On the relationships between implied volatility indices and stock index returns

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ABSTRACT

For the S&P100 and NASDAQ100 indices, we show that there is a negative and statistically significant relationship between the returns of the stock and implied volatility (VIX and VXN) indices. For the S&P100 index, this relationship is asymmetric as negative stock index returns yield bigger changes in VIX than do positive returns. The VIX's response to negative stock index returns is sharper in low-volatility periods, which suggests that option traders react aggressively to negative returns in low-volatility periods by strongly bidding up implied volatility. For the NASDAQ100 index, the asymmetric effect is rather weak but the VXN response to the index is also somewhat muted in high-volatility trading environments. In a second step, we assess the relationship between implied volatility and forward looking stock index returns. There is some evidence that positive (negative) forward looking returns are to be expected for long positions triggered by extremely high (low) levels of the implied volatility indices.

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In an option pricing framework, volatility is the only input that cannot be directly observed by the market participants. Indeed, call/put feature, time-to-maturity and strike price are the basic characteristics of the option contract, while the risk-free interest rate and dividend payment are fairly easy to agree upon. Thus the unknown input when computing the price of the option is the expected volatility over the life of the option.[1] In a market economy with actively traded option contracts which express the market's view of the relevant prices for those contracts, one can solve for the volatility that equates the observed market price of the option contract with the price given by the chosen option pricing formula. This yields the implied volatility. Because of the growing importance of modelling and predicting asset volatility in modern finance, the relevance of implied volatility as a rational forecast of future realized volatility and the information content of implied volatility w.r.t. historical volatility are two important (related) research topics in the academic literature. This topic has spawned a large number of empirical studies reviewed in a recent paper by Poon and Granger (2003).

These studies focus on the link between implied volatility and future realized volatility. Quite surprisingly, few studies deal with the possible relationship between implied volatility and future stock *returns*. This probably stems from the belief that financial markets are efficient and, as such, implied volatility cannot provide relevant information as to whether stock prices are going up or down. This is in contrast with the opinion of non-academic market participants for whom very large implied volatility levels are usually seen as signalling attractive entry levels for long traders. Their rationale is that very high implied volatility levels are seen during periods of financial turmoil where investors are believed to be over-reacting and hence selling indiscriminately their financial assets to raise cash or limit losses.[2] For example, the VIX implied volatility index of the CBOE is now routinely discussed in financial newspapers such as Barron's or the Wall Street Journal. Quite interestingly, there is a clear reference to a possible relationship between extremely high levels of implied volatility and a 'market bottom'. For example, in an article whose title is "Fixated on the VIX: soaring volatility means fear - and opportunity", K. Tan was writing in the July 29, 2002 issue of Barron's that "A big VIX spike indicates the kind of extreme fear contrarians associate with market bottoms".

Even in the academic literature, the VIX implied volatility index of the CBOE for S&P100 index option contracts is dubbed the 'fear indicator' (Whaley, 2000).

With respect to that framework, this paper focuses on two closely related topics which deal with the empirical link between implied volatility indices and stock index returns. More precisely we assess (a) the contemporaneous relationship between relative changes in implied volatility and stock market returns and (b) the possible relationship between implied volatility and future stock market returns. In the first case we thus look at the simultaneous changes in the implied volatility and underlying stock indices. In the second case, we focus on the "does fear mean opportunity?" question as we assess possible trading gains for long positions triggered by very large levels of the implied volatility index. Regarding the empirical application, we deal with the S&P100 and NASDAQ100 indices for which the implied volatility indices VIX and VXN are readily available. Because the VIX and VXN indices are freely available at the CBOE internet website and are widely disseminated by data vendors, they can truly be viewed as public information available to all investors and hence can reasonably be considered as possible trading signals. The S&P100 and NASDAQ100 indices are also representatives of two different class of stocks. Constituents of the S&P100 index are widely-held stocks representatives of the U.S. economy. These include financial, industrial and technological firms. As such, it is a proxy for the U.S. market 'as a whole', although not as general as the broader S&P500 index but for which no pre-computed implied volatility index exists. On the other hand, the NASDAQ100 index includes almost exclusively technological and biotechnological firms. Our study thus deals with two types of stock market measures for which the relationship between implied volatility and returns can differ. For both indices we also estimate the contemporaneous relationship model during distinct sub-periods which pertain to different trading environments. More specifically we focus on the August 1, 1994 - May 30, 1997 (low volatility, bull market), June 2, 1997 - March 31, 2000 (high volatility, bull market) and April 3, 2000 - January 31, 2003 (high volatility, bear market) time periods.

In a first step, we thus first consider 1-day contemporaneous changes in the stock indices (S&P100 and NASDAQ100 indices) and corresponding implied volatility indices (VIX and VXN indices). Not surprisingly and as documented in the previous literature (e.g. see Whaley, 2000), there is a negative and statistically significant relationship between the returns of the two stock and implied volatility indices: positive stock index returns lead to decreased implied volatility levels, while negative returns lead to higher implied volatility levels. For the S&P100 index, this relationship is also asymmetric in the sense that negative stock index returns yield bigger proportional changes in implied volatility measures than do positive returns. As a new contribution to the literature, we show that there are however important differences across sub-periods as the implied volatility's response to negative stock index returns is much sharper in low-volatility trading environment. A possible explanation is that option traders react aggressively to negative returns in low-volatility periods by strongly bidding up implied volatility, but are somewhat reluctant to do so in continued high-volatility trading environments such as experienced since the summer of 1997 (and more particularly since mid-2000). For the NASDAQ100 index, the asymmetric effect is rather weak but the VXN response to the index is also somewhat muted in high-volatility trading environments. Moreover, there are no real quadratic (see below for definition) effects for either stock index.

In a second step, we focus on the possible relationship between implied volatility and future (i.e. forward looking) stock index returns. Our aim is to ascertain if, as thought by some market practitioners, large or very large implied volatility levels do indeed indicate over-sold markets and hence could be viewed as short term to middle term 'buy signals'. Our empirical methodology is close to that of Campbell and Shiller (2001) where they study the link between observed price-earnings ratios (at a time t for example) and future stock index returns (over a time period ranging from $t+1$ to $t+n$ where n is the time horizon). Next to the study of the mean return achieved over a 1-, 5-, 10- and 60-day time horizon (long position in the stock index) subsequent to a 'signal' given by the implied volatility index, we also assess the trading risk incurred by taking those positions. Not surprisingly, results are very different from the ones given regarding the 1-day contemporaneous changes in the stock indices. In this case, there is some weak evidence that positive (negative) forward looking returns are to be expected for long positions triggered by extremely high (low) levels of the implied volatility indices. We also get the same type of results using regression analysis. This seems to somewhat validate the practitioners' point of view although one should stress that the evidence is rather sketchy and seems to hold only for long trades triggered by extremely high levels of implied volatility. We also briefly put our results in the light of the academic literature that focused on the link between expected returns and (conditional) volatility.

The rest of the paper is structured as follows. After this introduction, we detail the VIX and VXN implied volatility indices in Section I. Contemporaneous changes in the stock index and implied volatility index are discussed in Section II. The possible relationship between implied volatility and forward looking stock index returns is detailed in Section III. Finally, Section IV concludes.

I. The VIX and VXN indices

The VIX and VXN implied volatility indices are computed on an intradaily basis by the CBOE.[3] By construction, the VIX (VXN) index is a weighted average of the implied volatilities computed from a total of eight call and put near-the-money, nearby and second nearby American option contracts on the underlying S&P100 (NASDAQ100) index. The weighting method ensures that VIX and VXN give the implied volatility of a hypothetical at-the-money option with a constant maturity of 22 trading days to expiry. Details regarding the construction of the VIX index are available in Whaley (1993). Most of the recent studies (reviewed in Poon and Granger, 2003) on the forecasting performance of implied volatility usually show that they compete very favorably with volatility measures that take as inputs historical returns. Because the VIX and VXN are readily computed and are widely available, they have attracted a lot of attention in the academic and non-academic literature recently as they provide a straightforward measure of the expected (by the market participants) future volatility.

II. Contemporaneous changes in the stock index and implied volatility index

Our empirical application deals with the S&P100 index and corresponding VIX implied volatility index, and the NASDAQ100 index and VXN implied volatility index. Both implied volatility indices were detailed in Section I. At the time of this writing (February 2003), it is now well known that the NASDAQ stock index has experienced a continued and formidable bear market, resulting in a slide of about 75% of its value since its all-time high reached on March 10, 2000 (for the NASDAQ100 index). The S&P100 index which reached its maximum on March 24, 2000 has since then shed about 50% of its value.

