THE FORECAST QUALITY OF CBOE IMPLIED VOLATILITY INDEXES

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We examine the forecast quality of Chicago Board Options Exchange (CBOE) implied volatility indexes based on the Nasdaq 100 and Standard and Poor's 100 and 500 stock indexes. We find that the forecast quality of CBOE implied volatilities for the S&P 100 (*VXO*) and S&P 500 (*VIX*) has improved since 1995. Implied volatilities for the Nasdaq 100 (*VXN*) appear to provide even higher quality forecasts of future volatility. We further find that attenuation biases induced by the econometric problem of errors in variables appear to have largely disappeared from CBOE volatility index data since 1995. © 2005 Wiley Periodicals, Inc. Jrl Fut Mark 25:339–373, 2005

INTRODUCTION

Most investors would agree that stock prices, even when rising, climb a wall of worry. Where volatility and investor sentiment about the future go hand in hand, the forward view offered by volatility implied by option

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prices is often regarded as a bona fide investor fear gauge (Whaley, 2000). Implied volatilities are sufficiently important so as to be routinely reported by financial news services and closely followed by many finance professionals. As a result, the information content and forecast quality of implied volatility stands as an important topic in financial markets research.

Latane and Rendleman (1976), Chiras and Manaster (1978), and Beckers (1981) provide early assessments of implied volatility forecast quality. They found that implied volatilities offered better estimates of future return volatility than ex post standard deviations calculated from historical returns data. More recently, Jorion (1995) finds that implied volatilities from currency options outperform volatility forecasts from historical price data.

In marked contrast to the first studies cited above, several later studies found weaknesses in implied volatility as a predictor of future realized volatility; these include Day and Lewis (1988), Lamoureux and Lastrapes (1993), and Canina and Figlewski (1993). Christenson and Prabhala (1998) suggest that some of these weaknesses are related to methodological issues, such as overlapping and mismatched sample periods. The validity of these concerns is supported by Fleming (1998) and Fleming, Ostdiek, and Whaley (1995), who find that implied volatilities from S&P 100 index options yield efficient forecasts of month-ahead S&P 100 index volatility. Further studies of the performance of S&P 100 implied volatility by Christensen and Prabhala (1998), Christensen and Strunk-Hansen (2002), and Fleming (1998) find that implied volatility forecasts are upwardly biased, but dominate historical volatility in terms of ex ante forecasting power. Fleming (1999) shows that the forecast bias of S&P 100 implied volatility is not economically significant after accounting for transaction costs. More recently, Blair, Poon, and Taylor (2001) conclude that implied volatilities from S&P 100 index option prices provide more accurate volatility forecasts than those obtained from either low- or high-frequency index returns.

Similar to prior studies, in this paper we examine the forecast quality of implied volatility by focusing on three implied volatility indexes published by the Chicago Board Options Exchange (CBOE). These volatility indexes are reported under the ticker symbols *VXO*, *VIX*, and *VXN*. The *VXO* and *VIX* volatility indexes are based on the Standard & Poor's 100 and 500 stock indexes, respectively, with ticker symbols *OEX* and *SPX*. The *VXN* volatility index is based on the Nasdaq 100 stock index, with ticker symbol *NDX*. The importance of the CBOE volatility indexes is attested to by the fact they merit their own three-letter ticker symbols. Current values for *VXO*, *VIX*, and *VXN* are accessible in real time, along with current values for the *OEX*, *SPX*, and *NDX* stock indexes.

Like previous studies of implied volatility, our benchmark for comparison is return volatility for the underlying index realized during the life of the option. We find that the *VXO*, *VIX*, and *VXN* volatility indexes published by the CBOE easily outperform historical volatility as predictors of future return volatility for both the S&P 100 index (*OEX*), S&P 500 index (*SPX*), and the Nasdaq 100 index (*NDX*). We also find that attenuation biases induced by the econometric problem of errors in variables reported in prior studies has largely disappeared from CBOE volatility index data since 1995. After 1995, instrumental variable regressions do not appear to yield assessments of forecast quality that are consistently superior to those obtained from ordinary least-squares (OLS) regressions.

This paper is organized as follows: In the next section, we present the volatility measures used in this study and summarize their basic statistical properties. A framework for analysis of volatility forecasts from realized and implied volatility measures is developed in the third section. In the fourth section, we present an empirical assessment of the forecast quality of CBOE volatility indexes using ordinary least-squares (OLS) regressions. Assessments based on an instrumental variables methodology are presented in the fifth section. In the sixth section, we analyze the statistical significance of volatility forecast errors embodied in CBOE implied volatilities. The seventh section provides a GARCH perspective of volatility forecast quality. A summary and conclusion follow in the final section.

DATA SOURCES AND VOLATILITY MEASURES

Data Sources

Data for this study span the period January 1988 through December 2003 and include index returns and option-implied volatilities for the Standard and Poor's 100 and 500 stock indexes and the Nasdaq 100 stock index. Index returns are computed from index data published by Reuters under the ticker symbols *OEX* for the S&P 100 index, *SPX* for the S&P 500 index, and *NDX* for the Nasdaq 100 index. Option-implied volatilities for these indexes are supplied by the Chicago Board Options Exchange (CBOE).

Volatility Measures

Two volatility measures are used in this study. The first volatility measure is the sample standard deviation of daily index returns, which serves as the benchmark for this study. Annualized index return volatility within month *m* is computed for each calendar month in the sample period as defined in Equation (1).

$$VOL_m = \sqrt{\frac{30}{22} \times \frac{252}{n_m - 1} \sum_{d=1}^{n_m} \left(r_{d,m} - \frac{1}{n_m} \sum_{h=1}^{n_m} r_{h,m} \right)^2} \tag{1}$$

In Equation (1), $r_{d,m}$ represents an index return on day d in month m, and n_m is the number of trading days in month m. The volatility measure VOL_m is computed separately in each month and represents a series of nonoverlapping monthly return standard deviations for the S&P 100 and Nasdaq 100 indexes.

The adjustment factor $\sqrt{30/22}$ embedded in Equation (1) produces a volatility series that conforms to the same 22-trading-day basis to which CBOE implied volatilities are calibrated. As explained in Fleming, Ostdiek, and Whaley (1995), the CBOE implied volatility calculations convert calendar days to trading-days via this function:

$$\textit{Trading days} = \textit{Calendar days} - 2 \times \mathrm{int}(\textit{Calendar days}/7)$$

The conversion from 30 calendar days to 22 trading days yields an adjustment of $\sqrt{30/22}$ (=1.1677), which restates the annualized return standard deviation to a 22-trading-day basis. This calibration is necessary to achieve comparability between the realized volatility series VOL_m and the CBOE implied volatility series *VXO*, *VIX*, and *VXN*. As discussed in Bilson (2003), an essentially identical adjustment $\sqrt{7/5}$ (=1.1832) also effectively calibrates volatility measures to the same day-count basis.

The second volatility measure, CBOE implied volatility, is the primary focus of this study. The Chicago Board Options Exchange (CBOE) provides three volatility series reported under the ticker symbols *VXO*, *VIX*, and *VXN* derived from options traded on the S&P 100, S&P 500, and Nasdaq 100 indexes, respectively.

Two methods are used by the CBOE to compute implied volatility indexes. The *VXO* volatility series for the S&P 100 (formerly *VIX*) is computed as a weighted average of separate implied volatilities from eight near-the-money call and put options from two nearby option expiration dates. Harvey and Whaley (1991) show that S&P 100 put and call implied volatilities are negatively correlated and so combining them results in a more efficient estimator. Corrado and Miller (1996) analyze various weighting schemes and find that the method used for the *VXO* index is expected to be as efficient as any other suggested in the literature. Calculation of *VXO* values follows the formula stated immediately below in which $IV_C(K, T)$ and $IV_P(K, T)$ are implied volatilities for call and put options, respectively, with strike K and maturity T.

$$VXO = \frac{\sum_{j=0}^{1} \sum_{h=1}^{2} (-1)^{j+h} (T_h - 22)(S_0 - K_{m+1-j})(IV_C(K_{m+j}, T_h) + IV_P(K_{m+j}, T_h))}{(T_2 - T_1)(K_{m+1} - K_m)} \quad (2)$$

In the above *VXO* formula, the nearest-the-money strikes K_m and K_{m+1} bracket the current index level, i.e., $K_m \leq S_0 \leq K_{m+1}$. The two nearest maturities are chosen such that T_2 and T_1 are not less than 22 and eight trading days, respectively, i.e., $T_2 \geq 22 \geq T_1 \geq 8$. Authoritative references for the exact algorithm used to compute *VXO* (formerly *VIX*) are Whaley (1993) and Fleming, Ostdiek, and Whaley (1995).

The *VIX* and *VXN* volatility series for the S&P 500 and Nasdaq 100 indexes, respectively, are computed as a weighted average of the prices of all out-of-the-money call and put options from two nearby expiration dates. Theoretical justification for this method is given in Britten-Jones and Neuberger (2000). Calculation of *VIX* and *VXN* volatility values follows the formula stated immediately below, in which $C(K, T)$ and $P(K, T)$ denote prices for call and put options with strike price K and time to maturity T. This formula assumes the option chain has strikes ordered as $K_{j+1} > K_j$ with the two nearest maturities chosen to satisfy the restriction $T_2 \geq 22 \geq T_1 \geq 8$.

$$VIX = \sum_{h=1}^{2} (-1)^h \frac{(T_h - 22)}{(T_2 - T_1)} \sum_{j=1}^{N} \frac{K_{j+1} - K_{j-1}}{K_j^2} \min(C(K_j, T_h), P(K_j, T_h)) \quad (3)$$

In this study, VXO_m, VIX_m, and VXN_m denote implied volatilities for S&P 100, S&P 500, and Nasdaq 100 indexes observed at the close of the last trading day in month m. Therefore these implied volatilities represent market forecasts of future return volatility in month $m + 1$.

Data Summary Statistics

Data for this study are distributed across several sample periods. Data for the *VXO* S&P 100 volatility index are partitioned into an 84-month period from January 1988 through December 1994 and a 108-month period from January 1995 through December 2003. The January 1988 start avoids the immediate post-1987 crash period. Data for the *VIX* S&P 500 volatility index are split into a 60-month period from January 1990 to December 1994 and a 108-month period from January 1995 through December 2003. Data for the *VXN* Nasdaq 100 volatility index span the 108-month period from January 1995 through December 2003. The January 1990 start date for *VIX* data and January 1995 start date for *VXN* data are imposed by data availability from the CBOE.

Figures 1, 2, and 3 provide a graphical display of the time series of CBOE implied volatilities and corresponding realized volatilities. Figure 1 plots implied and realized volatilities VXO_{m-1} and VOL_m, respectively, for the S&P 100 index over the 16-year period 1988–2003. Figure 2 plots implied and realized volatilities VIX_{m-1} and VOL_m, respectively, for the S&P 500 index over the 14-year period 1990–2003. Figure 3 plots implied and realized volatilities VXN_{m-1} and VOL_m, respectively, for the Nasdaq 100 index over the nine-year period 1995–2003. Implied volatilities are plotted with solid lines and realized volatilities are plotted with dashed lines. These volatility series are synchronized so that realized volatility in month m is aligned with implied volatility observed on the last trading day of month $m - 1$. Differences between realized volatility in month m and implied volatility observed on the last trading day of the prior month represent observed forecast errors.

