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Differences in Options Investors' Expectations and the Cross-Section of Stock Returns*

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Abstract

We provide strong evidence that the dispersion of individual stock options trading volume across moneynesses (IDISP) contains valuable information about future stock returns. Stocks with high IDISP consistently underperform those with low IDISP by more than 1% per month. In line with the idea that IDISP reflects dispersion in investors' beliefs, we find that the negative IDISP-return relationship is particularly pronounced around earnings announcements, in high sentiment periods and among stocks that exhibit relatively high short-selling impediments. Moreover, the IDISP effect is highly persistent and robustly distinct from the effects of a large array of previously documented cross-sectional return predictors.

JEL Classification: G10, G11, G12, G14

Keywords: Dispersion of beliefs; Disagreement in options market; Cross-section of stock returns; Equity options; Option trading volume

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1 Introduction

The bet-like nature of options' payoffs combined with their embedded leverage render them an ideal instrument for investors to reflect their expectations about the future direction of the underlying asset price. In this spirit, Bali and Hovakimian (2009), Xing, Zhang and Zhao (2010), Cremers and Weinbaum (2010) and An, Ang, Bali and Cakici (2014), among others, show that various empirical measures extracted from option prices encapsulate valuable information about the cross-section of individual stock returns. Unlike previous studies, this paper focuses on the information content embedded in the trading activity of the options market. In particular, it shows that the dispersion of individual stock options trading volume across different moneyness levels (denoted IDISP) is a strong predictor of the cross-section of expected returns.

We postulate that the dispersion of trading volume across moneynesses can be viewed as a proxy for differences in expectations among investors. This dispersion measurement stems from the trading activity in the stock options market, which is mainly driven by investors' directional expectations about the future price of the underlying asset (Lakonishok, Lee, Pearson and Poteshman, 2007). In this spirit, studies such as those of Pan and Poteshman (2006) and Johnson and So (2012) rely on measures of stock options trading activity as the source of information to capture investors' beliefs. The options dispersion measure can be motivated in a stylized framework of optimal trading behavior that maximizes investors' expected utility. Intuitively, this framework presumes that investors who speculate based on their directional expectations about the future stock price choose to trade at the moneyness level that best fulfills their optimistic or pessimistic views. Within this framework, we demonstrate that the optimal moneyness for an investor is proportional to her level of optimism or pessimism. Thus, a more optimistic investor chooses to buy calls or sell puts of a higher strike price, whilst a more pessimistic investor chooses to buy puts or sell calls of a lower strike price. Therefore, high differences of opinion should be associated with high dispersion of volume traded across a large range of strike prices, implying that investors share rather divergent beliefs. Likewise, low differences of opinion should be associated with low dispersion of volume traded at a few adjacent strike prices, implying that investors share rather homogeneous beliefs.

Compared to previously proposed measures, which are based on either the predictions of professional forecasters, investors' portfolio holdings or stock trading volume, the suggested IDISP measure exhibits several advantageous properties.[1] First, unlike survey-type proxies, which represent only a restricted subset of opinions, our measure emerges directly from transactions in the options market, which provides a perfect venue for a massive pool of investors to explicitly express their opinions. Second, most of the divergence proxies based on forecasts are influenced by behavioral biases and agency issues between firms and investments banks (see, for example, Trueman, 1994; Dechow, Hutton and Sloan, 2000; Cen, Hilary and Wei, 2013), and are mainly related to earnings or other corporate information. By contrast, our IDISP measure is unlikely to be affected by such biases and directly relates to future stock price movements. Third, unlike dispersion proxies that rely on portfolio holdings data or aggregate volume, our measure can equally incorporate different levels of both optimistic and pessimistic expectations, since the options market is less likely to be influenced by the short-sale constraints present in the equity market (Lakonishok, Lee, Pearson and Poteshman, 2007). Finally, in comparison to forecasts that are typically released monthly or quarterly, our measure is easily computable at any frequency and can provide investors with direct access to the information about the belief dispersion level for any optioned stock at any time.[2]

Our empirical results show that high IDISP stocks earn substantially lower returns than low IDISP stocks. In particular, a portfolio-level analysis indicates that stocks sorted into the highest IDISP decile consistently underperform stocks in the lowest IDISP decile, by about 1.5% per month for equal- as well as value-weighted returns. After adjusting for the Carhart (1997) and the Pastor and Stambaugh (2003) factors, the equal-weighted (value-weighted) alpha of a strategy that buys

[1]Diether, Malloy and Scherbina (2002), Park (2005), Anderson, Ghysels and Juergens (2009), Yu (2011) and Carlin, Longstaff and Matoba (2014) utilize the dispersion in the opinions of professional forecasters. Chen, Hong and Stein (2002), Goetzmann and Massa (2005) and Jiang and Sun (2014) create dispersion proxies using investor portfolio holdings. Garfinkel and Sokobin (2006) and Garfinkel (2009) measure dispersion in beliefs via the trading volume that is not attributable to liquidity or informedness effects, while Sarkar and Schwartz (2009) compute a sidedness measure based on buyer- and seller-initiated trades.

[2]In a recent study that appears subsequent to the first draft of this paper, Fournier, Goyenko and Grass (2017) also construct a disagreement proxy from the options trading activity. There are two key differences between the two measures. First, their measure stems from a distinction between optimistic and pessimistic trades, while our measure also distinguishes different degrees of optimism or pessimism. Second, the construction of their measure requires the usage of proprietary signed volume data, while our measure can be constructed either by unsigned or signed volume data and we show that the two constructions of our measure exhibit very similar information content. It is important to note that both studies document negative predictability of options investors' disagreement for the cross-section of stock returns.

high IDISP stocks and sells low IDISP stocks remains economically substantial and statistically significant, earning -1.54% (-1.59%) per month, with associated t-statistics of -4.88 (-4.23). Due to the fact that our sample consists of stocks for which an options market exists, it is by construction tilted towards relatively big, more liquid and more investable stocks. However, a profitable long-short strategy would also require IDISP to be a persistent stock characteristic, in order to ensure low rebalancing and hence low transaction costs. In light of this, we demonstrate that high IDISP stocks in one month remain high in the subsequent month, with a 56% probability.[3] Furthermore, the persistence of IDISP as a stock characteristic implies that the return predictability might be significant even at long horizons. Consistent with this expectation, we show that the risk-adjusted return of a strategy that buys high IDISP stocks and sells low IDISP stocks remains economically and statistically significant even when considering a 12-month holding period.[4] Finally, we find that the information content of IDISP for future stock returns is not subsumed by more than twenty previously documented predictive characteristics such as idiosyncratic volatility, maximum return, default risk, risk-neutral skewness, and volatility of volatility.

As discussed above, our theoretical framework describes an environment where investors express their directional views via naked option positions. However, it can be easily extended to cases where investors rely on the put-call parity to create synthetic positions. For example, an optimistic investor can replicate an out-of-the-money (OTM) call purchase or an in-the-money (ITM) put sale by purchasing a matched-strike ITM put or selling a matched strike OTM call respectively. The main prediction of our framework – that the optimal moneyness level for an investor is proportional to her level of optimism or pessimism – holds in the case of synthetic positions as well. On the other hand, such complicated put-call parity strategies might be relatively difficult for investors to implement. Therefore, we examine the predictability of an IDISP measure that is estimated using only the trades that are easily implementable and are clearly associated with investors' expectations, i.e. the buy-side volume of OTM options and the sell-side volume of ITM options. The

[3]Note that the trading strategy that exploits the information content of IDISP requires short-selling the high IDISP stocks and hence the average investor would typically find it difficult to implement. However, the strategy would be easily implementable by certain institutional investors, such as hedge funds, who face low short-sale constraints. For example, recent literature emphasizes that some institutional investors do short-sell overpriced stocks regularly and realize significant gains (Boehmer, Jones, and Zhang, 2008; Diether, Lee and Werner, 2009).