In this section, we deal with the first topic on our research agenda, i.e. the 1-day relative changes in the levels of the implied volatility and underlying stock indices on which the option contracts are written. More specifically we want to ascertain the relationship between the 1-day relative changes in VIX_t and OEX_t (S&P100 index), and VXN_t and NDX_t (NASDAQ100 index). As indicated in the introduction, we estimate these relationships in three distinct time periods:[4] the August 1, 1994 - May 30, 1997 (low volatility, bull market), June 2, 1997 - March 31, 2000 (high volatility, bull market) and April 3, 2000 - January 31, 2003 (high volatility, bear market) time periods. These three time periods feature almost exactly the same number of observations and will give us insight on the models in three different trading environments. Some brief characteristics of the stock indices and implied volatility indices for these three time periods are given in Table I. Figures 1 and 2 show (top and middle panels) how the stock and implied volatility indices increase/decrease as time goes by, i.e. over the global August 1, 1994 - January 31, 2003 time period for the S&P100 index and for the January 3, 1995 - January 31, 2003 time period for the NASDAQ100 index. They also plot (bottom panel) the rolling 60-day correlation between the 1-day returns of the stock and implied volatility indices. This rolling correlation is negative and hovers around -0.8 for the S&P100 index (it is somewhat larger during sub-period 1). For the NASDAQ100 index, it fluctuates around -0.7

for most of the sample. Thus for both the S&P100 and NASDAQ100, the stock and implied volatility indices are negatively correlated: implied volatility goes up (down) when the stock indices increase (decrease).

To set our analysis in the linear regression framework, let us define $r_{OEX,t} = ln(OEX_t) - ln(OEX_{t-1})$ as the 1-day return on then S&P100 index and $r_{NDX,t} = ln(NDX_t) - ln(NDX_{t-1})$ as the 1-day return on the NASDAQ100 index. Correspondingly, we define $r_{VIX,t} = ln(VIX_t) - ln(VIX_{t-1})$ and $r_{VXN,t} = ln(VXN_t) - ln(VXN_{t-1})$ as the 1-day relative changes in the level of the implied volatility indices. For the global August 1, 1994 - January 31, 2003 time period and for the three sub-periods, we assess the contemporaneous relationship between the relative changes in the stock and implied volatility indices using OLS analysis. Because we strongly suspect an asymmetric relationship (i.e. that negative stock index returns affect differently 1-day relative changes in the implied volatility index than do positive stock index returns), we introduce dummy variables that highlight the effect of positive and negative returns. The first regressions are thus:

$$r_{VIX,t} = \beta_0^- D_t^- + \beta_0^+ D_t^+ + \beta_1^- (r_{OEX,t} D_t^-) + \beta_1^+ (r_{OEX,t} D_t^+) + \varepsilon_t \tag{1}$$

for the S&P100 index, where D_t^- is a dummy variable that is equal to 1 (0) when $r_{OEX,t}$ is negative (positive) and $D_t^+ = 1 - D_t^-$ and

$$r_{VXN,t} = \beta_0^- D_t^- + \beta_0^+ D_t^+ + \beta_1^- (r_{NDX,t} D_t^-) + \beta_1^+ (r_{NDX,t} D_t^+) + \varepsilon_t \tag{2}$$

for the NASDAQ100 index.

Estimation results are given in the first row of each panel of Tables II and III. Note that we report the White's heteroscedastic consistent standard errors in all cases. The fitted response of $r_{VIX,t}$ to $r_{OEX,t}$ and $r_{VXN,t}$ to $r_{NDX,t}$ are displayed in the top panels of Figures 4 and 5 (P1 is for the first sub-period, P2 for the second sub-period, P3 for the third sub-period and P1P2P3 stands for the global period). Let us first discuss the results for the S&P100 index. Focusing on

β_1^+ and β_1^- in the tables and on the slopes of the response curves in the figure, it is obvious that an asymmetric effect is at play. Indeed β_1^+ and β_1^- are sharply different from each other (using a Wald type test as preprogrammed in the PcGive econometric software package, we have that their difference is statistically different from 0 in all sub-periods). In all cases, β_1^- is larger in absolute value than β_1^+, which indicates that negative returns for the stock index yield much larger relative changes in the implied volatility index than do positive returns. This is also obvious in Figure 4 as the slopes on the left part of the diagram are much larger than the slopes on the right part. As expected, positive stock index returns decrease implied volatility while negative stock index returns lead to larger values for the implied volatility indices.[5] What is however surprising is that the asymmetric effect is much stronger in sub-period 1 than in sub-periods 2 and 3, although sub-period 1 represents the low-volatility trading environment, i.e. the sub-period which precedes the major financial and geopolitical crises. Actually β_1^+ increases in absolute value and β_1^- decreases in absolute value when switching from sub-period 1 to sub-periods 2 or 3. Therefore the increase (respectively decrease) in implied volatility following negative (resp. positive) stock index returns is somewhat smaller (resp. larger) in high-volatility trading environments than in low-volatility markets. A possible explanation is that volatility had reached a permanently high state in sub-periods 2 and 3 and option traders were unwilling to bid it aggressively higher when the stock market fell; in the low-volatility market of sub-period 1, the response of implied volatility to negative stock index returns was much larger as option traders reacted aggressively to these negative returns.

Results are quite different for the NASDAQ100 index. Indeed the asymmetric effect is not statistically validated as $\beta_1^+ - \beta_1^-$ is not statistically different from 0, except in sub-period 2 although the P-value for the equality test is equal to 0.035 and is thus barely rejected. Note also that the slopes on the left and right parts of Figure 5 are quite close. For the asymmetric effect, there are no sharp differences across the sub-periods. However β_1^+ and β_1^- are much smaller in absolute value in sub-period 3 than in sub-period 1. Therefore the volatility response to increases/decreases in the NASDAQ100 index is somewhat muted in the high-volatility (and bear market) trading environment. We conjecture that, similar to what has been shown for the

S&P100 index, option traders were reluctant to sharply increase/decrease implied volatility as the market was in a prolonged state of continuously high volatility.

In a second step, we introduce the quadratic terms $r^2_{OEX,t}$ and $r^2_{NDX,t}$ in the linear regressions to assess the size effect of the returns. Indeed, small or large stock index returns can impact differently the 1-day relative changes in the implied volatility indices. The second set of regressions are thus:

$$r_{VIX,t} = \beta_0^- D_t^- + \beta_0^+ D_t^+ + \beta_1^- (r_{OEX,t} D_t^-) + \beta_1^+ (r_{OEX,t} D_t^+) + \beta_2^- (r^2_{OEX,t} D_t^-) + \beta_2^+ (r^2_{OEX,t} D_t^+) + \varepsilon_t, \tag{3}$$

and

$$r_{VXN,t} = \beta_0^- D_t^- + \beta_0^+ D_t^+ + \beta_1^- (r_{NDX,t} D_t^-) + \beta_1^+ (r_{NDX,t} D_t^+) + \beta_2^- (r^2_{NDX,t} D_t^-) + \beta_2^+ (r^2_{NDX,t} D_t^+) + \varepsilon_t. \tag{4}$$

The estimated coefficients are given in the second rows of each panel of Tables II and III. The fitted response of $r_{VIX,t}$ to $r_{OEX,t}$ and $r_{VXN,t}$ to $r_{NDX,t}$ are displayed in the bottom panels of Figures 4 and 5. For the S&P100 index, β_2^+ is (barely) statistically different from 0 in sub-period 2 only; β_2^+ is not statistically different from 0 in all periods. Note that the R^2 are almost the same as in Equation 1. The figures in the top and bottom panels of Figure II are quite similar, except for the right part of the response curve in sub-period 1 (in that case, coefficient β_2^+ is quite large and significant). For the NASDAQ100 index, the quadratic effect is also rather weak as β_2^- is never significant and β_2^+ is only significant in the global period. The top and bottom panels of Figure 5 tell the same story as the two set of response curves are almost identical. Taking into account all these empirical results, we conclude that an asymmetric effect is at play for the S&P100 index, but that there are no quadratic effects. For the NASDAQ100 index, there are no quadratic effects and almost no asymmetric effect. Regarding both indices, there are however important differences in the asymmetric effect across sub-periods as the implied volatility's response to negative stock index returns is much sharper in low-volatility trading environment.

