The Dissertation Committee for Jie Cao
Certifies that this is the approved version of the following dissertation:

TWO ESSAYS ON THE IMPACT OF IDIOSYNCRATIC RISK ON ASSET RETURNS

Committee:

____
Sheridan Titman, Supervisor

____
Bing Han, Co-Supervisor

____
Alok Kumar

____
Robert P. Lieli

____
Laura Starks

TWO ESSAYS ON THE IMPACT OF IDIOSYNCRATIC RISK ON ASSET RETURNS

by

Jie Cao, B.A.; M.S.

Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

August, 2009

Dedication

To my wife and my parents

Acknowledgements

I am grateful to my committee co-supervisors, Sheridan Titman and Bing Han, for their encouragement and guidance throughout the entire process. Many thanks to my committee members, Alok Kumar, Robert Lieli, and Laura Starks for their valuable advices and comments. Last but not least, I appreciate the endless support of my wife Rao Fu.

TWO ESSAYS ON THE IMPACT OF IDIOSYNCRATIC RISK

ON ASSET RETURNS

Publication No.______________

Jie Cao, Ph.D.

The University of Texas at Austin, 2009

Co-Supervisors: Bing Han and Sheridan Titman

In this dissertation, I explore the impact of idiosyncratic risk on asset returns. The first essay examines how idiosyncratic risk affects the cross-section of stock returns. I use an exponential GARCH model to forecast expected idiosyncratic volatility and employ a combination of the size effect, value premium, return momentum and short-term reversal to measure relative mispricing. I find that stock returns monotonically increase in idiosyncratic risk for relatively undervalued stocks and monotonically decrease in idiosyncratic risk for relatively overvalued stocks. This phenomenon is robust to various subsamples and industries, and cannot be explained by risk factors or firm characteristics. Further, transaction costs, short-sale constraints and information uncertainty cannot account for the role of idiosyncratic risk. Overall, these

findings are consistent with the limits of arbitrage arguments and demonstrate the importance of idiosyncratic risk as an arbitrage cost.

The second essay studies the cross-sectional determinants of delta-hedged stock option returns with an emphasis on the pricing of volatility risk. We find that the average delta-hedged option returns are significantly negative for most stocks, and they decrease monotonically with both total and idiosyncratic volatility of the underlying stock. Our results are robust and cannot be explained by the Fama-French factors, market volatility risk, jump risk, or the effect of past stock return and volatility-related option mispricing. Our results strongly support a negative market price of volatility risk specification that is proportional to the volatility level. Reflecting this volatility risk premium, writing covered calls on high volatility stocks on average earns about 2% more per month than selling covered calls on low volatility stocks. This spread is higher when it is more difficult to arbitrage between stock and option.

Table of Contents

List of Tables

List of Figures

1. Introduction

Whether and how idiosyncratic risk affects asset returns has drawn considerable attention recently. There has been a long and lively debate on the pricing of idiosyncratic volatility in the cross-section of stock returns. For example, modern finance theory such as CAPM suggests that investors hold a portfolio of stocks to diversify away idiosyncratic risk. Therefore, only systematic risk is priced in equilibrium while idiosyncratic risk is not. However, Merton (1987) proposes a capital market equilibrium model with incomplete information and implies a positive relation between idiosyncratic risk and expected return if investors hold under-diversified portfolios. Different from the view of classical finance, behavioral finance research such as Shleifer and Vishny (1997) argues that idiosyncratic risk is a large holding cost for risk adverse arbitrageurs. Pontiff (2006) further points out that there should be no systematic cross-sectional relation between expected return and arbitrage cost such as idiosyncratic risk. However, the conditional relations, if any, should rely on the variables that are related to mis-valuation and arbitrage opportunities.

Similar to the debate in the theoretical evidence, the existing empirical findings are also mixed. For example, the unconditional relation between idiosyncratic volatility and stock returns is uncertain. Some studies find a positive relation, while others find a negative or insignificant relation. [1] Moreover, the

[1] Ang, Hodrick, Xing, and Zhang (2006, 2009) document that stocks with high past realized idiosyncratic volatility of daily returns have low value-weighted average returns. Bali and Cakici (2008) find that negative relation in Ang et al. (2006) is not robust under different choices of data frequency, weighting scheme and breakpoints in the construction of idiosyncratic volatility sorted portfolios. Fu (2009) and Spiegel and Wang (2006) use exponential GARCH models to estimate idiosyncratic volatility and both document an unconditionally

conditional relation implied by the limits of arbitrage argument is also questioned. [2]

In contrast to the vast literature on the cross-section of stock returns, few studies have been conducted on the cross-section of the returns on stock options, although options are more sensitive to changes in volatility than stocks. In stochastic volatility option pricing models (e.g., (Heston (1993)), both the market prices of the stochastic volatility risk and option depend on the total volatility of the underlying asset rather than just the systematic risk exposure. That implies that idiosyncratic risk may also affect the cross-sectional option returns. [3] Therefore, understanding the role of idiosyncratic risk in asset pricing and how idiosyncratic risk affects both stock and option returns would not only help investors to effectively manage their risk, but also improve our understanding of asset pricing model and marekt efficiency.

This dissertation includes two essays that contribute to these literatures. In particular, I examine the impact of the idiosyncratic risk of stock returns on (1) the cross-section of stock returns and (2) the cross-section of stock option returns.

The first essay examines the conditional relation between idiosyncratic risk and cross-sectional of stock returns. I use an exponential GARCH model to forecast expected idiosyncratic volatility and employ a combination of the size

positive relation.

[2] For example, Brav, Heaton, and Li (2009) document that value-weighted returns do not increase in idiosyncratic volatility among "undervalued" stocks (small firms, value firms or recent winners).

[3] Bakshi and Kapadia (2003b) report that idiosyncratic volatility at individual stock level is negatively but insignificantly related to delta-hedged option returns.

effect, value premium, return momentum and short-term reversal to measure relative mispricing. I find that stock returns monotonically increase in idiosyncratic risk for relatively undervalued stocks and monotonically decrease in idiosyncratic risk for relatively overvalued stocks. This pattern is consistent with the limits of arbitrage arguments that idiosyncratic risk is an arbitrage cost.

The second essay studies the cross-sectional determinants of delta-hedged stock option returns with an emphasis on the pricing of volatility risk. We find that the average delta-hedged option returns are significantly negative for most stocks, and they decrease monotonically with both total and idiosyncratic volatility of the underlying stock. Our results are robust to other model specifications and cannot be explained by the Fama-French factors, market volatility risk, jump risk, or the effect of past stock return and volatility-related option mispricing. Our results strongly support a negative market price of volatility risk specification that is proportional to the volatility level. Reflecting this volatility risk premium, writing covered calls on high volatility stocks on average earns about 2% more per month than selling covered calls on low volatility stocks. This spread is higher when it is more difficult to arbitrage between stock and option.

1.1. Idiosyncratic Risk, Costly Arbitrage, and the Cross-Section of Stock Returns

It has been well established that stock returns are predictable in the cross-section by a variety of firm characteristics (e.g. the book-to-market ratio). In contrast to risk-based explanations, behavioral finance research commonly interprets such return predictability as evidence of mispricing and market inefficiency. To study the magnitude of mispricing, a number of authors have examined settings with both rational and irrational investors. In these settings, the investment choices of the rational investors partially offset the choices of the irrational investors, who drive prices away from rational levels. However, because of costs, i.e., limits to arbitrage, the rational investors do not fully offset the choices of the irrational investors, so mispricing remains.

In this essay, I attempt to test the limits of arbitrage explanation by examining the impact of idiosyncratic risk on stock returns.[4] Shleifer and Vishny (1997) argue that idiosyncratic risk represents a large cost for risk-averse arbitrageurs, who cannot hedge the idiosyncratic risk of individual stocks. Pontiff (2006) further shows that risk-averse arbitrageurs will assign smaller portfolio weights to stocks with higher idiosyncratic risk. Hence, idiosyncratic risk is likely to deter arbitrage.

If idiosyncratic risk does prevent arbitrageurs from offsetting the choices of irrational inventors, then there are two main implications. First, the abnormal returns associated with various anomalies will be greater among high idiosyn-

[4] Trading and holding costs create limits to arbitrage. Idiosyncratic risk is the most common proxy for holding cost.

cratic risk stocks. Existing empirical studies (e.g. Ali, Hwang, and Trombley (2003), Mendenhall (2004), Mashruwala, Rajgopal, and Shevlin (2006), and Wei and Zhang (2007)) take this approach.[5] Second, the cross-sectional relation between idiosyncratic risk and stock returns should vary with the direction of mispricing; idiosyncratic risk deters arbitrageurs from buying undervalued stocks and short selling overvalued stocks. It implies that returns will monotonically increase in idiosyncratic risk for relatively undervalued stocks and monotonically decrease in idiosyncratic risk for relatively overvalued stocks.[6]

To address these issues, I examine the conditional relation between idiosyncratic risk and weekly stock returns.[7] To capture the time-variation of expected idiosyncratic risk, I use historical weekly returns and an exponential GARCH model to forecast the conditional idiosyncratic volatility in the next week.[8] In addition to analyzing the interactions between idiosyncratic risk and individ-

[5] See Ali, Hwang, and Trombley (2003) for book-to-market effect, Mendehall (2004) for post-earnings-announcement drift, Mashruwala, Rajgopal, and Shevlin (2006) for accrual anomaly, and Wei and Zhang (2007) for value-to-price anomaly. The empirical findings in Zhang (2006) are also consistent with this prediction for momentum effect.

[6] For the cross-sectional study, it is more appropriate to use the term of relative mispricing. The cross-sectional distribution of absolute mispricing could vary over periods. There could be more (less) undervalued stocks than overvalued stocks during certain periods. Nevertheless, sophisticated arbitrageurs can always profit form buying relatively undervalued stocks and selling relatively overvalued stocks.

[7] While previous papers on this topic mainly study annual returns, I focus on weekly returns because it is more realistic that arbitrageurs care about the short-term time-varying risk of their long and short positions. The resources of arbitrageurs are limited by risk aversion, short horizons, and agency problems (see Shleifer (2000)). For example, arbitrageurs with poor perform over even short time periods are subject to the pressure of fund outflows. Even if some variables (signals) forecasting returns are updated every year (e.g. the book-to-market ratio), arbitrageurs may change the portfolio weights of mispriced stocks more frequently, because expected idiosyncratic risk varies over the short-horizon.

[8] Exponential GARCH models are capable to capture both the clustering and asymmetric properties of time-varying volatility. The idiosyncratic volatility estimate is relative to the Fama-French (1993) three-factor model.

ual anomalies, I measure the relative mispricing for each stock by combining four prominent anomalies into an easily interpretable measure: the size effect, value premium, return momentum and the short-term reversal. I then examine the conditional relation between idiosyncratic risk and returns among relatively undervalued and relatively overvalued stocks, using this combined metric.

Consistent with the previous studies and the mispricing explanation, I find that stock market anomalies such as the size effect, value premium, return momentum and post-earnings-announcement drift are more pronounced for stocks with higher idiosyncratic risk. However, when I measure the relative mispricing using individual anomalies, there is no consistent evidence that returns increase in idiosyncratic risk among relatively undervalued stocks or decrease in idiosyncratic risk among relatively overvalued stocks. The results differ across various anomalies and even depend on the weighting-scheme. For example, firms with higher idiosyncratic risk have significantly higher equal-weighted returns among small stocks, value stocks, and firms with high earnings-announcement shocks. But the significance disappears after switching to value-weighted returns. In addition, firms with higher idiosyncratic risk experience significantly lower value-weighted returns among recent losers and growth stocks, while such pattern is not significant for large stocks or firms with low earnings-announcement shocks.

Using a single anomaly to define mispricing might be inappropriate, since the same stock could be subject to different anomalies which are not perfectly correlated. For instance, small stocks could contain both recent losers and growth firms. To better capture the level of mispricing, I employ an arbitrage score method based on the aggregate decile ranks of book-to-market ratio, past one year return by skipping one month, negative size and negative return of previous week.[9] These four firm characteristics, which are readily available on most stocks, are known to forecast future returns and cannot be fully accounted for by risk-based explanations.

This score method gives each anomaly an equal weight in predicting future returns, such that no single anomaly dominates others.[10] The arbitrage score is highly correlated with all these four anomalies and strongly forecasts future returns in the cross-section. I find that high score stocks outperform low score stocks by 0.88% (0.59%) per week for equal-weighted (value-weighted) returns. The difference is statistically significant and cannot be explained by common risk factors.[11]

I then use the arbitrage score to proxy for the mispricing. Consistent with the limits of arbitrage hypotheses, I find that stock returns strongly increase in idiosyncratic risk among relatively undervalued (high score) stocks and decrease in idiosyncratic risk among relatively overvalued (low score) stocks. For stocks within the highest arbitrage score quintile, high idiosyncratic risk stocks outperform low idiosyncratic risk stocks by 0.96% (0.34%) per week for equal-weighted (value-weighted) returns. In contrast, for stocks within the lowest arbitrage score quintile, high idiosyncratic risk stocks underperform low idiosyncratic

[9] At the beginning of each week, all stocks are independently sorted into deciles from low to high, based on book-to-market, the compound gross return from t-52 weeks to t-4 weeks, negative size and negative return of previous week. Stocks obtain the corresponding score of its decile rank. Arbitrage score is the total score based on four different rankings and ranges from 4 to 40.

[10] For robustness, I conduct another method in the multivariate cross-sectional regression framework, which allows each anomaly to have its own marginal effect.

[11] The risk adjustments include the CAPM alphas, Fama-French (1993) three-factor alphas and Carhart (1997) four-factor alphas.

risk stocks by 0.67% (0.36%) per week for equal-weighted (value-weighted) returns. For stocks within the middle arbitrage score quintile, I find no significant relation between idiosyncratic risk and returns.

In the final analysis, I investigate the robustness of the conditional relation. First, I find a similar pattern for stocks traded on different exchanges, for stocks with different levels of size, book-to-market ratio and trading volume, and for stocks with price over $5. The results are also consistent over various subperiods. Second, because some arbitrageurs may be limited to or specialize in firms within specific industry sectors, I repeat the tests among the Fama-French 12 industries and find similar results. Third, because idiosyncratic risk is highly correlated with other arbitrage costs, I separate the effect of idiosyncratic risk from bid-ask spreads, illiquidity and short-sale constraints. I examine the interactions among these measures for undervalued and overvalued stocks.[12] The results indicate that the strength of idiosyncratic risk as an impediment to arbitrage extends transaction costs and short-sale constraints, even at the short horizon.[13] Fourth, the Fama-MacBeth regressions provide the same results at the individual stock level and confirm that this pattern cannot be explained by systematic risk, firm characteristics, or other arbitrage costs. Finally, the main results hold for alternative estimates of expected idiosyncratic risk.

[12] I use price level to proxy for the bid-ask spreads. The proxy for illiquidity is the Amihud (2002) measure. Following Nagel (2005), I use institutional ownership as a proxy for short-sale constrains.

[13] Different from transaction costs, idiosyncratic risk and short-sale constraints are considered as holding costs (Pontiff (2006)). The relative importance of holding cost over transaction costs increases with holding period. Prior empirical studies extensively emphasize the impact of transaction costs on short-term mispricing and not much attention is given to idiosyncratic risk.

This essay contributes to a growing literature that examines the limits of arbitrage. Ali, Hwang, and Trombley (2003), and Mendenhall (2004) emphasize the impact of idiosyncratic risk on individual anomalies such as the value premium and post-earnings-announcement drift. This essay not only confirms their results at weekly horizon but more importantly, goes further and tests the relations between idiosyncratic risk and returns conditioning on the relative mispricing. A recent study by Brav, Heaton, and Li (2009) documents that value-weighted annual returns do not increase in annually updated idiosyncratic volatility among "undervalued" stocks (small firms, value firms or recent winners), and thus they cast doubt on the existence of the limits of arbitrage. One limitation of their approach is that the undervaluation or overvaluation is likely to be determined by a combination of multiple factors. In this essay, I measure the relative mispricing of stocks by combining four different anomalies and find strong support that idiosyncratic risk is an arbitrage cost. Another study by Duan, Hu, and McLean (2009) also argues that idiosyncratic risk deters arbitrages.[14] However, they focus on the most heavily shorted stocks and I study the full cross-section of stocks.

This study also sheds some light on the debate on the pricing of idiosyncratic risk.[15] For example, Fu (2009) and Spiegel and Wang (2006) use exponential GARCH models to estimate idiosyncratic volatility and both document an unconditionally positive relation. Using a similar sample and the same method-

[14]Duan, Hu, and McLean (2009) assume that high short interest could proxy for overvaluation. They find a negative relation between idiosyncratic risk and returns among high short interest stocks, while no relation among low short interest stocks.

[15]For example, Merton (1987) implies a positive relation between idiosyncratic risk and expected returns if investors hold under-diversified portfolios.

ology to calculate volatility, I find strong evidence of conditional relation. "All cross-sectional asset pricing models whether risk based, tax based, or transaction cost based, should rely on unconditionally monotonic relations between expected return and the variable that drive expected returns."[16] Therefore, my findings cast doubt on any argument that idiosyncratic risk is positively or negative priced.[17]

1.2. Individual Stock Volatility Risk Premium and the Cross-Section of Stock Option Returns

There has been a long and lively debate on the pricing of idiosyncratic volatility in the cross-section of stocks.[18] Some essay find a positive relation between idiosyncratic volatility and stock returns, while others find a negative or insignificant relation. This study provides fresh evidence and new insights on this topic by examining the pricing of idiosyncratic volatility risk using a cross-section of individual stock options.

Despite the inherent link between stocks and stock options, studies of stocks and stock options have distinct focuses and approaches. Central to equity valuation is diversification and exposure to systematic risks. On the other hand, options are valued relative to the underlying stocks by replication and

[16] See Pontiff (2006), Page 49.

[17] Ang, Hodrick, Xing, and Zhang (2006, 2009) document that stocks with high past realized idiosyncratic volatility of daily returns have low value-weighted average returns.

[18] See Lintner (1965), Miller and Scholes (1972), Fama and Macbeth (1973), Lehmann (1990), Ang, Hodrick, Xing, and Zhang (2006, 2009), Spiegel and Wang (2006), Fu (2009) and others.

no-arbitrage. The option literature typically focuses on fitting the time-series dynamics of option prices or explaining relative valuation of options of different moneyness on the same stock. In contrast to the vast literature on the cross-section of stock returns, there are no studies about the cross-sectional determinants of individual stock option returns. Our study fills this void.

One advantage of our study is that options are more sensitive to changes in volatility than stocks. To ensure our findings are new rather than mere reflections of known results from the stock market, we adjust option returns for their exposure to the underlying stock returns using daily rebalanced delta-hedges. Our test is motivated by stochastic volatility option pricing models (e.g., Heston (1993)). In these models, both market price of volatility risk and option price depend on the total volatility of the underlying asset rather than just the systematic risk exposure. We take advantage of a theoretic relation between volatility risk premium and delta-hedged option returns (see Bakshi and Kapadia (2003a)). Our results speak directly about market price of volatility risk.

In contrast, previous studies in the stock market do not model the volatility dynamics or its implication for stock prices. They typically measure idiosyncratic volatility as a firm characteristic. The relation between idiosyncratic volatility and stock return is interpreted as evidence of market imperfection and mis-specification of the factor model used to compute idiosyncratic volatility. It may not represent a priced risk factor. Even if it represents a risk factor, it does not have to be the volatility risk. Thus, there are important differences between our study and previous studies of pricing of idiosyncratic volatility in the stock market. This study is not merely an extension of previous studies to a new asset class.

Our main empirical tests are Fama-MacBeth type cross-sectional regressions with delta-hedged option returns as the dependent variable. Each month and for each optionable stock, we choose one call option and one put option that are closest to being at-the-money, because such options are the most sensitive to changes in volatility. Each month, all chosen options (on different underlying stocks) have the same expiration date (about one and a half month till maturity). These short-term options are the most actively traded, and thus their prices provide the most reliable information. We hold these options till maturity. The delta-hedged call option return is measured as change in the value of a self-financing portfolio which is long the call and short the underlying stock. The portfolio is rebalanced daily so that it is not sensitive to stock price movement. Our results are obtained from about 160,000 delta-hedged option returns for more than 5,000 underlying stocks over 11 years.

If individual stock options are redundant such as the case under the Black-Scholes model, then there should be no systematic pattern in the cross-section of delta-hedged option returns. In contrast, we find significant cross-sectional determinants of the delta-hedged option returns. Our results confirm that individual stock options are nonredundant, complementing previous finding that stock index options are not redundant (e.g., Buraschi and Jackwerth (2001), Coval and Shumway (2001), Jones (2006)).

Consistent with the prediction of a stochastic volatility option pricing model where market price of volatility risk is negative and proportional to the volatility level, we find that the average delta-hedged option returns are negative for most stocks, and they decrease monotonically with the total volatility of the underlying stock. This result is entirely driven by stock's idiosyncratic volatility (measured relative to Fama-French three factors model), as there is no significant relation between delta-hedged option returns and the betas with respect to the Fama-French three factors. The same pattern holds for both call options and put options. It holds after we control for the contemporaneous stock returns and their higher order terms, as well as stock's exposure to the market volatility risk.

In addition to the Fama-MacBeth regressions, we also compare monthly returns of portfolios of options sorted by the idiosyncratic or total volatility of the underlying stocks. Covered call writing on top quintile idiosyncratic volatility stocks significantly outperforms covered call writing on bottom idiosyncratic volatility stocks, with an average monthly return difference ranging from 1.59% (for stock value-weighted portfolio) to 2.32% (for equal-weighted portfolio) which is both economically and statistically significant.[19] The difference can not be explained by CAPM, Fama-French three factors model, or the Carhart four factor model. The superior return of writing covered calls on high idiosyncratic volatility stocks remains significant for all subsample of stocks sorted by size, and holds in all sub-sample periods.

[19] We form covered call as a delta-neutral position that sells calls against a long position of the underlying stock. It is essentially the opposite of delta-hedged call position (which is long the call and short the underlying stock) except there is no daily rebalancing of the delta hedge. Lakonishok, Lee, Pearson, Poteshman (2007) finds that call writing is the most important category of option trade, and a large percentage of call writing is part of covered call positions.

To further test the robustness of the negative relation between delta-hedged option returns and stock's idiosyncratic or total volatility, we control for several variables (motivated by various option pricing models other than the stochastic volatility model) that may be correlated with both stock's volatility and delta-hedged option return. First, previous studies have extended the stochastic volatility model to incorporate the possibility of jumps in stock returns. We include proxies for jump risk in stock return as additional independent variables in the Fama-MacBeth regressions. The delta-hedged option return is stocks more negative for stocks with high jump risk, but the regression coefficient for stock volatility is still significant negative.

Second, the traditional option pricing models (including stochastic volatility model) abstract away from market imperfections such as transaction costs. High volatility stocks tend to be more illiquid according to Amihud's price impact measure. Thus, options on high volatility stocks are more difficult to hedge, and any relative mispricing between stock and options are more difficult to arbitrage. Consistent with the impact of market friction and limits to arbitrage, we find that delta-hedged option return is significantly related to Amihud illiquidity measure of the underlying stock. However, the volatility coefficient is still significant in the presence of Amihud illiquidity measure. The negative relation between delta-hedged option return and stock volatility is also robust to controlling for stock price level.

We also control for the open interests and trading volume of individual stock options, to pick up the effects of option demand and liquidity. Garleanu, Pedersen, and Poteshman (2008) develop an option pricing model which considers liquidity provision by option market makers and captures the pricing effect of the demand pressure from option end-users. Consistent with the idea that option market makers charge higher premium for options with large end-users demand, we find that delta-hedged option returns decrease with option open interest. But again, the negative relation between delta-hedged option return and stock volatility persists after controlling for option open interests.

Another variable correlated with stock volatility that we control for is past stock return. Huang, Liu, Ghee, and Zhang (2009) find that the volatility-return relation in the cross-section of stocks is insignificant when past one-month return is used as a control variable. Amin, Coval, and Seyhun (2002) show that past 60 days stock market return affects the index option prices: index call options become more expensive and index puts become less expensive after the stock has gone up. Our cross-sectional regressions show that delta-hedged option return is positively related to the past return of the underlying stock. The "option momentum" pattern holds for both individual stock call options and put options, and for past returns of different horizons such as one month, one year and three years. Thus, the positive relation between delta-hedged option return and past stock return is not driven by the well-known short-term/long-run reversal and intermediate-term momentum patterns in stock returns. It does not change materially the negative relation between delta-hedged option return and stock volatility.

Finally, the negative relation between delta-hedged option return and stock volatility can not be explained by volatility-related mispricing in the stock options recently documented by Goyal and Saretto (2009). They find that expensive options with high implied volatility (relative to historical realized volatility) earn low returns and cheap options with low implied volatility (relative to historical realized volatility) earn high returns. In our Fama-MacBeth regressions, we find that delta-hedged option return is significantly and positively related to the difference between historical realized volatility and at-the-money implied volatility, which is consistent with the finding of Goyal and Saretto (2009). After controlling for the difference between historical realized volatility and implied volatility, the coefficient for stock's total volatility becomes even more negative and remains statistically significant.

In summary, our study of the cross-sectional determinants of delta-hedged option returns provides a new way to test option pricing model, and our results provide useful insights for option valuation. In particular, our results strong support a negative volatility risk premium specification for individual stocks that is proportional to the volatility level.

It is well known that at-the-money option implied volatilities are consistently higher than their realized volatilities (e.g., Jackwerth and Rubinstein (1996), Bakshi and Kapadia (2003b)). This has been informally interpreted as evidence of a negative volatility premium. However, Goyal and Saretto (2009) show that for individual stocks, the difference between at-the-money option implied volatility and historical realized volatility contains volatility mispricing due to investors' failure to incorporate the information contained in the cross-sectional distribution of implied volatilities when forecasting individual stock's volatility. Thus, caution is needed to draw conclusions about individual stock volatility risk premium based on the difference between at-the-money option implied volatility and historical realized volatility.

