The Journal of Portfolio Management 2005.31.3:92-100. Downloaded from www.iijournals.com by NEW YORK UNIVERSITY on 05/14/15.
It is illegal to make unauthorized copies of this article, forward to an unauthorized user or to post electronically without Publisher permission.

Relationships Between Implied Volatility Indexes and Stock Index Returns

Are implied volatility indexes leading indicators?

Pierre Giot

In an option pricing framework, volatility is the only input that cannot be directly observed by market participants. The call/put feature, time to maturity, and strike price are agreed-upon characteristics, and the risk-free interest rate and dividend payment are fairly easy to agree upon. The unknown input for computing the price of the option in the Black-Scholes [1973] model is expected volatility over the option's life.

In a market economy with actively traded option contracts that 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.

With the growing importance of modeling 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 with regard to historical volatility are two important research topics. The result is the many empirical studies reviewed by Poon and Granger [2003].

Researchers have focused 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, so implied volatility cannot provide relevant information as to whether stock prices are going up or down.

Pierre Giot is a professor of finance in the department of business administration and CEREFIM at the University of Namur in Namur, Belgium.
pierre.giot@fundp.ac.be

Compare this to the opinions of non-academic market participants for whom very high implied volatility levels are usually seen as signaling attractive entry levels for long traders. Their rationale is that very high implied volatility levels occur during periods of financial turmoil when investors are believed to be overreacting and hence selling financial assets indiscriminantly to raise cash or limit losses.[1]

The implied volatility index (VIX) of the Chicago Board Options Exchange is now routinely discussed in financial periodicals such as *Barron's* or the *Wall Street Journal*, with clear reference to a possible relationship between extremely high levels of implied volatility and a market bottom. For example, Tan [2002] writes that "a big VIX spike indicates the kind of extreme fear contrarians associate with market bottoms." Even in the academic literature, the VIX of the CBOE for S&P 100 index option contracts is dubbed the "fear indicator" (see Whaley [2000]).

I focus on two closely related topics that deal with the empirical link between implied volatility indexes and stock index returns, assessing 1) the contemporaneous relationship between relative changes in implied volatility and stock market returns, and 2) the possible relationship between implied volatility and future stock market returns. In the first case, I thus look at the simultaneous changes in the implied volatility and underlying stock indexes. In the second case, I focus on the "does fear mean opportunity" question in examining possible trading gains for long positions triggered by very high levels of the implied volatility index. The measures are the S&P 100 and Nasdaq 100 indexes for which the implied volatility indexes VIX and VXN are readily available.[2]

Because the VIX and VXN 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 possible trading signals. The S&P 100 and Nasdaq 100 indexes are also representative of two different class of stocks. Constituents of the S&P 100 index are widely held stocks representative of the U.S. economy, including financial, industrial, and technological firms. This is a good proxy for the U.S. market as a whole (although not as general as the broader S&P 500 index). The Nasdaq 100 includes almost exclusively technological and biotechnological firms. The study thus deals with two types of stock market measures for which the relationship between implied volatility and returns can differ.

For both indexes I estimate the contemporaneous relationship model during distinct subperiods representing different trading environments. Specifically, I examine a 1994–1997 low-volatility bull market; a 1997–2000 high-volatility bull market; and a 2000–2003 high-volatility bear market.

In the first step, I consider one-day contemporaneous changes in the stock indexes (S&P 100 and Nasdaq 100) and the corresponding implied volatility indexes (VIX and VXN). Not surprisingly, and as Whaley [2000] documents, there is a negative and statistically significant relationship between the returns of the two stock and implied volatility indexes; positive stock index returns are associated with declining implied volatility levels, while negative returns are associated with increasing implied volatility levels. For the S&P 100 index, this relationship is also asymmetric in the sense that negative stock index returns are associated with greater proportional changes in implied volatility measures than are positive returns.

In a new contribution to the literature, I show there are important differences across subperiods, as the contemporaneous relationship between the implied volatility indexes and negative stock index returns is much stronger in a low-volatility trading environment. One explanation is that options 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). Another possible explanation would be that sharp volatility shocks in low-volatility periods lead to proportionally much higher discount factors for equity markets, and thus much lower stock prices today.