III. VIX and VXN indices as forward looking indicators of future stock indices returns?

While it is clear that negative returns are associated with increased implied volatility, there is a growing debate as to how implied volatility indices can indicate over-bought or over-sold market conditions. In this section, we tackle this issue by looking at the relationship between the level of the implied volatility indices VIX and VXN at a given time (say time t) and the forward looking (or n-day-ahead) 1-, 5-, 20- and 60-day relative changes in the underlying stock index, i.e. the S&P100 and the NASDAQ100 indices. More specifically, we thus focus on the relationship between VIX_t and $r1d_t$, $r5d_t$, $r20d_t$ and $r60d_t$, where $r1d_t$, $r5d_t$, $r20d_t$ and $r60d_t$ are the forward looking 1-, 5-, 20- and 60-day relative changes in the level of the S&P100 index.[6] We then repeat the exercise with VXN and forward looking relative changes in the level of the NASDAQ100 index. An immediate graphical analysis is given in Figure 6 which shows scatter plots of the $r1d_t$ vs VIX_t, $r5d_t$ vs VIX_t, $r20d_t$ vs VIX_t and $r60d_t$ vs VIX_t relationships for the S&P100 index. The time index ranges from August 1, 1994 to January 31, 2003. Similar graphs are plotted in Figure 7 for the NASDAQ100 index and the June 2, 1997 - January 31, 2003 time period.[7] Results are quite different from what was given in Figure 3 for the relationship between contemporaneous relative changes in the stock index and implied volatility index. In this case, there appears to be a somewhat positive relationship between VIX_t and the n-day-ahead returns on the S&P100 (for very large levels of the VIX), but the evidence is hardly conclusive. For the NASDAQ100 index, this also seems to be the case, at least regarding the 1- and 5-day forward looking returns.

To assess if very large implied volatility levels turn out to be relevant trading signals for long positions, we put forward the following algorithm. Because we must define what we mean by very large implied volatility levels, we use a classification based on the rolling 20 equally spaced percentiles of the implied volatility index observed at any given time.[8] Let us illustrate with the S&P100 index. At a given time t, the 20 equally spaced percentiles are computed for the set of $\{VIX_i\}$ values where $i \in t - T_0 \ldots t - 1$, i.e. the information set which includes the past history of the VIX index up to time $t - 1$. Then VIX_t is compared to these 20 equally spaced percentiles and ranked accordingly, say in position R_t. For example, if VIX_t is large, then it will probably be ranked number 15 or above. If VIX_t is very large, R_t will be much closer to 20. If VIX_t is larger than the maximum of all VIX_i, then it is ranked as $R_t = 21$. Given that rank R_t observed at time t, one computes the forward looking returns for the S&P100 index $r1d_t$, $r5d_t$, $r20d_t$ and $r60d_t$ which thus correspond to the forward looking returns for a long position in the S&P100 index (for a predetermined time horizon of 1, 5, 20 and 60 days) triggered by the observed VIX_t. Therefore we switch from a qualitative description of the trading environment (the VIX level is very 'high') to a quantitative measure that can be used to rank the observed levels of the implied volatility index. In that framework, T_0 specifies the backward looking time horizon (i.e. size of information set) used to compute the rank of VIX_t. This trading rule is implemented for all available observations in our S&P100 and NASDAQ100 datasets. Note that it is programmed as a rolling measure as the time index t goes from $T_0 + 1$ to T (end date of the sample). Once the rolling classification has been run and the $r1d_t$, $r5d_t$, $r20d_t$ and $r60d_t$ recorded for all times t, the last step involves computing the expected value and variance of the 1-, 5-, 20- and 60-day forward looking returns for all ranks (which range from 0 to 21). If very large levels of the implied volatility index really indicate oversold markets where fear predominates, then on average $r1d_t$, $r5d_t$, $r20d_t$ and $r60d_t$ should be quite large for R close to 20.

We report the outcomes of this trading strategy in Tables IV and V for the S&P100 and NASDAQ100 indices respectively. Columns 3 to 10 of each table give respectively the average and coefficient of variation of the 1-, 5-, 20- and 60-day forward looking returns which belong to category R (first column). The number of trades within each category is given in column 2. For both stock indices, we choose $T_0 = 2$ years, which implied that, on a given day t, VIX_t (VXN_t) is compared with the 20 equally spaced percentiles based on a rolling 2-year history of VIX (VXN).[9] The time period is August 1, 1994 - January 31, 2003 for the S&P100 index and June 2, 1997 - January 31, 2003 for the NASDAQ100 index.[10] The results given in both tables indicate that there is no clear pattern in the mean forward looking returns or their coefficient of variation. It is however interesting to note that, for low levels of VIX or VXN (R between 1 and 5), expected forward looking returns are always negative, whatever the time horizon. Correspondingly, forward looking returns in categories $R = 20$ and $R = 21$ are always positive on average. More importantly, forward looking returns triggered by levels of implied volatility belonging to category $R = 21$ (i.e. we enter a long position on date t if VIX_t is larger that its maximum over the last 2 years) are characterized by large positive average values and very low coefficients of variation (unfortunately these do not occur often). For example the 11 occurrences in category $R = 21$ for the NASDAQ100 index led to an average return of 27.19% within the next 60 days with a coefficient of variation of only 0.63.

We get the same type of results by using an econometric analysis set in the framework of the linear regression. Indeed, for both the S&P100 and NASDAQ100 indexes, we can estimate the following regressions:

$$r1d_t = \delta_1 D1_t + \delta_2 D2_t + \ldots + \delta_{21} D21_t + \eta_t \tag{5}$$

$$r5d_t = \delta_1 D1_t + \delta_2 D2_t + \ldots + \delta_{21} D21_t + \eta_t, \tag{6}$$

$$r20d_t = \delta_1 D1_t + \delta_2 D2_t + \ldots + \delta_{21} D21_t + \eta_t, \tag{7}$$

$$r60d_t = \delta_1 D1_t + \delta_2 D2_t + \ldots + \delta_{21} D21_t + \eta_t, \tag{8}$$

where $D1_t$, $D2_t$, $\ldots$, $D21_t$ are dummy variables defined such that $Di_t = 1$ if $R_t = i$ and η_t is the OLS error term. Thus we map the R_t classification variable into 21 distinct dummy variables which can be used in a linear regression model. Therefore each coefficient can be directly interpreted as the expected return at the given time horizon when VIX_t or VXN_t is ranked into category R_t at time t. For example, the estimated δ_{20} for the $S\&P100$ index at the 20-day time horizon gives the expected return for the $S\&P100$ index whenever the level of the VIX is classified at rank 20. Estimation results for the coefficients of the dummy variables are given in Tables VI and VII. We also show the Newey-West standard errors in parenthesis as the $r5d$, $r20d$ and $r60d$ returns are by definition overlapping returns, which leads to some autocorrelation in the error term. We get the same results as given in the previous tables but the standard errors allow us to test if the coefficients are significant. Note indeed that most coefficients in the (center of the) tables are not significant, but that the coefficients in the utmost top, respectively bottom, of the tables tend to be strongly negatively significant, respectively positively significant.

These results lend some support to the hypothesis that extremely high levels of implied volatility do indeed signal attractive 'buy' entry points for traders who want to take long positions in the underlying index. This seems consistent with traders' insights that extremely high volatility markets are oversold, which should benefit traders entering long positions. Note that the academic literature suggests a link between high expected returns and high conditional volatility. Indeed, this was already highlighted by Merton (1973), with the intertemporal CAPM model or Merton (1980), and motivates the ARCH-M type model of Engle, Lilien, and Robins (1987) (as concisely stated in Whaley, 2000: "if expected market volatility increases, investors demand higher rates of return on stocks"). Because the implied volatility tracks and forecasts well the future realized volatility (Christensen and Prabhala, 1998 or Blair, Poon, and Taylor, 2001), it is not unreasonable to think of the same relationship between observed implied volatility and forward looking returns. Therefore our results are not at odds with the previous literature on the relationship between returns and market volatility.

IV. A concise summary of our results and possible extensions

The empirical analysis of Section II has shown that there is a strong negative relationship between contemporaneous changes in implied volatility indices and underlying stock indices, both for the S&P100 and NASDAQ100 indices. For the S&P100 index, this contemporaneous relationship is also asymmetric in the sense that negative returns for the stock index yield much larger relative changes in the implied volatility index (VIX) than do positive returns. We also show that the magnitude of this asymmetric effect depends on the sub-period under study. By splitting our sample into 3 sub-periods, August 1, 1994 - May 30, 1997 (low volatility, bull market), June 2, 1997 - March 31, 2000 (high volatility, bull market) and April 3, 2000 - January 31, 2003 (high volatility, bear market), it is shown that the increase (respectively decrease) in implied volatility following negative (resp. positive) stock index returns is somewhat smaller (resp. larger) in high-volatility trading environments than in low-volatility periods. A possible explanation is that option traders react aggressively to negative returns in low-volatility periods by strongly bidding up implied volatility, but are somewhat reluctant to do so in high-volatility trading environments such as experienced since the summer of 1997. For the NASDAQ100 index, the asymmetric effect is rather weak as the relative changes in the VXN index due to positive and negative returns for the NDX index are quite close in absolute value. As for the S&P100 index, the response in VXN to increases/decreases in the NASDAQ100 index is somewhat muted in the high-volatility trading environments.

