Options-Implied Variance and Future Stock Returns

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Abstract

Existing studies document mixed evidence on Merton's (1987) conjecture of a positive relation between conditional idiosyncratic stock variance and future stock returns. We revisit this issue using options-implied variance as a proxy for conditional variance because, as a forward-looking variable, options-implied variance has superior predictive power for future realized variance. In both cross-sectional (for individual stocks) and time-series (for the market index) regressions, we uncover a significantly *negative* relation between options-implied variance and future stock returns. Consistent with Miller's (1977) divergence of opinion hypothesis, the negative relation is stronger (1) for stocks with more stringent short-sale constraints or (2) when shorting stocks becomes more difficult.

Keywords: stock return predictability, implied variance, realized variance, CAPM, and ICAPM

JEL Codes: G1

1. Introduction

Merton (1987) argues that there is a positive relation between *conditional* idiosyncratic stock variance and future stock returns when market friction, e.g., information costs, prevents investors from holding a mean-variance efficient portfolio.[1] Because many individual investors hold under-diversified portfolios (e.g., Blume and Friend (1975) and Goetzmann and Kumar (2008)), Merton's conjecture may be economically important and has inspired intensive empirical research. Existing evidence, however, is mixed. In cross-sectional studies, Malkeil and Xu (2002), Fu (2009), and Chua, Goh, and Zhang (2010) find that stocks with large idiosyncratic variance have high future returns but Ang, Hodrick, Xing, and Zhang (2006) uncover a negative relation between idiosyncratic variance and future stock returns. In time-series studies, Goyal and Santa-Clara (2003) find a positive relation between aggregate idiosyncratic variance and future excess market returns; Bali, Cakici, Yan, and Zhang (2005) and Wei and Zhang (2005) show that the relation is rather weak; and Guo and Savickas (2008) document a negative relation.

The inconclusive empirical evidence may reflect measurement errors in conditional stock variance, which is unobservable and was estimated using either the realized variance model or the GARCH model in the aforementioned studies. Specifically, because Ghysels, Santa-Clara, and Valkanov (2005) find that conditional variance is a function of long distributed lags of squared daily returns, the monthly realized variance, as commonly used in these studies, is arguably a noisy measure of conditional variance. Moreover, many stocks have no transactions in consecutive trading days, and Han and Lesmond (2010) show that micro-structure noises due to the nonsynchronous trading generate substantial measurement errors in realized variance. Similarly, one needs long time-series samples to obtain reliable parameter estimates of the GARCH model, while existing studies require a minimum of only 30 to 60 monthly stock return observations to estimate the GARCH model due to data limitations.

In this paper, we revisit Merton's (1987) conjecture using options-implied variance as a measure of conditional variance. Many authors, e.g., Christensen and Prabhala (1998) and Fleming (1998), show

[1] In a preceding study, Levy (1978) develops an equilibrium model in which idiosyncratic risk is priced because investors hold under-diversified portfolios. See also Malkeil and Xu (2002).

that forward-looking options-implied variance subsumes the information content of other standard measures of conditional variance, including both realized variance and GARCH variance, in the forecast of future realized variance. Our approach, which alleviates the concern about the measurement error problem, should shed new light on Merton's (1987) conjecture.[2] Note that options-implied variance is a measure of total variance—the sum of (1) variance due to comovement with systematic risks and (2) idiosyncratic variance. To identify precisely effects of idiosyncratic variance on future stock returns, we need to control for its correlation with risk factors that are important determinants of expected stock returns in both cross-sectional and time-series regressions.

We obtained daily options-implied stock variance constructed using close options prices from OptionMetrics database. Because it is a forward-looking variable, options-implied variance from the last business day of period t provides a sufficient summary of market participants' expectations about the variance of period $t+1$. This specification, however, is inappropriate for our study due to different trading hours in options and primary markets (e.g., Battalio and Schultz (2006)). Prior to February 13, 2006, trading of equity options closed at 4:02pm ET at the Chicago Board of Options Exchange (CBOE)—two minutes after the close of equity trading at the New York Stock Exchange, the American Stock Exchange, and NASDAQ. Different close times generate an artificial lead-lag relation between close options prices and close equity prices. To avoid such a look-ahead bias, we use options-implied variance of the second-to-last business day of period t as the proxy for conditional variance of period $t+1$.

We uncover a *negative* cross-sectional relation between options-implied variance and future stock returns using Fama and MacBeth (1973) regressions. In the univariate regression, stocks with small options-implied variance have higher future returns than do stocks with large options-implied variance,

[2] Guo and Whitelaw (2006) and others advocate using options-implied variance instead of realized variance or GARCH variance adopted in previous studies (e.g., French, Stambaugh, and Schwert (1987)) to uncover the positive stock market risk-return relation, as stipulated in Merton's (1973) intertemporal capital asset pricing model (ICAPM). Because stock market variance may be priced (e.g., Bakshi and Kapadia (2003) and Ang, Hodrick, Xing, and Zhang (2006)), options-implied variance is an upward biased estimate of conditional variance. Specifically, Bollerslev, Tauchen, and Zhou (2009) and Drechsler and Yaron (2010) show that the variance premium, the difference between options-implied variance and realized variance, correlate positively with future market returns. We find that controlling for the variance premium does not change our time-series results in any qualitatively manner. Similarly, volatility risk cannot explain our cross-sectional results because it implies a positive relation between options-implied variance and future stock returns, while we find the relation to be negative.

although the difference is only marginally significant at the 10% level. The negative relation between options-implied variance and future stock returns becomes statistically significant at the 1% level when we control for commonly used determinants of the cross-section of stock returns, including market beta, market capitalization, the book-to-market equity ratio, the momentum effect, and Amihud's (2002) illiquidity measure. The different results between univariate and multivariate regressions reflect an omitted variable problem—high variance stocks tend to have large market betas (e.g., Ang, Hodrick, Xing, and Zhang (2006)), to have small market capitalization (e.g., Pastor and Veronesi (2003)), and to be illiquid (e.g., Spiegel and Wang (2005)). Ang, Hodrick, Xing, and Zhang (2006) document a negative relation between realized idiosyncratic variance and future stock returns. We find that options-implied variance drives out realized idiosyncratic variance from cross-sectional regressions, indicating that realized idiosyncratic variance forecasts stock returns mainly because of its correlation with conditional idiosyncratic variance. Huang, Liu, Rhee, and Zhang (2010) and Bali, Cakici, and Whitelaw (2010) find that realized idiosyncratic variance loses its explanatory power for the cross-section of stock returns when controlling for the one-month lagged stock return and the maximum daily return in the previous month, respectively. Controlling for these variables, however, does not change our finding of a negative relation between options-implied variance and future stock returns in any qualitative manner.

The time-series relation between aggregate options-implied variance and future market returns is negative as well. In the univariate time-series regression, the relation between value-weighted aggregate options-implied variance and one-month-ahead excess market returns is negative albeit statistically significant at only the 10% level. The weak relation reflects the fact that, as mentioned above, options implied variance is a measure of total variance, while Merton (1987) stipulates a positive relation between *idiosyncratic* variance and future stock returns. Specifically, total variance is the sum of market variance and idiosyncratic variance in the CAPM. We address this issue in two ways. First, we orthogonalize aggregate options-implied variance by VIX, options-implied variance of the S&P500 index, and find a negative and significant relation between the orthogonalized aggregate options-implied variance and future excess market returns at the 1% level. Second, we include VIX as an additional forecasting variable, and find that the negative relation between aggregate options-implied variance and future excess market returns becomes statistically significant at the 1% level. Interestingly, consistent with Merton's (1973) ICAPM, the relation between VIX and future excess market returns is significantly positive. The finding of a negative relation between aggregate options-implied variance and future excess market returns is robust to a number of robustness tests, including the log transformation of both aggregate options-implied variance and VIX; subsamples; out-of-sample forecasts; controlling for commonly used stock market return predictors; weekly, quarterly, and annual forecast horizons; equal-weighted aggregate options-implied variance; and aggregate realized idiosyncratic variance.

The negative relation between options-implied variance and future stock returns poses a challenge to Merton's (1987) conjecture, and we investigate three alternative explanations using cross-sectional data. First, options-implied variance may be a proxy for divergence of opinion, which, in the presence of short-sale constraints, leads stocks to be overvalued initially and to have low returns subsequently (Miller (1977)).[3] Second, as Johnson (2004) points out, because stocks are call options on issuing companies' total assets, for a levered company, expected equity returns in general decrease with the level of idiosyncratic variance. Last, Cao, Simin, and Zhao (2008) argue that stocks of companies with abundant investment opportunities tend to have high idiosyncratic variance, and asset growth correlates negatively with future stock returns (e.g., Cooper, Gulen, and Schill (2008)).

We find support for Miller's (1977) refutable implication that divergence of opinion affects only stocks with binding short-sale constraints. Specifically, the interaction term of options-implied variance with proxies for short-sale constraints subsumes completely the information content of options-implied variance about future stock returns. Interestingly, results are qualitatively similar when we use realized idiosyncratic variance as a proxy for divergence of opinion. Moreover, Danielsen and Sorescu (2001) argue that stocks with options trading are less susceptible to short-sale constraints than are stocks without options trading, and we observe a stronger negative relation between realized idiosyncratic variance and future stock returns for the latter. We find little support for the other two hypotheses, however.

[3] See also Harrison and Kreps (1978), Chen, Hong, and Stein (2002), and Scheinkman and Xiong (2003).

Securities and Exchange Commission's (SEC) permanent ban on naked short selling in all U.S. stocks effective from September 18, 2008 provides a natural experiment to test Miller's (1977) hypothesis using time-series data. Specifically, because the ban makes it more difficult to short stocks, the negative relation between aggregate options-implied variance and future excess market returns should become stronger following the ban. We confirm this conjecture using weekly, monthly, and quarterly data.[4]

While our evidence is consistent with Miller's (1977) hypothesis, there is an important complementary explanation to the documented time-series relation. In the presence of multiple risk factors, as in Merton's (1973) ICAPM, by construction, aggregate (options-implied) variance correlates with the variance of hedging risk factor(s). Therefore, VWAOIV forecasts excess market returns possibly because of its comovement with the conditional variance of the hedging risk factor. Consistent with this conjecture, we find a strong correlation of VWAOIV with the realized variance of the value premium—a risk factor in the commonly used Fama and French (1996) three-factor model. More importantly, the predictive power of VWAOIV for excess market returns attenuates substantially when we control for its correlation with the realized variance of the value premium.