For the Nasdaq 100 index, the asymmetric effect is rather weak, but the VXN-Nasdaq 100 co-movement is also somewhat muted in high-volatility trading environments. Moreover, there are no real quadratic effects for either stock index.

In a second step, I focus on the possible relationship between implied volatility and forward-looking stock index returns. The aim is to ascertain if, as thought by some market practitioners, high or very high implied volatility levels do indeed indicate oversold markets and hence could be viewed as short-term to middle-term buy signals. The empirical methodology is similar to that of Campbell and Shiller [1998], who 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).

Besides examining the mean return achieved over a

The Journal of Portfolio Management 2005.31.3:92-100. Downloaded from www.iijournals.com by NEW YORK UNIVERSITY on 05/14/15.
It is illegal to make unauthorized copies of this article, forward to an unauthorized user or to post electronically without Publisher permission.

The Journal of Portfolio Management 2005.31.3:92-100. Downloaded from www.iijournals.com by NEW YORK UNIVERSITY on 05/14/15.
It is illegal to make unauthorized copies of this article, forward to an unauthorized user or to post electronically without Publisher permission.

EXHIBIT 1
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

1-, 5-, 10-, and 60-day horizon (long position in the stock index) subsequent to a signal given by the implied volatility index, I also assess the trading risk incurred by taking those positions. Not surprisingly, results are very different from results for the one-day contemporaneous changes in the stock indexes. 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 indexes.

I also obtain the same type of results using regression analysis. This seems to somewhat validate the practitioners' point of view, although the evidence remains rather sketchy, and seems to hold only for long trades triggered by extremely high levels of implied volatility.

VIX AND VXN

The implied volatility indexes, VIX and VXN, are computed on an intradaily basis by the CBOE.[3] By construction, the VIX (VXN) 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&P 100 (Nasdaq 100) 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 expiration. Details regarding construction of the VIX are available in Whaley [1993].

Most research on the forecasting performance of implied volatility usually shows that the indexes compare very favorably with volatility measures that take as inputs historical returns. Because the VIX and the VXN are readily computed and are widely available, they have attracted attention in the academic and non-academic literature as a straightforward measure of the future volatility that market participants expect.

CONTEMPORANEOUS CHANGES IN THE STOCK AND IMPLIED VOLATILITY INDEXES

Our empirical application deals with the S&P 100 index and its corresponding implied volatility index, VIX, and the Nasdaq 100 index and its implied volatility index, VXN. The Nasdaq stock index has experienced a formidable bear market, losing more than half of its value since the Nasdaq 100 all-time high reached on March 10, 2000. The S&P 100 index, which reached its maximum on March 24, 2000, has since then also shed a considerable amount of its value.

I estimate the relationship between the one-day relative changes in the VIX_t and OEX_t (S&P 100 index) and the VXN_t and NDX_t (Nasdaq 100 index) in three distinct time 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) 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.

Exhibit 1 presents some brief characteristics of the stock indexes and implied volatility indexes for these three time periods.

For the linear regression framework, we define $r_{OEX,t} = \ln(OEX_t) - \ln(OEX_{t-1})$ as the one-day return on the S&P 100 index and $r_{NDX,t} = \ln(NDX_t) - \ln(NDX_{t-1})$as the one-day return on the Nasdaq 100 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 one-day relative changes in the level of the implied volatility indexes.

For the overall August 1, 1994–January 31, 2003, time period and for the three subperiods, we assess the contemporaneous relationship between the relative changes in the stock and implied volatility indexes using ordinary least squares. Because we strongly suspect an asymmetric relationship (i.e., the contemporaneous relationship would be different for negative and positive stock index returns), we introduce dummy variables that highlight the effect of positive and negative returns. The first regressions are thus:

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

for the S&P 100 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

The Journal of Portfolio Management 2005.31.3:92-100. Downloaded from www.iijournals.com by NEW YORK UNIVERSITY on 05/14/15.
It is illegal to make unauthorized copies of this article, forward to an unauthorized user or to post electronically without Publisher permission.