In the second part of the empirical application given in Section III, we assessed the possible relationship between implied volatility and forward looking stock index returns. If, as thought by some market practitioners, large or very large implied volatility levels do indeed indicate oversold markets, then forward looking returns for long positions in the underlying stock index triggered by these large implied volatility levels should be attractive. In our application, implied volatility levels are classified with respect to their 2-year rolling history, i.e. for all days in our sample, we compare VIX_t or VXN_t with the 20 equally spaced percentiles computed from their past 2-year rolling history. There is some evidence that positive (negative) forward looking returns are to be expected for long positions in the stock index triggered by extremely high (low) levels of the implied volatility indices. However one must wait for extremely high levels of implied volatility to get attractive positive forward looking returns.

A possible extension of our study would be to focus on individual stocks. In this case however, computing meaningful implied volatility measures can be quite a challenge as large cross-sectional option prices datasets are needed and the stale quotes problem can be tricky to overcome. Hence the attractiveness of the VIX and VXN implied volatility indices. It would however be possible to stick with VIX and VXN implied volatility indices and deal with forward looking returns on individual stocks, for example by making a distinction between low-beta and high-beta stock. Indeed, for an aggressive trader who is keen on taking risky positions, it could be argued that he should buy high-beta stocks (and not the index) when implied volatility indices reach very large levels.

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Table I
Descriptive data

	S&P100 index		VIX index		
	Start	End	Start	End	Mean
August 1, 1994 - May 30, 1997	213.93	413.35	10.27	22.12	15.84
June 2, 1997 - March 31, 2000	413.47	815.06	22.12	27.21	25.56
April 3, 2000 - January 31, 2003	820.62	432.57	25.66	35.78	28.63
	NASDAQ100 index		VXN index		
	Start	End	Start	End	Mean
January 3, 1995 - May 30, 1997	398	958.85	21.08	32.11	27.57
June 2, 1997 - March 31, 2000	958.69	4397.84	33.24	61.56	38.98
April 3, 2000 - January 31, 2003	4077.02	983.05	64.5	46.81	57.17

Descriptive statistics for the OEX and NDX stock indices, and the VIX and VXN implied volatility indices. This table gives the start and end values of the stock indices (OEX and NDX) in the three sub-periods and the start, end and mean values of the implied volatility indices (VIX and VXN).

Table II
Contemporaneous relative changes in VIX vs OEX (daily returns)

Panel A: August 1, 1994 - January 31, 2003						
β_0^+	β_0^-	β_1^+	β_1^-	β_2^+	β_2^-	R^2
-0.64 (0.17)	0.06 (0.21)	-2.95 (0.18)	-4.00 (0.23)			0.59
-0.35 (0.22)	-0.02 (0.25)	-3.57 (0.41)	-4.17 (0.54)	0.18 (0.12)	-0.04 (0.18)	0.59
Panel B: August 1, 1994 - May 30, 1997						
β_0^+	β_0^-	β_1^+	β_1^-	β_2^+	β_2^-	R^2
-1.10 (0.36)	-0.32 (0.34)	-1.70 (0.68)	-6.25 (0.69)			0.38
-0.32 (0.41)	-0.08 (0.43)	-4.83 (1.43)	-5.31 (1.66)	1.84 (0.94)	0.45 (0.97)	0.39
Panel C: June 2, 1997 - March 31, 2000						
β_0^+	β_0^-	β_1^+	β_1^-	β_2^+	β_2^-	R^2
-0.17 (0.32)	0.29 (0.50)	-3.90 (0.32)	-4.72 (0.54)			0.70
0.10 (0.41)	-0.17 (0.45)	-4.44 (0.71)	-5.52 (0.82)	0.16 (0.23)	-0.18 (0.27)	0.70
Panel D: April 3, 2000 - January 31, 2003						
β_0^+	β_0^-	β_1^+	β_1^-	β_2^+	β_2^-	R^2
-0.94 (0.26)	-0.88 (0.28)	-2.49 (0.20)	-3.61 (0.22)			0.70
-0.47 (0.33)	-0.75 (0.36)	-3.30 (0.47)	-3.40 (0.58)	0.20 (0.12)	0.06 (0.18)	0.71

S&P100 index: linear and quadratic response curves of VIX_t vs OEX_t. We give the estimated OLS coefficients of $r_{VIX,t} = \beta_0^- D_t^- + \beta_0^+ D_t^+ + \beta_1^-(r_{OEX,t} D_t^-) + \beta_1^+(r_{OEX,t} D_t^+) + \varepsilon_t$ (first row of each panel) and $r_{VIX,t} = \beta_0^- D_t^- + \beta_0^+ D_t^+ + \beta_1^-(r_{OEX,t} D_t^-) + \beta_1^+(r_{OEX,t} D_t^+) + \beta_2^-(r_{OEX,t}^2 D_t^-) + \beta_2^+(r_{OEX,t}^2 D_t^+) + \varepsilon_t$ (second row of each panel), where D_t^- is a dummy variable that is equal to 1 (0) when $r_{OEX,t}$ is negative (positive) and $D_t^+ = 1 - D_t^-$. White's heteroscedastic consistent standard errors are given in parenthesis.

Table III

Contemporaneous relative changes in VXN vs NDX (daily returns)

Panel A: January 3, 1995 - January 31, 2003						
β_0^+	β_0^-	β_1^+	β_1^-	β_2^+	β_2^-	R^2
-0.64 (0.15)	0.85 (0.17)	-0.93 (0.08)	-0.98 (0.09)			0.45
-0.31 (0.16)	0.74 (0.21)	-1.28 (0.12)	-1.10 (0.21)	0.05 (0.01)	-0.02 (0.04)	0.45
Panel B: January 3, 1995 - May 30, 1997						
β_0^+	β_0^-	β_1^+	β_1^-	β_2^+	β_2^-	R^2
0.13 (0.25)	0.74 (0.24)	-1.75 (0.19)	-1.60 (0.14)			0.47
-0.08 (0.32)	0.74 (0.32)	-1.34 (0.51)	-1.59 (0.39)	-0.13 (0.15)	0.00 (0.08)	0.47
Panel C: June 2, 1997 - March 31, 2000						
β_0^+	β_0^-	β_1^+	β_1^-	β_2^+	β_2^-	R^2
-0.18 (0.26)	0.45 (0.35)	-1.30 (0.16)	-1.70 (0.21)			0.51
-0.15 (0.33)	0.45 (0.36)	-1.33 (0.38)	-1.70 (0.38)	0.01 (0.08)	0.00 (0.08)	0.51
Panel D: April 3, 2000 - January 31, 2003						
β_0^+	β_0^-	β_1^+	β_1^-	β_2^+	β_2^-	R^2
-0.82 (0.25)	-0.03 (0.30)	-0.74 (0.09)	-0.89 (0.11)			0.47
-0.66 (0.31)	0.05 (0.40)	-0.86 (0.16)	-0.82 (0.31)	0.01 (0.01)	0.01 (0.05)	0.47

NASDAQ100 index: linear and quadratic response curves of VXN_t vs NDX_t. We give the estimated OLS coefficients of $r_{VXN,t} = \beta_0^- D_t^- + \beta_0^+ D_t^+ + \beta_1^-(r_{NDX,t} D_t^-) + \beta_1^+(r_{NDX,t} D_t^+) + \varepsilon_t$ (first row of each panel) and $r_{VXN,t} = \beta_0^- D_t^- + \beta_0^+ D_t^+ + \beta_1^-(r_{NDX,t} D_t^-) + \beta_1^+(r_{NDX,t} D_t^+) + \beta_2^-(r_{NDX,t}^2 D_t^-) + \beta_2^+(r_{NDX,t}^2 D_t^+) + \varepsilon_t$ (second row of each panel), where D_t^- is a dummy variable that is equal to 1 (0) when $r_{NDX,t}$ is negative (positive) and $D_t^+ = 1 - D_t^-$. White's heteroscedastic consistent standard errors are given in parenthesis.