Several papers have studied the market volatility risk premium based on delta-hedged option returns. Coval and Shumway (2001) examine the expected returns on delta-hedged index options, and find large deviations from the CAPM, concluding that some other systematic factor, such as stochastic volatility, might be priced by the market. Bakshi and Kapadia (2003a) provide direct evidence of negative price of market volatility risk by examining delta-hedged S&P 500 index option returns.[20] They conduct time-series tests and find that the volatility risk premium is even more negative during periods of high market volatility. Duarte and Jones (2007) analyze the market volatility risk premium using a large cross section of individual stock option returns. They find that unconditionally market volatility risk premium cannot reliably be distinguished from zero, but they find strong conditional evidence that the market volatility risk premium varies positively with the level of implied volatilities from S&P 500 index options. The key variable in their test is stock's loading (i.e., beta) to the market volatility risk, which we control for. They do not examine how delta-hedged stock option return is related to the total or idiosyncratic volatility of the underlying stock, which is the focus of our study. In addition, this study tests many additional theory-motivated variables (not examined in studies) that are expected to be related to delta-hedged stock option returns.

Bakshi and Kapadia (2003b) and Carr and Wu (2009) are the only papers we

[20] There are also options studies documenting large negative premium for market volatility risk without relying on delta-hedged option returns (see, e.g., Bates (2000), Chernov and Ghysels (2000), Buraschi and Jackwerth (2001), Bakshi and Kapadia (2003a), Driessen and Maenhout (2007), Jones (2003, 2006), and Pan (2002)).

are aware of that present evidence on the idiosyncratic volatility risk premium using data on individual equity options. Bakshi and Kapadia (2003b) report that idiosyncratic volatility at individual stock level is negatively but insignificantly related to delta-hedged option returns.[21] This result is obtained from a panel regression on 25 individual stock options between 1991 and 1995. Our results are based on a more recent and comprehensive sample. Carr and Wu (2009) also examine the pricing of individual stock volatility but using a different approach from Bakshi and Kapadia (2003b) and this study. They quantify the return variance risk premium on an asset using the notion of a variance swap. Based on options on 35 individual stocks, they find that the premium on individual stock volatility is negative and cannot be explained by traditional pricing factors such as the market and the Fama and French (1993) three-factor model. This is consistent with our result. They do not compare the magnitude of the premium on individual stock volatility across stocks. We show that the magnitude of the negative premium on individual stock volatility increase with the stock volatility level.

Previous studies have estimated the market price of volatility risk by calibrating the option pricing models such as stochastic volatility models to best fit the prices of options on the same underlying stock. In contrast, this study takes advantage of the variation in the volatility and delta-hedged option returns across different stocks. Duarte and Jones (2007) also adopts this approach. A major advantage of this framework, besides its simplicity, is that it imposes

[21] The focus of Bakshi and Kapadia (2003b) is market volatility risk premium. They find that individual equity options also embed a negative market volatility risk premium, but with a much smaller magnitude than for the index options.

minimal parametric structure, unlike most alternative approaches that rely on a complete specification of a stochastic volatility model for each underlying stock.

2. Idiosyncratic Risk, Costly Arbitrage, and the Cross-Section of Stock Returns

This chapter is structured as follows. Subsection 1 describes the data and presents summary statistics. Subsection 2 investigates the interaction between idiosyncratic risk and individual anomalies. Subsection 3 describes the arbitrage score computation method and examines the cross-sectional relation between idiosyncratic risk and returns conditioning on the relative mispricing. Subsection 4 presents the results from robustness tests. Subsection 5 concludes.

2.1. Data and Measures

2.1.1. The Sample and Conditional Idiosyncratic Risk Measure

The data include daily stock returns for NYSE, AMEX, and NASDAQ stocks, which are compounded to obtain weekly returns (Monday – Friday) from July 1963 to December 2006.[22] I obtain stock level data such as price, return, trading volume and shares outstanding from the Center for Research in Security Prices (CRSP). The weekly returns of common risk factors and risk-free rate are taken from Kenneth French's website. The annual accounting data and

[22] To be consistent with the public Fama-French weekly factors, I measure weekly stock returns from Monday to Friday. To mitigate nonsynchronous trading or bid-ask bounce effects in daily prices, I also use Thursday-Wednesday weekly stock return and reconstruct corresponding Fama-French weekly factors using the daily data. All results are robust to the change.

quarterly earnings-announcement data of all firms are obtained from Compustat. I obtain analyst coverage and earnings forecasts data from I/B/E/S. The quarterly institutional holding data are from CDA/Spectrum Institutional (13f) database. A stock is included in a particular week only if CRSP provides return, price and shares outstanding data histories of at least 260 weeks. In a given week, there are between 1,021 and 6,946 common stocks in the sample, where the mean (median) is 4,791 (4973). The sample covers 20,548 stocks and 7,405,088 stock-week observations.

Theoretically, idiosyncratic risk equals the return innovation's standard deviation beyond what is expected, given that period's market return. I follow recent studies and assume that the Fama-French (1993) three-factor model is the right model used by market for expected returns.[23] Given this, idiosyncratic risk equals the standard deviation of the regression residual from:

$$R_{it} - r_t = \alpha_i + \beta_i (R_{mt} - r_t) + s_i SMB_t + h_i HML_t + \varepsilon_{it},$$

Since volatility is time-varying, risk-averse arbitrageurs should care about the expected idiosyncratic risk in the same period that the expected returns are measured. Previous research mainly uses OLS model to calculate the realized idiosyncratic volatility for empirical tests. However, Fu (2009) argues that past realized idiosyncratic volatility is not an appropriate proxy for expected

[23] Practitioners may use models with more factors like Barron's E3 model. The majority of the extra factors are industry dummies (about 50). These extra factors help to model the risk of under-diversified portfolio. However, in the context of arbitrage, these models are most likely over-specified since it is difficult to hedge out the systematic risk associated with so many common factors.

idiosyncratic risk, because the idiosyncratic volatility of a typical stock does not follow a random walk.

To capture the time-variation of expected idiosyncratic risk, I use exponential GARCH (EGARCH) models. GARCH models have been widely used to model the conditional (expected) volatility of returns. Pagan and Schwert (1990) fit a number of different models to monthly U.S. stock returns and find that Nelson (1991)'s EGARCH model is the best in overall performance. EGARCH models are able to capture the asymmetric effects of volatility. Moreover, EGARCH models do not require restricting parameter values to avoid negative variance as do other ARCH and GARCH models. Assuming that arbitrageurs could utilize available historical information to forecast the expected idiosyncratic risk of the next period, I employ EGARCH (1,1) and weekly returns to estimate the out-of-sample conditional idiosyncratic volatility of next week via:[24]

$$R_{it} - r_t = \alpha_i + \beta_i(R_{mt} - r_t) + s_i SMB_t + h_i HML_t + \varepsilon_{it},\ \varepsilon_{it} \sim N(0, \sigma_{it}^2),$$
$$\ln \sigma_{it}^2 \ = \ a_i + \sum_{l=1}^{p} b_{i,l} \ln \sigma_{i,t-l}^2 + \sum_{k=1}^{q} c_{i,k} \left\{ \theta \left(\frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}} \right) + \gamma \left[\left| \frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}} \right| - (2/\pi)^{1/2} \right] \right\}.$$

At the beginning of each week during the holding period, I calculate each stock's conditional idiosyncratic volatility by estimating an EGARCH (1, 1) model on the Fama-French three-factor model and all the available historical

[24] Using weekly returns to estimate idiosyncratic risk is a compromise compared with using monthly or daily returns. The monthly return history is short for GARCH based estimations and thus weekly returns could offer improved estimation accuracy (See Table 2.A1)). Although daily or even intra-daily returns can improve precision further, they may also introduce confounding microstructure influences (such as bid-ask bounce and nonsynchronous trading). In addition, it is difficult to use GARCH based conditional volatility models on daily returns to provide precise volatility forecasts of longer horizons such as one week.

data. To avoid the problem of short regression sample periods, estimates are only conducted if at least 260 weekly return observations exist.[25] The full sample is from July 1963 to December 2006, including 2269 weeks. Since five-year return history is required to forecast volatility, the testing period starts from June 1968, and covers 2010 weeks. A total of 7.4 million EGARCH estimations are conducted with a mean (median) sample size of 724 (592) weekly observations.

Estimating EGARCH model each period for all individual stocks at a high frequency is costly in practice.[26] Since the estimation sample used to conduct EGARCH for individual stock overlaps, the conditional idiosyncratic volatility could be time-varying but very persistent. If conditional idiosyncratic volatility is highly persistent across time and has a stable cross-sectional rank, then it might not be necessary to update it each week.

Table 2.1 presents the time-series property of EGARCH (1,1) estimated conditional idiosyncratic volatility (Eidio). Panel A reports the cross-sectional distribution of the autocorrelation functions of Eidio, up to five lags. The median correlation is 0.51 for the first lag and decays slowly to 0.24 for the fifth lag. However, the correlation is lower and decays much faster for about 40% stocks. It indicates that the persistence of Eidio varies significantly across individual stocks.

Since the main focus in this study is on the cross-sectional ranking of Eidio,

[25] This is a compromise between having precise volatility estimates and keeping enough young firms. Table 2.A1 shows the relation between regression sample size and the accuracy of EGARCH estimations.

[26] It incurs large computational burden for more than 7 million times EGARCH estimations.

Panel B reports the likelihood of being independently included in the same Eidio decile after 1 to 52 weeks. The likelihood value indicates the probability that a stock will stay in the same Eidio decile in the later periods. The results show that the likelihood is not very high even after just one week. For stocks in decile 1, 13.47% of them move to other groups and for stocks in decile 10, 28.66% of them leave the group. The turnover is higher for middle deciles. Overall, the results in Table 2.1 suggest that weekly updating the Eidio measure is necessary for the cross-sectional analysis. Moreover, linking weekly Eidio to the future returns of longer than one week could lead to imprecise inference.[27]

2.1.2. Arbitrage Costs and Firm Characteristics

2.1.2.1. Idiosyncratic Risk as An Arbitrage Cost Proxy

Several studies have argued that idiosyncratic risk will deter arbitrage. Shleifer and Vishny (1997) argue the importance of arbitrage risk in the existence of mispricing. Arbitrageurs carefully analyze each stock they invest in and include only a limited number of stocks in their arbitrage portfolios. Arbitrageurs get compensated for undertaking systematic risk, or they can eliminate it by hedging. On the other hand, idiosyncratic risk cannot be hedged. Also, since arbitrageurs are not well diversified, idiosyncratic risk adds to total portfolio risk, without a corresponding increase in expected returns. Therefore, risk-averse arbitrageurs are concerned about idiosyncratic risk. Hence, Shleifer and Vishny (1997) predict that idiosyncratic risk could deter arbitrage activi-

[27] For example if weekly Eidio is used to forecast monthly stock returns by portfolio sorting, then it implicitly assumes that weekly Eidio never change its cross-sectional rank in the next four weeks.

ties.

Pontiff (2006) argues that idiosyncratic risk is the single largest impediment to market efficiency as it imposes an significant holding cost for arbitrageurs. Different from the view of Shleifer and Vishny (1997), he proposes a framework in which idiosyncratic risk is important, regardless of whether arbitrageurs have access to many or few arbitrage opportunities. The active portfolio management theory such as Treynor and Black (1973) shows in a mean-variance framework that the portfolio weights chosen by an informed arbitrageur are positively related to a security's alpha and negatively related to a security's idiosyncratic risk.[28] Pontiff (2006) further points out that this implies an arbitrageur's weight in a given mispriced security is independent of the number of other mispriced securities in her portfolio. As a result, the position an arbitrageur takes in any individual security will be limited by the security's idiosyncratic risk.

Furthermore, a recent study by Bennett and Sias (2008) finds that the formation of well-diversified portfolios is essentially impossible and a large number of stocks are required to diversify away idiosyncratic risk for portfolios. In deciding which mispriced stocks to take positions in, all these studies contend that risk-averse arbitrageurs would prefer or give more weights to stocks with lower expected idiosyncratic risk. In this study, I use the conditional idiosyncratic volatility (Eidio) based on EGARCH (1,1) to measure the expected idiosyncratic risk over the next holding period (one week).

2.1.2.2. Transaction Costs, Short-Sale Constraint and Information Uncer-

[28] Bodie, Kane, and Marcus (2006) discuss these results of Treynor and Black (1973) in Chapter 27, "The theory of active portfolio management."

tainty

Prior studies have found that idiosyncratic risk is correlated with other arbitrage cost measures such as transaction costs, short-sale constraints and information uncertainty. The transaction costs usually have two types: direct transaction costs and indirect transaction costs (illiquidity). The direct transaction costs are bid-ask spreads, defined as 2(ask-bid)/(ask+bid). However, due to data limitations, I use *stock price* at the end of the previous week as an alternative measure since it is well established that stock prices are highly negatively correlated with quoted bid-ask spreads as percentage of stock prices.[29] Indirect transaction costs or illiquidity are the adverse price impacts of the trade and the delay in processing the transaction. Amihud (2002) contends that the absolute value of daily return divided by daily dollar volume can be used as a proxy for illiquidity. I define *illiquidity* as the daily average Amihud measure over previous week. Like idiosyncratic risk, short-sale constraint induces an additional holding cost. Prior studies posit that short-sale constraints are strongly linked to the amount of shares available for borrowing.[30] When institutional ownership increases, short-sale constraints are relaxed. In this study, I follow Nagel (2005) and use the *percentage of institutional ownership* at the end of the most recent quarter as a proxy for the constraints of short-selling. [31]

Information uncertainty is a risk that arbitrageurs are uncertain about the true fundamental value of their arbitrage positions due to information or val-

[29] Bhardwaj and Brooks (1992) and Blume and Goldstein (1992) suggest that quoted bid-ask spreads per share as percentage of share price are inversely related to the share price.

[30] Dechow, Hutton, Meulbroek and Sloan (2001), and Chen, Hong and Stein (2002).

[31] To purge the size effects, Nagel (2005) also employs residual institutional ownership for portfolio analysis.

uation uncertainty. Following Zhang (2006), I evaluate this risk by using firm age, analyst coverage and dispersion in analyst forecasts. The first proxy is *firm age*, which is the number of years since the firm appeared in the CRSP database. Normally, firms with a long history have more information available to the market. Then I use two proxies based on analyst information. The second proxy is *analyst coverage*, measured as the number of analysts following the firm in the previous month. There is evidence that high analyst coverage is likely to correspond to more information available about the firm, which implies less uncertainty. The third proxy is *dispersion in analyst earnings forecasts*. The value of stock could be ambiguous if there is large difference of opinions among investors. I follow Zhang (2006) and measure the forecast dispersion as the standard deviation of analyst forecasts in the previous month scaled by the prior year-end stock price to mitigate heteroskedasticity. [32]

2.1.2.3. Other Firm Characteristics

The *CAPM beta* is estimated each week using OLS regressions applied to previous 104 weeks return data. *Firm size (ME)* is measured as the market value at the end of previous week. Following Fama and French (1992), I define *BE/ME* (BM) as the fiscal-yearend book value of book equity divided by the calendar-yearend market value of equity. The *one year past return by skipping a month* ($Ret_{(-52,-4)}$) is the compound gross return from week t-52 to week t-4. $Ret_{(-1,\ 0)}$ is the raw return of previous week. *Volume* is the weekly total

[32] Following Diether, Malloy, and Scherbina (2002), I use the standard deviation of analyst forecasts scaled by the absolute value of the mean forecast as an alternative measure. All relevant results keep the same.

trading volume of last week.

2.1.3. Summary Statistics

Panel A of Table 2.2 presents the pooled descriptive statistics of conditional idiosyncratic volatility (Eidio) and other variables for all stocks in the sample. To avoid giving extreme observations heavy weight in the return regressions, the observations on Eidio, Ln(ME), BE/ME, Ret $_{(-52,-4)}$, Ret $_{(-1,0)}$, illiquidity, institutional ownership, and analyst dispersion are winsorized each week at 0.5% level. Panel B of Table 2.2 further presents the firm characteristics across Eidio quintiles formed each week. The time-series averages of the cross-sectional mean (median for BE/ME) are reported. The average Eidio in quintile 5 is 0.11, almost five times higher than the number of 0.02 in quintile 1. Consistent with previous studies, most market capitalization is concentrated in low Eidio stocks. Quintile 1 has an average market share of 51.76% while quintile 5 contains only 1.87% of the CRSP market capitalization. Table 2.2 also indicates monotonic relations between Eidio and many other variables, particularly other arbitrage cost measures. For example, stocks with higher idiosyncratic risk tend to have higher market beta, smaller size and lower price. These stocks also have higher analyst dispersion and are generally more illiquid. Moreover, analyst coverage is lower for stocks with higher Eidio, which indicates lower investor sophistication on those stocks.

The pooled descriptive statistics cannot control for the time effect of individual variables, hence I run pooled OLS of firm characteristics on idiosyncratic risk quintile dummies and year dummies; I conducted two models, which are essentially equivalent. Table 2.3 reports the coefficients of each quintile dummy. The results are quite similar to Table 2.2.

The correlations between Eidio and other variables are further documented in Table 2.4. I estimate both Pearson and nonparametric Spearman correlations each week and then compute their time-series means. The results are consistent with Table 2.2. Eidio is highly correlated with most other arbitrage cost measures, and these measures are also highly correlated with each other. As for variables known to predict returns such as size, BE/ME, Ret $_{(-52,-4)}$, and Ret $_{(-1,0)}$, their correlations with Eidio are mixed. Eidio is highly correlated with size, but not obviously related to Ln(BE/ME) or Ret $_{(-1,0)}$.

2.2. Idiosyncratic Risk and Individual Anomalies

In this subsection I examine the interactions between idiosyncratic risk and individual anomalies. Following Brav, Heaton, and Li (2009), I study the size effect, value premium, return momentum and the post-earnings-announcement drift (PEAD). Size, book-to-market ratio and past return (Ret $_{(-52,-4)}$) are defined in subsection 2.1 Unlike Mendenhall (2004), which conducts event-time analysis on PEAD, I employ a calendar time trading strategy based on earnings-announcement shocks proposed in Frazzini (2005).[33] To be consistent with prior

[33] The quarterly earnings-announcement shocks are measured using the market model cumulative abnormal returns (CAR) for a [-1, 1] event window around the quarterly announcement dates. The standard estimation windows is [-255, -46] with a minimum of 30 trading days data available. The tests are repeated using alternative measures: CAR [-2, 2], CAR [-3, 3] and earning surprise (SUE). The basic results are the same. Using Fama-French three-factor model based CARs does not change the results.

studies, stocks with price below $5 at the end of last week are dropped for the tests on return momentum and PEAD. The data availability requirement leads to different sample sizes for different anomalies. In the empirical analysis below, I do not impose the requirement that all variables are jointly available, but only those that are used in a particular test. [34]

In Table 2.5, all stocks each week are independently sorted into quintiles based on Eidio, size, BE/ME, Ret $_{(-52,-4)}$ and the most recent earnings-announcement shocks. Panel A, B, C and D present the results of Eidio intersected with size, BE/ME, Ret $_{(-52,-4)}$ and earnings-announcement shocks, respectively. Both equal-weighed and value-weighted portfolio returns are reported.

Consistent with pervious studies using annual or monthly returns, all these anomalies are strongly related to idiosyncratic risk at the weekly level. For equal-weighed returns, large stocks underperform small stocks by only 0.04% per week (P5-P1) in the low Eidio stocks (G1), but by 0.61% in the high Eidio class (G5). The difference in (P5-P1) premium between top and bottom idiosyncratic risk group is 0.57% with a t-stat at 6.27. Similarly, high BE/ME stocks outperform low BE/ME stocks by 0.07% per week (P5-P1) in the low Eidio stocks, but by 0.39% in the high Eidio stocks. The difference in (P5-P1) premium between top and bottom idiosyncratic risk group is 0.33% with a t-stat at 6.49. The similar patterns can also be observed for other return predictors. The momentum effect and PEAD profit become stronger both economically and statistically when moving from low Eidio group (G1) to high Eidio group (G5).

[34] Due to the data availability, the sample of post-earnings-announcement drift is from 1980 to 2006.

The difference in momentum profit between top and bottom idiosyncratic risk group is 0.28% with a t-stat at 6.15. In the same way, the difference in PEAD profit is 0.18% with a t-stat at 4.39. All results are robust to value-weighted returns.

As discussed above, the effect of idiosyncratic risk on individual anomalies is very significant. It seems to indicate that these anomalies are due to mispricing. If the relative mispricing can be defined based on any single anomaly, then stock returns should increase in idiosyncratic risk in small stocks, value firms, recent winners and firms with positive earnings-announcement shocks. In addition, stock returns should decrease in idiosyncratic risk among large stocks, growth firms, recent losers and firms with negative earnings-announcement shocks.

However, Table 2.5 does not provide strong support to this prediction. The results seem to differ across various anomalies and even depend on the weighting scheme. For example, among small stocks, high Eidio stocks outperform low Eidio stocks by 0.46% per week (t-statistic 5.23) for equal-weighted returns. However, the return difference (G5-G1) disappears for value-weighted returns (0.12%; t-statistic 1.42). I find the same inconsistency for value firms and firms with high earnings-announcement shocks. On the contrary, among recent winners the return difference (G5-G1) is significant for value-weighted rather than equal-weighted returns.

The negative relation between idiosyncratic risk and returns is also ambiguous. For instance, stocks with higher idiosyncratic risk experience significantly lower value-weighted returns in recent losers and growth firms, while such pattern is not significant for large stocks or firms with low earnings-announcement shocks. For equal-weighted returns, the pattern only holds for recent losers.

These results are comparable to Brav, Heaton, and Li (2009). They document that the value-weighted annual returns do not increase in annually updated idiosyncratic volatility among "undervalued" stocks (small firms, value firms or recent winners). Using different volatility measure and horizon, I find that value-weighted weekly returns significantly increase in weekly updated idiosyncratic risk only for recent winners while not for small stocks or value firms. However, these empirical results may not necessarily contradict limits-to-arbitrage argument. Rather, it could mean that it might be inappropriate to rely on a single measure of mispricing.

2.3. Idiosyncratic Risk and Arbitrage Score Strategy

2.3.1. Construction of Aggregate Mispricing: Arbitrage Score Strategy

It is possible that using an individual anomaly to define mispricing is problematic, since the same stock could be subject to several anomalies simultaneously, which are not perfectly correlated. For instance, small stocks could contain both recent losers and growth firms. As a result, simply attributing all small stock as undervalued is not precise. To address this concern, I construct an arbitrage strategy based on a mix of both quantitative and fundamental information, and a mix of both long-term and short-term information. Similar to the statistical arbitrage recently used by hedge fund industry, I first include the return of last week to profit from short-term return reversals, and then include size, book-to-market ratio and return momentum. These four firm characteristics are known to forecast future returns and are not fully accounted for by risk-based explanations. Another reason to employ only these four variables is that they are available for most of the stocks and for the entire sample period. Due to data limitations, including other anomalies such as accruals and post-earning-announcements drift will reduce the number of observations significantly and would induce sample selection bias. In addition, I keep stocks with price below $5 in the sample because these stocks usually have the highest idiosyncratic risk.

Because these four variables driving returns are not very correlated with each other as shown in Table 2.4, I employ a simple method to combine them. I expect that the generated aggregate mispricing measure could be highly correlated with its four components. Specifically, At the beginning of each week, all stocks are independently sorted into deciles from low to high, based on BE/ME, the compound gross return from t-52 week to t-4 week, negative size and negative return of previous week. Stocks are given the corresponding score of its decile rank. Arbitrage score is the total score based on four different rankings and ranges from 4 to 40.[35] Stocks with high arbitrage scores are more likely to be relatively undervalued and arbitrageurs are more likely to buy them. In con-

[35] This simple method gives each anomaly an equal weight in predicting future returns, such that no single anomaly dominates others. For robustness, I conduct another method in the multivariate regression framework, which allows each anomaly to have its own marginal effect. Specifically, each week I run Fama-MacBeth regression of realized return on ex-ante variables: firm size, book-to-market, compound gross return from t-52 week to t-4 week and last week return, by using previous 52-week rolling data. The time-series average of these coefficients are then used to predict next week return based on the firm characteristics of current week. I then sort stocks based on their predict returns, rather then their total arbitrage scores. The main results are consistent.

trast, stocks with low arbitrage scores are more likely to be relatively overvalued and arbitrageurs are more likely to short sell them.

Panel A of Table 2.6 shows the firm characteristics across arbitrage score quintiles. To avoid the impact from extreme values, both mean values and the average decile ranks are reported. First, arbitrage score is slightly related to idiosyncratic risk. The average Eidio is 0.05 in arbitrage score quintile 1 and increases to 0.07 in quintile 5. However, the spread (0.02) is actually small relative to the standard deviation of Eidio (0.04). Moreover, as anticipated, arbitrage score is highly correlated with its four components, whose mean values monotonically increase or decrease across arbitrage score quintiles. Further, as shown by the average decile ranks, arbitrage score generates appropriate dispersion for all component anomalies, while no single anomaly dominates others. This pattern is further confirmed by the Spearman correlations. Arbitrage score has high correlation coefficients with its four components, ranging from 0.36 (BE/ME) to 0.56 (size).

I then examine whether the arbitrage score predicts future returns. As shown in Panel B, stocks with higher arbitrage scores exhibit higher returns next week. The (5-1) difference is 0.88% (t-statistic 21.04) per week for equal-weighted returns and 0.59% per week (t-statistic 14.65) for value-weighted returns. Both are economically large and statistically significant. The results change little for CAPM alphas, Fama-French three-factor alphas and Carhart (1997) four-factor alphas. It suggests that the arbitrage score does proxy for certain kind of mispricing.

