Disagreement in Option Market and Cross Section Stock Returns

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Abstract

In the paper, we find out that there is a significant relation between option trading volume and open interest distributions across various strike levels and expected stock returns. Specifically, we construct volume and open interest weighted option strike dispersions. Portfolio level analysis and firm-level cross-sectional regression both indicate a negative and significant relation between expected returns and option strike dispersion. The results are consistent with Miller (1977) theory. The option strike dispersion can be regarded as a proxy for investors' belief dispersion. Long-short strategy purchasing stocks with low option strike dispersion and shorting those with high option strike dispersion earns annualized abnormal return 14.05% with sharp ratio 0.79.

1 Introduction

Since Miller (1977), disagreement is considered as an important factor affecting equilibrium asset prices. The intuition is that when pessimists are forced to sit out of the market, asset prices reflect the demand from optimists only, which causes prices (returns) to increase (decrease). In this paper, we propose to link investors' dispersion for future equity price in option market with future cross

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section stock returns. Specifically, we consider trading volume or open interest weighted option strike dispersion as a measure for investors' disagreement in option market.

Intuitively, the range of strike prices for traded equity options can be interpreted as the set of expected stock price levels, and the proportion of trading volume or open interest attributed to each strike price can be regarded as the probability or belief of investors attached to each view. Based on such measure, we find that stocks with high option strike dispersion underperform significantly, comparing to stocks with low option strike dispersion, consistent with Miller (1977) argument. Portfolio longing stocks with low strike dispersion and shorting those with high strike dispersion earns annualized abnormal return 14.05% with sharpe ratio 0.79, both economically and statistically significant.

The contribution of our study is twofolds. On one hand, we use trading activity information from option market as a measure of belief dispersion. As far as disagreement is concerned, there are several proxies used in literature, for instance, analyst forecast dispersion (Diether, Malloy, and Scherbina, 2002), change of institutional ownership breath (Chen, Hong, and Stein, 2002), active mutual fund holdings (Jiang and Sun, 2014), economists' forecast (Buraschi and Jiltsov, 2006; Buraschi, Trojani and Vedolin, 2014), stock trading volume (Garfinkel and Sokobin, 2006) and future open interest (Bessimbinder, Chan and Seguin, 1996).

In comparison with other proxies, we believe that dispersion measure constructed from option trading activity aggregates information from a large number of investors, therefore, can be served as a stronger signal. Existing measures commonly are based on knowledge from tens of people, and could be affected significantly by various bias, such as herding behaviors of analysts and fund managers. We compare our trading strategy with those based on analyst forecast dispersion, and find that in the same sample period, the analyst-based trading strategy only earns 1/3 of our return.

One possible concern for studies about effect of disagreement on stock price is that it is difficult to distinguish disagreement from private information, especially when using trading volume and open interest as proxies. The other contribution of our paper is that we compare results via put

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option strike dispersion and call option strike dispersion. Such a design is able to ease the private information concern. If dispersion of strike is driven by private information, it is likely that call option strike dispersion is driven by good news and put option strike dispersion is driven by bad news. As as result, stocks with higher call option strike dispersion should have higher future returns, while those with larger put option strike dispersion should have lower future returns. However, our results show that both put and call option strike dispersion are negatively related to future stock returns, consistently with Miller (1977) story, instead of private information argument.

Our study is motivated by Bessimbinder, Chan and Seguin (1996) and Andreou, Kagkadis, Maio and Philip (2014). Bessimbinder, Chan and Seguin (1996) use S&P 500 index future open interest as a measure of traders' divergences of opinion. Andreou, Kagkagis, Maio and Philip (2014) use volume-weighted option strike dispersion as a proxy for disagreement. Our paper is different from theirs in three aspects. First of all, our paper focus on cross-section stock returns, instead of aggregate market. Secondly, we use put and call option strike dispersion separately and get similar results, distinguishing disagreement with private information mechanism, which does not appear in aggregate market. Moreover, we show that open interest and trading volume contain almost same information related to investors' disagreement.

The structure for the rest of this paper is as follows. Section 2 reviews the related literature. In Section 3, we describe our data and present general framework for our empirical study. Section 4 analyzes and discusses our empirical results. Section 5 makes conclusions and provides some possible directions for future research.

2 Literature Review

Our study is closely linked with two strands of literature. The first is effect of investors' disagreement on asset price. As pointed by Carlin, Longstaff and Matoba (2014) , there is a controversy in the literature about how disagreement risk affects expected returns. One one hand, disagreement is able to generate trade among investors, it appears that investors should be compensated for bearing trading risk. Varian (1985), Abel (1989) and David (2008) study effect of disagreement on asset price in equilibrium, and support positive risk premium argument. However, when disagreement meets short-sale constraints, we have negative relation between disagreement and expected returns. The intuition is that when pessimists are unable to trade their views, stock prices reflect merely demand from optimists only, which causes current price increase and future return decrease. Furthermore, Chen, Joslin and Tran (2010) provide an equilibrium model with affine disagreement about fundamentals, and their conclusion is that disagreement risk premium depends on whether disasters strike. In normal period, optimistic agents accumulate wealth and there is a decline in the risk premium. When market is in turmoil, pessimistic agents become wealthier, leading to increasing risk premium.

Miller (1977) argument has been tested in several empirical studies and results are mixed. Chen, Hong, and Stein (2002), Diether, Malloy, and Scherbina (2002) analyze the role of dispersion in predicting the cross section future stock returns. They find that stocks with higher belief dispersion earn significantly lower future returns. Park (2005) and Yu (2011) extend such studies to aggregate stock market. Their results show that dispersion in expectations among market analysts negatively predicts future market returns.

One common feature among these studies lies in the fact that Miller's theorem is tested in a market with short sale constraints. Suppose there is no short-sale constraints, what could happen? Beber, Breedon and Buraschi (2010) examine effect of disagreement in currency market. Their studies support the predictions of the heterogeneous agent neoclassical literature, where differences in beliefs represent an additional risk factor. During periods with high belief difference, carry trades are unwound, low interest rate currencies appreciate and currency carry trade return decreases a lot. Carlin, Longstaff and Matoba (2014) show that higher level of disagreement among Wall Street mortgage dealers about prepayment speeds leads to higher expected returns, higher return volatility, and larger trading volume in the mortgage-backed security market.

Our study contributes to this literature in the way that we construct measure of dispersion from option trading activity, and show that consistent with Miller's argument, in stock market, higher disagreement leads to lower future stock returns.

Our paper is also related to the literature about forecasting cross section stock returns using information extracted from option market. Many studies suggest that information from both index and individual options have valuable information regarded to cross section expected stock returns. Ang, Hodrick, Xing and Zhang (2006) first apply an option-implied risk factor to explain cross section stock returns. The authors use daily change of CBOE volatility index (VIX) as market-wide volatility risk factor, and find that stocks with higher loadings on VIX factor have lower future returns. Chang, Christoffersen and Jacobs (2013) calculate risk neutral skewness from S&P 500 index options via similar method used by CBOE to calculate VIX index, and take daily change of their skewness index as a proxy for market wide skewness risk. Their results show that stock exposure to skewness factor negatively predicts its future return. Cremers, Halling and Weinbaum (2014) extract jump risk and volatility risk factors separately using index option portfolios, and show that, in addition to volatility risk, market wide jump risk plays an important role to explain cross section stock returns. Higher jump risk exposure leads to lower future stock returns.

Apart from aggregate risk factors embedded in index options, several other variables, calculated from individual option price structures, also contain useful information about expected stock returns. Put-call parity represents a useful benchmark to assess if the relative pricing of call and put options contain information about the underlying stock. Pan and Poteshman (2006) calculate the Put-Call Ratio (P/C ratio hereafter) as buyer-initiated put volume scaled by total option (both put and call) volume. They show that daily P/C ratios are negatively related to next day returns. Cremers and Weinbaum (2010) use the implied volatility gap between put and call options with the same maturity and strike as a proxy for deviation from put-call parity, and discover that stocks having higher put-call implied volatility spread suffer lower future returns. Bali and Hovakimian (2009) identify a negative and significant relation between expected returns and the realized-implied volatility spread. Xing, Zhang and Zhao (2010) use slope of implied volatility smile as a proxy for negative jump risk, and show that stocks with larger implied volatility slope underperform. Johnson and So (2012) apply Miller (1977) intuition, arguing that due to equity short-sale costs, investors with negative information tend to trade in option market. Therefore, there is a negative relation between option/stock volume ratio and future stock returns. Conrad, Dittmar and Ghysels (2013) compute option implied volatility, skewness and kurtosis for each stock and show that individual skewness negatively predicts expected stock return and link the results with investors' gamble preference.

In our paper, we also extract information from option trading activity, however, our measure is different from existing ones, such as Pan and Poteshman (2006) and Johnson and So (2012). Pan and Poteshman (2006) use data which is not available to public. Johnson and So (2012) use total option trading volume as a proxy. In comparison, we use information embedded in cross section option trading volume and open interest, whose effect on cross section stock return is never been studied in literature before.