Table IV
Outcome of trading strategy (S&P100 index)

Rank (R)	#	*r1d*	*cv1d*	*r5d*	*cv5d*	*r20d*	*cv20d*	*r60d*	*cv60d*
1	39	-0.32	-2.52	-1.00	-1.78	-5.01	-0.61	-12.66	-0.47
2	67	-0.20	-4.70	-0.82	-2.51	-2.60	-1.68	-6.23	-1.35
3	58	-0.14	-6.09	-0.70	-2.73	-2.17	-2.06	-5.68	-1.60
4	68	-0.06	-15.66	-0.22	-9.80	-0.56	-7.84	-3.82	-2.33
5	57	-0.10	-8.44	-0.27	-7.92	-0.34	-14.31	-0.82	-11.00
6	61	0.06	18.31	0.20	11.79	-0.55	-9.09	-1.48	-6.40
7	70	-0.15	-6.89	0.07	35.39	0.39	12.42	1.00	7.85
8	81	0.09	10.18	0.01	183.33	0.35	12.91	0.92	8.21
9	84	0.26	4.62	0.28	8.35	0.72	6.58	0.55	14.73
10	82	0.04	23.65	-0.04	-62.08	-0.51	-9.68	1.01	7.62
11	73	0.03	40.59	0.44	4.35	0.57	8.59	3.01	2.33
12	70	0.00	-275.02	0.65	2.96	1.64	2.54	2.37	3.28
13	95	0.02	45.65	0.03	90.08	0.97	5.31	2.63	2.83
14	110	0.07	15.85	0.31	9.41	1.06	4.80	2.16	3.49
15	113	0.00	-460.74	-0.23	-10.23	1.06	4.20	3.97	1.71
16	126	0.04	30.18	-0.11	-26.26	0.32	17.46	2.57	3.11
17	125	0.14	7.99	0.28	8.88	0.86	6.11	3.40	2.14
18	150	-0.08	-15.89	0.37	6.30	1.61	3.38	4.57	1.74
19	190	-0.02	-63.73	-0.09	-32.20	0.15	32.87	3.44	1.83
20	365	0.18	8.88	0.90	3.64	2.85	1.76	5.92	1.27
21	15	1.06	3.04	2.85	1.67	6.02	1.02	10.65	0.68

This table gives the results of the trading strategy detailed in Section III for the S&P100 index. Columns 3 to 10 give respectively the average and coefficient of variation of the 1-, 5-, 20- and 60-day forward looking returns which belong to category *R* (first column). The number of trades within each category is given in column 2. The time period is August 1, 1994 - January 31, 2003.

Table V
Outcome of trading strategy (NASDAQ100 index)

Rank (R)	#	*r1d*	*cv1d*	*r5d*	*cv5d*	*r20d*	*cv20d*	*r60d*	*cv60d*
1	64	-0.61	-3.18	-1.84	-2.41	-6.14	-0.99	-21.81	-0.44
2	40	-0.04	-51.84	-0.61	-7.65	-4.46	-1.79	-14.73	-0.75
3	38	0.02	113.28	-0.48	-8.02	-4.90	-1.55	-15.01	-0.73
4	25	-0.34	-5.71	-2.06	-2.29	-7.99	-1.36	-6.11	-1.94
5	40	-0.05	-42.23	-2.39	-1.99	-9.24	-1.23	-6.64	-2.19
6	38	-0.22	-13.40	-0.55	-9.54	-3.34	-3.38	-6.60	-2.73
7	44	-0.11	-16.52	0.08	62.81	-1.99	-4.40	-5.42	-3.39
8	41	-0.12	-18.80	-0.70	-7.84	-0.39	-26.75	-4.97	-3.96
9	49	-0.05	-43.27	-0.01	-839.12	-0.03	-353.19	-0.44	-38.44
10	49	0.13	15.58	0.44	10.57	2.50	3.64	4.67	3.81
11	60	-0.19	-13.52	-0.76	-6.92	1.52	6.73	7.51	2.56
12	57	0.05	55.64	1.17	3.85	1.69	5.12	6.98	2.66
13	62	0.14	15.81	0.66	8.23	2.01	5.39	4.80	4.61
14	63	0.07	39.86	1.01	5.01	2.02	4.84	1.92	11.23
15	79	0.09	25.17	0.68	7.96	3.13	3.25	2.71	7.28
16	81	-0.16	-16.86	-0.54	-11.18	-0.28	-45.71	-1.24	-16.12
17	92	0.16	15.71	-1.36	-4.01	0.05	273.61	1.82	9.27
18	107	-0.14	-18.39	0.63	8.83	3.27	3.62	7.45	2.27
19	138	0.00	703.56	0.36	17.23	1.49	7.40	3.02	6.80
20	203	0.36	10.99	1.15	6.31	1.20	10.01	1.57	14.52
21	11	0.75	7.99	3.73	1.80	11.16	0.85	27.19	0.63

This table gives the results of the trading strategy detailed in Section III for the NASDAQ100 index. Columns 3 to 10 give respectively the average and coefficient of variation of the 1-, 5-, 20- and 60-day forward looking returns which belong to category *R* (first column). The number of trades within each category is given in column 2. The time period is June 2, 1997 - January 31, 2003.

Table VI
Outcome of trading strategy: regression results (S&P100 index)

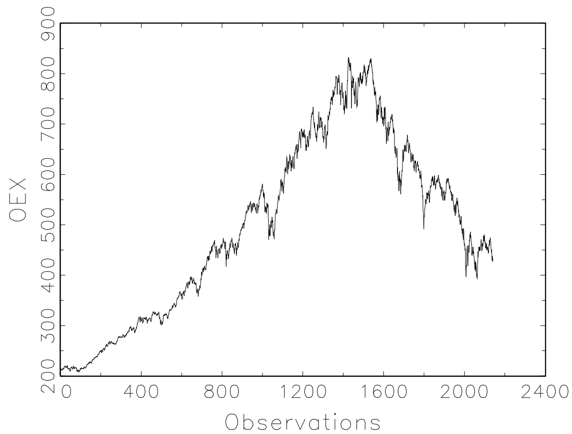
Dummy variable	$r1d$	$r5d$	$r20d$	$r60d$
$D1_t$	-0.32 (0.15)	-1.00 (0.48)	-5.00 (0.74)	-12.66 (1.23)
$D2_t$	-0.20 (0.12)	-0.82 (0.35)	-2.60 (0.86)	-6.23 (0.94)
$D3_t$	-0.14 (0.10)	-0.70 (0.31)	-2.17 (0.78)	-5.68 (1.00)
$D4_t$	-0.06 (0.12)	-0.22 (0.30)	-0.56 (0.73)	-3.82 (0.93)
$D5_t$	-0.10 (0.11)	-0.27 (0.34)	-0.34 (0.80)	-0.82 (1.01)
$D6_t$	0.06 (0.16)	0.20 (0.40)	-0.55 (0.79)	-1.48 (0.98)
$D7_t$	-0.15 (0.13)	0.07 (0.33)	0.39 (0.79)	1.00 (0.92)
$D8_t$	0.09 (0.10)	0.01 (0.29)	0.35 (0.71)	0.92 (0.85)
$D9_t$	0.26 (0.12)	0.28 (0.34)	0.72 (0.74)	0.55 (0.84)
$D10_t$	0.04 (0.10)	-0.04 (0.28)	-0.51 (0.69)	1.01 (0.85)
$D11_t$	0.03 (0.13)	0.44 (0.24)	0.57 (0.66)	3.01 (0.90)
$D12_t$	0 (0.12)	0.65 (0.27)	1.64 (0.57)	2.37 (0.92)
$D13_t$	0.02 (0.10)	0.03 (0.35)	0.97 (0.69)	2.63 (0.79)
$D14_t$	0.07 (0.11)	0.31 (0.31)	1.06 (0.67)	2.16 (0.73)
$D15_t$	0 (0.09)	-0.23 (0.26)	1.06 (0.52)	3.97 (0.72)
$D16_t$	0.04 (0.10)	-0.11 (0.34)	0.32 (0.73)	2.57 (0.68)
$D17_t$	0.14 (0.09)	0.28 (0.30)	0.86 (0.66)	3.40 (0.69)
$D18_t$	-0.08 (0.10)	0.37 (0.24)	1.61 (0.68)	4.57 (0.63)
$D19_t$	-0.02 (0.10)	-0.09 (0.28)	0.15 (0.57)	3.44 (0.56)
$D20_t$	0.18 (0.08)	0.90 (0.28)	2.85 (0.55)	5.92 (0.40)
$D21_t$	1.06 (0.68)	2.85 (1.08)	6.02 (1.66)	10.65 (1.98)

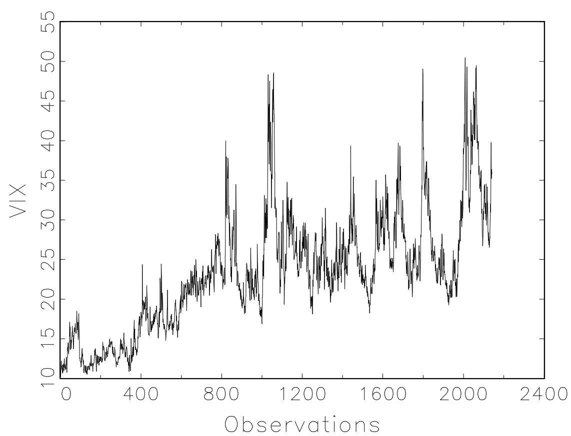
This table gives the robust regression results for the trading strategy detailed in Section III for the S&P100 index. Each column, respectively for the 1-, 5-, 20- and 60-day forward looking returns, gives the estimated OLS coefficient for the dummy variable listed in the first column. Newey-West standard errors are given in parenthesis. The time period is August 1, 1994 - January 31, 2003.