2.3.2. Interaction between Idiosyncratic Risk and Arbitrage Score Strategy

Each week, stocks are first sorted on their arbitrage scores into quintiles and then sorted within each quintile into five portfolios based on expected idiosyncratic risk (Eidio). I then investigate the relation between idiosyncratic risk and returns across each arbitrage score quintile. Table 2.6 presents the results. As shown in Table 2.6, stocks within the highest arbitrage score quintile have higher future returns. Because idiosyncratic risk is an arbitrage cost, risk-averse arbitrageurs are reluctant to buy stocks with high idiosyncratic risk. As a result, stock returns increase in idiosyncratic risk among those high score stocks. On the other hand, stocks within the lowest arbitrage score quintile have lower future returns and arbitrageurs want to short sell them. However, risk-averse arbitrageurs are reluctant to sell stocks with high idiosyncratic risk. Therefore, stock returns decrease in idiosyncratic risk among those low score stocks.

The empirical results in Panel A and Panel B of Table 2.7 exactly support this prediction. When moving from low arbitrage score quintile to high arbitrage score quintile, the return differences between high and low idiosyncratic risk quintiles change from significantly negative to insignificant, then to significantly positive. For instance, within arbitrage score quintile 1, stock returns monotonically decrease in idiosyncratic risk. The (5-1) difference is -0.67% per week (t-statistic -8.36) for equal-weighted returns and -0.36% (t-statistic -4.75) for value-weighted returns. In contrast, within arbitrage score quintile 5, stock returns monotonically increase in idiosyncratic risk. The (5-1) difference is 0.96% per week (t-statistic 11.79) for equal-weighted return and 0.34% (t-statistic 4.07) for value-weighted returns. Within arbitrage score quintile 3, there is no clear relation between idiosyncratic risk and returns. The (5-1) difference is insignificant for both equal-weighted and value-weighted returns. Moreover, the differences in Fama-French three-factor alphas exhibit the similar results. Adjusting for DGTW (1997) benchmark does not change the results, either. These results suggest that common risk factors and firm characteristics cannot explain the conditional relation between idiosyncratic risk and returns. This pattern on raw returns is also plotted in Figure 2.1.

An alternative explanation for the results in Table 2.7 is that the arbitrage score is correlated with idiosyncratic risk within each arbitrage score quintile. For instance, arbitrage score may be positively (negatively) correlated with idiosyncratic risk among stocks with high (low) arbitrage score. To address this concern, Panel C reports the average arbitrage score of each 5x5 portfolio. Within each arbitrage score quintile, it is clear that the average arbitrage score does not vary much with idiosyncratic risk. Therefore, the conditional relation between idiosyncratic risk and returns is not caused by the variation of arbitrage score itself.

Since idiosyncratic risk is only slightly correlated with the arbitrage score (a correlation coefficient of 0.18), the difference between independent sorting and dependent sorting is very small. Panel D and Panel E show the results for portfolios independently sorted on arbitrage score and idiosyncratic risk. The conditional relation between idiosyncratic risk and returns is quite similar to the results of dependent sorting. In addition, the abnormal returns associated with arbitrage score strategy are strongly related to the level of idiosyncratic risk, which is also consistent with the limits of arbitrage prediction.

2.4. Robustness

2.4.1. Subsample Evidence

In this subsubsection, I examine the robustness of my findings in various subsamples. I first repeat the tests for stocks traded on the NYSE only and NASDAQ only, for S&P 500 stocks only, for stocks with prices over $5 only, and for stocks with different levels of size, book-to-market ratio and trading volume. There are two reasons to check the robustness among these subsamples. On one hand, my results could be driven by cheap, tiny, or illiquid stocks which are more prone to microstructure bias and thus not profitable to trade. On the other hand, arbitrageurs are not identical in practice. Due to competition, some arbitrageurs may specialize in stocks with specific characteristics such as small cap stocks and growth stocks. Because of regulations, some arbitrageurs may be prevented from holding illiquid stocks.

Panel A of Table 2.8 presents the (5-1) spreads in value-weighted three-factor alphas within each arbitrage score quintile. For all subsamples, the (5-1) spreads monotonically increase from significantly negative in arbitrage score quintile 1, to significantly positive in arbitrage score quintile 5. It demonstrates that the conditional relation is quite robust. The main results are not driven by cheap, tiny, or illiquid stocks.

Moreover, the magnitude of (5-1) spreads in arbitrage quintile 1 and 5 apparently varies across different samples. NASDAQ stocks, small firms and firms with low trading volume usually have larger spreads than NYSE stocks, big firms and firms with high trading volume. For example, undervalued NYSE stocks have a low (5-1) spread of 0.23% (t-statistic 3.97), compared with 0.57% (t-statistic 5.67) for undervalued NASDAQ stocks. Generally, it is consistent with the notion that there is more mispricing among small or illiquid stocks.

Next, I examine the robustness of the conditional relation over different subperiods. Panel B of Table 2.8 presents the (5-1) spreads in value-weighted three-factor alphas within each arbitrage score quintile. The pattern is strikingly similar during 1968-1980, 1981-1993, and 1994-2006 subperiods. In every period, the (5-1) spreads are significantly negative for overvalued stocks and significantly positive for undervalued stocks. The influence of idiosyncratic risk on undervalued stocks increases over time while its impact on overvalued stocks turns weak in the most recent period. It may reflect the fact that there are more short-selling activities in recent period.

Since the "stock market decimalization" in 2000 could encourage arbitrage activities, I further compare 1994-2000 and 2001-2006 subperiods. The conditional relation between idiosyncratic risk and return is very strong during 1994-2000, and turns much weaker during 2001-2006. As market becomes more efficient, the impact of idiosyncratic risk as an arbitrage cost diminishes.

Another concern is that my results only derive from the periods when the average idiosyncratic risk is abnormally high.[36] To address this issue, I repeat

[36]When the average idiosyncratic risk is high, the cross-sectional dispersion of idiosyncratic

the same tests over the low Eidio and high Eidio periods, which refer to the weeks with the lowest and highest 33% average idiosyncratic risk, respectively. Again, I find that the conditional relation is strongly significant over both periods, showing that they are not driven by high risk periods.

2.4.2. Industry Analysis

There are two reasons to examine whether the results are robust to different industry sectors. First, I employ Fama-French three-factor model to estimate idiosyncratic risk. If the true asset pricing model contains industry factors, then the exposures to industry factors are not taken into account in my idiosyncratic volatility measures. Therefore, the cross-sectional ranks based on my measure would not be precise. However, this problem could be mitigated for stocks within the same industry, since these stocks are likely to have similar exposures to industry factors. Second, in practice some arbitrageurs are either restricted to or specialize in stocks within specific industries. For example, the managers of energy sector funds probably have no interests in a technology firm, even if they know that it is mispriced. As a result, it is necessary to investigate whether the main results hold within different industries.

To examine the conditional relation within industries, at the end of June of each year from 1963 to 2006, I assign all firms in my sample to one of 12 industries based on their four-digit SIC code, following the industry definitions obtained from Ken French's website.[37] Each week, stocks within each industry

risk is large.

[37] Assigning firms into 12 industries represents a compromise between having a reasonable number of distinct industries and having enough firms within each industry so that sort-

are first sorted on their arbitrage scores into quintiles and then sorted within each quintile into five portfolios based on expected idiosyncratic risk (Eidio). Table 2.9 reports the (5-1) spread in value-weighted three-factor alphas within each arbitrage score quintile for Fama-French 12 industries. The results of equal-weighted returns are similar.

As shown in Table 2.9, the conditional relation between idiosyncratic risk and return are quite strong across industries. In arbitrage score quintile 1, the (5-1) spread is significantly negative for all industries except for the utility sector. In arbitrage score quintile 5, the (5-1) spread is significantly positive for all industries except for finance and utility sectors. Since utility firms are subject to regulations and finance firms have extremely high leverage ratios, stocks within these two industries might be valued differently from others. By and large, the basic results are robust to different industry sectors.

2.4.3. Idiosyncratic Risk versus Transaction Costs and Short-Sale Constraints

Table 2.4 shows that idiosyncratic risk is highly correlated with several other proxies for arbitrage costs. Hence, the conditional relation between idiosyncratic risk and stocks returns may actually reflect the impact of other arbitrage cost measures. In this subsubsection, I compare the strength of idiosyncratic risk

ing within industries will not produce portfolios that are too thin. The 12 industries are: (1) consumer nondurables; (2) consumer durables; (3) manufacturing; (4) oil, gas, and coal extraction and products; (5) chemicals and allied products; (6) business equipment; (7) telephone and television transmission; (8) utilities; (9) wholesale, retail, and some services; (10) healthcare, medical equipment, and drugs; (11) finance; and (12) others.

and other arbitrage costs in deterring arbitrage. The three alternative arbitrage cost measures are price level as a proxy for bid-ask spreads, Amihud (2002) measure as a proxy for illiquidity, and institutional ownership as a proxy for short-sale constraints. Due to the high correlations among these measures, each week I independently sort all stocks based on arbitrage score (5 groups), price level (3 groups), illiquidity (3 groups), institutional ownership (3 groups if available) and Eidio (5 groups). To investigate the impacts of these arbitrage costs on undervalued and overvalued stocks, I focus on stocks within arbitrage score quintile 1 and 5. Table 2.10 presents the portfolio sorting results using value-weighted raw returns.

In Panel A, I compare price level with idiosyncratic risk. In arbitrage score quintile 1 (overvalued stocks), returns strongly decrease in Eidio across all three price level groups. In contrast, price level predicts returns only when Eidio is high. In arbitrage score quintile 5 (undervalued stocks), Eidio also slightly outperforms price level. Though both measures prevent arbitrage, the influence of idiosyncratic risk seems to be stronger than price level. Previous studies usually emphasize the impact of transaction costs on short-term mispricing and not much attention is given to idiosyncratic risk. However, my results suggest that idiosyncratic risk is equally or more important than transaction costs, even at the short horizon.

Panel B reports the results comparing illiquidity with idiosyncratic risk. Among overvalued stocks, both measures strongly predict returns in the anticipated directions. Among undervalued stocks, the impact of Eidio exceeds illiquidity to some extent. In both cases, illiquidity cannot explain the role of

Eidio.[38] In Panel C, I compare institutional ownership (IO) with idiosyncratic risk. Different from other measures, short-sale constraints only prevent arbitrageurs from short-selling overvalued stocks. Consistent with this notion, IO does not predict returns in undervalued stocks. Among overvalued stocks, IO only matters when idiosyncratic risk is high. In either case, IO cannot account for the role of Eido.

In summary, the horse races between idiosyncratic risk and other arbitrage costs indicate that idiosyncratic risk is more important than transaction costs and short-sale constraints, even if these different arbitrage costs are highly correlated.

2.4.4. Fama-MacBeth Regression Results

The results of the portfolio analysis show robust conditional relation between idiosyncratic risk and returns among relatively undervalued and relatively overvalued stocks. The shortcoming of the portfolio sorting approach is that I cannot control for other related variables. In this subsubsection, I examine whether such pattern exists at the individual stock level after taking various controls into account. Each week, for each arbitrage score quintile, I regress weekly stock returns on Eidio as well as other variables that vary across model specifications. Table 2.11 reports the time-series average of these coefficients and the robust Newey-West (1987) t-statistics.

[38] Spiegel and Wang (2006) also argue that idiosyncratic risk outperforms liquidity in explaining returns. However, they assume that idiosyncratic risk or liquidity is systematically priced and thus study the unconditionally relation for the full cross-section. In contrast, I assume that both idiosyncratic risk and liquidity predict returns in opposite ways among overvalued and undervalued stocks.

Panel A presents the coefficients of Eidio without other control variables. Consistent with the portfolio sorting results in Table 2.7, Eidio predicts low returns among low arbitrage score quintile and predicts high returns among high arbitrage score quintile. In the middle arbitrage score quintile, Eidio cannot predict returns. In more details, in arbitrage score quintile 1, Eidio has a coefficient of -10.979 with a t-stat of -10.55. In arbitrage score quintile 5, Eidio has a coefficient of 9.702 with a t-stat of 12.83. In arbitrage score quintile 3, Eidio has a coefficient of -1.381 with an insignificant t-stat of -1.46.

Since idiosyncratic risk is positively correlated with systematic risk, I then control for the CAPM beta and the results are reported in Panel B. Including beta almost causes no change to the coefficients of Eidio and the associated t-statistics. In addition, beta itself has a significantly positive coefficient from quintile 2 to quintile 5. It confirms that idiosyncratic risk is an arbitrage cost while systematic risk can be hedged out by arbitrageurs.

In Panel C, I further control for firm characteristics driving returns include Ln(ME), Ln(BE/ME), Ret $_{(-52,-4)}$, and Ret $_{(-1,0)}$. Including these four variables seems to reduce the power of Eidio but cannot fully explain the effect of Eidio on returns.[39] For instance, in arbitrage score quintile 1, the coefficient of Eidio reduces to -5.964 with a t-stat of -6.87. In arbitrage score quintile 5, Eidio has a smaller coefficient of 2.900 with a t-stat of 3.92. In arbitrage score quin-

[39] Huang, Liu, Rhee, and Zhang (2007) point out that the short term return reversals could affect the relation between idiosyncratic volatility (risk) and returns. They find that the negative relation between past realized idiosyncratic volatility and returns in Ang et al. (2006) is driven by monthly stock return reversals. In contrast, the conditional relation between idiosyncratic risk and returns in this study cannot be explained by the weekly stock return reversals.

tile 3, Eidio does not predict returns just as before. Consistent with Fama and French (1992), beta loses explanatory power after including firm characteristics. In contrast, Ln(ME), Ln(BE/ME), Ret $_{(-52,-4)}$, and Ret $_{(-1,0)}$ all have significant impacts on returns across all five groups. Specifically, returns increase in Ln(BE/ME) and Ret $_{(-52,-4)}$, while decreases in Ln(ME) and Ret $_{(-1,0)}$.

Moreover, idiosyncratic risk is highly correlated with many other arbitrage cost measures, the conditional relation between idiosyncratic risk and stocks returns may actually reflect the impacts of other arbitrage costs such as transaction costs, short-sale constraints and information uncertainty on returns. To address this concern, I repeat the regressions in Panel C and control for several other arbitrage costs. Panel D shows the results and only reports the coefficients of Eidio. First, I control for price level, firm age and illiquidity since they are available for the full sample. The coefficient of Eidio monotonically increases from -4.783 (t-statistic -5.46) in arbitrages score quintile 1, to 2.105 (t-statistic 3.02) in arbitrage score quintile 5. Second, I control for institution ownership, analyst coverage and analyst dispersion for the subsample of 1980-2006. This sample is much smaller due to the availability of analyst forecasts data. The coefficients of Eidio monotonically increase from -3.381 (t-statistic -3.09) to 2.916 (t-statistic 2.92) across arbitrage score quintiles. Finally, the results are quite similar after including all these variables for the 1980-2006 subsample.

In summary, the multivariate regression tests are consistent with the results of portfolio analysis. At the individual stock level, expected idiosyncratic risk predicts high returns among relatively undervalued stock while predicts low returns among relatively overvalued stocks. This pattern cannot be explained by systematic risk, firm characteristics, or other arbitrage costs such as transaction costs, short-sale constraints and information uncertainty.

2.4.5. Alternative Model Specifications for Idiosyncratic Volatility Measures

To ensure that the results presented in this study are not driven by specific model settings of volatility estimation, I address several potential concerns and my solutions in this subsubsection. First, I examine the robustness of main results to the lead-lag effect at weekly horizon. Market frictions could delay the information diffusion, which will be more pronounced at the higher frequency. It is possible that some stocks do not respond to the common risk factors in a timely manner, particularly certain small stocks. Besides using Fama-French three-factor model to estimate the idiosyncratic volatility, I also add three lagged factors to control for the lead-lag effect. The volatility measure based on the six-factor model generates similar results.

Second, I examine the robustness of main results to different sets of EGARCH parameters. In a general EGARCH (p,q) model specification, the conditional variance is a function of the past p-period of residual variance and q-period of return shocks. Besides using EGARCH (1,1) in the main tests, I also apply alternative (p,q) specifications including EGARCH (1,2), EGARCH (1,3), EGARCH (2,1), EGARCH (2,2), EGARCH (2,3), EGARCH (3,1), EGARCH (3,2), EGARCH (3,3). The alternative EGARCH (p,q) volatility estimates do not change the main empirical results described in the previous sections.

Third, I examine the robustness of the main results to different regression sample sizes. There are two possible channels that the regression sample size in EGARCH may affect the volatility measures and empirical results. On one hand, at least 260 weeks of return data are required to conduct the EGARCH regressions; it excludes a considerable amount of young firms from the sample. To address this concern, I include all stocks with at least 120 weeks of return data into the sample. It increases the total observations from 7.4 million to 9.6 million.[40] Although more noisy volatility estimates are mixed into the data, the major empirical results do not change. On the other hand, each week the EGARCH regressions use all available historical return data to estimate the idiosyncratic volatility. It introduces the problem of structural breaks if a firm experiences substantial changes during the interval. To control for this problem, I set the maximum regression sample size at 520 weeks (about 10-year return history). Again, the major results are not sensitive to this change.

[40] Table 2.A1 presents the relation between regression sample size and the probability of convergence for EGARCH Estimations.

2.5. Conclusion

The evidence presented in this chapter supports the limit of arbitrage theory, an important building block of behavioral finance. The most commonly accepted proxy for arbitrage cost is idiosyncratic risk. If idiosyncratic risk indeed prevents arbitrageurs from buying undervalued stocks and short selling overvalued stocks, then the cross-sectional relation between idiosyncratic risk and stock returns will depend on the direction of mispricing.

The empirical findings in this study are consistent with this argument. I use an exponential GARCH model to forecast expected idiosyncratic volatility and construct arbitrage score by combining the size effect, value premium, return momentum and short-term reversal. I then use arbitrage score to define the relative undervaluation and overvaluation in the cross-section. The results show that stock returns monotonically increase in idiosyncratic risk for relatively undervalued stocks and monotonically decrease in idiosyncratic risk for relatively overvalued stocks. This pattern is consistent for both equal-weighted and value-weighted returns and robust to various subsamples and industries. Furthermore, systematic risk, firm characteristics and other arbitrage cost measurs cannot account for the role of idiosyncratic risk.

The results are robust to certain alternative explanations, which suggest that idiosyncratic risk predicts returns for systematic reasons that unrelated to the arbitrageurs' decisions. First, I study the full cross-section of stocks and use expected measures of idiosyncratic volatility. Hence, my evidence is immune to sample selection bias and concerns about the precision of volatility estimation. Second, for stocks within the middle arbitrage score quintile, I find that returns are unrelated to idiosyncratic risk. These fairly valued (relatively speaking) stocks do not attract arbitrageurs' attentions and thus are unrelated to their decisions. It suggests that idiosyncratic risk does not affect returns in the absence of arbitrageurs. [41]

This work, however, might be subject to the joint hypotheses problem. One important assumption in this study is that arbitrage score could proxy for mispricing, but it is not possible to test mispricing without jointly testing some model of expected returns (Fama (1970)). The arbitrage score may actually proxy for the exposures to certain underlying risk factors and thus stocks with high scores are more risky. However, the risk-based explanation is unlikely to be convincing unless all four anomalies can be explained by the same risk-based model. Furthermore, under the risk-based hypothesis, there is no reason why idiosyncratic risk predicts high returns for more risky stocks while predicts low returns for less risky stocks.

[41] The empirical evidence can be also consistent with other behavioral explanations. For example, Zhang (2006) uses idiosyncractic risk as a proxy for information uncertainty. Han and Kumar (2009) argue that idiosyncractic volatility could be a proxy for gambling and speculation.

3. Individual Stock Volatility Risk Premium and the Cross-Section of Stock Option Returns

This chapter is organized as follows. Subsection 1 describes the data and the methodology for the empirical tests. Subsection 2 presents test results. Subsection 3 provides further discussion of the results and concludes.

3.1. Data and Methodology

3.1.1. Data

We use data from both the equity option and stock markets. We obtain daily and monthly split-adjusted stock returns, stock prices, and trading volume from the Center for Research on Security Prices (CRSP). For each stock, we also compute the book-to-market ratio using the book value from COMPUSTAT. Further, we obtain the daily and monthly Fama-French factor returns and risk-free rates from Kenneth French's data library.[42]

For the 1996 to 2006 time period, we obtain data on U.S. individual stock options from the Ivy DB database provided by Optionmetrics.[43] The data fields we use include daily closing bid and ask quotes, trading volume and open interest of each option, implied volatility as well as the option's delta and vega computed by OptionMetrics based on standard market conventions. At the end of each month and for each optionable stock, we collect a pair of options (one

[42] The data library is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[43] OptionMetrics compiles the Ivy DB data from raw end-of-day pricing information provided by FT Interactive Data Corporation.

call and one put) that are closest to being at-the-money and have the shortest maturity among those with more than 1 month to expiration.

We apply several filters to the extracted option data. First, U.S. individual stock options are of the American type, so the option prices embed early exercise premiums. Our main analyses use call options whose underlying stocks do not have ex-dividend dates prior to option expiration (i.e., we exclude an option if the underlying stock paid a dividend during the remaining life of the option). These call options we analyze are effectively European (e.g., Merton (1973)).[44] Second, we exclude all option observations that violate obvious no-arbitrage conditions such as $S \geq C \geq max(0, S - Ke^{-rT})$ for a call option C where S is the underlying stock price, and K is the option strike price, T is time to maturity of the option, and r is the riskfree rate. Third, to avoid microstructure related bias, we only retain options that have positive trading volume, positive bid quotes and where the bid price is strictly smaller than the ask price, and the mid-point of bid and ask quotes is at least \$1/8. Fourth, the majority of the options we pick each month have the same maturity (with about one and a half months of remaining life), but there are some options with longer maturity. We ensure all options in our cross-sectional analysis each month have the same maturity by dropping options whose maturity is longer than that of the majority of options. Finally, although we pick options that are closest to being at-the-money, there are a small sample of the chosen options whose moneyness (S/K) is quite different from one. We exclude options whose moneyness is lower

[44]For the short-maturity options used in our study, the early exercise premium is small. We verify that our results do not change materially when we include options for which the underlying stock paid a dividend before option expire.

than 0.8 or higher than 1.2. We control for any remaining difference in option moneyness using option's vega.

Thus, we obtain, in each month, reliable data on a cross-section of options that are approximately at-the-money with a common short-term maturity. Our final sample in each month contains on average options on 1394 stocks. Table 3.1 shows that the average moneyness of the chosen options is 1, with a standard deviation of only 0.05. The time to maturity of the chosen options range from 47 to 52 days across different months, with an average of 50 days. These short-term options are the most actively traded, have the smallest bid-ask spread and provide the most reliable pricing information. We utilize this option data to study the cross-sectional determinants of expected option returns and pricing of volatility risk.

3.1.2. Theory and Methodology

Under the assumption of no-arbitrage in a frictionless market, there exists a pricing kernel m so that the price of a call option C on the underlying stock S with a strike price K is

$$C_t = \int_{S_T=K}^{\infty} (S_T - K) m_S f(S_T) dS_T,$$

where $f(S_T)$ is the probability density of stock price at option expiration T, and $m_S = \mathrm{E}[m_T|S_T]$ is the projection of the pricing kernel m on the underlying stock price. The expected return to holding till maturity a call option is

$$\mathrm{E}[C_T - C_t] = \int_{S_T=K}^{\infty} (S_T - K)(1 - m_S) f(S_T) dS_T.$$

Thus, the expected option returns are determined by the pricing kernel, or equivalently, the market prices of risks. For example, under the Black-Scholes model, the only risk factor is the equity risk. Under extended models (e.g., with stochastic volatility or jumps), the expected option returns reflect multiple sources of priced risks. Our focus is on the volatility risk premium at individual stock level. But we will control for other risks (such as jump risk or exposure to market volatility risk). We also control for the possibility that the pricing kernel depends on other variables such as the difficulty of option market makers supplying enough options to meet customer demand (e.g., Garleanu, Pedersen, and Poteshman (2008)) as well as option mispricing (e.g., Goyal and Saretto (2009)).

We remove the part of option return that is due to the exposure to the underlying stock. We delta-hedge the options and rebalance daily.[45] Our construct is also similar to Coval and Shumway (2001) who form daily-rebalanced portfolios of index options that have zero market-beta.

To measure delta-hedged call option return, we first define delta-hedged option gain, which is change in the value of a self-financing portfolio consisting of a long call position, hedged by a short position in the underlying stock so that the portfolio is not sensitive to stock price movement, with the net investment

[45] We also examine delta-hedged option returns without daily rebalancing the hedges (see Table 3.8).

earning riskfree rate. Following Bakshi and Kapadia (2003a), we define delta-hedged gain for a call option portfolio over a period $[t, t+\tau]$ as

$$\hat{\Pi}(t, t+\tau) \equiv C_{t+\tau} - C_t - \int_t^{t+\tau} \Delta_u dS_u - \int_t^{t+\tau} r_u (C_u - \Delta_u S_u) du, \tag{1}$$

where C_t is the call option price, $\Delta_t = \partial C_t / \partial S_t$ is the delta of the call option, r is the riskfree rate.

Our empirical analysis uses a discretized version of (1). Specifically, consider a portfolio of a call option that is hedged discretely N times over a period $[t, t+\tau]$, where the hedge is rebalanced at each of the dates t_n, $n = 0, 1, \cdots, N-1$ (where we define $t_0 = t$, $t_N = t + \tau$). The discrete delta-hedged call option gain is

$$\Pi(t, t+\tau) = C_{t+\tau} - C_t - \sum_{n=0}^{N-1} \Delta_{C,t_n} [S(t_{n+1}) - S(t_n)] - \sum_{n=0}^{N-1} \frac{a_n r_{t_n}}{365} [C(t_n) - \Delta_{C,t_n} S(t_n)], \tag{2}$$

where Δ_{C,t_n} is the delta of the call option on date t_n, r_{t_n} is annualized riskfree rate on date t_n, a_n is the number of calendar days between t_n and t_{n+1}. Definition for the delta-hedged put option gain is the same as (2), except with put option price and delta replacing call option price and delta.