EXHIBIT 2

Contemporaneous Relative Changes in VIX versus OEX (daily returns)

β_0^+	β_0^-	β_1^+	β_1^-	β_2^+	β_2^-	R^2	$\tilde{R}^2$	N
Panel A: August 1, 1994 - January 31, 2003								
-0.64 (0.17)	0.06 (0.21)	-2.95 (0.18)	-4.00 (0.23)			0.59	0.59	2,142
-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	0.59	2,142
Panel B: August 1, 1994 - May 30, 1997								
-1.10 (0.36)	-0.32 (0.34)	-1.70 (0.68)	-6.25 (0.69)			0.38	0.38	716
-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	0.39	716
Panel C: June 2, 1997 - March 31, 2000								
-0.17 (0.32)	0.29 (0.50)	-3.90 (0.32)	-4.72 (0.54)			0.70	0.70	716
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	0.70	716
Panel D: April 3, 2000 - January 31, 2003								
-0.94 (0.26)	-0.88 (0.28)	-2.49 (0.20)	-3.61 (0.22)			0.70	0.70	710
-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	0.70	710

White's heteroscedastic consistent standard errors are given in parentheses. N is the number of observations per period.

EXHIBIT 3

Contemporaneous Relative Changes in VXN versus NDX (daily returns)

β_0^+	β_0^-	β_1^+	β_1^-	β_2^+	β_2^-	R^2	$\tilde{R}^2$	N
Panel A: January 3, 1995 - January 31, 2003								
-0.64 (0.15)	0.85 (0.17)	-0.93 (0.08)	-0.98 (0.09)			0.45	0.45	2,036
-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	0.45	2,036
Panel B: January 3, 1995 - May 30, 1997								
0.13 (0.25)	0.74 (0.24)	-1.75 (0.19)	-1.60 (0.14)			0.47	0.47	610
-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	0.47	610
Panel C: June 2, 1997 - March 31, 2000								
-0.18 (0.26)	0.45 (0.35)	-1.30 (0.16)	-1.70 (0.21)			0.51	0.51	716
-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	0.51	716
Panel D: April 3, 2000 - January 31, 2003								
-0.82 (0.25)	-0.03 (0.30)	-0.74 (0.09)	-0.89 (0.11)			0.47	0.47	710
-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	0.47	710

White's heteroscedastic consistent standard errors are given in parentheses. N is the number of observations per period.

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

for the Nasdaq 100 index.

Estimation results are given in the first row in each panel in Exhibits 2 and 3. White's heteroscedastic consistent standard errors are reported in all cases. The fitted responses in $r_{VIX,t}$ to $r_{OEX,t}$ and in $r_{VXN,t}$ to $r_{NDX,t}$ are displayed in the first graphs in Exhibits 4 and 5. Let us first discuss the results for the S&P 100 index.

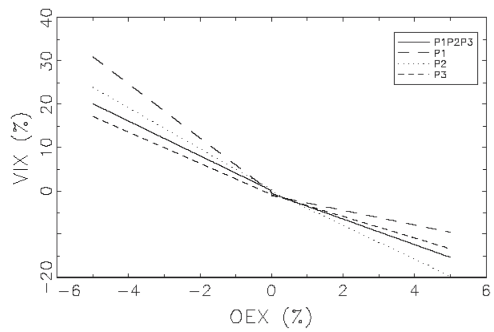
When we look at β_1^+ and β_1^- in the tables and the slopes of the response curves in the graph, it is obvious that an asymmetric effect is at work. β_1^+ and β_1^- are sharply different (the difference according to a Wald test is statistically different from 0 in all subperiods). In all cases, β_1^- is higher in absolute value than β_1^+, which indicates that negative returns for the stock index are associated with much greater relative changes in the implied volatility index than are positive returns.

This is also obvious in Exhibit 4 as the slopes at the left are much steeper than the slopes to the right. As expected, positive stock index returns are associated with declining implied volatility, while negative stock index

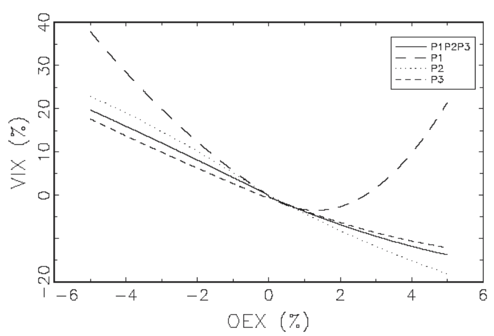
The Journal of Portfolio Management 2005.31.3:92-100. Downloaded from www.iijournals.com by NEW YORK UNIVERSITY on 05/14/15.
It is illegal to make unauthorized copies of this article, forward to an unauthorized user or to post electronically without Publisher permission.