Several recent studies have investigated information content of options-implied variance for future stock returns. Cremers and Weinbaum (2011) find that stocks with relatively expensive calls outperform stocks with relatively expensive puts. Xing, Zhang, and Zhao (2011) find that option volatility smirk correlates negatively with future stock returns. Ang, Bali, and Cakici (2010) find that stocks with large increases in call implied volatility tend to rise over the following month whereas increases in put implied volatility forecast future decreases in next-month stock returns. Bali, Demirtas, and Atilgan (2011) find that the difference between out-of-the-money put and at-the-money call options written on the S&P 500 index correlates negatively with future market returns. In this paper, we find that

[4] Doran, Jiang, and Peterson (2010) use the temporary short-sale ban on financial stocks to investigate the cross-sectional relation between idiosyncratic volatility and future stock returns and find support for Miller's (1977) divergence of opinion hypothesis. Boehmer, Jones, and Zhang (2009), however, caution that the cross-sectional evidence from the event study may also reflect the Troubled Asset Relief Program (TARP) and other initiatives announced on the same day as the short-sale ban. In contrast, our time-series analysis provides a cleaner test of Miller's (1977) hypothesis because there is no compelling reason that TARP and other initiatives should affect the time-series relation between aggregate options-implied variance and future excess market returns.

the *level* of options-implied variance also forecast stock returns and that our results are robust to using call options, put options, or the average of the call and put options.

The remainder of the paper proceeds as follows. We describe data in Section 2. We investigate the cross-sectional relation between options-implied variance and future stock returns in Section 3. We examine the time-series relation between aggregate options-implied variance and future excess market returns in Section 4. We explore potential explanations of our main empirical findings in Section 5. We offer some concluding remarks in Section 6.

2. Data

OptionMetrics database provides daily options-implied stock volatility constructed using close prices of stock options. We square implied volatility to obtain implied variance. Over the January 4, 1996 to October 29, 2010 period, in each trading day and for each stock, we use the average of daily implied variance of (1) an at-the-money call options contract and (2) an at-the-money put options contract with the expirations closest to 30 days as the measure of the stock's conditional variance.[5] Specifically, we select the call or put options contract with (1) non-zero trading volume and (2) the strike price closest to the close stock price of the day. As we mentioned in the introduction, prior to February 13, 2006, trading of equity options at CBOE closed two minutes after the close of equity trading. To avoid the look-ahead bias, we use options-implied variance of the second-to-last business day in period t as the proxy for conditional variance of period $t+1$.

For the cross-sectional analysis, we obtain stock return and accounting data from the merged CRSP-COMPUSTAT database over the period January 1996 to October 2010. Following Jegadeesh and Titman (2001) and others, to alleviate the influence of micro-structure noises, we exclude stocks with a price less than $5. We follow Fama and French (1992) in the construction of market beta, market capitalization (as a proxy for size), and the book-to-market equity ratio. Our illiquidity measure is the

[5] We obtain qualitatively similar results using implied variance constructed using either (1) at-the-money call options or (2) at-the-money put options. As an additional robustness test, we further use the theoretical call and put options (at the money, 30-day expirations, delta=50 for call and delta=-50 for put) from the volatility surface database, and find qualitatively similar results.

same as that proposed by Amihud (2002). The leverage is book value of debt over the sum of book value of debt and market value of equity, as in Johnson (2004) and Ang, Hodrick, Xing, and Zhang (2009). The institution ownership is the fraction of a stock's outstanding shares held by all institutional shareholders constructed using the most recent 13f filings from Thomson Financial 13f database. As in Cooper, Gulen, and Schill (2008) and others, the asset growth is the year-over-year growth rate of total asset. Lastly, we follow Ang, Hodrick, Xing, and Zhang (2006) in the construction of monthly realized idiosyncratic variance using daily stock returns and daily Fama and French (1996) three factors with a minimum of 17 daily observations.

After merging the OptionMetrics database with the CRSP-COMPUSTAT database, we have about 1,556 stocks per month with valid options-implied variance observations over the period January 1996 to October 2010. The options sample is a fraction (40%) of the CRSP-COMPUSTAT universe, which has about 3,969 stocks per month with valid realized idiosyncratic variance observations. In Table 1, we provide summary statistics of selected stock characteristics for both the options sample (panel A) and CRSP-COMPUSTAT universe (panel B). Average (median) market capitalization of the options sample is about twice (four times) as big as that of the CRSP-COMPUSTAT universe. Moreover, stocks with options trading are substantially more liquid and have lower book-to-market equity ratios.

Big stocks are in general less vulnerable to market friction such as information costs (e.g., Merton (1987)). Moreover, Danielsen and Sorescu (2001) and others emphasize that options introduction substantially alleviates short-sale constraints. By excluding many small stocks and stocks without options trading, our options sample provides a statistically stringent test for both Merton's (1987) and Miller's (1977) hypotheses. On the other hand, by including mainly big stocks, our sample allows us to identify economically important anomalies that practitioners can exploit because of low trading costs.

For the time-series analysis, we use the market capitalization at the end of the previous month as the weight to construct value-weighted aggregate options-implied variance, VWAOIV. For comparison, we also construct aggregate options-implied variance using the equal weight, EWAOIV. We obtain daily VIX data from CBOE as a proxy for conditional market variance. Because trading of VIX at CBOE closes at 4:15pm ET—fifteen minutes after the close of equity trading, we use VIX of the second-to-last business day in period t as the proxy for conditional market variance of period $t+1$. For the time-series analysis, we obtain weekly and monthly market return and risk-free rate data ending in December 2010 from Kenneth French at Dartmouth College. We construct quarterly and annual returns by compounding monthly returns. We obtain stock market return predictors used in Welch and Goyal (2008) from Amit Goyal at Emory University and acquire variance premium data used in Bollerslev, Tauchen, and Zhou (2009) from Hao Zhou at the Federal Reserve Board.

In Figure 1, we plot monthly VWAOIV (solid line) along with EWAOIV (dashed line) over the January 1996 to October 2010 period. Table 2 reports their summary statistics. Consistent with the finding reported in earlier studies, e.g., Goyal and Santa-Clara (2003), EWAOIV is substantially larger than VWAOIV. The sample average is 2.6% for EWAOIV, about twice as large as the sample average of 1.4% for VWAOIV. The result indicates that small stocks are substantially more volatile than big stocks. The two variables tend to move closely to each other, with a correlation coefficient of 84%. Specifically, they increase sharply during the 2001 stock market meltdown and the 2008 financial crisis. Both variables appear to be quite persistent, with an autocorrelation coefficient of 84% and 92% for VWAOIV and EWAOIV, respectively. Nevertheless, using the augmented Dickey-Fuller test, we reject the null hypothesis of a unit root at the 1% level for VWAOIV and at the 10% level for EWAOIV.

Figure 2 plots monthly VIX (dashed line) along with VWAOIV (solid line). The two variables tend to move closely to each other, especially during the 2008 financial crisis. This is because options-implied variance is a measure of total variance, which is the sum of market variance and idiosyncratic variance in the CAPM. To illustrate this point, we write the excess return on stock i as

(1) $$R_{i,t} = \beta_i R_{M,t} + \varepsilon_{i,t},$$

where β_i is market beta, $R_{M,t}$ is the excess market return, and $\varepsilon_{i,t}$ is the idiosyncratic return. Because by definition the idiosyncratic return is orthogonal to the excess market return, total variance of stock i is

(2) $$\sigma_{i,t}^2 = \beta_i^2 \sigma_{M,t}^2 + \sigma_{i,\varepsilon,t}^2,$$

where $\sigma_{M,t}^2$ is market variance and $\sigma_{i,\varepsilon,t}^2$ is idiosyncratic variance. The aggregate total variance across N stocks is

$$(3) \qquad \sum_{i=1}^{N} \omega_{i,t}\sigma_{i,t}^2 = (\sum_{i=1}^{N} \omega_{i,t}\beta_i^2)\sigma_{M,t}^2 + \sum_{i=1}^{N} \omega_{i,t}\sigma_{i,\varepsilon,t}^2 ,$$

where the weight $\omega_{i,t}$ equals 1/N for the equal-weighted measure and equals stock *i*'s market capitalization share for the value-weighted measure. Equation (3) demonstrates a close correlation of aggregate total variance with market variance.[6] Consistent with this observation, in our data, the coefficient of correlation between VIX and VWAOIV is 84% (Table 2). Merton (1987) argues that, in the presence of market friction, both market and idiosyncratic risks affect expected stock returns. Because Merton's (1987) model implies a positive relation between aggregate *idiosyncratic* variance and future market returns, it is important to control for its comovement with market variance when we use aggregate options-implied variance to forecast excess market returns.

Figure 2 shows that VWAOIV is substantially larger than VIX, indicating that idiosyncratic variance is an important component of total variance. VIX appears to be relatively persistent in Figure 2, and Table 2 shows that it has an autocorrelation coefficient of 80%. Nevertheless, we reject the null hypothesis that VIX has a unit root at the 1% level using the augmented Dickey-Fuller test.

3. Options-Implied Variance and Future Stock Returns: Cross-Sectional Evidence

Existing studies have tested Merton's (1987) conjecture using either cross-sectional or time-series regressions. In this paper, we unify the two separate strands of research by revisiting the relation between conditional idiosyncratic variance and future stock returns using both cross-sectional and time-series regressions. Our approach alleviates the concern about data mining and helps differentiate alternative hypotheses advanced in existing literature. In this section, we investigate the cross-sectional implication that stocks with high idiosyncratic variance tend to have higher future returns than do stocks with low

[6] There are more risk factors in Merton's (1973) ICAPM. In this case, loadings on other risk factors also contribute to a stock's total variance. We will revisit this issue later.

idiosyncratic variance. In the next section, we further examine the time-series relation between aggregate options-implied variance and future excess market returns.

In Table 3, we investigate the cross-sectional relation between options-implied variance, IVOL, and future stock returns using monthly data and Fama-Macbeth regressions. In the univariate regression (column 1), the relation is negative albeit only marginally significant at the 10% level. The weak relation reflects *partly* an omitted variable problem. For example, Equation (2) shows that stocks with high market beta have large total variance, *ceteris paribus*. In a similar vein, if there are additional risk factors, as in Merton's (1973) ICAPM, total variance may correlate with loadings on these additional risk factors. To identify precisely the effect of conditional *idiosyncratic* variance on future stock returns, we control for loadings on systematic risks using commonly used determinants of the cross-section of stock returns.