We define delta-hedged call option return as delta-hedged option gain scaled by the price of the underlying stock $\Pi(t, t+\tau)/S_t$.[46] Merton (1973) shows that option price is homogeneous of degree one in the stock price and the strike

[46] We verify that our results are robust when we scale the delta-hedged option gain by the option price $\Pi(t, t+\tau)/C_t$ (see Table 3.6).

price. So for a fixed moneyness, the option price scales with the price of the underlying stock. We scale the delta-hedged option gains by the prices of the underlying stocks so that they are comparable across stocks.

Under the Black-Scholes model, the call option can be replicated by trading the underlying stock and riskfree bond, and $\hat{\Pi}(t, t+\tau) = 0$. The corresponding discrete delta-hedged gain $\Pi(t, t+\tau)$ has a symmetric distribution centered around zero (e.g., Bertsimas, Kogan, and Lo (2000)).

Consider a (generic) stochastic volatility model, where the dynamics of the underlying stock and its return volatility under the empirical measure are given by

$$\begin{aligned} \frac{dS_t}{S_t} &= \mu_t[S_t, \sigma_t]dt + \sigma_t dW_t^1, \\ d\sigma_t &= \theta_t(\sigma_t)dt + \eta_t(\sigma_t)dW_t^2, \end{aligned}$$

with $\text{Corr}(dW_t^1, dW_t^2) = \rho dt$. Without imposing restrictions on the pricing kernel or the volatility process, Bakshi and Kapadia (2003a) show that delta-hedged call option gain satisfies

$$\hat{\Pi}(t, t+\tau) = \int_t^{t+\tau} \lambda_u(\sigma_u) \frac{\partial C_u}{\partial \sigma_u} du + \int_t^{t+\tau} \eta_u(\sigma_u) \frac{\partial C_u}{\partial \sigma_u} dW_u, \qquad (3)$$

where $\lambda_t(\sigma_t) \equiv -\text{Cov}_t(\frac{dm_t}{m_t}, d\sigma_t)$ is the market price of volatility risk. Thus, under the stochastic volatility model, the mean of $\hat{\Pi}(t, t+\tau)$ is determined by the market price of volatility risk:

$$\mathrm{E}_t[\hat{\Pi}(t, t+\tau)] = \int_t^{t+\tau} \mathrm{E}_t \left(\lambda_u(\sigma_u) \frac{\partial C_u}{\partial \sigma_u} \right) du. \tag{4}$$

Equation (4) provides a method using short-term at-the-money options to test whether volatility risk is priced in the equity options market, and if it is, the sign and the magnitude of the volatility premium. We use at-the-money options because they are the most sensitive to changes in the volatility of the underlying asset. Further, short-term at-the-money option is almost linear in volatility (e.g., Stein (1989)). Thus, vega of short-term at-the-money option is practically independent of the volatility level.[47] This implies that under stochastic volatility model and for the options we use, the functional dependence of delta-hedged option return on volatility is determined entirely by the volatility risk premium.

In Heston (1993), the volatility risk premium is linear in volatility $\lambda_u[\sigma_u] = \lambda \sigma_u$, where λ is a constant (see also Bates (2000) and Pan (2002)).[48] Substituting this specification of volatility risk premium into (4), expected delta-hedged option return $\mathrm{E}_t[\hat{\Pi}(t, t+\tau)]/S_t$ is linearly related to the volatility of the underlying stock return.

In subsection 3.2, we test this relation using Fama-MacBeth type regressions. Each month, regressions are run using the cross-section of short-term at-the-money equity options. The dependent variable is delta-hedged option return $\Pi(t, t+\tau)/S_t$, where τ is the common time-to-maturity of the options (about

[47] For example, it is straightforward to verify that the Black-Scholes option vega $\frac{1}{S}\frac{\partial C}{\partial \sigma}$ for at-the-money options is practically a constant (equals to 0.14).

[48] All of these papers study stock index options.

one and half month). The key independent variable is stock's total volatility σ. The regression coefficient on σ provides an estimate of the market price of volatility risk parameter λ.

There are several practical issues in measuring delta-hedged option returns. First, option delta has to be measured under a specific model, which leads to potential error due to model mis-specification. Like Carr and Wu (2009), Goyal and Saretto (2009), our delta hedges rely on implied volatilities and "Greeks" from the Black-Scholes model. This approach, while approximate, is standard practice in industry and has been shown in academic research to be quite accurate (e.g., Hull and Suo (2002)). Branger and Schlag (2004) find that using the Black-Scholes delta when the true model is Heston (1993) stochastic volatility model makes the expected discretized delta-hedged gain larger. Thus, our test is biased against finding negative volatility risk premium (i.e., the test too often falsely concludes that the volatility risk premium is positive when it is actually zero or negative). Yet as will be shown later, our empirical results strongly support stochastic volatility model with negative volatility risk premium.

Second, discretely rebalanced hedge may introduce a bias in the expected discrete delta-hedged gain. However, the bias is small, especially when the rebalance is done frequently (such as daily). Bakshi and Kapadia (2003a) show that when volatility is unpriced, the mean discrete delta-hedged gain is zero, up to terms of $O(1/N)^2$, where N is the frequency of discrete hedging. Branger and Schlag (2004) show that under the Black-Scholes model, the expected discretized delta-hedged gain is positive for any non-vanishing equity risk premium (although the theoretical value should be zero). Further, under Heston model with zero market price of volatility risk, the expected discretized delta-hedged gain is also strictly positive. Thus, the bias in discretely rebalancing makes it hard to find a negative volatility risk premium.

3.2. Empirical Results

Using the methodology in subsubsection 3.1.2, we compute delta-hedged option returns for a cross-section of stocks each month. First, we examine the time-series average of delta-hedged option returns for individual stocks. Table 3.1 Panel A and B show that for both call options and put options, the cross-sectional mean and median of the time-series average delta-hedged option returns are negative. For example, held to maturity, delta-hedged call option position on average loses 0.49% (4.32%) of the the stock (call option) value at the beginning of the period. This pattern is similar for delta-hedged gains of one month holding period.

Table 3.1 Panel C reports results of t-test for the time-series mean of individual delta-hedged option returns. We have time series observations of call options on 5,159 stocks. About 75% of them have negative average delta-hedged gains and 40% of them have significantly negative average delta-hedged gains, with t-statistic less than two. In contrast, the average delta-hedged gains is positive only for less than 20% of the sample. Further, it is significantly positive ($t >2$) for about only 1% of the cases. The pattern for the put options is almost the same.

Table 3.2 show the distribution of delta-hedged call option returns (scaled by stock price), over size and stock price quintiles. The median values are negative in all groups, and it tend to be more negative for small or cheap stocks. It is consistent with the notion that small or cheap stocks are assoiated with more frictions.

While the negative average delta-hedged option returns suggests that volatility risk premium is negative, our conclusions about the volatility risk premium is not automatically drawn from the result in Table 3.1. Our main results (Table 3.3 to Table 3.6) are derived from Fama-MacBeth type regressions of delta-hedged option returns on individual stock's volatility VOL estimated from the daily stock returns over the previous month, with many control variables.[49] We also provide results using portfolio sorting approach. Our results are robust both for call options and put options, and for alternative measures of delta-hedged option returns. To save space, our tables focus on delta-hedged call option gain till maturity scaled by stock price as the dependent variable.

3.2.1. Basic Results

Table 3.3 Model (1) is the univariate regression of delta-hedged option returns on VOL. The coefficient estimate is -0.0113, with a significant t-stat of -7.38.[50] Thus, delta-hedged option return decreases with the total volatility of the underlying stock. In Model (2), we control for option vega and contemporaneous return (i.e., over the same period that the options are held) of the underlying

[49] In an unreported robustness check, we re-estimate our models using panel regressions similar to Bakshi and Kapadia (2003b). The results are consistent with those obtained from Fama-MacBeth regressions.

[50] In all tables, we report robust Newey-West (1987) t-statistics.

stock. We control for vega to pick up potential effect of difference in the option moneyness. We control for the contemporaneous stock return to pick up potential measurement error in the Black-Scholes delta.[51] In the presence of these controls, the point estimate and t-stat of the VOL coefficient barely change. In unreported regressions, we find that the VOL coefficient remains significantly negative even when we further control for higher power (up to order four) of the contemporaneous stock return.

In Model (3) of Table 3.3, we decompose individual stock volatility into two components: idiosyncratic volatility $IVOL$ and systematic volatility $SysVol$. Following Ang, Hodrick, Xing, and Zhang (2006), we measure idiosyncratic volatility IVOL as the standard deviation of the residuals of the Fama-French 3-factors model estimated using the daily stock returns over the previous month. $SysVOL$ is the square root of $VOL^2 - IVOL^2$. We are motivated by Duan and Wei (2009). Using option quotes on the S&P 100 index and its 30 largest component stocks, they find that the proportion of stock's total volatility that is systematic can help differentiate the price structure across individual equity options. For example, a higher systematic risk proportion leads to a higher level of option implied volatility. Thus, other things equal, options on stocks with high systematic risk would tend to have higher prices and lower return. Consistent with this, we find delta-hedged option return is negatively (but not significantly) related to stock's systematic volatility. On the other hand, the coefficient of idiosyncratic volatility is highly significant, with a t-stat of -18.6.

[51] We find delta-hedged call option return is positively related to the contemporaneous return of the underlying stock. This can arise if the Black-Scholes model under-estimates the true delta.

In Model (4) of Table 3.3, we control for the stock's exposure to the Fama-French three factors as well as the market volatility risk factor. The MKTRF Beta, SMB Beta and HML Beta are estimated on Fama-French 3-factors model. Following Ang, Hodrick, Xing, and Zhang (2006), the market volatility risk factor is proxied by change of CBOE's Volatility Index (VIX). $\triangle$VIX Beta is estimated on a two factors model: market return and $\triangle$VIX. All these Betas are estimated using daily data over the previous month. We find $\triangle$VIX Beta is positive but insignificantly related to the delta-hedged option return. None of the Fama-French 3-factors betas are significant. More importantly, the coefficient estimate for idiosyncratic volatility and its t-stat barely change from Model (3).

We conclude that the negative relation between the delta-hedged option return and individual stock volatility comes entirely from stock's idiosyncratic volatility, and is not due to stock's exposure to Fama-French factors or market volatility risk. Though we use total volatility as the main variable in the remaining tests, all results hold if using idiosyncratic volatility.

3.2.2. Controlling for Jump Risk

We interpret the negative volatility coefficient as evidence that the market price of volatility risk is significantly negative and decrease with the level of volatility. But it could also reflects, at least partially, a state-dependent jump risk premium. For example, Pan (2002) specifies the jump-arrive intensity to be linear in the volatility level, which implies that the jump-risk premium is linear in VOL.

Following Bakshi and Kapadia (2003a), we control for the jump risk by including the risk-neutral skewness and kurtosis of the underlying stock return in Model (5) of Table 3.3. The appendix contains a brief account of the measurement of risk-neutral skewness and kurtosis for each stock over a given horizon from a cross-section of out of the money calls and puts. The method is originally proposed by Bakshi, Kapadia, and Madan (2003).[52] We find that the coefficients of risk-neutral skewness and kurtosis are negative and statistically significant. However, after controlling for risk-neutral skewness and kurtosis, there is still a significant negative relation between delta-hedged option return and individual stock return volatility. Thus, our findings are not driven by the impact of possible jump risk in stock returns on option prices.

3.2.3. Controlling for Other Volatility-Related Variables

In Model (6) of Table 3.3, we control for two volatility related variables. One is the log difference between historical realized volatility and at-the-money Black-Scholes implied volatility at the beginning of the formation of delta-hedged portfolio. This variable has been shown to contain volatility mis-estimation and help predict delta-hedged option return as well as return of option straddles (see Goyal and Saretto (2009)). In the Table 3.3 Model (6) regression, this variable has a significant positive coefficient. In other words, we find that delta-hedged option return is higher for stocks whose historical realized volatility is higher than at-the-money Black-Scholes implied volatility. This is consistent

[52] Due to data constraint, the option implied risk-neutral skewness and kurtosis are only available for about half of the sample. Hence, the regression coefficients in Model (5) are not directly comparable to other models in Table 3.3.

with Goyal and Saretto (2009)'s finding that expensive options with high implied volatility (relative to historical realized volatility) earn low returns and cheap options with low implied volatility (relative to historical realized volatility) earn high returns. However, after controlling for the difference between historical realized volatility and implied volatility, the coefficient for stock's total volatility becomes even more negative and remains statistically significant. Thus, our results are not driven by volatility-related mispricing documented by Goyal and Saretto (2009).

We also control for change in the at-the-money Black-Schles implied volatility over the same holding period as delta-hedged option return. Intuitively, the delta-hedged option gains are positively related to contemporaneous change in implied volatility. A high level of volatility may predict negative change in volatility because volatility dynamics is mean reverting. This may explain the negative relation between delta-hedged option return and (lagged) stock volatility. However, our empirical result does not support this idea. While the regression Model (6) of Table 3.3 confirms that delta-hedged option gains are positively related to contemporaneous change in implied volatility, the coefficient for (lagged) stock volatility remains significantly negative even after controlling for contemporaneous change in implied volatility.

3.2.4. Controlling for Past Stock Returns

In Table 3.4, we control for stock returns over various past horizons. We have several reasons to do so. First, it is well known that stochastic volatility of stock return is correlated with the return itself. Volatility tends to be high when return is low. Second, Lo and Wang (1995) argue that stock return predictability will have an effect on option pricing through the estimation of the variance of stock returns, although the option pricing formula is not affected by the predictability in the drift term. In particular, the variance will be underestimated when stock returns are negatively autocorrelated, and overestimated when stock returns are positively autocorrelated. This implies that Black-Scholes underprices options when returns exhibit mean reversion, and overprices options when returns exhibit momentum. Given individual stock returns tend to display reversal at both short-horizon and long-horizon, as well as intermediate-term momentum, we control for stock returns over past one month, past one year (excluding past one month), as well as between three years and one year ago.

Third, Amin, Coval, and Seyhun (2002) show past stock market return affects index option prices. They argue that in an imperfect market in which options are nonredundant assets, option prices can be affected by the past return of the underlying asset through a number of channels, such as investors' expectations about future returns, their demand for portfolio insurance, or their attitude towards the higher moments of stock return distributions. Amin, Coval and Seyhun (2002) use time series analysis to examine how past index returns affect differences between the implied volatility of a pair of call and put index options and the slope of index option implied volatilty smile. We examine how the cross-section of delta-hedged option return depend on stock's past return, and whether it affects the relation between delta-hedged option return and individual stock volatility.

We find that delta-hedged call option return is significantly and positively related to the underlying stock return over past one month, past one year as well as between three years and one year ago. The same results hold in the case of put options, except the coefficient of past one month is negative (see Table 3.6 Panel B). We also use the portfolio approach (similar to the momentum strategy documented by Jegadeesh and Titman (1993)) to confirm the profitability of the strategy that buys call options on past winner stocks and sells call options on past loser stocks (both delta-hedged).

We leave it to future studies to explore the explanations for our "option momentum" findings. What is important for the main theme of the current paper is that the negative relation between delta-hedged option return and individual stock volatility remains significant after controlling for past stock returns.

Further, we also control for the size (ME) and book-to-market ratio (BE/ME) of the underlying stock in Table 3.4 Model (5) and (6). Following Fama and French (1992), we measure ME as the product of monthly closing stock price and the number of outstanding common shares in previous June. BE/ME is the fiscal-yearend book value of common equity divided by the calendar-yearend market value of equity. We find that delta-hedged option return is significantly more negative for smaller firms. There is no reliable relation between delta-hedged option return and book-to-market ratio of the underlying stock. These variables do not materially affect the significant negative coefficient on the individual stock return volatility.

3.2.5. Controlling for Limits to Arbitrage

The derivation of the relation between delta-hedged option return and stock volatility in subsubsection 3.1.2 implicitly assumes perfect market and no-arbitrage. However, in reality, there are limits to arbitrage in the options market (see, e.g., Bollen and Whaley (2004) for recent evidence). One implication is that investors' net buying pressure affects option prices (see Bollen and Whaley (2004), Garleanu, Pedersen, and Poteshman (2008)). Investors' demand for stock options are likely higher when the underlying stock has higher volatility. Such higher demand could arise both for hedging purpose and for speculative motive. In Table 3.5, we control for the effect of option demand pressure using individual option's open interest as a proxy,[53] and examine how it affects the relation between delta-hedged option returns and stock volatility.

In the presence of market frictions (e.g., transaction cost and price impact), cross-sectional difference in the delta-hedged option returns would be related to the liquidity of options and underlying stocks. On the other hand, one of the reason a stock has high volatility is because it is less liquid and thus the arbitrage between stock and option are more difficult to implement. Thus, as a robust check of the relation between delta-hedged option returns and stock volatility, we control for various liquidity measures for options and underlying stocks, such as option's bid-ask spread, stock price and the Amihud (2002)

[53] More precisely, we use (option open interest / stock volume)$\times 10^3$, where open interest is measured at the end of the month and stock volume is the monthly total trading volume. We verify our results are qualitatively the same if we use option trading volume instead of open interest, or if we scale by stock's total shares outstanding. The scaling (by stock trading volume or shares outstanding) is necessary so that the option open interest or trading volume is comparable across different stocks.

measure of the price impact for stocks. The Amihud illiquidity measure for stock i at month t is defined as

$$IL_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} |R_{i,d}|/VOLUME_{i,d},$$

where D_t is the number of trading days in month t, $R_{i,d}$ and $VOLUME_{i,d}$ are, respectively, stock i's daily return and trading volume in day d of month t.

Table 3.5 Model (1) shows that delta-hedged option returns decrease with option open interest, which has a significantly negative coefficient of -0.0266 (t-stat -9.14). This is consistent with the idea that option market makers charge higher premium for options with large end-users demand. Consistent with the impact of market friction and limits to arbitrage, Model (3) shows that that delta-hedged option return is negatively related to the Amihud measure of the price impact for stocks (coef -0.0025; t-stat -11.29). Model (2) and (4) further indicate that delta-hedged option return is lower (more negative) when option bid-ask spread is high and underlying stock price is low. Importantly, the significant negative relation between delta-hedged option return and stock volatility still holds in the presence of these controls. Thus, while our regression results support the idea that limits to arbitrage plays an important role in determining delta-hedged option return, it can not explain our main finding, the negative relation between delta-hedged option return and stock volatility.

3.2.6. Further Regression Tests

In previous tests, we have demonstrated the strong negative impact of volatility on delta-hedged option returns. Our analysis centers on call options. In Table 3.6, we re-run the regression tests for put options and use alternative measures of delta-hedged option returns. Previously, delta-hedged option returns are measured as delta-hedged option gain till maturity scaled by the initial stock price. Now we measure it by delta-hedged option gain till next month scaled by stock price, or delta-hedged option gain till maturity scaled by the initial option price.

Table 3.6 Panel A reports the regression results for call options. We include most of the control variables we have examined in the same regression model specification. The dependent variables in the first, second, and third column are delta-hedged option gain till maturity scaled by stock price, gain till next month scaled by stock price, and gain till maturity scaled by option price, respectively. The corresponding coefficients of stock volatility (VOL) are -0.264 (t-stat -18.81), -0.0174 (t-stat -17.98), and -0.2106 (t-stat -10.11). Therefore, the strong negative impact of volatility is consistent across different measures of delta-hedged option returns.

Results in Table 3.6 Panel B show that delta-hedged put option returns are also negatively related to the volatility of underlying stock, and can not be explained by all the control variables. We conclude that the significant negative relation between delta-hedged option return and stock volatility holds for both call options and put options, and for alternative measures of delta-hedged option returns.

Moreover, Fu (2009) and Spiegel and Wang (2006) use exponential GARCH models to estimate expected idiosyncratic volatility and both document a positive relation between idiosyncraric risk and stock returns. To ensure that the results on option returns are not driven by specific model of volatility estimation, we repeat the tests using EGARCH (1, 1) idiosyncraric risk measure following Spiegel and Wang (2006) . Table 3.7 shows a consistent result for both realized and expected idiosyncraric risk measures, with or without other control variables.

3.2.7. Portfolio Analysis

So far our results are obtained from Fama-MacBeth regressions. Next, we conduct portfolio based analysis to provide additional robustness tests and shed more lights on the individual stock volatility risk premium.

In the regression tests, the dependent variable is delta-hedged option gain (scaled properly to make them comparable across stocks of different price levels). The delta-hedged option gain measure is theoretically motivated, but it is not convenient for portfolio analysis. First, because we use self-financing portfolio, the delta-hedged option return in our regression analysis is not the return of a portfolio in the traditional sense. Second, portfolio analysis takes the buy-and-hold approach while our delta-hedged option gain measure involves daily rebalancing.

In the portfolio analysis, we consider writing covered call options and hold it for one month. We no longer daily rebalance the delta-hedges. Specifically, the return to selling a covered call over $[t, t+1]$ is $H_{t+1}/H_t - 1$, where $H_t = \Delta_t S_t - C_t$, with C and S denoting call option price and the underlying stock price, Δ_t being the Black-Scholes call option delta at initial t.

Table 3.8 reports the average return of portfolios of covered calls sorted by the total volatility (Panel A) or by the idiosyncratic volatility (Panel B) of the underlying stocks. We try three weighting schemes in computing the average portfolio return: equal weight, weighted by the market capitalization of the underlying stock (at the beginning of the period), or weighted by the market value of total option open interest (at the beginning of the period). Our results are consistent across different weighting schemes. Results are very similar for total volatility sorts and for idiosyncratic volatility sorts.

Table 3.8 shows that the average return of covered call writing is positive. This is consistent with the negative average delta-hedged call option gains reported in Table 3.1, which is long the options and short the underlying stock, just the opposite of covered call writing. Corresponding to the significant negative relation between delta-hedged option return and stock volatility in the regression tests, we find that the returns to writing covered calls on high volatility stocks is on average significantly higher than that on low volatility stocks. The difference ranges from 1.66% to 2.33% per month, depending on the weighting scheme, when we sort on total stock volatility. It is between 1.59% and 2.32% per month when we sort on idiosyncratic stock volatility. All of these return spreads are highly significant statistically. Further, controlling for the Fama-French factors or the momentum factor has almost no effect on the average return spreads between writing covered calls on high versus low volatility stocks. Thus, our finding is independent of the familiar factors from the stock market.

Table 3.8 Panel C reports several subsample results. The average return spread between writing covered calls on high versus low volatility stocks is significantly positive in all subsample of stocks sorted by size, although its magnitude decreases monotonically with the market capitalization of the underlying stock. It shows up both in January and in the rest of the year. It exists in various sub-periods of our sample with about the same strength.

The returns of portfolios of covered calls are related to both the stock price change and the option price change, hence we further decompose the portfolio return as:

$$\frac{(\Delta_t \cdot S_{t+1} - C_{t+1}) - (\Delta_t \cdot S_t - C_t)}{(\Delta_t \cdot S_t - C_t)} = \frac{\Delta_t \cdot (S_{t+1} - S_t)}{(\Delta_t \cdot S_t - C_t)} + \frac{(C_{t+1} - C_t)}{(\Delta_t \cdot S_t - C_t)},$$

where $\frac{\Delta_t \cdot (S_{t+1} - S_t)}{(\Delta_t \cdot S_t - C_t)}$ is the part of return due to stock price movement, and $\frac{(C_{t+1} - C_t)}{(\Delta_t \cdot S_t - C_t)}$ is the part of return due to option price movement. Table 3.9 reports the equal-weighted returns of two parts sorted by the idiosyncratic volatility ($IVOL$). For the stock part, return increases with $IVOL$, however, the spread is insignificant. For the option part, there is no relation.

The results could be further illustrated in Figure 3.1, in which we plot the time-series of the (5-1) spread for total portfolio return, stock part, and option part. It is clear that combing stock and option part generates a much more stable profit over time. Overall, it indicates that the positive relation presented in Table 3.8 is driven by the exact combination of stock and option, not by stock or option alone.

3.2.8. Volatility Risk Premium, Transaction Cost and Liquidity

To better understand the volatility risk premium, Table 3.10 Panel A examines the impact of transaction cost on the magnitude of the average return spread between writing covered calls on high versus low volatility stocks. Panel B documents how does the return spread vary with liquidity measures of stock and option.

In all of our previous results, we use the mid-point of the closing option bid and ask quotes. Quoted bid-ask spreads (expressed in percentage) are larger for options (even for at-the-money options used in our study) than for stocks. In Table 3.10 Panel A, we consider the costs associated with buying or selling options, assuming three effective spread measures equal to 50%, 75%, and 100% of the quoted spread, respectively. Corresponding to these transaction cost assumptions, the average return spread between writing covered calls on high versus low volatility stocks decreases from 2.33% per month when evaluated at the mid-point of bid and ask to 1.25%, 0.73% and 0.22% respectively with transaction costs. The t-stat of the return spread also declines as transaction cost gets bigger. When the effective spread equals the quoted spread, the 0.22% monthly return spread is no longer statistically significant.

Table 3.10 Panel B reports the average return spread between writing covered calls on high versus low volatility stocks for each quintile sorted by liquidity measures of stock and option. Each month, we first sort the option sample into five quintiles by the price or Amihud (2002) illiquidity measure of the underlying stock, or by option bid-ask spread. Then within each quintile, we further sort by the volatility of the underlying stock. Panel B shows that the average return spread between writing covered calls on high versus low volatility stocks is significantly higher for illiquid stocks, low priced stocks, as well as for options with high bid-ask spread. We interpret these results as evidence of interactions between the magnitude of volatility risk premium and liquidity measures of stock and option. In unreported tables, we also verify these interaction effects using Fama-MacBeth regression. The regressors include VOL, stock price, Amihud illiquidity measure, option bid-ask spread, as well as $VOL\times$ stock price, $VOL\times$ Amihud measure, and $VOL\times$ option bid-ask spread together with other controls.

3.3. Conclusion

This study provides the first comprehensive study of the cross-sectional determinants for delta-hedged option returns. The focus is on the volatility risk premium at the individual stock level. We are motivated by a theoretical relation between delta-hedged option return and volatility of the underlying stock. Consistent with a negative market price of volatility risk that is proportional to the volatility level, we find that the average delta-hedged option returns are significantly negative for most stocks, and they decrease monotonically with the total volatility of the underlying stock. This result is driven entirely by stock's idiosyncratic volatility. It holds for both calls and puts. It is robust to controlling for the contemporaneous stock returns and their higher order terms.