Table VII
Outcome of trading strategy: regression results (NASDAQ100 index)

Dummy variable	$r1d$	$r5d$	$r20d$	$r60d$
$D1_t$	-0.60 (0.20)	-1.84 (0.96)	-6.14 (1.38)	-21.81 (2.39)
$D2_t$	-0.04 (0.37)	-0.61 (1.03)	-4.46 (2.03)	-14.73 (2.80)
$D3_t$	0.02 (0.40)	-0.48 (0.69)	-4.90 (1.93)	-15.01 (3.03)
$D4_t$	-0.34 (0.39)	-2.06 (1.07)	-8.00 (2.78)	-6.11 (3.03)
$D5_t$	-0.05 (0.28)	-2.39 (1.06)	-9.24 (3.08)	-6.64 (3.60)
$D6_t$	-0.22 (0.52)	-0.55 (1.01)	-3.34 (2.89)	-6.60 (4.46)
$D7_t$	-0.11 (0.29)	0.08 (0.88)	-1.99 (1.71)	-5.42 (4.22)
$D8_t$	-0.12 (0.30)	-0.70 (1.27)	-0.39 (2.73)	-4.97 (4.27)
$D9_t$	-0.05 (0.30)	0 (0.78)	-0.03 (1.86)	-0.44 (3.30)
$D10_t$	0.13 (0.29)	0.44 (0.84)	2.50 (1.80)	4.67 (3.55)
$D11_t$	-0.19 (0.29)	-0.76 (0.87)	1.52 (2.00)	7.51 (3.45)
$D12_t$	0.05 (0.38)	1.17 (0.70)	1.69 (1.54)	6.98 (3.20)
$D13_t$	0.14 (0.25)	0.66 (0.97)	2.01 (2.17)	4.80 (4.10)
$D14_t$	0.07 (0.33)	1.01 (0.75)	2.02 (1.82)	1.92 (4.22)
$D15_t$	0.09 (0.30)	0.68 (0.83)	3.13 (1.64)	2.71 (3.53)
$D16_t$	-0.16 (0.31)	-0.54 (0.93)	-0.28 (1.55)	-1.24 (3.67)
$D17_t$	0.16 (0.26)	-1.36 (0.75)	0.05 (2.09)	1.82 (2.74)
$D18_t$	-0.14 (0.23)	0.63 (0.72)	3.27 (1.73)	7.45 (2.55)
$D19_t$	0 (0.28)	0.36 (0.79)	1.49 (1.69)	3.02 (3.39)
$D20_t$	0.35 (0.23)	1.15 (0.89)	1.20 (1.89)	1.57 (3.84)
$D21_t$	0.75 (1.39)	3.73 (1.73)	11.16 (3.63)	27.19 (7.38)

This table gives the robust regression results for the trading strategy detailed in Section III for the NASDAQ100 index. Each column, respectively for the 1-, 5-, 20- and 60-day forward looking returns, gives the estimated OLS coefficient for the dummy variable listed in the first column. Newey-West standard errors are given in parenthesis. The time period is June 2, 1997 - January 31, 2003.





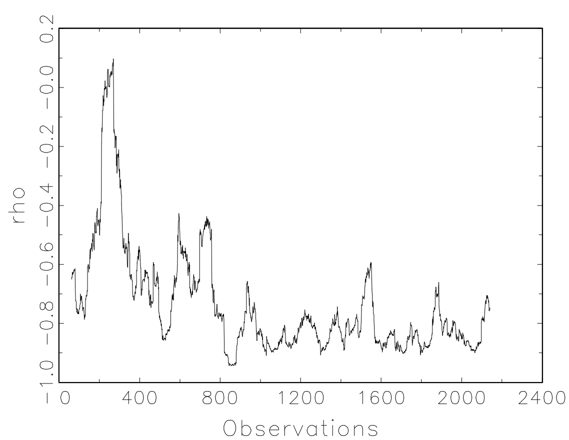


Figure 1. S&P100 index, VIX index and rolling 60-day correlation. This figure shows the S&P100 index, implied volatility VIX index and rolling 60-day correlation between the 1-day returns of these two indices. The time period is August 1, 1994 - January 31, 2003.

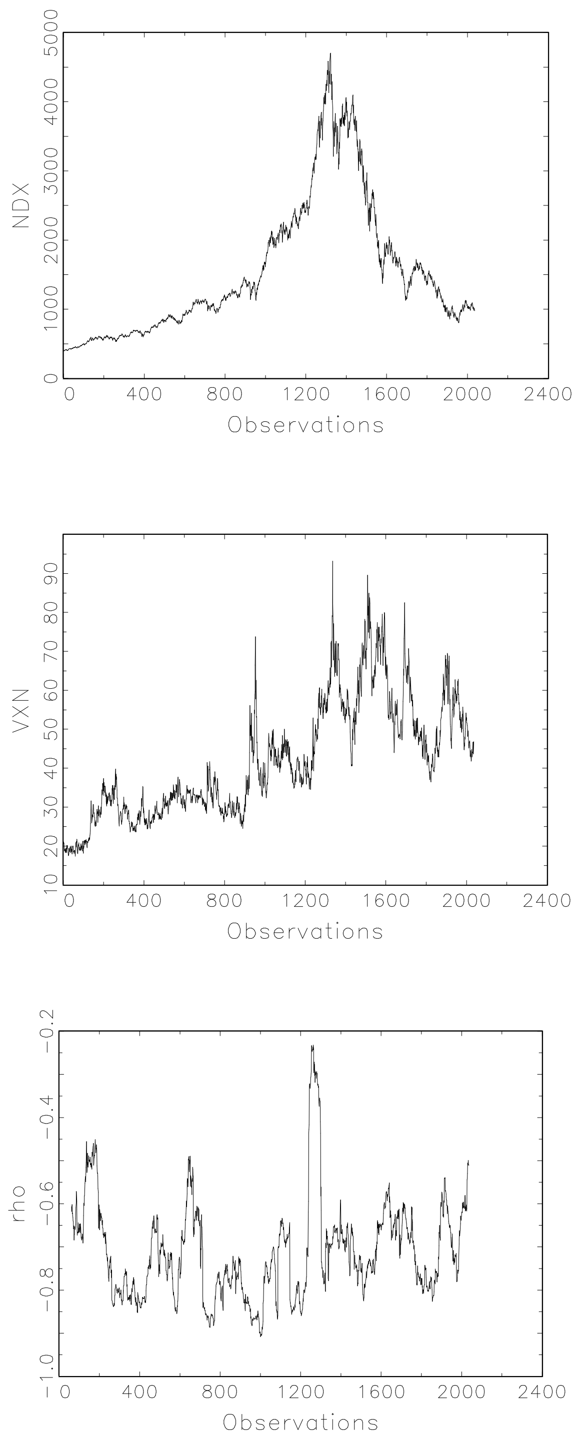
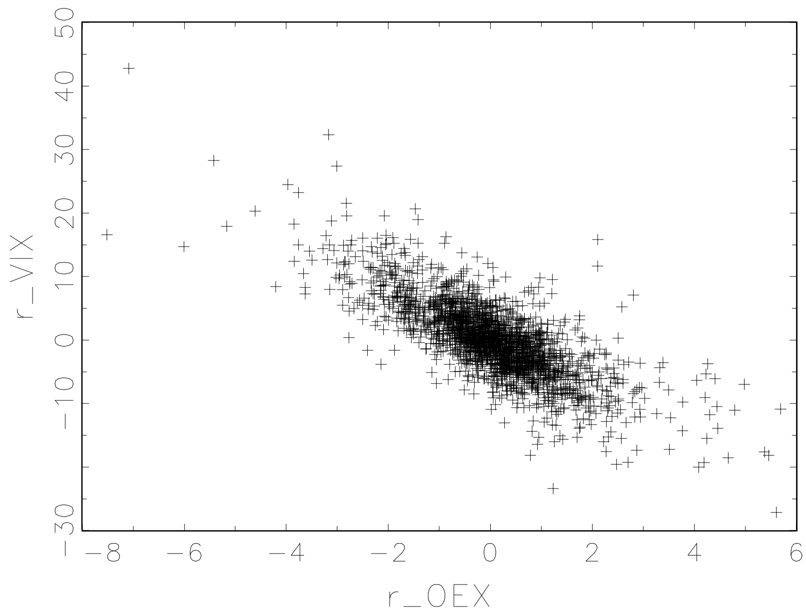


Figure 2. NASDAQ100 index, VXN index and rolling 60-day correlation. This figure shows the NASDAQ100 index, implied volatility VXN index and rolling 60-day correlation between the 1-day returns of these two indices. The time period is January 3, 1995 - January 31, 2003.