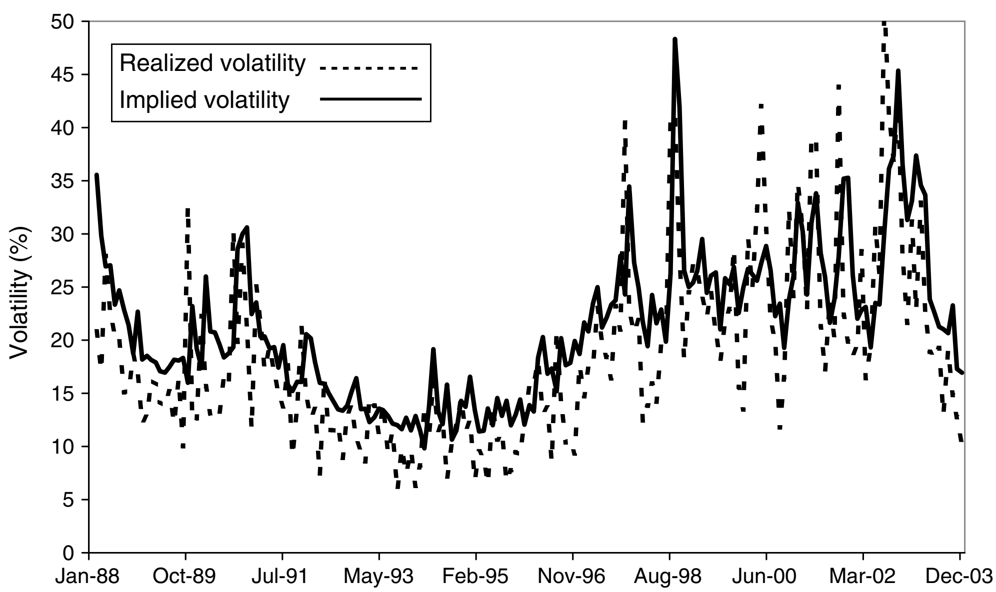

FIGURE 1
S&P 100 index realized vs. implied volatility.

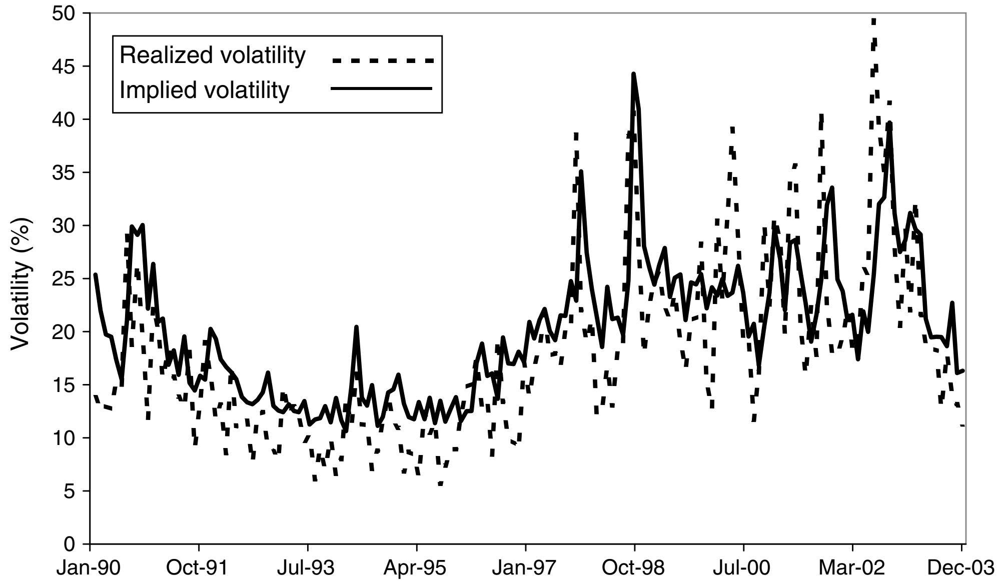

FIGURE 2

S&P 500 index realized vs. implied volatility.

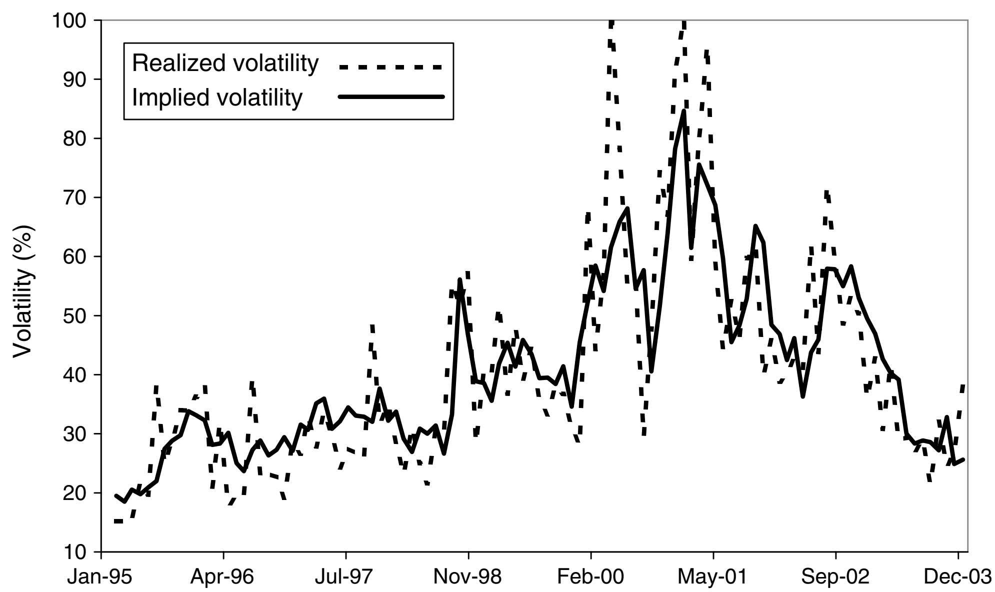

FIGURE 3

Nasdaq 100 index realized vs. implied volatility.

Summary descriptive statistics for these volatility data are provided in Table I. Table I reveals marked differences between realized and implied volatility series. Average S&P 100 implied volatility VXO_m was greater than average realized volatility VOL_m by 2.91% = 17.63% − 14.72% over the period 1988–1994 and by 2.71% = 24.08% − 21.37%

TABLE I
Descriptive Statistics for Monthly Volatility Measures

	Mean (%)	*Std dev (%)*	*Skewness*	*Kurtosis*
Panel A: S&P 100 January 1988–December 1994				
VOL_m	14.72	5.28	1.18	4.79
VXO_m	17.63	4.78	0.83	3.37
$\ln(VOL_m)$	2.63	0.34	0.05	3.30
$\ln(VXO_m)$	2.84	0.26	0.24	2.54
Panel B: S&P 100 January 1995–December 2003				
VOL_m	21.37	9.46	0.82	3.50
VXO_m	24.08	7.11	0.62	3.98
$\ln(VOL_m)$	2.97	0.45	−0.24	2.79
$\ln(VXO_m)$	3.14	0.30	−0.31	3.12
Panel C: S&P 500 January 1990–December 1994				
VOL_m	13.19	4.66	1.19	4.93
VIX_m	16.41	4.71	1.35	4.45
$\ln(VOL_m)$	2.52	0.36	0.17	3.00
$\ln(VIX_m)$	2.76	0.26	0.80	3.03
Panel D: S&P 500 January 1995–December 2003				
VOL_m	20.32	8.83	0.89	3.65
VIX_m	22.30	6.32	0.67	4.19
$\ln(VOL_m)$	2.92	0.45	−0.28	2.98
$\ln(VIX_m)$	3.06	0.29	−0.28	3.09
Panel E: Nasdaq 100 January 1995–December 2003				
VOL_m	40.39	18.34	1.33	4.88
VXN_m	40.78	14.42	0.82	3.08
$\ln(VOL_m)$	3.61	0.42	0.25	2.76
$\ln(VXN_m)$	3.65	0.34	0.16	2.34

Note. Sample moments of monthly volatility: VOL_m represents realized volatility in month m computed from daily returns within the month. VXO_m, VIX_m, and VXN_m denote CBOE implied volatility indexes for the S&P 100, S&P 500, and Nasdaq 100 indexes, respectively.

in the period 1995–2003. Similarly, average S&P 500 implied volatility VIX_m exceeded average realized volatility VOL_m by 3.22% = 16.41% − 13.19% during the period 1990–1994 and by 1.98% = 22.30% − 20.32% in the period 1995–2003. Average Nasdaq 100 implied volatility VXN_m was greater than average realized volatility VOL_m by 0.39% = 40.78% − 40.39% over the period 1995–2003.

Two-sample matched-pair t tests are used to test for significant differences between mean values of realized and implied volatilities. The S&P 100 volatility measures yield t test values of −6.89 and −5.31 from the periods 1988–1994 and 1995–2003, respectively. The S&P 500 volatility measures yield t test values of −7.87 and −4.02 from the periods 1990–1994 and 1995–2003. The Nasdaq 100 index yields a t test value of −0.55 for the period 1995–2003. These t values indicate statistically significant biases for S&P 100 and S&P 500 index volatility forecasts, but an insignificant bias for Nasdaq 100 index volatility forecasts.

At least part of the observed forecast bias might be attributed to the algorithm used to compute implied volatility. For example, Fleming, Ostdiek, and Whaley (1995) show that 35 basis points of the difference between S&P 100 implied and realized volatilities is explained by intraday effects associated with the algorithm used to compute CBOE implied volatilities. Fleming and Whaley (1994) report an additional bias of about 60 basis points attributable to the wildcard option embedded in S&P 100 index options. S&P 500 and Nasdaq 100 index options do not have a wildcard feature.

Naive Volatility Forecasts

Visible co-movement between the volatility time series displayed in Figures 1 and 2 suggest that naive forecasts might forecast future return volatility. For example, consider naive volatility forecasts based on a simple weighted average of lagged realized volatility VOL_{m-1} and implied volatility $IVOL_{m-1}$. We evaluate three cases using the mean square error criteria stated immediately below: $\alpha = 1$, $\alpha = 0$, and $\alpha = \alpha^*$, where α^* is chosen to minimize mean square error subject to $0 \leq \alpha \leq 1$.

$$MSE(\alpha) = \frac{1}{M}\sum_{m=1}^{M}(VOL_m - \alpha \times VOL_{m-1} - (1-\alpha) \times IVOL_{m-1})^2 \quad (4)$$

Mean square errors for these naive forecasts are reported in Table II.