In column 2 of Table 3, we include market beta, BETA, as an additional explanatory variable in the cross-sectional regression. IVOL becomes statistically significant at the 5% level, while BETA is statistically insignificant in the cross-sectional regression. The latter result should not be too surprising because existing studies find that BETA has negligible explanatory power for the cross-section of stock returns possibly because it has substantial measurement errors. Column 3 shows that the negative effect of IVOL on future stock returns becomes statistically significant at the 1% level when we control for log market capitalization (SIZE), the log book-to-market equity ratio (BM), and past returns over the period *t-7 to t-2* ($R_{t-7,t-2}$) in the cross-sectional regression.[7] Consistent with earlier studies, e.g., Fama and French (1992), SIZE correlates negatively with future stock returns and the relation is statistically significant at the 1% level.[8] The difference between the results in columns 1 and 3 reflects mainly an omitted variable problem. Specifically, IVOL correlates negatively with SIZE, e.g., high idiosyncratic variance stocks tend to have small market capitalization (e.g., Pastor and Veronesi (2003)), while both variables correlates

[7] Including BETA as an additional explanatory variable does not affect the results in any qualitative manner.
[8] The book-to-market equity effect and the momentum effect are statistically insignificant in Table 3. This result is due to the 1996 to 2010 period rather than our options sample. Specifically, as we show in Table 8, results are qualitatively similar for the CRSP-COMPUSTAT universe over the same period, while the coefficients of these two variables become statistically significant and have the expected signs for the CRSP-COMPUSTAT universe over the longer period from 1980 to 2010.

negatively with future stock returns. When we exclude SIZE from cross-sectional regressions, as in column 1, the omitted variable problem biases the effect of IVOL on future stock returns toward zero.

Jegadeesh (1990) and others document strong short-term return reversals, e.g., stocks with low returns in month *t-1* tend to have high returns in month *t*. Because there is a positive contemporaneous relation between stock returns and realized variance (e.g., Duffee (1995)), the negative relation between realized idiosyncratic variance and future stock returns documented by Ang, Hodrick, Xing, and Zhang (2006) might reflect short-term return reversals. Specifically, Huang, Liu, Rhee, and Zhang (2010) show that the predictive power of realized idiosyncratic variance for stock returns becomes negligible when controlling for one-month lagged stock returns in cross-sectional regressions. Because realized idiosyncratic variance and options-implied variance correlate closely with each other, short-term return reversals might explain the negative correlation of IVOL with future stock returns as well. To address this issue, following Huang, Liu, Rhee, and Zhang (2010), we include the one-month lagged stock return, R_{t-1}, as a control for short-term return reversals. Column 4 of Table 3 shows that, while we confirm the strong negative effect of R_{t-1} on future stock returns, the effect of IVOL on future returns remains negative and statistically significant at the 1% level. Therefore, short-term return reversals do not explain the negative relation between IVOL and future stock returns.

Amihud and Mendelson (1986) and many subsequent studies show that illiquid stocks have higher future returns than do liquid stocks. Because there is a strong positive relation between conditional stock variance and standard illiquidity measures, Spiegel and Wang (2005) argue that stocks with large idiosyncratic variance should have high expected returns. To address this issue, we include Amihud's (2002) illiquidity measure, AMIHUD, in the cross-sectional regression and report the results in column 5 of Table 3. Again, we find that the negative relation between IVOL and future stock returns remains statistically significant at the 5% level. The effect of AMIHUD on expected stock returns is negligible for two possible reasons. First, Amihud and Mendelson (1986) and many others document a significant cross-sectional illiquidity effect among small stocks, while our options sample includes largely big stocks.

Second, Ben-Rephael, Kadan, and Wohl (2008) show that the cross-sectional illiquidity effect has diminished substantially in recent periods.

Bali, Cakici, and Whitelaw (2010) show that MAX, the maximum daily stork return in month *t-1*, correlates negatively with the stock return of month *t*. Specifically, after controlling for MAX in the cross-sectional regression, the relation between realized idiosyncratic variance and future stock returns becomes negligible or even positive. Column 6 of Table 3 shows that including MAX as an additional explanatory variable does not affect the negative relation between IVOL and future stock returns.

Lastly, Ang, Hodrick, Xing, and Zhang (2006) document a strong negative relation between realized idiosyncratic variance and future stock returns. In column 7 of Table 3, we find a negative albeit statistically insignificant relation between realized idiosyncratic variance, RVOL, and future stock returns. This result is specific to the options sample. As we will discuss in Section 5, over the same sample period, the negative relation is statistically significant at the 5% level for the CRSP-COMPUSTAT universe. Because investors can express their negative opinion about a stock through trading options on the stock, stocks with options trading are less vulnerable to short-sale constraints than are stocks without options trading (e.g., Danielsen and Sorescu (2001)). Therefore, realized idiosyncratic variance forecasts future stock returns possibly because it is a measure of divergence of opinion, which has a negative effect on expected returns for stocks with binding short-sale constraints (e.g., Miller (1977)). In the next section, we will discuss this conjecture in details.

Nevertheless, column 8 of Table 3 shows that the negative relation between RVOL and future stock returns becomes statistically significant at the 5% level when we control for other commonly used cross-sectional stock return predictors. IVOL forecasts stock returns possibly because of its close correlation with RVOL and vice versa. In column 9, we investigate this issue by including both IVOL and RVOL in the cross-sectional regression. The coefficient on options-implied variance remains significantly negative at the 1% level, while the coefficient on realized idiosyncratic variance becomes insignificant. This result provides an interesting explanation for the finding by Ang, Hodrick, Xing, and

Zhang (2006). That is, realized idiosyncratic variance forecasts stock returns mainly because of its correlation with conditional variance.

To summarize, we document a strong negative cross-sectional relation between options-implied variance and future stock returns.[9]

4. Aggregate Options-Implied Variance and Future Excess Market Returns

In this section, we show that, consistent with cross-sectional evidence, there is also a strong negative correlation of aggregate options-implied variance with future excess market returns in time series data.

4.1. Value-Weighted Aggregate Options-Implied Variance

In Table 4, we report the ordinary least squares (OLS) regression results of forecasting excess market returns using VWAOIV as the proxy for aggregate conditional idiosyncratic variance. For robustness, we estimate the forecast model using nonoverlapping weekly, monthly, quarterly, and annual data. We discuss first the results for monthly data (panel B), which have been commonly used in previous studies. Row 7 shows that, in the univariate OLS regression, VWAOIV correlates *negatively* with one-month-ahead excess market returns but the relation is only marginally significant at the 10% level. VWAOIV is a measure of aggregate total variance, which, as we show in equation (3), is the sum of market variance and aggregate idiosyncratic variance. Because conditional market variance is an

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[9] Using OptionMetrics data, Diavatopoulos, Doran, and Peterson (2008) document a positive cross-sectional relation between options-implied idiosyncratic variance and future stock returns. Their results differ from ours for two reasons. First, these authors use options-implied variance of the last business day in time *t* as a proxy for the conditional variance of time *t+1*. Because cross-sectional stock returns have a positive skewness (e.g., Duffee (1995)), the different close times in options and primary markets (e.g., Battalio and Schultz (2006)) introduce a positive bias in their estimated relation between options-implied idiosyncratic variance and future stock returns. Second, Diavatopoulos, Doran, and Peterson (2008) measure a stock's idiosyncratic variance as the difference between the stock's options-implied variance and options-implied market variance (VIX) multiplied by squared market beta. Table 2 shows a strong negative relation between VIX and excess market returns. Moreover, market beta correlates closely with options-implied variance, with a positive correlation coefficient of 42% in our sample. Together with the look-ahead bias in VIX (due to its 4:15pm ET close time), their measure generates a positive bias in the estimated relation between options-implied idiosyncratic variance and future stock returns. In this paper, we address the look-ahead bias by using the next-to-last business day options-implied volatility. Moreover, we include market beta and other commonly used cross-sectional explanatory variables as controls for systematic risks instead of constructing a direct measure of options-implied idiosyncratic variance.

important determinant of conditional equity premium, the result in row 7 does not necessarily imply a negative relation between aggregate conditional idiosyncratic variance and future excess market returns.

We address the measurement error issue in two ways. First, we orthogonalize VWAOIV by VIX and use the residual, $\text{VWAOIV}^{+}_{\text{VIX}}$, to forecast excess market returns. $\text{VWAOIV}^{+}_{\text{VIX}}$ can be viewed as a proxy for aggregate conditional idiosyncratic variance in the CAPM. Moreover, as we will discuss later, our results are qualitatively similar when we control for commonly used stock market predictors as proxies for hedging risk factor(s). Row 8 of Table 4 shows that $\text{VWAOIV}^{+}_{\text{VIX}}$ correlates negatively with one-month-ahead excess market returns, and the relation is statistically significant at the 1% level.

Second, in row 9 of Table 4, we include VIX in the forecast regression along with VWAOIV. This specification is consistent with equation (24) in Merton (1987), who argues that conditional equity premium is a linear function of conditional market variance and aggregate conditional idiosyncratic variance. Again, in contrast with Merton's (1987) conjecture, we find a negative and statistically significant relation between VWAOIV and one-month-ahead excess market returns at the 1% level.[10] Consistent with Merton's (1973) ICAPM, the relation between VIX and conditional excess market returns is positive and statistically significant at the 1% level, although the relation is negative albeit statistically insignificant in the univariate regression (row 6).[11] The Wald test shows that the joint explanatory power of VWAOIV and VIX is statistically significant at the 1% level. Figure 2 shows that both VWAOIV and VIX increase sharply during the 2008 financial market crisis. To investigate whether influential observations are the main driver of our findings, in row 10, we use log transformations of VWAOIV and VIX as the forecasting variables and find qualitatively similar results.

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[10] In multivariate OLS regressions, we can obtain the coefficient on VWAOIV in two steps (see, e.g., Wooldridge (2006)). First, we run an OLS regression of VWAOIV on a constant and the other independent variable(s). Second, we run an OLS regression of excess market returns on the residual obtained from the first step. Therefore, the coefficient on VWAOIV in the bivariate regression (row 9) is identical to the coefficient on $\text{VWAOIV}^{+}_{\text{VIX}}$ in the univariate regression (row 8), while their standard errors are different.

[11] VIX is statistically insignificant in the univariate regression because of a classic omitted variables problem. Suppose ERET is the dependent variable, VWAOIV is the omitted variable with the true parameter *B1*, and VIX is the included variable with the true parameter *B2*. The point estimate of the coefficient on VIX is $B2 = B2 + \frac{Cov(\text{VIX},\text{VWAOIV})}{Var(\text{VIX})} B1$. Because *B1* is negative and the covariance of VIX with VWAOIV is positive, the point estimate of *B2* is biased downward toward zero.

As a robustness check, we investigate the relation between VWAOIV and future excess market returns using weekly, quarterly, and annual data in panels A, C, and D, respectively, of Table 4, and find qualitatively similar results. When in conjunction with VIX, VWAOIV correlates negatively with future excess market returns, and the relation is statistically significant at the 1% level. The effect of VIX on conditional excess market returns is always significantly positive as well. Moreover, using log transformations of VIX and VWAOIV does not change the results in any qualitative manner.

