Differential Pricing of Stock Market Volatility Risks *

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Abstract

This paper studies the pricing of realized, option implied (i.e., expected risk neutral volatility), and expected (physical) market volatilities in the cross-section of stock returns. Consistent with the notion that volatility shocks are viewed as bad and investors pay a premium for hedging against increases in volatility, I find that stocks with high sensitivities to changes in realized volatility and expected volatility have significantly low average returns. On the other hand, implied volatility is not priced in the cross-section of stock returns. The differential pricing of market volatility risks is hard to reconcile with standard theories of the volatility risk premium, but is potentially consistent with segmentation between options and equity markets.

JEL classification: G12

Keywords: the pricing of volatility risk, realized volatility, option implied volatility, expected volatility, the cross-section of stock returns, market segmentation

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1 Introduction

The behavior of stock market volatility is hard to explain. Shiller (1981) shows that stock prices appear to fluctuate too much relative to the ex-post variability of dividends. Closely related, LeRoy and Porter (1981) also confirm "excess volatility" using tests based on implied variance bounds. Furthermore, Schwert (1989) finds the dynamics in aggregate stock volatility are also puzzling in that common measures of economic activities can only explain a small part of movements in volatility, especially during the Great Depression.

This paper contributes to the literature by documenting that various measures of stock market volatility are priced differently and this differential pricing of volatility risks cannot be explained by existing theories of volatility. Stock market volatility is inherently latent and can be measured in different ways. Figure 1 plots three measures of stock market volatility over the sample period 1986 - 2020. The first one is realized volatility which is calculated from intraday data and reflects return variation that has been realized. The second one is the implied volatility extracted from options market. Option implied volatility is the expected volatility under the risk neutral measure and potentially embedded with a time varying risk premium component. The third measure is the expected volatility under the physical measure (expected volatility, hereafter) which reflects genuine expectation about future volatility.[1] Figure 1 shows that while the three measures of stock market volatility share common patterns and respond similarly to changes in underlying economic conditions, they are not perfectly correlated and each has its own idiosyncratic dynamics.

This paper focuses on the pricing of realized, implied, and expected market volatilities in the cross-section of stock returns. The empirical strategy closely follows Cremers, Halling, and Weinbaum (2015) and Ang, Chen, and Xing (2006) by examining whether stocks with

[1] With a abuse of notation, I will refer to the expected physical volatility as expected volatility.

higher volatility betas have lower average returns contemporaneously. A contemporaneous relation between factor loadings and average returns is the foundation of a cross-sectional risk-return relation. Using both portfolio sorts and Fama-MacBeth regressions, I find that realized and expected market volatilities are negatively priced in the cross-section of equity returns. Stocks that perform well when realized and expected market volatilities are high earn significantly lower average returns. This is consistent with the notion that aggregate volatility shocks are viewed as bad and investors pay a premium for hedging against increases in volatility. In contrast, option implied market volatility is not priced in the cross-section. There is no statistically significant relationship between stock returns and implied volatility betas. These findings are robust to different empirical implementations. I further investigate how the pricing of realized and expected market volatilities varies across different stock characteristics. While the pricing of realized and expected volatilities is pervasive, the effect is more stronger among stocks that are small and have high volume, high volatility, large coskewness, and large cokurtosis.

The differential pricing of stock market volatility risks is hard to reconcile with existing theories. In intertemporal asset pricing models (e.g., Merton, 1973; Campbell, 1993, 1996; Campbell, Giglio, Polk, and Turley, 2018) in which market volatility is a state variable that drives the investment opportunity set, investors pay a premium to hedge against changes in market volatility because increasing volatility represents a deterioration in future investment opportunity set. This implies that realized, implied, and expected market volatilities could carry different risk premiums if they contain different information about future investment opportunities. In the data, however, option implied volatility predicts future returns and volatility similarly to realized and expected volatilities, which suggests that investors should equally care about fluctuations in implied volatility and be willing to pay a premium to hedge against increases in implied volatility.

Another theory of the volatility risk premium relates the pricing of volatility risk to downside protection (e.g., Bakshi and Kapadia, 2003; Ang, Hodrick, Xing, and Zhang, 2006), as periods of high volatility tend to coincide with downward market movements. However, this theory cannot explain why realized and expected market volatilities carry a negative risk premium but implied volatility does not. In the data, implied volatility comoves more negatively with index returns than both realized and expected volatilities, and therefore one would expect, if anything, implied volatility should be priced more strongly.

The differential pricing of realized, implied, and expected market volatilities is potentially consistent with market friction and segmentation between options and equity markets. Compared to equity investment, option trading involves significant constraints (e.g., high transaction costs and margin requirement), and therefore options market may be segmented from equity market and option implied volatility may not reflect the preferences of the average investor. In addition, existing studies also suggest that financial intermediaries play an important role in options markets and option prices are affected by financial intermediaries' ability to bear risk and take on leverage. See, among others, Barras and Malkhozov (2016), Chen, Joslin, and Ni (2019), and Gârleanu, Pedersen, and Poteshman (2009). Option implied volatility is not priced in the cross-section of stock returns because it captures not only shocks to the underlying economy but also shocks that are specific to options market.

Related Literature

The seminal articles by Shiller (1981) and LeRoy and Porter (1981) demonstrate that the level of stock market volatility is too high relative to standard models with rational expectation and constant discount rate. Their findings have motivated many subsequent studies. For example, Gabaix, Gopikrishnan, Plerou, and Stanley (2006) develop a model in which excess volatility is caused by trades of large institution investors. Adam, Marcet, and Nicolini (2016) show that consumptions-based asset pricing models with time-separable preferences can generate realistic amounts of stock price volatility with small deviation from rational expectation. My paper differs from this literature in that I focus on the pricing of stock market volatility risk rather than the level of volatility.