TABLE II
Mean Squared Errors of Naive Volatility Forecasts

	S&P 100		*S&P 500*		*Nasdaq 100*
	1988–1994	*1995–2003*	*1990–1994*	*1995–2003*	*1995–2003*
$MSE(1)$	41.48	66.69	21.76	57.47	195.87
$MSE(0)$	31.52	48.60	25.81	43.43	96.37
$MSE(\alpha^*)$	30.09	46.63	18.46	41.42	96.37
α^*	0.262	0.239	0.599	0.262	0.000

Note. Mean squared errors (MSE) of naive volatility forecasts of realized volatility (VOL_m) based on weighted averages of lagged volatility (VOL_{m-1}) and implied volatility ($IVOL_{m-1}$).

$$MSE(\alpha) = \frac{1}{M}\sum_{m=1}^{M}(VOL_m - \alpha \times VOL_{m-1} - (1-\alpha) \times IVOL_{m-1})^2$$

Three cases are evaluated: $\alpha = 1$, $\alpha = 0$, and $\alpha = \alpha^*$, where α^* is chosen to minimize mean square error subject to $0 \leq \alpha \leq 1$.

As shown in Table II, the $\alpha = 0$ case yields smaller mean square errors than the $\alpha = 1$ case in all instances except for the S&P 500 index in the period 1990–1994. However, in the period 1995–2003, the implied volatilities VXO_{m-1}, VIX_{m-1}, and VXN_{m-1} for the S&P 100, S&P 500, and Nasdaq 100 indexes, respectively, clearly dominate lagged volatility VOL_{m-1} in forming naive forecasts of realized volatility VOL_m. Indeed, the case $\alpha^* = 0$ is optimal for the Nasdaq 100 index in the period 1995–2003.

A MODEL FRAMEWORK FOR ASSESSING VOLATILITY FORECASTS

In this section, we develop a framework for a further analysis of monthly volatility forecasts. This framework may be interpreted as a null hypothesis for empirical testing, or as a model for interpretation of empirical results.

Specification of Model Variables

Volatility realized in month m is denoted by VOL_m as specified in Equation (1). We assume that realized volatility has two components: a latent volatility σ_m evolving according to the true, but unknown, underlying economic model and a random deviation χ_m of realized volatility from latent volatility. We further assume that the deviations χ_m are mean zero, independently distributed random variables.

$$VOL_m = \sigma_m + \chi_m, \quad E(\chi_m) = 0, \quad E(\sigma_m \chi_m) = 0 \tag{5}$$

Consequently, the total variance of realized volatility is a sum of component variances.

$$Var(VOL_m) = Var(\sigma_m) + Var(\chi_m) \tag{6}$$

The assumptions underlying Equations (5) and (6) are essentially those made by Andersen and Bollerslev (1998) in the context of daily volatility forecasts. They argue that rational volatility forecasts represent predictions of latent volatility and not realized volatility, since deviations between realized and latent volatility are unpredictable noise.

Equations (5) and (6) imply that a regression of current volatility VOL_m on lagged volatility VOL_{m-1} yields a regression slope coefficient attenuated by an errors-in-variables bias.

$$\lim_{M\to\infty} \frac{\sum_{m=2}^{M} (Vol_m Vol_{m-1} - \overline{Vol}^2)}{\sum_{m=2}^{M} (Vol_{m-1}^2 - \overline{Vol}^2)} = \frac{Cov(\sigma_m, \sigma_{m-1})}{Var(\sigma_{m-1}) + Var(\chi_{m-1})} \tag{7}$$

Nota bene, $Var(\sigma_{m-1})$, $Var(\chi_{m-1})$, and $Var(\xi_{m-1})$ (introduced immediately below) are asymptotically equivalent to $Var(\sigma_m)$, $Var(\chi_m)$, and $Var(\xi_m)$, respectively. The finite sample index $m - 1$ is retained for convenience in referring to the original finite sample formula.

A similar framework in the sense of Andersen and Bollerslev (1998) is applicable to implied volatility. Specifically, let $IVOL_{m-1}$ denote an option-implied volatility observed at the end of month $m - 1$. Under a null hypothesis of unbiasedness, $IVOL_{m-1}$ is an unbiased forecast of the true latent volatility σ_m in month m in the sense that it represents a rational market expectation based on information available at the end of month $m - 1$, i.e., $IVOL_{m-1} = E_{m-1}(\sigma_m)$. However, the true but unobserved value of latent volatility in month m will differ from $IVOL_{m-1}$ by a random forecast error ξ_{m-1}. This forecast error ξ_{m-1} would reflect incomplete availability of information required to forecast latent volatility σ_m exactly. Some part of the error ξ_{m-1} might also be attributable to inexact observation of the true implied volatility due to the presence of market frictions in price data. Combining the equality $\sigma_m = E_{m-1}(\sigma_m) + \xi_{m-1}$ with $IVOL_{m-1} = E_{m-1}(\sigma_m)$ specified by a null hypothesis of unbiasedness yields Equation (8) immediately below.

$$IVOL_{m-1} = \sigma_m - \xi_{m-1} \tag{8}$$

Under the null hypothesis that $IVOL_{m-1}$ represents a forecast of σ_m without systematically exploitable arbitrage opportunities, forecast errors will be orthogonal to latent volatilities, that is, $Cov(\sigma_m \xi_{m-1}) = 0$. In turn, this implies that the total variance of implied volatility is the sum of component variances.

$$Var(IVOL_{m-1}) = Var(\sigma_m) + Var(\xi_{m-1}) \tag{9}$$

As a consequence of Equations (5), (8), and (9), a regression of realized volatility VOL_m on implied volatility $IVOL_{m-1}$ yields a regression slope coefficient attenuated by an errors-in-variables bias.

$$\lim_{M\to\infty} \frac{\sum_{m=2}^{M} (VOL_m IVOL_{m-1} - \overline{VOL}\,\overline{IVOL})}{\sum_{m=2}^{M} (IVOL_{m-1}^2 - \overline{IVOL}^2)} = \frac{Var(\sigma_m)}{Var(\sigma_m) + Var(\xi_{m-1})} \tag{10}$$

Equation (10) suggests that a one-sided test for a slope coefficient significantly less than one is equivalent to a test for a significant forecast error variance $Var(\xi_{m-1})$.

The errors-in-variables bias also affects multivariate regressions of current volatility VOL_m on implied volatility $IVOL_{m-1}$ and lagged volatility VOL_{m-1}.

$$VOL_m = b_0 + b_1 \times IVOL_{m-1} + b_2 \times VOL_{m-1} \tag{11}$$

Asymptotic values for the slope coefficients b_1 and b_2 in Equation (11) within the framework developed above reflect biases induced by the variances $Var(\chi_m)$ and $Var(\xi_{m-1})$.

$$
\begin{aligned}
\lim_{M\to\infty} b_1 &= 1 - \frac{Var(\xi_{m-1})[Var(\sigma_{m-1}) + Var(\chi_{m-1})]}{D} \\
\lim_{M\to\infty} b_2 &= \frac{Cov(\sigma_m, \sigma_{m-1})Var(\xi_{m-1})}{D} \\
D &= [Var(\sigma_m) + Var(\xi_{m-1})][Var(\sigma_{m-1}) + Var(\chi_{m-1})] \\
&\quad - Cov^2(\sigma_m, \sigma_{m-1})
\end{aligned}
\tag{12}
$$

Equation (12) reveals that the slope coefficient b_1 is biased downward below one and the slope coefficient b_2 is biased upward above zero. As the forecast error variance $Var(\xi_{m-1})$ diminishes, the slope coefficient b_1 approaches unity and b_2 approaches zero.

OLS VOLATILITY FORECAST REGRESSIONS

Christenson and Prabhala (1998) and Fleming, Ostdiek, and Whaley (1995) point out that implied volatilities may contain observation errors that could affect regressions using implied volatility as an independent variable. However, Fleming, Ostdiek, and Whaley (1995) argue that observation error is minimized in CBOE volatility indexes because an equal number of call and put options are used to compute volatility index values. Nevertheless, as discussed in the previous section, CBOE implied volatilities may still contain forecast errors that could affect regressions using implied volatility as an independent variable.

Christenson and Prabhala (1998) and Strunk-Hansen (2001) use log-transformed data in their regressions, i.e., $\ln(VOL_m)$ and $\ln(IVOL_m)$. This transformation brings the skewness and kurtosis of their volatility data closer to that of a normal distribution. Table I reveals that this is also the case for the data used in this study. However, Fleming (1998), Fleming, Ostdiek, and Whaley (1995) and other studies use untransformed volatility data. There are reasons to support the use of both log-transformed and untransformed volatility data. Consequently, we perform parallel regressions using both the original volatility measures VOL_m and $IVOL_m$, and the log-transformed volatility measures $\ln(VOL_m)$ and $\ln(IVOL_m)$.

Univariate Forecast Regressions

Table III contains empirical results from both univariate and multivariate forecast regressions. We first focus on univariate regressions comparing

TABLE III
OLS Regressions with Realized Volatility and Implied Volatility

	Intercept	$IVOL_{m-1}$	VOL_{m-1}	*Adj.* R^2	*Chi-square* (*p value*)	*B-G* (*p value*)
Panel A: S&P 100 January 1988–December 1994						
S&P 100	3.076	0.639		0.350	79.37	2.83
VOL_m	(1.516)	(0.087)			(0.000)	(0.093)
	8.871		0.344	0.124	62.82	2.24
	(1.412)		(0.088)		(0.000)	(0.134)
	3.013	0.864	−0.248	0.375	4.94	0.49
	(1.398)	(0.135)	(0.109)		(0.085)	(0.484)
S&P 100	0.312	0.814		0.395	87.46	2.64
$\ln(VOL_m)$	(0.281)	(0.097)			(0.000)	(0.105)
	1.344		0.480	0.186	39.28	7.15
	(0.232)		(0.086)		(0.000)	(0.008)
	0.266	0.971	−0.149	0.399	1.29	1.38
	(0.291)	(0.160)	(0.119)		(0.523)	(0.240)
Panel B: S&P 100 January 1995–December 2003						
S&P 100	−0.736	0.894		0.510	30.64	4.02
VOL_m	(1.755)	(0.081)			(0.000)	(0.045)
	6.931		0.625	0.357	31.79	5.35
	(1.382)		(0.065)		(0.000)	(0.021)
	−0.602	0.829	0.068	0.507	3.98	4.50
	(1.720)	(0.132)	(0.114)		(0.137)	(0.034)
S&P 100	−0.561	1.119		0.600	49.79	1.99
$\ln(VOL_m)$	(0.281)	(0.089)			(0.000)	(0.158)
	0.845		0.710	0.484	24.53	5.13
	(0.178)		(0.059)		(0.000)	(0.024)
	−0.443	0.970	0.118	0.600	7.54	0.92
	(0.289)	(0.165)	(0.113)		(0.023)	(0.338)
Panel C: S&P 500 January 1990–December 1994						
S&P 500	2.517	0.637		0.436	71.51	0.07
VOL_m	(1.308)	(0.083)			(0.000)	(0.792)
	6.515		0.455	0.208	49.26	4.82
	(1.079)		(0.081)		(0.000)	(0.028)
	2.474	0.699	−0.070	0.428	5.17	0.09
	(1.319)	(0.139)	(0.127)		(0.076)	(0.764)
S&P 500	0.238	0.818		0.404	76.42	0.07
$\ln(VOL_m)$	(0.334)	(0.119)			(0.000)	(0.787)
	1.236		0.498	0.236	31.48	4.47
	(0.235)		(0.093)		(0.000)	(0.035)
	0.228	0.812	0.016	0.406	1.47	0.15
	(0.309)	(0.159)	(0.109)		(0.481)	(0.703)