The adjusted R^2 increases with forecast horizons. Campbell, Lo, and MacKinlay (1997) and Cochrane (2005) argue that the adjusted R^2 increases with forecast horizons because conditional equity premium is persistent. Consistent with this interpretation, the fitted value of weekly conditional equity premium has an autocorrelation coefficient of 86% (untabulated). The adjusted R^2 appears to be quite large relative to those reported in previous studies. There are two possible explanations. First, we have a relatively short time-series sample of options-implied variance, with 178 monthly observations or 58 quarterly observations. To address partially this issue, we use overlapping 4-week and 12-week returns as dependent variables. Again, we find that VIX and VWAOIV or their log transformations jointly have significant predictive power for excess market returns. The adjusted R^2 is 5% for 4-week returns and is 11% for 12-week returns. If we use log transformations of VIX and VWAOIV, the adjusted R^2 is about 6% for 4-week returns and is 13% for 12-week returns. For brevity, we do not tabulate these results but they are available on request. Second, as we discuss in subsection 4.5, VIX and VWAOIV have significant forecasting power for market returns even when we control for other commonly used market return predictors.

4.2. Equal-Weighted Options-Implied Variance

Because small stocks are arguably more susceptible to idiosyncratic risk than are big stocks, many earlier studies, e.g., Goyal and Santa-Clara (2003), Frazzini and Marsh (2003), Brown and Ferreira (2005), and Jiang and Lee (2006), advocate for using equal-weighted aggregate idiosyncratic variance in the test of Merton's (1987) conjecture. We address this issue in Table A1 in the Appendix. Similar to results reported in Table 3, EWAOIV correlates negatively with future market returns when we control for its correlation with VIX. For brevity, unless otherwise indicated, we use VWAOIV as the proxy for aggregate conditional variance in the remainder of the paper.

4.3. Subsamples

As shown in Figure 2, both VIX and VWAOIV have big spikes during the 2008 financial crisis. To address whether this episode has significant effects on our main findings, in Table A2 in the Appendix, we investigate the relation between VWAOIV and future excess market returns using two half samples. Panels A and B report the OLS estimation results for the first half sample using levels and logs of options-implied variances, respectively. For monthly data, VWAOIV correlates negatively with future excess market returns when in conjunction with VIX, and the relation is statistically significant at the 1% level. The results are qualitatively similar for quarterly and annual data—the negative relation between VWAOIV and future excess market returns is statistically significant at the 1% level. For weekly data, the relation is negative but statistically insignificant at the conventional level. Panel C and D show that the results are qualitatively similar for the second half sample. To summarize, the negative correlation of VWAOIV with future excess market returns is robust across two half samples.

4.4. Out-of-Sample Forecast

Welch and Goyal (2008) cast doubt on existing evidence of stock market return predictability because commonly used stock market return predictors have negligible out-of-sample forecasting power. To address this issue, we conduct out-of-sample tests and report the results in Table 5. As in Lettau and Ludvigson (2001), we use the first third observations for initial in-sample regression and make out-of-sample forecast for the remaining period recursively using an expanding sample. We compare the forecasting model using VIX and VWAOIV as the predictive variables of excess market returns with the benchmark model using historical sample average as the forecast of the one-period-ahead excess market return. We compare the performance of the two forecasting models using two statistics—(1) the ratio of mean squared-forecast-error of the forecasting model to that of the benchmark model and (2) Clark and McCracken's (2001) encompassing test. To address the small sample problem, we follow Lettau and Ludvigson (2001) and use bootstrapped critical values obtained from 10,000 simulations for inferences.

Panel B of Table 5 reports the results for monthly data. The proposed forecasting model with VIX and VWAOIV as the predictive variables has a smaller mean squared-forecast-error than does the benchmark model, and the encompassing test shows that the difference in out-of-sample predictive power is statistically significant at the 10% level. We find stronger results using log transformations of VIX and VWAOIV as the predictive variables: The ratio of mean squared-forecast-error becomes smaller and the encompassing test indicates that the difference between the two forecasting models is statistically significant at the 5% level. Results are qualitatively similar or stronger for quarterly data (panel C). For weekly data, log variances have significant out-of-sample predictive power for excess market returns, while levels of variances have negligible out-of-sample predictive power.

The out-of-sample stock market return predictability is economically important as well. For example, at the monthly or quarterly frequency, if adopting a simple switching strategy, i.e., holding a market index when the expected excess market return is positive and holding a Treasury bill otherwise, we can outperform the strategy of buying and holding the market index substantially. For brevity, we do not report these results but they are available on request.

4.5. Controlling for Commonly Used Forecasting Variables

Using quarterly data, Guo and Savickas (2008) show that value-weighted aggregate realized idiosyncratic variance, VWARIV, correlates negatively with future excess market returns when in conjunction with proxies for conditional market variance. Because options-implied variance is a better measure of conditional variance than realized variance, we expect that VWAOIV should subsume the information content of VWARIV about future excess market returns if the two variables contain similar information about future excess market returns. Table 6 reports the results for monthly data. Row 1 shows that, when in conjunction with VIX, VWARIV correlates negatively with future excess market returns. However, as conjectured, the predictive power of VWARIV becomes negligible when we control for VWAOIV in the forecast regression (row 2). In contrast, the effect of VWAOIV on future market returns remains statistically significant at the 5% level. As we have shown in Section 3, options-implied variance also drives out realized idiosyncratic variance in cross-sectional regressions. These results highlight the importance of using options-implied variance because it is a better measure of conditional variance than realized variance.

Bollerslev, Tauchen, and Zhou (2009) and Drechsler and Yaron (2010) show that the variance premium—the difference between options-implied market variance and expected future realized variance—has significant predictive power for excess market returns. It is interesting to investigate whether the predictive power of VWAOIV and VIX reflects their correlations with the variance premium. Row 3 of Table 6 shows that, consistent with the finding by Bollerslev, Tauchen, and Zhou (2009) and Drechsler and Yaron (2010), the variance premium, VP, correlates positively with future excess market returns even when we control for VIX and VWAOIV. Both VIX and VWAOIV remain statistically significant at the 1% level in the multivariate regression as well. Therefore, the predictive power of VIX and VWAOIV is different from that of the variance premium.

Lastly, in rows 4 to 9, we control for the predictive variables considered in Welch and Goyal (2008), including the default premium (DEF), the term premium (TERM), the dividend yield (DP), the earnings-to-price ratio (EP), the aggregate book-to-market equity ratio (BM), and the share of equities in new issuances (NTIS). Many of the control variables have negligible predictive power for market returns. In contrast, both VIX and VWAOIV always remain statistically significant at least at the 5% level in the multivariate regressions.

We find qualitatively similar results using quarterly data (untabulated). Specifically, aggregate options-implied variance drives out aggregate realized idiosyncratic variance from the regression of forecasting excess market returns. To summarize, the predictive power of VWAOIV and VIX does not reflect their correlations with commonly used forecasting variables of stock market returns.

5. Discussion

We uncover a strong negative relation between options-implied variance and future stock returns in both cross-sectional (Section 3) and time-series (Section 4) analyses. The finding poses a challenge to Merton's (1987) under-diversification hypothesis that suggests that the relation should be positive. In this section, we investigate whether our results are consistent with alternative hypotheses advanced in existing studies. Note that cross-sectional stock return predictability does not have to be consistent with time-series stock return predictability because they may reflect different economic phenomena. For example, while market capitalization forecasts the cross-section of stock returns, it does not forecast market returns across time. Similarly, Sloan (1996) and many subsequent studies find a negative cross-sectional relation between accruals and future stock returns, while Hirshleifer, Hou, and Teoh (2009) show that value-weighted aggregate accruals correlate positively with future excess market returns. Therefore, a coherent explanation of both cross-sectional and time-series relations provides a high hurdle for alternative hypotheses. In this section, we show that both cross-sectional and time-series results are potentially consistent with Miller's (1977) divergence of opinion hypothesis.

5.1. Cross-Sectional Relation

In this subsection, we explore three alternative explanations for the negative cross-sectional relation between options-implied variance and future stock returns. First, Cao, Simin, and Zhao (2008) argue that stocks of firms with abundant investment opportunities tend to have high idiosyncratic variance. Similarly, Pastor and Veronesi (2003) and others show that stocks with low book-to-market equity ratio tend to have high idiosyncratic variance. However, in column 3 of Table 3, we find that IVOL remains a significant explanatory variable of the cross-section of stock returns when controlling for the log book-to-market equity ratio. For robustness, in column 10 of Table 3, we consider the growth rate of total assets, ΔASSET, as an alternative measure of investment opportunities. Cooper, Gulen, and Schill (2008) and others find that ΔASSET remains a strong predictor of the cross-section of stock returns even when controlling for other standard growth measures or when restricting the analysis to big stocks.

Arguably, firms with plentiful investment opportunities tend to have high growth rates of total assets. In column 10, we replicate Cooper, Gulen, and Shill's (2008) main finding that ΔASSET correlates negatively and significantly with future stock returns at the 1% level. Nevertheless, the coefficient on IVOL remains significantly negative at the 1% level with the control for ΔASSET. Our results indicate that investment opportunities do not explain the negative relation between options-implied variance and future stock returns.

Second, Johnson (2004) points out that, because a firm's stocks are call options on the firm's total assets, for levered firms, expected stock returns in general decrease with conditional stock variance. Johnson (2004) uses this hypothesis to explain the negative relation between standard deviation of analysts' earnings forecasts and future stock returns, as documented by Diether, Malloy, and Scherbina (2002). This hypothesis is directly relevant for our results because we use options-implied stock variance. Johnson (2004) proposes a straightforward test of his conjecture—the interaction term of conditional stock variance with leverage should dominate conditional stock variance in the cross-sectional regression. We investigate this refutable implication in column 11 of Table 3 by including both leverage, LEV, and its interaction term with IVOL, LEV*IVOL, in the cross-sectional regression. As in Johnson (2004), LEV is the ratio of book value of debt to the sum of book value of debt and market value of equity. We find qualitatively similar results using the ratio of book value of debt to book value of total assets (untabulated). In contrast with Johnson's (2004) conjecture, the interaction term correlates *positively* with future stock returns and such a relation is marginally significant. Moreover, the coefficient on IVOL remains negative and statistically significant at the 1% level. These findings are qualitatively similar to those reported by Ang, Hodrick, Xing, and Zhang (2009) for realized idiosyncratic variance. Therefore, the leverage hypothesis does not explain the negative relation between options-implied variance and future stock returns either.