This paper is closely related to Dew-Becker, Giglio, Le, and Rodriguez (2017) and Dew-Becker, Giglio, and Kelly (2021). Using derivatives data, the two papers show that exposure to realized volatility earns a significant premium whereas exposure to implied volatility does not. Confirming their results, I find that stocks with high sensitivities to realized market volatility risk have significantly low average returns, whereas stocks with high sensitivities to implied volatility do not seem to earn a risk premium. Moreover, I also show that exposure to expected volatility is priced with a significantly negative risk premium. This finding is consistent with Bloom (2009) and Bloom, Floetotto, Jaimovich, SaportaEksten, and Terry (2018) which argue that uncertainty shocks lead to a drop in aggregate output and employment, to the extent that expected volatility is a good proxy for uncertainty.

There are several previous studies that investigate the pricing of volatility risk in the cross-section of stock returns. Cremers, Halling, and Weinbaum (2015) use a novel option trading strategy as a proxy for aggregate volatility risk, finding that volatility risk is negatively priced in the cross-section. Adrian and Rosenberg (2008) extract short-run and long-run components of market volatility by fitting a GARCH-type model to index returns and further show that the price of risk is negative and significant for both components. Ang, Hodrick, Xing, and Zhang (2006) document that innovations in the VIX carry a statistically significant negative price of risk, while Chang, Christoffersen, and Jacobs (2013) find a insignificant price of risk for option implied volatility.[2] This paper contributes to the literature by examining the pricing of different measures of market volatility risk in a unified empirical framework and

[2]My results with implied volatility are more consistent with Chang, Christoffersen, and Jacobs (2013). The difference could well be driven by the differences in sample period and empirical strategy.

highlights the implications of differential pricing of realized, implied, and expected volatility risks.

There is a separate literature that examines the pricing of volatility risk using options and volatility claims such as VIX futures and variance swaps. See, among others, Bates (2000), Pan (2002), Coval and Shumway (2001), Bakshi and Kapadia (2003), Eraker and Wu (2014), Cheng (2019), and Egloff, Leippold, and Wu (2010). This study differs from this literature in that the focus here is on the pricing of volatility risk in the equity market. Using the cross-section of stock returns allows me to easily control for exposures to common risk factors that have been shown to be related to expected returns.

Lastly, this study is related to the long standing literature that examines the time series relation between market volatility and the expected return on the market. The empirical evidence regarding the mean-variance relation is inconclusive.[3] Different from these papers, this study focuses on the cross-sectional pricing of market volatility risk.

The rest of the paper is organized as follows. Section 2 computes and compares realized, option implied, and expected market volatilities. Section 3 presents the empirical results on the pricing of the three measures of market volatility risk in the cross-section of stock returns and discusses the implications of these findings. Section 4 contains robustness analysis, and Section 5 concludes the paper.

[3] The empirical evidence regarding the mean-variance relation is inconclusive. Some studies find a positive relation (e.g., Scruggs, 1998; Ghysels, Santa-Clara, and Valkanov, 2005; Guo and Whitelaw, 2006; Pastor, Sinha, and Swaminathan, 2008; Lundblad, 2007; Ludvigson and Ng, 2007), but others report a negative relation (e.g., Campbell, 1987; Turner, Startz, and Nelson, 1989; Campbell and Hentschel, 1992; Glosten, Jagannathan, and Runkle, 1993; Brandt and Kang, 2004) or find no statistically significant relation (e.g., French, Schwert, and Stambaugh, 1987).

2 Measuring Stock Market Volatility

This section constructs and compares three measures of stock market volatility over the sample period from January 1986 to December 2020. Throughout the paper, stock market volatility refers to the volatility of the S&P 500 index. The first volatility measure is realized volatility (RV), which is back-forward looking and reflects historical volatility that has been realized. The recent realized volatility literature highlights using high frequency data can lead to more precise estimates of realized volatility. The basic idea dates back to Merton (1980)'s insight: volatilities can be approximated arbitrarily well as the sampling frequency goes to infinity.[4] Motivated by this literature, I compute daily realized volatility of the S&P 500 index as the square root of the sum of the squared 5 min log index returns.[5] I obtain intraday price data on the S&P 500 index from Thomson Reuters Tick History database.

The second volatility measure is option implied volatility (IV) which is inferred from options market. Formally, option implied volatility is the expected volatility under the risk neutral measure. While it is a forward looking measure, implied volatility is potentially embedded with a time varying risk premium component. The first generation of option implied volatility measures is based on inverting a parametric option pricing model such as the the Black-Scholes-Merton model (Black and Scholes, 1973; Merton, 1973). More recently, a number of papers demonstrate that option implied volatility can be calculated in an essentially model free way without relying on any option pricing model (see, among others, Dupire, 1994; Neuberger, 1994; Britten-Jones and Neuberger, 2000; Jiang and Tian,

[4]The theoretical properties of realized volatility are formally established by a number of studies including Andersen, Bollerslev, Diebold, and Ebens (2001), Andersen, Bollerslev, Diebold, and Labys (2003), and Barndorff-Nielsen and Shephard (2002).

[5]I focus on 5-minute interval because Liu, Patton, and Sheppard (2015) show that it is difficult to outperform five-minute realized variance even with more sophisticated sampling techniques. Moreover, following the literature (e.g., Bollerslev, Tauchen, and Zhou, 2009), I treat overnight and weekend as an additional 5-minute interval.

2005). In this paper, I construct an extended time series of option implied volatility over the sample period from 1986 to 2020 by combining the VIX index, which is based on the model-free approach, and the VXO index, which is based on inverting the Black-Scholes-Merton model. Specifically, I use the VIX index as a proxy for implied volatility over the sample period from 1990 to 2020. Prior to 1990 when the VIX index is not available, I use the VXO as a proxy for implied volatility.[6] I download the data on VIX and VXO from the Chicago Board Options Exchange (CBOE) website.