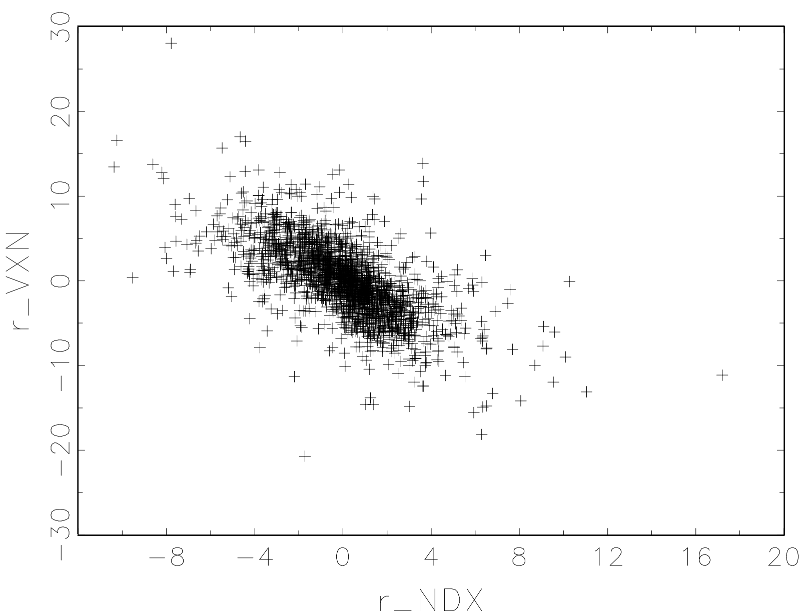


Figure 3. Contemporaneous changes in the stock and implied volatility indices. This figure shows the relationship between the 1-day contemporaneous relative changes in the level of the stock and implied volatility indices. The top figure is for the relative changes in the VIX index vs the OEX index; bottom figure is for the relative changes in the VXN index vs the NDX index. The time period is August 1, 1994 - January 31, 2003 (S&P100 index) and January 3, 1995 - January 31, 2003 (NASDAQ100 index).

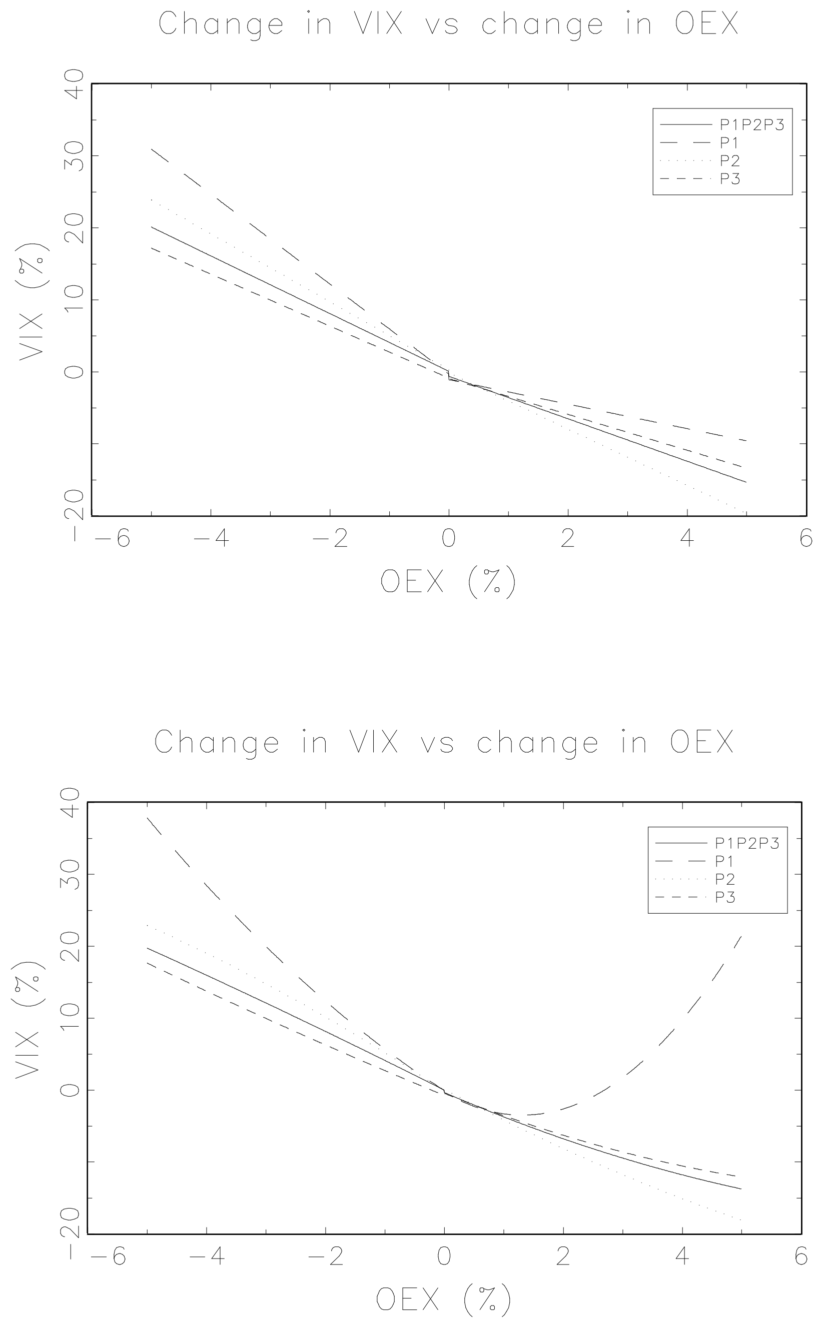
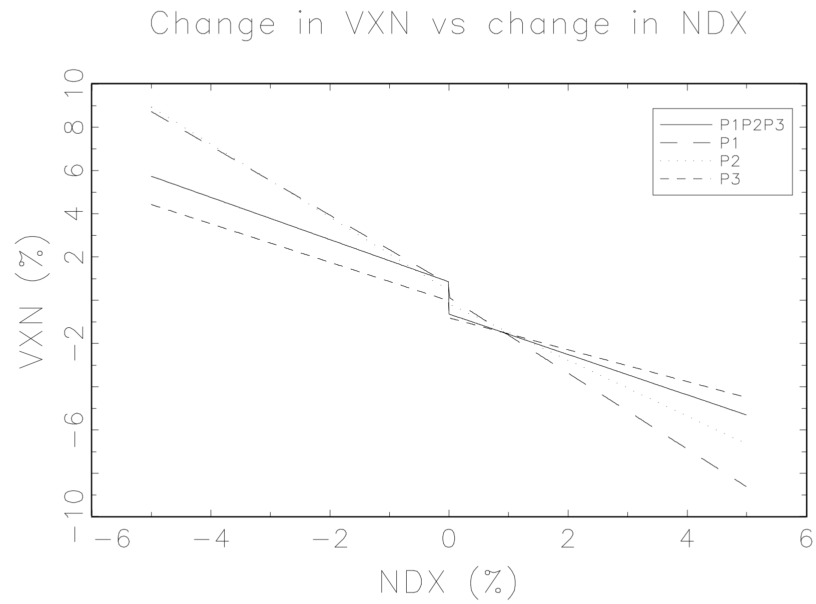


Figure 4. VIX/OEX response curves for the S&P100 index. This figure gives the expected relative change in VIX for the given relative change in OEX. The top panel is for Equation 1 (linear effects only) while the bottom panel is for Equation 3 (it includes quadratic effects). P1 stands for the first sub-period, i.e. August 1, 1994 - May 30, 1997, P2 for the second sub-period, i.e. June 2, 1997 - March 31, 2000, P3 for the third sub-period, i.e. April 3, 2000 - January 31, 2003 and P1P2P3 is for all three sub-periods combined.