3 Empirical Framework

In this section, we first give definitions of variables used in the paper. Then the general framework for our empirical study is presented.

3.1 Data Description

We use end-of-day option close price, trading volume, open interest and implied volatility surface from OptionMetrics. The analyst forecast data about EPS is obtained from I/B/E/S. Firm financial statements data is downloaded from Compustat. The definitions of variables involved in the paper are given as follows.

Implied volatility. We calculate daily implied volatility for each stock as the average of implied volatility of Δ-50 (at-the-money) put option and Δ-50 (at-the-money) call option, with time-to-maturity of 30 days,

$$IV_{day} = \frac{1}{2}PutIV_{\Delta 50} + \frac{1}{2}CallIV_{\Delta 50}.$$

The monthly implied volatility is average daily implied volatilities in that month.

Implied volatility skew. We calculate daily implied volatility skew for each stock as the spread of implied volatility of Δ-50 (at-the-money) put option and Δ-50 (at-the-money) call option, with time-to-maturity of 30 days, scaled by daily implied volatility

$$IVSKEW_{day} = \frac{PutIV_{\Delta 50} - CallIV_{\Delta 50}}{\frac{1}{2}PutIV_{\Delta 50} + \frac{1}{2}CallIV_{\Delta 50}}.$$

The monthly implied volatility skew is average daily implied volatility skews in that month.

Realized volatility. We calculate daily realized variance as square of daily returns. Then we sum daily realized variance in the month to get monthly realized variance. At last, we take square-root of monthly realized variance and scaled to get annualized monthly realized volatility, comparable with our monthly implied volatility measure,

$$RV = \sqrt{\sum RET_{daily}^2} * \sqrt{12}.$$

Volatility spread. The volatility spread is the difference between monthly implied volatility and monthly realized volatility.

Market beta and idiosyncratic volatility. At the end of each month, for each stock, we regress its daily returns on market returns, using past 252 days data,

$$RET_{stock,t} = \alpha + \beta RET_{market,t} + \epsilon_t,$$

We take β as stock's exposure on market portfolio, and calculate annualized idiosyncratic volatility from time-series of ϵ_t.

Stock bid-ask spread. Each month, for each stock, we calculate end-of-day bid-ask spread as follows

$$BASP = \frac{Ask - Bid}{\frac{1}{2}Bid + \frac{1}{2}Ask}.$$

The monthly bid-ask spread is average of daily ones.

Option/Stock trading volume ratio. Each month, for each stock, we sum all its daily option trading volumes together, including both put and call options, to get monthly option trading volume

(OPVOL). Similarly, we sum all its daily stock trading volumes to get its monthly stock trading trading volume (SVOL), then we divide monthly option trading volume by monthly stock trading volume. Since one option contract gives investor the right to trade 100 underlying stocks, we scale the ratio by 100 and take logarithm,

$$OS = \log(\frac{100 * \sum OPVOL_{daily}}{\sum SVOL_{daily}}).$$

Put/Call trading volume spread. Each month, for each stock, we sum all its daily option trading volumes, for put and call options separately, and divide monthly put option trading volume by monthly call option trading volume.

Firm size. We update firm size quarterly as Logarithm of firm total assets (atq).

Market leverage ratio. First of all, we calculate total debt value as sum of current liabilities and total long-term debt. Then divide it by firm equity market value plus debt value,

$$MarLEV = \frac{dlcq + dlttq}{dlcq + dlttq + prccq * cshoq}.$$

Market-to-book ratio. We update firm market-to-book ratio as follows

$$MTB = \frac{prccq * cshoq + tdq + pstkq - txditcq}{atq},$$

where numerator is sum of traded equity market value (price times number of share outstanding), total debt value and preferred stock minus deferred taxes and investment tax credit.

Analyst coverage and forecast dispersion. We get analyst forecast standard deviation for long-term EPS and next-quarter EPS directly from I/B/E/S summary statistics. Analyst coverage is defined as the number of analysts making forecast about next-quarter EPS.

Volume-weighted option strike dispersions. Each month, each stock, for each option strike level X, we aggregate daily trading volume of options on that strike to get monthly trading volume V, with time-to-maturity from 10 days to 360 days. Then average strike using V as weight is calculated. The strike dispersion is given by

$$w_i = \frac{V_i}{\sum_i V_i},$$
$$DISP_{volume} = \sum_i w_i|X_i - \sum_i w_i X_i|.$$
$$DISP_{volume,scale} = (\sum_i w_i|X_i - \sum_i w_i X_i|)/\sum_i w_i X_i.$$

In our empirical test, strike dispersion is scaled by its weighted mean value.

Open-Interest-weighted option strike dispersions. The calculation method is similar with that of volume-weighted option strike dispersion. Each month, each stock, for each option strike level X, we get its open interest O of last trading day of the month. Then average strike using O as weight is calculated. The strike dispersion is given by

$$w_i = \frac{O_i}{\sum_i O_i},$$
$$DISP_{opint} = \sum_i w_i|X_i - \sum_i w_i X_i|.$$
$$DISP_{opint,scale} = (\sum_i w_i|X_i - \sum_i w_i X_i|)/\sum_i w_i X_i.$$

In our empirical test, strike dispersion is scaled by its weighted mean value.

3.2 Empirical Methods

Firstly, at the end of each month, we sort stocks in the whole sample [1], by volume-weighted and open-interest weighted option strike dispersion, into ten portfolios. Then we long stocks with lowest option strike dispersion (portfolio 1) and short stocks with highest option strike dispersion (portfolio 10) during next month. The equal-weighted portfolio returns are calculated. We compare results based on several variations of option strike dispersions, for instance, volume-weighted option strike dispersion using both put and call options, volume-weighted option strike dispersion using only put or call options, open-interest weighted option strike dispersion using both put and call options,

[1] we only use common stocks, with shrcd = (10, 11).

open-interest weighted option strike dispersion using only put or call options. The results are also be compared with monthly portfolio returns sorted by analyst forecast dispersion, market excess returns, value premium, size premium, momentum premium and liquidity premium.

Since it is possible that our results may be driven by other established factors, after the univariate-sorting test, we further conduct Fama-Mecbeth regression and double sorting exercise, controlling for firm characteristics and other popular predictors for cross section stock returns. Fama-Mecbeth regression proceeds as follows,

$$RET_{i,t+1} = \alpha + \beta DISP_{option,i,t} + \rho X_{i,t} + \epsilon_{i,t},$$

where RET is monthly individual stock returns. $DISP_{option}$ is our dispersion measure extracted from option trading activities. X is a vector of control variables, motivated by literature, including standard firm characteristics, such as firm size, market-to-book ratio, and market leverage ratio. X also contains volatility spread (Bali and Hovakimian, 2009), implied volatility skewness (Cremers and Weinbaum, 2010; Xing, Zhang and Zhao, 2010), option-to-stock trading volume ratio (Johnson and So, 2012), put-call option trading volume ratio (Pan and Poteshman, 2006), market beta (Chang, Christoffersen, Jacobs and Vainberg, 2012; Frazzini and Pedersen, 2014), idiosyncratic volatility (Ang, Hodrick, Xing and Zhang, 2006), past month stock return (An, Ang, Bali and Cakici, 2014) and stock liquidity measure.

The double sorting procedure follows Ang, Hodrick, Xing and Zhang (2006) and Bali and Hovakimian (2009). Specifically, each month, the stocks are first sorted into deciles based on the control characteristic (e.g., size). Then, within each characteristic deciles, the stocks are further sorted into deciles based on our option strike dispersion measure. Each characteristic decile, thus, contains 10 option strike dispersion deciles. Next, strike dispersion decile 1 from each control characteristic decile are averaged into a single decile 1, strike dispersion decile 2 are averaged into a single decile 2, etc. The resulting option strike deciles contain stocks with all values of the characteristic and, hence, represent option strike dispersion decile portfolios controlling for the characteristic.

At last, we examine the time-varying volatility of our option strike dispersion based long-short portfolio, and provide a refined trading strategy. Similar with the studies conducted by Barroso and Santa-Clara (2014), we first generate daily returns of our strategy. Then we aggregate squared daily return to obtain monthly realized variance. The variance is high predictable, and managing this risk virtually eliminates the large drawdown of our strategy during 2000-2003 dot com bubble crash and 2008 sub-prime crash.

4 Empirical Results

In this section, we first examine results from univariate-sorting test. Then results of Fama-Mecbeth regression are discussed. Finally, we examine the volatility of our strategy and provide a risk management version of our strategy.

4.1 Summary Statistics

Table 1 contains summary statistics for firm characteristics. For our volatility measures, consistent with literature, implied volatility is high than realized one. Implied volatility smile curve has negative slope, put option implied volatility is larger than that of call option. idiosyncratic volatility takes up only a small portion of total volatility. For absolute trading volume, underlying stocks have larger trading volume than their options. Consistent with Lemmon and Ni (2014), investors trade more call options than put, for individual equity market, since speculation motivation overwhelm hedge motivation.

