Stock Returns, Implied Volatility Innovations, and the Asymmetric Volatility Phenomenon

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Abstract

We study the dynamic relation between daily stock returns and daily innovations in option-derived implied volatilities. By simultaneously analyzing innovations in index- and firm-level implied volatilities, we distinguish between innovations in systematic and idiosyncratic volatility in an effort to better understand the asymmetric volatility phenomenon. Our results indicate that the relation between stock returns and innovations in systematic volatility (idiosyncratic volatility) is substantially negative (near zero). These results suggest that asymmetric volatility is primarily attributed to systematic market-wide factors rather than aggregated firm-level effects. We also present evidence that supports our assumption that innovations in implied volatility are good proxies for innovations in expected stock volatility.

I. Introduction

Understanding the relation between stock returns and innovations in expected volatility is a fundamental issue in understanding financial markets. This relation has long been studied by financial economists (see, e.g., Cox and Ross (1976), Black (1976), and Christie (1982)), and it is of practical importance for areas such as risk management, option pricing, and event studies.

Asymmetric volatility is a well-documented empirical regularity in this area. The asymmetric volatility phenomenon (AVP) refers to the stylized fact that negative return shocks tend to imply higher future volatility than do positive return shocks of the same magnitude (see, e.g., Wu (2001), Bekaert and Wu (2000)). The AVP has also been described as a negative correlation between stock returns...
and innovations in expected volatility. The AVP literature has debated whether
the AVP may be more attributable to firm-level effects such as leverage (a nega-
tive return shock causes increased volatility) or systematic market-wide influences
such as volatility feedback (an increase in expected market-level volatility causes
a negative return).\(^2\)

In this paper, we study the time series of stock returns and option-derived
implied volatilities for the S&P 100 index and 50 large U.S. firms. By simultane-
ously analyzing daily innovations in both index- and firm-level implied volatili-
ties, we distinguish between innovations in systematic and idiosyncratic volatility.
This decomposition allows us to contribute to the asymmetric volatility literature
by distinguishing between systematic market-wide explanations and firm-level
explanations for the phenomenon. Our findings also bear on other related lit-
erature where the relation between stock returns and volatility innovations is an
important consideration.

Our empirical investigation relies on the following intuition. Just as a firm’s
stock return can be decomposed into systematic and idiosyncratic components,
innovations to a stock’s volatility may be attributed to changes in systematic or
idiosyncratic volatility. Systematic volatility shocks may result from macro events
such as an interest rate shock or international financial crisis, while idiosyncratic
volatility shocks may originate from firm-specific events such as product introduc-
tions and patent events. If the AVP is attributed more to systematic, market-level
factors, then the negative relation between firm-level stock returns and volatility
innovations should be primarily evident in the relation between the stock returns
and market-level volatility innovations. In contrast, if the AVP is attributed more
to firm-level effects, then the negative relation between firm-level stock returns
and volatility innovations should be similar for both market-level volatility inno-
vations and idiosyncratic volatility innovations.

For the implied volatility in our empirical work, we use a standardized im-
plied volatility (IV) that may be interpreted as an average IV from at-the-money
call and put options with one month to expiration. Specifically, our standardized
IV is a weighted average of eight different IVs, where our weighting method fol-
lows the Chicago Board Options Exchange’s procedure for calculating their im-
plied volatility index (VIX) over our sample period (see Whaley (1993)). Use of
this standardized IV both reduces measurement errors and mitigates the concern
that daily IV changes are linked to variations in the option’s moneyness and time
to expiration. Our empirical approach is to assume that the daily change in our
standardized IV is an observable proxy for innovations in the expected volatility
of stock returns. We present new evidence that supports this assumption.

\(^1\)The strong form of the AVP, as termed by Bekaert and Wu (2000), suggests a simple negative
correlation between stock returns and volatility innovations where negative (positive) return shocks
imply an increase (decrease) in expected volatility. By contrast, the weak form of the AVP suggests a
negative correlation between stock returns and innovations in expected volatility, after controlling for
the relation between the absolute return shock and the volatility innovation.

\(^2\)By referring to the leverage effect as a firm-level effect, we do not mean that changes in leverage
could not induce changes in expected market-level volatility. For example, a decrease in expected
future market-wide cash flows (or an increase in systematic risk aversion) is likely to devalue eq-
uity more than corporate debt and thus increase market-level leverage, which could induce a higher
expected market-level volatility. However, the leverage effect applies for each firm in isolation, re-
gardless of whether changes in leverage are related across firms.
Our empirical contributions may be broken down into the following five areas, discussed in order of prominence for our study. First, we present new evidence about the dynamic relation between stock returns and innovations in expected volatility, as proxied for by the daily change in IV. We find that the relation between index returns and index-level volatility innovations is substantially more negative (with a correlation of $-0.679$) than the relation between individual stock returns and the respective firm-level volatility innovation (with a median correlation of $-0.165$). Further, the negative relation between individual stock returns and index-level volatility innovations (with a median correlation of $-0.339$) is notably stronger than the negative relation between individual stock returns and their respective firm-level volatility innovation.

Second, we use a market-model variance decomposition to obtain an implied idiosyncratic volatility for each firm. We find that the relation between the individual stock returns and their respective innovation in implied idiosyncratic volatility is only marginally negative (with a median correlation of $-0.046$). This relation is not statistically different than zero for 37 of the 50 firms. These first two empirical contributions suggest that the AVP is more related to systematic market-wide influences, rather than an aggregation of firm-level effects.

Third, we present new evidence supporting the assumption that the daily IV changes are good proxies for the innovation in expected volatility. Many studies have evaluated the information in the IV level for the future volatility of realized stock returns and recent findings indicate that the IV level impounds nearly all information about future realized volatility. However, the critical issue for our study is whether the daily changes in IV contain reliable incremental information about future return volatility beyond the previous IV level. We are unaware of any other studies that have evaluated the incremental volatility information in the daily IV change. Controlling for the IV level from period $t - 2$, we find that the IV innovation over period $t - 1$ contains reliable incremental information for stock volatility in period $t$. Further, we find that daily firm-level IV innovations contain more information about the respective firm-level volatility innovation than does the daily index-level IV innovation. These findings support the assumption that daily IV changes are a good proxy for the daily innovation in expected volatility.

Fourth, we reexamine the AVP in the traditional way by evaluating the relation between conditional volatility and lagged returns shocks in a time-series model. Our new wrinkle is to distinguish between firm- and market-level return shocks when examining the AVP at the firm level. This exploration is motivated by our prior findings, which suggest that the asymmetry in the relation between conditional firm-level volatility and lagged return shocks will be greater for lagged market-level return shocks than for lagged firm-level return shocks. Consistent with earlier evidence (see, e.g., Andersen, Bollerslev, Diebold, and Ebens (2001)), we find that the AVP is stronger for index returns than for firm-level stock returns. Consistent with our first two empirical contributions discussed above, we also find that AVP behavior in firm-level conditional volatility is stronger and more reliable when relating firm-level conditional volatility to lagged market-level return shocks rather than to lagged own-firm return shocks.

Fifth, studying the relation between stock returns and volatility innovations may also provide insight into other related areas of the literature, such as the IV
smile, the bias in IV, and return skewness. Accordingly, we perform additional data analysis related to these topics and then discuss what our collective findings suggest for these areas. One key finding is that "index versus firm" differences in the relation between stock returns and volatility innovations are consistent with "index versus firm" differences in the slope of the IV smiles. However, even when controlling for the movements in IV suggested by last period’s IV smile and the day’s stock price change, the relation between stock returns and the residual IV innovations remains reliably and sizably negative. Overall, our additional analysis supports conclusions in other studies that indicate there are important differences between individual stocks and indices in the areas of option pricing and stock return behavior (see, e.g., Bakshi and Kapadia (2003a), Bollen and Whaley (2004), and Andersen et al. (2001)).

The remainder of this study is organized as follows. Section II describes our data and variable construction. Section III presents our primary findings on the dynamic relation between stock returns and innovations in expected volatility. Section IV presents new supporting evidence on the information content in IV with respect to the future volatility of spot stock returns. Section V reexamines the AVP in the traditional approach that focuses only on stock returns and presents evidence that complements our primary findings in Section III. Finally, Section VI discusses other analysis and potential implications of our findings, and Section VII concludes.

II. Data and Variable Construction

A. Stock Returns and Standardized Implied Volatility

We analyze 50 individual stocks with options traded on the Chicago Board Options Exchange (CBOE). Daily dividend-adjusted returns were obtained from CRSP for the period January 4, 1988, through December 31, 1995. The sample contains the 50 firms that had the highest total option trading volume over the period 1988 to 1995 and that met the following additional screens. First, the stock had to have the complete set of daily returns from CRSP and have the same ticker over our sample period. Second, each stock had to have adequate option data so that we could construct our standardized IV for at least 1,800 of the 2,022 daily periods.

We also examine two different stock indices in our empirical work. The primary index is the S&P 100 since it is the underlying asset for the index options that we examine. Total returns for the S&P 100 are obtained from Datastream International. For comparison, we also analyze returns of the value-weighted NYSE/AMEX/NASDAQ stock index from CRSP in order to evaluate a different, 

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3We choose an option-volume screen because of evidence in Mayhew and Stivers (2003) that the quality of volatility information in IV degrades appreciably for firms with thinly traded options. The Berkeley Options Data base lists 150 firms that have option volume listed in every year of our sample. The average trading volume for the largest 10 option-volume firms is about nine times the average for option-volume firms 41-50, 33 times the average for option-volume firms 91-100, and 323 times the average for option-volume firms 141-150. Thus, we feel that 50 firms is a good compromise between sample size (number of firms) and information quality in the data. The additional screens for return availability and standardized IV availability removed only eight of the top 58 option-volume firms.
broader market index. In our empirical work, when we refer to the market-level stock return, we mean this broad CRSP index.