(*Continued*)

TABLE III

OLS Regressions with Realized Volatility and Implied Volatility (*Continued*)

	Intercept	$IVOL_{m-1}$	VOL_{m-1}	Adj. R^2	Chi-square (p value)	B-G (p value)
Panel D: S&P 500 January 1995–December 2003						
S&P 500	−2.051	0.979		0.468	19.90	5.33
VOL_m	(1.923)	(0.096)			(0.000)	(0.021)
	6.400		0.636	0.367	28.51	4.62
	(1.310)		(0.067)		(0.000)	(0.032)
	−1.694	0.851	0.128	0.473	5.75	2.85
	(1.897)	(0.164)	(0.132)		(0.057)	(0.092)
S&P 500	−0.647	1.160		0.559	31.77	2.90
$\ln(VOL_m)$	(0.319)	(0.103)			(0.010)	(0.088)
	0.795		0.722	0.494	22.71	4.86
	(0.172)		(0.058)		(0.000)	(0.028)
	−0.369	0.817	0.266	0.570	13.51	0.48
	(0.318)	(0.184)	(0.118)		(0.001)	(0.487)
Panel E: Nasdaq 100 January 1995–December 2003						
Nasdaq 100	−0.755	0.985		0.704	3.09	3.17
VOL_m	(3.031)	(0.082)			(0.213)	(0.075)
	11.273		0.678	0.486	22.82	8.60
	(2.490)		(0.067)		(0.000)	(0.003)
	−2.244	1.172	−0.146	0.710	1.95	1.95
	(3.082)	(0.131)	(0.091)		(0.377)	(0.163)
Nasdaq 100	−0.171	1.032		0.711	7.71	1.15
$\ln(VOL_m)$	(0.248)	(0.068)			(0.021)	(0.285)
	0.908		0.744	0.533	18.05	14.55
	(0.211)		(0.059)		(0.000)	(0.001)
	−0.259	1.180	−0.125	0.712	2.08	0.35
	(0.258)	(0.126)	(0.092)		(0.353)	(0.554)

Note. OLS regressions of realized volatility (VOL_m) on lagged CBOE implied volatility and lagged realized volatility. Multivariate regressions have this general form (with log-volatilities substituted in logarithmic regressions), where $IVOL_m$ denotes either VXO_m, VIX_m, or VXN_m, respectively, for the S&P 100, S&P 500, or Nasdaq 100 volatility index as appropriate.

$$VOL_m = a_0 + a_1 IVOL_{m-1} + a_2 VOL_{m-1}$$

Newey-West standard errors are reported in parentheses. Chi-square (p value) corresponds to a null hypothesis of zero intercept and unit slope ($a_0 = 0$, $a_1 = 1$) in univariate regressions; and a null of zero intercept and unit slope for implied volatility in multivariate regressions. B-G (p value) indicates a Breusch-Godfrey test for autocorrelated regression residuals.

the ability of realized and implied volatility to forecast future realized volatility. In Table III, regression parameter estimates are reported in columns two through four, with Newey and West (1987) standard errors shown in parentheses below each regression coefficient. We found no significant differences affecting our conclusions using either ordinary least squares or White (1980) standard errors. Column five lists adjusted

R-squared statistics for each regression. Column six reports chi-square statistics based on the Newey and West (1987) covariance matrix testing the joint null hypothesis of a zero intercept and unit slope. The corresponding p values appear in parentheses under each chi-square statistic. The last column lists Breusch (1978) and Godfrey (1978) statistics testing for serial dependencies in regression residuals, with corresponding p values in parentheses below each statistic. We first discuss results obtained from S&P 100 volatility measures and then follow with the S&P 500 and Nasdaq 100 volatility measures.

S&P 100 Univariate Regressions

Panels A and B of Table III report regression results for the S&P 100 index over the periods 1988–1994 and 1995–2003, respectively. In the period 1988–1994, regressions of current volatility on lagged volatility (VOL_m on VOL_{m-1} and $\ln(VOL_m)$ on $\ln(VOL_{m-1})$) yield slope coefficients of just 0.344 and 0.480, respectively. Slope coefficients for regressions of current volatility on implied volatility (VOL_m on VXO_{m-1} and $\ln(VOL_m)$ on $\ln(VXO_{m-1})$) yield higher slope coefficients of 0.639 and 0.814, respectively, though these are still significantly less than one.

For the period 1995–2003, panel B reveals that regressions of current on lagged realized volatility (VOL_m on VOL_{m-1} and $\ln(VOL_m)$ on $\ln(VOL_{m-1})$) yield slope coefficients of 0.625 and 0.710, respectively, both significantly less than one. By contrast, regressions of current realized volatility on implied volatility (VOL_m on VXO_{m-1} and $\ln(VOL_m)$ on $\ln(VXO_{m-1})$) yield slope coefficients of 0.894 and 1.119, respectively—both insignificantly different from one. However, Newey-West chi-square statistics of 30.64 and 49.79 for both regressions reject the joint null hypothesis of a zero intercept and unit slope.

Figures 4 and 5 provide scatter plots of S&P 100 realized volatility VOL_m against implied volatility VIX_{m-1} for the periods 1988–1994 and 1995–2003, respectively. For reference, both figures contain a solid line with zero intercept and unit slope along with a dashed line representing an OLS fit to the data. In Figure 3, which corresponds to the period 1988–1994, the significant bias of the OLS slope coefficient is visually obvious. However, in Figure 4, representing the period 1995–2003, the dashed OLS line is nearly parallel to the solid unit slope reference line.

S&P 500 Univariate Regressions

Panels C and D of Table III report regression results for the S&P 500 index over the periods 1990–1994 and 1995–2003, respectively. In the

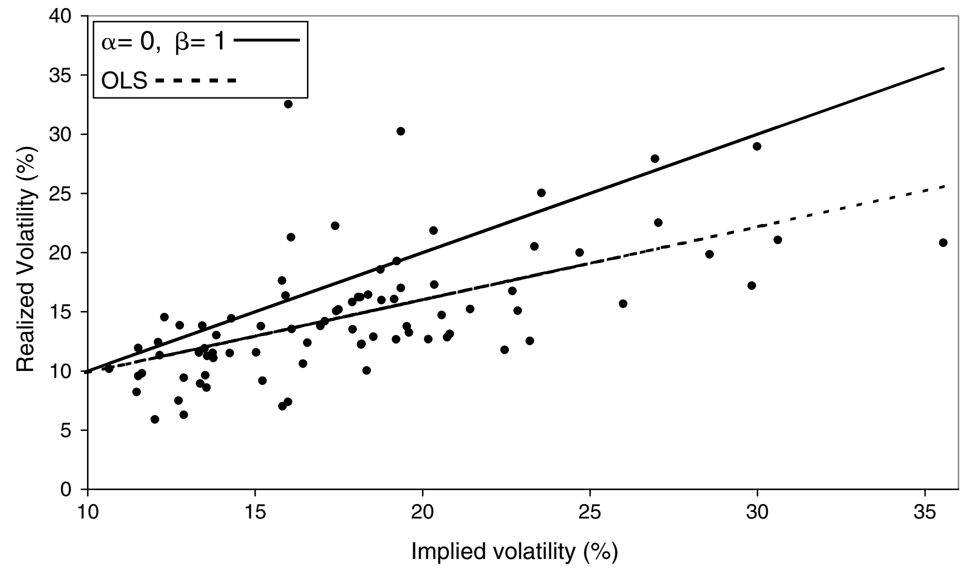

FIGURE 4
S&P 100 Index (1988–1994).

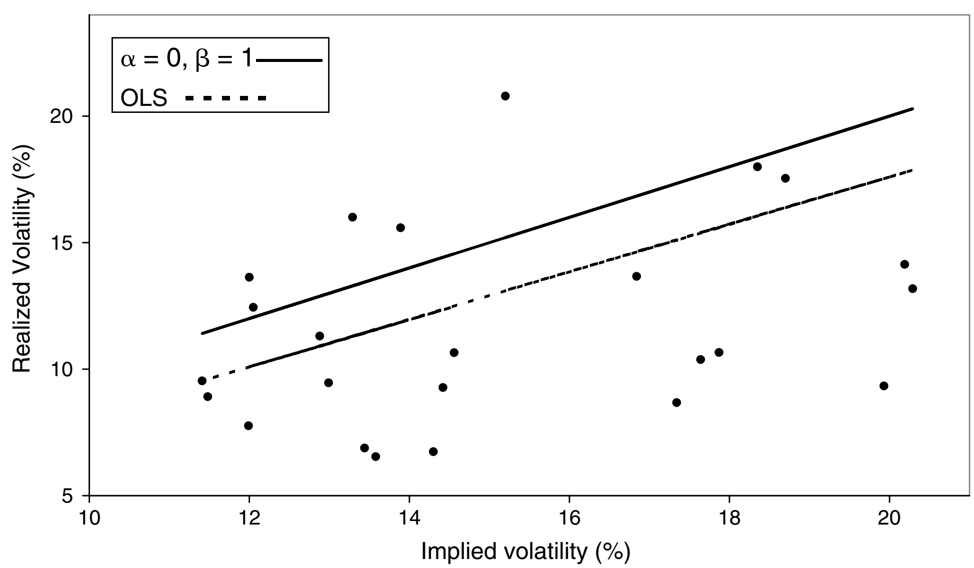

FIGURE 5
S&P 100 Index (1995–2003).

period 1990–1994, regressions of current on lagged volatility (VOL_m on VOL_{m-1} and $\ln(VOL_m)$ on $\ln(VOL_{m-1})$) yield slope coefficients of just 0.455 and 0.498, respectively. Regressions of current on implied volatility (VOL_m on VIX_{m-1} and $\ln(VOL_m)$ on $\ln(VIX_{m-1})$) yield higher slope coefficients of 0.637 and 0.818, respectively, though still both significantly less than one.

For the period 1995–2003, panel D reveals that regressing current on lagged volatility realized (VOL_m on VOL_{m-1} and $\ln(VOL_m)$ on $\ln(VOL_{m-1})$) yields slope coefficients of 0.636 and 0.722, respectively, both significantly less than one. However, regressing current realized volatility on implied volatility (VOL_m on VIX_{m-1} and $\ln(VOL_m)$ on $\ln(VIX_{m-1})$) yields slope coefficients of 0.979 and 1.160, respectively—both insignificantly different from one. Nevertheless, Newey-West chi-square statistics of 19.90 and 31.77 for both regressions reject the joint null hypothesis of a zero intercept and unit slope.

Figures 6 and 7 provide scatter plots of S&P 500 realized volatility VOL_m against implied volatility VIX_{m-1} for the periods 1990–1994 and 1995–2003, respectively. In both figures, the solid line has a zero intercept and unit slope and the dashed line represents an OLS fit to the data. In Figure 6, corresponding to the period 1990–1994, the significant bias of the OLS slope is readily apparent. However, in Figure 7, representing the period 1995–2003, the dashed OLS line is nearly parallel to the solid unit slope reference line.