It can not be explained by stock's exposure to the Fama-French factors, market volatility risk, jump risk, effect of past stock return, or volatility-related option mispricing.

To quantify the magnitude of the volatility risk premium at individual stock level, we examine the return spread between writing covered calls on high versus low volatility stocks. This return spread averages to around 2% per month. The superior returns to writing covered calls on high volatility stocks exist in all subperiods and all subsamples sorted by size and various stock and option liquidity measures. It is significantly higher for small firms, low priced and illiquid stocks, as well as for options with high bid-ask spread.

There could be multiple economic forces underlying the market price of individual stock volatility risk implicit in the equity options data. One possibility is that marginal investors hold undiversified portfolios, and they are willing to pay a premium for assets that are positively correlated with idiosyncratic (or total) volatility of the stocks they hold. The reason is that such assets (e.g., delta-hedged options, option straddles, and variance swaps) provide valuable hedges (i.e., they have high returns when stocks drop and volatility increases).

Volatility risk premium could also be related to market makers and supply of options. Market makers practice delta-neutral trading to hedge their directional risk. However, they are unable to costlessly and continuously rebalance an option portfolio, and this imposes undiversifiable risks on options market makers (see Jameson and Wilhelm (1992)). Such risks are high for more volatile stocks. Even if option sellers can perfectly delta-hedge option's exposure to the underlying asset, they are exposed to substantial volatility risk which can produce very large losses (see Figlewski and Green (1999)). Thus, volatility risk premium could be compensation for option market makers who are unable to eliminate volatility risk through hedging and diversification.

We leave detailed economic explanation of the individual stock volatility risk premium for future studies. This essay documents another new empirical finding: delta-hedged call options on past winner stocks significantly outperforms delta-hedged call options on past loser stocks. We exclude several possible explanations. Further research is need to better understand this option momentum phenomena.

Table 2.1: Time-Series Properties of Idiosyncratic Risk

This table presents the relative persistence of individual stock idiosyncratic risk. The conditional expected idiosyncratic volatility (Eidio) is estimated from EGARCH(1,1) on Fama-French 3-factor model by all the historical weekly data. Estimates are only conducted if at least 260 observations exist. The autocorrelation functions up to lag 5 are calculated for each stock. Panel A reports the cross-sectional distribution of the autocorrelation functions. Panel B reports the likelihood that a stock will be independently included in the same Eidio decile after 1 to 52 weeks. The sample period is from July 1963 to December 2006. The expected idiosyncratic volatility measure starts from June 1968.

Panel A: Cross-Sectional Distribution of Autocorrelation Function of Eidio

LAG	P10	P20	P30	P40	P50	P60	P70	P80	P90
1	-0.12	0.05	0.20	0.36	0.51	0.65	0.76	0.85	0.92
2	0.04	0.15	0.26	0.37	0.48	0.59	0.70	0.80	0.89
3	-0.08	0.01	0.09	0.19	0.31	0.45	0.59	0.72	0.84
4	-0.01	0.07	0.14	0.23	0.34	0.45	0.57	0.69	0.82
5	-0.06	0.00	0.07	0.14	0.24	0.36	0.50	0.64	0.78

Panel B: Likelihood (%) of Being Independently Included in the Same Eidio Decile

Eidio Decile Week t	Week t+1	Week t+2	Week t+3	Week t+4	Week t+9	Week t+13	Week t+52
1-Low	86.53	84.45	81.50	80.49	75.55	73.54	65.69
2	71.70	66.52	61.64	59.47	51.76	48.84	40.01
3	64.06	58.08	52.69	50.39	42.52	39.91	32.05
4	59.26	53.40	47.89	45.81	38.44	36.12	28.86
5	55.74	50.36	44.75	43.06	36.07	33.92	27.23
6	52.94	48.20	42.80	41.46	35.09	33.12	26.79
7	51.03	46.95	41.80	40.77	34.94	33.10	27.16
8	51.04	47.73	42.61	41.93	36.38	34.74	29.30
9	55.04	52.58	47.39	46.95	41.38	39.86	34.05
10-High	71.34	71.11	65.87	66.30	60.81	59.19	51.69

Table 2.2: Summary Statistics

This table reports the summary statistics of stocks traded in the NYSE, AMEX, or Nasdaq during July 1963 to December 2006. Panel A presents the pooled descriptive statistics. Panel B reports the firm characteristics across expected idiosyncratic risk (Eidio) quintiles. Time-series averages of the cross-sectional mean (median for BM) are reported in Panel B. Stocks are included if they have at least 260 weeks of return data. The sample contains 7,405,088 firm-week observations. There average 4701 stocks in each week over 2010 weeks from June 1968 to December 2006. Eidio is the estimated weekly expected idiosyncratic volatility from EGARCH(1,1) on Fama-French 3-factor model. Every week, conditional volatility is estimated by all the historical weekly data. Estimates are only conducted if at least 260 observations exist. Beta is the weekly CAPM beta and estimated weekly over previous 104 weeks. ME is the firm's market capitalization at the end of week t-1. BE/ME is the fiscal-yearend book value of common equity divided by the calendar-yearend market value of equity. $Ret_{(-52,-4)}$ is the compound gross return from t-52 weeks to t-4 weeks. $Ret_{(-1,0)}$ is the raw return of previous week. Price is the closing price at the end of week t-1. Firm age is defined as the number of years since a stock first appeared in the CRSP. Illiquidity is the weekly illiquidity measure calculated following Amihud (2002) and measured at week t-1. Institutional Ownership is the percentage of common stocks owned by institutions in the precious quarter. Analyst Coverage is the number of analysts following the firm in the previous month. Analyst Dispersion is the standard deviation of analyst forecasts in the previous month scaled by the prior year-end stock price. Market Shares (%) is the time-series average of portfolio market value relative to total market value at then end of week t-1. To avoid giving extreme observations heavy weight in the return regressions, the observations on Eidio, Ln(ME), BM, $Ret_{(-52,-4)}$, $Ret_{(-1, 0)}$, Illiquidity, Institutional Ownership, and Analyst Dispersion are winsorized each week at 0.5% level.

	Panel A Pooled Descriptive Statistics					Panel B Across Idiosyncratic Risk Quintiles				
Variables	Mean	Std Dev	Median	Q1	Q3	Low Eidio	2	3	4	High Eidio
Eidio	0.06	0.04	0.05	0.03	0.07	0.02	0.04	0.05	0.07	0.11
Beta	0.94	0.75	0.89	0.48	1.35	0.68	0.90	1.00	1.07	1.09
Ln(ME)	4.66	2.13	4.55	3.12	6.12	5.78	5.45	4.69	3.88	2.86
BM	1.79	7.52	0.75	0.43	1.25	0.89	0.83	0.86	0.86	0.83
$Ret_{(-52,-4)}$ (%)	15.16	53.14	7.88	-14.99	33.33	13.62	15.09	15.59	15.34	10.85
$Ret_{(-1, 0)}$ (%)	0.36	8.00	0.00	-2.64	2.72	0.22	0.25	0.24	0.25	0.69
Stock Price	18.94	18.18	14.01	5.88	26.25	30.40	27.43	19.48	12.66	6.59
Age	13.93	8.15	11.38	7.63	17.96	14.78	14.96	13.36	11.76	10.45
Ln(Volume+1)	4.29	2.35	4.23	2.66	5.92	3.93	4.12	4.10	3.94	3.81
Illiquidity	4.95	23.83	0.10	0.01	0.93	0.53	1.06	2.31	5.37	16.43
Institutional Ownership	0.31	0.27	0.24	0.07	0.50	0.29	0.39	0.36	0.27	0.15
Analyst Coverage	7.41	7.33	5.00	2.00	11.00	10.30	8.40	6.67	5.08	3.39
Analyst Dispersion (%)	1.19	4.88	0.21	0.08	0.63	0.34	0.54	1.06	2.06	5.45
Market Shares (%)						51.76	27.48	13.17	5.72	1.87

Table 2.3: The Relation between Idiosyncratic Risk and Other Variables

This table reports the pooled regression coefficients of firm variables on idiosyncratic risk quintile dummies, after controlling for the year-fixed effect. Eidio is the estimated weekly expected idiosyncratic volatility from EGARCH(1,1) on Fama-French 3-factor model. Beta is the weekly CAPM beta and estimated weekly over previous 104 weeks. ME is the firm's market capitalization at the end of week t-1. BE/ME is the fiscal-yearend book value of common equity divided by the calendar-yearend market value of equity. $Ret_{(-52,-4)}$ is the compound gross return from t-52 weeks to t-4 weeks. $Ret_{(-1,0)}$ is the raw return of previous week. Price is the closing price at the end of week t-1. Firm age is defined as the number of years since a stock first appeared in the CRSP. Institutional Ownership is the percentage of common stocks owned by institutions in the precious quarter. Analyst Coverage is the number of analysts following the firm in the previous month. To avoid giving extreme observations heavy weight in the return regressions, all variables are winsorized each week at 0.5% level. Every week, all stocks are sorted into quintiles based on Eidio. The Eidio quintile dummy G*i* equals one for stocks in quintile *i*. Two models are conducted as follows:

Model I: $\text{firm variable} = \alpha_1 \cdot \text{intercept} + \alpha_2 \cdot G2 + \alpha_3 \cdot G3 + \alpha_4 \cdot G4 + \alpha_5 \cdot G5 + \text{year\_dummies}$

Model II: $\text{firm variable} = \beta_1 \cdot G1 + \beta_2 \cdot G2 + \beta_3 \cdot G3 + \beta_4 \cdot G4 + \beta_5 \cdot G5 + \text{year\_dummies}$

	Estimates of Model I: α_s					Estimates of Model II: β_s				
Variables	Intercept	G2	G3	G4	G5	G1	G2	G3	G4	G5
Beta	0.62	0.22	0.33	0.42	0.45	0.62	0.84	0.95	1.04	1.07
Ln(ME)	7.64	-0.57	-1.34	-2.15	-3.10	7.64	7.07	6.30	5.50	4.55
BM	1.69	0.75	0.43	-0.25	-0.41	1.69	2.43	2.12	1.44	1.27
$Ret_{(-52,-4)}$ (%)	13.63	1.77	2.66	2.78	-2.19	13.63	15.40	16.29	16.42	11.45
$Ret_{(-1, 0)}$ (%)	0.23	0.04	0.04	0.04	0.53	0.23	0.27	0.27	0.27	0.76
Stock Price	35.08	-2.47	-10.47	-17.40	-23.59	35.08	32.61	24.61	17.68	11.50
Ln(Volume+1)	6.27	0.05	-0.08	-0.18	-0.33	6.27	6.32	6.19	6.08	5.94
Institutional Ownership	0.48	0.11	0.09	0.00	-0.14	0.48	0.59	0.56	0.47	0.34
Analyst Coverage	10.63	-2.16	-3.76	-5.28	-6.92	10.63	8.47	6.88	5.36	3.71

Table 2.4: Correlations

This table reports time-series average of both Pearson and Spearman correlations among listed variables. The Pearson correlations are shown above the diagonal with Spearman correlations below the diagonal. Eidio is the estimated weekly expected idiosyncratic volatility from EGARCH(1,1) on Fama-French 3-factor model. Eidio is estimated by all the historical weekly data with at least 260 weeks of return data. Beta is the weekly CAPM beta and estimated weekly over previous 104 weeks. ME is the firm's market capitalization at the end of week t-1. BE/ME is the fiscal-yearend book value of common equity divided by the calendar-yearend market value of equity. $Ret_{(-52,-4)}$ is the compound gross return from t-52 weeks to t-4 weeks. $Ret_{(-1,0)}$ is the raw return of previous week. Price is the closing price at the end of week t-1. VOL is weekly total trading volume of week t-1. Illiquidity is the Amihud (2002)'s illiquidity measure estimated at week t-1. IO is institutional ownership defined as the percentage of common stocks owned by institutions in the previous quarter. Analyst Cov. is analyst coverage defined as the number of analysts following the firm in the previous month. Analyst Disp. is the analyst dispersion defined as the standard deviation of analyst forecasts in the previous month scaled by the prior year-end stock price.

	Eidio	Beta	LnME	LnBM	Ret (-52,-4)	Ret (-1, 0)	Price	LnVOL	Illiquidity	IO	Analyst Cov.	Analyst Disp.
Eidio	1	0.17	-0.51	-0.08	-0.07	0.03	-0.45	-0.08	0.27	-0.28	-0.29	0.27
Beta	0.22	1	0.11	-0.08	0.00	0.00	-0.01	0.25	-0.05	0.15	0.05	0.10
LnME	-0.53	0.14	1	-0.29	0.15	0.02	0.70	0.70	-0.33	0.61	0.78	-0.20
LnBM	-0.05	-0.10	-0.32	1	0.02	0.01	-0.16	-0.29	0.13	-0.01	-0.19	0.09
$Ret_{(-52,-4)}$	-0.17	-0.02	0.21	0.03	1	0.01	0.21	0.07	-0.12	0.06	-0.03	-0.17
$Ret_{(-1, 0)}$	-0.05	-0.01	0.06	0.01	0.03	1	0.03	0.05	-0.02	0.00	-0.01	-0.01
Price	-0.62	0.02	0.80	-0.23	0.34	0.09	1	0.32	-0.20	0.50	0.47	-0.21
LnVOL	-0.10	0.28	0.70	-0.32	0.06	0.06	0.36	1	-0.28	0.51	0.66	0.00
Illiquidity	0.43	-0.12	-0.80	0.28	-0.19	-0.06	-0.65	-0.72	1	-0.17	-0.13	0.11
IO	-0.25	0.21	0.65	-0.11	0.11	0.03	0.58	0.53	-0.56	1	0.46	-0.14
Analyst Cov.	-0.32	0.10	0.79	-0.23	0.02	0.01	0.51	0.69	-0.74	0.55	1	-0.10
Analyst Disp.	0.28	0.14	-0.28	0.30	-0.29	-0.03	-0.47	-0.02	0.23	-0.17	-0.15	1

Table 2.5: Interaction of Idiosyncratic Risk with Stock Market Anomalies

This table reports the interactions between idiosyncratic risk and stock market anomalies including the size effect, value premium, return momentum and post-earnings-announcement drift. Each week, stocks are independently sorted on each anomaly and expected idiosyncratic volatility into quintiles. Average return is measured in weekly percentage terms and applies to the out of sample returns. Eidio is the estimated weekly expected idiosyncratic volatility from EGARCH(1,1) on Fama-French 3-factor model. Eidio is estimated by all the historical weekly data with at least 260 weeks of return data. Size is the firm's market capitalization at the end of week t-1. BE/ME is the fiscal-yearend book value of common equity divided by the calendar-yearend market value of equity. $Ret_{(-52,-4)}$ is the compound gross return from t-52 weeks to t-4 weeks. Earnings-announcement shock is the market model cumulative abnormal return with a (-1, 1) event window around the most recent quarterly earnings announcement dates. Price is the closing price at the end of week t-1. The sample period is from July 1963 to December 2006 and the testing period starts from June 1968. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

	G1-Low Eidio	G2	G3	G4	G5-High Eidio	G5-G1	t-stat	G1-Low Eidio	G2	G3	G4	G5-High Eidio	G5-G1	t-stat
	Equal-Weighted Returns (%)							Value-Weighted Returns (%)						
Panel A: Intersection with Size: ME														
P1 Small	0.29	0.33	0.40	0.49	0.75	0.46***	(5.23)	0.32	0.35	0.41	0.43	0.44	0.12	(1.42)
P2	0.31	0.36	0.35	0.33	0.11	-0.19***	(-2.58)	0.31	0.36	0.35	0.32	0.10	-0.21***	(-2.76)
P3	0.27	0.33	0.32	0.28	0.08	-0.19**	(-2.40)	0.27	0.33	0.32	0.28	0.09	-0.18**	(-2.32)
P4	0.28	0.30	0.29	0.25	0.09	-0.19**	(-2.36)	0.27	0.29	0.29	0.24	0.09	-0.18**	(-2.29)
P5 Big	0.24	0.27	0.25	0.25	0.10	-0.11	(-1.15)	0.23	0.25	0.23	0.24	0.08	-0.12	(-1.24)
P5-P1	-0.04	-0.07	-0.15***	-0.24***	-0.61***	-0.57***	(-6.27)	-0.09**	-0.10**	-0.18***	-0.19***	-0.32***	-0.23***	(-2.76)
t-stat	(-1.08)	(-1.63)	(-3.42)	(-3.88)	(-6.44)			(-2.20)	(-2.37)	(-3.94)	(-3.02)	(-3.57)		
Panel B: Intersection with Book-to-Market Ratio: BE/ME														
P1 Growth	0.26	0.27	0.25	0.23	0.25	-0.01	(-0.05)	0.22	0.23	0.23	0.23	0.01	-0.22***	(-2.67)
P2	0.26	0.27	0.31	0.33	0.39	0.13*	(1.71)	0.23	0.25	0.27	0.29	0.17	-0.07	(-0.85)
P3	0.28	0.31	0.32	0.35	0.47	0.19**	(2.38)	0.25	0.28	0.26	0.26	0.27	0.02	(0.26)
P4	0.31	0.33	0.36	0.41	0.46	0.16**	(2.15)	0.27	0.29	0.32	0.34	0.18	-0.09	(-1.02)
P5 Value	0.32	0.36	0.39	0.43	0.65	0.32***	(4.63)	0.29	0.32	0.33	0.28	0.30	0.02	(0.19)
P5-P1	0.07**	0.09***	0.14***	0.20***	0.39***	0.33***	(6.49)	0.06	0.09**	0.10**	0.05	0.30***	0.23***	(2.98)
t-stat	(2.34)	(2.72)	(3.67)	(4.37)	(7.74)			(1.63)	(2.14)	(2.03)	(0.84)	(3.75)		

	Equal-Weighted Returns (%): G1-Low Eidio	G2	G3	G4	G5-High Eidio	G5-G1	t-stat	Value-Weighted Returns (%): G1-Low Eidio	G2	G3	G4	G5-High Eidio	G5-G1	t-stat
Panel C: Intersection with Momentum (Price>$5): Ret $_{(-52,-4)}$														
P1 Loser	0.21	0.21	0.18	0.15	-0.03	-0.24***	(-4.25)	0.20	0.17	0.12	0.09	-0.05	-0.25***	(-3.50)
P2	0.23	0.26	0.26	0.26	0.16	-0.07	(-1.23)	0.23	0.21	0.20	0.20	0.10	-0.13*	(-1.82)
P3	0.26	0.28	0.31	0.29	0.20	-0.06	(-1.00)	0.21	0.21	0.23	0.20	0.15	-0.06	(-0.88)
P4	0.30	0.34	0.35	0.34	0.29	-0.01	(-0.13)	0.24	0.28	0.29	0.22	0.18	-0.06	(-0.87)
P5 Winner	0.34	0.39	0.42	0.46	0.38	0.04	(0.61)	0.29	0.33	0.36	0.35	0.38	0.09**	(2.13)
P5-P1	0.13***	0.18***	0.24***	0.31***	0.41***	0.28***	(6.15)	0.09	0.15***	0.24***	0.26***	0.43***	0.34***	(4.69)
t-stat	(2.84)	(4.95)	(6.34)	(7.46)	(9.10)			(1.44)	(2.71)	(4.07)	(4.25)	(6.69)		
Panel D Intersection with Earnings-Announcement Shock (Price>$5 and 1980-2006)														
P1 Low	0.29	0.28	0.30	0.33	0.26	-0.03	(-0.44)	0.31	0.23	0.29	0.31	0.20	-0.10	(-1.02)
P2	0.32	0.32	0.35	0.31	0.33	0.01	(0.15)	0.27	0.30	0.34	0.28	0.33	0.06	(0.74)
P3	0.34	0.37	0.38	0.37	0.38	0.05	(0.68)	0.29	0.35	0.32	0.28	0.24	-0.04	(-0.47)
P4	0.34	0.35	0.40	0.44	0.43	0.09	(1.21)	0.30	0.31	0.35	0.39	0.35	0.05	(0.57)
P5 High	0.37	0.41	0.45	0.50	0.51	0.14**	(1.99)	0.28	0.37	0.40	0.31	0.38	0.10	(1.16)
P5-P1	0.08***	0.13***	0.15***	0.17***	0.25***	0.18***	(4.39)	-0.02	0.14***	0.12**	0.00	0.18***	0.20***	(2.67)
t-stat	(2.77)	(4.99)	(5.90)	(6.29)	(8.50)			(-0.51)	(3.35)	(2.49)	(0)	(2.87)		

Table 2.6: The Arbitrage Score Strategy

This table reports both firm characteristics and portfolio returns across arbitrage score quintiles. At the beginning of each week, all stocks are independently sorted into deciles from low to high, based on BE/ME, the compound gross return from t-52 weeks to t-4 weeks, negative size and negative return of previous week. Stocks obtain the corresponding score of its decile rank. Arbitrage score is the total score based on four different rankings and ranges from 4 to 40. Eidio is the estimated weekly expected idiosyncratic volatility from EGARCH(1,1) on Fama-French 3-factor model. Each week, stocks are sorted on their arbitrage scores into quintiles. Panel A reports the time-series averages of both the cross-sectional mean (median for BM) and average decile rank. Panel A also reports the time-series average of Spearman correlation coefficients between arbitrage score and other variables. Panel B reports the results for both the equal-weighted and value-weighted portfolio returns. Average return is measured in weekly percentage terms and applies to the out of sample returns. CAPM alphas, FF-3 alphas and Carhart-4 alphas are calculated using the CAPM, Fama-French 3-factor model and Carhart (1997) 4-factor model, respectively. The Sharpe ratio of weekly returns is defined as portfolio excess return over the standard deviation of portfolio raw returns. The sample period is from July 1963 to December 2006 and the testing period starts from June 1968. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Firm Characteristics across Arbitrage Score Quintiles and Correlations

Arbitrage Score Quintile	1-Low	2	3	4	5-High	1-Low	2	3	4	5-High	Spearman Correlations
	Mean Value (Median for BM)					Average Decile Ranks					Arbitrage Score
Eidio	0.05	0.05	0.06	0.06	0.07	5.00	5.00	5.34	5.68	6.49	0.18
Ln(ME)	6.13	5.36	4.63	3.95	3.01	7.62	6.61	5.56	4.55	3.10	-0.56
BM	0.44	0.68	0.86	1.08	1.51	2.90	4.48	5.52	6.65	8.12	0.64
$Ret_{(-52,-4)}$ (%)	-5.32	7.19	12.62	20.93	38.82	3.99	5.05	5.46	6.00	7.03	0.36
$Ret_{(-1,0)}$ (%)	4.00	1.54	0.37	-0.88	-3.41	7.52	6.17	5.47	4.81	3.50	-0.47

Panel B: Weekly Portfolio Returns (%) across Arbitrage Score Quintiles

Arbitrage Score Quintile	1-Low	2	3	4	5-High	H-L	t-stat	1-Low	2	3	4	5-High	H-L	t-stat
	Equal-Weighted Returns (%)							Value-Weighted Returns (%)						
Raw returns	-0.03	0.15	0.28	0.44	0.86	0.88***	(21.04)	0.12	0.30	0.38	0.47	0.71	0.59***	(14.65)
CAPM α	-0.24	-0.05	0.08	0.24	0.67	0.91***	(21.92)	-0.10	0.09	0.17	0.26	0.50	0.59***	(14.58)
FF-3 α	-0.26	-0.10	0.02	0.17	0.60	0.85***	(23.22)	-0.08	0.06	0.12	0.18	0.42	0.50***	(15.46)
Carhart-4 α	-0.19	-0.07	0.04	0.18	0.60	0.79***	(23.92)	-0.05	0.05	0.09	0.14	0.38	0.43***	(15.55)
Sharpe Ratio	-0.06	0.02	0.08	0.15	0.33	0.59		0.00	0.09	0.12	0.15	0.23	0.35	

Table 2.7: Interaction of Idiosyncratic Risk with Arbitrage Score

This table examines the relation between idiosyncratic risk and returns conditioning on arbitrage score. At the beginning of each week, all stocks are independently sorted into deciles from low to high, based on BE/ME, the compound gross return from t-52 weeks to t-4 weeks, negative size and negative return of previous week. Stocks obtain the corresponding score of its decile rank. Arbitrage score is the total score based on four different rankings and ranges from 4 to 40. Eidio is the estimated weekly expected idiosyncratic volatility from EGARCH(1,1) on Fama-French 3-factor model. Eidio is estimated by all the historical weekly data with at least 260 weeks of return data. FF-3 alphas are calculated using Fama-French 3-factor model. Characteristics-adjusted returns are calculated using DGTW (1997) benchmarks. Panel A reports the results of equal-weighted returns and Panel B reports the results of value-weighted returns for dependent sorting. Each week, stocks are first sorted on their arbitrage scores into quintiles and then sorted within each quintile into quintiles based on expected idiosyncratic volatility. Panel C reports the average arbitrage scores over each 5x5 portfolio. Panel D reports the results of equal-weighted returns and Panel E reports the results of value-weighted returns for independent sorting. Each week, stocks are independently sorted on arbitrage score and expected idiosyncratic volatility into quintiles. The sample period is from July 1963 to December 2006 and the testing period starts from June 1968. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Equal-Weighted Portfolio Returns (%) of Dependent Sorting