For the index IV in our empirical work, we use the Volatility Index (VIX) from the CBOE. This index represents the IV of an at-the-money option on the S&P 100 index with 22 trading days (30 calendar days) to expiration. It is constructed by taking a weighted average of the IVs for eight options, including a call and a put at the two strike prices closest to the money and the nearest two expirations (excluding options within one week of expiration). Each of the eight component IVs is calculated from the bid-ask quote midpoint using a binomial tree that accounts for early exercise and dividends. Note that each of the eight component IVs is a single observation of the traditional IV that features the assumptions of the Black-Scholes framework, except that the binomial model must be used to allow for early exercise. This procedure was designed to reduce noise and mitigate measurement errors (see details in Whaley (1993) and Fleming, Ostdiek, and Whaley (1995)).

For each firm, we construct daily standardized IVs using eight individual stock options, where our weighting method follows the CBOE's procedure for calculating VIX over our sample period. We believe this standardized IV is a good choice for our empirical work for the following reasons. First, when modeling return volatility, this type of IV has been shown to subsume nearly all of the information from the historical time series of returns, at least for widely traded options (see, e.g., Christensen and Prabhala (1998), Fleming (1998), Blair, Poon, and Taylor (2001), and Mayhew and Stivers (2003)). Second, we are interested in the relation between daily returns and daily changes in IV in the time series. Errors in absolute pricing with the Black-Scholes framework should be less important for analysis that relies on IV innovations rather than the IV level. In other words, we are not assuming that the Black-Scholes framework gives the correct option price, but that it is a good enough model to empirically control for changes in moneyness, the riskless interest rate, and time to expiration so that we can use market prices of options to investigate changes in the volatility implied from option prices. Third, our procedure focuses on near at-the-money options, which are the most widely traded and typically yield IVs that are relatively less biased. Focusing on near-at-the-money options also serves to standardize the daily IV observations since the IV may vary with the moneyness of the options (the well-known IV smile). Fourth, this standardization procedure mitigates measurement errors and avoids IV biases that may occur if one only examines calls (or puts). Fifth, we present additional evidence in Section IV that supports our assumption that the daily changes in our standardized IV are good proxies for the daily innovation in the expected volatility of spot stock returns. Finally, our use of this IV follows from many previous studies.\(^4\)

We use option price data from the Berkeley Options Data Base, realized dividends from CRSP, and T-bill rates from Datastream. For each stock on every trading day, we calculate the eight designated IVs using midpoints of the final

\(^4\) Other option pricing models could conceivably be used to back out an alternate IV. For example, the Heston (1993) option pricing model incorporates stochastic volatility. However, the Heston model requires the estimation of seven unobserved parameters to specify the dynamics of the underlying asset and this model was not in existence for over half of our sample.
quote of the day, matched with a contemporaneous observation of the underlying stock price. The eight estimates are then aggregated using the VIX weighting procedure. For a few days, one or more of the eight options was unavailable or else a reported option price was below the lower arbitrage bound. We treat these days as missing observations for our standardized IV.\(^5\)

In our subsequent empirical testing, we treat the missing standardized IVs as follows. First, for the testing that requires an IV level, we simply use the previous day's IV estimate. Using stale IV data in this case will create a small bias that suggests weaker explanatory power for the IV when trying to explain subsequent spot volatility. Second, when calculating correlations between daily stock returns and standardized IV changes (Table 2), we throw out the observation whenever there is a missing standardized IV observation that prevents us from calculating a daily IV change. Third, for the maximum likelihood estimation in Tables 3 through 8, we fill in missing values with the prior day's value of IV. For these models, this means the "daily IV change" is set equal to zero for days that originally had missing IV values. This treatment means that our analysis will tend to slightly understate the comovement between returns and IV changes for these models.\(^6\)

Table 1 reports summary statistics for our sample of 50 firms including the stocks' market capitalization (size), volatility of spot stock returns, IV level, daily IV variability, option trading volume, and the number of available standardized IV observations per firm. On average, over 92% of the days have valid observations for the standardized IV. We analyze the days with missing standardized IVs and do not find any apparent clustering where missing values tend to occur on the same day across firms, so we do not believe there is any systematic relation in the missing values. We also note that the number of standardized IV observations varies little with firm size. This suggests that any differences in our results related to firm size are unlikely to be related to variation in the number of available standardized IV observations.

Table 1 also reports summary statistics for the largest and smallest size-based quintiles of the 50 firms, based on the firms' average size over our sample period. First, note that the median size of the largest 10 firms is about 20 times that of the smallest 10 firms. Second, note that the return standard deviation, the IV level, and the daily variability in IV are all appreciably larger for the smaller firms as compared to the larger firms. Third, note that the median option trading volume

\(^5\)This procedure of averaging the call and put IVs when calculating the standardized IV reduces the estimation error for two reasons. First, to the extent that the noise due to microstructure is independent across options, it can be reduced by averaging multiple observations. Second, errors induced by using an incorrect dividend or interest rate will bias call and put estimates of IV in opposite directions. So, averaging call and put IVs mitigates such errors. For these reasons and because we felt it was more conservative, we only calculated a standardized IV when all eight individual IVs were available.

\(^6\)An alternate way to handle missing standardized IVs is to interpolate and assume that a missing observation of the standardized IV is equal to the average of the preceding period's value and the subsequent period's value. With this approximation, we could analyze the data set as if there are no missing values. Using this alternate interpolation method to handle missing values, we re-estimate our primary results in Section III and find essentially identical results (the correlations with this alternate approach are within 0.01 of the summary correlations reported in Table 2). Since both methods for handling missing values give the same answer, we present our tabular results using the method described in the main text since this method seems more conservative.
TABLE 1
Sample Description

Table 1 reports descriptive statistics for our sample of 50 large firms: GE, AT&T, IBM, Wal-Mart, Coca-Cola, Merck, Bristol Myers, GM, Johnson & Johnson, Mobil, Amoco, PepsiCo, Ford, Bell Atlantic, 3M, Hewlett-Packard, ARCO, Dow Chemical, Eastman Kodak, McDonalds, Sears, Boeing, Schlumberger, Bank of America, Chrysler, Heinz, ITT, Toy R Us, K-Mart, Baxter, Xerox, International Paper, Limited, Occidental Petroleum, ALCOA, Texas Instruments, Computer Associates, Honeywell, Halliburton, Gap, First Interstate, Fluor, Avon, Delta Airlines, Mead, Homestake Mining, Polaroid, Bethlehem Steel, Black & Decker, and Battle Mountain Gold (largest to smallest, based on average firm size over 1988-1995). We report means and medians of each statistic for the 50 firms and for the largest and smallest stock quintiles, where the quintile sorts are based on the firms' average size over our 1988 to 1995 sample. The following statistics are reported in columns one through six, respectively: the average daily market capitalization of the firm's stock in millions of dollars, the daily standard deviation of spot stock returns, the mean of our standardized implied volatility (IV), the time-series standard deviation of the daily change in our standardized IV (where \( \Delta t \) refers to the daily change), the median daily option trading volume in contracts, and the number of standardized IV observations (out of a maximum of 2,022).

For brevity in our tables and because the most interesting variation is between the largest and smallest decile, we do not report the results for the other size quintiles.

B. Implied Idiosyncratic Volatility

Our work in the next section also uses an estimate of an individual stock's implied idiosyncratic volatility. We use the market model to decompose a stock's total IV into a systematic market-level component and an idiosyncratic component. Our procedure is as follows.

We start by estimating the following market-model regression for each firm,

\[
R_{i,t} = \alpha_i + \beta_i R_{S&P100,t} + \epsilon_{i,t},
\]

where \( R_{i,t} \) is the stock return of firm \( i \), \( R_{S&P100,t} \) is the S&P 100 return, \( \epsilon_{i,t} \) is the residual, and \( \alpha_i \) and \( \beta_i \) are coefficients to be estimated for each firm \( i \). The median (average) \( R^2 \) of the market model (1) for our sample is 23.4% (24.7%), which indicates the substantial majority of the firms' volatility is firm specific.

Then, using the \( \beta_i \) retained from estimating (1) and the variance decomposition implied by the market model, we calculate an estimate of a firm's implied idiosyncratic variance as

\[
IV_{i,t}^{2, idio} = IV_{i,t}^2 - \beta_i^2 \text{VIX}_t^2,
\]

where \( IV_{i,t}^{2, idio} \) is the estimate of firm \( i \)'s idiosyncratic variance at time \( t \), \( IV_{i,t}^2 \) is firm \( i \)'s standardized implied variance, \( \beta_i \) is firm \( i \)'s market beta estimated from (1), and \( \text{VIX}_t^2 \) is the standardized implied variance of the S&P 100. We convert
the implied idiosyncratic return variance to a standard deviation and then calculate the daily change in the implied standard deviation of the idiosyncratic return component (ΔIVi,t,\text{id}).

This procedure results in a few firm-days where the estimate of implied idiosyncratic variance is negative. Across the 50 firms, the median (mean) number of days for a firm where the estimate of the implied idiosyncratic variance is negative is only two (25). Seventeen (32) of the 50 firms have no days (five days or less) where the estimate of the implied idiosyncratic variance is negative. Negative values are implausible and we cannot convert the variance into a standard deviation. Accordingly, we set the implied idiosyncratic variance to zero for these few firm-days where its value is negative.\(^7\)

The estimates of the implied idiosyncratic volatility seem reasonable. The average (median) value of the implied idiosyncratic volatility across the 50 firms is 1.45% (1.41%) per day. We also compute the ratio of a firm’s implied idiosyncratic variance divided by its total implied variance for each firm for each day. Across the 50 firms, the median (average) of this ratio is 0.755 (0.736), which is consistent with the \(R^2\) obtained from estimating the market model, equation (1), and also indicates that the substantial majority of a firm’s volatility is idiosyncratic.

