)	(1.83)
Fourth	15.1	0.191	−102.518*	−10.393	12.741	1.000	−0.182*	−0.012	−0.128	−0.399
		(0.55)	(−2.98)	(−1.30)	(1.87)	(0.11)	(−2.72)	(−0.20)	(−1.74)	(−0.23)
Fifth	37.8	−0.264	−69.166*	14.063	3.968	3.727	−0.060	−0.136	−0.134	3.957*
		(−1.34)	(−7.77)	(1.59)	(0.48)	(0.45)	(−0.78)	(−1.81)	(−1.77)	(2.36)
Panel B: Negative return quintiles										
First	12.4	0.041	−118.345	−3.552	0.634	15.851*	−0.064	−0.060	0.021	6.104*
		(0.45)	(−1.68)	(−0.48)	(0.09)	(2.21)	(−1.00)	(−0.850)	(0.33)	(3.59)
Second	10.1	0.178	6.182	5.527	7.519	11.577	−0.055	0.039	0.043	4.418*
		(0.98)	(0.12)	(1.01)	(1.18)	(1.93)	(−1.21)	(0.68)	(0.83)	(3.27)
Third	14.2	0.249	−30.879	−5.057	−0.225	3.745	−0.120*	−0.090	−0.063	4.178*
		(0.75)	(−0.61)	(−0.73)	(−0.03)	(0.50)	(−2.13)	(−1.44)	(−0.91)	(3.05)
Fourth	11.2	0.099	−74.985*	3.805	−8.979	−15.607	0.097	−0.108	−0.053	3.242
		(0.29)	(−2.33)	(0.43)	(−1.07)	(−1.99)	(1.26)	(−1.53)	(−0.73)	(1.76)
Fifth	38.8	−0.131	−101.194*	−9.052	6.826	4.322	−0.014	−0.004	0.051	2.847
		(−0.58)	(−9.59)	(−0.88)	(0.77)	(0.49)	(−0.15)	(−0.06)	(0.70)	(1.30)

This table provides regression results for model M1, as described in the text and previous tables, for quintiles of positive and negative R_t. Quintile 1 is the smallest return category and quintile 5 is the largest return category.

Our results also show that the asymmetry of the return–volatility relation is heavily dependent on the extreme quintiles, a validation of both Hypotheses VI and VII. While these conclusions are consistent with Low's (2004), the results for models M4 and M5 provide low R^2 (13.7% and 7.9% for the extreme quintiles and below 3% for the others), and the asymmetry is not evident in those results. Thus, the form and strength of the relation is better described by model M1 than by Low's model. Finally, the near-the-money implied volatility results show mostly inconsistent significant contemporaneous returns and an unstable pattern of significant variables. Hence, model M2 does not conform to the results found for the other models throughout this paper.

8. Summary and conclusions

This paper takes a different approach to investigating the negative asymmetric risk–return relation by using the new VIX implied volatility measure, comparing different models of implied volatility, analyzing intraday and Nasdaq results, and examining the effect of quintile rankings of returns. Our results imply that the leverage hypothesis and the volatility feedback hypothesis are not the *primary* explanations of the return–implied volatility relation. We propose a behavioral approach that is consistent with the results, which involves representativeness, affect, and extrapolation bias.

Both the daily and intraday 30- and 5-min return–volatility results provide additional support for the negative and asymmetric relation, as do the quintile results. The reasons for the weaker results for the Nasdaq market needs further study, but could be directly related to the greater level of volatility found in this market.

Finally, regressions by quintile show that the extreme changes are most strongly associated with the return–implied volatility relation, and that using changes in the new VIX for the volatility measure provides a better explanation for the relation than either using changes in the near-the-money implied volatility or employing realized volatility.

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