[4]The dispersion in options investors' beliefs is also shown to be a strong negative predictor of the equity premium across various horizons (see Andreou, Kagkadis, Maio and Philip, 2018).

underperformance of high IDISP stocks relative to low IDISP stocks is reconfirmed in this case, even though this analysis covers a smaller sample period since the respective signed volume data are first recorded in 2005. For example, the equal- and value-weighted five-factor alphas of a high minus low IDISP portfolio are both about -1.7% per month and highly significant at the 1% level.

The observed negative predictability of IDISP for the cross-section of stock returns implies that high IDISP firms tend to be overpriced and hence investors earn, on average, a negative risk premium when holding such stocks. This result is in line with the findings of several other studies (e.g. Diether, Malloy and Scherbina, 2002; Chen, Hong and Stein, 2002; Goetzmann and Massa, 2005; Boehme, Danielsen and Sorescu, 2006) which show that various proxies for disagreement forecast negative individual stock returns. The well-documented negative relation between dispersion in beliefs and future stock returns can be explained in the context of the theoretical mechanism described by Miller (1977). In particular, Miller (1977) suggests that binding short-sale constraints prevents pessimistic agents from revealing their negative valuations and hence the equilibrium price is determined only by the most optimistic of the investors. Therefore, in the presence of short-sale constraints, a high dispersion in beliefs leads to an upward bias in the stock price and hence high differences of opinion are associated with negative future returns.

We further explore the economic nature of the documented relation between IDISP and future stock returns. First, Miller's (1977) theory requires that the predictability of any dispersion in beliefs proxy be stronger among stocks that exhibit higher short-sale costs and limits to arbitrage. Intuitively, high short-sale costs allow the overpricing to be generated, while high limits to arbitrage prevent an instant correction. In line with the notion that IDISP captures investors' diverse beliefs, we find that its predictability is mostly associated with those stocks in our sample that exhibit lower levels of residual institutional ownership (proxying for higher short-sale costs) and with stocks that have relatively small market capitalization, low liquidity and high idiosyncratic volatility (proxying for higher limits to arbitrage). Second, the relation between dispersion in beliefs and returns is expected to be very strong around earnings announcements. This is because the pre-announcement period provides fertile grounds for investors with diverse views to speculate on the outcome, and hence the overpricing related to disagreement and the subsequent correction that comes when new information is released in the market should be particularly pronounced (Berkman, Dimitrov, Jain, Koch and Tice, 2009). Our results demonstrate a very strong IDISP effect around earnings announcements, which is consistent with the idea that IDISP behaves as an effective proxy for dispersion in investors' beliefs. Finally, the effect of dispersion in beliefs on asset prices is expected to be mainly associated with relatively optimistic periods. This is because the overpricing generated by disagreement in the presence of short-sales constraints is more severe when the optimistic investors who end up holding the stock are excessively optimistic (Stambaugh, Yu and Yuan, 2012). In line with the interpretation of IDISP as a proxy for dispersion in beliefs, we show that the predictability of IDISP is mainly driven by relatively optimistic periods.

In summary, this paper creates a novel option-implied firm-level disagreement proxy and shows that it is a strong and robust negative predictor of future stock returns. In this respect, it contributes to an existing literature that develops various disagreement proxies and examines the implications of heterogeneity in beliefs for asset prices (see, for example, Diether, Malloy and Scherbina, 2002; Chen, Hong and Stein, 2002; Carlin, Longstaff and Matoba, 2014; Jiang and Sun, 2014, among others). Moreover, the predictability documented in the paper relies on the notion that IDISP serves as a proxy for the true unobservable equity market disagreement which leads to stock overpricing in the presence of short-sales constraints. In this respect, our paper further contributes to a growing literature that attributes the return predictability of some option-implied variables to their ability to identify stock mispricings (Ofek, Richardson and Whitelaw, 2004; Goncalves-Pinto, Grundy, Hameed, van der Heijden and Zhu, 2018; Hiraki and Skiadopoulos, 2018). Additionally, such a mechanism distinguishes our paper from a long literature that relies on the presence of informed traders in the options market to predict future stock price movements (see, for example, Chakravarty, Gulen and Mayhew, 2004; Johnson and So, 2012; An, Ang, Bali and Cakici, 2014, among others).

The remainder of the paper is organized as follows. Section 2 outlines the construction of the IDISP measure and describes the data used in the study. Section 3 presents the main empirical results regarding the predictability of IDISP for stock returns. Section 4 investigates the economic drivers behind the IDISP-return relation. Section 5 presents a series of robustness checks and additional analyses, confirming the stability of the findings. Finally, Section 6 concludes.

2 Measurement of IDISP and Data

In this section, we first present the construction of the dispersion of trading volume across moneynesses measure, following which we describe the data and key screening criteria applied in the study. Finally, we provide sample descriptive statistics.

2.1 Construction of the IDISP Measure

We define the individual stock options dispersion measure as the volume-weighted mean absolute deviation of moneyness levels around the volume-weighted average moneyness level. In particular, given the range of strike prices K_j for $j = 1, .., N$ and stock price S, we estimate on a given day:

$$IDISP_{daily} = \sum_{j=1}^{N} w_j \left| M_j - \sum_{j=1}^{N} w_j M_j \right|, \tag{1}$$

where w_j is the proportion of trading volume attached to the moneyness level $M_j = \frac{K_j}{S}$. Since we employ moneyness levels in the computation, IDISP$_{daily}$ is comparable across stocks and over time. Intuitively, holding the range of traded strikes fixed, IDISP increases when the volume is more spread out across the different moneyness levels. Moreover, holding the different proportions of volume constant, IDISP increases when the range of traded moneynesses becomes larger.[5] To encapsulate adequate information about dispersion in investors' beliefs, we construct the monthly IDISP measure by averaging the IDISP$_{daily}$ values within a month.

The dispersion of trading volume across moneyness levels can be interpreted as a proxy for differences of opinion among options investors in the context of an options market where the majority of the trades are between end-users and market makers, and are triggered by end-users' expectations regarding the future price of the underlying asset.[6] Recent studies empirically confirm that such

[5]The supplementary material online utilizes actual options trading activity data to provide an exposition of how the differential proportions of trading volume and the range of traded moneyness levels interact to determine the magnitude of IDISP$_{daily}$. It also highlights that the differential volume allocations across moneynesses play an important role with regard to the cross-sectional return predictability of IDISP.

[6]It is important to note that, in our setting, options investors can be either professional or retail investors. This is because, unlike index options, which are well-known to be mostly utilized by professional investors, individual stock

a trading environment is prevalent in stock options markets. In particular, Ge, Lin and Pearson (2016) examine the options exchange trading activity and observe that the norm is for a market maker to be on the other side of the trade made by an end-user. More importantly, Lakonishok, Lee, Pearson and Poteshman (2007) show that the majority of end-users' stock options trading activity is associated with speculation on the directional movement of the underlying asset through naked positions.

Within the above context, we present in Appendix A a stylized expected utility maximization framework which provides a direct link between the optimal strike price that an investor selects and her level of optimism or pessimism. This evidence forms the basis for considering the dispersion in trading volume across moneyness levels as a proxy for dispersion in investors' expectations. More specifically, we show in Figure 1 that the more optimistic an investor, the higher the strike price chosen when buying calls or selling puts, while the more pessimistic an investor, the lower the strike price chosen when buying puts or selling calls. Intuitively, option buyers benefit from the higher leverage offered by more OTM options, while option sellers benefit from the higher premium provided by more ITM options. In general, we observe that the selected strike prices (or moneyness levels) are reflective of investors' expectations about future stock price movements. Therefore, based on the above framework, we advocate the dispersion in trading volume across moneyness levels as a proxy for dispersion in investors' expectations.