### III. The Dynamic Relation between Stock Returns and Expected Volatility Innovations

Here, we evaluate the dynamic relation between spot stock returns and innovations in expected volatility. In this section, we assume that the daily change in our standardized IV is a good proxy for the innovation in expected return volatility, an assumption that is supported by findings in Section IV. We analyze innovations in expected index-level volatility, firm-level total volatility, and firm-level idiosyncratic volatility. Since the AVP implies a negative correlation between stock returns and IV innovations, our analysis should have implications for understanding the nature of the AVP.

\(^7\)This simple method to estimate the daily change in a firm’s implied idiosyncratic volatility is open to other criticisms. First, it assumes a constant beta over the entire sample period. For robustness evaluation, we have recomputed the time series of the daily changes in idiosyncratic volatility using time-varying betas, calculated from rolling regressions on the preceding 500 daily observations. Across the 50 firms, the average correlation (median correlation) between the “daily change in idiosyncratic volatility using time-varying betas” and the “daily change in idiosyncratic volatility using a fixed beta” is 0.988 (0.992). Thus, over our sample, the dynamic behavior of the daily change in idiosyncratic volatility is nearly identical, whether one uses a constant beta or time-varying beta. Second, since we need both the market VIX and the firm’s IV to estimate a day’s implied idiosyncratic variance, the method is subject to noise in both these implied volatilities. Further, to calculate the daily change in implied idiosyncratic volatility, we need both the VIX and firm IV in consecutive trading days. Since we have some missing values in our daily time series of our standardized IV, this means the average number of observations for the daily change in idiosyncratic volatility is limited to 1,744 (out of 2,022 possible days) across the 50 firms. Despite these criticisms, we feel that this measure of idiosyncratic volatility is useful because of the clear intuition of the measure, the consistency of the results across our sample of 50 firms, the consistency of the results across subperiods, and the results in Section IV that indicate the “change in our implied idiosyncratic volatility” contains reliable incremental information for a firm’s future idiosyncratic return volatility.
A. Correlation Analysis

We begin by computing the simple correlations between the daily stock returns and innovations in expected volatility. Results are reported in Table 2. There are a number of notable findings. First, we find that the correlation between the S&P 100 index return (CRSP index return) and the index volatility innovation is negative and large at $-0.679$ ($-0.663$). Poteshman (2000), Benzoni (2002), and Pan (2002) use different methods to estimate this correlation, yet each of these studies comes up with correlation estimates that are close to our point estimate.8

### TABLE 2
Correlations between Stock Returns and Implied Volatility Innovations

Table 2 reports correlations between the daily time series of spot stock returns and the daily changes in our standardized implied volatility. We report on our sample of 50 large U.S. stocks, the S&P 100 index, and the CRSP value-weighted index over the 1988 to 1995 period. For the individual stocks, we report means and medians for each correlation for the group of stocks in column one. In the table, $R_{i,t}$ is the daily stock return, $\Delta IV_{i,t}$ is the daily change in the respective stock's standardized IV, $\Delta VIX_t$ is the daily change in the CBOE's VIX, and $\Delta IV_{i,t}^{IV}$ is the daily change in a firm's implied idiosyncratic volatility based on a market-model variance decomposition.

<table>
<thead>
<tr>
<th></th>
<th>$R_{i,t}, \Delta IV_{i,t}$</th>
<th>$R_{i,t}, \Delta VIX_t$</th>
<th>$R_{i,t}, \Delta IV_{i,t}^{IV}$</th>
<th>$\Delta IV_{i,t}, \Delta VIX_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>All 50 firms</td>
<td>Mean: $-0.163$</td>
<td>Mean: $-0.330$</td>
<td>Mean: $-0.047$</td>
<td>Mean: $0.172$</td>
</tr>
<tr>
<td></td>
<td>Median: $-0.165$</td>
<td>Median: $-0.339$</td>
<td>Median: $-0.046$</td>
<td>Median: $0.156$</td>
</tr>
<tr>
<td>Largest 10 firms</td>
<td>Mean: $-0.291$</td>
<td>Mean: $-0.421$</td>
<td>Mean: $-0.078$</td>
<td>Mean: $0.208$</td>
</tr>
<tr>
<td></td>
<td>Median: $-0.280$</td>
<td>Median: $-0.417$</td>
<td>Median: $-0.049$</td>
<td>Median: $0.317$</td>
</tr>
<tr>
<td>Smallest 10 firms</td>
<td>Mean: $-0.042$</td>
<td>Mean: $-0.208$</td>
<td>Mean: $0.002$</td>
<td>Mean: $0.107$</td>
</tr>
<tr>
<td></td>
<td>Median: $-0.040$</td>
<td>Median: $-0.270$</td>
<td>Median: $0.002$</td>
<td>Median: $0.123$</td>
</tr>
<tr>
<td>S&amp;P 100</td>
<td>n/a</td>
<td>$-0.679$</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>CRSP Index</td>
<td>n/a</td>
<td>$-0.663$</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>

Second, in contrast to the sizable negative correlation for the index, the average (median) correlation between individual stock returns and the respective own-firm volatility innovation is only $-0.163$ ($-0.165$). Thus, the correlation at the index level is over four times the average value for the individual stocks.

Third, we find that the mean (median) correlation between the individual stock returns and the index volatility innovation is $-0.330$ ($-0.339$) across the 50 stocks. The correlation between the individual stock returns and the index volatility innovation is more negative than the correlation between the individual stock returns and the respective own-firm volatility innovation for 46 of the 50 firms. In our view, these results in Table 2 suggest that the AVP is more related to systematic, market-level factors rather than firm-level influences because: i) the correlation between index returns and index volatility innovations is much

8Poteshman (2000) uses S&P 500 option prices over June 1988 to August 1997 and estimates the correlation to be $-0.61$ by minimizing the sum of squared option pricing errors. Benzoni (2002) uses a two-stage approach where he first estimates the structural parameters of the dynamic process from daily S&P 500 index prices by using a simulated method of moments estimation. In the second stage, he uses the estimated price dynamics to examine S&P 500 index options and estimates the risk adjustment necessary for option pricing. His estimate of the correlation between the spot price increment and the variance increment is $-0.58$. Finally, Pan (2002) uses an "implied-state" generalized method of moments estimation that uses spot prices and option prices jointly. She examines weekly observations over the January 1989 to December 1996 period and estimates a correlation of $-0.53$ for the case that allows a risk premia for stochastic volatility but no jump dynamics.
more negative than the correlation between firm returns and own-firm volatility innovations, and ii) the correlation between firm returns and index volatility innovations is appreciably more negative than the correlation between firm returns and own-firm volatility innovations. Though our results do not allow us to pinpoint the market-level factors behind the AVP, some plausible explanations might be the volatility feedback effect (Bekaert and Wu (2000)) or herding on the part of traders (Avramov, Chordia, and Goyal (2006)).

Fourth, the notion that the AVP is primarily related to market-level volatility innovations suggests that the correlation between the individual stock returns and innovations in their expected idiosyncratic volatility should be near zero. We calculate the correlation between the individual stock returns and the change in their respective implied idiosyncratic volatility (calculated per Section II.B). As reported in column 3 of Table 2, the mean (median) of these correlations is near zero at only \(-0.047\) \((-0.046)\).

Finally, as reported in the final column in Table 2, note that the correlations between the firm IV innovations and the VIX innovations are modest. This is consistent with the fact that most of a firm’s volatility is firm specific and mitigates any multicollinearity concerns about the firm IV innovations and the VIX innovations.

B. Multivariate Analysis

Next, we investigate the dynamic relation between stock returns and expected volatility innovations in a multivariate framework that allows for conditional heteroskedasticity in the return residuals. We point out that our specifications here are not meant to imply economic causality between stock returns and innovations in the standardized IVs. Rather, the specifications are meant to examine the reliability of the statistical relation between stock returns and volatility innovations, which is important for practical applications such as risk management, option pricing, and event studies.

To begin with, we investigate the relation between stock returns and volatility innovations in a specification that includes own-firm IV innovations and index IV innovations simultaneously. We estimate the following system,

\[
R_{i,t} = \psi_0 + \psi_1 \Delta IV_{i,t} + \psi_2 \Delta VIX_t + \epsilon_{i,t},
\]

\[
h_{i,t} = \psi_3 + \psi_4 IV_{i,t-1}^2 + \psi_5 \epsilon_{i,t-1}^2 + \psi_6 D_{i,t-1} \epsilon_{i,t-1}^2,
\]

where \(R_{i,t}\) is the daily return of individual stock or stock index \(i\), \(\epsilon_{i,t}\) is the return residual, \(h_{i,t}\) is the conditional variance of \(\epsilon_{i,t}\), \(IV_{i,t}\) is the standardized implied variance of stock \(i\) (VIX\(^2\) for the S&P 100 and CRSP index), \(\Delta IV_{i,t}\) is the daily change in the individual firm’s implied volatility, \(\Delta VIX_t\) is the daily change in the CBOE’s VIX, \(D_{i,t-1}\) is a dummy variable that equals one if \(\epsilon_{i,t-1}\) is negative, and the \(\psi\)s are coefficients to be estimated for each stock or index. The implied volatility variables are in “annualized standard deviation” units for the mean equation and are in “daily implied variance” units for the variance equation. The coefficients of interest are \(\psi_1\) and \(\psi_2\) in (3). We choose the variance equation based on results in Mayhew and Stivers (2003).
For this system and all our subsequent specifications that specify both a conditional mean and conditional variance, the system is estimated simultaneously by maximum likelihood estimation using the conditional normal density. Inference about estimated coefficients for our maximum likelihood estimation in this paper is based on robust quasi-maximum likelihood standard errors, in accordance with Bollerslev and Wooldridge (1992).