Last, there is a close relation between stock variance and divergence of opinion both theoretically and empirically (e.g., Shalen (1993) and Harris and Raviv (1993)). The negative relation between IVOL and future stock returns is thus potentially consistent with Miller's (1977) divergence of opinion hypothesis. Specifically, Miller (1977) argue that, in the presence of short-sale constraints, divergence of opinion leads stocks to be overvalued initially and to have low returns subsequently. Boehme, Danielsen, and Sorescu (2006) emphasize that short-sale constraints are a necessary condition for Miller's (1977) conjecture. That is, we should observe the negative effect of divergence of opinion on future stock returns only for stocks that have binding short-sale constraints. One ideal measure of short-sale constraints used in the literature is the lending fees on shorted shares (e.g., D'Avolio (2002) and Boehme, Danielsen, and Sorescu (2006)). Unfortunately, we have no access to these proprietary data. Moreover, these data, when available, typically cover a period of only several months to several years, which is too short for the purpose of our analysis.[12] Alternatively, many authors, e.g., Chen, Hong, and Stein (2002), D'Avolio (2002), Asquith, Pathak, and Ritter (2005), Nagel (2005), and Saffi and Sturgess (2009) show that institutional ownership is a good proxy for short-sale constraints—increases in institutional ownership increase the supply of equity shares available for lending and thus relieves short-sale constraints. Specifically, D'Avolio (2002) shows that stocks with a large fraction of institution ownership tend to have low lending fees on shorted shares. Following this literature, we use institutional ownership as a proxy for the extent to which short-sale constraints are binding. We define the variable INST as *one minus the fraction of institution ownership*; therefore, borrowing constraints are more likely to bind as INST increases. To test Miller's (1977) hypothesis, we include INST and its interaction term with IVOL, INST*IVOL, in the cross-sectional regression. We expect that the interaction term should correlate negatively with future stock returns under Miller's hypothesis. Moreover, if divergence of opinion is the main driver of the negative relation between IVOL and future stock returns, we expect that the interaction term should drive out IVOL from the cross-sectional regression. Column 12 of Table 3 shows that, as conjectured, the interaction term correlates negatively and significantly with future stock returns at the 1% level, while the effect of IVOL on expected stock returns becomes statistically insignificant.[13] In

[12] The short interest is a potential measure of short-sale constraints. Autore, Boulton, and Braga-Alves (2011), however, find a U-shaped relation between the short interest and short-sale constraints.

[13] Merton's (1987) incomplete-information model implies that the positive relation between idiosyncratic variance and future stock returns should be more pronounced for stocks with smaller investor base. Thus, if institutional ownership is a proxy for investor base, Merton's (1987) model implies that the interaction term, INST*IVOL,

untabulated univariate regression results, we find that the coefficient on the interaction term is significantly negative (P-value 0.012) even without the control of other commonly used explanatory variables of the cross-section of stock returns.[14] Therefore, the relatively weak relation between IVOL and future stock returns in the univariate regression (column 1 of Table 3) partly reflects the fact that the divergence of opinion has negligible effects on stocks that have nonbinding short-sale constraints.

As a robustness check, in Table 7, we further investigate the interaction between IVOL and INST by forming portfolios. Because of the strong correlation of IVOL with SIZE, we control for SIZE explicitly. Specifically, in each month we first sort stocks equally into three portfolios by market capitalization. For each size tercile, we then sort stocks equally into three portfolios by INST. Last, for each INST tercile, we sort stocks equally into three portfolios by IVOL. Panels A and B of Table 7 respectively report the alphas of the equal-weighted and value-weighted portfolio returns obtained using the Fama and French (1996) three factors and the momentum factor as controls for systematic risks. The results are consistent with those obtained from the Fama and MacBeth (1973) regression. When we control for SIZE, the alphas of the hedge portfolios that are short in stocks with high IVOL and long in stocks with low IVOL increase with INST almost monotonically. More importantly, for the terciles with high INST, the alphas are both economically large (i.e., exceed 1% per month) and statistically significant (at the 1% level) for stocks with small and median market capitalization. For big stocks with high INST, the hedge portfolio alphas are economically important (about 4.5% to 6% a year) albeit statistically insignificant. Note that our results provide a lower bound of the divergence of opinion effect on future stock returns because, as we show below, stocks with options trading are less susceptible to short-sale

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should correlate positively with future stock returns. The documented negative relation between INST*IVOL and future returns and the similar negative relation between INST*RVOL and future returns (presented in Table 8) are hence at odds with Merton's (1987) implication. INST correlates positively with future stock returns in Table 3. This result is specific to the 1996 to 2010 sample. In Table 8, we show that the relation becomes insignificant in the full sample spanning the 1980 to 2010 period.

[14] Following Chen, Hong, and Stein (2002), we also use one minus the breadth of institutional ownership as an alternative short-sale constraints proxy. The untabulated results are qualitatively similar to those obtained using INST as a proxy. Specifically, the interaction term, (1-BREADTH)*IVOL, is significantly negatively related to future stock returns at the 5% level, and this interaction term drives out IVOL from the cross-sectional regression.

constraints than are stocks without options trading. With this caveat in mind, our results provide strong support for Miller's (1977) hypothesis.

In Table 3, we show that realized idiosyncratic variance correlates negatively with future stock returns mainly because of its comovement with options-implied variance (column 9). Therefore, it is possible that Miller's (1977) divergence of opinion hypothesis also explains the finding by Ang, Hodrick, Xing, and Zhang (2006). In Table 8, we investigate this issue in two ways. First, as we mentioned above, Danielsen and Sorescu (2001) and others argue that options trading can alleviate short-sale constraints. Therefore, we expect that the negative relation between realized idiosyncratic variance and future stock returns is stronger for stocks without options trading than for stocks with options trading. Consistent with this conjecture, we show in column 1 of Table 8 that, in contrast with the options sample (column 7 of Table 3), in the univariate regression, the negative relation between RVOL and future stock returns is statistically significant at the 5% level for the CRSP-COMPUSTAT universe, which include both stocks with options trading and stocks without options trading. Column 2 of Table 8 shows that the negative relation remains significant at the 5% level even when we control for other commonly used predictors of the cross-section of stock returns. In column 3, we conduct a formal test of the difference between stocks with options trading and stocks without options trading. OPTION is a dummy variable that equals 1 for stocks *without* options trading and equals 0 otherwise. As conjectured, the interaction term, OPTION*RVOL, correlates negatively and significantly with future stock returns at the 5% level, while the effect of RVOL on expected stock returns becomes statistically insignificant.[15] Second, in column 4, we use INST as a proxy for short-sale constraints. Consistent with the finding reported by Nagel (2005), we find that the interaction term, INST*RVOL, drives out RVOL from the cross-sectional regression. As a robustness check, we investigate the interaction of RVOL with INST using a longer sample over the January 1980 to June 2010 period, during which we have institutional ownership data. Column 5 shows a strong negative relation between RVOL and future stock returns (statistically significant at the 1% level).

[15] Battalio and Schultz (2011) show that during the 2008 short-sale ban, because trading costs for options increased sharply, options trading became less attractive to investors. As a robustness check, we drop the ban period from the sample and find that the result remains unchanged.

In column 6, we include INST and its interaction term with RVOL, INST*RVOL, in the cross-sectional regression and find that the interaction term again drives out RVOL. Adding other forecasting variables does not change the main results in any qualitative manner (column 7). Therefore, Miller's (1977) divergence of opinion hypothesis helps explain the negative relation between realized idiosyncratic variance and future stock returns as well.[16]

To summarize, the negative cross-sectional relation between options-implied variance and future stock returns is potentially consistent with Miller's (1977) divergence of opinion hypothesis.[17]

5.2. Time-Series Relation

In the previous subsection, we find that the negative cross-sectional relation between IVOL and future stock returns is potentially consistent with Miller's (1977) divergence of opinion hypothesis. The SEC permanent ban on naked short selling in all U.S. stocks effective from September 18, 2008 provides a natural experiment to test Miller's (1977) hypothesis using time-series data. Specifically, because the ban makes it more costly to short stocks, we expect that the negative relation between aggregate options-implied variance and future market returns should become stronger following the ban. We investigate this refutable implication in Table 9. We use the orthogonalized value-weighted aggregate options-implied variance, $\mathrm{VWAOIV}_{\mathrm{VIX}}^{+}$, as the predictive variable. The dummy variable $\mathrm{DUM}_{\mathrm{BAN}}$ equals 0 for the observations before the naked short-sale ban and equals 1 otherwise. Under Miller's (1977) hypothesis, we expect that the interaction term of $\mathrm{VWAOIV}_{\mathrm{VIX}}^{+}$ with $\mathrm{DUM}_{\mathrm{BAN}}$ should correlate

[16] Diether, Malloy, and Scherbina (2002) use the standard deviation of analysts' earnings forecasts as a proxy for divergence of opinion. Consistent with Ang, Hodrick, Xing, and Zhang (2009), we find that controlling for analyst forecast dispersion does not affect the negative relation between realized idiosyncratic variance and future stock returns in any qualitatively manner over the period 1996 to 2010. Similarly, the negative relation between options-implied variance and future stock returns remains statistically significant (at the 5% level) when we control for analyst forecast dispersion in the cross-sectional regressions.

[17] Jiang, Xu, and Yao (2009) argue that firms with poor perspective of future earnings tend to disclose less (negative) information, resulting in a high idiosyncratic variance. That is, the negative relation between idiosyncratic variance and future stock returns reflects the fact that stocks with high idiosyncratic variance is more susceptible to negative earnings news than are stocks with low idiosyncratic variance, especially for stocks with low institutional ownership. However, using options-implied variance as a measure of conditional idiosyncratic variance, we do not find that the negative relation between conditional idiosyncratic variance and future earnings news is more pronounced for stocks with lower institutional ownership.

negatively with future excess market returns. Table 9 shows that the interaction term is negative and statistically significant at the 1% level for all of weekly, monthly, and quarterly data.

5.3. ICAPM Explanation for Time-Series Relation

While the evidence in Table 9 is consistent with Miller's (1977) divergence of opinion hypothesis, it does not necessarily imply that Miller's conjecture is the only explanation of the negative time-series relation between aggregate options-implied variance and future excess market returns. We explore an alternative explanation. In Merton's (1973) ICAPM, the stock return depends on its covariances with both the excess market return and a hedging risk factor, $R_{H,t}$:

$$R_{i,t} = \beta_{iM} R_{M,t} + \beta_{iH} R_{H,t} + \varepsilon_{i,t} . \tag{4}$$

By construction, aggregate options-implied variance is approximately the sum of (1) conditional market variance, (2) conditional variance of the hedging risk factor, and (3) conditional idiosyncratic variance. In the ICAPM, conditional equity premium is a linear function of (1) conditional market variance and (2) conditional variance of the hedging risk factor if market beta of the hedging risk factor is constant:

$$ER_{M,t} = \gamma\sigma_{M,t}^2 + \lambda\sigma_{M,H,t} = \gamma\sigma_{M,t}^2 + \lambda\beta_{HM}\sigma_{H,t}^2 . \tag{5}$$

Therefore, aggregate options-implied variance forecasts excess market returns possibly because of its comovement with conditional variance of the hedging risk factor.

The ICAPM hypothesis is appealing because the ICAPM appears to provide a better explanation for both cross-sectional and time-series stock return predictability than does the CAPM. For example, many authors show that the book-to-market effect poses a challenge to the CAPM, and Fama and French (1996) argue that it reflects loadings on a hedging risk in the ICAPM. In a similar vein, many authors, e.g., Campbell (1987), document a weak or negative relation between conditional excess market return and variance, and Scruggs (1998) and Guo and Whitelaw (2006) argue that this puzzling finding is partly due to the omission of the hedging component of conditional excess market returns.