2.2 Data

For the main analysis, we obtain options data including volume, strike prices, best bid and ask prices, open interest, delta and implied volatilities for individual stocks covering the period from January 1996 to August 2015 from Ivy DB's OptionMetrics. Apart from estimating our dispersion measure, we use raw options data to construct four option-related characteristics – call-put volatility spread (VS), option to stock trading volume ratio (O/S), volatility of volatility (VoV) and log of

options are actively traded by retail investors as well (Lemmon and Ni, 2014; Chang, Hsieh and Wang, 2015). In addition, Lemmon and Ni (2014) demonstrate that the demand for individual stock options is significantly affected by the level of optimism/pessimism of retail investors. Consequently, the trading activity in the individual stock options market reflects to a large extent the expectations of retail investors and is not limited to the expectations of professional investors.

total trading volume (OVlm). Further, we use the 30-days-to-maturity standardized volatility surface file to estimate the rest of the alternative option-related characteristics: risk-neutral skewness (RNS), risk-neutral kurtosis (RNK), realized-implied volatility spread (VolSpr), out-of-the-money skew (QSkew), and call and put implied volatility innovations (InnCall and InnPut).

For each stock, we follow Equation (1) to compute IDISP_{daily} on a daily frequency, using all call and put contracts with time to maturity between 5 and 60 calendar days, since these options tend to be the most actively traded. We discard near-the-money options (moneyness between 0.975 and 1.025) because they exhibit the highest sensitivity to volatility changes and hence their trading is more likely to be related to volatility expectations (Bakshi and Kapadia, 2003; Ni, Pan and Poteshman, 2008). We exclude days where options are thinly traded by keeping only those days where there are at least 4 contracts with non-zero trading volume. We also require that a firm has a minimum of 5 non-missing daily observations within a given month in order to be included in our sample for that month. Additionally, all firms with an end-of-month stock price, at the portfolio formation month, lower than 5 USD are excluded, to mitigate the role of bid-ask bounce and tick sizes. Finally, the monthly IDISP measure is created by averaging the IDISP_{daily} values within a month, excluding the last trading day of the month. Therefore, the monthly values of IDISP as well as all other option-implied variables are estimated on the last-but-one trading day of a month and are matched with stock returns over the next month, from February 1996 to September 2015. This method of lagging the options data by one day helps to eliminate the effect of non-synchronous trading between stocks and options due to different closing hours of exchanges (Battalio and Schultz, 2006; Baltussen, Van Bekkum, and Van Der Grient, 2015). In the additional analysis section, we show that our results are robust to alternative IDISP specifications, including utilizing standard deviation rather than mean absolute deviation, strike prices rather than moneyness levels, last-but-one trading day of a month values rather than average-of-month values and different filtering rules.

The data on monthly closing prices, stock returns, shares outstanding, and trading volume are obtained from CRSP. From the entire universe of securities, we select ordinary shares (share codes 10 and 11) and exclude closed-end funds and REITs. We also keep firms that are listed on NYSE, AMEX or NASDAQ and have options written on their stock. We adjust our stock returns data for delisting events (see Shumway, 1997; Shumway and Wartner, 1999) by using a delisting return of -30% for NYSE and AMEX stocks and -55% for NASDAQ stocks if the delisting code is performance-related (CRSP delisting codes 500, 505-588). We use this information to compute the log market capitalization (Size), idiosyncratic volatility (IdV), illiquidity (Illiq), maximum return within a month (MAX), stock return within a month (STR), stock beta (Beta), momentum (Mom), volatility of liquidity (Vliq) and share turnover (Turn). Data required for the estimations of book-to-market ratio (BM) and distress risk (DRisk) are taken from both CRSP and Compustat, while data for the estimation of the residual institutional ownership (IO) are obtained from the Thomson Financial 13f database. Finally, to compute the dispersion in analysts' earnings forecasts (AFD), we use the unadjusted I/B/E/S summary data file. The detailed description of all stock- and option-related characteristics as well as the applied filtering rules are provided in Appendix B.

2.3 Summary Statistics

Table 1 presents the descriptive statistics of our sample. Specifically, we report the total yearly number of firms for which we can obtain IDISP estimates and that survive our screening criteria. Additionally, we provide the yearly averages of monthly mean, median, 25^{th} and 75^{th} percentile values of IDISP across all firms in our sample and monthly mean proportions of calls, puts, as well as OTM and ITM options traded relative to the total trading volume. We observe that the average and median IDISP estimates tend to escalate before periods of market turbulence. For instance, during the 2000-2001 dotcom bubble and the start of the financial crisis period in 2008, the average and 75^{th} percentile are highest across all years, reaching values of 0.124 and 0.146 in 2000 and 0.111 and 0.127 in 2008, respectively. Low levels of IDISP are documented during the economic recovery periods. In terms of the contracts used in IDISP computation, the proportion of calls is higher than that of puts, with the two types becoming more equitable in the last part of the sample. Furthermore, OTM options dominate the trading activity, especially in the most recent period.

Figure 2 shows a time-series plot of yearly IDISP averages for ten industries based on the Fama-French classification. More specifically, each month, we sort stocks into ten industries and for each industry, we plot the yearly averages of monthly mean IDISP values across all the years in the sample. Interestingly and as expected, we observe that IDISP peaks for the HiTech industry during the dotcom bubble in 2001 and for the Money industry during the financial crisis period in 2008-2009. Additionally, the graph highlights the nature of the dispersion in beliefs that existed during the two crises – we observe that, while IDISP across the various industries is rather dispersed during the dotcom bubble, the financial crisis in 2008-2009 has a systemic impact, with IDISP concurrently peaking across all the various industries. Overall, the figure illustrates that the IDISP measure seems to effectively encapsulate investors' divergence of opinions, increasing during periods of market crashes and being more pronounced for industries that experience higher turbulence.

3 IDISP and Stock Return Predictability

In this section, we investigate the predictability of IDISP for the cross-section of stock returns, as well as its relation with other popular firm characteristics. We further investigate the robustness of the documented IDISP-return relation after controlling for a wide range of alternative stock-related and option-related return predictors.

3.1 Returns on IDISP Portfolios

We start the empirical analysis by examining the average monthly performance of IDISP portfolios. Each month, we sort stocks in ascending order into ten portfolios based on IDISP, from low IDISP (decile 1) to high IDISP (decile 10). Next, for each IDISP decile portfolio, we estimate the time-series averages of monthly mean IDISP values, equal-weighted and value-weighted monthly returns in excess of the risk-free rate, and the alphas from the Carhart (1997) four-factor model as well as a five-factor model, which augments the Carhart model with the Pastor and Stambaugh (2003) liquidity factor.[7] Finally, we compute returns and alphas for the strategy that buys the high IDISP portfolio and sells the low IDISP portfolio ($H - L$).[8]

Table 2 presents the results. The performance of the decile portfolios declines in terms of the average monthly excess returns as IDISP increases, although this decline is not monotonic. Strik-

[7] The supplementary material online also considers the alphas from the recently proposed models of Fama and French (2015), Hou, Xue and Zhang (2015) and Stambaugh and Yuan (2016). We find that the IDISP effect is not fully explained by any of the aforementioned alternative models.

[8] To keep the tables readable, for most of the subsequent portfolio-level analysis the value-weighted results are provided in the supplementary material, as they are qualitatively very similar to the equal-weighted ones.

ingly, the largest jump in dispersion levels observed from decile 9 to decile 10 (from 0.115 to 0.165) corresponds to the most dramatic decline in the equal-weighted excess return across deciles (from 0.17% for decile 9 to -0.52% for decile 10). A similar pattern is also found for risk-adjusted returns, with the five-factor alpha showing the largest reduction in monthly profits from -0.69% for decile 9 to -1.38% for decile 10. This evidence suggests that investors holding higher IDISP portfolios experience negative future payoffs. The raw as well as the risk-adjusted returns on the $H - L$ portfolio further support the above arguments, with high IDISP stocks on average underperforming low IDISP stocks by 1.49% per month (17.88% per annum) in terms of raw returns, by 1.62% per month (19.44% per annum) after adjusting for risk from the four-factor model, and by 1.54% per month (18.48% per annum) after adjusting for risk from the five-factor model. Both the $H - L$ return, and the four-factor and five-factor alpha differentials show a strong statistical significance, with Newey and West (1987) t-statistics (with six lags) of -2.77, -5.27, and -4.88, respectively.