EXHIBIT 4
VIX/OEX Response Curves for S&P 100 Index

Change in VIX versus Change in OEX—
Linear Effects Only



Change in VIX versus Change in OEX—
Quadratic Effects



P1: August 1, 1994–May 30, 1997; P2: June 2, 1997–March 31, 2000; P3: April 3, 2000–January 31, 2003; P1P2P3 overall 1994–2003 period.

returns are associated with increasing implied volatility.[5]

What is surprising, however, is that the asymmetric effect is much stronger in subperiod 1 than in subperiods 2 and 3, although subperiod 1 represents the low-volatility trading environment (the period that precedes the major financial and geopolitical crises). Actually, β_1^+ increases in absolute value and β_1^- declines in absolute value going from subperiod 1 to subperiods 2 or 3. Therefore the increase in implied volatility associated with negative stock index returns is somewhat smaller in high-volatility trading environments than in low-volatility markets (and vice versa).

A possible explanation is that volatility had reached a very high level in subperiods 2 and 3, and options traders were unwilling to bid it higher when the stock market fell; in the low-volatility market of subperiod 1, the co-movement of implied volatility and negative stock index returns was much sharper, as options traders reacted aggressively to these negative returns. It could also be argued that sharp volatility shocks in low-volatility periods lead to proportionally much higher discount factors for equity markets, and thus result in much lower stock prices today. (See Schwert [1990] for further discussion.)

Results are quite different for the Nasdaq 100 index. The asymmetric effect is not statistically validated as $\beta_1^+ - \beta_1^-$ is not statistically different from 0, except in subperiod 2, although the P-value for the equality test is equal to 0.035 and equality is thus barely rejected. Note also that the slopes at the left and the right in Exhibit 5 are quite similar. Neither are there sharp differences across the subperiods, although β_1^+ and β_1^- are much smaller in absolute value in subperiod 3 than in subperiod 1. Therefore the co-movement between volatility and increases/declines in the Nasdaq 100 index is somewhat muted in the high-volatility (and bear market) trading environment.

In a second step, we add the quadratic terms $r^2_{OEX,t}$ and $r^2_{NDX,t}$ to the linear regressions to assess the size effect of the returns. High or low stock index returns can co-move differently with one-day relative changes in the implied volatility indexes. The second set of regressions is:

$$\begin{aligned} r_{VIX,t} = {} & \beta_0^+ D_t^+ + \beta_0^- D_t^- + \\ & \beta_1^+ r_{OEX,t} D_t^+ + \beta_1^- r_{OEX,t} D_t^- + \\ & \beta_2^+ r_{OEX,t}^2 D_t^+ + \beta_2^- r_{OEX,t}^2 D_t^- + \varepsilon_t \end{aligned} \quad (3)$$

and

$$\begin{aligned} r_{VXN,t} = {} & \beta_0^+ D_t^+ + \beta_0^- D_t^- + \\ & \beta_1^+ r_{NDX,t} D_t^+ + \beta_1^- r_{NDX,t} D_t^- + \\ & \beta_2^+ r_{NDX,t}^2 D_t^+ + \beta_2^- r_{NDX,t}^2 D_t^- + \varepsilon_t \end{aligned} \quad (4)$$

The estimated coefficients are given in the second row of each panel in Exhibits 2 and 3. The fitted responses of $r_{VIX,t}$ to $r_{OEX,t}$ and $r_{VXN,t}$ to $r_{NDX,t}$ are displayed in the second graphs in Exhibits 4 and 5.

For the S&P 100 index, β_2^+ is (barely) statistically different from 0 in subperiod 2 only; β_2^+ is not statistically different from 0 in any period. Note that the R^2 are almost the same as in Equation (1). The first and second graphs in Exhibit 4 are quite similar, except for the right side of the response curve in subperiod 1 (in that case, coefficient β_2^+ is quite high and significant).