The third volatility measure is the expected volatility under the physical measure (expected volatility or EV). The expected volatility reflects the genuine expectation of future volatility and does not contain any risk premium. Estimating EV requires one to specify a statistical forecasting model and estimate the conditional expectation of future realized volatility. Following Bekaert and Hoerova (2014), I consider the following model:

$$\log RV^2_{t\to t+22} = \delta_0 + \delta_1 \log RV^2_{t-22\to t} + \delta_2 \log RV^2_{t-5\to t} + \delta_3 \log RV^2_{t-1\to t} + \delta_4 \log VIX^2_t + \epsilon_{t\to t+22}, \quad (1)$$

where $RV^2_{t-22\to t}$, $RV^2_{t-5\to t}$, and $RV^2_{t-1\to t}$ represent realized variances over the past month (22 trading days), week (5 trading days), and day, respectively.[7] I estimate the above regression based on full sample data and take the (square root of) fitted values as the expected volatilities. Note that as with the implied volatility, the expected volatility is measured over a horizon of one month. Section 4.4 conducts robustness analysis with respect to the volatility

[6]The CBOE introduced the original version of the VIX volatility index (now called VXO) in 1993, which was based on the average BSM implied volatility of S&P 100 at-the-money options. The CBOE provides historical data on VXO going back to 1986. In 2003, the CBOE developed a new VIX index. The new VIX index is based on the model-free approach. The CBOE provides historical data on the VIX back to 1990. Despite the difference in methodology, VIX and VXO are highly correlated.

[7]Because realized variances are approximately log normal, it is more appropriate to forecast logarithmic variance with linear models. The log specification also ensures volatility forecasts always remain positive.

forecasting model.

Panel A of Table 1 reports the summary statistics of the three stock market volatility measures. Throughout the paper, I express market volatility in annualized volatility percentage term. Consistent with the findings in Carr and Wu (2009) and Bollerslev, Tauchen, and Zhou (2009), implied volatility is on average higher than realized and expected volatilities (19.92% v.s 12.45% and 13.83% per year). Moreover, all three measures of stock market volatility exhibit positive skewness and large kurtosis.

Figure 1 plots the three measures of market volatility over the 1986-2020 sample period. Realized volatility, implied volatility, and expected volatility follow common patterns and respond similarly to changes in underlying economic conditions. However, perhaps more importantly, Figure 1 also shows that the three volatility measures are not perfectly correlated and each exhibits its own idiosyncratic dynamics. For example, realized volatility reached the historical high on March 16, 2020 at the beginning of the COVID-19 pandemic whereas the all time high of implied volatility occurred on October 19, 1987 (the Black Monday) when the S&P 500 index dropped by more than 20%. Moreover, the expected volatility is smoother than implied volatility. This is not entirely surprising as the time varying risk premium is removed.

To further investigate the imperfect co-movements among different volatility measures, Panel B of Table 1 reports pairwise correlations of the changes in the three volatility measures. Realized volatility and expected volatility have a high correlation of 0.9, but their correlations with implied volatility is modest, 0.31 and 0.5 respectively. Lastly, Panel B shows that all three volatility measures are negatively correlated with index returns. The negative correlation between index returns and volatility has been well documented and is often referred to as the leverage effect in the literature (e.g., Black, 1976; Christie, 1982).

3 The Pricing of Realized, Implied, and Expected Market Volatilities

This section presents main results on the pricing of realized, implied, and expected market volatility risks in the cross-section of stock returns. Section 3.1 discusses the empirical design. Section 3.2 considers portfolio sorts. Section 3.3 reports the results of Fama-MacBeth regressions. Section 3.4 investigates how the pricing of volatility risks vary across different stock characteristics. Section 3.5 explores the implications of the differential pricing of market volatility risks.

3.1 Empirical Design

This paper conducts an investigation of different measures of stock market volatility risk as pricing factors in the cross-section of stock returns. The empirical design closely follows Ang, Chen, and Xing (2006) and Cremers, Halling, and Weinbaum (2015) by considering the the contemporaneous relation between realized factor loadings and realized stock returns. Uncovering a contemporaneous effect is important because a contemporaneous relation between factor loadings and average returns is the foundation of a cross-sectional risk-return relation (e.g., Fama and French, 1993; Jagannathan and Wang, 1996).

To measure a stock's sensitivity to market volatility risk, I follow Ang, Chen, and Xing (2006) and Cremers, Halling, and Weinbaum (2015), and estimate the following time series regressions using daily data over rolling annual periods:

$$R_t^i = \alpha_t^i + \beta_{MKT,t}^i * MKT_t + \beta_{RV,t}^i * \Delta RV_t + \epsilon \tag{2}$$

$$R_t^i = \alpha_t^i + \beta_{MKT,t}^i * MKT_t + \beta_{IV,t}^i * \Delta IV_t + \epsilon \tag{3}$$

$$R_t^i = \alpha_t^i + \beta_{MKT,t}^i * MKT_t + \beta_{EV,t}^i * \Delta EV_t + \epsilon \tag{4}$$

where R_t^i is the excess return of stock i, MKT_t is the excess return of the market, and ΔRV_t, ΔIV_t, and ΔEV_t denote changes in realized, implied, and expected market volatilities. As in Ang, Chen, and Xing (2006) and Cremers, Halling, and Weinbaum (2015), I consider a two-factor specification and only include the market factor when estimating volatility betas. However, I control for exposures to other systematic risk factors extensively in the cross-sectional tests. The empirical analysis focuses on U.S. equity returns from CRSP and includes all stocks with an average stock price above $3 during the previous year.

3.2 Portfolio Sorts

This section constructs quintile portfolios with heterogeneous exposures to market volatility risk and compares the relative performance of these portfolios contemporaneously. If volatility risk is priced, stocks with different volatility betas would exhibit different returns on average. Specifically, for each month in my sample, I sort stocks into five quintile portfolios based on their sensitivities to market volatility risk, which are estimated from the time-series regressions in equations (2)-(4) using daily data over the past 12 months, so that portfolio L contains stocks with the lowest volatility betas, and portfolio H contains stocks with the highest volatility betas. I then compute the returns of these portfolios over the same 12-month period, using both equal-weighting and value-weighting schemes. Evaluating annual returns at the monthly frequency employs overlapping information, which introduces autocorrelation. Following Cremers, Halling, and Weinbaum (2015), I calculate t-statistics using Newey and West (1987) standard error with 12 lags.