Table 3, Panel A reports the firm-level results. We find that the estimated coefficients on the $\Delta \text{VIX}_t$ term ($\psi_2$) are negative and statistically significant at a 1% $p$-value for 48 of the 50 firms. The relation between the firm returns and the own-firm IV innovations also tends to be negative, but the relation is less reliable. For 28 of the 50 firms, the estimated coefficients on the $\Delta \text{IV}_{i,t}$ term ($\psi_1$) are negative and statistically significant at a 1% $p$-value. For 48 of the 50 firms, the $\psi_2$ estimates are more reliably negative than the $\psi_1$ estimates.

In Table 3, Panel A we also report the $R^2$ from an ordinary least-squares (OLS) estimation of different variations of the mean equation (3). For the OLS estimation with both $\Delta \text{VIX}_t$ and $\Delta \text{IV}_{i,t}$ as explanatory variables, the average of the $R^2$s is 13.5% across the 50 firms. The sizable $R^2$ also suggests a substantial

| Panel A. Firm-Level Results with VIX Innovations and Firm-Level IV Innovations ($\phi_6 = 0$). |
|---|---|---|---|---|
| $\psi_1$ Mean/Median | $\psi_2$ Mean/Median | $R^2$ | $R^2 = 0$ Mean | $R^2 = 0$ Mean |
| 1988 to 1995 Period | All 50 firms | $-0.067 / -0.066$ | $-0.444 / -0.447$ | 0.135 | 0.034 | 0.119 |
| | Largest 10 firms | $-0.121 / -0.102$ | $-0.464 / -0.455$ | 0.208 | 0.077 | 0.178 |
| | Smallest 10 firms | $-0.010 / 0.002$ | $-0.336 / -0.449$ | 0.071 | 0.007 | 0.085 |
| 1988 to 1991 Subperiod | All 50 firms | $-0.052 / -0.040$ | $-0.456 / -0.483$ | 0.189 | 0.041 | 0.175 |
| | 1992 to 1995 Subperiod | All 50 firms | $-0.108 / -0.101$ | $-0.419 / -0.394$ | 0.078 | 0.032 | 0.055 |

(continued on next page)
negative relation between stock returns and volatility innovations. Next, in a variation of (3) where the own-firm IV innovation is the only explanatory variable, the average $R^2$ across the 50 firms is only 3.4%. In contrast, in a variation of (3) where the VIX innovation is the only explanatory variable, the average $R^2$ across the 50 firms is over three times as large at 11.9%. Thus, both in terms of statistical significance of the coefficients and of $R^2$ evaluation, the relation between the firm returns and index volatility innovations is stronger than the relation between the firm returns and own-firm volatility innovations.

We also estimate the model over the 1988–1991 and 1992–1995 subperiods and report summary results in Table 3. The subperiod results are qualitatively similar to the overall sample results.

Next, we isolate the relation between individual stock returns and the innovations in their respective implied idiosyncratic volatility by estimating the following system,

\begin{align*}
R_{i,t} &= \psi_0 + \psi_6 \Delta IV_{i,t}^{\text{idio}} + \epsilon_{i,t}, \\
h_{i,t} &= \psi_3 + \psi_4 IV_{i,t-1}^2 + \psi_5 \epsilon_{i,t-1}^2 + \psi_6 D_{i,t-1}^- \epsilon_{i,t-1}^2.
\end{align*}
where $\Delta IV_{t,t}^{\text{idio}}$ is the daily change in the individual firm’s implied idiosyncratic volatility (based on the market-model variance decomposition described in Section II.B) and the other terms are as defined for (3) and (4).

Table 3, Panel B, reports the results. We find that the estimated coefficients on the $\Delta IV_{t,t}^{\text{idio}}$ term ($\psi_6$) are negative and significant for only 13 of the 50 firms with a modest mean (median) value of $-0.021 (-0.013)$. Further, the average $R^2$ for an OLS estimation of (5) is only 0.66%, which is quite small compared to the $R^2$ values in Panel A. Subperiod results are consistent.

Finally, in Table 3, Panel C, we report index-level results for the S&P 100 and CRSP indices. We find a very reliable negative relation between the index return and the index volatility innovation. The $R^2$s are very substantial at 46.9% for the S&P 100 and 43.8% for the CRSP index, as compared to the firm-level results. Again, subperiod results are consistent. Thus, the evidence in Table 3 reinforces the findings in Table 2, again indicating that the negative relation between stock returns and expected volatility innovations is primarily related to the market-wide component of expected volatility.

In Table 3, we do not report the estimated coefficients for the variance equations for brevity. The coefficients are consistent with findings in Mayhew and Stivers (2003). The $\psi_4$ estimates on the $IV_{t,t-1}^2$ term are positive and significant at a 1% $p$-value for all 50 firms and both indices. The $IV_{t,t-1}^2$ term captures nearly all of the volatility information.\(^9\)

C. Cross-Sectional Variation in Results

We do not attempt a formal analysis of cross-sectional variation in our results because we have only 50 individual firms in our sample, because we employ reduced form empirical models, and because we have no obvious theoretical motivation. Further, since options are widely traded for only a modest proportion of publicly traded firms, a broad cross-sectional analysis is not possible.

However, as we noted in Section II, there are appreciable differences across the size quintiles of firms in terms of the stock’s spot return volatility, the IV level, the daily variability in IV, and the option trading volume. These size-related variations motivate our choice to differentiate our results across size quintiles in each table.

For all five quintiles, the correlation between stock returns and index IV innovations is appreciably more negative than the correlation between stock returns and own-firm IV innovations. This consistency is important when considering what our evidence suggests about the AVP.

We do note a few apparent size-related differences. We note that the negative relation between stock returns and IV innovations is appreciably more negative than the correlation between stock returns and own-firm volatility innovations and in the relation between stock returns and index volatility innovations. The relation between stock returns and own-firm volatility innovations

---

\(^9\)The estimated $\psi_3$ coefficients on the lagged return residuals are only positive and significant for about half the firms (26 firms at a 5% $p$-value), and the estimated $\psi_6$ coefficients that allow for the sign asymmetry are only positive and significant for three firms. For the indices, only $\psi_3$ is positive and significant and only for the CRSP index (at a 0.04 $p$-value).
is especially prominently weaker for the smallest quintile of firms, which may be due to poorer quality information in IV for the smaller firms with appreciably lower option trading volume. Consistent with this conjecture, we also find in later analysis that the volatility information from the IV innovation appears somewhat weaker for the smallest quintile of firms (see Table 4).

We perform additional cross-sectional analysis regarding the relation between VIX innovations and stock returns. Specifically, we evaluate the correlation between daily VIX innovations and stock returns of 10 size-based stock portfolios from CRSP (formed from NYSE/AMEX stocks). We find that the correlations between the daily VIX innovations and the size-based portfolio returns are reliably negative for all 10 size-based decile portfolios. The magnitude of the correlation declines monotonically with size, with correlations of $-0.671$, $-0.601$, $-0.567$, $-0.533$, $-0.520$, $-0.507$, $-0.470$, $-0.450$, $-0.361$, and $-0.238$ for decile-10 (the largest firms) through decile-1 (the smallest firms). This additional evidence suggests that the sizable negative correlations between stock returns and VIX innovations extend beyond large firms (such as the large firms in our sample).

IV. Daily Changes in Implied Volatility and the Future Volatility of Spot Stock Returns

Our findings in Section III have clear implications for understanding the AVP, provided that the daily IV change is a good proxy for the daily innovation in expected stock return volatility. In this section, we present new evidence that supports this key assumption. The fundamental question is whether the daily IV innovation over period $t-1$ ($\Delta IV_{i,t-1}$) contains reliable incremental information for the conditional volatility of period $t$, beyond the information contained in the IV level at $t-2$. If daily changes in individual stock IVs reflect primarily measurement error and noise, then these IV changes may contain relatively little incremental information about future stock return volatility. For example, results in Bollen and Whaley (2004) suggest that supply and demand imbalances may have a material influence on day to day IV changes. If so, it is not clear that daily IV changes will contain substantial incremental information about future stock volatility. Thus, from a practical perspective, the signal-to-noise ratio in daily IV innovations is an empirical issue.

Another concern is that the daily VIX innovation might contain more incremental information about future firm-level volatility than does the respective firm-level IV innovation, perhaps due to a higher signal-to-noise ratio in the more widely traded index options. If so, this could help explain why we find larger comovements between individual stock returns and index IV innovations than between individual stock returns and own-firm IV innovations.

First, we investigate the incremental volatility information in the lagged own-firm IV innovations by estimating the following system,

\begin{align}
R_{i,t} &= \gamma_0 + \gamma_1 R_{i,t-1} + \gamma_2 R_{M,t-1} + \varepsilon_{i,t}, \\
\varepsilon_{i,t} &= 1 + \gamma_3 IV_{i,t-2} + \gamma_4 \Delta IV_{i,t-1},
\end{align}

where $R_{i,t}$ is the daily return of individual stock $i$, $R_{M,t}$ is the market-level stock return, $\varepsilon_{i,t}$ is the return residual, $h_{i,t}$ is the conditional variance of $\varepsilon_{i,t}$, $IV_{i,t-2}$ is
the implied daily variance of stock \( i \) at the end of period \( t - 2 \), \( \Delta IV^2_{i,t-1} \) is the one-day change in the stock option's implied variance from the end of period \( t - 2 \) to the end of period \( t - 1 \), and the \( \gamma_s \) are estimated coefficients.\(^{10}\) The coefficient of interest is \( \gamma_5 \) on the \( \Delta IV^2_{i,t-1} \) term.