We investigate the ICAPM hypothesis in Table 10. Following Fama and French's (1996) conjecture, we use the value premium—the return difference between stocks with high and low book-to-market equity ratios—as the proxy for the hedging risk factor. This specification is consistent with the empirical results by Campbell and Vuolteenaho (2004), Brennan, Wang, and Xia (2004), Petkova (2006), and Hahn and Lee (2006) that the value premium correlates with shocks to the discount rate, a measure of investment opportunities. We construct quarterly realized variance of the value premium, V_HML, using daily value premium data obtained from Ken French at Dartmouth College.[18] Consistent with the ICAPM interpretation, Figure 3 reveals a strong correlation of VWAOIV with V_HML. Therefore, VWAOIV forecasts market returns possibly because of its correlation with V_HML and vice versa.

Row 1 of Table 10 shows that, in the univariate regression, V_HML correlates negatively with one-quarter-ahead excess market returns but the relation is only marginally significant. Following ICAPM's implication, as in equation (5), we add VIX to the forecasting regression as a proxy for conditional market variance. Row 2 shows that the negative correlation between V_HML and future market returns becomes substantially larger in magnitude and becomes statistically significant at the 1% level. Similarly, compared with that obtained from the univariate regression (row 11 of Table 3), the coefficient on VIX becomes substantially larger in the bivariate regression as well. The result again reflects an omitted variable problem. V_HML and VIX correlate positively with each other, while they have opposite effects on conditional equity premium. In row 3, we add VWAOIV to the forecast regression and find that it subsumes the information content of V_HML about future market returns. Lastly, to investigate formally whether VWAOIV forecasts market returns because of its correlation with V_HML, we regress VWAOIV on V_HML and a constant and then use the residual, $\text{VWAOIV}^{+}_{\text{V\_HML}}$ to forecast excess market returns. Consistent with the ICAPM hypothesis, we find that $\text{VWAOIV}^{+}_{\text{V\_HML}}$ has negligible predictive power even when in conjunction with VIX (row 4).

[18] Results are weaker for monthly realized variance of the value premium possibly because realized variance is a poor measure of conditional variance at the monthly frequency.

To summarize, although we find evidence that the time-series predictive power of VWAOIV for market returns is potentially consistent with Miller's (1977) divergence of opinion hypothesis, there is an alternative explanation—VWAOIV forecasts excess market returns possibly because of its comovement with the conditional variance of the hedging risk factors. Consistent with this conjecture, we find a strong correlation of VWAOIV with the realized variance of the value premium—a risk factor in the commonly used Fama and French (1996) three-factor model. More importantly, the predictive power of VWAOIV for excess market returns attenuates substantially when we control for its correlation with the realized variance of the value premium.

6. Conclusion

Many financial economists are sympathetic to the notion that investors require a positive risk premium for bearing idiosyncratic risk. Existing studies, however, provide mixed evidence. Employing options-implied variance as a measure of conditional variance, we shed new light on this important hypothesis by showing that there is little support for the under-diversification hypothesis advocated by Levy (1978), Merton (1987), Malkeil and Xu (2002) and others. Specifically, In both time-series and cross-sectional analysis, we find an unambiguously *negative* relation when controlling for other commonly used predictive variables.

Because stocks with options trading are mainly big stocks with a broad investor base, our results are potentially biased against the under-diversification hypothesis. The bias, if exists, is likely to be small. Specifically, Ang, Hodrick, Xing, and Zhang (2006) find a strong negative relation between realized idiosyncratic variance and future stock returns using all CRSP stocks, and we find that the predictive power of realized idiosyncratic variance mainly reflects its correlation with conditional variance proxied by options-implied variance. More importantly, the under-diversification hypothesis is economically unimportant if it affects only small stocks.

The negative relation between conditional variance and future stock returns is puzzling if we interpret conditional variance as a measure of risk. We show that our finding is consistent with Miller's

(1977) divergence of opinion hypothesis. Specifically, conditional variance is a measure of divergence of opinion. When pessimistic investors cannot express their negative opinions by short selling due to binding short-sale constraints, stocks with large dispersion of opinion can be overpriced initially but will have low returns subsequently. Consistent with this hypothesis, we show that the negative relation between conditional variance and future stock returns is more pronounced (1) for stocks with more stringent short-sale constraints or (2) when shorting stocks becomes more difficult. However, consistent with the conjecture of ICAPM, we also find that aggregate options-implied variance forecasts market returns possibly because of its comovement with the conditional variance of the hedging risk factors.

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Figure 1
Monthly Value-Weighted (Solid Line) and Equal-Weighted (Dashed Line) Aggregate Options-Implied Variance

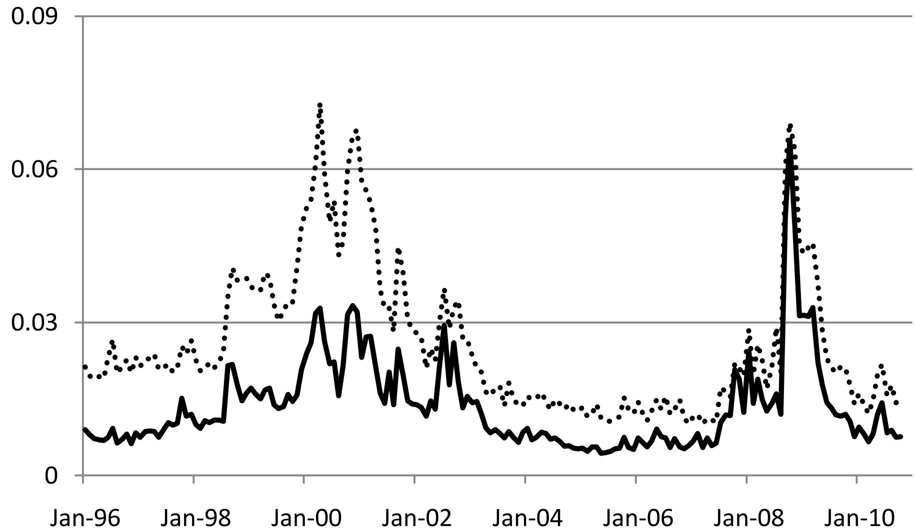

Figure 2
Monthly Value-Weighted Aggregate Options-Implied Variance (Solid Line) and Options-Implied Market Variance (Dashed Line)

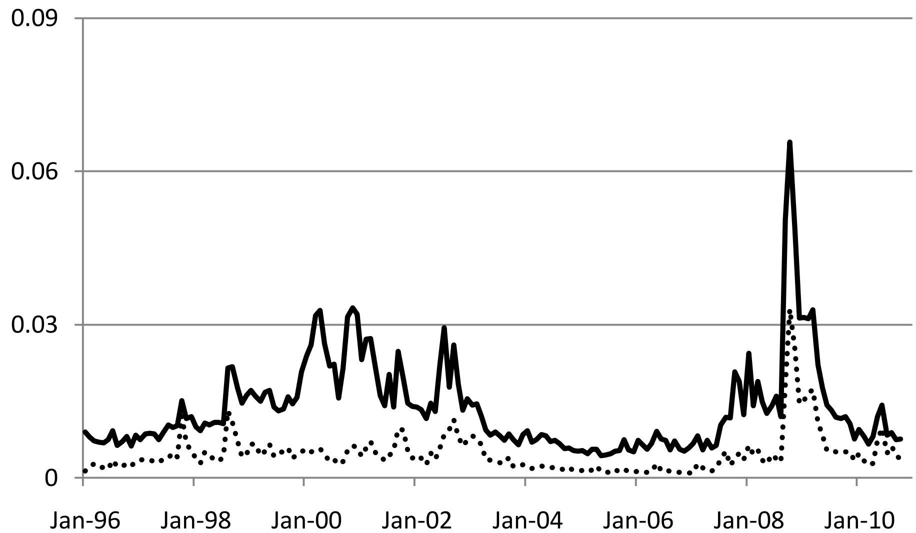

Figure 3
Value-Weighted Aggregate Options-Implied Variance (Solid Line, Left Scale) and Realized Variance of the Value Premium (Dashed Line, Right Scale)

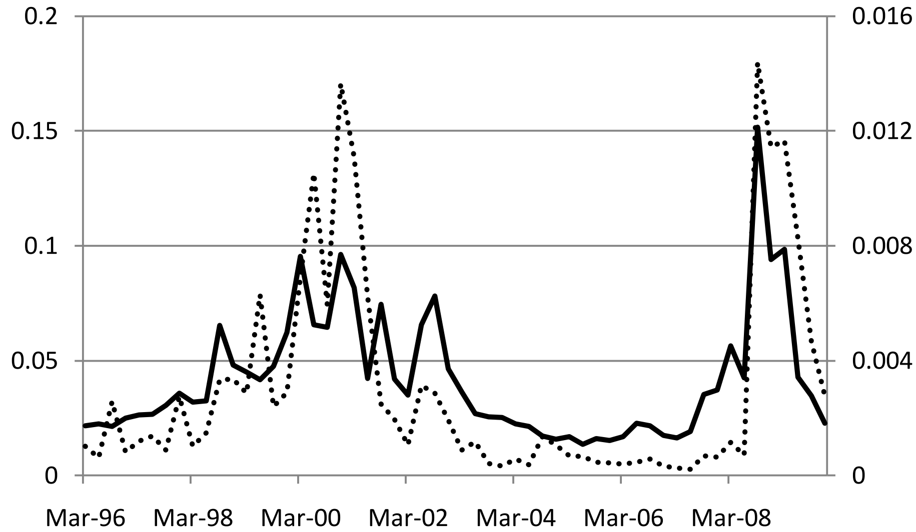

Table 1
Summary Statistics of Cross-Sectional Data: January 1996 to October 2010

	Average NOB	Mean	Median	Lower Quartile	Upper Quartile
Panel A: Merged OptionMetrics, CRSP, and COMPUSTAT					
IVOL	1556	2.444	1.560	0.832	3.014
BETA	1393	1.222	1.187	0.969	1.528
SIZE	1556	7.101	1.539	0.614	4.628
BM	1445	0.458	0.368	0.214	0.582
AMIHUD	1237	0.960	0.185	0.048	0.711
Panel B: Merged CRSP and COMPUSTAT					
BETA	3238	1.158	1.137	0.860	1.415
SIZE	3969	3.030	0.345	0.103	1.264
BM	3473	0.595	0.488	0.286	0.755
AMIHUD	3037	178.557	2.295	0.255	25.903

Note: The table reports summary statistics of selected stock characteristics. IVOL is options-implied variance in percentage. BETA is market beta. SIZE is market capitalization in billion dollars. BM is the book-to-market equity ratio. AMIHUD is Amihud's (2002) illiquidity measure.