Table 2 reports the averages returns of quintile portfolios sorted on $\beta_{RV,t}$, $\beta_{IV,t}$, and $\beta_{EV,t}$, as well as the average returns, CAPM alphas, and Fama-French Three-Factor Model alphas of a hedge portfolio that is long the highest quintile portfolio and short the lowest quintile portfolio, denoted as H-L. Panels A and C of Table 2 show that average stock returns exhibit a negative and statistically significant relationship with both realized and expected volatility betas. For example, when sorting on $\beta_{RV,t}$ ($\beta_{EV,t}$), the average returns of equally weighted portfolios decrease monotonically from 20.4% (20.9%) per year for portfolio L to 12.1% (12.0%) per year for portfolio H. The return spreads between the two extreme portfolios are statistically significant with a Newey-West t-stat of -5.149 and -5.371 respectively, and cannot be explained by the CAPM or the Fama-French Three-Factor Model. Panels A and C also confirm that the pricing of realized and expected market volatilities holds for value-weighted portfolios as well. A negative volatility risk premium is consistent with the notion that volatility shocks are viewed as bad and investors are willing to pay a premium for hedging against increases in volatility.

In contrast, Panel B of Table 2 shows that there is no statistically significant relationship between stock returns and implied volatility betas. The average stock return first decreases and then increases with $\beta_{IV,t}$. The return difference between stocks with highest and lowest sensitivities to changes in implied volatility is statistically insignificant. This result is somewhat surprising because it suggests that investors don't view increases in option implied volatility as being bad and do not pay a premium to hedge implied volatility risk. Section 3.5 contains a detailed discussion on the implications of differential pricing of market volatility risks.

3.3 Fama-MacBeth Regressions

This section estimates Fama and MacBeth (1973) cross-sectional regressions to control as comprehensively as possible for exposures to other systematic risk factors that have been shown in the existing literature to be related to expected stock returns. For each month in my sample, I estimate the following cross-sectional regressions:

$$R_t^i = \gamma_{0,t} + \gamma_{RV,t} * \beta_{RV,t}^i + \Phi_t * Z_t^i + \epsilon \tag{5}$$

$$R_t^i = \gamma_{0,t} + \gamma_{IV,t} * \beta_{IV,t}^i + \Phi_t * Z_t^i + \epsilon \tag{6}$$

$$R_t^i = \gamma_{0,t} + \gamma_{EV,t} * \beta_{EV,t}^i + \Phi_t * Z_t^i + \epsilon \tag{7}$$

where as before $\beta_{RV,t}^i$, $\beta_{IV,t}^i$, and $\beta_{EV,t}^i$ are the volatility betas with respect to realized, implied, and expected market volatilities, R_t^i is the contemporaneous 12-month stock return, and Z_t^i is a vector of factor loadings estimated over the same 12-month period.

Table 3 reports the time-series averages of the cross-sectional γ and Φ estimates, along with Newey and West (1987) t-statistics which adjust for autocorrelation and heteroscedasticity. Columns 1 to 3 report the results for the first specification where I estimate a univariate regression of stock returns against their volatility betas without any controls. Consistent with the sorting results, the slope coefficients on β_{RV} and β_{EV} are strongly negative and statistically significant, while the slope coefficient on β_{IV} is insignificant. Columns 4 to 6 show the results for the second specification in which I control for the exposure to the market factor in the CAPM. The coefficients on realized and expected volatility betas decrease but still highly significant. Columns 7-9 consider the Fama-French 3-Factor Model and add exposures to size and value factors as additional controls. In this case, realized and expected volatility betas remain statistically significant, and interestingly implied volatility beta also becomes marginally significant. The final two specifications include systematic risk factors in the 5-Factor model of Fama and French (2015) (columns 10-12) and the 5-factor q-factor model of Hou, Mo, Xue, and Zhang (2021) (columns 13-15). The results suggest that the strong negative relationship between stock returns and realized and expected volatility betas still persists even after accounting for exposures to systematic risk factors in the Fama-French 5-factor and the q-factor models. In contrast, there is no statistically significant relationship between stock returns and implied volatility beta.

Table 3 also shows that the slope coefficient on the market factor is positive and statistically significant, which is consistent with the CAPM prediction. Of course, this does not imply the CAPM holds because the variation in expected returns cannot be explained by the market beta alone.

In summary, the results in Table 3 confirm the sorting results in Table 2. Realized and expected volatilities are strongly and negatively priced in the cross-section of stock returns. Stocks that have high betas with respect to realized and expected market volatilities earn significantly lower average returns and this finding cannot be explained by exposures to other common risk factors. On the other hand, implied market volatility does not seem to be priced in the cross-section.

3.4 How Does the Pricing of Volatility Risk Vary Across Characteristics?

The previous section shows that realized and expected market volatilities carry a negative and statistically significant risk premium. This section further studies how the pricing of market volatility risk varies across different stock characteristics via double sorts. Each month I first form five quintile portfolios based on some stock characteristic, and then within each quintile stocks are further sorted into five quintile portfolios according to $\beta_{RV,t}$ and $\beta_{EV,t}$. I consider a variety of well known characteristics including size, book-to-market, total volatility, volume, liquidity, coskewness, and cokurtosis.[8] For brevity, I report double sorting results only for equally weighted portfolios. The results with value-weight portfolios are very similar.

Panel A of Table 4 reports the difference in average returns between the two extreme portfolios with highest and lowest $\beta_{RV,t}$ within each quintile portfolio sorted by characteristics. The results suggest that the pricing of realized volatility is pervasive. Stocks with highest sensitivities to realized market volatility continue to earn significantly low average returns across most characteristic quintile. Moreover, the effect is more stronger among stocks that are small and have high volume, high volatility, large coskewness, and large cokurtosis. For example, the H-L return difference is -15.7% per year among smallest stocks whereas it drops, in magnitude, to -4.3% per year among stocks with largest market cap.

Pane B of Table 4 reports the corresponding results for expected market volatility. The pricing of expected volatility is overall very similar to that of realized volatility. A notable difference is that the pricing of expected volatility risk tends to be more stronger for value stocks than growth stocks. In particular, the return spread is -8.9% per year among growth stocks while it increases, in magnitude, to -12.2% per year for value stocks.