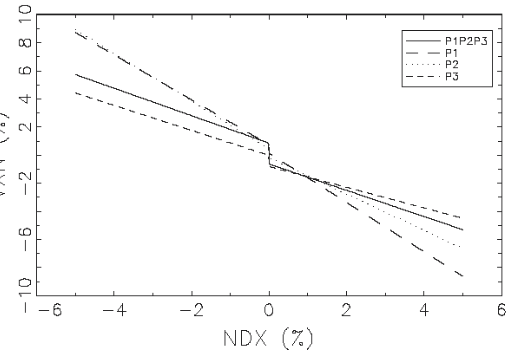
For the Nasdaq 100 index, the quadratic effect is also rather weak as β_2^- is never significant and β_2^+ is significant only in the overall period. The first and second graphs in Exhibit 5 tell the same story, as the two sets of response curves are almost identical.

The Journal of Portfolio Management 2005.31.3:92-100. Downloaded from www.iijournals.com by NEW YORK UNIVERSITY on 05/14/15.
It is illegal to make unauthorized copies of this article, forward to an unauthorized user or to post electronically without Publisher permission.

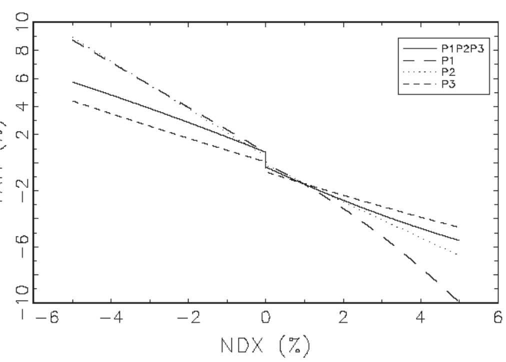
EXHIBIT 5

VXN/NDX Response Curves for Nasdaq 100 Index

Change in VXN versus Change in NDX—
Linear Effects Only



Change in VXN versus Change in NDX—
Quadratic Effects



P1: August 1, 1994–May 30, 1997; P2: June 2, 1997–March 31, 2000; P3: April 3, 2000–January 31, 2003; P1P2P3 overall 1994–2003 period.

Taking into account all these empirical results, we conclude that an asymmetric effect is at work for the S&P 100 index, but that there are no quadratic effects. For the Nasdaq 100 index, there are no quadratic effects and almost no asymmetric effect. There are, however, important differences for both indexes in the asymmetric effect across subperiods, as the implied volatility-negative stock index return co-movement is much stronger in the low-volatility trading environment.

ARE VIX AND VXN FORWARD-LOOKING INDICATORS?

While it is clear that negative returns are associated with increased implied volatility, there is a growing debate as to how implied volatility indexes can indicate overbought or oversold market conditions. I tackle this issue by looking at the relationship between the level of the implied volatility indexes, 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 S&P 100 and Nasdaq 100 indexes. I 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&P 100 index.[6]

The exercise is repeated with the VXN and forward-looking relative changes in the level of the Nasdaq 100 index.

To see whether very high implied volatility levels turn out to be relevant trading signals for long positions, I use an algorithm as follows. Implied volatility levels are classified according to 20 rolling equally spaced percentiles of the implied volatility index observed at any time.[7]

Let us illustrate with the S&P 100 index. At a given time t, the 20 equally spaced percentiles are computed for the set of $\{VIX_i\}$ values where $i \in t - T_0 \ldots t - 1$, that is, the information set that 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. If VIX_t is high, it will probably be ranked at 15 or above. If VIX_t is very high, R_t will be much closer to 20. If VIX_t is higher than the maximum of all VIX_i, it is ranked as $R_t = 21$. Given the rank R_t observed at time t, forward-looking returns are computed for the S&P 100 index $r1d_t$, $r5d_t$, $r20d_t$, and $r60d_t$, which then correspond to the forward-looking returns for a long position in the S&P 100 index (for the particular time horizon) triggered by the observed VIX_t.

In this way 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 this framework, T_0 specifies the backward-looking time horizon (i.e., size of the information set) used to compute the rank of VIX_t. This trading rule is implemented for all available observations in the S&P 100 and Nasdaq 100 datasets. It is programmed as a rolling measure as the time index 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 time t, the last step is to compute the expected value and variance of the 1-, 5-, 20-, and 60-day forward-looking returns for all ranks (ranging from 0 to 21). If very high levels of the implied volatility index really indicate oversold markets dominated by fear, then on average $r1d_t$, $r5d_t$, $r20d_t$, and $r60d_t$ should be quite high for R close to 20.