Arbitrage Scores	G1-Low Eidio	G2	G3	G4	G5-High Eidio	G5-G1 raw returns	G5-G1 FF-3 α	G5-G1 DGTW α
P1 Low	0.17	0.15	0.07	-0.02	-0.50	-0.67***	-0.67***	-0.66***
(Most Overpriced)	(3.76)	(2.75)	(1.09)	(-0.22)	(-4.94)	(-8.36)	(-13.66)	(-14.88)
P2	0.27	0.27	0.24	0.16	-0.17	-0.43***	-0.45***	-0.43***
	(6.55)	(5.3)	(3.87)	(2.03)	(-1.71)	(-5.49)	(-9.60)	(-9.78)
P3	0.29	0.33	0.29	0.26	0.23	-0.06	-0.08	-0.08
	(7.30)	(6.43)	(4.6)	(3.39)	(2.28)	(-0.72)	(-1.44)	(-1.55)
P4	0.34	0.41	0.41	0.40	0.61	0.27***	0.25***	0.26***
	(8.36)	(7.78)	(6.34)	(5.27)	(6.14)	(3.50)	(4.88)	(4.89)
P5 High	0.47	0.63	0.76	1.00	1.43	0.96***	0.91***	0.90***
(Most Underpriced)	(11.43)	(11.28)	(10.97)	(12.15)	(13.54)	(11.79)	(14.68)	(13.93)

Panel B: Value-Weighted Portfolio Returns (%) of Dependent Sorting

Arbitrage Scores	G1-Low Eidio	G2	G3	G4	G5-High Eidio	G5-G1 raw returns	G5-G1 FF-3 α	G5-G1 DGTW α
P1 Low	0.15	0.13	0.10	0.05	-0.22	-0.36***	-0.36***	-0.36***
(Most Overpriced)	(3.31)	(2.44)	(1.45)	(0.66)	(-2.20)	(-4.75)	(-6.55)	(-7.13)
P2	0.30	0.33	0.35	0.31	0.17	-0.12	-0.11**	-0.12**
	(7.20)	(6.36)	(5.52)	(3.97)	(1.80)	(-1.54)	(-2.19)	(-2.30)
P3	0.34	0.44	0.46	0.47	0.35	0.01	0.04	0.00
	(8.27)	(8.05)	(7.12)	(5.51)	(3.34)	(0.10)	(0.60)	(0.08)
P4	0.44	0.52	0.55	0.50	0.53	0.10	0.12**	0.05
	(9.25)	(8.92)	(7.81)	(6.09)	(5.35)	(1.20)	(2.17)	(0.98)
P5 High	0.60	0.69	0.78	0.90	0.95	0.34***	0.34***	0.33***
(Most Underpriced)	(12.03)	(10.79)	(10.26)	(10.26)	(9.08)	(4.07)	(5.48)	(4.95)

Panel C: Average Arbitrage Score across 5x5 Dependently Sorted Portfolios

Arbitrage Scores	G1- Low Eidio	G2	G3	G4	G5- High Eidio
P1 Low	14.10	13.81	13.64	13.61	13.74
P2	18.63	18.62	18.65	18.67	18.71
P3	21.91	21.94	21.97	21.98	21.97
P4	25.19	25.26	25.31	25.34	25.36
P5 High	29.66	29.99	30.35	30.72	31.05

Panel D: Equal-Weighted Portfolio Returns (%) of Independent Sorting

Arbitrage Scores	G1-Low Eidio	G2	G3	G4	G5-High Eidio	G5-G1 raw returns	G5-G1 FF-3 α	G5-G1 DGTW α
P1 Low	0.16	0.11	0.02	-0.14	-0.67	-0.83***	-0.84***	-0.82***
(Most Overpriced)	(3.67)	(1.96)	(0.30)	(-1.57)	(-6.27)	(-9.65)	(-14.99)	(-15.86)
P2	0.27	0.27	0.21	0.07	-0.22	-0.49***	-0.50***	-0.49***
	(6.50)	(4.79)	(3.23)	(0.90)	(-2.11)	(-5.89)	(-9.85)	(-10.11)
P3	0.30	0.33	0.30	0.25	0.23	-0.06	-0.08	-0.07
	(7.40)	(6.31)	(4.55)	(3.17)	(2.28)	(-0.74)	(-1.47)	(-1.40)
P4	0.34	0.42	0.42	0.41	0.61	0.27***	0.24***	0.26***
	(8.73)	(8.15)	(6.66)	(5.38)	(6.21)	(3.49)	(4.74)	(4.90)
P5 High	0.46	0.53	0.67	0.87	1.33	0.87***	0.81***	0.81***
(Most Underpriced)	(11.53)	(10.97)	(11.43)	(11.63)	(13.62)	(11.49)	(14.66)	(13.46)
P5-P1 raw returns	0.30***	0.42***	0.65***	1.01***	2.00***	1.70***		
t-stat	(9.27)	(12.70)	(17.43)	(21.14)	(28.22)	(25.25)		

Panel E: Value-Weighted Portfolio Returns (%) of Independent Sorting

Arbitrage Scores	G1-Low Eidio	G2	G3	G4	G5-High Eidio	G5-G1 raw returns	G5-G1 FF-3 α	G5-G1 DGTW α
P1 Low	0.15	0.10	0.06	0.01	-0.41	-0.56***	-0.56***	-0.52***
(Most Overpriced)	(3.31)	(1.77)	(0.90)	(0.08)	(-3.94)	(-6.61)	(-9.15)	(-9.07)
P2	0.30	0.34	0.32	0.30	0.07	-0.24***	-0.23***	-0.23***
	(7.28)	(6.13)	(4.77)	(3.57)	(0.65)	(-2.77)	(-4.15)	(-4.25)
P3	0.35	0.44	0.46	0.45	0.35	0.01	0.03	-0.00
	(8.40)	(7.95)	(6.93)	(5.06)	(3.35)	(0.06)	(0.44)	(-0.07)
P4	0.42	0.51	0.55	0.51	0.56	0.14*	0.16***	0.09*
	(9.14)	(9.08)	(7.96)	(6.22)	(5.77)	(1.74)	(2.79)	(1.69)
P5 High	0.59	0.65	0.70	0.84	0.95	0.36***	0.34***	0.34***
(Most Underpriced)	(11.54)	(11.23)	(10.57)	(10.51)	(9.73)	(4.43)	(5.66)	(5.56)
P5-P1 raw returns	0.44***	0.55***	0.64***	0.83***	1.36***	0.92***		
t-stat	(9.96)	(12.55)	(14.57)	(14.36)	(18.48)	(11.74)		

Table 2.8: Interaction of Idiosyncratic Risk with Arbitrage Score: Subsample

This table examines the relation between idiosyncratic risk and returns conditioning on arbitrage score over subsamples. At the beginning of each week, all stocks are independently sorted into deciles from low to high, based on BE/ME, the compound gross return from t-52 weeks to t-4 weeks, negative size and negative return of previous week. Stocks obtain the corresponding score of its decile rank. Arbitrage score is the total score based on four different rankings and ranges from 4 to 40. Each week, stocks within the specific subgroups are first sorted on their arbitrage scores into quintiles and then sorted within each quintile into quintiles based on expected idiosyncratic volatility. FF-3 alphas are calculated using Fama-French 3-factor model. Panel A reports the (5-1) spreads in value-weighted FF-3 alphas within each arbitrage score quintile for different group of stocks over the whole sample period. Panel B reports the (5-1) spreads in value-weighted FF-3 alphas within each arbitrage score quintile for all stocks but over different subperiods. Volume is the weekly total trading volume of week t-1. The low Eidio and high Eidio periods refer to the weeks with the lowest and highest 33% average expected idiosyncratic volatility, respectively. The sample period is from July 1963 to December 2006 and the testing period starts from June 1968. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: (5-1) Spread in FF-3 α within Arbitrage Scores Quintiles for Subgroups

	Value-Weighted (5-1) Spread in FF-3 α (%)				
	Arbitrage Scores Low	2	3	4	Arbitrage Scores High
NYSE Stocks Only	-0.22***	-0.10**	-0.01	0.11**	0.23***
	(-4.90)	(-2.29)	(-0.27)	(2.05)	(3.97)
NASDAQ Stocks Only	-0.91***	-0.25**	0.10	0.14	0.57***
	(-7.75)	(-2.04)	(0.88)	(1.13)	(5.67)
S&P 500 stocks only	-0.15***	0.02	-0.01	0.11**	0.22***
	(-2.69)	(0.30)	(-0.26)	(1.96)	(3.59)
Price>$5	-0.21***	-0.08*	0.02	0.09*	0.19***
	(-4.52)	(-1.84)	(0.36)	(1.76)	(3.62)
Size-Small	-0.89***	0.04	0.16**	0.36***	0.74***
	(-11.15)	(0.58)	(2.08)	(5.20)	(10.50)
Size-Medium	-0.68***	-0.15***	-0.06	0.09	0.29***
	(-11.69)	(-2.73)	(-1.13)	(1.59)	(5.29)
Size-Big	-0.21***	0.05	0.01	0.15***	0.20***
	(-4.29)	(0.98)	(0.29)	(3.09)	(3.97)
Volume-Low	-0.99***	-0.59***	-0.30***	-0.10*	0.57***
	(-15.20)	(-9.44)	(-5.52)	(-1.70)	(9.27)
Volume-Medium	-0.65***	-0.30***	-0.06	0.08	0.39***
	(-11.11)	(-5.30)	(-0.93)	(1.34)	(4.26)
Volume-High	-0.39***	-0.05	0.04	0.19***	0.38***
	(-6.33)	(-0.91)	(0.67)	(2.82)	(4.80)

BM-Low	-0.53***	-0.23***	-0.23***	-0.14*	0.16*
	(-7.42)	(-3.10)	(-3.28)	(-1.65)	(1.71)
BM-Medium	-0.36***	-0.09	-0.06	-0.11*	0.28***
	(-5.65)	(-1.44)	(-0.97)	(-1.76)	(3.61)
BM-High	-0.58***	-0.18**	-0.15**	0.05	0.47***
	(-7.97)	(-2.26)	(-2.10)	(0.56)	(6.41)

Panel B: (5-1) Spread in FF-3 α within Arbitrage Scores Quintiles over Subperiods

	Value-Weighted (5-1) Spread in FF-3 α (%)				
	Arbitrage Scores Low	2	3	4	Arbitrage Scores High
1968-1980	-0.47***	-0.16**	0.02	0.01	0.31***
	(-6.80)	(-2.03)	(0.20)	(0.08)	(3.15)
1981-1993	-0.49***	-0.12*	-0.09	0.13	0.28***
	(-6.25)	(-1.67)	(-1.08)	(1.48)	(3.00)
1994-2006	-0.18*	-0.08	0.15	0.18*	0.41***
	(-1.71)	(-0.81)	(1.20)	(1.96)	(3.30)
1994-2000	-0.30**	-0.13	0.17	0.31**	0.48***
	(-2.22)	(-0.98)	(1.00)	(2.34)	(2.67)
2001-2006	0.13	0.09	0.11	0.06	0.34**
	(0.85)	(0.65)	(0.57)	(0.39)	(2.05)
Low Eidio Periods	-0.42***	-0.05	0.01	0.05	0.18**
	(-5.59)	(-0.66)	(0.16)	(0.58)	(2.07)
High Eidio Periods	-0.35***	-0.14	0.19	0.23**	0.55***
	(-3.13)	(-1.34)	(1.42)	(2.30)	(4.23)

Table 2.9: Interaction of Idiosyncratic Risk with Arbitrage Score across Industries

This table examines the relation between idiosyncratic risk and returns conditioning on arbitrage score across all Fama-French 12 industries. At the beginning of each week, all stocks are independently sorted into deciles from low to high, based on BE/ME, the compound gross return from t-52 weeks to t-4 weeks, negative size and negative return of previous week. Stocks obtain the corresponding score of its decile rank. Arbitrage score is the total score based on four different rankings and ranges from 4 to 40. Each week, stocks within each industry sector are first sorted on their arbitrage scores into quintiles and then sorted within each quintile into quintiles based on expected idiosyncratic volatility. FF-3 alphas are calculated using Fama-French 3-factor model. The (5-1) spreads in value-weighted FF-3 alphas are reported within each arbitrage score quintile for Fama-French 12 industries. The sample period is from July 1963 to December 2006 and the testing period starts from June 1968. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

(5-1) Spread in FF-3 α within Arbitrage Scores Quintiles for Fama-French 12 Industries

	Value-Weighted (5-1) Spread in FF-3 α (%)				
	Arbitrage Scores Low	2	3	4	Arbitrage Scores High
Consumer NonDurables	-0.38***	-0.38***	-0.50***	-0.17*	0.35***
	(-5.01)	(-4.25)	(-5.00)	(-1.71)	(3.17)
Consumer Durables	-0.71***	-0.49***	-0.24	-0.29**	0.64***
	(-5.08)	(-3.85)	(-1.58)	(-2.09)	(4.02)
Manufacturing	-0.33***	-0.24***	-0.16*	-0.04	0.55***
	(-4.30)	(-3.14)	(-1.86)	(-0.44)	(5.39)
Energy	-0.50***	-0.40***	-0.35***	-0.35***	0.58***
	(-4.09)	(-3.08)	(-2.96)	(-2.66)	(4.08)
Chemicals	-0.30***	-0.34***	0.13	-0.11	0.61***
	(-2.75)	(-2.87)	(0.97)	(-0.75)	(3.61)
Business Equipment	-0.55***	-0.53***	-0.23**	0.03	0.56***
	(-5.78)	(-4.93)	(-1.98)	(0.29)	(4.49)
Telecom	-0.37**	-0.07	0.15	0.53***	0.51***
	(-2.11)	(-0.44)	(0.85)	(2.66)	(2.71)
Utilities	-0.04	0.07	0.07	0.04	0.11
	(-0.57)	(1.07)	(1.02)	(0.52)	(1.32)
Wholesale & Retail	-0.44***	-0.23***	-0.13	-0.12	0.39***
	(-5.09)	(-2.65)	(-1.28)	(-1.20)	(3.82)
Healthcare	-0.36***	-0.43***	-0.14	0.02	0.39**
	(-2.80)	(-3.73)	(-1.05)	(0.17)	(2.48)
Finance	-0.26***	-0.10	-0.21**	-0.21**	0.18
	(-3.20)	(-1.23)	(-2.2)	(-2.34)	(1.49)
Others	-0.68***	-0.42***	-0.24**	-0.08	0.51***
	(-7.38)	(-4.22)	(-2.21)	(-0.84)	(4.77)

The Fama-French 12 industry definition is from Kenneth R. French's website

Table 2.10: Idiosyncratic Risk and Other Arbitrage Costs

This table examines the relation between idiosyncratic risk and other arbitrage cost measures among the most overvalued (low arbitrage score) stocks and the most undervalued (high arbitrage score) stocks, respectively. At the beginning of each week, all stocks are independently sorted into deciles from low to high, based on BE/ME, the compound gross return from t-52 weeks to t-4 weeks, negative size and negative return of previous week. Stocks obtain the corresponding score of its decile rank. Arbitrage score is the total score based on four different rankings and ranges from 4 to 40. Eidio is the estimated weekly expected idiosyncratic volatility from EGARCH(1,1) on Fama-French 3-factor model. The proxy for direct transaction cost is price level, measured as the closing price at the end of week t-1. The proxy for indirect transaction cost is illiquidity, calculated as daily average Amihud (2002) measure over week t-1. The proxy for short-sale constraint is institutional ownership (IO), measured as the percentage of common stocks owned by institutions in the precious quarter. Each week, stocks are independently sorted on their arbitrage score (5 groups), price (3 groups), illiquidity (3 groups), institutional ownership (3 groups if available) and expected idiosyncratic volatility (5 groups). Panel A reports the results on the interaction between Eidio and price. Panel B reports the results on the interaction between Eidio and illiquidity. Panel C reports the results on the interaction between Eidio and institutional ownership. Value-weighted raw returns (%) are reported. The sample period is from July 1963 to December 2006 and the testing period starts from June 1968. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Idiosyncratic risk and Direct Transaction Cost (Price Level)

Value-Weighted Raw Returns (%)

	1-Low Eidio	2	3	4	5-High Eidio	H-L	t-stat	1-Low Eidio	2	3	4	5-High Eidio	H-L	t-stat
	Within Arbitrage Score Quintile 1 (Most Overvalued)							Within Arbitrage Score Quintile 5 (Most Undervalued)						
1-Low Price	0.02	0.21	-0.05	-0.28	-0.78	-0.84***	(-6.12)	0.46	0.66	0.80	0.93	1.09	0.61***	(6.84)
2	0.20	0.18	0.08	-0.00	-0.38	-0.57***	(-6.03)	0.54	0.65	0.67	0.78	0.78	0.24***	(2.77)
3-High Price	0.14	0.08	0.06	0.01	-0.22	-0.38***	(-3.33)	0.57	0.61	0.67	0.77	0.60	0.08	(0.53)
3-1	0.02	-0.08	0.11	0.30***	0.54***			0.10	-0.05	-0.13*	-0.15*	-0.38***		
t-stat	(0.23)	(-0.80)	(1.14)	(3.21)	(4.39)			(1.42)	(-0.64)	(-1.87)	(-1.65)	(-2.74)		

Panel B: Idiosyncratic Risk and Indirect Transaction Cost (Illiquidity)

Value-Weighted Raw Returns (%)

	1-Low Eidio	2	3	4	5-High Eidio	H-L	t-stat	1-Low Eidio	2	3	4	5-High Eidio	H-L	t-stat
	Within Arbitrage Score Quintile 1 (Most Overvalued)							Within Arbitrage Score Quintile 5 (Most Undervalued)						
1-Low Price	0.15	0.10	0.06	0.05	-0.19	-0.33***	(-3.48)	0.60	0.61	0.73	0.79	0.73	0.10	(0.74)
2	0.05	-0.00	-0.02	-0.20	-0.64	-0.69***	(-7.45)	0.54	0.65	0.70	0.88	0.90	0.36***	(4.07)
3-High Price	0.22	-0.23	-0.17	-0.59	-1.31	-1.41***	(-11.87)	0.54	0.55	0.69	0.81	1.02	0.49***	(6.96)
3-1	0.01	-0.32***	-0.24***	-0.64***	-1.12***			-0.05	-0.07	-0.05	0.02	0.30**		
t-stat	(0.14)	(-4.61)	(-2.95)	(-7.71)	(-10.57)			(-0.75)	(-0.90)	(-0.65)	(0.24)	(2.44)		

Panel C: Idiosyncratic Risk and Short-Sale Constraints (Institutional Ownership): 1980-2006

Value-Weighted Raw Returns (%)

	1-Low Eidio	2	3	4	5-High Eidio	H-L	t-stat	1-Low Eidio	2	3	4	5-High Eidio	H-L	t-stat
	Within Arbitrage Score Quintile 1 (Most Overvalued)							Within Arbitrage Score Quintile 5 (Most Undervalued)						
1-Low Price	0.22	0.16	0.07	-0.00	-0.75	-0.96***	(-6.80)	0.61	0.55	0.67	0.83	0.94	0.33***	(3.19)
2	0.25	0.19	0.12	0.06	-0.33	-0.58***	(-4.25)	0.50	0.59	0.61	0.82	1.02	0.52***	(4.41)
3-High Price	0.20	0.14	0.10	0.07	-0.04	-0.24**	(-2.17)	0.59	0.67	0.74	0.88	0.83	0.24	(1.53)
3-1	-0.02	-0.02	0.03	0.07	0.71***			-0.02	0.12	0.07	0.05	-0.11		
t-stat	(-0.38)	(-0.23)	(0.32)	(0.68)	(5.98)			(-0.23)	(1.61)	(1.03)	(0.49)	(-0.65)		

Table 2.11: Interaction of Idiosyncratic Risk with Arbitrage Score: Weekly Fama-MacBeth Regressions

This table reports weekly Fama-MacBeth regressions of stock returns (constant not reported) among stocks with different arbitrage scores. At the beginning of each week, all stocks are independently sorted into deciles from low to high, based on BE/ME, the compound gross return from t-52 weeks to t-4 weeks, negative size and negative return of previous week. Stocks obtain the corresponding score of its decile rank. Arbitrage score is the total score based on four different rankings and ranges from 4 to 40. Each week, stocks are sorted on their arbitrage scores into quintiles and the Fama-MacBeth regressions are conducted within each quintile. The dependent variable is weekly stock return (%). Eidio is the estimated weekly expected idiosyncratic volatility from EGARCH(1,1) on Fama-French 3-factor model. Eidio is estimated by all the historical weekly data with at least 260 weeks of return data. Beta is the weekly CAPM beta and estimated weekly over previous 104 weeks. ME is the firm's market capitalization at the end of week t-1. BE/ME is the fiscal-yearend book value of common equity divided by the calendar-yearend market value of equity. $Ret_{(-52,-4)}$ is the compound gross return from t-52 weeks to t-4 weeks. $Ret_{(-1,0)}$ is the raw return of previous week. Price is the closing price at the end of week t-1. Firm age is defined as the number of years since a stock first appeared in the CRSP. Illiquidity is the weekly illiquidity measure calculated following Amihud (2002) and measured at week t-1. Institutional Ownership is the percentage of common stocks owned by institutions in the previous quarter. Analyst Coverage is the number of analysts following the firm in the previous month. Analyst Dispersion is the standard deviation of analyst forecasts in previous month scaled by the prior year-end stock price. To avoid giving extreme observations heavy weight in the return regressions, all independent variables are winsorized each week at 0.5% level. Panel A reports the basic results within each arbitrage score quintile. Panel B reports the results after including the systematic risk. Panel C reports the results after including firm characteristics. Panel D reports the key results after including additional control variables to the model in Panel C. The sample period is from July 1963 to December 2006 and the testing period starts from June 1968. Robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Panel A: Stocks within Arbitrage Score Quintiles

	Arbitrage Scores Quintile 1	Arbitrage Scores Quintile 2	Arbitrage Scores Quintile 3	Arbitrage Scores Quintile 4	Arbitrage Scores Quintile 5
Eidio	-10.979***	-7.019***	-1.381	3.289***	9.702***
	(-10.55)	(-7.19)	(-1.46)	(3.55)	(12.83)
Average Adj. R^2	2.20%	1.80%	1.50%	1.20%	1.10%

Panel B: Controlling for Systematic Risk

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Eidio	-10.861***	-7.178***	-1.524	3.159***	10.585***
	(-10.59)	(-7.48)	(-1.64)	(3.53)	(12.75)
Beta	0.003	0.073***	0.058**	0.068***	0.052**
	(0.11)	(2.93)	(2.49)	(3.14)	(2.47)
Average Adj. R^2	3.00%	2.60%	2.20%	1.80%	1.50%

Panel C: Controlling for Firm Characteristics

	Arbitrage Scores Quintile 1	Arbitrage Scores Quintile 2	Arbitrage Scores Quintile 3	Arbitrage Scores Quintile 4	Arbitrage Scores Quintile 5
Eidio	-5.964***	-3.627***	0.217	1.853**	2.900***
	(-6.87)	(-4.50)	(0.26)	(2.21)	(3.92)
Beta	-0.015	0.023	-0.007	0.010	0.014
	(-0.59)	(0.94)	(-0.31)	(0.44)	(0.68)
Ln(ME)	-0.048***	-0.046***	-0.071***	-0.082***	-0.146***
	(-4.29)	(-4.49)	(-6.50)	(-7.20)	(-10.59)
Ln(BM)	0.045**	0.072***	0.107***	0.124***	0.086***
	(2.42)	(3.63)	(5.18)	(6.47)	(5.64)
$Ret_{(-52, -4)}$	0.229***	0.379***	0.370***	0.324***	0.071*
	(3.31)	(7.08)	(7.13)	(7.17)	(1.94)
$Ret_{(-1, 0)}$	-6.024***	-7.451***	-10.049***	-10.943***	-16.244***
	(-20.28)	(-20.39)	(-27.9)	(-26.36)	(-32.54)
Average Adj. R^2	5.70%	5.20%	5.10%	4.40%	4.60%

Panel D: Controlling for Other Arbitrage Cost Measures

Basic control variables include Beta, Ln(ME), Ln(BM), $Ret_{(-52, -4)}$ and $Ret_{(-1, 0)}$

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Control for Price, Firm Age and Illiquidity: 1968-2006					
Eidio	-4.783***	-2.426***	0.367	1.259*	2.105***
	(-5.46)	(-2.86)	(0.43)	(1.91)	(3.02)
Control for Institution Ownership, Analyst Coverage and Analyst Dispersion: 1980-2006					
Eidio	-3.381***	-1.937*	-0.162	2.583**	2.916***
	(-3.09)	(-1.84)	(-0.15)	(2.32)	(2.92)
Control for All Above: 1980-2006					
Eidio	-3.096***	-2.148**	-0.361	1.879*	2.975***
	(-2.83)	(-2.04)	(-0.33)	(1.70)	(2.87)

Table 2.A1: Regression Sample Size and the Probability of Convergence for EGARCH Estimations

This table shows the relation between the accuracy of EGARCH(1,1) estimations and the number of observations used in the regression. The probability of convergence is defined as cross-sectional percentage of successful convergence in the MLE procedures. The time-series mean and other statistics are reported. The regression sample size intervals are listed in the square bracket, with a maximum of 2270 weeks. The sample period is from July 1963 to December 2006.

Probability of Convergence	Sample Size Intervals		
	[52,120]	[120, 260]	[260, 360]
Min	60.64%	81.03%	91.47%
Max	84.93%	93.16%	98.90%
Median	73.49%	88.44%	95.21%
Mean	73.52%	88.29%	95.04%
Std	4.23%	2.30%	1.60%
	[52, 2270]	[120, 2270]	[260, 2270]
Min	60.64%	81.03%	91.47%
Max	99.62%	99.62%	99.62%
Median	90.87%	93.49%	97.75%
Mean	89.65%	93.20%	97.38%
Std	4.77%	2.41%	0.96%
Total observations	12.6 million	9.6 million	7.4 million

Table 3.1: Summary Statistics

This table reports the descriptive statistics of delta-hedged option returns for the pooled data. The option sample period is from Jan 1996 to Dec 2006. At the end of each month, we extract from the Ivy DB database of Optionmetrics one call and one put on each optionable stock. The selected options are approximately at-the-money with a common maturity of about one and a half month. We exclude the following option observations: (1) moneyness is lower than 0.8 or higher than 1.2; (2) option price violates obvious no-arbitrage option bounds; (3) reported option trading volume is zero; (4) option bid quote is zero or mid-point of bid and ask quotes is less than $1/8; (5) the underlying stock paid a dividend during the remaining life of the option. Delta-hedged gain is the change in the value of a self-financing portfolio consisting of a long call position, re-hedged daily by shorting a proper amount of the underlying stock so that the portfolio is not sensitive to stock price movement, with the net investment earning riskfree rate. The total number of underlying stocks involved over the whole sample period is 5225. The average number of optionable stocks per month in our final sample is 1394. The pooled data has 159,346 observations for delta-hedged call returns and 143,017 observations for delta-hedged put returns. Days to maturity is the total number of calendar days till the option expiration. Moneyness is the ratio of stock price over option strike price. Vega is the option vega according to the Black-Sholes model scaled by stock price. Vega, moneyness and days to maturity are measured at the end of each month.