Summary statistics for volume and open interest weighted option strike mean values and dispersions are given by Table 2. The weighted average strike value is scaled by end-of-month stock price. If we take the weighted average value of option strikes as investor's expectation, such expectation is close to current stock price. The expectation extracted from put options is lower than current stock price, while expectation extracted from call options is larger than current stock price. The value calculated using both put and call options lies between them. For strike dispersions, put option strike dispersion is at the same level with call option strike dispersion, both less than strike dispersion calculated using all options.

4.2 Portfolio Sorting Results

Table 3 shows some basic statistics for our long-short portfolios using univariate-sorting method. Specifically, at the end of month t, we will sort the whole sample of stocks into 10 portfolios, with portfolio 1 containing stocks having lowest strike dispersion, and portfolio 10 containing stocks having highest strike dispersion. Then we long portfolio 1 and short portfolio 10 for month $t+1$. At the end of month $t+1$, we rebalance our portfolios. The time-period ranges from 1996 to 2012.

For comparison, we also consider two kinds of benchmark portfolios. The first category contains long-short portfolios sorted by analyst forecast dispersion for EPS. We consider two analyst forecast dispersion measures. One is forecast dispersion for next quarter's EPS, representing short-term dispersion. The other is forecast dispersion for long-term EPS, representing long-term dispersion. The other category includes factor mimicking portfolios for Fama-French three factors (Fama and French, 1993), momentum (Jagadeesh and Titman, 1993) and liquidity risk factor (Pastor and Stambaugh, 2003).

For our benchmarks, strategies holding market portfolio or investing in size, value premium and momentum yield low realized returns, only around 5% annualized returns, with low sharpe ratio. Long-short portfolio based on short-term analyst forecast dispersion gives similar statistics, while long-short portfolio based on long-term analyst forecast dispersion cannot generate economically significant returns. One exception is strategy investing in liquidity risk premium. The realized annualized return and sharp ratio is high, along with a positive skewness. The reason lies in the fact that liquidity is a crisis factor. In the time of crisis, especially during 2008 crisis, liquidty is extremely valuable. Hence investment for liquity generates high return.

Compared with benchmarks, the hedged portfolios based on our investor dispersion measure gives better results. For various versions of strike dispersion, the realized annualized returns are at the same level, ranging from 9% to 13%. Sharpe ratios range from 0.3 to 0.5. Much better than classical risk factors, such as value and momentum. Based on the Table 3, we can see that our dispersion measure also yields better performance than analyst forecast dispersion. We argue that our measure contains more information than analyst forecast dispersion. Because our measure is extracted based on a large amount of investors' expectation, while analyst forecast dispersion is calculated based on much less number of people's perspective. Although these people are professionals, due to the small number, the resulted dispersion measure could suffer from their behavioral bias and limited attention.

Our results illustrate that there is a negative relation between dispersion and future stock returns. Low dispersion stocks outperform high dispersion stocks, which is consistent with Miller (1977) theorem. Due to short-sale constraints, it is costly and difficult to incorporate negative news into stock price. Thus, high dispersion stocks are overpriced, and their future returns should be low.

One disadvantage of using volume-based dispersion measure is that the results could be driven by private information. Traditional volume-based dispersion measure is stock trading volume, however, it is not regarded as a clean measure for belief dispersion. Because informed investors will try to gain from their private information and push the trading volume high. Thus high trading volume could be driven by their behaviors, not difference in beliefs. Our dispersion measure could ease this concern. We calculate strike dispersion measure for put and call option separately. Suppose our results are driven by informed investor trading, then high call strike dispersion should lead to high future stock returns, while high put strike dispersion should lead to low future stock returns. Because if one informed investor has good information, he will trade call options with suitable strikes. His behavior will increase call option volume dispersion, leading to high strike dispersion. If his information is reliable, future stock price should increase. The same mechanism also works for the case if the informed investor has negative information. At this time, he will choose to trade put option with desirable strikes, pushing put option strike dispersion high, and future stock return should be low if his information is solid. Our results do not show such pattern, for all version of strike dispersion, no matter calculated using put or call option trading activities, yield similar negative relation between belief dispersion and future stock returns. Therefore, our measure is able to distinguish these two mechanisms: belief dispersion and private information.

Table 4 further contains statistical test using Fama-French regression. Consistent with preliminary sorting results in Table 3, option strike dispersion generates impressive abnormal return compared with other benchmarks. Considering that our strategy has negative skewness, in the later section, we consider one refined strategy using its time-varying volatility. Since different versions of our measure yield similar results, we focus on volume-weighted put option strike dispersion in all later analysis. Table 5 contains detailed information for Fama-French regression of portfolios sorted by volume-weighted put option strike dispersion. Based on the mean return of each portfolio, short-leg takes up around 80% returns of our long-short strategy, which is a strong support for Miller (1977) theory.

4.3 Double Sorting and Fama-Mecbeth Regression

In literature, there are other variables, extracted from stock and option markets, being able to predict expected cross section stock returns. Since it is possible that our results may be driven by these variables, after the univariate-sorting test, we further conduct double sorting test and Fama-Mecbeth regression, controlling for firm characteristics and other popular predictors for cross section stock returns. The cross section regression has formula

$$RET_{i,t+1} = \alpha + \beta DISP_{option,i,t} + \rho X_{i,t} + \epsilon_{i,t},$$

where RET is monthly individual stock returns. $DISP_{option}$ is our dispersion measure extracted from option trading activities. X is a vector of control variables, motivated by literature. Standard firm characterstics, such as firm size, market-to-book ratio, and market leverage ratio, are includes. X also contains volatility spread (Bali and Hovakimian, 2009), implied volatility skewness (Cremers and Weinbaum, 2010; Xing, Zhang and Zhao, 2010), option-to-stock trading volume ratio (Johnson and So, 2012), put-call option trading volume ratio (Pan and Poteshman, 2006), market beta (Chang, Christoffersen, Jacobs and Vainberg, 2012; Frazzini and Pedersen, 2014), idiosyncratic volatility (Ang, Hodrick, Xing and Zhang, 2006), past month return (An, Ang, Bali and Cakici, 2014) and stock liquidity measure.

Table 6 gives a rough description about the trend for various stock characteristics across portfolios sorted by strike dispersion. For risk measures, higher dispersion firms have lower past month returns, higher implied volatility, realized volatility, volatility spread and idiosyncratic volatility. Therefore, high dispersion firms are riskier. Since belief dispersion should be correlated, high strike dispersion firms also have high analyst forecast dispersion, for both long-term and short-term forecast. For financial statement variables, higher dispersion firms are smaller firm, with larger market-to-book ratio, and market leverage ratio does not vary much across different portfolios. For trading activities, higher dispersion firms have larger stock and option trading volume, however, the O/S ration and put-call volume ratio for such firms are lower.

Fama-Mecbeth regression results is illustrated in Table 8. Coefficient for our core variable: volume-weighted put option strike dispersion is negative and significant, indicating that high strike dispersion leads to low future stock returns. The coefficient for volatility spread is consistent with findings in Bali and Hovakimian (2009). The authors find a negative and significant relation between expected returns and the realized-implied volatility spread that can be viewed as a proxy for volatility risk. Since our volatility spread measures the implied-realized volatility gap, the coefficient should be positive.The significant negative coefficient for past 1-month return indicates short-term reversal effect. The coefficients for two well established variables, implied volatility skew and option-stock trading volume, are statistically significant and consistent with theories. There is significant negative relation between stock market liquidity and future stock returns, consistent with liquidity premium argument. The coefficient for idiosyncratic volatility, market beta and firm financial statement variables are not significant.

Moreover, the results for double-sorting long-short portfolios in Table 7 basically confirm conclusion from Fama-Mecbeth regression. Although the risk adjusted abnormal returns are lower than those in Table 3, they are still statistically significant and at the same level with returns of other well-established factors.

4.4 Risk Management

Table 3 shows that our strategy based on option strike dispersion has negative skewness, indicating that there should be large drawdowns during our sample period. Figure 1 virtually identify one large drawdown around beginning of the year 2009. Specifically, our strategy has a negative total return of -31.41% during March, April and May, 2009.

Such pattern has been found also in other long-short strategies, for example, momentum crash (Daniel and Moskowitz, 2013) and carry trade crash (Brunnermeier, Nagel and Pedersen, 2009). One explanation for this pattern is the time-varying systematic risk, such as market return exposure (Grundy and Martin, 2001). During 2007 - 2008 two years, our strategy has positive total return of 43.54%. Based on similar insights from Daniel and Moskowitz (2013), such large positive returns indicates that following market declines our dispersion portfolio is likely to be long low-beta stocks, and short high-beta stocks. Figure 3 and Figure 4 support this intuition. Figure 3 shows that in our sample period, stocks with high strike dispersion have high market risk exposure. The ratio of market beta for the short-leg and long-leg of our hedged portfolio is time-varying, and high during crisis. Figure 4 gives a snapshot for market beta dynamics during 2008 crisis. Combining Figure 4 with Figure 5, we clear see that due to its higher market risk exposure, stocks with high belief dispersion depreciate more than the ones with low belief dispersion, during the year 2008. However, after Feb, 2009, when market rebounds, exactly due to its high beta, stocks with high belief dispersion appreciate more than the ones with low belief dispersion. Therefore, our strategy generates large variance and negative skewness during turbulent time, as is shown in Figure 6.