The Journal of Portfolio Management 2005.31.3:92-100. Downloaded from www.iijournals.com by NEW YORK UNIVERSITY on 05/14/15.
It is illegal to make unauthorized copies of this article, forward to an unauthorized user or to post electronically without Publisher permission.

EXHIBIT 6

Outcome of Trading Strategy (S&P 100 Index)—8/94–1/03

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)

Estimated OLS coefficients. Newey-West standard errors are given in parentheses.

EXHIBIT 7

Outcome of Trading Strategy (Nasdaq 100 Index)—6/97–1/03

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)

Estimated OLS coefficients. Newey-West standard errors are given in parentheses.

Outcomes of this trading strategy are reported in Exhibits 6 and 7 for the S&P 100 and Nasdaq 100. For both stock indexes, $T_0 = 2$ years, which implies that on a given day t VIX_t (VXN_t) is compared with the 20 equally spaced percentiles based on a rolling two-year history of VIX (VXN).[8] The time period is August 1, 1994–January 31, 2003, for the S&P 100 index and June 2, 1997–January 31, 2003, for the Nasdaq 100 index.

While there is no clear pattern for the middle categories, for low levels of VIX or VXN (R between 1 and 5), expected forward-looking returns are always negative, whatever the time horizon. At the other end of the scale, forward-looking returns in categories $R = 20$ and $R = 21$ are always positive on average.

More important, forward-looking returns triggered by levels of implied volatility in category $R = 21$ (i.e., we enter a long position on date t if VIX_t is higher than its maximum over the last two years) are characterized by high positive average values and very low coefficients of variation (not tabulated). For example, the 11 occurrences in category $R = 21$ for the Nasdaq 100 index produce an average return of 27.19% within the next 60 days with a coefficient of variation of only 0.63.

To assess the statistical relevance of our results, we estimate the 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 $D1_t$, $D2_t$, …, $D21_t$ 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 that can be used in a linear regression model.

Each coefficient can be directly interpreted as the expected return at the given time horizon when VIX_t or VXN_t is ranked in category R_t at time t. For example, the estimated δ_{20} for the S&P 100 index at the 20-day time horizon gives the expected return for the S&P 100 index whenever the level of the VIX is classified at rank 20. Estimation results for the coefficients of the dummy variables are equal to the average forward-looking returns computed already.

To indicate whether the coefficients are significantly different from zero, I show in Exhibits 6 and 7 the Newey-West standard errors in parentheses. We can see that most coefficients in the middle of the exhibits are not significant, while those at the very top tend to be strongly negatively significant, and those at the very bottom are strongly positively significant.

These results lend some support to the hypothesis that extremely high levels of implied volatility signal attractive buy points for traders who want to take long positions in the underlying index. This seems consistent with trader conclusions that extremely high-volatility markets are oversold, which should benefit traders entering long positions.

The academic literature certainly suggests a link between high expected returns and high conditional volatility. Merton's work [1973, 1980] motivates the ARCH-M model of Engle, Lilien, and Robins [1987] (as Whaley [2000] states: "if expected market volatility increases, investors demand higher rates of return on stocks"). Christensen and Prabhala [1998] and Blair, Poon, and Taylor [2001] note that the implied volatility tracks and forecasts future realized volatility well, so it is not unreasonable to think of the same relationship between observed implied volatility and forward-looking returns. Our results are thus consistent with the literature on the relationship between returns and market volatility.

CONCLUSION

This research shows there is a strong negative relationship between contemporaneous changes in implied volatility indexes and the underlying stock indexes for both the S&P 100 and the Nasdaq 100. For the S&P 100 index, the relationship is asymmetric; negative returns for the stock index are associated with much greater relative changes than positive returns in the implied volatility index (VIX).

The extent of this asymmetric effect depends on the period. The increase in implied volatility when negative stock index returns occur is somewhat lower in high-volatility trading environments than in low-volatility periods; the converse is true for a decline in implied volatility.

For the Nasdaq 100 index, the asymmetric effect is rather weak, as the changes in the VXN index observed for positive and negative returns for the NDX index are quite similar. For the S&P 100 index, the co-movement between the VXN and the Nadaq 100 index is somewhat muted in high-volatility trading environments.