Variable		Mean	Median	StDev	10 Pctl	Lower Quartile	Upper Quartile	90 Pctl
Panel A: Call Options (159,346 Obs)								
Delta-hedged gain till maturity / stock price	(%)	-0.49	-0.65	3.66	-3.58	-1.90	0.51	2.24
Delta-hedged gain till maturity / option price	(%)	-4.99	-10.17	58.30	-44.65	-27.05	7.78	31.70
Delta-hedged gain till month-end / stock price	(%)	-0.38	-0.47	2.21	-2.51	-1.36	0.41	1.72
Delta-hedged gain till month-end / option price	(%)	-4.32	-7.33	30.12	-31.86	-19.39	6.31	24.37
Days to maturity		50	50	2	47	50	51	52
Moneyness = S/K	(%)	100.51	100.11	5.10	94.72	97.25	103.36	106.51
Vega		0.14	0.14	0.01	0.13	0.14	0.15	0.15

Variable		Mean	Median	StDev	10 Pctl	Lower Quartile	Upper Quartile	90 Pctl
Panel B: Put Options (139,285 Obs)								
Delta-hedged gain till maturity / stock price	(%)	-0.54	-0.67	3.18	-3.58	-1.92	0.55	2.41
Delta-hedged gain till maturity / option price	(%)	-6.58	-11.12	44.97	-46.71	-28.87	8.51	34.72
Delta-hedged gain till month-end / stock price	(%)	-0.24	-0.42	2.38	-2.45	-1.31	0.52	2.00
Delta-hedged gain till month-end / option price	(%)	-2.30	-6.92	35.26	-31.95	-19.66	8.25	29.06
Days to maturity		50	50	2	47	50	51	52
Moneyness = S/K	(%)	99.84	99.72	4.86	94.23	96.83	102.75	105.63
Vega		0.14	0.14	0.01	0.13	0.14	0.15	0.15

Panel C: Average Delta-hedged Gain till Maturity / Stock Price

Option Type	Total stocks	mean<0	t<-2	mean>0	t>2	P10	P25	P50	P75	P90
Call	5159	3890	1898	1269	62	-2.39%	-1.28%	-0.54%	-0.10%	0.65%
Put	5073	3975	1928	1098	68	-2.27%	-1.21%	-0.55%	-0.10%	0.66%

Table 3.2: Distribution of Delta-Hedged Call Option Returns: Subsamples

This table reports the descriptive statistics of delta-hedged call option returns for the pooled data. The option sample period is from Jan 1996 to Dec 2006. At the end of each month, we extract from the Ivy DB database of Optionmetrics one call and one put on each optionable stock. The selected options are approximately at-the-money with a common maturity of about one and a half month. We exclude the following option observations: (1) moneyness is lower than 0.8 or higher than 1.2; (2) option price violates obvious no-arbitrage option bounds; (3) reported option trading volume is zero; (4) option bid quote is zero or mid-point of bid and ask quotes is less than $1/8; (5) the underlying stock paid a dividend during the remaining life of the option. Delta-hedged gain is the change in the value of a self-financing portfolio consisting of a long call position, re-hedged daily by shorting a proper amount of the underlying stock so that the portfolio is not sensitive to stock price movement, with the net investment earning riskfree rate.

The Pooled Distribution of <Delta-Hedged Gain till Maturity of Call / Stock Price> (%)

Subsamples	Mean	StDev	10 Pctl	Lower Quartile	Median	Upper Quartile	90 Pctl
Full Sample	-0.49	3.66	-3.58	-1.90	-0.65	0.51	2.24
Size Quintile 1	-1.31	4.45	-5.83	-3.56	-1.50	0.45	2.95
Size Quintile 2	-0.64	3.41	-3.89	-2.31	-0.89	0.59	2.61
Size Quintile 3	-0.35	3.31	-3.06	-1.78	-0.64	0.54	2.26
Size Quintile 4	-0.18	3.21	-2.48	-1.43	-0.50	0.49	1.86
Size Quintile 5	0.10	3.43	-1.79	-1.02	-0.30	0.48	1.66
Price Quintile 1	-1.51	4.53	-6.09	-3.81	-1.72	0.29	2.92
Price Quintile 2	-0.71	2.96	-3.76	-2.23	-0.86	0.54	2.35
Price Quintile 3	-0.35	2.66	-2.90	-1.65	-0.55	0.61	2.21
Price Quintile 4	-0.21	2.73	-2.41	-1.37	-0.47	0.51	1.93
Price Quintile 5	0.32	4.63	-2.00	-1.11	-0.34	0.51	1.92

Table 3.3: Delta-Hedged Option Returns and Stock Volatility

This table reports the average coefficients from monthly Fama-MacBeth regressions of delta-hedged call option gains till maturity scaled by the underlying stock price at the beginning of the period. Total volatility (VOL) is the standard deviation of daily stock returns over the previous month. Idiosyncratic volatility (IVOL) is the standard deviation of the residuals of the Fama-French 3-factors model estimated using the daily stock returns over the previous month. Systematic volatility (SysVOL) is the square root of (VOL^2-$IVOL^2$). MKTRF Beta, SMB Beta and HML Beta are estimated on Fama-French 3-factors model. ΔVIX Beta is estimated on a two factor model: market return and the change of CBOE's Volatility Index (VIX). All Betas are estimated using daily data over the previous month. IV is the at-the-money Black-Sholes option implied volatility at the end of each month. Vega is the Black-Scholes option vega scaled by the underlying stock price at the beginning of the period. Contemporaneous stock return is the return of the underlying stock over the same period as the dependent variable. Option implied skewness and kurtosis are the risk-neutral skewness and kurtosis of stock returns inferred from a cross-section of out of the money calls and puts at the end of previous month following Bakshi and Kapadia (2003a). All independent variables are winsorized each month at 0.5% level. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.0007	0.0250	0.0136	0.0137	0.0162	0.0136
	(0.85)	(8.03)	(4.65)	(4.74)	(3.49)	(4.56)
VOL	-0.0113	-0.0124			-0.0066	-0.0271
	(-7.38)	(-8.62)			(-4.67)	(-15.13)
IVOL			-0.0279	-0.0291		
			(-18.60)	(-19.52)		
SysVOL			-0.0058			
			(-1.36)			
ΔVIX Beta				0.0200		
				(1.53)		
MKTRF Beta				-0.0002		
				(-0.91)		
SMB Beta				-0.0001		
				(-1.32)		
HML Beta				-0.0003		
				(-1.64)		
Ln (VOL_{t-1} / IV_{t-1})			0.0219	0.0217		0.0223
			(20.63)	(20.41)		(20.71)
Ln (IV_t / IV_{t-1})			0.0341	0.0341		0.0340
			(23.68)	(24.16)		(23.55)
Option Implied Skewness					-0.0019	
					(-7.88)	
Option Implied Kurtosis					-0.0565	
					(-9.86)	
Vega		-0.1825	-0.0485	-0.0485	-0.1410	-0.0469
		(-8.38)	(-2.43)	(-2.50)	(-4.48)	(-2.30)
Contemporaneous stock return		0.0326	0.0302	0.0306	0.0403	0.0300
		(11.46)	(11.36)	(11.91)	(10.25)	(11.10)
Average Adj. R^2	0.0160	0.0500	0.1464	0.1496	0.0927	0.1445

Table 3.4: Controlling for Past Stock Returns

This table reports the average coefficients from monthly Fama-MacBeth cross-sectional regressions of delta-hedged call option returns (delta-hedged option gain till maturity scaled by the underlying stock price at the beginning of the period). $Ret_{(-1, 0)}$ is the stock return in the prior month. $Ret_{(-12, -1)}$ is the cumulative stock return from the prior 2^{nd} through 12^{th} month. $Ret_{(-36, -13)}$ is the cumulative stock return from the prior 13^{th} through 36^{th} month. ME is the product of monthly closing price and the number of outstanding shares in previous June. Book-to-market is the fiscal-yearend book value of common equity divided by the calendar-yearend market value of equity. Total volatility (VOL) is the standard deviation of daily stock returns over the previous month. IV is the at-the-money Black-Sholes option implied volatility at the end of each month. Vega is the Black-Scholes option vega scaled by the underlying stock price at the beginning of the period. Contemporaneous stock return is the return of the underlying stock over the same period as the dependent variable. All independent variables are winsorized each month at 0.5% level. The sample period is from January 1996 to December 2006. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.0227	0.0229	0.0230	0.0222	0.0030	0.0045
	(8.98)	(9.31)	(8.91)	(9.27)	(1.27)	(1.93)
VOL	-0.0138	-0.0138	-0.0130	-0.0157	-0.0100	-0.0313
	(-10.36)	(-10.63)	(-10.36)	(-13.49)	(-8.50)	(-20.44)
$Ret_{(-1,0)}$	0.0117			0.0125	0.0130	0.0046
	(8.29)			(9.16)	(9.53)	(3.25)
$Ret_{(-12,-1)}$		0.0033		0.0035	0.0035	0.0035
		(9.97)		(10.78)	(11.58)	(12.30)
$Ret_{(-36, -13)}$			0.0006	0.0007	0.0005	0.0006
			(4.00)	(4.53)	(3.96)	(5.03)
Ln (ME)					0.0024	0.0008
					(10.73)	(4.54)
Ln (BE/ME)					0.0001	-0.0009
					(0.33)	(-4.48)
Ln (VOL_{t-1} / IV_{t-1})						0.0217
						(22.54)
Ln (IV_t / IV_{t-1})						0.0333
						(26.60)
Vega	-0.1690	-0.1727	-0.1718	-0.1688	-0.1736	-0.0316
	(-9.15)	(-9.62)	(-9.15)	(-9.73)	(-9.89)	(-2.13)
Contemporaneous stock return	0.0345	0.0345	0.0346	0.0351	0.0355	0.0327
	(12.86)	(12.97)	(13.04)	(13.44)	(13.43)	(13.28)
Average Adj. R^2	0.0564	0.0576	0.0530	0.0656	0.0784	0.1631

Table 3.5: Controlling for Option Demand Pressure and Liquidity

This table reports the average coefficients from monthly Fama-MacBeth cross-sectional regressions of delta-hedged call option returns (delta-hedged gain till maturity scaled by the underlying stock price at the beginning of the period). Open interest is the option open interest at the end of the previous month. Stock volume is the monthly total stock trading volume of last month. Option bid-ask spread is the ratio of bid-ask spread of option quotes over the mid-point of bid and ask quotes. Illiquidity is the daily average of the Amihud (2002) illiquidity measure over the previous month. Stock price is closing price at the end of last month. Total volatility (VOL) is the standard deviation of daily stock returns over the previous month. $Ret_{(-12,-1)}$ is the cumulative stock return from the prior 2^{nd} through 12^{th} month. ME is the product of monthly closing price and the number of outstanding shares in previous June. IV is the at-the-money Black-Sholes option implied volatility at the end of each month. Vega is the Black-Scholes option vega scaled by the underlying stock price at the beginning of the period. Contemporaneous stock return is the return of the underlying stock over the same period as the dependent variable (delta-hedged option return). All independent variables are winsorized each month at 0.5% level. The sample period is from January 1996 to December 2006. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.0240	0.0249	0.0082	0.0078	0.0026	0.0029
	(8.74)	(9.04)	(3.28)	(2.53)	(0.84)	(1.00)
VOL	-0.0125	-0.0125	-0.0077	-0.0059	-0.0053	-0.0236
	(-9.11)	(-9.37)	(-5.51)	(-4.67)	(-4.49)	(-13.69)
(Option open interest / stock volume) $*10^3$	-0.0266				-0.0197	-0.0167
	(-9.14)				(-8.89)	(-8.39)
Option bid-ask spread (%)		-0.0059			0.0140	0.0070
		(-3.68)			(8.61)	(5.09)
Ln (Illiquidity)			-0.0025		-0.0016	-0.0023
			(-11.29)		(-6.99)	(-11.36)
Stock price				0.0002	0.0002	0.0001
				(16.01)	(13.94)	(9.96)
$Ret_{(-12,-1)}$					0.0015	0.0014
					(6.07)	(5.95)
Ln (ME)					-0.0004	-0.0022
					(-1.86)	(-10.46)
Ln (VOL_{t-1} / IV_{t-1})						0.0190
						(20.66)
Ln (IV_t / IV_{t-1})						0.0349
						(27.33)
Vega	-0.1733	-0.1775	-0.1903	-0.1423	-0.1656	-0.0194
	(-8.72)	(-9.12)	(-9.51)	(-6.26)	(-7.42)	(-1.08)
Contemporaneous stock return	0.0342	0.0340	0.0348	0.0352	0.0375	0.0336
	(11.91)	(11.73)	(12.18)	(12.35)	(13.24)	(12.73)
Average Adj. R^2	0.0556	0.0548	0.0692	0.0775	0.0907	0.1716

Table 3.6: Alternative Measures of Delta-Hedged Option Returns

This table reports the average coefficients from monthly Fama-MacBeth cross-sectional regressions, using alternative measures of delta-hedged option returns as the dependent variable, for both call options (Panel A) and put options (Panel B). The first model uses delta-hedged option gain till maturity defined in Equation (2) scaled by stock price at the beginning of the period. In the second model, delta-hedged option positions are held for one month rather than till option maturity. In the third model, the dependent variable is delta-hedged option gains till maturity divided by the option price at the beginning of the period. All independent variables are the same as defined in Table 2 to 4, and winsorized each month at 0.5% level. The sample period is from January 1996 to December 2006. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets.

Panel A: Delta-Hedged Call Option Returns

Dependent Variables	Gain till maturity / stock price	Gain till month-end / stock price	Gain till maturity / option price
Intercept	0.0036	-0.0038	0.0973
	(1.35)	(-2.18)	(2.33)
VOL	-0.0264	-0.0174	-0.2106
	(-18.81)	(-17.98)	(-10.11)
Ret $_{(-1,0)}$	0.0016	-0.0003	0.0130
	(1.20)	(-0.38)	(0.68)
Ret $_{(-12,-1)}$	0.0017	0.0010	0.0204
	(7.50)	(8.13)	(6.07)
Ret $_{(-36, -13)}$	0.0005	0.0002	0.0044
	(3.87)	(4.00)	(3.23)
(Option open interest / stock volume) $*10^3$	-0.0162	-0.0142	-0.2009
	(-8.54)	(-10.24)	(-10.57)
Option bid-ask spread (%)	0.0070	0.0007	-0.0395
	(5.34)	(0.92)	(-2.09)
Ln (Illiquidity)	-0.0022	-0.0010	-0.0162
	(-11.05)	(-9.42)	(-5.90)
Stock price	0.0001	0.0000	0.0024
	(10.11)	(0.93)	(8.85)
Ln (ME)	-0.0021	-0.0008	-0.0232
	(-9.97)	(-7.52)	(-6.93)
Ln (VOL_{t-1} / IV_{t-1})	0.0197	0.0129	0.1956
	(20.09)	(24.92)	(12.69)
Ln (IV_t / IV_{t-1})	0.0340	0.0476	0.5337
	(27.56)	(28.63)	(38.46)
Vega	-0.0184	0.0452	-0.6067
	(-1.06)	(4.51)	(-2.14)
Contemporaneous stock return	0.0336	0.0034	0.4569
	(13.85)	(4.50)	(11.05)
Average Adj. R^2	0.1749	0.4432	0.1205

Panel B: Delta-Hedged Put Option Returns

Dependent Variables	Gain till maturity stock price	Gain till month-end stock price	Gain till maturity option price
Intercept	-0.0179	-0.0077	0.0029
	(-6.00)	(-3.61)	(5.23)
VOL	-0.0266	-0.0159	-0.0039
	(-18.40)	(-13.96)	(-8.07)
Ret $_{(-1,0)}$	-0.0025	-0.0019	-0.0019
	(-1.89)	(-1.90)	(-3.76)
Ret $_{(-12,-1)}$	0.0015	0.0010	0.0002
	(8.20)	(8.50)	(1.86)
Ret $_{(-36,-13)}$	0.0004	0.0002	0.0001
	(5.21)	(4.99)	(3.64)
(Option open interest / stock volume) *10^3	-0.0241	-0.0191	-0.0034
	(-9.54)	(-12.10)	(-5.04)
Option bid-ask spread (%)	0.0133	0.0024	-0.0007
	(9.03)	(2.59)	(-1.32)
Ln (Illiquidity)	-0.0028	-0.0010	-0.0004
	(-11.69)	(-8.86)	(-6.66)
Stock price	0.0000	0.0000	-0.0000
	(1.41)	(0.34)	(-4.35)
Ln (ME)	-0.0020	-0.0008	-0.0003
	(-10.40)	(-7.84)	(-6.18)
Ln (VOL_{t-1} / IV_{t-1})	0.0211	0.0126	0.0044
	(23.57)	(23.59)	(15.21)
Ln (IV_t / IV_{t-1})	0.0367	0.0507	0.0101
	(26.77)	(29.67)	(23.09)
Vega	0.1172	0.0633	-0.0054
	(7.17)	(5.53)	(-1.40)
Contemporaneous stock return	-0.0242	-0.0021	0.0001
	(-7.64)	(-2.70)	(0.39)
Average Adj. R^2	0.2394	0.4400	0.1184

Table 3.7: Delta-Hedged Option Returns and Volatility: EGARCH Measures

This table reports the average coefficients from monthly Fama-MacBeth regressions of delta-hedged call option gains till maturity scaled by the underlying stock price at the beginning of the period. Realized idiosyncratic volatility (IVOL) is the standard deviation of the residuals of the Fama-French 3-factors model estimated using the daily stock returns over the previous month. Expected idiosyncratic volatility (Eidio) is the estimated monthly expected idiosyncratic volatility from EGARCH(1,1) on Fama-French 3-factor model. $Ret_{(-1, 0)}$ is the stock return in the prior month. $Ret_{(-12, -1)}$ is the cumulative stock return from the prior 2nd through 12th month. $Ret_{(-36, -13)}$ is the cumulative stock return from the prior 13th through 36th month. ME is the product of monthly closing price and the number of outstanding shares in previous June. Open interest is the option open interest at the end of the previous month. Stock volume is the monthly total stock trading volume of last month. Option bid-ask spread is the ratio of bid-ask spread of option quotes over the mid-point of bid and ask quotes. Illiquidity is the daily average of the Amihud (2002) illiquidity measure over the previous month. Stock price is closing price at the end of last month. IV is the at-the-money Black-Sholes option implied volatility at the end of each month. Vega is the Black-Scholes option vega scaled by the underlying stock price at the beginning of the period. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets.

Dependent Variables	Model 1	Model 2	Model 3	Model 4
Intercept	0.0019	0.0309	0.0022	0.0101
	(2.46)	(11.05)	(2.7)	(3.44)
IVOL	-0.0162	-0.0367		
	(-11.74)	(-26.58)		
Eidio			-0.0152	-0.0081
			(-10.72)	(-8.74)
$Ret_{(-1,0)}$		0.0013		0.0044
		(0.72)		(2.78)
$Ret_{(-12,-1)}$		0.0014		0.0015
		(3.94)		(4.25)
$Ret_{(-36, -13)}$		0.0003		0.0001
		(2.14)		(0.61)
(Option open interest / stock volume) $*10^3$		-0.0028		-0.0009
		(-10.16)		(-3.58)
Option bid-ask spread (%)		-0.0192		-0.0197
		(-10.46)		(-10.29)
Ln (Illiquidity)		-0.0050		0.0008
		(-4.16)		(0.63)
Stock price		-0.0020		-0.0015
		(-7.42)		(-5.76)
Ln (ME)		0.0001		0.0002
		(5.77)		(11.33)
Ln (VOL_{t-1} / IV_{t-1})		0.0247		0.0110
		(21.3)		(12.9)
Vega		-0.0918		-0.1286
		(-4.62)		(-6.44)
Average Adj. R^2	0.0196	0.0950	0.0170	0.0707

Table 3.8: Returns to Covered Call and Stock Volatility: Portfolio Analysis

This table reports the average return of portfolios of covered calls sorted by the total volatility (Panel A) or by the idiosyncratic volatility (Panel B) of the underlying stocks. We continue to use the sample of short-term at-the-money call options on individual stocks. Each covered call involves selling a call option against Delta shares of the underlying stock owned, where Delta is the Black-Scholes call option delta at initial date. Each covered call position is held for one month (without rebalancing the delta-hedge) and then closed. Total volatility is the standard deviation of daily stock returns over the previous month. Idiosyncratic volatility is the standard deviation of the residuals of the Fama-French 3-factors model estimated using the daily stock returns over the previous month. All the numbers in this table are expressed in percent. We try three weighting schemes in computing the average portfolio return: equal weight, weighted by the market capitalization of the underlying stock (at the beginning of the period), or weighted by the market value of total option open interest (at the beginning of the period). Besides the average raw returns of portfolios of covered calls, we also report their CAPM alphas, FF-3 alphas and Carhart-4 Alphas. Panel C reports some subsample results. The sample period is from January 1996 to December 2006. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in the brackets.

Quintile	Option Type	1-Low	2	3	4	5-High	5-1	CAPM Alpha	FF-3 Alpha	Carhart-4 Alpha
Panel A: Return to Covered Call Writing Sorted on Total Volatility										
Equal-weighted	C	1.62	2.05	2.56	2.98	3.95	2.33	2.32	2.32	2.31
		(13.18)	(13.24)	(14.01)	(12.32)	(15.05)	(10.37)	(9.69)	(9.23)	(9.64)
Stock-value-weighted	C	1.52	1.65	2.02	2.41	3.18	1.66	1.61	1.70	1.77
		(11.43)	(10.94)	(12.81)	(9.21)	(11.52)	(6.77)	(5.83)	(5.77)	(6.32)
Option-value-weighted	C	1.45	1.71	2.27	2.55	3.76	2.31	2.25	2.31	2.31
		(9.72)	(9.61)	(11.86)	(7.66)	(12.16)	(7.87)	(7.03)	(6.47)	(6.90)
Panel B: Return to Covered Call Writing Sorted on Idiosyncratic Volatility										
Equal-weighted	C	1.62	2.03	2.52	3.05	3.94	2.32	2.32	2.30	2.27
		(13.55)	(12.73)	(12.87)	(13.65)	(15.43)	(11.37)	(10.72)	(9.82)	(10.01)
Stock-value-weighted	C	1.53	1.70	2.10	2.52	3.12	1.59	1.54	1.61	1.64
		(11.28)	(11.87)	(10.38)	(10.85)	(11.40)	(7.00)	(6.04)	(5.83)	(6.32)
Option-value-weighted	C	1.53	1.64	2.51	2.92	3.40	1.87	1.81	1.73	1.65
		(10.25)	(9.06)	(11.15)	(10.03)	(9.17)	(5.44)	(4.97)	(3.77)	(3.44)

Panel C: Subsample Evidence: Equal-weighted Portfolio Returns (%) Sorted on VOL

	Option Type	1-Low	2	3	4	5-High	5-1	t-stat
Size Quintile 1	C	2.78	3.52	3.67	4.15	5.00	2.22	(8.15)
Size Quintile 2	C	2.15	2.59	2.91	3.04	3.94	1.79	(6.90)
Size Quintile 3	C	1.78	2.18	2.28	2.64	3.39	1.61	(6.34)
Size Quintile 4	C	1.43	1.77	2.04	2.39	2.92	1.49	(5.59)
Size Quintile 5	C	1.36	1.56	1.59	1.83	2.58	1.23	(5.74)
January	C	1.85	2.24	2.54	3.31	4.62	2.76	(3.87)
Feb-Dec	C	1.60	2.03	2.56	2.95	3.89	2.29	(9.03)
1996 - 1999	C	1.62	1.98	2.45	2.95	4.02	2.40	(6.69)
2000 - 2003	C	1.91	2.43	2.98	3.38	4.12	2.22	(4.82)
2004 - 2006	C	1.25	1.63	2.15	2.49	3.64	2.38	(14.76)

Table 3.9: Returns to Covered Call and Stock Volatility: Decomposition

This table reports the average return of portfolios of covered calls sorted by the idiosyncratic volatility of the underlying stocks. We use the sample of short-term at-the-money call options on individual stocks. Each covered call involves selling a call option against Delta shares of the underlying stock owned, where Delta is the Black-Scholes call option delta at initial date. Each covered call position is held for one month (without rebalancing the delta-hedge) and then closed. The returns to covered call are decomposed into two parts: return generated by stock price change, and return generated by option price changes. Idiosyncratic volatility (IVOL) is the standard deviation of the residuals of the Fama-French 3-factors model estimated using the daily stock returns over the previous month. All the numbers in this table are expressed in percent. The sample period is from January 1996 to December 2006. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in the brackets.