Table 2

Summary Statistics of Time-Series Data: January 1996 to October 2010

	ERET	VIX	VWAOIV	EWAOIV
Panel A: Cross-Correlation				
ERET	1.000			
VIX	-0.421	1.000		
VWAOIV	-0.441	0.836	1.000	
EWAOIV	-0.291	0.608	0.843	1.000
Panel B: Univariate Statistics				
Mean	0.412	0.469	1.364	2.589
Standard Deviation	4.939	0.409	0.905	1.436
Autocorrelation	0.140	0.803	0.843	0.924
ADF Test	-11.444***	-3.758***	-3.845***	-2.578*

Note: The table provides summary statistics of selected variables used in the time-series regressions. ERET is the excess market return. VIX is options-implied variance of S&P 500 index. VWAOIV is value-weighted aggregate options-implied variance. EWAOIV is equal-weighted aggregate options-implied variance. We report Mean and Standard Deviation in percentage. ***, **, and * indicate significance levels at the 1%, 5%, and 10% levels, respectively.

Table 3
Options-Implied Variance and Future Stock Returns: Cross-Sectional Evidence

Variables	Model											
	1	2	3	4	5	6	7	8	9	10	11	12
IVOL	-0.198*	-0.176**	-0.255***	-0.223***	-0.216**	-0.226***			-0.220***	-0.206***	-0.269***	-0.070
	(0.106)	(0.086)	(0.089)	(0.075)	(0.084)	(0.077)			(0.070)	(0.074)	(0.085)	(0.094)
BETA		0.004		0.002	0.003	0.003		-0.000	0.001	0.003	0.002	0.002
		(0.004)		(0.004)	(0.004)	(0.003)		(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
SIZE			-0.205***	-0.196***	-0.176**	-0.166**		-0.126*	-0.189***	-0.182***	-0.171**	-0.195***
			(0.075)	(0.068)	(0.068)	(0.067)		(0.068)	(0.068)	(0.068)	(0.067)	(0.067)
BM			0.045	0.014	0.066	0.072		0.081	0.047	-0.011	0.066	0.010
			(0.133)	(0.123)	(0.118)	(0.116)		(0.134)	(0.123)	(0.121)	(0.092)	(0.123)
$R_{t-7,t-2}$			0.366	0.090	-0.039	-0.030		0.037	0.095	0.053	0.082	0.122
			(0.474)	(0.479)	(0.504)	(0.497)		(0.509)	(0.488)	(0.483)	(0.472)	(0.480)
R_{t-1}				-0.021***	-0.021***	-0.025***		-0.018**	-0.019***	-0.021***	-0.023***	-0.020***
				(0.007)	(0.008)	(0.008)		(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
AMIHUD					0.005	0.001						
					(0.028)	(0.028)						
MAX						0.026						
						(0.019)						
RVOL							-0.202	-0.149**	-0.008			
							(0.140)	(0.074)	(0.053)			
ΔASSET										-0.271***		
										(0.077)		
INST												0.006**
												(0.003)
INST*IVOL												-0.298***
												(0.108)
LEV											-0.005	
											(0.004)	
LEV*IVOL											0.316*	
											(0.185)	
Adjusted R^2	0.043	0.052	0.069	0.085	0.092	0.095	0.030	0.077	0.086	0.086	0.093	0.088

Note: The table reports Fama and MacBeth (1973) cross-sectional regression results for monthly sample over the January 1996 to October 2010 period. The dependent variable is the one-month-ahead stock return. We use merged OptionMetrics, CRSP, and COMPUSTAT data and exclude stocks with a price less than $5. IVOL is options-implied variance. BETA is market beta. SIZE is log market capitalization. BM is the log book-to-market equity ratio. $R_{t-7,t-2}$ is the sum of returns over the month *t-7* to the month *t-2*. R_{t-1} is the return of month *t-1*. AMIHUD is Amihud's (2002) illiquidity measure. MAX is the maximum daily return in month *t-1*. RVOL is realized idiosyncratic variance. ΔASSET is the year-over-year growth rate of total asset. INST is one minus the fraction of institutional ownership. LEV is book value of debt over the sum of book value of debt and market value of equity. Newey and West (1987) corrected standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. We scale the coefficients on Size, BM, $R_{t-7,t-2}$, and ΔAsset by 100.

Table 4
Value-Weighted Aggregate Options-Implied Variance and Expected Market Returns

	VIX	VWAOIV	$VWAOIV^{+}_{VIX}$	LVIX	LVWAOIV	Wald Test p-value	Adjusted R-Squared
			Panel A Weekly Data				
1	1.130						0.001
	(1.300)						
2		-0.262					-0.001
		(0.656)					
3			-2.642**				0.013
			(1.064)				
4	5.935***	-2.642**				9.229	0.014
	(1.956)	(1.106)				(0.010)	
5				0.008***	-0.011***	14.160	0.012
				(0.002)	(0.003)	(0.000)	
			Panel B Monthly Data				
6	-0.653						-0.003
	(1.665)						
7		-1.073*					0.033
		(0.555)					
8			-2.743***				0.071
			(0.750)				
9	4.409***	-2.743***				14.773	0.069
	(1.601)	(0.746)				(0.001)	
10				0.029***	-0.044***	20.569	0.059
				(0.007)	(0.011)	(0.000)	
			Panel C Quarterly Data				
11	0.440						-0.015
	(1.732)						
12		-0.909**					0.048
		(0.436)					
13			-3.575***				0.285
			(0.875)				
14	7.802***	-3.575***				21.561	0.274
	(1.783)	(0.873)				(0.000)	
15				0.129***	-0.168***	29.448	0.232
				(0.026)	(0.033)	(0.000)	
			Panel D Annual Data				
16	1.653**						0.021
	(0.689)						
17		-0.165					-0.076
		(0.552)					
18			-2.027***				0.273
			(0.571)				
19	5.922***	-2.027***				60.129	0.321
	(0.880)	(0.428)				(0.000)	
20				0.408***	-0.487***	52.234	0.278
				(0.082)	(0.069)	(0.000)	

Note: The table reports the OLS estimation results of forecasting excess market returns. The dependent variable is the one-period-ahead excess market return, i.e., the difference between the value-weighted CRSP market return and the risk-free rate. The sample spans the January 1996 to October 2010 period. VIX is options-implied variance of S&P500 index. VWAOIV is value-weighted aggregate options-implied variance. $\text{VWAOIV}^{+}_{\text{VIX}}$ is the residual from the OLS regression of VWAOIV on VIX and a constant. LVIX and LVWAOIV are the log transformations of VIX and VWAOIV, respectively. Newey and West (1987) corrected standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Out-of-Sample Forecast Tests

	Models	MSE_A / MSE_B	ENC-NEW Statistic	ENC-NEW 10% C.V.	ENC-NEW 5% C.V.
	Panel A Weekly Options-Implied Variance Data				
1	C+VIX +VWAOIV vs. C	1.015	-1.137	2.049	3.087
2	C+LVIX +LVWAOIV vs. C	0.993	4.266	2.050	3.092
	Panel B: Monthly Options-Implied Variance Data				
3	C+VIX +VWAOIV vs. C	0.986	2.971	2.096	3.245
4	C+LVIX +LVWAOIV vs. C	0.966	4.660	2.109	3.307
	Panel C: Quarterly Options-Implied Variance Data				
5	C+VIX +VWAOIV vs. C	0.964	7.621	2.268	3.454
6	C+LVIX +LVWAOIV vs. C	0.898	8.975	2.271	3.539

Note: The table compares the out-of-sample performance of the proposed forecasting model with that of the benchmark model using the historical average equity premium as the forecast of the one-period-ahead equity premium. Over the January 1996 to October 2010 period, we use one third of observations for initial in-sample estimations and make out-of-sample forecasts for the remaining observations using an expanding sample. We use two statistics to gauge the out-of-sample forecast power. First, MSE_A / MSE_B is the ratio of the mean squared-forecasting-error of the forecasting model to that of the benchmark model. Second, ENC-NEW is the encompassing test proposed by Clark and McCracken (2001). As in Lettau and Ludvigson (2001), we use bootstrapped critical values obtained from 10,000 simulations for inferences.

Table 6

Controlling for Commonly Used Forecasting Variables: Monthly Data

	VIX	VWAOIV	VWARIV	VP	DEF	TERM	DP	EP	BM	NTIS	Adjusted R-Squared
1	0.717		-1.425***								0.022
	(1.717)		(0.507)								
2	5.348***	-4.079**	1.399								0.070
	(1.812)	(1.639)	(1.200)								
3	3.557***	-2.281***		0.041***							0.101
	(1.247)	(0.728)		(0.009)							
4	4.599***	-2.428***			-2.739***						0.098
	(1.232)	(0.649)			(0.809)						
5	3.699***	-2.655***				-0.352					0.076
	(1.280)	(0.694)				(0.239)					
6	4.481***	-2.926***					-1.767				0.080
	(1.569)	(0.866)					(1.301)				
7	3.021**	-2.212**						0.361			0.071
	(1.427)	(0.817)						(0.441)			
8	3.911***	-2.906***							-0.100		0.081
	(1.282)	(0.668)							(0.063)		
9	2.696**	-2.059***								0.377**	0.092
	(1.170)	(0.585)								(0.192)	

Note: The table reports the OLS regression results of forecasting one-month-ahead excess market returns. The dependent variable is the one-period-ahead excess market return, i.e., the difference between the value-weighted CRSP market return and the risk-free rate. VIX is options-implied variance of S&P500 index. VWAOIV is value-weighted aggregate options-implied variance. VWARIV is value-weighed aggregate realized idiosyncratic variance. VP is the value premium. DEF is the default premium. TERM is the term premium. DP is the dividend yield. EP is the earnings-price ratio. BM is the aggregate book-to-market equity ratio. NTIS is the share of equities in new issuances. VIX, VWAOIV, VWARIV, and VP are available over the January 1996 to October 2010 period, and the other variables are available over the January 1996 to December 2008 period. Newey and West (1987) corrected standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7

Alphas of Portfolios Sorted by Options-Implied Variance

Panel A: Four-Factor Alphas of Equal-Weighted Portfolios

	Small Cap			Median Cap			Big Cap		
	Low INST	Median INST	High INST	Low INST	Median INST	High INST	Low INST	Median INST	High INST
Low IVOL	-0.112	0.403	0.153	0.051	0.355	-0.005	-0.012	0.150	0.070
Median IVOL	0.187	0.148	-0.138	0.014	0.218	-0.064	-0.044	0.358	0.056
High IVOL	-0.147	-0.124	-1.004	-0.182	0.169	-1.246	0.082	0.106	-0.413
Low–High	0.035	0.527	1.157***	0.233	0.187	1.241***	-0.094	0.044	0.483
T-stat	0.100	1.430	3.070	0.820	0.600	2.820	-0.290	0.160	1.110