If, as some market practitioners think, high or very high implied volatility levels indicate oversold markets, forward-looking returns for long positions in the underlying stock index triggered by these large implied volatility levels should be attractive. There is some evidence that positive forward-looking returns are to be expected for long positions in the stock index triggered by high levels of the implied volatility indexes, but one must wait for extremely high levels of implied volatility to get very attractive positive forward-looking returns.

ENDNOTES

The author thanks Carol Alexander, Helena Beltran, Apostolos Katsaris, Mikael Petitjean, Armin Schwienbacher, and an anonymous referee for useful suggestions.

[1]Traders and market participants thus suppose these are short-lived periods when market participants do not act rationally but engage in herding behaviors that drive down asset prices.

[2]Note that this is the "old" VIX, as this research was completed in 2003. Early in 2004, the CBOE introduced a new VIX (whose underlying index is now the S&P 500 index).

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

[4]For the Nasdaq 100 index, the first subperiod starts January 3, 1995, as the VXN data are not available before that date.

[5]The asymmetric effect in the volatility versus returns relationship has been widely documented in the finance literature; see, for example, 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 five-day forward-looking return relative to the VIX level observed at time t.

[7]By 20 equally spaced percentiles, we mean the 5, 10, …, 95 percentiles.

[8]Results are similar for shorter T_0.

REFERENCES

Black, Fischer, and Myron Scholes. "The Pricing of Options and Corporate Liabilities." *Journal of Political Economy*, 81 (1973), pp. 637-659.

Blair, Bevan J., Ser-Huang Poon, and Stephen J. Taylor. "Forecasting S&P 100 Volatility: The Incremental Information Content of Implied Volatility and High-Frequency Index Returns." *Journal of Econometrics*, 105 (2001), pp. 5-26.

Campbell, John Y., and Robert J. Shiller. "Valuation Ratios and the Long-Run Stock Market Outlook." *The Journal of Portfolio Management*, 24 (1998), pp. 11-26.

The Journal of Portfolio Management 2005.31.3:92-100. Downloaded from www.iijournals.com by NEW YORK UNIVERSITY on 05/14/15.
It is illegal to make unauthorized copies of this article, forward to an unauthorized user or to post electronically without Publisher permission.

Christensen, Bent J., and Nagpurnanand R. Prabhala. "The Relation between Implied and Realized Volatility." *Journal of Financial Economics*, 50 (1998), pp. 125-150.

Engle, Robert F., David M. Lilien, and Russell P. Robins. "Estimating Time Varying Risk Premia in the Term Structure." *Econometrica*, 55 (1987), pp. 391-407.

French, Kenneth, G. William Schwert, and Robert F. Stambaugh. "Expected Stock Returns and Volatility." *Journal of Financial Economics*, 19 (1987), pp. 3-29.

Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle. "On the Relation between Expected Value and the Volatility of the Nominal Excess Return on Stocks." *Journal of Finance*, 48 (1993), pp. 1779-1801.

Merton, Robert C. "On Estimating the Expected Return on the Market: An Exploratory Investigation." *Journal of Financial Economics*, 8 (1980), pp. 323-361.

——. "An Intertemporal Capital Asset Pricing Model." *Econometrica*, 42 (1973), pp. 867-887.

Poon, Ser-Huang, and Clive Granger. "Forecasting Volatility in Financial Markets: A Review." *Journal of Economic Literature*, 41 (2003), pp. 478-539.

Schwert, G. William. "Stock Volatility and the Crash of '87." *The Review of Financial Studies*, 3 (1990), pp. 77-102.

Tan, K. "Fixated on the VIX." *Barron's*, July 29, 2002.

Whaley, Robert E. "Derivatives on Market Volatility: Hedging Tools Long Overdue." *The Journal of Derivatives*, 1 (1993), pp. 71-84.

——. "The Investor Fear Gauge." *The Journal of Portfolio Management*, 26 (2000), pp. 12-17.

To order reprints of this article, please contact Ajani Malik at amalik@iijournals.com or 212-224-3205.

The Journal of Portfolio Management 2005.31.3:92-100. Downloaded from www.iijournals.com by NEW YORK UNIVERSITY on 05/14/15.
It is illegal to make unauthorized copies of this article, forward to an unauthorized user or to post electronically without Publisher permission.