We report results in Table 4. We find that the \( \Delta IV^2_{i,t-1} \) term provides reliable incremental information about future stock volatility. For 37 of the 50 firms, the estimated coefficient on the \( \Delta IV^2_{i,t-1} \) term (\( \gamma_5 \)) is positive and statistically significant at a 5% level or better. Further, the mean (median) \( \gamma_5 \) is 0.766 (0.746), as compared to a mean (median) \( \gamma_4 \) of 0.912 (0.895) for the \( IV^2_{i,t-2} \) term, which suggests a high signal-to-noise ratio in the \( \Delta IV^2_{i,t-1} \) term. These results are consistent across the size quintiles in Table 4, although the information in the IV innovation for the larger firms (with higher option trading volume) appears to be of somewhat higher quality.

### Table 4

Conditional Volatility Information from the Daily IV Change for Individual Stocks

<table>
<thead>
<tr>
<th></th>
<th>( \gamma_1 )</th>
<th>( \gamma_2 )</th>
<th>( \gamma_4 )</th>
<th>( \gamma_5 )</th>
<th>Lk. Function Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>All 50 firms</td>
<td>0.001</td>
<td>0.055</td>
<td>0.912</td>
<td>0.766</td>
<td>7276.03</td>
</tr>
<tr>
<td>Mean:</td>
<td>0.007</td>
<td>0.049</td>
<td>0.895</td>
<td>0.746</td>
<td>[49]</td>
</tr>
<tr>
<td>Median:</td>
<td>[4/4]</td>
<td>[16/4]</td>
<td>[50/0]</td>
<td>[37/0]</td>
<td></td>
</tr>
<tr>
<td>Largest 10 firms</td>
<td>0.012</td>
<td>-0.075</td>
<td>0.937</td>
<td>0.822</td>
<td>7624.14</td>
</tr>
<tr>
<td>Mean:</td>
<td>0.020</td>
<td>-0.075</td>
<td>0.917</td>
<td>0.823</td>
<td>[10]</td>
</tr>
<tr>
<td>Median:</td>
<td>[0/0]</td>
<td>[0/0]</td>
<td>[0/0]</td>
<td>[0/0]</td>
<td></td>
</tr>
<tr>
<td>Smallest 10 firms</td>
<td>-0.010</td>
<td>0.171</td>
<td>0.863</td>
<td>0.680</td>
<td>6874.97</td>
</tr>
<tr>
<td>Mean:</td>
<td>-0.015</td>
<td>0.186</td>
<td>0.879</td>
<td>0.672</td>
<td>[9]</td>
</tr>
<tr>
<td>Median:</td>
<td>[1/2]</td>
<td>[7/2]</td>
<td>[10/0]</td>
<td>[9/0]</td>
<td></td>
</tr>
</tbody>
</table>

The interpretation of the results in Section III also depends on whether there is reliable volatility information in the daily innovation in the index IV. To address this issue, we estimate a specification that retains (7) as the conditional mean equation and uses the following conditional variance equation,

\[
h_{i,t} = \gamma_3 + \gamma_4 IV^2_{i,t-2} + \gamma_5 \Delta IV^2_{i,t-1},
\]

\(^{10}\)We include the lagged returns as explanatory variables in (7) and subsequent mean equations in Sections IV, V, and VI in order to control for microstructure effects and as a crude control for time-varying expected returns. In practice, the lagged return terms explain almost nothing. Across the 50 firms, the average (median) \( R^2 \) for an OLS estimation of (7) is only 0.0036 (0.0027). In Section III, we did not include lagged returns as explanatory variables in (3) and (5) because they complicate the interpretation of the \( R^2 \)'s reported in Table 3 and because of the unimportance of the lagged return terms relative to the IV innovation terms.
where $\Delta VIX_{t-1}^2$ is the one-day change in the implied variance of the S&P 100 index from the end of period $t - 2$ to the end of period $t - 1$ and the other terms are as defined for (7) and (8). Here, the coefficient of interest is $\gamma_6$ on the $\Delta VIX_{t-1}^2$ term.

The results are reported in Table 5. We find that the daily VIX innovation provides very reliable incremental information about future volatility for both the S&P 100 and CRSP stock index. At the firm level, the daily VIX innovation also tends to provide incremental volatility information. Across the 50 firms, the mean (median) of the $\gamma_6$ estimates is 0.866 (0.714), which is close to the $\gamma_6$ estimated for the S&P 100 return. The $\gamma_6$ estimates are positive (negative) and statistically significant for 14 (1) of the 50 firms at the 5% level. For the individual stocks, the number of $\gamma_6$ estimates that are statistically significant seems modest, which likely reflects the high proportion of idiosyncratic volatility in firm returns and our use of the sizable quasi-maximum likelihood robust standard errors.

<table>
<thead>
<tr>
<th>TABLE 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conditional Volatility Information from the Daily Index-Level IV Change</td>
</tr>
</tbody>
</table>

Table 5 reports on the information content of the daily VIX change for the conditional volatility of individual stock returns and index returns. We estimate the following model,

$$
\begin{align*}
R_{i,t} & = \gamma_0 + \gamma_1 R_{i,t-1} + \gamma_2 R_{M,t-1} + \epsilon_{i,t}, \\
\sigma_{i,t}^2 & = \gamma_3 + \gamma_4 \sigma_{i,t-1}^2 + \gamma_6 \Delta VIX_{t-1}^2,
\end{align*}
$$

where $R_{i,t}$ is stock or index $i$'s daily return, $R_{M,t}$ is the market-level stock return, $\epsilon_{i,t}$ is the return residual, $\sigma_{i,t}^2$ is the conditional variance of $\epsilon_{i,t}$, $\sigma_{i,t-1}^2$ is the daily implied variance for stock $i$ (VIX$^2_i$ for the indices), $\Delta VIX_{t-1}^2$ is the one-day change in the implied variance of the S&P 100 index from the end of period $t - 2$ to the end of period $t - 1$, and the $\gamma$s are coefficients to be estimated for each stock or index. The $\gamma_2$ term is omitted for the indices. For each size-based grouping of individual stocks in column one, we report the mean and median coefficients. The numbers in brackets indicate the number of firms where the respective coefficient is positive/negative and significant at a 5% $p$-value. For the stock index results, $t$-statistics are reported in parentheses. The sample period is 1988 through 1995.

<table>
<thead>
<tr>
<th></th>
<th>$\gamma_1$</th>
<th>$\gamma_2$</th>
<th>$\gamma_3$</th>
<th>$\gamma_4$</th>
<th>$\gamma_6$</th>
<th>Lk. Function Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>All 50 firms</td>
<td>Mean:</td>
<td>0.001</td>
<td>0.054</td>
<td>0.867</td>
<td>0.866</td>
<td>7265.11</td>
</tr>
<tr>
<td></td>
<td>Median:</td>
<td>0.001</td>
<td>0.049</td>
<td>0.856</td>
<td>0.714</td>
<td>7614.51</td>
</tr>
<tr>
<td></td>
<td>[5/5]</td>
<td>[15/6]</td>
<td>[5/0]</td>
<td>[14/1]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Largest 10 firms</td>
<td>Mean:</td>
<td>0.013</td>
<td>-0.073</td>
<td>0.900</td>
<td>0.903</td>
<td>6864.20</td>
</tr>
<tr>
<td></td>
<td>Median:</td>
<td>0.028</td>
<td>-0.075</td>
<td>0.875</td>
<td>0.939</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0/0]</td>
<td>[1/4]</td>
<td>[1/0]</td>
<td>[1/0]</td>
<td>[5/0]</td>
<td></td>
</tr>
<tr>
<td>Smallest 10 firms</td>
<td>Mean:</td>
<td>-0.015</td>
<td>0.166</td>
<td>0.823</td>
<td>1.757</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Median:</td>
<td>-0.025</td>
<td>0.180</td>
<td>0.796</td>
<td>1.377</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[1/3]</td>
<td>[5/0]</td>
<td>[1/0]</td>
<td>[1/0]</td>
<td>[4/1]</td>
<td></td>
</tr>
<tr>
<td>S&amp;P 100</td>
<td>Mean:</td>
<td>0.004</td>
<td>0.769</td>
<td>0.817</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Median:</td>
<td>0.122</td>
<td>0.461</td>
<td>0.550</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.18]</td>
<td>(6.17)</td>
<td>(7.61)</td>
<td>(2.94)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

For 49 of the 50 firms, we find that the likelihood function value for the system of equations (7) and (9) is less than the comparable system of (7) and (8), which indicates there is more incremental volatility information from own-firm IV changes than from VIX changes. Overall, the results in Tables 4 and 5 support our use of the daily IV innovation as a proxy for the change in the expected return volatility at both the firm and market level.

Finally, our interpretation of the implied idiosyncratic volatility from Section III requires that this measure be informative about the conditional volatility of the...
idiosyncratic component of firm-level stock returns. We evaluate this issue with the following model,

\[
R_{i,t} = \phi_0 + \phi_1 R_{S&P100,t} + \varepsilon_{i,t}^{\text{idio}},
\]

\[
h_{i,t}^{\text{idio}} = \phi_2 + \phi_3 IV_{i,t-2}^{2,\text{idio}} + \phi_4 \Delta IV_{i,t-1}^{2,\text{idio}},
\]

where \( R_{i,t} \) is the daily return of stock \( i \), \( R_{S&P100,t} \) is the daily S&P 100 index return, \( \varepsilon_{i,t}^{\text{idio}} \) is the idiosyncratic return residual, \( h_{i,t}^{\text{idio}} \) is the conditional idiosyncratic return variance, \( IV_{i,t-2}^{2,\text{idio}} \) is the implied daily idiosyncratic variance of stock \( i \) at the end of period \( t-2 \) (as estimated per Section II.B), \( \Delta IV_{i,t-1}^{2,\text{idio}} \) is the daily change in the firm’s implied idiosyncratic variance, and the \( \phi \)s are coefficients to be estimated.