Equally significant results, both economically and statistically, are observed with value-weighted average returns. The underperformance of high IDISP, compared to low IDISP, stocks is economically large and statistically significant, generating a negative return on the $H - L$ portfolio of -1.50% per month (-18% per annum), with a t-statistic of -2.52. High IDISP stocks continue to earn considerably lower future risk-adjusted returns than low IDISP stocks. Four-factor and five-factor alpha differentials between high IDISP and low IDISP portfolios are -1.70% per month, with a t-statistic of -4.39, and -1.59% per month, with a t-statistic of -4.23, respectively. Overall, our results suggest that negative IDISP predictability is economically substantial and statistically significant (both for equal-weighted and value-weighted portfolios) and is unlikely to be driven by market, size, value, momentum or liquidity factors.

The above findings are in line with implications from the static and dynamic theoretical models developed by Miller (1977), Harrison and Kreps (1978), Morris (1996) and Scheinkman and Xiong (2003). These models predict that, in the presence of short-sale constraints, the stock price largely reflects the views of the most optimistic investors, since pessimistic investors sit out of the market. Therefore, higher dispersion in beliefs is accompanied by an overpricing and lower subsequent returns.[9]

If dispersion in beliefs is a persistent rather than a random stock characteristic, the trading strategy that is necessary for exploiting the generated overpricing will require low rebalancing and hence relatively low transaction costs. To this end, we examine the average month-to-month transition probabilities for a stock, i.e. the average probability that a stock in decile portfolio i in one month will be in decile portfolio j in the next month, for ten portfolios sorted on IDISP. In Table 3, we observe that all the diagonal elements of the transition probability matrix exceed 10%, with stocks in high (low) IDISP portfolio having a huge almost 56% (40%) likelihood of remaining in the same portfolio next month. Additionally, we group stocks into quintile portfolios based on their IDISP values (from low IDISP, quintile 1 to high IDISP, quintile 5), and plot in Figure 3 the average monthly IDISP for each of the portfolios, for the eleven months before and after portfolio formation. The highest (lowest) IDISP value of 0.142 (0.045) is observed at the time of portfolio construction. Moreover, the results show a clear difference across the IDISP quintile portfolios, with a strong persistent ranking of the IDISP portfolios across each of the eleven months around portfolio formation. The above results indicate that IDISP is a persistent stock characteristic and far from being random.

Overall, the findings presented in this section establish a strong negative relation between IDISP and future stock returns. Moreover, they provide evidence suggesting that stocks with a high IDISP characteristic in one month also tend to exhibit high IDISP in the following months.

3.2 IDISP and Other Firm Characteristics

In this section, we study the relation between IDISP and various firm characteristics to explore the distinct information content driving the IDISP measure. We begin by examining the characteristics of firms across various IDISP portfolios. For each month, we construct decile portfolios based on

[9] While it is possible that some constrained pessimistic investors migrate to the options market in order to take negative positions, this does not necessarily mean that the overpricing of the underlying asset will instantly vanish. For the mispricing to be eliminated there must be actual selling/shorting activity in the equity market following the trading activity in the options market. In this spirit, Ofek, Richardson and Whitelaw (2004) compare actual stock prices with the stock prices implied by the put-call parity relation in the option market and observe widespread stock overpricing that is stronger when the underlying short-sales constraints are more severe. Grundy, Lim and Verwijmeren (2012) provide similar empirical evidence for the period of the 2008 short-sales ban.

IDISP, and for each decile portfolio, we report the time-series averages of monthly mean values of all the stock-related variables examined in the study.

Table 2 (bottom panel) reports some interesting results. First, high IDISP stocks are less likely to be held by institutional investors, as suggested by the very low IO values observed for the two deciles with the highest IDISP stocks (average IO of -0.005 and -0.574 for deciles 9 and 10 respectively). The results, therefore, imply that high IDISP stocks are more difficult to short-sell (see Nagel, 2005). Second, as IDISP increases across portfolios, stocks with more dispersed beliefs tend to be relatively small, risky (both systematically and idiosyncratically, as captured by Beta and IdV, respectively), and illiquid.[10] Third, high IDISP stocks show a greater propensity to exhibit lottery-type payoffs, with MAX values monotonically rising from the low IDISP to the high IDISP portfolio. The average MAX value in the lowest IDISP portfolio is 4.0%, whereas stocks in the highest IDISP portfolio have the maximum daily return over the past month of 10.9%.[11] Fourth, a striking pattern is observed for book-to-market ratios – across the first nine deciles, the book-to-market ratio is similar; however it increases substantially from decile 9 (0.42) to decile 10 (0.563). This indicates a strong dominance of value stocks in the high IDISP portfolio. Fifth, comparing IDISP with the well-established proxy for beliefs dispersion among analysts' forecasts, AFD, we document that the two measures comove uniformly across portfolios, implying cross-sectional commonalities in informational content of both dispersion measures. As IDISP increases, the average values of AFD gradually rise from 0.076 in the low IDISP portfolio to 0.50 in the high IDISP portfolio. Also, the spike from decile 9 to 10 (0.340 to 0.50) for AFD is similar to the spike observed in the IDISP measure (0.115 to 0.165). Finally, we find that firms in the highest IDISP decile portfolio exhibit higher share turnover and higher probability of default relative to the firms in the lowest IDISP portfolio, with the respective relations monotonically increasing across deciles. It is also noteworthy that the average characteristic differential between high and low IDISP portfolios is statistically significant at the 1% level in almost all cases (the sole exception being in the case of momentum).

[10] It is noteworthy that the so-called small and illiquid stocks in our optioned sample are still relatively large and liquid when compared with the full universe of stocks.

[11] Since high IDISP stocks tend to have lottery-type payoffs, we also investigate whether the IDISP-return relation is affected by the January seasonality, discussed by Doran, Jiang, and Peterson (2011). Similarly to their study, we find that IDISP predicts positive returns in January. However, this relation is statistically insignificant, implying that, while IDISP shares some common features with lottery-type characteristics, its information content is distinct. This additional analysis is reported in the supplementary material online.

Next, we investigate the ability of the above firm characteristics to forecast the next-period IDISP. More specifically, we perform a Fama and MacBeth (1973) monthly cross-sectional regression of IDISP at the end of month $t+1$ on IDISP and other firm characteristics measured at the end of month t. Table 4 presents the time-series average of monthly cross-sectional coefficient estimates and corresponding t-statistics. We observe that lagged IDISP has the largest positive predictability and is highly statistically significant. This confirms the persistent nature of the IDISP measure, as observed in Table 3. More notably, we observe that IdV presents a very strong predictability for IDISP (with a t-statistic of 10.27), followed by AFD (with a t-statistic of 7.77). The fact that idiosyncratic volatility is a strong predictor of IDISP does not come as a surprise, since it is expected that more extreme price movements will be associated with higher uncertainty about the firm's fundamentals. In fact, Berkman, Dimitrov, Jain, Koch and Tice (2009) use IdV as another proxy for differences of opinion. The strong predictive power of AFD is also expected, since it captures the dispersion in analysts' expectations about future earnings. With the exception of BM and Turn, all the firm characteristics examined exhibit some significant predictability for IDISP. As a result, the R^2 is equal to 59%, indicating overall strong explanatory power of the characteristic variables for next-period IDISP.

In summary, the findings of this section suggest that high IDISP stocks, as compared to low IDISP stocks, are relatively small, riskier, relatively illiquid, value- (rather than growth-) oriented, with less institutional ownership, preferred by investors with lottery-type preferences, have higher analysts' forecast dispersion and probability of default. Moreover, idiosyncratic volatility and secondarily the dispersion in analysts' forecasts are the strongest predictors of IDISP.

3.3 Controlling for Other Cross-Sectional Characteristics

3.3.1 Bivariate Portfolio-Level Analysis

In this section, we analyze the interaction of the negative IDISP-return relationship with various stock- and option-related characteristics by performing dependent bivariate portfolio-level analysis.