3.5 Implications

The previous sections document strong statistical evidence for the pricing of realized and expected market volatilities in the cross-section of stock returns, while find no evidence that option implied market volatility risk is priced. These results suggest that investors

[8]Size and book-to-market are measured at the beginning of each annual period while total volatility, volume, liquidity, coskewness, and cokurtosis are calculated contemporaneously over the same 12-month period.

view increases in realized and expected market volatilities as bad and pay a premium to hedge against them. On the other hand, shocks to option implied market volatility are not associated with high marginal utility.

The differential pricing of realized, implied, and expected market volatility risks is difficult to reconcile with standard theories of the volatility risk premium. In intertemporal asset pricing models (e.g., Merton, 1973; Campbell, 1993; Campbell, Giglio, Polk, and Turley, 2018), if market volatility is a state variable that drives the investment opportunity set, investors pay premium to hedge against changes in market volatility because increasing volatility represents a deterioration in future investment opportunity set. Investment opportunities in the stock market can deteriorate either because expected stock returns decline or because the volatility of stock returns increases. As such, realized, implied, and expected market volatilities can carry different prices of risk if they relate to future returns and volatility differently. To test this hypothesis, I estimate predictive regressions in which I use three measures of market volatility to forecast futures returns and volatility over different horizons (h) ranging from 1 month to 12 months:

$$r_{t\to t+h} = \alpha_{t+h} + \beta_{t+h} * x_t + \epsilon_{t+h}, \tag{8}$$

$$rv_{t\to t+h} = \alpha_{t+h} + \beta_{t+h} * x + \epsilon_{t+h}, \tag{9}$$

where $r_{t\to t+h}$ and $rv_{t\to t+h}$ are future returns and future realized volatility respectively, and x is realized, implied, or expected market volatilities. I estimate the above predictive regressions at daily frequency and use Hansen and Hodrick (1980) standard errors to account for overlapping returns.

Table 5 reports the predictive regression results. First, all three measures of market volatility are positively but insignificantly related to futures stock market returns with very low R^2, confirming the week risk return trade off documented in the literature (e.g., French, Schwert, and Stambaugh, 1987). On the other hand, realized, implied, and expected market volatilities are strong predictors of future realized volatility. Overall Table 5 shows that realized, implied, and expected market volatilities are very similar in terms of forecasting future returns and volatility and therefore, according to intertemporal asset pricing models, should be priced similarly, which is inconsistent with the data.

Another theory of the volatility risk premium relates the pricing of volatility risk to downside protection. Investors want to hedged changes in market volatility because of the so-called leverage effect: periods of high volatility tend to coincide with downward market movements. The leverage effect, however, cannot explain the differential pricing of realized, implied, and expected market volatilities. As Table 1 shows, option implied volatility has a more negative correlation with index returns than both realized and expected volatilities, and therefore we would expect, if anything, implied volatility should be more strongly priced and carry a larger risk premium.[9]

The differential pricing of market volatility risks is potentially consistent with segmentation and friction between index options and equity markets. Options market may be segmented from equity market and option implied volatility may not reflect the preferences of the average investor because, unlike equity investment, option trading involves significant constraints (e.g., high transaction costs and margin requirement) that limit investor participation. Moreover, a growing literature (e.g., Barras and Malkhozov, 2016; Chen, Joslin, and Ni, 2019; Gârleanu, Pedersen, and Poteshman, 2009) suggests that financial intermediaries play a key role in index options market and option prices are affected by financial intermediaries' ability to bear risk and take on leverage. As such, option implied volatility

[9] Hu, Jacobs, and Seo (2019) demonstrate that covariance is a more relevant measure for the variance risk premium. In unreported results, I find that implied volatility also has a larger covariance (e.g., more negative) with index returns than realized and expected volatilities.

captures not only shocks to the economic fundamentals but also shocks that are specific to option markets. Option implied volatility is not priced in the cross-section of stock returns because equity investors may not want to hedge shocks that are specific to options market.

4 Robustness

This section investigates the robustness of the results in Table 2 to a number of implementation choices. Section 4.1 examines the effect of penny stocks. Section 4.2 analyzes if the empirical results are driven by a few data points. Section 4.3 studies whether the findings are robust to other estimation windows for computing volatility betas. Section 4.4 considers an alternative forecasting model for estimating expected market volatility.

4.1 Excluding Penny Stocks

The main analysis excludes stocks with price below \$3. To further reduce the effect of penny stocks, this section repeats the sorting exercise by excluding stocks with an average price below \$5. The results are reported in Table 6. Consistent with the benchmark results, I find average stock returns exhibit a negative and statistically significant relationship with $\beta_{RV,t}$ and $\beta_{EV,t}$, whereas the relationship between stock return and $\beta_{IV,t}$ is not significant.

4.2 Subsample Analysis

To ensure the empirical findings are robust to potential outliers, this section repeats the sorting exercise by excluding the Great Recession (December 2007 to June 2009). Table 7 shows that excluding the Great Recession does not affect the conclusions. Confirming the benchmark results, stocks with high $\beta_{RV,t}$ and $\beta_{EV,t}$ continue to earn significantly lower average returns. In unreported results, I also examine a sample without the 1987 market crash and conclusions remain the same.

4.3 Estimation Window

The main analysis investigates whether stocks with higher volatility betas have lower average returns contemporaneously and volatility betas and stock returns are measured over rolling periods of 12 months. In this section, I consider an estimation window of 6 months. Table 8 shows that the empirical results are not sensitive to the estimation window. Realized and expected market volatilities are strongly priced in the cross-section of stock returns with a negative price of risk while implied volatility is not priced.

4.4 Alternative Volatility Forecasting Model

To estimate expected market volatilities, one needs to specify a statistical model of volatility forecasting. The main analysis is based on the model recommended in Bekaert and Hoerova (2014). To ensure the results with expected market volatilities are not driven by this assumption, I use an alternative model to estimate expected market volatilities. In particular, I adopt the HAR model of Corsi (2009) in which future realized variance is related to past realized variances over the previous month, week, and day. I find the pricing of expected market volatilities still persists with the HAR model and the results are available upon request.