Nasdaq 100 Univariate Regressions

Panel E of Table III reports regression results for the Nasdaq 100 index over the period 1995–2003. For this period, regressions of current volatility on lagged volatility (VOL_m on VOL_{m-1} and $\ln(VOL_m)$ on

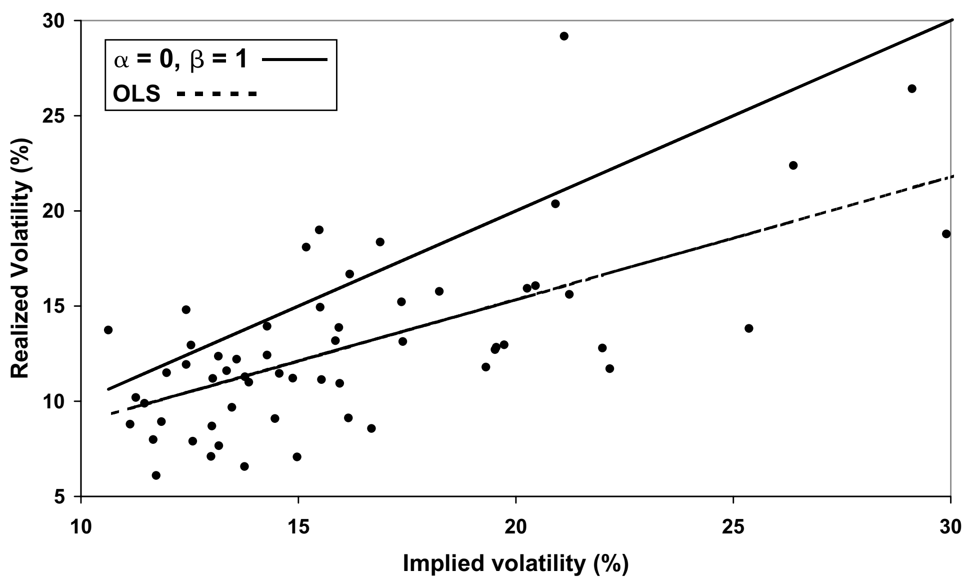

FIGURE 6
S&P 500 Index (1990–1994).

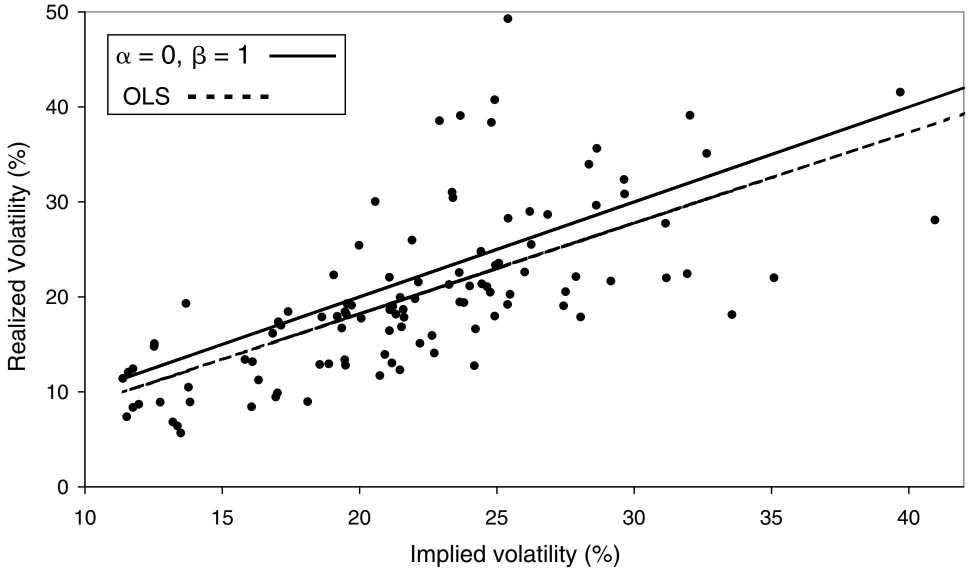

FIGURE 7
S&P 500 Index (1995–2003).

$\ln(VOL_{m-1})$) yield slope coefficients of 0.678 and 0.744, respectively. In contrast, slope coefficients for regressions of current realized volatility on implied volatility (VOL_m on VXN_{m-1} and $\ln(VOL_m)$ on $\ln(VXN_{m-1})$) yield slope coefficients of 0.985 and 1.032, respectively—both close to one. The Newey-West chi-square statistic of 3.09 for the implied volatility regression is insignificant, but the chi-square statistic of 7.71 for the corresponding log-regression rejects the joint null hypothesis of a zero intercept and unit slope at the 5-percent significance level.

Figure 8 provides a scatter plot of Nasdaq 100 realized volatility VOL_m against implied volatility VXN_{m-1} for the period 1995–2003. The dashed OLS regression line in this figure is approximately congruent with the solid reference line with zero intercept and unit slope. Thus the Nasdaq 100 regression results reported in Table III and displayed in Figure 8 yield strong graphic support for the Nasdaq 100 volatility index as an efficient predictor of future realized volatility.

Multivariate Forecast Regressions

S&P 100 Multivariate Regressions

Panel A of Table III reports multivariate regression results using both log-transformed and untransformed volatility data for the S&P 100 index from the period 1988–1994. Regressing current realized volatility VOL_m

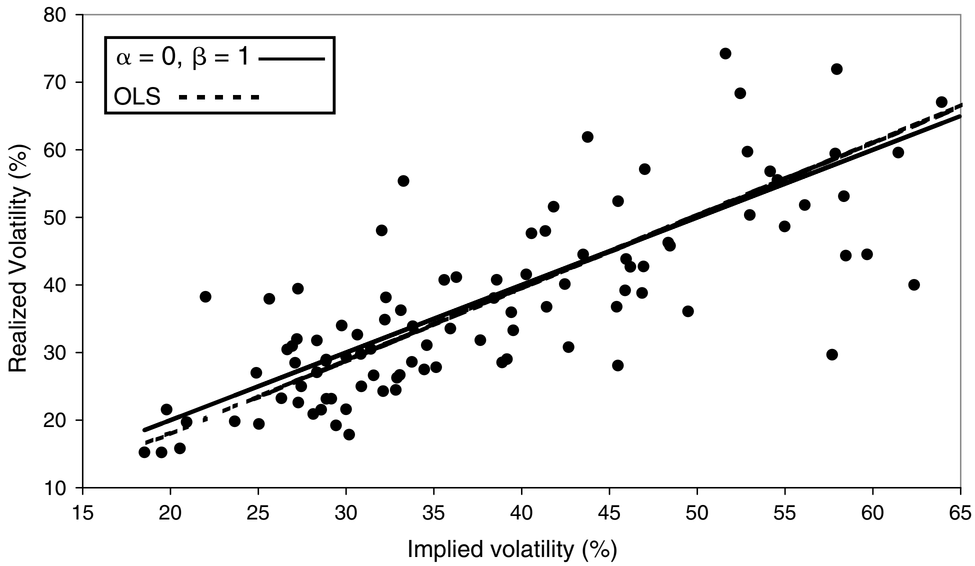

FIGURE 8
Nasdaq 100 Index (1995–2003).

on lagged implied volatility VXO_{m-1} and lagged realized volatility VOL_{m-1} yields slope coefficients of 0.864 and −0.248, respectively. The chi-square statistic of 4.94 for this regression does not reject the joint null hypothesis of a zero intercept and slope coefficient of one for implied volatility at the 5% significance level. The regression of $\ln(VOL_m)$ on $\ln(VXO_{m-1})$ and $\ln(VOL_{m-1})$ yields slope coefficients of 0.971 and −0.149, respectively, and a chi-square statistic of 1.29 that does not reject the joint null of a zero intercept and slope coefficient of one for $\ln(VIX_{m-1})$. Insignificant Breusch-Godfrey statistics for these multivariate regressions do not indicate the presence of significant serial dependence in regression residuals.

Multivariate regression results for S&P 100 volatility for the period 1995–2003 are reported in panel B of Table III. Regressing VOL_m on VXO_{m-1} and VOL_{m-1} yields slope coefficients of 0.829 and 0.068, respectively. Again, the chi-square statistic of 3.98 does not reject the joint null hypothesis of a zero intercept and unit slope coefficient for implied volatility, although the Breusch-Godfrey statistic indicates significant sample dependence in the residuals for this regression. The regression of $\ln(VOL_m)$ on $\ln(VXO_{m-1})$ and $\ln(VOL_{m-1})$ yields slope coefficients of 0.970 and 0.118, respectively. However, the chi-square statistic of 7.54 rejects the joint null of a zero intercept and unit slope coefficient for $\ln(VXO_{m-1})$.

An important aspect of the regressions based on S&P 100 volatility data is the fact that adjusted R-squared values from multivariate regressions do not exhibit substantial differences from adjusted R-squared values obtained from univariate regressions using only the implied volatility measures VXO_{m-1} or $\ln(VXO_{m-1})$ as independent variables. Thus, on the basis of adjusted R-squared values, adding independent variables beyond implied volatility does not appear to improve the explanatory power of the regressions.

S&P 500 Multivariate Regressions

Panel C of Table III reports multivariate regression results using log-transformed and untransformed volatility data for the S&P 500 index for the period 1990–1994. Here, regressing current realized volatility VOL_m on lagged implied volatility VIX_{m-1} and lagged realized volatility VOL_{m-1} yields slope coefficients of 0.699 and −0.070, respectively. The chi-square statistic of 5.17 does not reject the joint null hypothesis of a zero intercept and slope coefficient of one for implied volatility at conventional significance levels. Regressing $\ln(VOL_m)$ on $\ln(VIX_{m-1})$ and $\ln(VOL_{m-1})$ yields slope coefficients of 0.812 and 0.016, respectively, and a chi-square statistic of 1.47 that does not reject the joint null of a zero intercept and slope coefficient of one for $\ln(VIX_{m-1})$. Breusch-Godfrey statistics for these multivariate regressions do not indicate the presence of significant serial dependencies in residuals.

Multivariate regression results for S&P 500 volatility for the period 1995–2003 are reported in panel D of Table III. Regressing VOL_m on VIX_{m-1} and VOL_{m-1} yields slope coefficients of 0.851 and 0.128, respectively, and the chi-square statistic of 5.75 does not reject the joint null of a zero intercept and unit slope coefficient for implied volatility. Regressing $\ln(VOL_m)$ on $\ln(VIX_{m-1})$ and $\ln(VOL_{m-1})$ yields slope coefficients of 0.817 and 0.266, respectively. However, the chi-square statistic of 13.51 rejects the joint null of a zero intercept and unit slope coefficient for $\ln(VIX_{m-1})$.

Similar to the S&P 100 volatility regressions, these S&P 500 volatility regressions also possess the property that adjusted R-squared values from multivariate regressions do not exhibit substantial differences from adjusted R-squared values from univariate regressions using only implied volatility measures as independent variables. Thus, for the S&P 500 volatility regressions, adding independent variables beyond implied volatility does not appear to improve explanatory power.