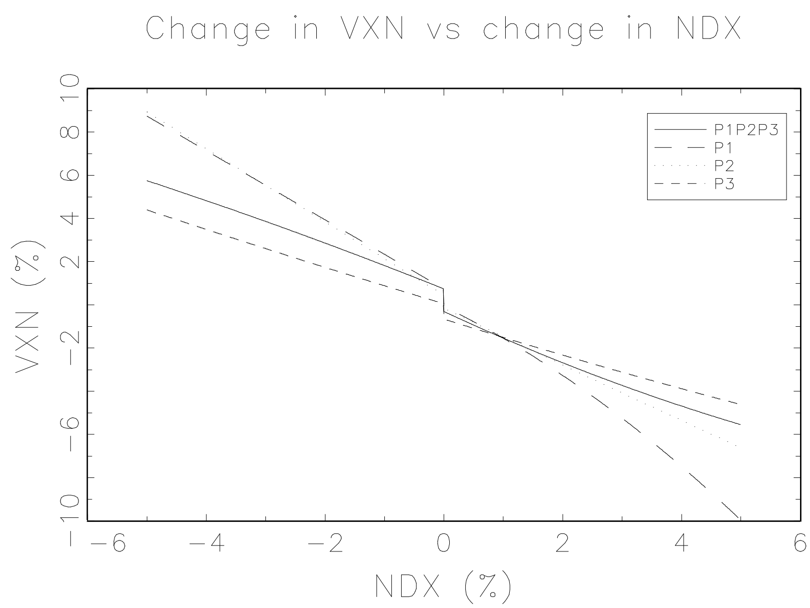


Figure 5. VXN/NDX response curves for the NASDAQ100 index. This figure gives the expected relative change in VXN for the given relative change in NDX. The top panel is for Equation 2 (linear effects only) while the bottom panel is for Equation 4 (it includes quadratic effects). P1 stands for the first sub-period, i.e. January 3, 1995 - May 30, 1997, P2 for the second sub-period, i.e. June 2, 1997 - March 31, 2000, P3 for the third sub-period, i.e. April 3, 2000 - January 31, 2003 and P1P2P3 is for all three sub-periods combined.

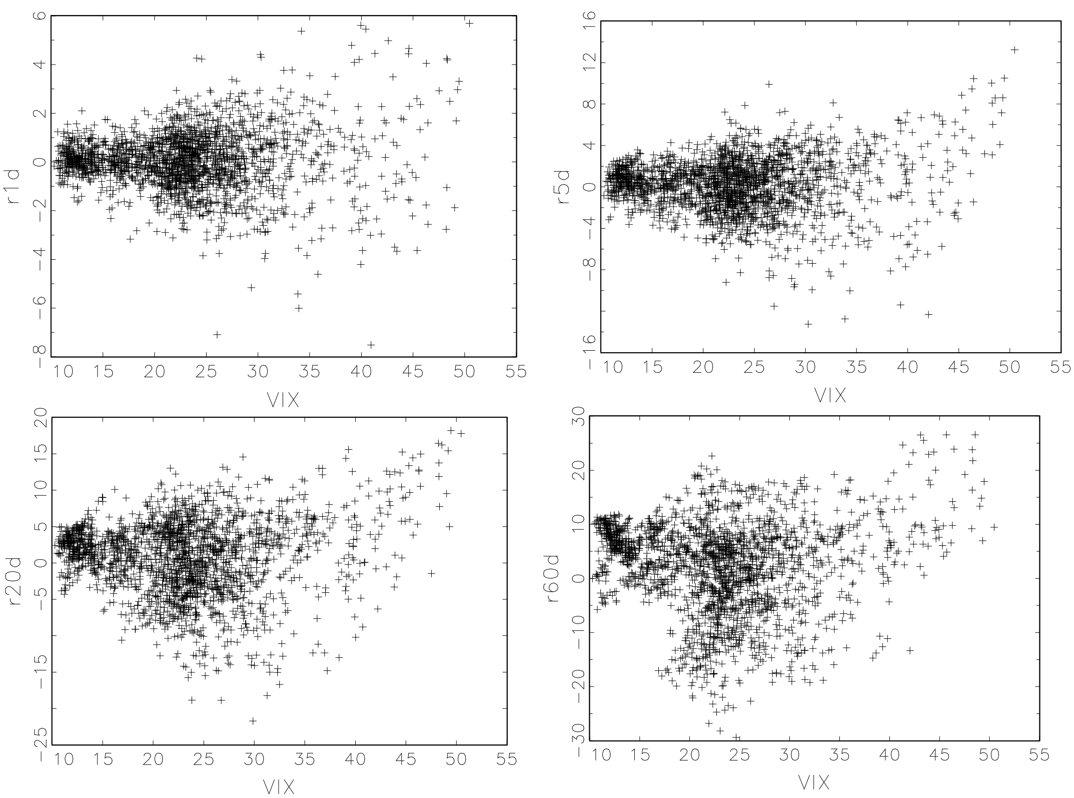


Figure 6. Scatter plots of the forward looking returns vs implied volatility index that triggered the trade (S&P100 index). This figure shows the relationship between the 1-, 5-, 20- and 60-day forward looking returns for the stock index and the level of implied volatility that triggered the trade. The time period is August 1, 1994 to January 31, 2003.

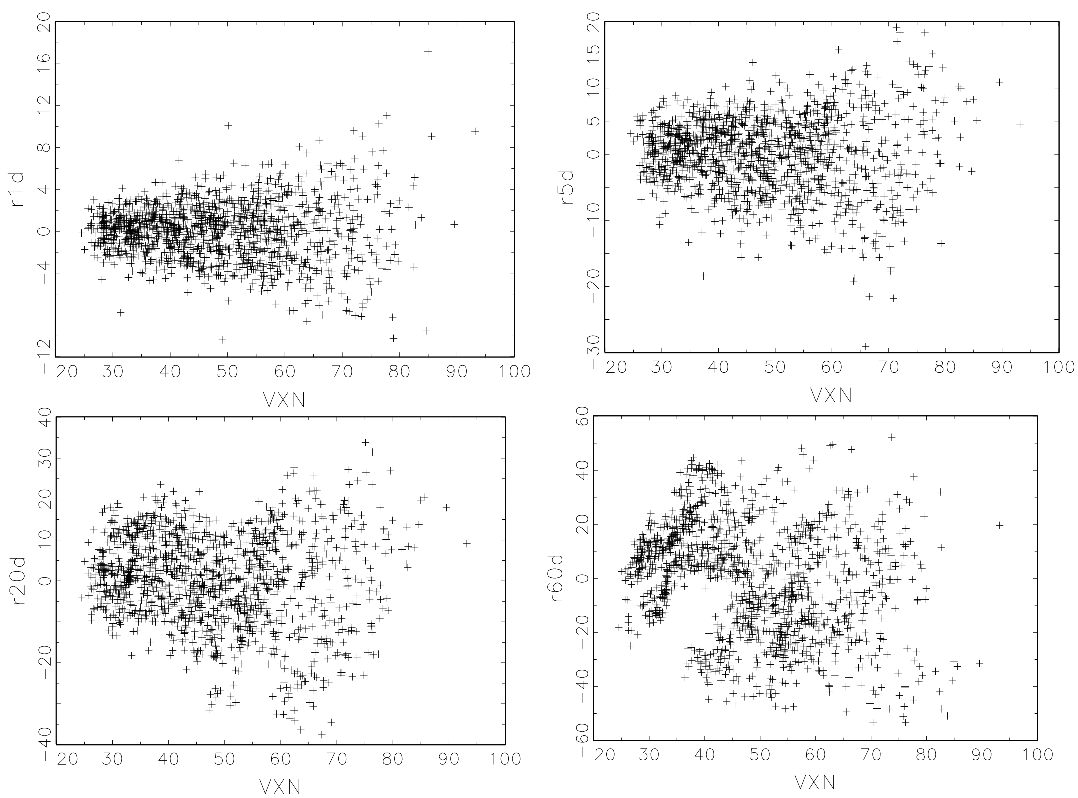


Figure 7. Scatter plots of the forward looking returns vs implied volatility index that triggered the trade (NASDAQ100 index). This figure shows the relationship between the 1-, 5-, 20- and 60-day forward looking returns for the stock index and the level of implied volatility that triggered the trade. The time period is June 2, 1997 to January 31, 2003.

Notes

[1]We assume in this paper that market participants agree on the option pricing formula, for example the usual Black and Scholes (1973) framework.

[2]They thus suppose that these are short-lived time periods where market participants do not act rationally but engage in ‘herding’ behaviors which drive down asset prices.

[3]See the CBOE website at http://www.cboe.com.

[4]For the NASDAQ100 index, the first sub-period starts on January 3, 1995 as the VXN data is not available before January 3, 1995.

[5]The asymmetric effect in the volatility vs returns relationship has been widely documented in the finance literature, see for example Black, 1976, French, Schwert, and Stambaugh, 1987 or Glosten, Jagannathan, and Runkle (1993).

[6]For example, $r5d_t$ is computed as $ln(P_{t+5}) - ln(P_t)$ and is the 5-day forward looking return relative to the VIX level observed at time t.

[7]The time period for the NASDAQ100 index is shorter than in Section II as we need the first 2 years of the dataset to initialize the trading algorithm (see below). Results are however similar if one starts the sample on January 3, 1995.

[8]By 20 equally spaced percentiles, we mean the 5%, 10%,..., 95% percentiles.

[9]We also experimented with shorter T_0 but the results were similar.

[10]Because $T_0 = 2$ years and the limited availability of the VXN data, we start the algorithm at a later data for the NASDAQ100 index.