Each month, we sort stocks into quintile portfolios based on one of the alternative stock- or option-related characteristics, and next, within each characteristic portfolio, we further sort stocks into five portfolios on the basis of IDISP. Finally, we compute the time-series averages of equal-weighted monthly excess returns for each of the IDISP quintiles across the five characteristic portfolios obtained from the first sort. This procedure of accounting for non-IDISP effects does not involve any regression-based tests and helps track the persistence of the negative IDISP effect across all characteristic quintiles. Additionally, we estimate the average raw returns, and the four- and five-factor alphas for the strategy that buys a high IDISP portfolio and sells a low IDISP portfolio.

The top panel of Table 5 reports the results when we control for all the stock characteristic variables considered in Tables 2 and 4. It can be seen that the IDISP effect remains strongly significant and economically substantial in all cases. This includes traditional cross-sectional return predictors such as Size, Illiq, BM or Mom but also all the newly-established characteristics that have been shown to provide negative predictability similar to that of IDISP, for example, IdV, MAX, AFD, or DRisk. The bottom panel of Table 5 presents the results when controlling for the alternative option-related predictors. We observe that the IDISP effect is robust to controlling for stocks' risk-neutral higher moments (RNS and RNK), measures of volatility and downside risk (VolSpr and QSkew), as well as proxies of informed trading in the options market (VS, O/S, InnCall and Innput).[12] Moreover, we find that the predictability of IDISP is not subsumed by that of the volatility of volatility and is also not mechanically driven by fluctuations in the level of the options trading volume.

To summarize, the findings indicate that the negative relationship between the IDISP measure and future stock returns cannot be subsumed by any of the known stock- and option-related cross-sectional return predictors documented in the literature.

[12] In the supplementary material we provide further empirical evidence with respect to the relation of IDISP and informed options trading. In particular, one might hypothesize that high IDISP stocks are stocks for which there is a high options trading activity stemming from pessimistic informed investors. If this was the case, we would expect to find that the high IDISP portfolio is dominated by pessimistic trading volume. However, our results show that the trading volume in the high IDISP portfolio actually leans towards optimistic rather than pessimistic trades. Therefore, an informed trading interpretation of the predictability of IDISP is not supported by the data.

3.3.2 Fama-MacBeth Regressions

The results of the portfolio-level analyses demonstrate that a stock portfolio with high IDISP, as compared to low IDISP, generates economically substantial and statistically significant negative returns that are not subsumed by a large set of control variables. Subsequently in this section, we perform Fama and MacBeth (1973) regressions that utilize the entire cross-sectional information in the data, so as to gauge whether the IDISP-return relationship persists after simultaneously controlling for other return predictors. In particular, each month, we perform cross-sectional regressions of excess stock returns in month *t+1* on the IDISP measure and the series of previously documented return drivers, all computed in month t. We report the time-series averages of the slope coefficients, along with Newey-West corrected t-statistics (with six lags), and the R^2s from the regressions. To mitigate the potential effects of outliers, we winsorize the control variables at the 1^{st} and 99^{th} percentile.

Table 6 presents the results for all the stock- and option-related characteristics considered in the previous section. In Panel A, we estimate univariate and multivariate regression specifications of excess returns on IDISP and various stock characteristic variables. First, the univariate Fama and MacBeth model shows that the coefficient on IDISP is negative (-0.1360) and statistically significant (with a t-statistic of -3.24). The economic magnitude of the IDISP effect is similar to that presented in univariate portfolio-level analysis. In particular, multiplying the difference in mean values between high IDISP and low IDISP deciles (from Table 2) by the slope coefficient yields a monthly risk premium differential between the high and low IDISP portfolio of -1.71%. Second, estimating bivariate regressions with IDISP and stock-related characteristics, the average slope coefficient on IDISP remains negative, statistically significant at the 1% level and economically large, with values ranging between -0.1338 and -0.1040. Of all stock-related characteristics, the residual institutional ownership, the idiosyncratic volatility and the distress risk exhibit a statistically significant predictability for future stock returns after controlling for IDISP, with the signs of their coefficients being consistent with Nagel (2005), Ang, Hodrick, Xing and Zhang (2006) and Gao, Parsons and Shen (2018), respectively. Interestingly, AFD does not exhibit any significant cross-sectional predictability after controlling for IDISP, even though it is significant (at the 5% level) in the univariate model. Finally, in the multivariate model specification with all the control variables, we observe that IDISP retains its significance (t-statistic of -2.31), with a slope coefficient value of -0.0543. In economic terms, this coefficient translates to a return differential of -0.68%.

In Panel B, we provide the predictability results from univariate and multivariate regression specifications involving IDISP and other option-related characteristic variables which were considered in the previous section. We observe that in bivariate regressions, the coefficient on IDISP is statistically significant at the 1% level in all but one case (when controlling for VoV, where it is significant at the 5% level), and economically substantial, with values ranging between -0.1366 and -0.1025. From the remainder of the variables, RNS and VS exhibit a positive and significant effect, consistent with the findings of Stilger, Kostakis and Poon (2017) and Cremers and Weinbaum (2010) respectively, while QSkew, O/S, InnPut and VoV exhibit a negative and significant effect, in line with the studies of Xing, Zhang and Zhao (2010), Johnson and So (2012), An, Ang, Bali and Cakici (2014) and Baltussen, Van Bekkum and Van Der Grient (2015), respectively. When all option-based characteristics are jointly considered in the regression specification, we observe that the slope coefficient associated with IDISP remains negative (-0.0697) and retains its statistical significance (t-statistic of -2.10). In economic terms, this coefficient translates to a return differential of -0.88%.

Overall, the Fama and MacBeth regression results confirm that the IDISP measure has strong explanatory power for future excess stock returns, which is robust to that of a wide range of stock- and option-related characteristics.

4 Dissecting the Predictability of IDISP

In this section, we delve into understanding the economic nature of the negative predictability of the IDISP measure. In particular, we investigate how the IDISP effect relates to short-selling impediments, earnings announcements and periods of market-wide optimism.

4.1 IDISP Effect and Short-Selling Impediments

Miller's (1977) theory predicts that stocks with a high dispersion of opinions tend to be overpriced and are expected to earn negative subsequent returns. However, a necessary condition for this overpricing to be generated is that there are high costs associated with short-selling that prevent pessimistic investors from taking negative positions. In addition, the reason the overpricing persists and is not instantly eliminated is due to the inability (or reluctance) of the average investor to short-sell the stock. Therefore, if the negative predictability of IDISP is indeed related to divergence of opinions leading to an overpricing, we would expect to find that the effect is stronger when short-selling is more costly and more difficult in the presence of limits to arbitrage.

To test this economic prediction, we use the level of residual institutional ownership (IO), market capitalization (Size), idiosyncratic volatility (IdV) and illiquidity (Illiq) as the dimensions commonly associated with shorting constraints and limits to arbitrage. Intuitively, the lower the level of institutional ownership, the lower the supply for loanable shares by institutions (Nagel, 2005) and hence the higher the fee that the short-seller needs to pay. Similarly, relatively small, volatile and illiquid stocks exhibit more severe limits to arbitrage (Shleifer and Vishny, 1997; Pontiff, 2006; Sadka and Scherbina, 2007; Gromb and Vayanos, 2010; Conrad, Kapadia and Xing, 2014) and hence investors are less willing to short-sell such stocks and exploit the mispricing.[13]

For the empirical investigation, we perform a dependent bivariate portfolio-level analysis. More specifically, each month we first sort stocks in ascending order into tercile portfolios on the basis of key firm characteristic variables associated with short-selling impediments, and next, within each characteristic portfolio, we further sort stocks into quintile portfolios based on IDISP values. Finally, for the resulting fifteen characteristic-IDISP portfolios, we calculate equal-weighted average future monthly excess returns and present a time-series average of these values over all the months in our sample. We also evaluate the average returns, four-factor and five-factor (after augmenting Carhart's model with the liquidity factor) alphas for the strategy that buys high IDISP stocks and

[13]Given that shorting constraints and limits to arbitrage are unobservable quantities, we base our analysis on various proxies that the prior literature has suggested. While it is plausible that our proxies are to some extent related to information asymmetry, we show earlier that the predictability of IDISP is unlikely to be driven by informed trading (see Section 3.3 and the discussion in the supplementary material).

sells low IDISP stocks within each characteristic portfolio quintile.