Since the market return term (the \( \phi_1 \) term in (10)) controls for market-wide volatility, this is a model of idiosyncratic volatility. We find that both the lag-two implied idiosyncratic variance term (the \( \phi_3 \) term) and the lag-one change in implied idiosyncratic variance term (the \( \phi_4 \) term) are both reliably positive. For our estimation across the 50 firms, the median \( \phi_3 \) is 0.68, and the \( \phi_3 \)s are positive and statistically significant for all 50 firms. The median \( \phi_4 \) is 0.52, and the \( \phi_4 \)s are positive and statistically significant for 35 firms. Thus, these results support our use of \( IV_{i,t}^{\text{idio}} \) as a measure of idiosyncratic volatility and \( \Delta IV_{i,t}^{\text{idio}} \) as a measure of the change in implied idiosyncratic volatility.

**V. Asymmetric Volatility: Lagged Firm-Level versus Market-Level Return Shocks**

Next, we investigate the AVP in our sample with the return-based approach that has been widely used in the literature. By return-based, we mean that the time-varying conditional volatility is estimated as a function of the previous period’s return shock (see, e.g., Glosten, Jagannathan, and Runkle (1993), Bekaert and Wu (2000), and Wu (2001)). This exploration is motivated by our results in Section III, which suggest: i) that the asymmetric relation between conditional volatility and lagged return shocks will be stronger for index returns than for firm-level returns, and ii) that firm-level asymmetric volatility will be stronger when modeling firm-level conditional volatility as a function of the lagged market-level return shock (rather than the firm’s own return shock). In terms of the modeling specification, our new wrinkle here is to distinguish between firm- and market-level return shocks when examining the AVP at the firm level.

To begin with, we first analyze the traditional asymmetric volatility behavior where the conditional firm volatility (index volatility) is modeled as a function of

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11Note that using the idiosyncratic volatility derived from equations (1) and (2) when estimating the system of (10) and (11) means the estimation is a two-step procedure, which assumes that the \( \phi_1 \) from (10) and the \( \beta_i \) from (1) are effectively the same. We present this two-stage method so that we can use the same simple idiosyncratic volatility that we use in Section III and Tables 2 and 3. For robustness, we also estimate a more complex one-stage model that replaces the \( IV_{i,t}^{\text{idio}} \) term with its primitive \((IV_{i,t}^{2,\text{idio}} - \phi_2^2 VIX_t^2)\) in (11). Thus, the one-stage estimation has \( \phi_1 \) terms in both the mean and variance equation. We find that the estimated \( \beta_i \)s from the two-stage approach and the estimated \( \phi_1 \)s from the one-stage approach are very close (the cross-sectional correlation is 0.98 across the 50 firms, with means within about 2% of each other). The estimated \( \phi_3 \)s (\( \phi_4 \)s) from the one-stage estimation are positive and statistically significant for 49 (34) of the firms at a 5% \( \rho \)-level. Thus, the one-stage estimation results are very similar to the two-stage results.
the own-firm (index) return shocks. Instead of estimating a traditional asymmetric GARCH model (such as in Glosten et al. (1993)), we use the IV from period $t - 2$ to control for volatility information from $t - 2$ and older. This specification allows us to isolate the AVP behavior related to the period $t - 1$ return shock and to incorporate empirical evidence that the volatility information in IV largely subsumes volatility information from older return shocks.

A. Asymmetric Volatility with Lagged Own-Stock Return Shocks

We estimate the following system to evaluate the traditional univariate AVP in a given firm's (or index's) returns,

\[
R_{i,t} = \theta_0 + \theta_1 R_{i,t-1} + \theta_2 R_{M,t-1} + \varepsilon_{i,t},
\]

\[
h_{i,t} = \theta_3 + \theta_4 \sigma_{i,t-2}^2 + \theta_5 \varepsilon_{i,t-1}^2 + \theta_6 D_{i,t-1} \varepsilon_{i,t-1}^2,
\]

where $R_{i,t}$ is the daily return of individual stock or index $i$, $R_{M,t}$ is the market-level return, $\varepsilon_{i,t}$ is the return residual, $h_{i,t}$ is the conditional variance of $\varepsilon_{i,t}$, $\sigma_{i,t-2}^2$ is the implied daily variance of stock $i$ (or VIX$_i^2$ for the indices) at the end of period $t - 2$, $D_{i,t-1}$ is a dummy variable that equals one if $\varepsilon_{i,t-1}$ is negative and zero otherwise, and the $\theta$s are coefficients to be estimated. The $\theta_2$ term is omitted for the indices. The primary coefficient of interest is $\theta_6$ since it allows for the volatility asymmetry.

Table 6, Panel A reports results for the indices. We find that the AVP is reliably evident as indicated by the size and statistical significance of the $\theta_6$ estimates. The relation between the conditional variance and the positive return shocks is $-0.067 (-0.063)$ for the CRSP (S&P 100) index. Conversely, the relation between the conditional variance and the negative market return shocks ($\theta_5 + \theta_6$) is $0.117 (0.045)$ for the CRSP (S&P 100) index. Note that this is the strong form of AVP behavior for the index returns, where positive (negative) return shocks imply a lower (higher) future volatility. Subperiod results are consistent.

Table 6, Panel B reports the comparable results for the individual stock returns. For the 50 individual stocks, the AVP related to the lagged own-firm's return shocks is much weaker than that for the indices. The mean (median) $\theta_6$ estimate across the 50 firms is only $0.033 (0.024)$ and the $\theta_6$ estimates are positive and statistically significant for only seven of the 50 firms. Further, in contrast to the strong form AVP in the index returns, both positive and negative return shocks are positively related to future volatility for the individual stock returns, with negative return shocks implying only a marginally higher volatility. There is little variation in this AVP across the different size quintiles, except for the smallest quintile where the AVP is essentially non-existent.

\[\text{Also note that the significance level denoted for Tables 6 and 7 is lessened to 10\% (rather than the 1\% and 5\% in Tables 3 through 5). We make this choice because the statistical relations are weaker for these return-based AVP models. Thus, we feel this significance notation is more informative since it qualifies more individual coefficients.}\]
TABLE 6
Asymmetric Volatility Behavior with Lagged Own-Stock Return Shocks

Table 6 reexamines the asymmetric volatility phenomenon in daily stock returns at the index and firm level. We report on the following model, where the focus is on the relation between the return shock in period \( t - 1 \) and the conditional volatility for period \( t \):

\[
R_{i,t} = \theta_0 + \theta_1 R_{i,t-1} + \theta_2 R_{M,t-1} + \epsilon_{i,t},
\]

\[
h_{i,t} = \theta_3 + \theta_4 \epsilon_{i,t-2}^2 + \theta_6 D_{M,t-1} R_{i,t-1} + \theta_8 \epsilon_{i,t-1}^2 ,
\]

where \( R_{i,t} \) is the daily return of individual stock or index \( i \), \( R_{M,t-1} \) is the lagged market-level return, \( \epsilon_{i,t} \) is the return residual, \( h_{i,t} \) is the conditional variance of \( \epsilon_{i,t} \), \( \epsilon_{i,t}^2 \) is the daily implied variance of stock \( i \) (or VIX\(_F^2 \) for the indices), \( D_{M,t-1} \) is a dummy variable that equals one if \( R_{M,t-1} \) is negative and zero otherwise, and the \( \theta \)s are coefficients to be estimated for each stock or index. The \( \theta_6 \) term is omitted for the indices. Panel A reports stock index results, and Panel B reports on firm-level results. For the S&P 100 and CRSP index returns, \( t \)-statistics are in parentheses. For Panel B, for each size-based grouping of individual stocks in column one, we report the mean and median for the coefficients of interest. The numbers in brackets report the number of firms where the estimated coefficient is positive/negative and statistically significant at a 10% p-value or better. The sample period is 1988 through 1995.

Panel A. Stock Index Results

<table>
<thead>
<tr>
<th>Index</th>
<th>( \theta_4 )</th>
<th>( \theta_5 )</th>
<th>( \theta_6 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRSP</td>
<td>0.434</td>
<td>(8.30)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.764</td>
<td>(8.27)</td>
<td>0.184</td>
</tr>
</tbody>
</table>

Panel B. Summary Firm-Level Results

<table>
<thead>
<tr>
<th></th>
<th>( \theta_4 ) Mean/Median</th>
<th>( \theta_5 ) Mean/Median</th>
<th>( \theta_6 ) Mean/Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>All 50 firms</td>
<td>0.786 / 0.778</td>
<td>0.075 / 0.062</td>
<td>0.033 / 0.024</td>
</tr>
<tr>
<td>Largest 10 firms</td>
<td>0.824 / 0.799</td>
<td>0.046 / 0.043</td>
<td>0.044 / 0.022</td>
</tr>
<tr>
<td>Smallest 10 firms</td>
<td>0.752 / 0.741</td>
<td>0.107 / 0.112</td>
<td>-0.003 / -0.007</td>
</tr>
</tbody>
</table>

B. Firm-Level Asymmetric Volatility with Lagged Market-Level Return Shocks

To evaluate the asymmetric volatility relation between firm-level return volatility and lagged market-level return shocks, we estimate a specification that retains (12) as the conditional mean equation and uses the following conditional variance equation,

\[
h_{i,t} = \theta_3 + \theta_4 \epsilon_{i,t-2}^2 + \theta_7 R_{M,t-1} + \theta_8 D_{M,t-1} R_{i,t-1}^2 ,
\]

where \( R_{M,t}^2 \) is the squared market-level return, \( D_{M,t} \) is a dummy variable that equals one if \( R_{M,t} \) is negative and zero otherwise, and the other terms are as defined for (12) and (13). The primary coefficient of interest is \( \theta_8 \), which allows for the AVP with the lagged market-level return shocks.