5 Conclusion

Stock market volatility is one of the most important quantity in finance playing a critical role in many applications such as calculating cost of capital, option valuation, and risk management, to just name a few. Common measures of stock market volatility share similar movements, but they are not perfectly correlated and each exhibits its own idiosyncratic dynamics. Over the sample period from 1986 to 2020, I show that realized and expected market volatilities are negatively priced in the cross-section of equity returns. Stocks that perform well when realized or expected market volatility is high earn significantly lower average returns contemporaneously. On the other hand, option implied volatility is not priced. There is no statistically significant relationship between stock returns and their sensitivities to implied volatility risk. These results are robust to different empirical implementations.

I go on and show that differential pricing of market volatility risks is difficult to reconcile with theories that relate the volatility risk premium to either hedging shifts in investment opportunities or downside protection. Instead, the findings are more consistent with segmentation and friction between options and equity markets. Option implied volatility is not priced because it reflects not only shocks to fundamentals but also shocks specific to options market.

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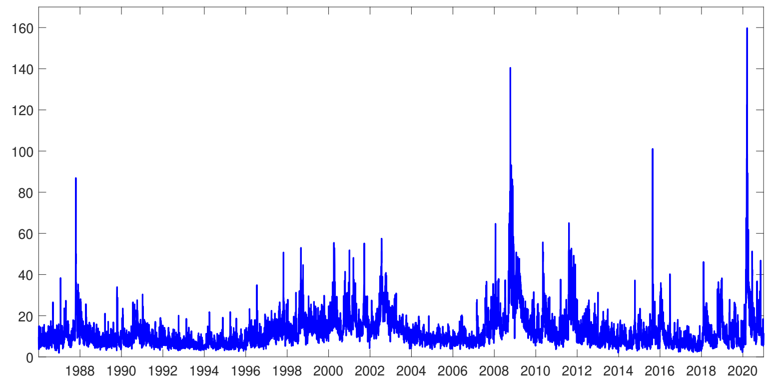
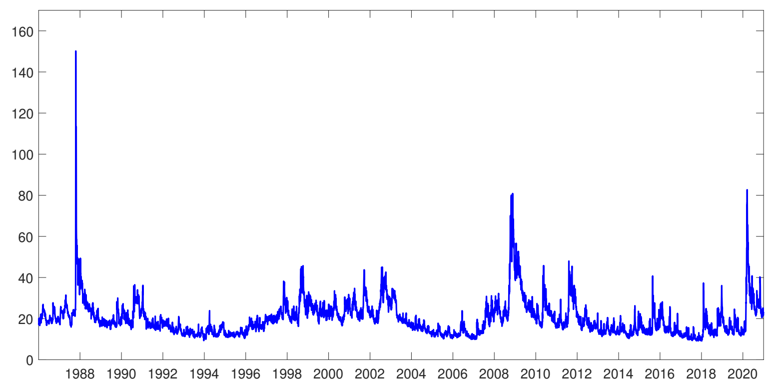
Figure 1: Time Series of Three Measures of Stock Market Volatility

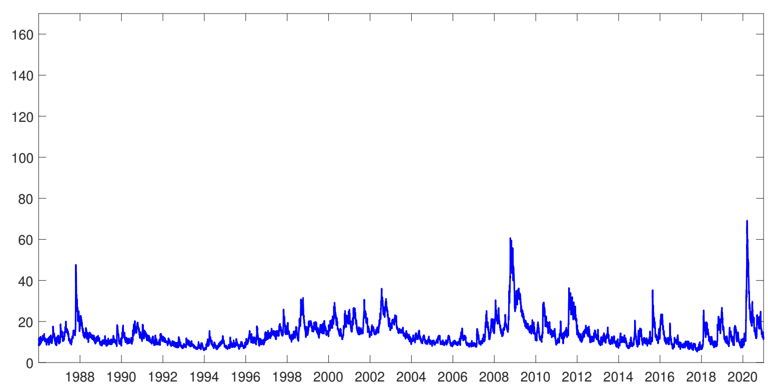
Panel A: RV



Panel B: IV



Panel C: EV



Notes: This figure plots realized market volatility (Panel A), option implied market volatility (Panel B), and expected market volatility (Panel C). Sample period: January 1986 to December 2020.

Table 1: Descriptive Statistics

Panel A: Summary Statistics				
	Mean	Std	Skew	Kurt
RV	12.45	8.97	4.02	31.20
VIX	19.92	8.51	3.02	21.21
EV	13.83	6.25	2.64	11.70
Panel B: Correlations				
	ΔRV	ΔVIX	ΔEV	SP
ΔRV	1.00			
ΔVIX	0.31	1.00		
ΔEV	0.90	0.50	1.00	
SP	-0.25	-0.70	-0.40	1.00

Notes: Panel A reports mean, standard deviation (std), skewness (skew), and kurtosis (kurt) of realized, implied, and expected market volatilities. Panel B reports the correlations of changes in the three measures of stock market volatility as well as their correlations with index returns. Sample period: January 1986 to December 2020.

Table 2: Average Returns of Portfolios Sorted on Volatility Betas

	L	2	3	4	H	H-L	CAPM alpha	FF3 alpha
Panel A: Sorting on β_{RV}								
	L	2	3	4	H	H-L	CAPM alpha	FF3 alpha
EW	0.204	0.147	0.130	0.125	0.121	-0.083***	-0.081***	-0.081***
						(-5.149)	(-5.077)	(-5.116)
VW	0.190	0.143	0.128	0.123	0.112	-0.078***	-0.077***	-0.077***
						(-5.155)	(-5.081)	(-5.116)
Panel B: Sorting on β_{IV}								
	L	2	3	4	H	H-L	CAPM alpha	FF3 alpha
EW	0.178	0.142	0.129	0.130	0.148	-0.030	-0.031	-0.031
						(-1.189)	(-1.224)	(-1.231)
VW	0.168	0.140	0.128	0.126	0.134	-0.034	-0.035	-0.035
						(-1.315)	(-1.352)	(-1.354)
Panel C: Sorting on β_{EV}								
	L	2	3	4	H	H-L	CAPM alpha	FF3 alpha
EW	0.209	0.148	0.127	0.124	0.120	-0.089***	-0.087***	-0.087***
						(-5.371)	(-5.345)	(-5.408)
VW	0.195	0.144	0.125	0.121	0.111	-0.084***	-0.082***	-0.082***
						(-5.321)	(-5.288)	(-5.348)

Notes: This table reports the average returns of both equally-weighted (EW) and value-weighted (VW) quintile portfolios sorted on sensitivities to realized, implied, and expected market volatility risks (β_{RV}, β_{IV}, and β_{EV}). Sample period: January 1986 to December 2020.