Panel B: Four-Factor Alphas of Value-Weighted Portfolios

	Small Cap			Median Cap			Big Cap		
	Low INST	Median INST	High INST	Low INST	Median INST	High INST	Low INST	Median INST	High INST
Low IVOL	-0.049	0.400	0.168	0.008	0.396	0.005	-0.222	-0.005	-0.041
Median IVOL	0.186	-0.022	-0.165	0.068	0.153	-0.042	-0.103	0.273	0.221
High IVOL	-0.154	-0.299	-1.191	-0.101	0.231	-1.281	-0.015	0.127	-0.407
Low–High	0.105	0.699*	1.359***	0.109	0.165	1.286***	-0.208	-0.132	0.366
T-stat	0.280	1.650	3.380	0.370	0.500	2.810	-0.550	-0.410	0.790

Note: In each month, we first sort stocks equally into three portfolios by market capitalization. Within each size tercile, we sort stocks equally into three portfolios by INST, one minus the fraction of institutional ownership. Within each INST tercile, we sort stocks equally into three portfolios by IVOL, options-implied variance. We construct the equal-weighted and value-weighted monthly portfolio returns and use the Fama and French (1996) three factors and the momentum factor to control for systematic risk. The sample spans the January 1996 to October 2010 period. "Low–High" is the alpha of the portfolio that is long in stocks with low IVOL and short in stocks with high IVOL, and T-stat is the Newey-West t-statistic. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8

Realized Idiosyncratic Variance and Future Stock Returns: Cross-Sectional Evidence

Variables	Models						
	1	2	3	4	5	6	7
RVOL	-0.232**	-0.123**	-0.060	0.073	-0.301***	-0.098	-0.005
	(0.099)	(0.060)	(0.078)	(0.092)	(0.056)	(0.092)	(0.071)
BETA		0.002	-0.001	0.001			0.000
		(0.004)	(0.003)	(0.004)			(0.002)
SIZE		-0.067	-0.209***	-0.143**			-0.059*
		(0.051)	(0.053)	(0.070)			(0.033)
BM		0.118	0.122	0.100			0.180**
		(0.116)	(0.114)	(0.128)			(0.073)
$R_{t-7,t-2}$		0.406	0.005	-0.026			0.007***
		(0.429)	(0.004)	(0.005)			(0.002)
R_{t-1}		-0.019***	-0.019***	-0.017**			-0.025***
		(0.007)	(0.006)	(0.008)			(0.005)
AMIHUD		-0.020*	-0.006	-0.005			-0.010
		(0.011)	(0.009)	(0.017)			(0.006)
OPTION			-0.005**				
			(0.002)				
OPTION*RVOL			-0.186**				
			(0.076)				
INST				0.009***		0.004*	0.001
				(0.003)		(0.002)	(0.002)
INST*RVOL				-0.548***		-0.271***	-0.210**
				(0.123)		(0.083)	(0.002)
Adjusted R^2	0.020	0.062	0.067	0.084	0.014	0.020	0.055

Note: The table reports the Fama and MacBeth (1973) cross-sectional regression results for monthly sample over the January 1996 to June 2010 period in rows 1 to 4 and January 1980 to June 2010 in rows 5 to 7. The dependent variable is the one-month-ahead stock return. We use merged CRSP and COMPUSTAT data and exclude stocks with a price less than $5. RVOL is realized idiosyncratic variance. BETA is market beta. SIZE is log market capitalization. BM is the log book-to-market equity ratio. $R_{t-7,t-2}$ is the sum of returns over the month *t-7* to the month *t-2*. R_{t-1} is the return of month *t-1*. AMIHUD is Amihud's (2002) illiquidity measure. OPTION is a dummy variable, which is equal to one for stocks without options trading and is equal to zero otherwise. INST is one minus the fraction of institutional ownership. Newey and West (1987) corrected standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. We scale the coefficients on Size, BM, $R_{t-7,t-2}$, and ΔAsset by 100.

Table 9

Value-Weighted Aggregate Options-Implied Variance and Expected Market Returns

	$VWAOIV^{+}_{VIX}$	DUM_{BAN}	$VWAOIV^{+}_{VIX} * DUM_{BAN}$	Adjusted R-Squared
Week	-1.507**	-0.007	-10.187***	0.032
	(0.707)	(0.005)	(3.828)	
Month	-2.029***	-0.034**	-10.133***	0.138
	(0.510)	(0.015)	(2.308)	
Quarter	-3.110***	-0.065***	-4.092***	0.335
	(0.676)	(0.022)	(0.975)	

Note: The table reports the OLS estimation results of forecasting excess market returns. The dependent variable is the one-period-ahead excess market return, i.e., the difference between the value-weighted CRSP market return and the risk-free rate. The sample spans the January 1996 to October 2010 period. $VWAOIV^{+}_{VIX}$ is the residual from the OLS regression of VWAOIV on VIX and a constant. DUM_{BAN} is a dummy variable, which is equal to one for observations after the September 18, 2008 short-sale ban and is equal to zero otherwise. Newey and West (1987) corrected standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10
Aggregate Options-Implied Variance and Expected Market Returns

	VIX	VWAOIV	$VWAOIV^{+}_{V\_HML}$	V_HML	Adjusted R-Squared
1				-6.196*	0.039
				(3.305)	
2	2.695			-11.672***	0.076
	(1.648)			(3.298)	
3	7.308***	-3.469***		2.135	0.270
	(1.695)	(0.949)		(5.209)	
4	1.154		-1.433		0.010
	(1.392)		(1.128)		

Note: The table reports the OLS estimation results of forecasting excess market returns. The dependent variable is the one-period-ahead excess market return, i.e., the difference between the value-weighted CRSP market return and the risk-free rate. The quarterly sample spans the 1996Q1 to 2010Q4 period. VIX is options-implied variance of S&P500 index. VWAOIV is value-weighted aggregate options-implied variance. V_HML is the realized variance of the value premium constructed using daily data. $VWAOIV^{+}_{V\_HML}$ is the residual from the OLS regression of VWAOIV on V_HML and a constant. Newey and West (1987) corrected standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix: Additional Empirical Results

Table A1
Equal-Weighted Aggregate Options-Implied Variance and Expected Market Returns

	VIX	EWAOIV	$EWAOIV^{+}_{VIX}$	LVIX	LEWAOIV	Wald Test p-value	Adjusted R-Squared
			Panel A Weekly Data				
1	1.130						0.001
	(1.300)						
2		-0.113					-0.001
		(0.301)					
3			-0.546*				0.002
			(0.305)				
4	2.226	-0.546*				4.067	0.002
	(1.447)	(0.299)				(0.131)	
5				0.004*	-0.005*	4.493	0.002
				(0.002)	(0.002)	(0.106)	
			Panel B Monthly Data				
6	-0.653						-0.003
	(1.665)						
7		-0.436					0.011
		(0.298)					
8			-0.214**				0.008
			(0.232)				
9	0.437	-0.214**				5.532	0.006
	(1.869)	(0.230)				(0.063)	
10				0.010	-0.021**	6.215	0.008
				(0.009)	(0.008)	(0.044)	
			Panel C Quarterly Data				
11	0.440						-0.015
	(1.732)						
12		-0.443*					0.022
		(0.262)					
13			-0.873***				0.074
			(0.185)				
14	2.633	-0.873***				18.159	0.060
	(1.899)	(0.205)				(0.000)	
15				0.062**	-0.090***	15.122	0.071
				(0.026)	(0.023)	(0.001)	
			Panel D Annual Data				
16	1.653						0.021
	(0.689)						
17		-0.167					-0.057
		(0.246)					
18			-0.586***				0.122
			(0.149)				
19	3.428***	-0.586***				37.557	0.156
	(0.559)	(0.142)				(0.000)	
20				0.226***	-0.268***	9.624	0.060
				(0.073)	(0.096)	(0.008)	

Note: The table reports the OLS estimation results of forecasting excess market returns. The dependent variable is the one-period-ahead excess market return, i.e., the difference between the value-weighted CRSP market return and the risk-free rate. The sample spans the January 1996 to October 2010 period. VIX is options-implied variance of S&P500 index. EWAOIV is equal-weighted aggregate options-implied variance. $\text{EWAOIV}^{+}_{\text{VIX}}$ is the residual from the OLS regression of EWAOIV on VIX and a constant. LVIX and LEWAOIV are the log transformations of VIX and EWAOIV, respectively. Newey and West (1987) corrected standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A2

Value-Weighted Aggregate Options-Implied Variance and Future Market Returns: Subsamples

	VIX	VWAOIV	LVIX	LVWAOIV	Wald Test p-value	Adjusted R-Squared
			Panel A Levels of Variances and First Half Sample			
Week	5.738**	-1.165			4.641	0.007
	(2.669)	(0.829)			(0.098)	
Month	5.910***	-1.895***			13.969	0.044
	(1.932)	(0.573)			(0.001)	
Quarter	11.470***	-3.152***			48.188	0.363
	(2.055)	(0.574)			(0.000)	
Annual	7.975***	-2.087***			142.980	0.346
	(2.625)	(0.309)			(0.000)	
			Panel B Logs of Variances and First Half Sample			
Week			0.008**	-0.007**	5.249	0.007
			(0.004)	(0.004)	(0.072)	
Month			0.034***	-0.037***	11.660	0.044
			(0.012)	(0.011)	(0.003)	
Quarter			0.202***	-0.178***	40.637	0.378
			(0.040)	(0.030)	(0.000)	
Annual			0.614***	-0.560***	116.666	0.488
			(0.156)	(0.053)	(0.000)	
			Panel C Levels of Variances and Second Half Sample			
Week	15.007***	-7.709**			6.677	0.046
	(5.904)	(3.214)			(0.035)	
Month	11.702***	-7.254***			10.970	0.217
	(3.738)	(2.115)			(0.004)	
Quarter	11.741***	-6.146***			66.382	0.451
	(1.905)	(0.823)			(0.000)	
Annual	22.371***	-10.622***			25.043	0.599
	(7.136)	(3.664)			(0.000)	
			Panel D Logs of Variances and Second Half Sample			
Week			0.012***	-0.018***	11.352	0.019
			(0.003)	(0.007)	(0.003)	
Month			0.038***	-0.065***	10.237	0.094
			(0.012)	(0.023)	(0.006)	
Quarter			0.111***	-0.180***	6.936	0.163
			(0.045)	(0.069)	(0.031)	
Annual			0.323**	-0.392*	5.563	-0.258
			(0.138)	(0.207)	(0.062)	

Note: The table reports the OLS estimation results of forecasting excess market returns for two half samples of the January 1996 to October 2010 period. The dependent variable is the one-period-ahead excess market return, i.e., the difference between the value-weighted CRSP market return and the risk-free rate. VIX is options-implied variance of S&P500 index. VVAOIV is value-weighted aggregate options-implied variance. LVIX and LVWAOIV are the log transformations of VIX and VWAOIV, respectively. Newey and West (1987) corrected standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.