Based on literature about momentum crash, there are two methods to reduce the negative skewness in our strategy. Grunday and Martin (2001) suggest that hedging the time-varying market exposure could produce stable momentum returns. Daniel and Moskowitz (2013) propose to dynamically weighting the momentum strategy based on the forecast of its return and variance. As pointed by Barroso and Santa-Clara (2014), momentum crashes are a feature of the naive $1-long/$1-short strategy typically used in academic studies. They argue that crashes can be avoided with a momentum portfolio which is scaled by the trailing volatility of the momentum portfolio. We adopt the same method for our long-short portfolios.

In each month, we compute the daily realized variance as square daily returns of our strategy. Then the monthly realized variance is just the sum of daily ones in the month. At the end of each month, after we sort the whole sample into deciles according to our strike dispersion measure, we further calculate average monthly realized variance in the past 6 month and transform it to annualized volatility $\hat{\sigma}_t$, using it to scale our exposure on the raw long-short portfolios,

$$r^s_{disp,t} = \frac{\sigma_{target}}{\hat{\sigma}_t} r_{disp,t},$$

where $r_{disp,t}$ is monthly return of raw strategy (long decile 1 and short decile 10). $r^s_{disp,t}$ is monthly return of our scaled strategy. σ_{target} is the target level of volatility, following Barroso and Santa-Clara (2014), it is set to be 12%.

Figure 7 shows the cumulative returns of risk-managed strategy compared to plain strategy. Virtually, the risk-managed momentum strategy achieves a higher cumulative return with less risk. More concrete, the scale method reduces negative skewness from -0.6469 to -0.4299, increase sharp ratio from 0.51 to 0.79, and enhance annualized return from 13.24% to 14.05%.

5 Short-Sale Constraints

Roughly speaking, there are three distinct kinds of empirical proxies related to short selling constraints. The first instrument is short interest ratios (shares sold short/shares outstanding). The second one uses the actual cost of short selling by looking at the rebate rate on borrowed stock. The third and most recent measure is based on the assumption that short sales depend on stock ownership by mutual funds and institutions. Such literature regards institution ownership as a proxy for short-sale constraints.

These three categories and their combinations all have been applied in literature. Chen, Hong and Stein (2002) use mutual fund ownership breadth as a proxy for short-sale constraints. The authors argue that the fact that few investors have long positions signals that the short-sales constraint is binding tightly. Ofek, Richardson and Whitelaw (2004) directly measure stocks' shorting costs by their rebate rate. This rebate rate is the interest rate that investors earn on the required cash deposit equal to the proceeds of the short sale. Asquith, Pathak and Ritter (2005) use data on both short interest (a proxy for demand) and institutional ownership (a proxy for supply) as instrument for difficulty of short selling. Their intuition is that stocks are short-sale constrained when there is a strong demand to sell short and a limited supply of shares to borrow. The source for borrowing is usually holdings of various funds and institutional investors. Johnson and So (2012) use institutional ownership, value-weighted average loan fee for institutional loans and the quantity of shares available for lending scaled by shares outstanding as proxies for short-sale costs.

Due to data limitation, we cannot directly measure short selling costs. Thus, following literature, we apply the indirect proxies: institutional ownership and change of institutional breadth. Institutional ownership is computed using equity holdings by institutions which file 13F reports. Institutional ownership level is calculated by adding up all shares for each security for each quarter, using data from Thomson-Reuters Mutual Fund database, and institutional ownership ratio (IOR) is the level divided by total shares outstanding at quarter end. Institutional breadth represents the number of institutions owning the stock during the quarter, and the change in institutional breadth reflects the net increase or decrease in the number of institutions holding this specific security. In the computation of changes in Breadth of Institutional Ownership (DIB), Lehavy and Sloan (2008) algorithm is applied, and DIB is computed using only 13F filers that exist in the database in both quarters t and $t-1$,

$$\Delta BREADTH_{it} = \frac{\#\text{of 13F Filters holding security } i \text{ at } t - \#\text{of 13F Filters holding security } i \; at \; (t-1)}{\text{Total Number of 13F Filters at } (t-1)},$$

where t denotes time and i denotes particular stock.

The results are show in Table 9. Since the major supply of shares for borrowing is institutional investors' holding. Less institutional investors hold the stock, more difficult to borrow (short) the stock. Therefore, according to Miller (1977), the stock tend to be over-valued, and our long-short portfolio should have better performance based on such stocks. Relative performance in Table 9 is consistent with our argument.

6 Conclusions

We document a statistically and economically significant relation between option trading activity and expected stock returns. We construct volume and open interest weighted option strike dispersion, and find out a significant negative relation between option strike dispersion and future stock returns, via both portfolio level and cross firm analysis. This result is robust to controls for numerous other potential risk factors and firm financial statement variables. We interpret interpret our results in the context of a market with investors' heterogeneous beliefs along with short-sale constraints, consistent with Miller (1977) intuition. We also examine the dynamics of our long-short portfolios, idenfying possible crash risk and apply a simple yet efficient risk management technique to improve the strategy performance.

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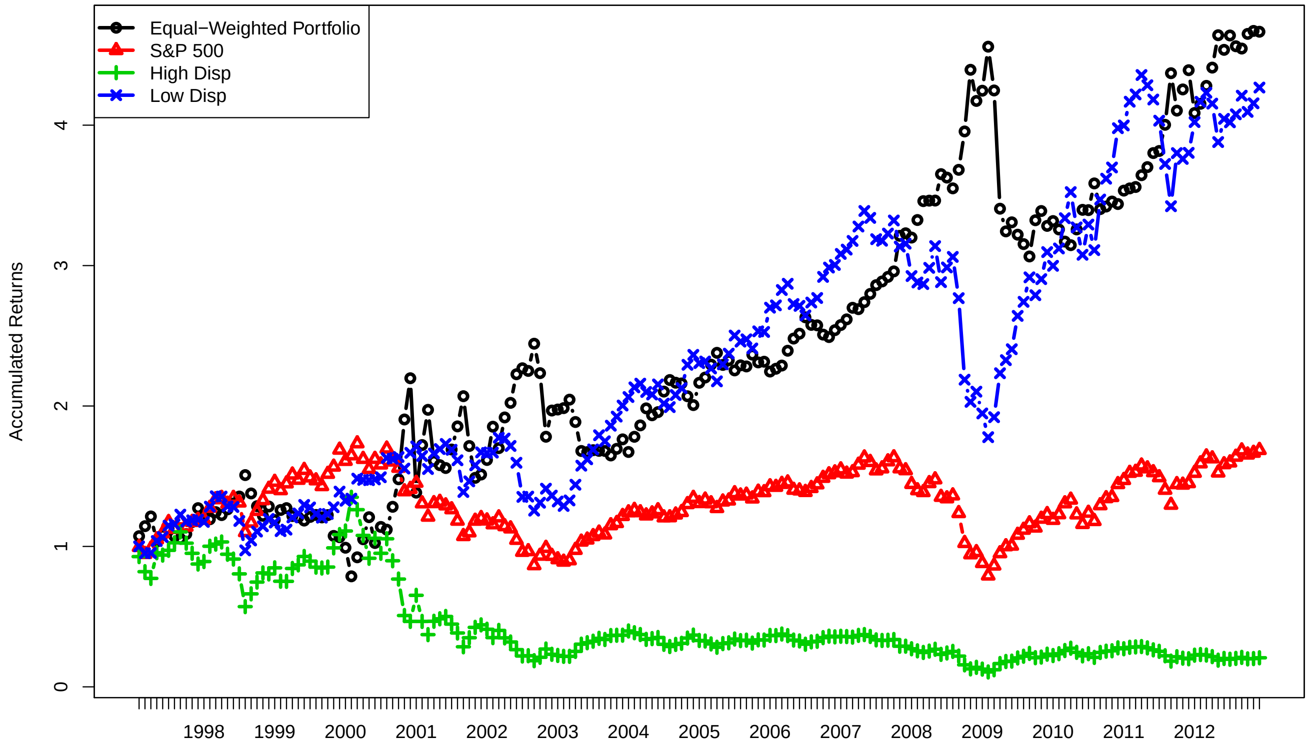

Figure 1: Portfolio performance: 1996 - 2012. The long-run cumulative returns of long-short portfolio based on volume-weighted put option strike dispersion compared to the market portfolio. Each strategy consists on investing $1 at the beginning of the sample.