Table 7 reports the results. We observe that the high IDISP portfolio underperforms the low IDISP portfolio by 1.77% per month (with a t-statistic of -3.06) if these firms have a low level of IO, whereas the return differential is only -0.61% per month (with an insignificant t-statistic of -1.41) for high IO firms. Moreover, the return differential decreases monotonically (in absolute terms) as we move from the low IO tercile to the high IO tercile. In line with the theoretical predictions of Miller (1977), the negative performance is mainly driven by high IDISP firms that appear in the lowest IO terciles. In particular, the high IDISP firms in the lowest IO portfolio earn on average -0.83% per month in excess of the risk-free rate, while high IDISP stocks with higher levels of IO earn instead a return premium. The idea that the IDISP effect is more pronounced among stocks with high short-sale costs is also confirmed when controlling for asset-pricing risk factors. More specifically, we observe that both the four- and five-factor model alpha spreads between high IDISP and low IDISP portfolios become larger (in absolute terms) and more statistically significant as we move from high to low IO firms. For example, the monthly five-factor alpha of the $H-L$ IDISP portfolio is -1.83% (with a t-statistic of -4.82) if the stocks in this portfolio are more difficult to short-sell, while high IDISP stocks underperform low IDISP stocks by 0.54% (with a t-statistic of -1.85) if one can short-sell these stocks at a relatively low cost. It is also important to note that the difference in the $H-L$ IDISP portfolio alphas between high IO and low IO firms is statistically significant at the 1% level (t-statistic of 2.95).

Further, we observe that the underperformance of high IDISP relative to low IDISP stocks is most pronounced when considering low market capitalization (-1.42% per month with a t-statistic of -3.33), high idiosyncratic risk (-1.86% per month with a t-statistic of -4.34) and low liquidity stocks (-1.42% per month with a t-statistic of -3.24). On the other hand, the returns on the $H-L$ portfolio are negligible and statistically insignificant for big, less risky and more liquid firms. In fact, the negative return differentials decrease in absolute terms (or even turn positive) almost monotonically as we move further away from the portfolios with the smallest, most volatile and least liquid stocks. In addition, we find that the negative $H-L$ IDISP portfolio returns mainly stem from high IDISP firms that appear in the lowest tercile of market capitalization and the highest terciles of idiosyncratic volatility and illiquidity. More specifically, high IDISP stocks in the lowest capitalization, highest idiosyncratic volatility and highest illiquidity portfolios earn average monthly excess returns of -0.40%, -1.11% and -0.48%, respectively. On the other hand, high IDISP stocks with high size, low volatility and high liquidity earn instead a large return premium. The result indicates that the underperformance of high IDISP stocks is pronounced for stocks that exhibit high arbitrage risk.

After controlling for asset-pricing risk factors, the four-factor and five-factor alphas remain economically substantial and highly significant for the portfolios with the smallest, most volatile and most illiquid stocks, while they become negligible and insignificant as we move further away from those portfolios. For example, the five-factor alpha differential between high IDISP and low IDISP portfolios is equal to -1.25% per month (with a t-statistic of -2.94) for low Size, -1.69% per month (with a t-statistic of -4.14) for high IdV and -1.25% per month (with a t-statistic of -3.22) for high Illiq stocks. By contrast, the risk-adjusted (by the four- or five-factor model) returns on the $H-L$ IDISP portfolio remain small and statistically insignificant for high Size, low IdV and low Illiq portfolios. Moreover, the difference in the $H-L$ IDISP portfolio alphas between high arbitrage risk firms and low arbitrage risk firms is statistically significant in all cases.

Overall, our results provide strong supportive evidence in favor of the role that shorting constraints and limits to arbitrage play in explaining the substantial return variations in high and low IDISP portfolios. Therefore, they are in line with the notion that the predictability of IDISP is associated with overpricing caused by increased dispersion in investors' opinions.

4.2 IDISP Effect around Earnings Announcements

Our empirical findings display systematically low returns for high IDISP stocks, which is expected when IDISP serves as a proxy for differences in expectations among investors. Quarterly earnings announcements feature fertile grounds for validating IDISP's information content. In particular, they constitute a firm-specific corporate event whereby optimistic and pessimistic investors speculate on the forthcoming earnings outcome (see, for example, Kim and Verrecchia, 1991; and Kandel and Pearson, 1995). In this regard, earnings announcements ideally fit within the stylized framework presented in Appendix A. Moreover, in the presence of short-sales constraints, the net effect of intensified speculative trading on prices is expected to be positive and should cause stocks to become overvalued in days preceding the earnings announcements, with higher differences of opinion leading to overvaluation. However, in the post-announcement period, the release of new information about earnings reduces differences in expectations among investors, and consequently, these announcements contribute to the reduction in overvaluation (Berkman, Dimitrov, Jain, Koch and Tice, 2009). As such, we would expect a particularly pronounced negative IDISP-return relationship surrounding the quarterly earnings announcements.

We investigate the above proposition using earnings announcement dates obtained from the Compustat Quarterly file for all available optionable stocks in our sample. For this analysis IDISP is estimated by averaging daily IDISP values within a month ending 10 trading days prior to the earnings announcement date ($\text{IDISP}_{(-31,-10)}$). In this fashion, IDISP is constructed from trading dates data available prior to earnings announcements and discards information up to two weeks prior to the announcement date to preclude possible contamination of the measure from investors who might trade options in order to capitalize on excessive volatility usually observed around such announcements (see, for example, Frazzini and Lamont, 2007). For robustness, we also estimate another two ex-ante IDISP versions, one that spans a month ending 2 trading days prior to the announcement ($\text{IDISP}_{(-23,-2)}$) and one ending 5 trading days prior to the announcement ($\text{IDISP}_{(-26,-5)}$).

To empirically investigate whether high IDISP stocks earn significantly lower returns around earnings announcements than low IDISP stocks, we follow in spirit the setting of Berkman, Dimitrov, Jain, Koch and Tice (2009). In particular, we estimate the average excess earnings announcement period returns for quintile portfolios formed using each of the three IDISP measures and also report the average excess returns for the portfolio $H - L$ that buys high IDISP stocks and sells low IDISP stocks. Excess returns are estimated as the difference between the buy-hold stock returns and the value-weighted CRSP index buy-hold returns, over the three trading days surrounding the earnings announcement date.[14] Table 8 displays the findings, showing that high IDISP stocks underperform low IDISP stocks by an economically large and statistically significant average announcement excess

[14]We exclude earnings announcements with at least one return value missing over the three days.

return ranging from 0.73 to 0.80%.[15]

Next, we study the dynamics of the IDISP measure around the earnings announcement dates by plotting the average daily IDISP values across all firms and announcements in our sample for the period covering seven days before and after the event date.[16] Figure 4 shows that the average IDISP exhibits an upward trending pattern in the period before the event, reaching its maximum value on the earnings announcement day. Following the announcement, it exhibits a dramatic decline as the uncertainty pertained to earnings is resolved. To further scrutinize the interaction between IDISP and earnings announcements, we also plot the average daily IDISP values across firms around a pseudo-event date that is selected randomly from the one-month period starting one month after the actual announcement date. As expected, Figure 4 shows that IDISP does not exhibit any systematic pattern around the pseudo-event date.

Finally, we plot the average cumulative excess returns for the $H - L$ portfolio over the same 15-trading-day period surrounding the earnings announcements. This analysis allows us to visualize the asymmetric effects of differences in expectations which should stimulate a price run-up for high IDISP stocks resulting in overpricing in the pre-announcement period, subsequently followed by a price correction in the post-announcement period. Figure 5 illustrates the results showing that the $H - L$ IDISP portfolio exhibits a large price run-up, as high as 0.33% over the 7-day period prior to the announcement, followed by a substantial price reversal, reaching as low as -1% by the end of the event window.