Nasdaq 100 Multivariate Regressions

Results from multivariate regressions for the Nasdaq 100 for the period 1995–2003 are reported in Panel E of Table III. The regression of VOL_m on VXN_{m-1} and VOL_{m-1} yields slope coefficients of 1.172 and -0.146, respectively, with corresponding standard errors of 0.131 and 0.091. The chi-square statistic of 1.95 does not reject the joint null hypothesis of a zero intercept and unit slope coefficient for implied volatility. Regressing of $\ln(VOL_m)$ on $\ln(VXN_{m-1})$ and $\ln(VOL_{m-1})$ yields slope coefficients of 1.180 and -0.125, respectively, and the chi-square statistic of 2.08 does not reject the joint null hypothesis of a zero intercept and unit slope for $\ln(VXN_{m-1})$. Breusch-Godfrey statistics for these multivariate regressions are not significant.

Nasdaq 100 volatility regressions also have the property that adjusted R-squared values from multivariate regressions are not substantially different from adjusted R-squared values obtained from univariate regressions with only implied volatility as an independent variable. Thus, for all three indexes in all periods examined, it does not appear that adding independent variables beyond implied volatility improves the explanatory power of the regressions.

INSTRUMENTAL VARIABLE REGRESSIONS

The econometric problem of errors in explanatory variables is widely accepted as an impediment to assessing the forecast quality of implied volatility. The standard econometric approach to dealing with this problem is the use of instrumental variables (see, for example, Greene (1993), Johnston (1984), or Maddala (1977)). Drawing on the analysis in Greene (1993), Christensen and Prabhala (1998) propose using lagged implied volatility as an instrument for implied volatility.

Instrumental Variables Procedure

To maximize the precision of the instrumental variables methodology, we employ several instruments in addition to lagged implied volatility. For example, the first-stage instrumental variables regression for the *VXN* volatility index for the period 1995–2003 is specified immediately below.

$$\widehat{VXN}_{m-1} = c_0 + c_1 \times VXN_{m-2} + c_2 \times VOL^{NDX}_{m-2} + c_3 \times VPA^{NDX}_{m-2} + c_4 \times VRS^{NDX}_{m-2} + c_5 \times VIX_{m-2} + c_6 \times VXO_{m-2} \qquad (16)$$

In Equation (16) above, the variable VOL_m was defined in Equation (1). The variable VPA_m denotes an estimate of volatility in month m using the method proposed by Parkinson (1980). In the current context, these estimates are calculated as shown in Equation (17), in which $H_{d,m}$ and $L_{d,m}$ represent high and low index levels, respectively, observed on day d in month m.

$$VPA_m = \sqrt{\frac{30}{22} \times \frac{252}{4 \ln 2} \sum_{d=1}^{n_m} \ln^2\left(\frac{H_{d,m}}{L_{d,m}}\right)} \tag{17}$$

The variable VRS_m denotes an estimate of volatility in month m using the method suggested by Rogers and Satchel (1991). These estimates are calculated as shown in Equation (18), in which $H_{d,m}$ and $L_{d,m}$ are as defined above and $O_{d,m}$ and $C_{d,m}$ represent index levels observed at the open and close, respectively, on day d in month m.

$$VRS_m = \sqrt{\frac{30}{22} \times 252 \sum_{d=1}^{n_m} \ln\left(\frac{H_{d,m}}{O_{d,m}}\right) \times \ln\left(\frac{H_{d,m}}{C_{d,m}}\right) + \ln\left(\frac{L_{d,m}}{O_{d,m}}\right) \times \ln\left(\frac{L_{d,m}}{C_{d,m}}\right)} \tag{18}$$

The first-stage instrumental variables regressions for the *VIX* and *VXO* volatility indexes in the period 1995–2003 are specified analogously in Equations (19) and (20) immediately below.

$$\begin{aligned} \widehat{VIX}_{m-1} = {} & c_0 + c_1 \times VIX_{m-2} + c_2 \times VOL_{m-2}^{SPX} + c_3 \times VPA_{m-2}^{SPX} \\ & + c_4 \times VRS_{m-2}^{SPX} + c_5 \times VXO_{m-2} + c_6 \times VXN_{m-2} \end{aligned} \tag{19}$$

$$\begin{aligned} \widehat{VXO}_{m-1} = {} & c_0 + c_1 \times VXO_{m-2} + c_2 \times VOL_{m-2}^{OEX} + c_3 \times VPA_{m-2}^{OEX} \\ & + c_4 \times VRS_{m-2}^{OEX} + c_5 \times VIX_{m-2} + c_6 \times VXN_{m-2} \end{aligned} \tag{20}$$

Because of data limitations for some instruments, first-stage instrumental variables regressions for the *VIX* volatility index in the period 1990–1994 and the *VXO* volatility index in the period 1988–1994 are specified as shown in Equations (21) and (22).

$$\begin{aligned} \widehat{VIX}_{m-1} = {} & c_0 + c_1 \times VIX_{m-2} + c_2 \times VOL_{m-2}^{SPX} + c_3 \times VPA_{m-2}^{SPX} \\ & + c_4 \times VRS_{m-2}^{SPX} + c_5 \times VXO_{m-2} + c_6 \times VIX_{m-3} \end{aligned} \tag{21}$$

$$\begin{aligned} \widehat{VXO}_{m-1} = {} & c_0 + c_1 \times VXO_{m-2} + c_2 \times VOL_{m-2}^{OEX} + c_3 \times VPA_{m-2}^{OEX} \\ & + c_4 \times VRS_{m-2}^{OEX} + c_5 \times I(m) \times VIX_{m-2} \\ & + c_6 \times (1 - I(m)) \times VOL_{m-3}^{OEX} + c_7 \times VIX_{m-3} \end{aligned} \tag{22}$$

For the *VXO* 1988–1994 instrumental variable regression above, the indicator function $I(m) = 1$ if month m is in the period 1990–1994 and is zero otherwise.

Table IV reports the results from the second stage of the instrumental variables procedures. Separate results are reported for the S&P 100 from the periods 1988–1994 and 1995–2003, the S&P 500 from the periods 1990–1994 and 1995–2003, and for the Nasdaq 100 from the period 1995–2003.

Instrumental Variable Regression Results

S&P 100 Instrumental Variable Regressions

Panel A of Table IV reports univariate and multivariate instrumental variable regression results based on the S&P 100 index for the period 1988–1994. The univariate regression of realized volatility VOL_m on the implied volatility instrument $\widehat{VXO}_{m-1}$ yields a slope coefficient of 0.860, which is not significantly less than one. The univariate regression of log volatility $\ln(VOL_m)$ on the log-implied volatility instrument $\ln(\widehat{VIX}_{m-1})$ yields a slope coefficient of 1.043. However, the chi-square statistics of 56.29 and 65.23 reject the joint null hypotheses of a zero intercept and unit slope in both regressions.

The multivariate regression of realized volatility VOL_m on the implied volatility instrument $\widehat{VXO}_{m-1}$ and lagged volatility VOL_{m-1} yields slope coefficients of 1.102 and -0.238, respectively. The chi-square statistic of 1.53 for this regression does not reject the joint null hypothesis of a zero intercept and unit slope for the implied volatility instrument. The regression of log-volatility $\ln(VOL_m)$ on the instrument $\ln(\widehat{VXO}_{m-1})$ and lagged log-volatility $\ln(VOL_{m-1})$ yields slope coefficients of 1.347 and -0.248. However, the chi-square statistic of 14.27 rejects the null of a zero intercept and unit slope for $\ln(\widehat{VXO}_{m-1})$.

Panel B of Table IV reports univariate and multivariate regression results for the S&P 100 in the period 1995–2003. The univariate regression of realized volatility VOL_m on the implied volatility instrument $\widehat{VXO}_{m-1}$ yields a slope coefficient of 1.284 with a standard error of 0.142, indicating a value insignificantly different from one. By contrast, the univariate regression of log-volatility $\ln(VOL_m)$ on the log-implied volatility instrument $\ln(\widehat{VXO}_{m-1})$ yields a slope coefficient of 1.430 with a standard error of 0.134, indicating a value significantly greater than one. Chi-square statistics of 50.27 and 82.55 reject the null hypothesis of a zero intercept and unit slope for both regressions.

TABLE IV
Instrumental Variable Regressions with Realized Volatility and Implied Volatility

	Intercept	$\widehat{IVOL}_{m-1}$	VOL_{m-1}	*Adj.* R^2	*Chi-square (p value)*	*B-G (p value)*
Panel A: S&P 100 January 1988–December 1994						
S&P 100	−0.384	0.860		0.346	56.29	6.05
VOL_m	(2.482)	(0.139)			(0.000)	(0.014)
	−1.096	1.102	−0.238	0.346	1.53	5.82
	(2.736)	(0.238)	(0.170)		(0.465)	(0.016)
S&P 100	−0.325	1.043		0.395	65.23	4.63
$\ln(VOL_m)$	(0.440)	(0.155)			(0.000)	(0.031)
	−0.532	1.347	−0.248	0.393	14.27	4.11
	(0.508)	(0.287)	(0.177)		(0.001)	(0.043)
Panel B: S&P 100 January 1995–December 2003						
S&P 100	−9.605	1.284		0.570	50.27	7.44
VOL_m	(3.539)	(0.142)			(0.000)	(0.006)
	−10.676	1.408	−0.090	0.566	36.43	7.38
	(4.179)	(0.266)	(0.159)		(0.000)	(0.007)
S&P 100	−1.523	1.430		0.634	82.55	3.79
$\ln(VOL_m)$	(0.424)	(0.134)			(0.000)	(0.052)
	−1.508	1.418	0.008	0.631	62.21	4.08
	(0.498)	(0.258)	(0.145)		(0.000)	(0.043)
Panel C: S&P 500 January 1990–December 1994						
S&P 500	−0.811	0.857		0.428	43.67	12.12
VOL_m	(2.420)	(0.146)			(0.000)	(0.001)
	−1.571	1.111	−0.254	0.424	2.17	11.83
	(2.800)	(0.294)	(0.236)		(0.338)	(0.001)
S&P 500	−0.447	1.076		0.397	50.10	6.97
$\ln(VOL_m)$	(0.520)	(0.189)			(0.000)	(0.008)
	−0.564	1.225	−0.115	0.387	9.21	6.89
	(0.592)	(0.344)	(0.212)		(0.010)	(0.009)
Panel D: S&P 500 January 1995–December 2003						
S&P 500	−11.157	1.410		0.576	46.10	7.39
VOL_m	(3.690)	(0.161)			(0.000)	(0.007)
	−13.024	1.614	−0.133	0.574	40.97	7.15
	(4.740)	(0.327)	(0.178)		(0.000)	(0.008)
S&P 500	−1.722	1.514		0.636	77.29	3.38
$\ln(VOL_m)$	(0.455)	(0.148)			(0.000)	(0.066)
	−1.732	1.522	−0.004	0.633	62.45	4.31
	(0.563)	(0.296)	(0.156)		(0.000)	(0.038)

TABLE IV
(Continued)

	Intercept	$\widehat{IVOL}_{m-1}$	VOL_{m-1}	Adj. R^2	Chi-square (p value)	B-G (p value)
Panel E: Nasdaq 100 January 1995–December 2003						
Nasdaq 100	−9.713	1.226		0.729	32.49	2.45
VOL_m	(3.918)	(0.091)			(0.000)	(0.117)
	−11.476	1.454	−0.188	0.728	40.89	1.62
	(4.473)	(0.201)	(0.140)		(0.000)	(0.203)
Nasdaq 100	−0.634	1.162		0.714	50.54	2.64
$\ln(VOL_m)$	(0.313)	(0.085)			(0.000)	(0.104)
	−0.739	1.319	−0.130	0.712	47.24	2.49
	(0.351)	(0.192)	(0.138)		(0.000)	(0.115)

Note. Instrumental variable regressions of realized volatility (VOL_m) on lagged CBOE implied volatility and lagged realized volatility. Here, $IVOL_m$ denotes either VXO_m, VIX_m, or VXN_m, respectively, for the S&P 100, S&P 500, or Nasdaq 100 volatility index as appropriate. Regressions have the general form specified below, in which hat notation ($\widehat{IVOL}$) denotes the generated implied volatility from a first stage instrumental variables regression.

$$VOL_m = b_0 + b_1 \times \widehat{IVOL}_{m-1} + b_2 \times VOL_{m-1}$$

Newey-West standard errors are reported in parentheses. Chi-square (p value) corresponds to a null hypothesis of zero intercept and unit slope ($b_0 = 0$, $b_1 = 1$) in univariate regressions; and a null of zero intercept and unit slope for implied volatility in multivariate regressions. B-G (p value) indicates a Breusch-Godfrey test for autocorrelation in regression residuals.