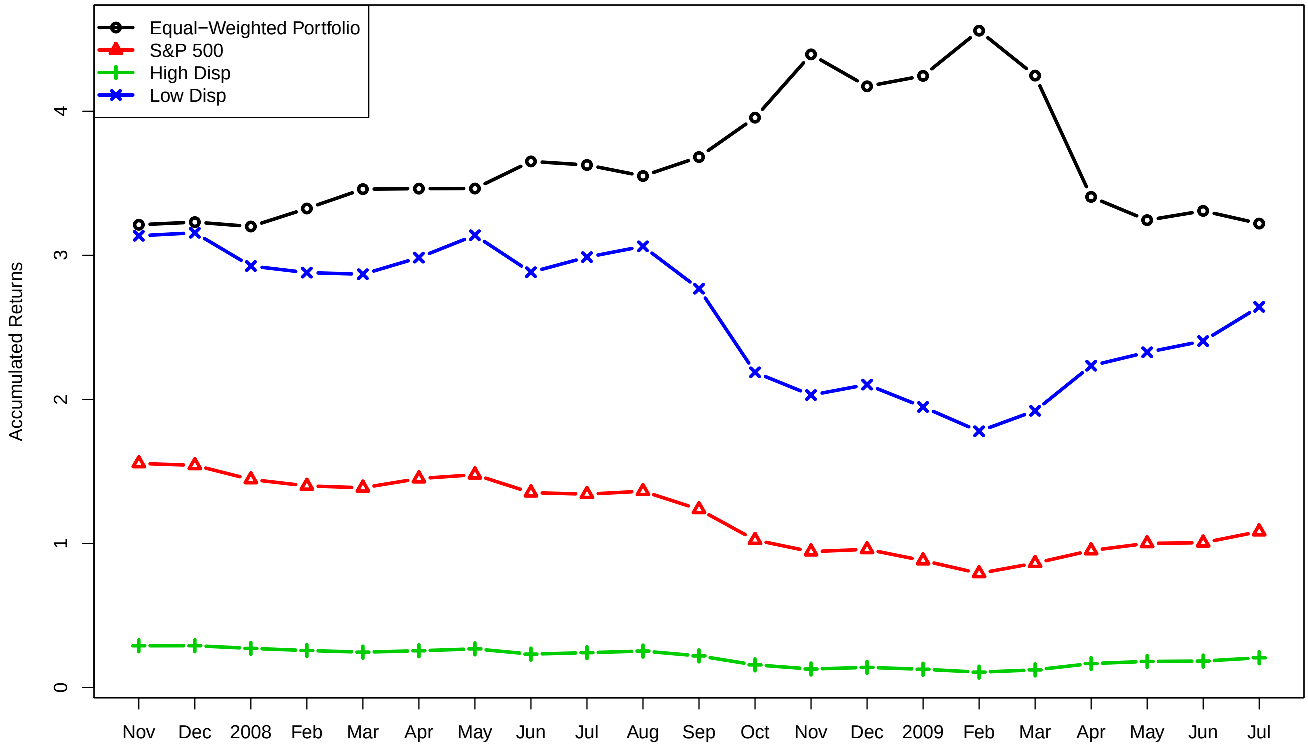

Figure 2: Portfolio performance: 2008 - 2009. The snapshot of long-run cumulative returns of long-short portfolio based on volume-weighted put option strike dispersion compared to the market portfolio, during the 2008 crisis period. Each strategy consists on investing $1 at the beginning of the year 1996.

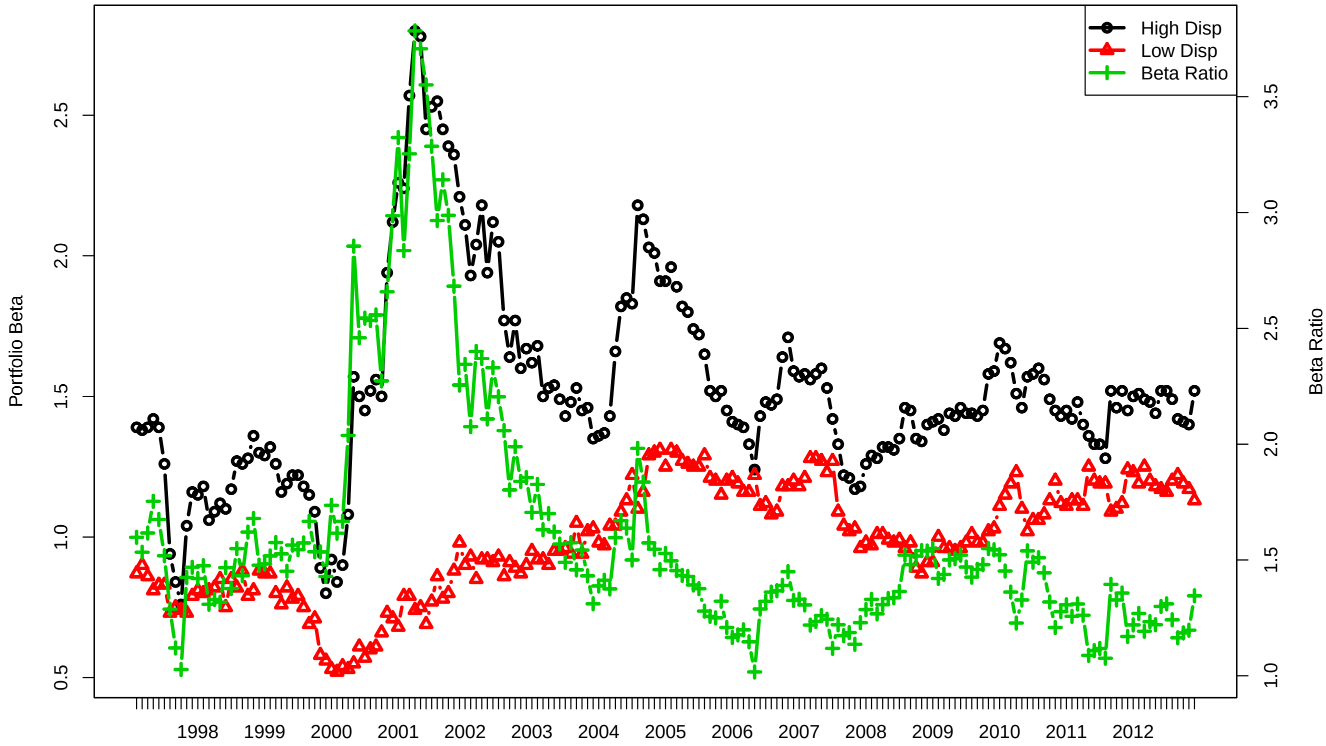

Figure 3: Dynamics of market portfolio exposure: 1996 - 2012. Each month, sort the whole sample into 10 portfolios, based on volume-weighted put option strike dispersion. For each portfolio, calculate aggregate market exposure (market beta) by averaging individual market exposure for stocks in the portfolio. Plot market betas for portfolio 1 (low disp) and portfolio 10 (high disp), along with beta ratio (high disp beta divided by low disp beta).

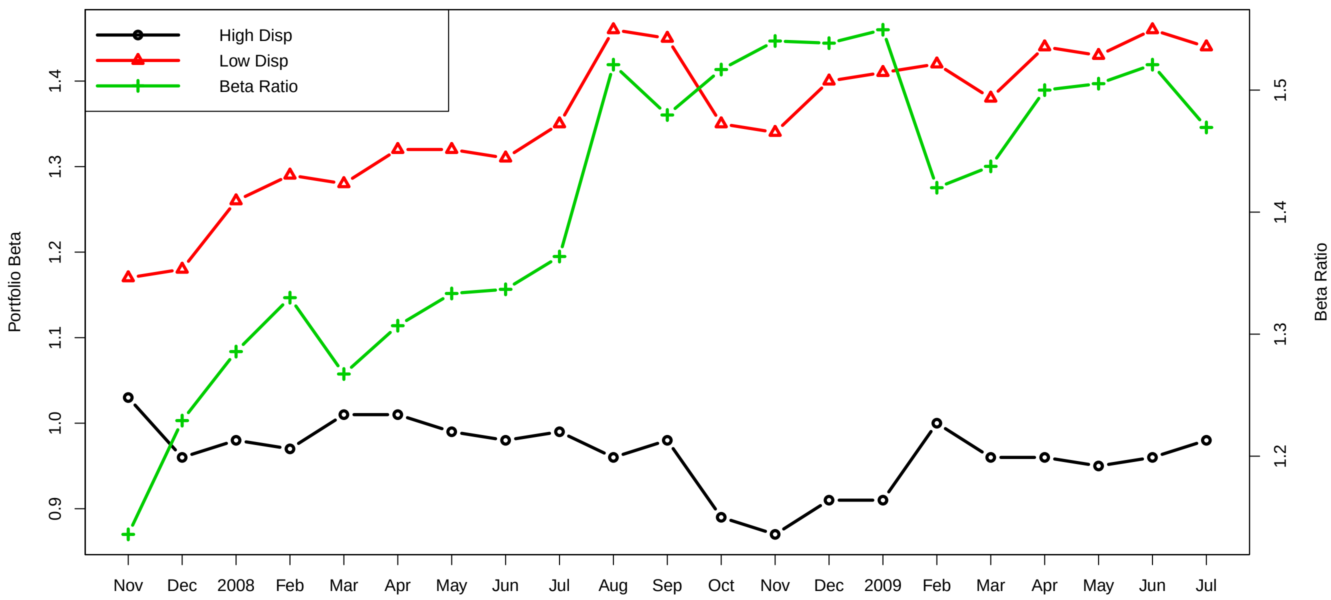

Figure 4: Dynamics of market portfolio exposure: 2008 - 2009. Snapshot of market beta dynamics during crisis. Each month, sort the whole sample into 10 portfolios, based on volume-weighted put option strike dispersion. For each portfolio, calculate aggregate market exposure (market beta) by averaging individual market exposure for stocks in the portfolio. Plot market betas for portfolio 1 (low disp) and portfolio 10 (high disp), along with beta ratio (high disp beta divided by low disp beta).