Summing up, we observe that the IDISP effect is particularly pronounced around earnings announcements. Moreover, the average daily IDISP measure exhibits an increasing pattern before an announcement and experiences a dramatic drop right after the event. We interpret these findings as evidence to support that IDISP indeed captures dispersion in beliefs among investors.

[15] In the supplementary material we show that the observed IDISP return predictability around earnings announcements is also not subsumed by various proxies of informed trading.

[16] We use only those firms' announcements for which IDISP values exist for all the 15 days under examination. Moreover, for better comparability, the daily IDISP values of each firm are scaled by the respective firm's average IDISP across the examination period.

4.3 IDISP Effect and Investor Sentiment

The negative relation between dispersion in beliefs and stock returns can be explained in the context of a market where short-sale constraints make it difficult for pessimistic investors to take negative positions and hence prices reflect only the views of the optimistic investors who end up holding the stock. As Stambaugh, Yu and Yuan (2012) postulate, when market-wide sentiment is high, the views of those investors who finally hold the asset tend to be excessively optimistic, resulting in a severe overpricing. On the other hand, when market-wide sentiment is low, the views of those investors who finally hold the asset are closer to being rational, and hence a pronounced overpricing is less probable. This implies that the negative relation between disagreement and stock returns is expected to stem mainly from periods of high sentiment in the market.[17,18] In this regard, we test whether the predictability of IDISP is consistent with the above premise by investigating the IDISP effect separately for times of high and low investor sentiment. In particular, we estimate monthly cross-sectional Fama and MacBeth (1973) regressions separately for high and low sentiment periods. Following Stambaugh, Yu and Yuan (2012), we define high (low) sentiment months as those when the Baker and Wurgler (2006) index in the previous month is above (below) the median value in the sample.

Table 9 presents the Fama and MacBeth (1973) slope coefficients for IDISP from the various regression specifications after controlling for stock- and option-related characteristics in high and low sentiment periods. In the panel with stock characteristics results, Model (1) shows univariate regression with IDISP, Models (2)-(14) show bivariate regressions with IDISP and the stock characteristic variable listed in the column header and Model (15) is the multivariate regression with IDISP and all the stock characteristic variables. Similarly, in the panel with option characteristics results, Models (1)-(10) show bivariate regressions with IDISP and an option characteristic variable, and Model (11) is the multivariate regression with IDISP and all the option variables. The results provide a consistent picture across all the regression specifications. Following periods of high sentiment, we

[17] Atmaz and Basak (2018) create a theoretical model which predicts that even without short-sale constraints, the negative relation between dispersion in beliefs and future returns should stem from optimistic periods.

[18] Recent studies that emphasize the importance of conditioning on market-wide investor sentiment for explaining asset prices include Yu and Yuan (2011), Stambaugh, Yu and Yuan (2012) and Antoniou, Doukas and Subrahmanyam (2015).

observe that the slope coefficients for IDISP are economically large, with strong statistical significance. The univariate analysis produces a significant (at the 1% level) slope coefficient of -0.2147 for the high sentiment period, compared to -0.0573 (and insignificant) for the low sentiment period. After controlling for various stock and option characteristics, IDISP retains its strong negative predictability for excess returns in high sentiment months. The effect is negligible following times of low sentiment, where the negative IDISP-return relationship remains statistically insignificant in most specifications. Furthermore, in the majority of the specifications (20 out of 26) the difference in the IDISP coefficients between high and low sentiment periods is statistically significant as well.

Overall, the findings confirm that the IDISP effect mainly stems from periods of high investor sentiment. This is in accordance with the notion that IDISP reflects investors' dispersion in beliefs which, in the presence of binding short-sales constraints, leads to overpricing.

5 Additional Analysis

This section complements the main findings in the paper by, first, examining the robustness of the IDISP-return predictability using signed volume data and various alternative empirical measurement definitions, and second, testing the IDISP-return relation for longer predictability horizons.

5.1 Construction of the IDISP Measure with Signed Volume Information

As discussed in Section 2.1 and Appendix A, the interpretation of IDISP as a proxy for dispersion in beliefs relies on the notion that, in the typical stock options trading environment, investors' optimal moneyness levels are proportional to their optimistic or pessimistic beliefs. In particular, investors with more optimistic (pessimistic) views will elect to either buy more OTM calls (puts) or sell more ITM puts (calls). While this theoretical prediction also holds for cases where the above strategies are replicated synthetically by purchasing matched-strike ITM puts (calls) and selling matched-strike OTM calls (puts) respectively, it is unclear how many investors actually implement such complicated put-call parity strategies. Moreover, Appendix A shows that in some cases it might be optimal for option buyers with slightly optimistic or pessimistic expectations to trade ITM rather than OTM options. Therefore, it is important to check the validity of our previously presented results using an alternative IDISP measure that utilizes signed volume data and more specifically only the buy-side trading volume of OTM options and the sell-side trading volume of ITM options. In other words, we use only the trading volume across different moneyness levels that reflects expectations more clearly, i.e. we retain only OTM call purchases and ITM put sales, which are undoubtedly optimistic trades related to positive expectations, and OTM put purchases and ITM call sales, which are undoubtedly pessimistic trades related to negative expectations.

To this end, we collect signed options volume data from the International Securities Exchange (ISE) Trade Profile. This dataset contains all end-users' trades disaggregated by whether each trade is a buy or a sell order. In the majority of cases, a market maker provides liquidity by being on the other side of the trade. While the ISE options volume data represent about 30% of the total individual stock options trading volume across all options exchanges, Ge, Lin and Pearson (2016) show that the data are representative of the total options volume provided by OptionMetrics. Since the ISE data are only available for a much shorter period (from May 2005 onwards), we consider the results obtained in this section as complementary to, and supportive of, those presented in the main empirical analysis. Hence, the IDISP measure constructed from signed volume can be seen as a robust version of the original measure presented in the paper. It is also important to note that, unlike signed volume data, daily unsigned volume data are publicly available and hence easily accessible to investors. Therefore, the usage of unsigned volume data in the main empirical analysis highlights the fact that a trading strategy based on the predictive power of IDISP would be relatively cheap and implementable by an investor in real time.

Table 10 displays equal- and value-weighted return predictability results for the new IDISP portfolios constructed with the ISE signed options volume. The results display a consistent picture, with returns that are of similar economic magnitude and statistical significance to those presented in Table 2. Moreover, we observe a striking resemblance in the return properties of the decile portfolios sorted on the new IDISP measure, with the largest decline in the average monthly excess return observed from decile 9 to decile 10. Further, the $H-L$ portfolio return is -1.28% per month for equal-weighted portfolios and -1.21% per month for value-weighted portfolios, significant at the 5% and 10% levels respectively. In line with Table 2, the results become stronger when considering risk-adjusted returns. For example, the five-factor alpha differential between high and low IDISP stocks is -1.66% and 1.67% per month for equal- and value-weighted portfolios, with t-statistics of -5.74 and -4.99 respectively. Overall, the findings suggest that the IDISP measure, capturing the trading activity at various moneyness levels, exhibits consistent negative predictability for the cross-section of stock returns, irrespective of whether we use unsigned or signed trading volume data.

5.2 Alternative Constructions of the IDISP Measure

Next, we test whether the negative IDISP-return relationship is robust to alternative definitions of dispersion. Hence we construct IDISP measures based on mean absolute deviations and standard deviations, of moneyness levels as well as strike prices. Additionally, we consider IDISP specifications using alternative screening criteria on the minimum number of days with non-missing IDISP values and inclusion of near-the-money options in the IDISP computation. Finally, we obtain results for IDISP measures estimated without averaging within a month.