The multivariate regression of realized volatility VOL_m on the implied volatility instrument $\widehat{VXO}_{m-1}$ and lagged volatility VOL_{m-1} yields slope coefficients of 1.408 and −0.090, respectively, and the chi-square statistic of 36.43 for this regression rejects the null of a zero intercept and unit slope for the implied volatility instrument. The regression of log-volatility $\ln(VOL_m)$ on the instrument $\ln(\widehat{VXO}_{m-1})$ and lagged log-volatility $\ln(VOL_{m-1})$ yields slope coefficients of 1.418 and 0.008, respectively, and the chi-square statistic of 62.21 rejects the null of a zero intercept and unit slope for the instrument $\ln(\widehat{VXO}_{m-1})$.

S&P 500 Instrumental Variable Regressions

Panel C of Table IV reports results from univariate and multivariate instrumental variable regressions based on the S&P 500 index for the period 1990–1994. The univariate regression of realized volatility VOL_m on the implied volatility instrument $\widehat{VIX}_{m-1}$ yields a slope coefficient of 0.857, which is not significantly less than one. The univariate regression of log-volatility $\ln(VOL_m)$ on the log-implied volatility instrument $\ln(\widehat{VIX}_{m-1})$ yields a slope coefficient of 1.076 not significantly different from one. Nevertheless, the chi-square statistics of 43.67 and 50.10 reject the null hypothesis of a zero intercept and unit slope in both univariate regressions.

The multivariate regression of realized volatility VOL_m on the implied volatility instrument $\widehat{VIX}_{m-1}$ and lagged volatility VOL_{m-1} yields slope coefficients of 1.111 and -0.254, respectively. The chi-square statistic of 2.17 for this regression does not reject the joint null hypothesis of a zero intercept and unit slope for the implied volatility instrument. The regression of log-volatility $\ln(VOL_m)$ on the instrument $\ln(\widehat{VIX}_{m-1})$ and lagged log-volatility $\ln(VOL_{m-1})$ yields slope coefficients of 1.225 and -0.115. The chi-square statistic of 9.21 for this regression rejects the null of a zero intercept and unit slope for the instrument $\ln(\widehat{VIX}_{m-1})$.

Panel D of Table IV reports univariate and multivariate regression results for the S&P 500 from the period 1995–2002. The univariate regression of realized volatility VOL_m on the implied volatility instrument $\widehat{VIX}_{m-1}$ yields a slope coefficient of 1.410 with a standard error of 0.161, indicating a value significantly greater than one. The univariate regression of log-volatility $\ln(VOL_m)$ on the log-implied volatility instrument $\ln(\widehat{VIX}_{m-1})$ yields a slope coefficient of 1.514 with a standard error of 0.148, indicating a value significantly greater than one. Chi-square statistics of 46.10 and 77.29 reject the null hypothesis of a zero intercept and unit slope for both regressions.

The multivariate regression of realized volatility VOL_m on the implied volatility instrument $\widehat{VIX}_{m-1}$ and lagged volatility VOL_{m-1} yields slope coefficients of 1.614 and -0.133, respectively, and the chi-square statistic of 40.97 for this regression rejects the null of a zero intercept and unit slope for the implied volatility instrument. The regression of log-volatility $\ln(VOL_m)$ on the instrument $\ln(\widehat{VIX}_{m-1})$ and lagged log-volatility $\ln(VOL_{m-1})$ yields slope coefficients of 1.522 and -0.004, respectively. The chi-square statistic of 62.45 rejects the null of a zero intercept and unit slope for the instrument $\ln(\widehat{VIX}_{m-1})$.

Nasdaq 100 Instrumental Variable Regressions

Panel E of Table IV reports univariate and multivariate instrumental variable regression results for the Nasdaq 100 from the period 1995–2003. The univariate regression of realized volatility VOL_m on the implied volatility instrument $\widehat{VXN}_{m-1}$ yields a slope coefficient of 1.226 with a standard error of 0.091, indicating a slope significantly greater than one. The univariate regression of log-volatility $\ln(VOL_m)$ on the log-implied volatility instrument $\ln(\widehat{VXN}_{m-1})$ yields a slope coefficient of

1.162 with a standard error of 0.085, suggesting a slope significantly greater than one. Chi-square statistics of 32.49 and 50.54 reject the null hypothesis of a zero intercept and unit slope for both implied volatility instruments.

The multivariate regression of realized volatility VOL_m on the implied volatility instrument $\widehat{VXN}_{m-1}$ and lagged volatility VOL_{m-1} yields slope coefficients of 1.454 and −0.188. The chi-square statistic of 40.89 for this regression rejects the joint null of a zero intercept and unit slope for the implied volatility instrument. The regression of log-volatility $\ln(VOL_m)$ on the instrument $\ln(\widehat{VXN}_{m-1})$ and lagged log-volatility $\ln(VOL_{m-1})$ yields slope coefficients of 1.319 and −0.130. The chi-square statistic for this regression of 47.24 rejects the null of a zero intercept and unit slope for the instrument $\ln(\widehat{VXN}_{m-1})$.

Comparing Conventional OLS and Instrumental Regressions

A comparison of regression results reported in panel A of Tables III and IV for the S&P 100 index for the period 1988–1994 reveals that the instrumental variables procedures yielded noticeable improvements upon the standard OLS regressions. Specifically, in panel A of Table IV, the regression slope coefficients for implied volatility instruments are typically closer to a value of one than the corresponding OLS coefficient values in panel A of Table III. An exception occurs within the multivariate log-regressions, where the implied volatility slope coefficient of 0.971 for the multivariate log-regression in Table III is much closer to a value of one than the corresponding implied volatility instrument coefficient of 1.347 in panel A of Table IV.

By contrast, panel B in Tables III and IV reveal that instrumental variables procedures did not improve upon standard OLS regressions in the period 1995–2003. Implied volatility slope coefficients in panel B of Table III obtained from standard OLS regressions are all closer to a value of one than the implied volatility slope coefficients in panel B of Table IV obtained from instrumental variables procedures. Thus for the S&P 100 volatility data, while the instrumental variables procedures improved regression results in the period 1988–1994, they did not improve regression results in the period 1995–2003.

Comparing regression results reported in panel C of Tables III and IV for the S&P 500 index in the period 1990–1994 reveals that instrumental variables procedures typically improved upon standard OLS regressions. In panel C of Table IV, slope coefficients for implied volatility obtained from instrumental variables procedures are typically closer to a value of one than corresponding slope coefficient values in panel C of Table III obtained from standard OLS regressions. A single exception occurs within the multivariate log-regressions, where the standard OLS slope coefficient of 0.812 for implied volatility in the multivariate log-regression in Table III is slightly closer to a value of one than the corresponding implied volatility instrument coefficient of 1.225 in panel C of Table IV.

However, comparing panel D in Tables III and IV reveals that instrumental variables procedures did not improve upon standard OLS regressions for the S&P 500 index in the period 1995–2003. Implied volatility slope coefficients in panel D of Table III obtained from standard OLS regressions are all closer to a value of one than corresponding implied volatility coefficients in panel D of Table IV obtained from instrumental variables procedures. Thus, for the S&P 500 volatility data, instrumental variables procedures improved regression results in the period 1990–1994, but did not improve results in the period 1995–2003.

Comparing panel E in Tables III and IV reveals that instrumental variables procedures also did not improve upon standard OLS regressions for the Nasdaq 100 volatility data. Implied volatility slope coefficients in panel E of Table III obtained from standard OLS regressions are all closer to a value of one than implied volatility slope coefficients in panel E of Table IV obtained from instrumental variables procedures. Thus, for the Nasdaq 100 volatility data in the period 1995–2003, instrumental variables procedures did not improve upon regression results obtained from standard OLS regressions.

In summary, attempts to correct an errors-in-variables attenuation bias via instrumental variable regressions appear to have only been effective for volatility data from the S&P 100 index in the period 1988–1994 and the S&P 500 index in the period 1990–1994. For these data samples, instrumental variables procedures typically yielded regression slope coefficients for implied volatility closer to a value of one than did standard OLS regressions. In contrast, for volatility data from the S&P 100, S&P 500, and Nasdaq 100 indexes in the period 1995–2003 instrumental variables procedures always yielded slope coefficients for implied volatility farther from a value of one than did standard OLS regressions. This suggests that attenuation biases caused by errors-in-variables effects on implied volatilities composing the CBOE volatility indexes has largely disappeared since 1995.

SIGNIFICANCE OF THE FORECAST ERROR VARIANCE

As suggested by the framework developed in the third section of this paper, a test for a significant forecast error variance $Var(\xi_{m-1})$ is obtained from a univariate regression of realized volatility VOL_m on implied volatility $IVOL_{m-1}$. Equation (10) implies that one minus the slope coefficient of the regression of VOL_m on $IVOL_{m-1}$ yields the following equality:

$$1 - b_{OLS}(VOL_m, IVOL_{m-1}) = \frac{Var(\xi_{m-1})}{Var(IVOL_{m-1})} \tag{23}$$

In finite samples, the left-hand side of Equation (23) could be negative. Despite this, a one-sided test for a positive forecast error variance, i.e., $Var(\xi_{m-1}) > 0$, is equivalent to a test for an OLS slope coefficient b_{OLS} significantly less than one. The required regression statistics for this test are reported in Table III.

From panel A of Table III for the 1988–1994 S&P 100 sample, we see that the slope coefficient of 0.639 with a standard error of 0.087 indicates rejection of the null hypothesis of $b_{\text{OLS}} = 1$. Similarly for the S&P 500 index, from panel C, the slope coefficient 0.637 with a standard error of 0.083 is significantly less than one. Thus, we appear to observe significantly positive forecast error variances for our pre-1995 samples. By contrast, in panels B, D, and E of Table III corresponding to the S&P 100, S&P 500, and Nasdaq 100 samples from the 1995–2003 period, the slope coefficients of 0.894, 0.979, and 0.985, respectively, do not reject the null hypothesis of $b_{\text{OLS}} = 1$. Thus, while the CBOE volatility indexes *VXO* and *VIX* appear to contain significant forecast errors in the pre-1995 period, we find no indication of significant forecast error variances for any of the CBOE volatility indexes in the period 1995–2003.