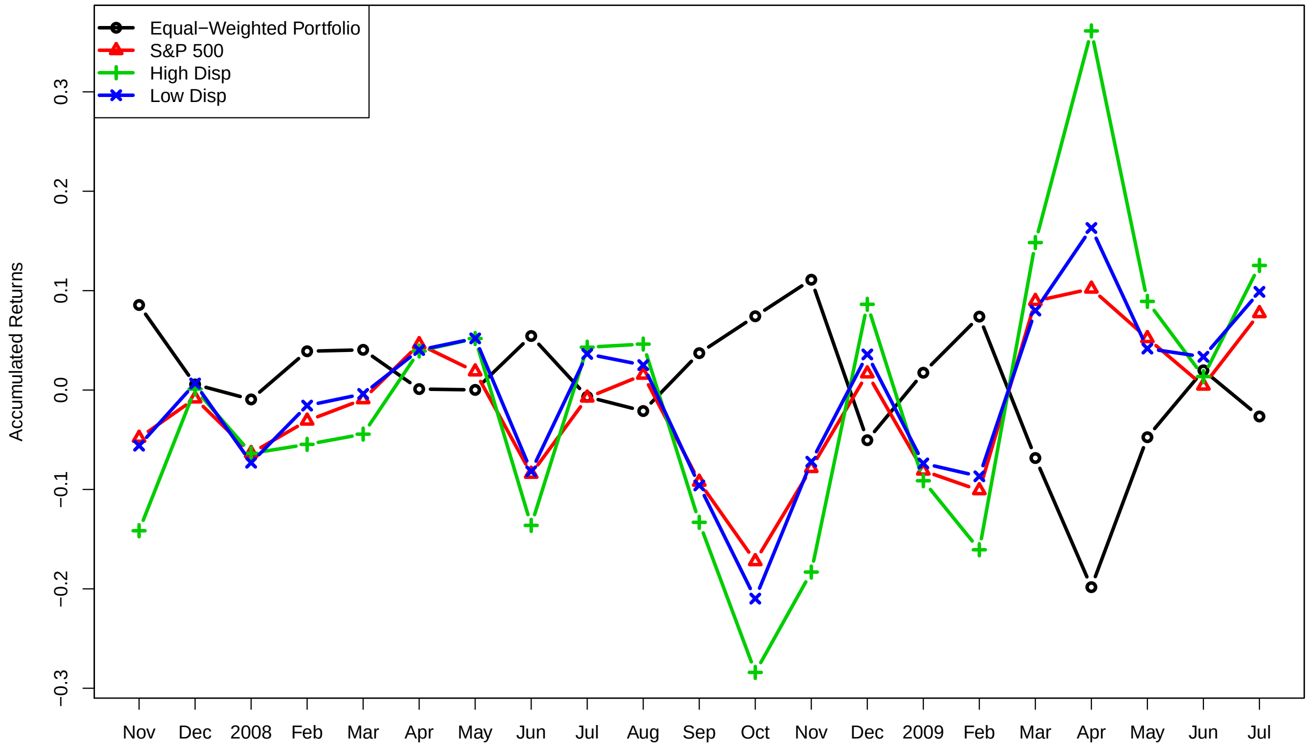

Figure 5: Strategy return dynamics: 2008 - 2009. Each month, sort the whole sample into 10 portfolios, based on volume-weighted put option strike dispersion. For each portfolio, calculate aggregated portfolio returns as average of individual stock returns in that portfolio. Plot monthly returns, during crisis, for portfolio 1 (low disp) and portfolio 10 (high disp), along with returns of long-short portfolio and market excess returns.

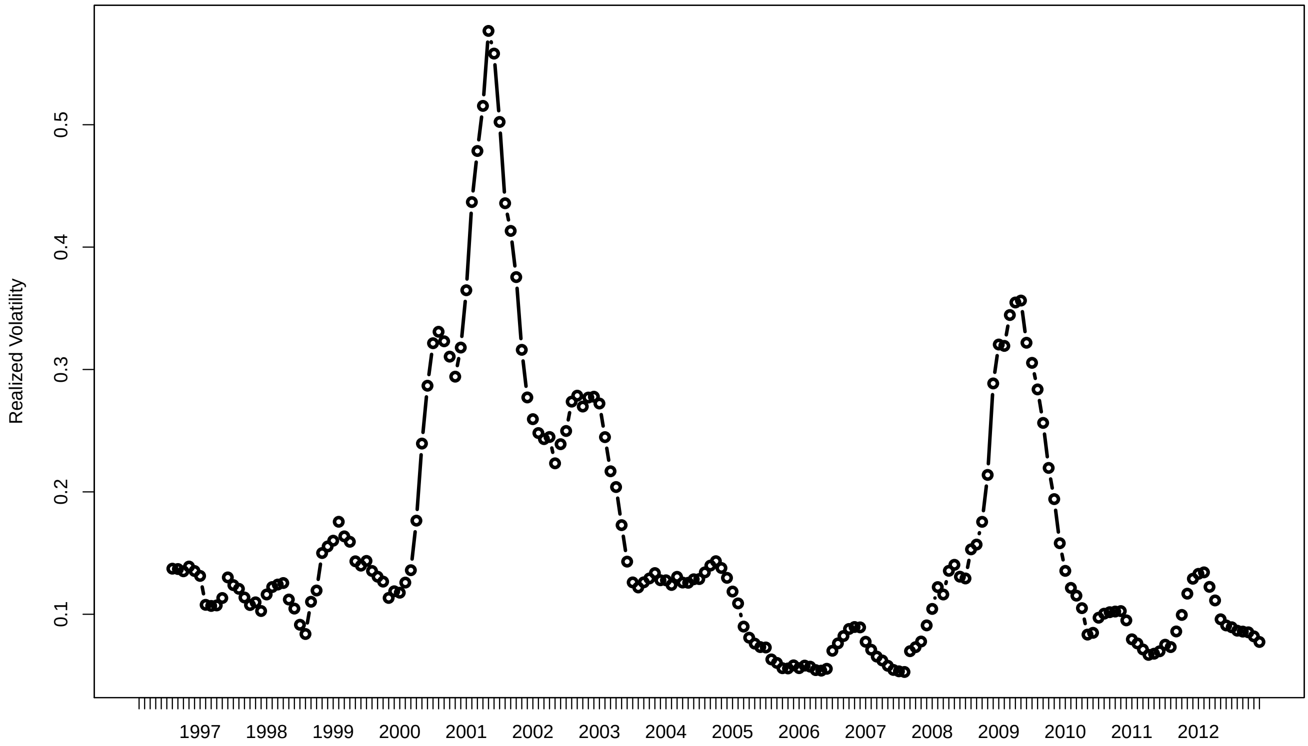

Figure 6: Realized volatility dynamics: 1996 - 2012. Monthly realized volatility for long-short strategy based on volume-weighted put option strike dispersion. Monthly realized volatility is calculated as sum of squared daily returns in that month.