Table 3: Fama MacBeth Regressions

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
β_{RV}	-61.711***			-48.241***			-27.658***			-24.464***			-38.717***		
	(-4.945)			(-4.275)			(-2.709)			(-2.602)			(-4.781)		
β_{IV}		-3.752			-3.967			-3.818*			-2.609			-0.841	
		(-1.099)			(-1.328)			(-1.841)			(-1.304)			(-0.381)	
β_{EV}			-12.626***			-9.759***			-5.476**			-4.680**			-7.129***
			(-5.347)			(-4.333)			(-2.488)			(-2.281)			(-4.195)
β_{MKT}				0.053**	0.054**	0.053**	0.061**	0.063***	0.062**	0.082***	0.082***	0.082***	0.086***	0.085***	0.086***
				(2.347)	(2.504)	(2.339)	(2.584)	(2.629)	(2.584)	(3.221)	(3.205)	(3.221)	(2.922)	(2.909)	(2.926)
β_{SIZE}							0.033*	0.037*	0.032	0.017	0.021	0.017	0.026	0.028	0.026
							(1.668)	(1.931)	(1.632)	(1.006)	(1.243)	(0.994)	(1.311)	(1.473)	(1.294)
β_{HML}							-0.055**	-0.052**	-0.055**	-0.057**	-0.054**	-0.057**			
							(-2.211)	(-2.077)	(-2.174)	(-2.409)	(-2.271)	(-2.385)			
β_{RMW}										-0.019	-0.018	-0.018			
										(-0.763)	(-0.754)	(-0.748)			
β_{CMA}										-0.007	-0.006	-0.007			
										(-0.486)	(-0.391)	(-0.466)			
β_{IA}													-0.011	-0.010	-0.011
													(-0.715)	(-0.657)	(-0.702)
β_{ROE}													0.037**	0.035**	0.037**
													(2.403)	(2.229)	(2.400)
β_{RV}													0.024*	0.024*	0.024*
													(1.840)	(1.740)	(1.862)
$Adj.R^2$	0.70%	1.00%	0.70%	3.10%	3.20%	3.20%	7.60%	7.50%	7.70%	9.40%	9.40%	9.50%	9.30%	9.30%	9.40%

Notes: This table reports the results of the Fama-MacBeth regressions of stock returns against exposures to the three measures of stock market volatility risk as well as exposures to other systematic risk factors in leading asset pricing models including the CAPM of Sharpe (1964), the three-factor and 5-factor models of Fama and French (1993) and Fama and French (2015), and the 5-factor q-model of Hou, Mo, Xue, and Zhang (2021). Sample period: January 1986 to December 2020.

Table 4: Portfolios Double Sorted by Stock Characteristics and Volatility Betas

Panel A: Portfolios Double Sorted by Characteristics and β_{RV}					
	1	2	3	4	5
size	-0.157***	-0.085***	-0.068***	-0.063***	-0.043***
	(-4.122)	(-3.463)	(-3.870)	(-4.161)	(-2.717)
btm	-0.092***	-0.078***	-0.087***	-0.093***	-0.109***
	(-4.565)	(-4.072)	(-4.700)	(-5.435)	(-4.028)
vol	-0.009	-0.016*	-0.043***	-0.083***	-0.152***
	(-1.447)	(-1.936)	(-4.498)	(-5.918)	(-4.683)
volume	-0.010	-0.040***	-0.084***	-0.133***	-0.134***
	(-1.337)	(-3.562)	(-5.239)	(-5.316)	(-4.434)
iliq	-0.072***	-0.090***	-0.103***	-0.094***	-0.063***
	(-4.651)	(-4.886)	(-4.456)	(-4.884)	(-3.243)
coskew	-0.118***	-0.064***	-0.042***	-0.057***	-0.078***
	(-3.559)	(-4.837)	(-4.416)	(-5.438)	(-4.782)
cokurt	-0.112***	-0.062***	-0.050***	-0.065***	-0.094***
	(-3.906)	(-4.740)	(-4.322)	(-5.027)	(-5.272)
Panel B: Portfolios Double Sorted by Characteristics and β_{EV}					
	1	2	3	4	5
size	-0.167***	-0.089***	-0.072***	-0.067***	-0.041***
	(-4.573)	(-3.522)	(-4.068)	(-4.414)	(-2.651)
btm	-0.089***	-0.085***	-0.091***	-0.096***	-0.122***
	(-4.157)	(-4.660)	(-5.060)	(-5.238)	(-4.575)
vol	-0.013*	-0.021**	-0.049***	-0.085***	-0.142***
	(-1.958)	(-2.340)	(-4.552)	(-5.964)	(-5.153)
volume	-0.012	-0.049***	-0.094***	-0.150***	-0.132***
	(-1.393)	(-3.846)	(-5.567)	(-5.651)	(-4.866)
iliq	-0.071***	-0.101***	-0.116***	-0.107***	-0.067***
	(-4.029)	(-5.265)	(-4.871)	(-5.070)	(-3.297)
coskew	-0.117***	-0.073***	-0.052***	-0.063***	-0.080***
	(-3.906)	(-5.284)	(-4.791)	(-5.432)	(-4.704)
cokurt	-0.111***	-0.071***	-0.059***	-0.071***	-0.093***
	(-4.438)	(-5.094)	(-4.825)	(-5.132)	(-5.196)

Notes: Stocks are first sorted into five quintile portfolios based on stock characteristics and then further sorted into five quintile portfolios according to β_{RV} and β_{EV}. This table reports the difference in average returns between stocks with highest and lowest volatility betas within each characteristic quintile. Sample period: January 1986 to December 2020.