A GARCH PERSPECTIVE

Influential studies by Canina and Figlewski (1993), Christensen and Prabhala (1998), Day and Lewis (1992), and Lamoureux and Lastrapes (1993) examine of the accuracy of implied volatility forecasts using linear econometric models. This contrasts with the many studies of volatility forecasts based on autoregressive conditional heteroscedasticity (ARCH) models. Following Blair, Poon, and Taylor (2001), we here adopt the GJR-GARCH(1,1) model developed by Glosten et al. (1993)

and Zakoian (1990) to evaluate the forecast quality of the CBOE implied volatility indexes. Our analysis is based on these three models:

Model 1, full GJR-GARCH model augmented with implied volatility

$$h_m^2 = \alpha_0 + \alpha_1 VOL_{m-1}^2 + \alpha_2 S_{m-1} VOL_{m-1}^2 + \alpha_3 h_{m-1}^2 + \alpha_4 IVOL_{m-1}^2 \quad (24)$$

Model 2, standard GJR-GARCH model

$$h_m^2 = \alpha_0 + \alpha_1 VOL_{m-1}^2 + \alpha_2 S_{m-1} VOL_{m-1}^2 + \alpha_3 h_{m-1}^2 \quad (25)$$

Model 3, conditional volatility as a function of only implied volatility

$$h_m^2 = \alpha_0 + \alpha_4 IVOL_{m-1}^2 \quad (26)$$

Model 1 imposes no coefficient restrictions, while models 2 and 3 impose the restrictions $\alpha_4 = 0$ and $\alpha_1 = \alpha_2 = \alpha_3 = 0$, respectively, that define the null hypotheses to be tested. Model 2 tests the null hypothesis H_0: $\alpha_4 = 0$ that implied volatility does not significantly improve forecasts beyond that provided by the GJR-GARCH model. Model 3 tests the null hypothesis H_0: $\alpha_1 = \alpha_2 = \alpha_3 = 0$ that the GJR-GARCH model does not significantly improve upon implied volatility forecasts.

Table V reports results obtained from each of the three models for all three stock indexes. Table V reveals that the coefficients α_1, α_2, α_3 for model 1 are typically insignificantly different from zero, which suggests that implied volatility dominates as a predictor of future volatility. However, there are two exceptions. The most notable is observed in panel A for the S&P 100 index in the period 1988–1994 for which the coefficients α_1, α_2, α_3 are all more than two standard errors away from zero. Another exception is seen in panel D for the S&P 500 index in the period 1995–2003, for which the coefficient α_2 is more than two standard errors greater than zero. By contrast, the coefficient α_4 for implied volatility is significant across all indexes and test periods. Thus, results obtained from model 1 suggest that implied volatility dominates realized volatility as a forecast of future volatility.

Table VI provides the results of tests of the restrictions leading to model 2 and model 3. In Table VI, F statistics in column 2 and their corresponding p values in column 3 indicate that the null hypothesis H_0: $\alpha_4 = 0$ is rejected across all stock indexes and time periods examined. Thus, the null hypothesis that implied volatility does not significantly improve forecasts from the GJR-GARCH specification is rejected for all samples examined. F statistics in column 4 and corresponding p values in column 5 indicate that the null hypothesis H_0: $\alpha_1 = \alpha_2 = \alpha_3 = 0$ is rejected only in the case of the S&P 100 index in the period 1988–1994.

TABLE V

GJR-GARCH Regressions with Realized Volatility and Implied Volatility

	Intercept	VOL^2_{m-1}	$S_{m-1}VOL^2_{m-1}$	h^2_{m-1}	$IVOL^2_{m-1}$	*Adj.* R^2
Panel A: S&P 100 January 1988–December 1994						
S&P 100	3.070	−0.660	0.217	1.127	0.314	0.508
VOL^2_m	(32.423)	(0.114)	(0.092)	(0.184)	(0.135)	
	7.339	−0.359	0.381	1.122		0.409
	(32.896)	(0.117)	(0.101)	(0.168)		
	83.556				0.464	0.268
	(34.641)				(0.085)	
Panel B: S&P 100 January 1995–December 2003						
S&P 100	89.221	−0.025	0.111	−0.200	0.871	0.433
VOL^2_m	(76.846)	(0.167)	(0.136)	(0.218)	(0.181)	
	124.918	0.032	0.409	0.534		0.358
	(83.725)	(0.156)	(0.124)	(0.187)		
	40.365				0.803	0.403
	(70.849)				(0.095)	
Panel C: S&P 500 January 1990–December 1994						
S&P 500	40.383	−0.128	−0.145	−0.173	0.759	0.445
VOL^2_m	(32.00)	(0.177)	(0.146)	(0.215)	(0.169)	
	61.267	0.270	0.135	0.332		0.226
	(41.394)	(0.176)	(0.150)	(0.206)		
	41.688				0.510	0.407
	(28.64)				(0.082)	
Panel D: S&P 500 January 1995–December 2003						
S&P 500	66.279	−0.060	0.334	0.218	0.501	0.401
VOL^2_m	(74.895)	(0.164)	(0.137)	(0.224)	(0.196)	
	107.216	0.065	0.397	0.527		0.358
	(75.427)	(0.148)	(0.120)	(0.185)		
	42.475				0.839	0.364
	(67.552)				(0.108)	
Panel E: Nasdaq 100 January 1995–December 2003						
Nasdaq 100	−299.491	−0.073	0.005	−0.094	1.384	0.695
VOL^2_m	(194.904)	(0.123)	(0.097)	(0.161)	(0.198)	
	353.937	0.185	0.333	0.453		0.490
	(240.893)	(0.130)	(0.105)	(0.144)		
	−281.584				1.202	0.687
	(182.849)				(0.079)	

Note. GJR-GARCH regressions of realized variance (VOL^2_m) on squared implied volatility ($IVOL^2_m$), where $IVOL_m$ denotes CBOE implied volatility indexes for the S&P 100 (VXO_m), S&P 500 (VIX_m), or Nasdaq 100 (VXN_m) as appropriate. The GJR-GARCH model augmented by implied volatility is specified as:

$$h^2_m = \alpha_0 + \alpha_1 VOL^2_{m-1} + \alpha_2 S_{m-1} VOL^2_{m-1} + \alpha_3 h^2_{m-1} + \alpha_4 IVOL^2_{m-1}$$

h^2_m represents conditional variance and the indicator $S_{m-1} = 1$ if $r_m < 0$, i.e., negative return in month m, and is zero otherwise. Standard errors are reported in parentheses.

TABLE VI
Regression Comparisons with Realized and Implied Volatility Measures

		H_0: $\alpha_4 = 0$		H_0: $\alpha_1 = \alpha_2 = \alpha_3 = 0$	
Stock index	*Time period*	*F statistic*	*p value*	*F statistic*	*p value*
S&P 100	1988–1994	19.061	0.000	12.563	0.000
	1995–2003	13.430	0.000	1.761	0.159
S&P 500	1990–1994	21.738	0.000	1.179	0.326
	1995–2003	6.976	0.010	2.036	0.114
Nasdaq 100	1995–2003	68.342	0.000	0.778	0.509

Note. Comparisons of three ARCH regression models specified as follows:

Model 1: $h_m^2 = \alpha_0 + \alpha_1 VOL_{m-1}^2 + \alpha_2 S_{m-1} VOL_{m-1}^2 + \alpha_3 h_{m-1}^2 + \alpha_4 IVOL_{m-1}^2$

Model 2: $h_m^2 = \alpha_0 + \alpha_1 VOL_{m-1}^2 + \alpha_2 S_{m-1} VOL_{m-1}^2 + \alpha_3 h_{m-1}^2$

Model 3: $h_m^2 = \alpha_0 + \alpha_4 IVOL_{m-1}^2$

Model 1 is the GJR-GARCH model augmented by implied volatility. Model 2 and Model 3 impose the restrictions $\alpha_4 = 0$ and $\alpha_1 = \alpha_2 = \alpha_3 = 0$, respectively, that define the null hypotheses tested. h_m^2 represents conditional variance and the indicator $S_{m-1} = 1$ if $r_m < 0$, i.e., negative return in month m, and is zero otherwise.

For all other stock indexes and test periods examined, the null hypothesis H_0: $\alpha_1 = \alpha_2 = \alpha_3 = 0$ cannot be rejected at conventional significance levels. Thus, the null hypothesis that the GJR-GARCH model does not significantly improve upon implied volatility forecasts is rejected only for the case of S&P 100 index in the period 1988–1994. In all other cases examined, we cannot reject the null hypothesis that the GJR-GARCH model did not significantly improve upon implied volatility forecasts.

Overall, the results reported here for the three CBOE implied volatility indexes *VXO*, *VIX*, and *VXN* are similar to the findings of Blair, Poon, and Taylor (2001), who report that the *VXO* implied volatility index (formerly *VIX*) provided the most accurate forecasts of S&P 100 index volatility over the period 1993 through 1999 at forecast horizons ranging from 1 to 20 days when compared to a GJR-GARCH model augmented with intraday realized volatility.

SUMMARY AND CONCLUSION

Assessing the information content and forecast quality of implied volatility has been an important and ongoing research issue among financial economists and econometricians. Early assessments lauded the forecast quality of option-implied volatility, while subsequent investigations found that option-implied volatility yielded biased and inefficient forecasts. More recent studies suggest that econometric problems are a potential pitfall in assessing the forecast quality of implied volatility, and in turn propose the use of an instrumental variable methodology.

This study compares the results of standard OLS regressions with those obtained from instrumental variable regressions. We find that for volatility data sampled from the period 1995–2003 instrumental variables procedures do not provide enhanced support for the forecast quality of implied volatility compared to standard OLS procedures.

The empirical analysis in this study is based on the CBOE implied volatility indexes *VXO*, *VIX*, and *VXN*, corresponding to options traded on the S&P 100, S&P 500, and Nasdaq 100 stock indexes, respectively. These CBOE indexes provide an excellent data source for studies of implied volatility. Indeed, with the recent release of the new *VIX* and *VXN* volatility indexes for the S&P 500 and Nasdaq 100 stock indexes, respectively, the CBOE has significantly expanded a valuable data resource. In this study, we find that the CBOE implied volatility indexes *VXO* and *VIX* yield upwardly biased volatility forecasts, but are still more efficient in terms of mean squared forecast errors than historical realized volatility. We also find that the *VXN* volatility is nearly unbiased and provides significantly more efficient forecasts than realized volatility.

Further regression analyses reveal that the highest regression R-squared values are obtained when implied volatility is an explanatory variable. Multivariate regressions indicate that adding historical volatility as an explanatory variable yields only trivial differences in regression R-squared values. A similar conclusion was reached through a GARCH analysis of forecast efficiency. Overall, the results reported in this paper suggest that the CBOE implied volatility indexes *VXO*, *VIX*, and *VXN* dominate historical index volatility in providing forecasts of future price volatility for the S&P 100, S&P 500, and Nasdaq 100 stock indexes. While CBOE implied volatilities appear to contain significant forecast errors in the pre-1995 period, we find little indication of significant forecast errors in the latter period (1995–2003) of our sample.

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