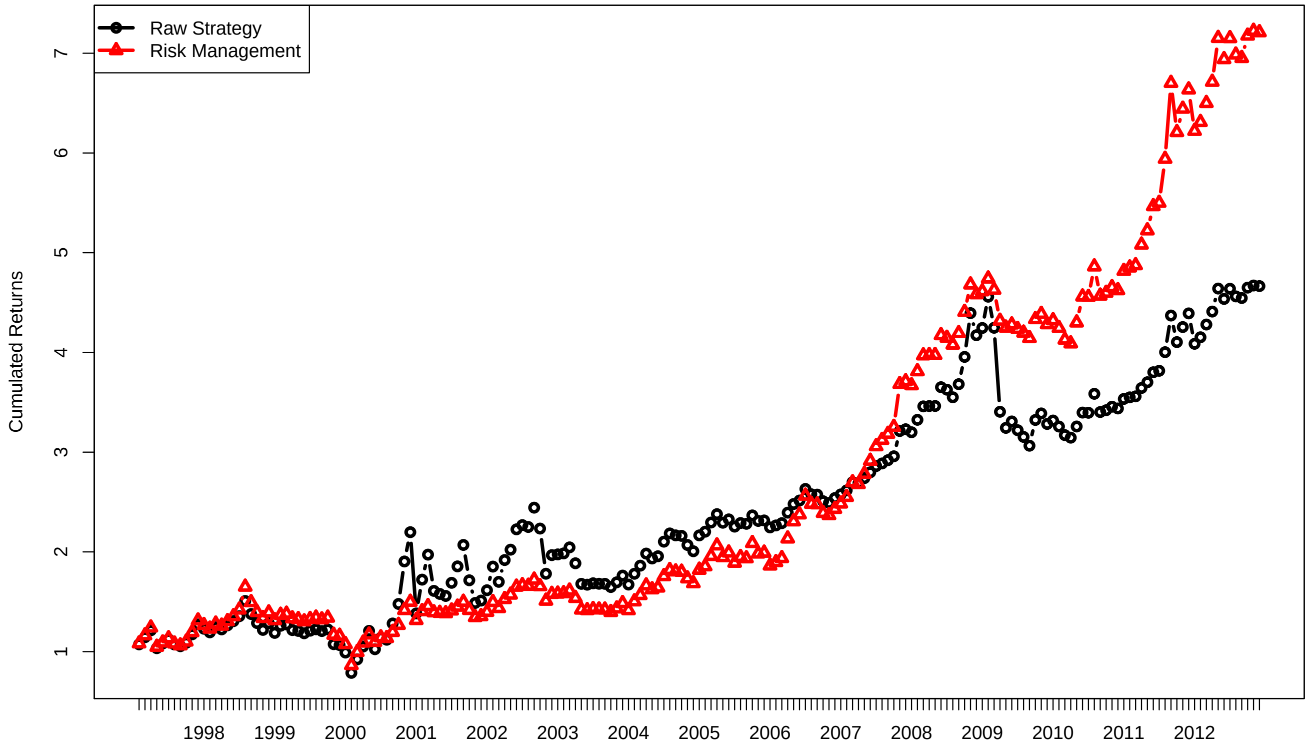

Figure 7: Performance of raw strategy and risk-managed strategy: 1996 - 2012. Each month, sort the whole sample into 10 portfolios, based on volume-weighted put option strike dispersion. Raw strategy longs stocks with lowest strike dispersion (portfolio 1) and shorts stocks with highest strike dispersion (portfolio 10). The risk-managed strategy scales the exposure to raw strategy using the realized variance in the previous 6-months. In the beginning of sample period, investing $ 1 in both strategies.

Table 1: **Summary Statistics: Stock Characteristics**

Summary statistics for various stock characteristics. RET is monthly equity returns. IV is implied volatility. RV is monthly total realized volatility. BETA is stock return loading on market portfolio. IdioVol is idiosyncratic volatility calculated from market model. IVS is implied volatility skew. SIZE is firm size. MTB is market-to-book ratio. LEV is market leverage ratio. SVOL and OPVOL are logarithm of monthly stock and option total trading volume. OS is logarithm of option and stock volume ratio. OPVOLSP is put and call option volume ratio. The sample period is from January, 1996 to December, 2012, trimmed by 1%. To avoid effect of extreme values, Data with IV and RV larger than 1 is deleted.

	RET	IV	RV	VS	IVS	SIZE	MTB
min	-0.3582	0.1556	0.0992	-0.2467	-0.0337	3.8745	0.2204
mean	0.0081	0.4376	0.3610	0.0767	0.0036	7.5306	1.6816
max	0.4122	0.9505	0.9286	0.4098	0.0603	11.9832	8.6249
sd	0.1155	0.1617	0.1651	0.0995	0.0091	1.5230	1.1995
	MarLEV	Beta	IdioVol	OS	OPVOLSP	SVOL	OPVOL
min	0.0001	0.1500	0.0076	-6.2584	0.0327	13.7274	4.6444
mean	0.2180	1.1318	0.0242	-3.2500	0.7358	16.4046	8.5494
max	0.8390	2.6700	0.0661	-0.6338	6.2476	19.7947	13.5247
sd	0.1852	0.4848	0.0106	1.1162	0.7637	1.1708	1.8512

Table 2: **Summary Statistics: Volume and Open Interest Weighted Option Strikes**

Panel A contains volume weighted variables. DispALL, DispPUT and DispCALL are scaled strike dispersion weighted by total option trading volume, put option trading volume and call option trading volume, respectively. AveALL, AvePUT, AveCALL are scaled average strike weighted by total option trading volume, put option trading volume and call option trading volume, respectively. Panel B presents results via option open interest as weight. Summary statistics for volume and open interest weighted option strikes. The sample period is from January, 1996 to December, 2012, trimmed by 1%. To avoid effect of extreme values, Data with IV and RV larger than 1 is deleted.

Panel A	Volume					
	DispALL	AveALL	DispPUT	AvePUT	DispCALL	AveCALL
min	0.0011	0.5147	0.0057	0.7426	0.0002	0.4784
mean	0.0928	1.0203	0.0830	0.9752	0.0829	1.0479
max	1.0622	3.2681	0.3183	1.5449	1.2370	6.0136
sd	0.0433	0.0934	0.0460	0.0993	0.0446	0.1031
Panel B	Opint					
	DispALL	AveALL	DispPUT	AvePUT	DispCALL	AveCALL
min	0.0006	0.0404	0.0001	0.0389	0.0001	0.0420
mean	0.1193	1.0219	0.1096	0.9810	0.1068	1.0492
max	0.7217	5.6096	0.9012	4.3831	0.6819	6.5695
sd	0.0590	0.1337	0.0650	0.1482	0.0567	0.1388

Table 3: **Summary Statistics: Various Trading Strategies**

Annualized mean returns and sharpe ratio. Skewness and kurtosis of monthly returns. PutVolume, CallVolume and AllVolume are strategies sort stocks via volume-weighted strike dispersion of put option, call option and both put and call option, respectively. PutOpint, CallOpint and AllOpint are strategies sort stocks via open-interest-weighted strike dispersion of put option, call option and both put and call option, respectively. EPSLong and EPSQuarter reprent strategies which sort stocks via analyst forecast dispersion regarded long-term EPS and next quarter EPS. MKTRF is excess returns from holding market portfolio. HML is value premium. SMB is size premium. UMD is momentum premiu. LIQ is liquidity premium. The sample period is from January, 1996 to December, 2012, trimmed by 1%. To avoid effect of extreme values, Data with IV and RV larger than 1 is deleted.

	MeanRET	SR	SKEW	KURT
PutVolume	0.1324	0.5082	-0.6469	4.5580
CallVolume	0.1066	0.3698	-0.6396	3.9389
AllVolume	0.1279	0.4101	-0.7261	4.3273
PutOpint	0.1163	0.3939	-0.8442	5.0848
CallOpint	0.0893	0.3066	-0.7796	4.3960
AllOpint	0.0895	0.2796	-0.7637	4.5680
EPSLong	0.0083	0.0824	-0.6282	2.4193
EPSQuarter	0.0433	0.2352	-0.7411	2.3725
MKTRF	0.0472	0.2809	-0.6201	0.6423
HML	0.0350	0.2859	-0.0040	2.4518
SMB	0.0349	0.2723	0.8372	7.5037
UMD	0.0503	0.2473	-1.4301	7.8736
LIQ	0.1009	0.7058	0.5448	2.7495

Table 4: **Fama-French Regression: Various Trading Strategies**

Alpha and factor loadings for various strategies. PutVolume, CallVolume and AllVolume are strategies sort stocks via volume-weighted strike dispersion of put option, call option and both put and call option, respectively. PutOpint, CallOpint and AllOpint are strategies sort stocks via open-interest-weighted strike dispersion of put option, call option and both put and call option, respectively. EPSLong and EPSQuarter reprent strategies which sort stocks via analyst forecast dispersion regarded long-term EPS and next quarter EPS. The sample period is from January, 1996 to December, 2012, trimmed by 1%. To avoid effect of extreme values, Data with IV and RV larger than 1 is deleted.

	Alpha	MKTRF	SMB	HML	UMD	LIQ
PutVolume	0.0097	-0.4281	-0.8323	0.8681	0.5429	0.0741
	(0.0026)	(0.0578)	(0.0735)	(0.0774)	(0.0458)	(0.0610)
CallVolume	0.0088	-0.5211	-0.9962	0.9284	0.4583	0.0448
	(0.0029)	(0.0657)	(0.0835)	(0.0878)	(0.0520)	(0.0693)
AllVolume	0.0100	-0.5547	-1.0736	1.0211	0.5688	0.0753
	(0.0029)	(0.0659)	(0.0838)	(0.0881)	(0.0522)	(0.0695)
PutOpint	0.0080	-0.5204	-0.8449	1.0061	0.6412	0.0702
	(0.0029)	(0.0652)	(0.0829)	(0.0872)	(0.0516)	(0.0687)
CallOpint	0.0074	-0.6289	-0.9228	0.9802	0.3660	0.0961
	(0.0029)	(0.0659)	(0.0839)	(0.0882)	(0.0522)	(0.0696)
AllOpint	0.0066	-0.6443	-1.0369	1.0680	0.5509	0.1170
	(0.0029)	(0.0662)	(0.0842)	(0.0886)	(0.0524)	(0.0699)
EPSLong	0.0015	-0.1269	-0.1227	0.0446	0.1475	-0.0971
	(0.0019)	(0.0430)	(0.0545)	(0.0578)	(0.0344)	(0.0447)
EPSQuarter	0.0046	-0.3599	-0.7787	0.2110	0.3508	0.1009
	(0.0020)	(0.0458)	(0.0580)	(0.0616)	(0.0367)	(0.0476)

Table 5: **Stock Portfolios Sorted by Dispersion of Volume-Weighed Put Option Strikes**

Monthly Fama-French regression for stock portfolio returns. The whole sample is sorted to 10 groups, according to dispersion of volume-weighed put option strikes. The portfolio is equal-weighted. Alpha is abnormal return after adjusting of systematic risk factors. MKTRF is market facor. SMB is size factor. HML is growth factor. UMD is momentum factor. LIQ is liquidity factor. RET is annualized raw return. SR is annualized sharp ratio. The first line of each portfolio is estimated values, and the second line is standard error. The sample period is from January, 1996 to December, 2012.