Table 7 reports the results. We find that the AVP in firm-level returns is much more prominent when modeling the volatility as a function of lagged market-level return shocks, as compared to the univariate approach in Table 6. Here, we find that the average (median) of the \( \theta_8 \) estimates is sizable at 0.188 (0.178), which indicates that lagged negative return shocks imply a higher future volatility as compared to lagged positive return shocks of the same size. The \( \theta_8 \) estimates are positive and statistically significant for 20 of the firms.
TABLE 7

Asymmetric Volatility Behavior with Lagged Market-Level Return Shocks

Table 7 reports on the following asymmetric volatility model for daily firm-level stock returns where the conditional variance is a function of lagged market-level return shocks:

\[ R_{i,t} = \theta_0 + \theta_1 R_{i,t-1} + \theta_2 R_{M,t-1} + \varepsilon_{i,t}, \]
\[ h_{i,t} = \theta_3 + \theta_4 (\varepsilon_{i,t-2}^2) + \theta_1 R_{M,t-1}^2 + \theta_6 D_{M,t-1} R_{M,t-1}^2, \]

where \( R_{i,t} \) is the daily return for stock \( i \), \( R_{M,t-1} \) is the lagged market-level return, \( \varepsilon_{i,t} \) is the return residual, \( h_{i,t} \) is the conditional variance of \( \varepsilon_{i,t} \), \( \varepsilon_{i,t}^2 \) is the daily implied variance of stock \( i \), \( D_{M,t-1} \) is a dummy variable that equals one if \( R_{M,t-1} \) is negative and zero otherwise, and the \( \theta \)'s are estimated coefficients for each stock. For each size-based grouping of individual stocks in column one, we report the mean and median for the coefficients of interest. The numbers in brackets report the number of firms where the estimated coefficient is positive/negative and statistically significant at a 10% p-value or better. The sample period is 1988 through 1995.

<table>
<thead>
<tr>
<th>Period</th>
<th>( \theta_6 ) Mean/Median</th>
<th>( \theta_7 ) Mean/Median</th>
<th>( \theta_8 ) Mean/Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>1988 to 1995</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All 50 firms</td>
<td>0.833 / 0.622</td>
<td>0.124 / 0.011</td>
<td>0.188 / 0.178</td>
</tr>
<tr>
<td>[50/0]</td>
<td>[2/6]</td>
<td>[20/0]</td>
<td></td>
</tr>
<tr>
<td>Largest 10 firms</td>
<td>0.862 / 0.824</td>
<td>-0.082 / -0.101</td>
<td>0.259 / 0.284</td>
</tr>
<tr>
<td>[10/0]</td>
<td>[0/3]</td>
<td>[9/0]</td>
<td></td>
</tr>
<tr>
<td>Smallest 10 firms</td>
<td>0.795 / 0.801</td>
<td>0.259 / 0.149</td>
<td>0.078 / 0.075</td>
</tr>
<tr>
<td>[10/0]</td>
<td>[1/1]</td>
<td>[2/0]</td>
<td></td>
</tr>
<tr>
<td>1992 to 1995</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All 50 firms</td>
<td>0.652 / 0.685</td>
<td>0.233 / 0.005</td>
<td>0.068 / 0.159</td>
</tr>
<tr>
<td>[49/0]</td>
<td>[3/6]</td>
<td>[17/0]</td>
<td></td>
</tr>
<tr>
<td>1992 to 1995 Subperiod</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All 50 firms</td>
<td>0.685 / 0.683</td>
<td>-0.011 / -0.066</td>
<td>0.409 / 0.167</td>
</tr>
<tr>
<td>[39/0]</td>
<td>[2/11]</td>
<td>[8/1]</td>
<td></td>
</tr>
</tbody>
</table>

By contrast, the lagged positive return shocks have little relation to future firm-level volatility. The median of the \( \theta_7 \) estimates is only 0.011, and the estimates display little statistical significance. Subperiod results are consistent; especially comparing the median of the \( \theta_8 \) estimates for the overall period (at 0.178) and the two subperiods (at 0.159 and 0.167, respectively).

In regard to cross-sectional variation, we note that the largest quintile of firms has noticeably stronger asymmetric volatility behavior with respect to the lagged market return shocks in the Table 7 model. On the other hand, there is little apparent variation across firm size in the univariate AVP in Table 6. If the AVP is more of a systematic market-level phenomenon, this result seems consistent with the observation that these large firm returns also have a more negative relation with the index volatility innovations (as reported in Section III).

To conclude, our examination of the asymmetric relation between conditional volatility and lagged return shocks yields two observations. First, asymmetric volatility is more reliably evident in the index returns than in the firm-level returns, which is consistent with prior findings that have contrasted index versus firm behavior (see, e.g., Andersen et al. (2001)). Second, we contribute with a new finding which indicates that asymmetric volatility is more sizable and reliably evident in firm-level volatility when relating a firm's conditional volatility to the lagged market-level return shock (rather than the own-firm return shock). Both observations above seem consistent with our primary findings in Section III.
VI. Discussion of Results and Other Related Analysis

In Section III, we presented our primary findings that indicated: i) index returns have a large negative relation with innovations in expected index volatility, ii) individual stock returns have only a modest negative relation with innovations in their own expected volatility, iii) the negative relation between individual stock returns and index volatility innovations is sizably stronger than the negative relation between individual stock returns and their own-firm volatility innovations, and iv) the relation between individual stock returns and their respective idiosyncratic volatility innovation is near zero. These findings support a systematic market-wide explanation for the AVP over a firm-level explanation.

In this section, we discuss how our primary results may relate to other areas of the literature. Specifically, a better understanding of the relation between stock returns and volatility innovations may also bear on issues such as the implied volatility smile, the bias in implied volatility, and return skewness. Additional data analysis is included to support our discussion.

A. The Implied Volatility Smile

The variation of IV across strike prices for options on the same underlying stock with the same expiration, commonly referred to as the IV smile, has been the subject of much research. As noted in Bollen and Whaley (2004), since October 1987 the IV from equity index options tends to decrease monotonically across exercise prices. Thus, the IV smile is really more of a skew. Previous findings in Dennis and Mayhew (2002), Bakshi, Kapadia, and Madan (2003), and Bollen and Whaley (2004) indicate that the slope in the IV smile is more negative for index options than for individual stock options.

In this subsection, we consider how the IV smile may relate to our primary dynamic findings in Section III. In this work, we characterize the variation in IV across strike prices with a single slope estimate since we are only interested in a modest strike price variation that is of comparable magnitude to daily stock price movements. Consistent with the previous studies, we find that the IV slope across strike prices for near at-the-money options is substantially more negative for the index options than for the individual stock options. Thus, the index versus individual stock differences in the IV smile are suggestive of the index versus individual stock differences in the dynamic relation that we find between stock returns and IV innovations.

The extent of the relation between the slope of the IV smile and our dynamic findings is an empirical question. If the IV variation across strike prices is substantially related to the moneyness of an option, then our results should not be appreciably related to the IV smile since we control for the option’s moneyness when forming our standardized IV. On the other hand, if the IV smile and our primary dynamic findings are both related to the influence of stochastic volatility in option pricing (see, e.g., Bakshi et al. (2003)), then the slope of the IV smiles may be appreciably related to our dynamic findings.

Further, evidence from Bollen and Whaley (2004) suggests that the shape of the IV smile is influenced by supply and demand forces in the option market. If so, then the relation between the slope of the IV smiles and our primary dynamic findings seems unclear.
To investigate this issue, we extend our analysis by calculating a daily excess IV change that equals the simple IV change minus the change in IV suggested by the slope of the prior period’s IV smile and the day’s realized stock price movement. We find that the dynamic relation between stock returns and the excess IV changes remains sizable and reliably negative. However, the magnitude of the correlation between a stock’s return and the excess IV change is smaller than the correlation between a stock’s return and the stock’s simple IV change (the negative correlations with the excess IV changes are about 31% smaller for the index and about 55% smaller for the individual stocks (median value), as compared to the Table 2 results). We conclude that the slope of the IV smiles is suggestive of our dynamic findings in Section III. However, the dynamic relation between stock returns and IV innovations remains sizable and reliably negative, even when controlling for the IV change suggested by the prior period’s IV smile and the day’s stock price change.14

B. The Bias in Implied Volatility

We are also interested in whether our primary dynamic findings might bear on understanding differences in the IV bias between firm- and index-level options. It is well known that the implied volatility from index options tends to be higher than the subsequent realized volatility from spot returns. See Poteshman (2000) and Chernov (2001) for a summary of this evidence. Recent findings indicate that the bias in implied volatility is smaller for individual stock options (see Bakshi and Kapadia (2003a) and Bollen and Whaley (2004)).

To investigate the IV bias in our sample, we estimate the following model,

\[ R_{i,t} = \lambda_0 + \lambda_1 R_{i,t-1} + \lambda_2 R_{M,t-1} + \varepsilon_{i,t}, \]

\[ h_{i,t} = \lambda_3 + \lambda_4 IV^2_{i,t-1}, \]

where \( R_{i,t} \) is the daily stock return of individual stock \( i \) or the S&P 100 index, \( R_{M,t} \) is the daily market-level stock return, \( \varepsilon_{i,t} \) is the return residual, \( h_{i,t} \) is the conditional variance of \( \varepsilon_{i,t} \), \( IV^2_{i,t} \) is the implied daily variance of either the S&P 100 index or the respective stock, and the \( \lambda \)'s are coefficients to be estimated for each stock. The \( \lambda_2 \) term is omitted for the index model.