Total Return to Covered Call Writing = Stock Part + Option Part

$$\frac{(\Delta_t \cdot S_{t+1} - C_{t+1}) - (\Delta_t \cdot S_t - C_t)}{(\Delta_t \cdot S_t - C_t)} = \frac{\Delta_t \cdot (S_{t+1} - S_t)}{(\Delta_t \cdot S_t - C_t)} + \frac{C_t - C_{t+1}}{(\Delta_t \cdot S_t - C_t)}$$

Equal-Weighted Return to Covered Call Writing (%) Sorted on Idiosyncratic Volatility (IVOL)

	Option Type	1-Low	2	3	4	5-High	5-1
Total Return	C	1.62	2.03	2.52	3.05	3.94	2.32
		(13.55)	(12.73)	(12.87)	(13.65)	(15.43)	(11.37)
Stock Part	C	2.01	2.61	3.06	3.34	3.57	1.56
		(7.67)	(7.49)	(6.11)	(4.92)	(3.91)	(1.89)
Option Part	C	-0.39	-0.58	-0.54	-0.29	0.38	0.77
		(-1.31)	(-1.48)	(-0.98)	(-0.39)	(0.38)	(0.87)

Table 3.10: Volatility Risk Premium, Liquidity and Transaction Costs

This table reports the impact of liquidity and transaction costs on volatility risk premium. Each number of the columns under 5-1 is the difference in the average return of covered calls on stocks in the top quintile versus bottom quintile ranked by total volatility. The returns are computed using the mid-point of bid and ask quotes (MidP) or assuming an effective bid-ask spread (ESPR) equal to 50%, 75%, and 100% of the quoted spread (QSPR). Panel B reports the average return spread between writing covered calls on high versus low volatility stocks for each quintile sorted by liquidity measures of stock and option. Each month, we first sort the option sample into five quintiles (G1 to G5) by the price or Amihud (2002) illiquidity measure of the underlying stock, or by option bid-ask spread. Then within each quintile, we further sort by the volatility of the underlying stock. Total volatility is the standard deviation of daily stock returns over the previous month. Illiquidity is the daily average of the Amihud (2002) illiquidity measure over the previous month. Stock price is closing price at the end of last month. Option bid-ask spread is the ratio of bid-ask spread of option quotes over the mid-quotes. All the numbers in this table are expressed in percent. The sample period is from January 1996 to December 2006. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in the brackets.

Panel A: Equal-Weighted Portfolio Returns (%) Sorted on Total Volatility (VOL)

	5-1				10-1			
		ESPR/QSPR				ESPR/QSPR		
Sorted on	MidP	50%	75%	100%	MidP	50%	75%	100%
Average Return	2.33	1.25	0.73	0.22	2.87	1.61	1.00	0.41
	(10.37)	(5.58)	(3.22)	(0.95)	(10.42)	(5.91)	(3.65)	(1.46)
FF-3 Alpha	2.32	1.25	0.73	0.22	2.90	1.65	1.04	0.45
	(9.23)	(5.17)	(3.05)	(0.93)	(9.15)	(5.46)	(3.50)	(1.51)

Panel B: Equal-Weighted (5-1) Spread (%) Sorted on Total Volatility (VOL)

	Illiquidity	Stock Price	Option Bid-ask Spread
G1- Low	1.07	2.92	1.63
	(3.44)	(9.64)	(5.25)
G2	1.85	1.93	2.43
	(6.56)	(8.39)	(7.80)
G3	1.92	1.48	2.70
	(6.77)	(6.10)	(10.69)
G4	2.26	1.13	2.68
	(8.99)	(4.34)	(10.87)
G5 –High	2.54	0.82	2.79
	(10.02)	(2.24)	(9.67)
G5 – G1	1.47	-2.10	1.16
	(4.33)	(-4.83)	(2.66)

Figure 2.1: Cross-Section of Stocks Returns and Idiosyncratic Risk across Arbitrage Score Quintiles

At the beginning of each week, all stocks are independently sorted into deciles from low to high, based on BE/ME, the compound gross return from t-52 weeks to t-4 weeks, negative size and negative previous week return. Stocks obtain the corresponding score of its decile rank. Arbitrage score is the total score based on four different rankings and ranges from 4 to 40. Each week, stock are first sorted on their arbitrage scores into quintiles and then sorted within each quintile into quintiles based on expected idiosyncratic volatility. Expected idiosyncratic volatility is estimated weekly from EGARCH(1,1) on Fama-French 3-factor model by all the historical weekly data. Estimates are only conducted if at least 260 observations exist. The left and right figures corresponds to Panel A and Panel B in Table 2.7, respectively.

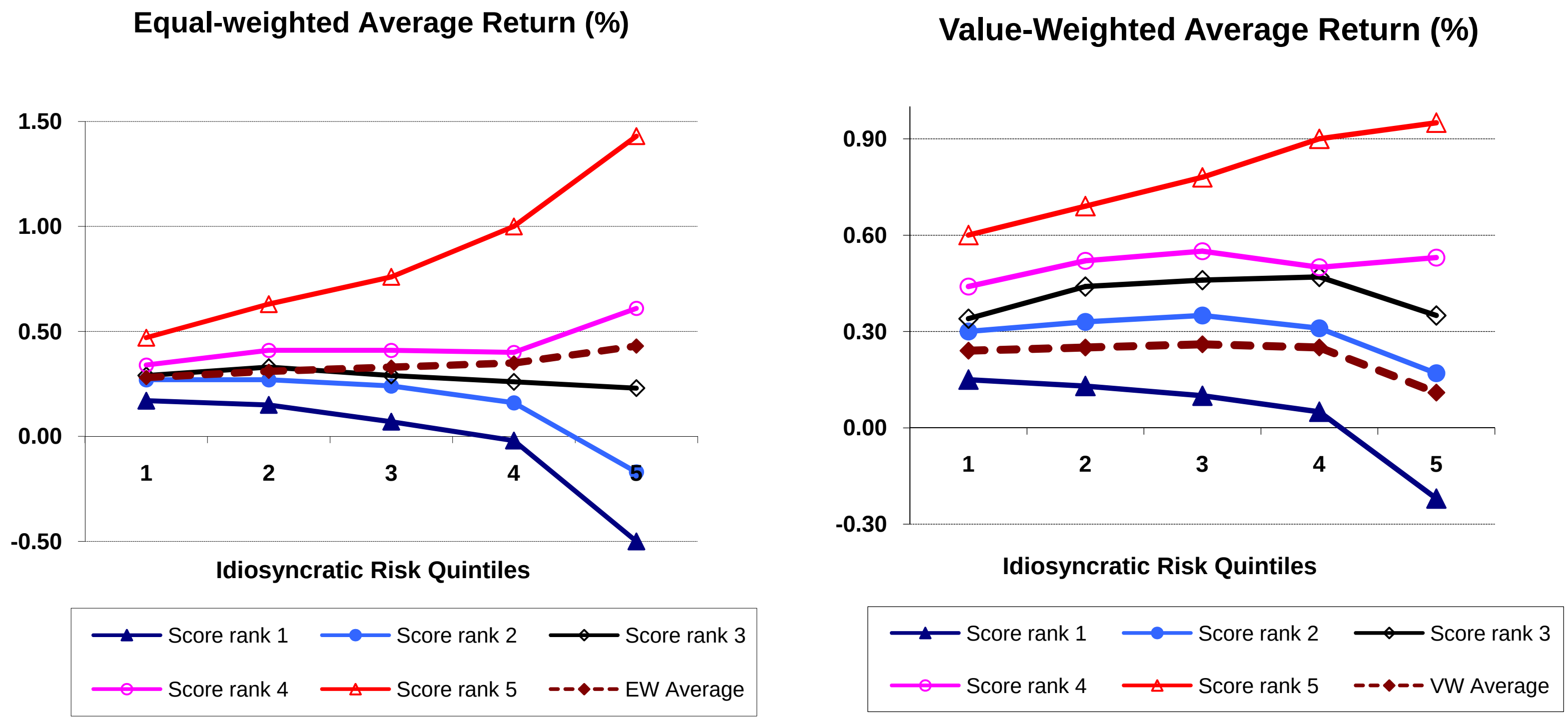
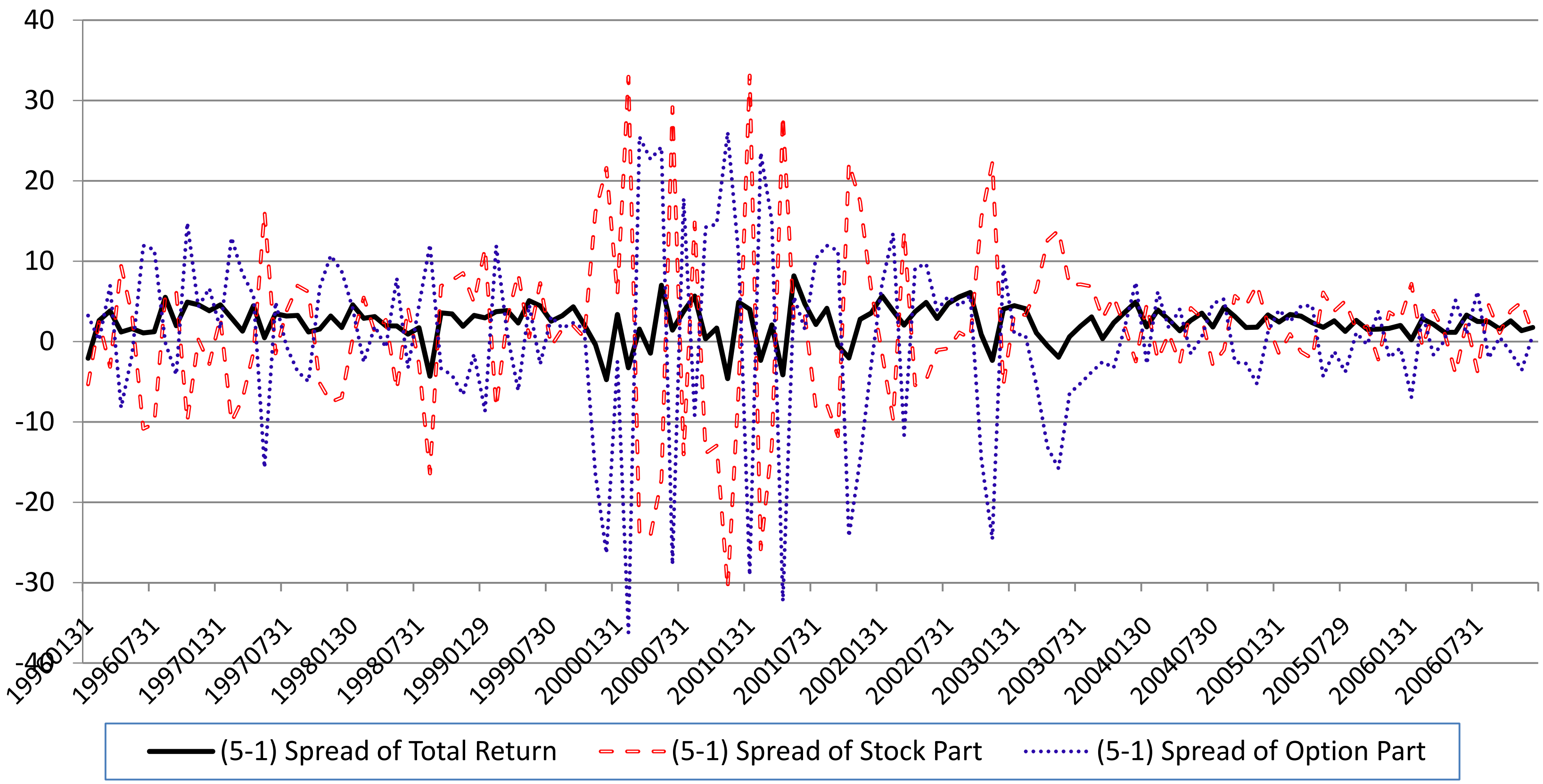


Figure 3.1: Returns to Covered Call and Stock Volatility: Time-Series Analysis

This figure plots the time-series (5-1) spread of covered calls sorted by the idiosyncratic volatility. We use the sample of short-term at-the-money call options on individual stocks. Each covered call involves selling a call option against Delta shares of the underlying stock owned, where Delta is the Black-Scholes call option delta at initial date. Each covered call position is held for one month (without rebalancing the delta-hedge) and then closed. The returns to covered call are decomposed into two parts: return generated by stock price change, and return generated by option price changes.

Total Return to Covered Call Writing = Stock Part + Option Part



Appendix: Risk-neutral Skewness and Kurtosis

We use a model-free and ex-ante measure of risk-neutral skewness and kurtosis given by Bakshi, Kapadia, and Madan (2003). For each stock on date t, the skewness and kurtosis of the risk-neutral density of the stock return over the period $[t, t+\tau]$ can be inferred from the contemporaneous prices of out-of-the-money call options and put options as follows:

$$Skew(t,\tau) = \frac{e^{r\tau}W(t,\tau) - 3\mu(t,\tau)e^{r\tau}V(t,\tau) + 2\mu(t,\tau)^3}{[e^{r\tau}V(t,\tau) - \mu(t,\tau)^2]^{3/2}}, \tag{5}$$

where

$$\mu(t,\tau) = e^{r\tau} - 1 - \frac{e^{r\tau}}{2}V(t,\tau) - \frac{e^{r\tau}}{6}W(t,\tau) - \frac{e^{r\tau}}{24}X(t,\tau), \tag{6}$$

and $V(t,\tau)$, $W(t,\tau)$ and $X(t,\tau)$ are the weighted sums of OTM call option prices $C(t,\tau,K)$ and put option prices $P(t,\tau,K)$, with time-to-maturity τ and strike price K, given the underlying asset price S_t:

$$V(t,\tau) = \int_{S_t}^{\infty} \frac{2(1 - ln(\frac{K}{S_t}))}{K^2} C(t,\tau,K)dK + \int_0^{S_t} \frac{2(1 + ln(\frac{S_t}{K}))}{K^2} P(t,\tau,K)dK, \tag{7}$$

$$W(t,\tau) = \int_{S_t}^{\infty} \frac{6ln(\frac{K}{S_t}) - 3[ln(\frac{K}{S_t})]^2}{K^2} C(t,\tau,K)dK - \int_0^{S_t} \frac{6ln(\frac{S_t}{K}) + 3[ln(\frac{S_t}{K})]^2}{K^2} P(t,\tau,K)dK, \tag{8}$$

$$X(t,\tau) = \int_{S_t}^{\infty} \frac{12[ln(\frac{K}{S_t})]^2 - 4[ln(\frac{K}{S_t})]^3}{K^2} C(t,\tau,K)dK + \int_0^{S_t} \frac{12[ln(\frac{S_t}{K})]^2 + 4[ln(\frac{S_t}{K})]^3}{K^2} P(t,\tau,K)dK. \tag{9}$$

The integrals are approximated in (7), (8) and (9) using the trapezoidal method. For accuracy, we require at least three out-of-the-money call options and three out-of-the-money put options. Due to this data constraint, the option implied skewness and kurtosis are only available for about half of the sample.

References

Ali, Ashik, Lee-Seok Hwang, and Mark A. Trombley, 2003, Arbitrage risk and the book-to-market anomaly, *Journal of Financial Economics* 69, 355-373.

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31-56.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259-299.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2009, High idiosyncratic volatility and low returns: international and further US evidence, *Journal of Financial Economics* 91, 1-23.

Bakshi, Gurdip, and Nikunj Kapadia, 2003a, Delta-hedged gains and the negative market volatility risk premium, *Review of Financial Studies* 16, 527-566.

Bakshi, Gurdip, and Nikunj Kapadia, 2003b, Volatility risk premium embedded in individual equity options: Some new insights, *Journal of Derivatives* 11, 45-54.

Bakshi, Gurdip, Nikunj Kapadia, and Dilip Madan, 2003, Stock return characteristics, skew laws, and differential pricing of individual equity options, *Review of Financial Studies* 16, 101-143.

Bali, Turan G., Nusret Cakici, 2008, Idiosyncratic volatility and the cross-section of expected returns, *Journal of Financial and Quantitative Analysis* 43, 29-58.

Bates, David S., 2000, Post-87 crash fears in the S&P 500 futures option market, *Journal of Econometrics* 94, 181-238

Barberis, Nicholas, and Richard Thaler 2003, A survey of behavioral finance. In *Handbook of the Economics of Finance*. George Constantinides, North-Holland, Amsterdam.

Bennett, James A., and Richard W. Sias, 2008, Portfolio diversification, Working paper.

Bertsimas, Dimitris, Leonid Kogan, and Andrew Lo, 2000, When is time continuous? *Journal of Financial Economics* 55, 173-204.

Bhardwaj, Ravinder, and Leory Brooks, 1992, The January anomaly: effects of low share price, transaction costs and bid-asked bias, *Journal of Finance* 47, 552-576.

Blume, Marshall, and Michael Goldstein, 1992, Displayed and effective spreads by market, Unpublished working paper, University of Pennsylvania.

Bodie, Zvi, Alex Kane, and Alan J. Marcus, 2006, Investments, 7th Edition, Chapter 27, The theory of active portfolio management, Irwin/McGraw-Hill.

Bollen, Nicolas, and Robert Whaley, 2004, Does net buying pressure affect the shape of implied volatility functions, *Journal of Finance* 59, 711-753.

Bollerslev, Tim, 1986, Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics* 31, 307-328.

Branger, Nicole, and Christian Schlag, 2008, Can tests based on option hedging errors correctly identify volatility risk premia? *Journal of Financial and Quantitative Analysis* 43, 1055-1090.

Brav, Alon, James B. Heaton, and Si Li, 2009, The limits of the limits of arbitrage, *Review of Finance,* forthcoming.

Broadie, Mark, Mikhail Chernov, and Michael S. Johannes, 2007, Model specification and risk premiums: Evidence from futures options, *Journal of Finance* 62, 1453-1490.

Buraschi, Andrea, and Jens Jackwerth, 2001, The price of a smile: hedging and spanning in option markets, *Review of Financial Studies* 14, 495-527.

Carhart, Mark M., 1997, On the persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Carr, Peter, and Liuren Wu, 2009, Variance risk premia, *Review of Financial Studies* 22, 1311-1341.

Carroll, Carolyn, and K.C. John Wei, 1988, Risk, return and equilibrium: An extension, *Journal of Business* 61, 485-499.

Chen, Joseph, Harrison Hong, and Jeremy Stein, 2002, Breadth of ownership and stock returns, *Journal of Financial Economics*, 66, 171-205.

Chernov, Mikhail, and Eric Ghysels, 2000, A study towards a unified approach to the joint estimation of objective and risk neutral measures for the purpose of options valuation, J*ournal of Financial Economics* 56, 407-458.

Coval, Joshua D., and Tyler Shumway, 2001, Expected options returns, *Journal of Finance* 56, 983-1009.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russell Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035-1058.

Dechow, Patricia, Amy Hutton, Lisa Meulbroek, and Richard Sloan, 2001, Short sellers, fundamental analysis and stock returns, *Journal of Financial Economics* 61, 77-106.

Diether, Karl B., Christopher J. Malloy, and Anna Scherbina, 2002, Differences of opinion and the cross section of stock returns, *Journal of Finance* 57, 2114-2141.

Duan, Ying, Gang Hu, and David R. McLean, 2009, Costly arbitrage and idiosyncratic risk: Evidence from short-sellers, *Journal of Financial Intermediation*, forthcoming.

Duan, Jin-Chuan, and Jason Wei, 2009, Systematic risk and the price structure of individual equity options, *Review of Financial Studies* 22, 1981-2006.

Duarte, J. and C. S. Jones, 2007, The price of market volatility risk, Working Paper.

Driessen, Joost, and Pascal Maenhout, 2007, A portfolio perspective on option pricing anomalies, *Review of Finance* 4, 561-603.

Engel, Robert F., 1982, Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation, *Econometrica* 50, 987-1007.

Fama, Eugene F., 1970, Efficient capital markets: a review of theory and empirical work, *Journal of Finance 25*, 383-417.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economics* 81, 607-636.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and Kenneth R. French, 2008, Dissecting anomalies, *Journal of Finance* 63, 1653-1678.

Figlewski, Stephen, and Clifton Green, 1999, Market risk and model risk for a financial institution writing options, *Journal of Finance* 54, 1465-1499.

Frazzini, Andrea, 2005, The disposition effect and underreaction to news, *Journal of Finance* 61, 2017-2046.

Fu, Fangjian, 2009, Idiosyncratic risk and the cross-section of expected stock returns, *Journal of Financial Economics* 91, 24-37.

Garleanu, Nicolae, Lasse Pedersen, and Allen Poteshman, 2008, Demand-based option pricing, *Review of Financial Studies*, forthcoming.

Goyal, Amit, and Alessio Saretto, 2009, Option returns and the cross-sectional predictability of implied volatility, *Journal of Financial Economics*, forthcoming.

Green, Clifton, and Stephen Figlewski, 1999, Market risk and model risk for a financial institution writing options, *Journal of Finance* 54, 1465-1499.

Han, Bing, and Alok Kumar, 2009, Speculation, realization utility, and volatility-induced retail habitat, Working paper, University of Texas at Austin.

Heston, Steven L., 1993, A closed-form solution for options with stochastic volatility, *Review of Financial Studies* 6, 327-343.

Huang, W., Q. Liu, S. R. Ghee, and L. Zhang, 2009, Return reversals, idiosyncratic risk, and expected returns, *Review of Financial Studies*, forthcoming.

Hull, John, and Wulin Shuo, 2002, A methodology for assessing model risk and its application to the implied volatility function model, *Journal of Financial and Quantitative Analysis* 37, 297-318.

Jackwerth, Jens Carsten, and Mark Rubinstein, 1996, Recovering probability distributions from option prices, *Journal of Finance 51*, 1611-1631.

Jameson, Melvin, and William Wilhelm, 1992, Market making in the options markets and the costs of discrete hedge rebalancing, *Journal of Finance* 43, 765-779.

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Jegadeesh, Narasimhan, and Sheridan Titman, 1995a, Overreaction, delayed reaction, and contrarian profits, *Review of Financial Studies* 8, 973-993.

Jegadeesh, Narasimhan, and Sheridan Titman, 1995b, Short-horizon return reversals and the bid-ask spread, *Journal of Financial Intermediation* 4, 116-132.

Jiang, George, and Yisong S. Tian, 2005, The model-free implied volatility and its information content, *Review of Financial Studies* 18, 1305-1342.

Jones, Christopher S., 2003, The dynamics of stochastic volatility: Evidence from underlying and options markets, *Journal of Econometrics* 116, 181-224.

Jones, Christopher S., 2006, A nonlinear factor analysis of S&P 500 index option returns, *Journal of Finance* 61, 2325-2363.

Lakonishok, Josef, Inmoo Lee, Neil Pearson, and Allen Poteshman, 2007, Option market activity, *Review of Financial Studies* 20, 813-857.

Lehmann, Bruce, 1990, Residual risk revisited, *Journal of Econometrics* 45, 71-97.

Lintner, John, 1965, The valuation of risky assets and the selection of risky investment in stock portfolio and capital budgets, *Review of Economics and Statistics* 47, 13-37.

Lo, Andrew W., and A. Craig MacKinlay, 1990, When are contrarian profits due to stock market overreaction? *Review of Financial Studies* 3, 175-205.

Mashruwala, Christina, Shivaram Rajgopal, and Terry Shevlin, 2006. Why is the accrual anomaly not arbitraged away? *Journal of Accounting and Economics* 42, 3-33.

Mendenhall, Richard, 2004, Arbitrage risk and post-earnings-announcement drift, *Journal of Business* 77, 875-894.

Merton, Robert C., 1973, An intertemporal capital asset pricing model, *Econometrica* 41, 867-887.

Merton, Robert C., 1987, Presidential address: A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42, 483-510.

Miller, Merton H., and Myron Scholes, 1972, Rates and return in relation to risk: A re-examination of some recent findings,in Michael C. Jensen, ed.: Studies in the Theory of Capital Markets (Praeger, NewYork).

Nagel, Stefan, 2005, Short sales, institutional investors, and the cross-section of stock returns, *Journal of Financial Economics* 78, 277-309.

Nelson, Daniel B., 1991, Conditional heteroskedasticity in asset returns: a new approach, *Econometrica* 59, 347-370.

Newey, Whitney K., and Kenneth D. West, 1987, A simple positive-definite heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Pagan, Adrian R., and G. William Schwert, 1990, Alternative models for conditional stock volatility, *Journal of Econometrics* 45, 267-290.

Pan, Jun, 2002, The jump-risk premia implicit in options: Evidence from an integrated time-series study, *Journal of Financial Economics* 63, 3-50.

Pontiff, Jeffrey, 1996, Costly arbitrage: Evidence from closed-end funds, *The Quarterly Journal of Economics* 111, 1135-1151.

Pontiff, Jeffrey, 2006, Costly arbitrage and the myth of idiosyncratic risk, *Journal of Accounting and Economics* 42, 35-52.

Shleifer, Andrei, 2000, Inefficient markets: An introduction to behavioral finance, Oxford: Oxford University Press.

Shleifer, Andrei, and Robert Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35-55.

Spiegel, Matthew, and Xiaotong Wang, 2006, Cross-sectional variation in stock returns: Liquidity and idiosyncratic risk, Working paper, Yale University.

Stein, Jeremy, 1989, Overreactions in options market, *Journal of Finance* 44, 1011-1023.

Treynor, Jack, and Fisher Black, 1973, How to use security analysis to improve portfolio selection, *Journal of Business* 46, 66-86.

Wei, John K.C., and Jie Zhang, 2007, Arbitrage risk and arbitrage returns: Evidence from the fundamental value-to-price anomaly, Working paper, Hong Kong University of Science and Technology.

Zhang, X. Frank, 2006, Information uncertainty and stock returns, *Journal of Finance* 61, 105-136.

Vita

Jie Cao was born in Dangtu, Anhui Province, P.R. China on February 5, 1981 and is the son of Jianmin Cao and Xiaolan Lv. After completing his work at Dangtu No.1 High School, Dangtu, China, in 1998, he enrolled at Peking University in Beijing, China. He received the degree of Bachelor of Economics from School of Economics in July 2002. Subsequently, he began his Ph.D. course work in economics at Rice University in Houston, Texas. In July 2004, he entered the doctoral program in finance at the McCombs School of Business at the University of Texas at Austin in Austin, Texas. He received the degree of Master of Science in Finance from the University of Texas at Austin in August 2007.

Permanent address: 2207 Wickersham Ln Apt 1106, Austin, TX 78741

This dissertation was typed by the author.