	Alpha	MKTRF	SMB	HML	UMD	LIQ	RET	SR
Low	0.0029	0.9689	0.3211	0.3695	-0.0702	0.0819	10.9150	0.5859
	(0.0013)	(0.0287)	(0.0365)	(0.0384)	(0.0227)	(0.0303)		
2	0.0019	0.9393	0.3061	0.3162	-0.0351	0.0457	9.1592	0.5185
	(0.0012)	(0.0262)	(0.0333)	(0.0351)	(0.0208)	(0.0277)		
3	0.0032	0.9907	0.2818	0.2056	-0.0407	0.0698	10.7147	0.5790
	(0.0011)	(0.0251)	(0.0320)	(0.0336)	(0.0199)	(0.0265)		
4	0.0035	1.0453	0.3552	0.1305	-0.0532	0.0791	11.3387	0.5631
	(0.0012)	(0.0275)	(0.0349)	(0.0368)	(0.0218)	(0.0290)		
5	0.0008	1.1095	0.4330	0.0237	-0.0903	0.0982	8.3162	0.3752
	(0.0012)	(0.0273)	(0.0347)	(0.0366)	(0.0216)	(0.0288)		
6	-0.0002	1.1536	0.5636	-0.0782	-0.0913	0.0885	7.3683	0.3056
	(0.0013)	(0.0288)	(0.0367)	(0.0386)	(0.0228)	(0.0304)		
7	0.0004	1.2616	0.6925	-0.1699	-0.1283	0.0798	8.4447	0.3084
	(0.0014)	(0.0319)	(0.0406)	(0.0427)	(0.0253)	(0.0336)		
8	-0.0010	1.2813	0.8440	-0.2908	-0.2567	0.0236	5.7654	0.1910
	(0.0016)	(0.0355)	(0.0452)	(0.0475)	(0.0281)	(0.0375)		
9	-0.0021	1.3666	1.0932	-0.4613	-0.3727	0.0474	4.6968	0.1336
	(0.0017)	(0.0384)	(0.0489)	(0.0514)	(0.0304)	(0.0406)		
High	-0.0068	1.3970	1.1534	-0.4985	-0.6131	0.0078	-2.3281	-0.0602
	(0.0022)	(0.0504)	(0.0641)	(0.0674)	(0.0399)	(0.0532)		
Hedged	0.0097	-0.4281	-0.8323	0.8681	0.5429	0.0741	13.2431	0.5082
	(0.0026)	(0.0578)	(0.0735)	(0.0774)	(0.0458)	(0.0610)		

Table 6: **Group Summary Statistics**

Summary statistics in portfolios sorted by volume-weighted put option strike dispersion. RET is next month stock returns after sorting. MOM1 is stock returns in the sorting month. IV is implied volatility. $IVS50$ is volatility skew for ATM options. RV is realzed volatility. VS is spread between implied and realized volatility. SIZE is firm size. MTB is market-to-book ratio. MarLEV is market leverage ratio. EPSDISPL is analyst forecast dispersion for long-term EPS. EPSDISPQ is analyst forecast dispersion for next quater EPS. NUMANA is analyst coverage. BETA is stock loading on market portfolio. IdioVol is idiosyncratic volatility from market model. SVOL and PVOL are monthly total trading volume for stocks and options. OS is ratio of option and stock trading volume. OPVOLSP is ratio between trading volume of put and call options. The sample period is from January, 1996 to December, 2012, trimmed by 1%. To avoid effect of extreme values, Data with IV and RV larger than 1 is deleted.

	RET	IV	IVS50	RV	VS	SIZE	MTB	MarLEV	EPSDISPL
Low	0.0074	0.3543	0.0033	0.2875	0.0667	8.0058	1.4881	0.2322	3.8657
2	0.0093	0.3604	0.0030	0.2976	0.0628	8.2967	1.5844	0.2179	4.0220
3	0.0083	0.3988	0.0030	0.3313	0.0675	8.0892	1.5992	0.2163	4.5690
4	0.0074	0.4433	0.0033	0.3682	0.0752	7.7812	1.6122	0.2207	5.1667
High	0.0053	0.4994	0.0035	0.4089	0.0905	7.4423	1.5180	0.2483	5.7139
	EPSDISPQ	NUMANA	BETA	IdioVol	MOM1	SVOL	OPVOL	OS	OPVOLSP
Low	0.0306	10.2889	0.8970	0.0193	0.0121	16.3194	8.1095	-3.6047	0.8727
2	0.0332	11.8436	0.9481	0.0197	0.0128	16.6632	8.8485	-3.2096	0.7432
3	0.0366	11.9863	1.0532	0.0219	0.0130	16.7291	9.0275	-3.0964	0.7283
4	0.0388	11.6636	1.1859	0.0246	0.0145	16.7527	9.1357	-3.0118	0.7151
High	0.0410	11.0044	1.3258	0.0280	0.0054	16.7902	9.1530	-3.0320	0.7200

Table 7: **Statistics for Double Sorted Long-Short Strategy Performance**

Double sort, based on volume-weighted option strike dispersion and one control variable listed below. VS is volatility spread. IdioVol is idiosyncratic volatility from market model. SIZE is log firm market value. MTB is market-to-book ratio. MarLEV is market leverage ratio. RET is lagged monthly underlying return. IVSKEW is implied volatility skew. SVOL and OPVOL are monthly total trading volumes for stocks and options. OS is ratio of option trading volume to stock trading volume. BETA is stock loading on market portfolio. OPVOLSP is ratio of put and call option trading volume. The sample period is from January, 1996 to December, 2012. The time window is month.

Controls	Alpha	Tvalue	SharpRatio	Skewness	Kurtosis
BETA	6.84	2.47	0.39	-1.22	6.29
IdioVol	7.44	2.46	0.44	-1.31	9.19
IVSKEW	9.60	3.09	0.43	-0.57	3.69
MarLEV	11.28	3.38	0.51	-0.91	5.93
RET	11.40	4.15	0.65	-0.25	2.74
MTB	9.36	3.05	0.44	-0.82	5.63
OPVOL	8.88	2.69	0.37	-1.11	6.73
OPVOLSP	10.20	3.22	0.44	-0.92	5.00
OS	8.64	2.69	0.39	-0.94	5.63
SIZE	8.52	2.82	0.42	-0.78	5.34
SVOL	10.32	3.29	0.43	-0.92	5.39
VS	10.80	3.60	0.50	-0.54	3.78

Table 8: **Stock Return and Volume-Weighted Put Option Strike Dispersion**

Fama-Macbeth cross-section regression. Effect of option strike dispersion on stock returns.

$$STRET_{i,t+1} = \alpha + \rho Pdisp_{i,t} + \gamma X_{i,t} + \epsilon_{i,t},$$

where $X_{i,t}$ is a vector of control variables. VS is volatility spread. IdioVol is idiosyncratic volatility from market model. SIZE is log firm market value. MTB is market-to-book ratio. LEV is market leverage ratio. RET is lagged monthly underlying return. ANA is number of analysts covering the firm. IVSKEW is implied volatility skew. SLIQ is stock bid-ask spread. OS is ratio of option trading volume to stock trading volume. BETA is stock loading on market portfolio. The sample period is from January, 1996 to December, 2012. The time window is month. Neway-West adjustment with 12 lags is used.

Pdisp	VS	IdioVol	RET	SIZE	MTB	LEV	IVSKEW	OS	SLIQ	BETA
-0.0152	0.0088	-0.0927	-0.0165	-0.0008	-0.0007	-0.0005	-0.1360	-0.0012	-0.9802	0.0002
(0.0075)	(0.0042)	(0.0985)	(0.0071)	(0.0007)	(0.0006)	(0.0037)	(0.0452)	(0.0006)	(0.4678)	(0.0030)

Table 9: **Long-Short Strategy Performance after Controling Institutional Onwership**

Portfolio performance. The whole sample is sorted into 3 portfolios, based on volume-weighted option strike dispersion and control variables. Control variables include institutional ownership (IOR) and change of institutional ownership breadth (DIB). The annulaized long-short alpha and its t value are reported. The sample period is from January, 1996 to December, 2012. The time window is month.

	IOR	DIB
Low	12.18	10.24
	5.38	4.92
Media	4.98	7.85
	2.68	4.09
High	5.63	7.34
	2.97	4.03