As pointed out by Lamoureux and Lastrapes (1993), this method is subject to the critique that the conditional volatility horizon is a one-day ahead volatility whereas the IV implies volatility over a 30-day horizon. However, it seems unlikely that this maturity mismatch will impart a systematic error in the bias over an eight-year sample of daily returns. Further, we are interested in the contrast in the IV bias when comparing index and individual stock options, rather than whether IV has an absolute bias. Thus, we believe this approach is valid for illustrating the contrast between the IV biases, especially given the magnitude of the differences that we find.

The results are reported in Table 8. First, Model 1 in Table 8 examines only the bias by restricting \( \lambda_3 \) to zero in the estimation. For the S&P 100, the IV is higher than the realized market volatility, which indicates the well-known bias in

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14Details of the method and results for the excess IV change are available from the authors.
The $\lambda_4$ estimate is significantly less than one, indicating that the implied variance is biased about 23% too high.

### TABLE 8

The Bias in Implied Volatility for the Future Realized Volatility

Table 8 reports on the bias and informativeness of the IV level for the conditional volatility of future stock returns. We estimate two variations of the following model,

$$
R_{i,t} = \lambda_0 + \lambda_1 R_{i,t-1} + \lambda_2 \rho_{M_{i,t-1}} + \epsilon_{t,i},
$$

$$
\eta_{t,i} = \lambda_3 + \lambda_4 \eta_{t,i-1},
$$

where $R_{i,t}$ is the daily return of individual stock $i$ or the S&P 100, $R_{M_{i,t}}$ is the market-level stock return, $\epsilon_{t,i}$ is the return residual, $\eta_{t,i}$ is the conditional variance of $\epsilon_{t,i}$, $\eta_{t,i}^2$ is the daily implied variance of stock $i$ (VIX for the S&P 100), and the $\lambda$s are estimated coefficients for each stock or index. The $\lambda_3$ term is omitted for the index. For each size-based group of individual stocks in column one, we report the mean and median for the coefficients of interest. For $\lambda_3$, the number in brackets reports the number of firms where the estimated coefficient is greater than zero/less than zero (greater than one/less than one) and significant at a 5% p-value. For the index, t-statistics are in parentheses for a test that the coefficient is different than zero (different than one) for $\lambda_3$ ($\lambda_4$). The sample period is 1988 through 1995.

<table>
<thead>
<tr>
<th></th>
<th>Mean:</th>
<th>Median:</th>
<th></th>
<th>Mean:</th>
<th>Median:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\lambda_3 = 0$</td>
<td>$\lambda_4$</td>
<td>$\lambda_3 \times 10^6$</td>
<td>$\lambda_4$</td>
<td></td>
</tr>
<tr>
<td>All 50 firms</td>
<td>n/a</td>
<td>0.999</td>
<td>3.18</td>
<td>0.897</td>
<td></td>
</tr>
<tr>
<td>Largest 10 firms</td>
<td>n/a</td>
<td>0.999</td>
<td>2.27</td>
<td>0.911</td>
<td></td>
</tr>
<tr>
<td>Smallest 10 firms</td>
<td>n/a</td>
<td>0.991</td>
<td>1.07</td>
<td>0.904</td>
<td></td>
</tr>
<tr>
<td>S&amp;P 100</td>
<td>n/a</td>
<td>0.999</td>
<td>1.97</td>
<td>0.925</td>
<td></td>
</tr>
</tbody>
</table>

However, the IV from the individual stock options exhibits little bias. For the 50 firms, the mean (median) of the $\lambda_4$ estimates is essentially one at a value of 0.999 (0.999). For 31 of the 50 firms, the statistical tests fail to reject a null hypothesis that $\lambda_4$ is equal to one. Further, for the 19 firms that reject the hypothesis that $\lambda_4$ equals one, the results are mixed as to whether $\lambda_4$ is greater than or less than one. For seven (12) firms, $\lambda_4$ is statistically greater than one (less than one). Thus, our findings do not indicate any systematic directional bias in IV at the firm level. The contrast in the IV bias between firm-level and index options is consistent with findings in Bakshi and Kapadia (2003a) and Bollen and Whaley (2004).

Model 2 in Table 8 reports on the unrestricted version of (15) and (16). If IV is informationally efficient and unbiased, then we expect to find the $\lambda_3$ estimate to be essentially zero and the $\lambda_4$ estimate to be essentially one. On average, our firm-level results are consistent with this notion of informational efficiency and unbiasedness. For 38 (37) of the 50 firms, we cannot reject the null that the $\lambda_3$ ($\lambda_4$) estimate equals zero (one). For the index-level results, we also find that we cannot reject the null that the $\lambda_3$ estimate equals zero. Thus, the results in Table 8 support our assumption that IV is informative about future spot return volatility.

As far as relating the firm versus index differences in the IV bias to the firm versus index differences in our primary findings in Section III, earlier work has argued that the bias in index options is likely due to a stochastic volatility risk premium in option prices (see, e.g., Coval and Shumway (2001) and Bakshi and
Kapadia (2003b)). Further, Bakshi and Kapadia (2003a) suggest that the volatility risk premium is smaller for individual stock options, as compared to index options. Our collective findings seem consistent with these conclusions. Since we find evidence that there seems to be a much smaller relation between stock returns and volatility innovations for individual stocks than for indices, it seems intuitive that there would also be a smaller volatility risk premium in individual stock option prices. These observations suggest that it is important to distinguish between systematic and idiosyncratic volatility.

C. Return Skewness

Prior studies such as Harvey and Siddique (1999) and Heston (1993) have noted a link between negative return skewness and the AVP. Accordingly, we evaluate the skewness in continuously compounded returns for our 50 firms and the S&P 100 index. We find that the S&P 100 index returns have a large negative skewness of $-0.520$ versus a near-zero skewness for the firm-level stock returns (with a median skewness of 0.043). These skewness differences are suggested by the large differences that we find when comparing the AVP behavior of index versus individual stock returns. Further, the largest 20 of our firms have both a more negative return skewness and a more negative correlation between the stock returns and index volatility innovations, as compared to the smallest 20 firms. Specifically, the 20 largest (smallest) firms have a median return skewness of $-0.043$ ($0.093$) and a median correlation with the index IV innovations of $-0.39$ ($-0.29$). Thus, the skewness characteristics of our sample reinforce the conclusions from earlier studies that link AVP behavior and return skewness.

VII. Conclusions

We study daily stock returns and option-derived implied volatilities for the S&P 100 equity index and 50 large U.S. firms. Our empirical investigation yields new evidence that promotes a better understanding of the dynamic relation between stock returns and volatility innovations and the nature of the asymmetric volatility phenomenon.

Our work assumes that the daily change in our standardized implied volatility (IV) is an observable proxy for innovations in the expected return volatility of stock prices. With this assumption, we can jointly analyze changes in firm- and index-level IV in order to distinguish between innovations in systematic and idiosyncratic volatility.

We have four primary findings concerning the dynamic relation between stock returns and expected volatility innovations. First, we find that index returns have a large negative relation with innovations in expected index volatility. Prior research has reported comparable index-level results but with methods substantially different than ours. Second, we find that individual stock returns have only a modest negative relation with innovations in their own expected volatility. Third, we find that the negative relation between individual stock returns and index volatility innovations is sizably stronger than the negative relation between
individual stock returns and their own-firm volatility innovations. Fourth, we decompose the total implied volatility of the individual stocks into a systematic and idiosyncratic component. We then find that the relation between individual stock returns and their respective idiosyncratic volatility innovation is near zero. Sub-period analysis yields consistent results for all these findings.

The implications of this evidence for the asymmetric volatility phenomenon depend upon the key assumption that IV changes are good proxies for innovations in the expected stock volatility. We present new evidence that indicates the daily changes in both firm- and index-level IVs contain reliable incremental information about the future volatility of the respective stock or index. Further, we find that changes in own-firm IV provide more incremental information about the future volatility of the respective firm than do changes in index IV. Thus, our findings support the key assumption that IV changes are good proxies for innovations in expected stock return volatility, both for the index and for individual stocks.

If one accepts this key assumption, then our comovement findings have clear implications for understanding the AVP. If asymmetric volatility is better explained by systematic market-wide factors, then the negative correlation between stock returns and volatility innovations should be primarily attributable to a negative correlation between stock returns and market-level volatility innovations. Conversely, if asymmetric volatility is better explained by firm-level effects (with the aggregation of firm-level effects explaining index return behavior), then the negative correlation between individual stock returns and volatility innovations should be similar for both market-level volatility innovations and idiosyncratic volatility innovations. Overall, our evidence clearly supports a systematic market-wide explanation for the AVP.

While our findings clearly suggest that systematic market-level influences are more important in understanding the AVP, it remains an open question as to what the actual systematic influences are. The volatility feedback effect is the best known systematic explanation, but this hypothesis requires a positive intertemporal relation between innovations in expected index volatility and future expected stock returns. The empirical evidence on this intertemporal relation is mixed, but recent findings in Ghysels, Santa-Clara, and Valkanov (2005) provide support for a positive intertemporal relation. Avramov et al. (2006) suggests a link between the AVP and trading patterns of contrarian and herding traders, which seems likely to have a market-wide commonality. Unfortunately, our evidence is not well suited to pinpoint the economics behind a systematic explanation for the asymmetric volatility phenomenon.

On a secondary level, we also discuss how our primary findings may relate to other areas of the literature, such as the IV smile, the bias in IV, and return skewness. We conduct additional data analysis to support this discussion. Our collective evidence supports conclusions in other studies that suggest important differences between individual stocks and stock indices in the areas of option pricing and return behavior. Our collective findings also suggest it is important to distinguish between idiosyncratic and systematic volatility in these areas.
References