Table 5: Forecasting Future Returns and Volatility

Panel A: *RV*											
	Forecasting Future Returns						Forecasting Future Volatility				
Horizon	1	2	3	6	12	Horizon	1	2	3	6	12
Intercept	0.067	0.061	0.066	0.070	0.094	Intercept	0.049	0.063	0.072	0.089	0.097
t	(1.761)	(1.690)	(1.868)	(2.034)	(2.682)	t	(13.869)	(11.625)	(10.620)	(9.115)	(7.494)
Slope	0.002	0.002	0.002	0.002	0.000	Slope	0.006	0.005	0.005	0.004	0.003
t	(0.884)	(1.097)	(0.957)	(0.867)	(-0.149)	t	(29.814)	(17.089)	(12.364)	(7.266)	(4.641)
R^2	0.10%	0.31%	0.32%	0.44%	0.01%	R^2	53.11%	41.57%	34.53%	24.00%	18.86%
Panel B: *IV*											
	Forecasting Future Returns						Forecasting Future Volatility				
Horizon	1	2	3	6	12	Horizon	1	2	3	6	12
Intercept	-0.008	-0.007	0.006	0.021	0.064	Intercept	0.003	0.024	0.038	0.062	0.081
t	(-0.138)	(-0.124)	(0.099)	(0.383)	(1.191)	t	(0.407)	(2.308)	(3.062)	(3.837)	(3.841)
Slope	0.005	0.005	0.004	0.003	0.001	Slope	0.006	0.005	0.005	0.004	0.003
t	(1.828)	(1.865)	(1.665)	(1.447)	(0.558)	t	(18.352)	(11.531)	(8.629)	(5.117)	(3.133)
R^2	0.63%	1.24%	1.43%	1.91%	0.49%	R^2	46.59%	36.61%	30.41%	20.47%	14.39%
Panel C: *EV*											
	Forecasting Future Returns						Forecasting Future Volatility				
Horizon	1	2	3	6	12	Horizon	1	2	3	6	12
Intercept	0.035	0.029	0.043	0.049	0.094	Intercept	-0.006	0.014	0.028	0.053	0.065
t	(0.600)	(0.512)	(0.805)	(0.957)	(1.819)	t	-1.071	(1.840)	(2.942)	(3.989)	(3.699)
Slope	0.004	0.004	0.003	0.003	0.000	Slope	0.010	0.008	0.008	0.006	0.005
t	(1.089)	(1.239)	(0.976)	(0.918)	(-0.085)	t	(26.609)	(16.488)	(12.164)	(7.208)	(4.694)
R^2	0.22%	0.55%	0.48%	0.74%	0.00%	R^2	59.95%	48.43%	41.13%	29.50%	24.34%

Notes: This table reports the results of the predictive regressions of future returns and realized volatility over different horizons (ranging from 1-month to 12-month) against the three measures of stock market volatility. The t-stats are based on Hansen and Hodrick (1980) standard error. Sample period is January 1986 to December 2020.

Table 6: Robustness: Excluding Penny Stocks

Panel A: Sorting on β_{RV}						
	L	2	3	4	H	H-L
EW	0.220	0.152	0.133	0.130	0.132	-0.088***
						(-5.271)
VW	0.206	0.148	0.131	0.127	0.123	-0.083***
						(-5.347)
Panel B: Sorting on β_{IV}						
	L	2	3	4	H	H-L
EW	0.193	0.147	0.134	0.135	0.159	-0.033
						(-1.241)
VW	0.183	0.144	0.132	0.132	0.146	-0.037
						(-1.361)
Panel C: Sorting on β_{EV}						
	L	2	3	4	H	H-L
EW	0.226	0.153	0.131	0.127	0.130	-0.096***
						(-5.471)
VW	0.212	0.149	0.129	0.125	0.122	-0.090***
						(-5.507)

Notes: This table repeats the sorting exercise in Table 2 by excluding stocks with an average price below $5 in the previous year. Sample period: January 1986 to December 2020.

Table 7: Robustness: Excluding the Great Recession

Panel A: Sorting on β_{RV}						
	L	2	3	4	H	H-L
EW	0.226	0.165	0.145	0.142	0.140	-0.086***
						(-5.252)
VW	0.212	0.160	0.143	0.139	0.130	-0.081***
						(-5.281)
Panel B: Sorting on β_{IV}						
	L	2	3	4	H	H-L
EW	0.196	0.157	0.145	0.148	0.172	-0.024
						(-0.936)
VW	0.185	0.155	0.143	0.144	0.157	-0.028
						(-1.058)
Panel C: Sorting on β_{EV}						
	L	2	3	4	H	H-L
EW	0.231	0.166	0.142	0.14	0.138	-0.093***
						(-5.494)
VW	0.216	0.162	0.140	0.137	0.129	-0.087***
						(-5.461)

Notes: This table repeats the sorting exercise in Table 2 by excluding the Great Recession (December 2007 to June 2009).

Table 8: Robustness: Estimation Window

Panel A: Sorting on β_{RV}						
	L	2	3	4	H	H-L
EW	0.097	0.07	0.063	0.066	0.067	-0.030***
						(-4.292)
VW	0.091	0.069	0.063	0.065	0.062	-0.029***
						(-4.237)
Panel B: Sorting on β_{IV}						
	L	2	3	4	H	H-L
EW	0.087	0.07	0.063	0.065	0.079	-0.009
						(-0.876)
VW	0.083	0.069	0.063	0.063	0.071	-0.011
						(-1.153)
Panel C: Sorting on β_{EV}						
	L	2	3	4	H	H-L
EW	0.099	0.071	0.063	0.064	0.067	-0.032***
						(-4.334)
VW	0.093	0.069	0.062	0.063	0.062	-0.030***
						(-4.247)

Notes: This table repeats the sorting exercise in Table 2 by estimating volatility betas over rolling 6-month period. Sample period: January 1986 to December 2020.