Thus, we construct nine alternative IDISP measures. IDISP1 is the standard deviation of stock options trading volume across moneyness levels. IDISP2 and IDISP3 are mean absolute and standard deviation measures respectively, of options trading volume across strike prices (rather than moneynesses), scaled by the volume-weighted average strike. IDISP4 and IDISP5 are similar to the original IDISP measure and to IDISP1 respectively, but we use alternative filtering criteria requiring within a month at least ten days of non-missing IDISP values. IDISP6 and IDISP7 are similar to the original IDISP measure and to IDISP1 respectively, but we include near-the-money options in calculating the measures. IDISP8 and IDISP9 are similar to the original IDISP measure and to IDISP1 respectively, but are measured at the penultimate day of a month (instead of averaged within a month excluding the last trading day).

Table 11 reports the average equal-weighted returns of portfolios with the lowest and highest IDISP in the previous month. For all nine alternative IDISP measures, we observe that the portfolios with the highest IDISP values consistently underperform the lowest IDISP portfolios, both on a raw return as well as a risk-adjusted return basis. For instance, the five-factor alpha differential between high and low IDISP portfolios ranges between -1.63% per month with a t-statistic of -4.38 (for IDISP4) and -1.15% per month with a t-statistic of -4.44 (for IDISP8). These findings indicate that the strong negative dispersion-return predictability is robust to various alternative specifications for IDISP.

5.3 Long-term IDISP Predictability

In the main analysis, we document a strong predictive relationship between IDISP and next-month stock returns. Since the IDISP measure is persistent across time, a natural question that arises is whether IDISP is able to generate significant predictive power over longer time-horizons. Following Jegadeesh and Titman's (1993) methodology, each month, we sort stocks into decile portfolios based on IDISP, and construct a trading strategy that buys high IDISP and sells low IDISP portfolios, while holding this position for T months, where T is equal to two (2m), three (3m), four (4m), five (5m), six (6m), nine (9m), and twelve (12m) months. The $H-L$ portfolios formed in past months are held until they mature, along with the $H-L$ portfolio selected in the current month based on the decile rankings. Hence, each month we allocate new weights on $1/T$ of the stocks in the entire portfolio and carry over the remainder from the past months. All open portfolios in a given month receive equal weights.[19] Finally, for each investment horizon, equal-weighted average raw returns, and four- and five-factor alphas are estimated for the above strategy.

Table 12 demonstrates the IDISP predictability results for the various investment horizons. As we increase the holding period, the negative returns of the $H-L$ portfolio decay monotonically in absolute terms, with strong significant predictability patterns up to six months holding periods for raw returns and weak significance afterwards. For instance, we observe that a portfolio holding high IDISP and selling low IDISP stocks for two, three and six months will incur an average monthly return of -1.39%, -1.26% and -1.11%, respectively. When adjusting for market, size, value, momentum and liquidity risk factors, the statistical significance of the $H-L$ IDISP portfolios

[19] This investment strategy requires a frequent portfolio rebalancing and hence its profitability would be less pronounced after accounting for transaction costs. To this end, as an additional analysis we implement the long-term predictability exercise using non-overlapping portfolios. These results are presented in the supplementary material and are very similar to those presented here.

remains strong even to twelve-month horizons. The results indicate that the IDISP effect undergoes a relatively long-term price correction rather than having a short-run temporal effect.

6 Conclusion

This paper shows that the dispersion of individual stock options trading volume across various moneyness levels (IDISP) exhibits strong predictive power for the cross-section of stock returns. We demonstrate that, in the context of an options market wherein investors trade with market makers based on their directional expectations, the selected moneyness levels are proportional to investors' optimism or pessimism. Hence, high dispersion of trading volume across moneyness levels indicates that investors' beliefs are diverse, while a low dispersion implies that options investors' beliefs are rather similar. The key results of the paper are obtained with a dispersion measure that is based on total trading volume for each moneyness level. Additionally, when the dispersion measure is constructed from trades that reflect expectations more clearly, i.e. by incorporating only the buy- and sell-side volumes of out-of-the-money and in-the-money options respectively, the results reveal a remarkably similar pricing impact in the cross-section of stock returns.

We document that high IDISP stocks consistently underperform low IDISP stocks by 1.49% (1.50%) per month on a raw return basis and by 1.54% (1.59%) per month on a risk-adjusted basis when considering equal-(value-)weighted portfolios. These results are in line with theoretical predictions from Miller's (1977) model that high differences of beliefs are associated with stock overpricing and a negative risk premium in the presence of binding short-sale constraints. Additionally, we show that the IDISP measure exhibits strong persistent patterns in the future, since stocks with the highest IDISP in one month tend to exhibit similar features in the subsequent month with an almost 56% chance. Moreover, the portfolio that buys high IDISP and sells low IDISP stocks generates economically large and statistically significant risk-adjusted returns for horizons up to 12 months ahead.

We shed more light on the economic origin of the IDISP effect by showing that the negative relation between IDISP and stock returns is mainly associated with stocks that exhibit higher short-selling impediments and mostly driven by periods of elevated investor sentiment. Moreover, the predictability of IDISP is particularly strong around quarterly earnings announcements. Collectively, these results provide further evidence in favor of the interpretation of IDISP as a proxy for options investors' disagreement. Finally, by performing a series of robustness checks, we observe that the negative IDISP-return relationship cannot be subsumed by previously documented stock-related return predictors and is distinct from the effect of various option-related return drivers.

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Appendices

A Theoretical Motivation

In this appendix, we provide a theoretical framework which illustrates that the dispersion in trading volume across moneyness levels serves as a proxy for dispersion in options investors' beliefs. Our framework relies on the typical stock options market where end-users trade with market makers, driven by speculative motives associated with their directional expectations about the future underlying asset price (Lakonishok, Lee, Pearson and Poteshman, 2007). Within this context, we consider an environment where each investor receives a signal about the expected stock return μ, updates her beliefs accordingly and trades in the options market by maximizing her expected utility.

We assume that investors' common prior about the expected return is given by $\mu \sim N\left(\bar{\mu}, \frac{1}{u}\right)$, with $\bar{\mu}$ denoting the mean stock return and $\frac{1}{u}$ its variance. In addition, each investor's signal is perceived to be represented by $z_i = \mu + \eta_i$, where $\eta_i \sim N\left(0, \frac{1}{q_i}\right)$ and the variance $\frac{1}{q_i}$ is driven by the perceived signal precision q_i. The signal is private in the sense that each z_i is observed only by a given investor i. Intuitively, the signal can refer to a corporate event that will determine the future stock return for a given horizon. It is also important to note that it can be either a true signal providing relevant information about the stock return or just pure noise. In both cases, the investor treats the signal as informative and updates her beliefs based on it. Therefore, our framework considers a stock options market that is populated by both sophisticated and unsophisticated investors.[20]

Given the signal, the investor's updated distribution is normal, with the following conditional moments μ_i and v_i:

$$\mu_i \equiv E_0\left[\mu | z_i\right] = \frac{u\bar{\mu} + q_i z_i}{u + q_i}, \tag{2}$$

$$v_i \equiv \sigma_0\left[\mu | z_i\right] = \sqrt{\frac{1}{u + q_i}}. \tag{3}$$

[20]Recent studies provide evidence supporting the presence of both sophisticated (for example, Lemmon and Ni, 2014) and unsophisticated investors in the stock options market (for example, Pan and Poteshman, 2006; An, Ang, Bali and Cakici, 2014).

Based on the signal received and her updated distribution, the investor trades at time $t = 0$ options with the strike price (K) that maximizes her expected utility at the expiration date $t = T$:

$$\max_K E_0 \left[U \left(W_T \right) \right], \tag{4}$$

where $U(W) = \frac{W^{1-\gamma}}{1-\gamma}$ is the power utility function, γ is the risk aversion coefficient and W_T is the terminal wealth. The option's time to maturity is assumed to match the horizon of the investor's expected return.

If the investor selects to buy options, the optimization problem takes the form:

$$\max_K E_0 \left[U \left(\left(W_0 - V_{0,d} \right) R_{f,T} + V_{0,d} R_{d,T} \right) \right], \tag{5}$$

where $R_{f,T} = 1 + rf \times T$, $R_{d,T}$ =max$(0, S_T - K)/C_0$ if calls are traded or $R_{d,T}$ =max$(0, K - S_T)/P_0$ if puts are traded, C_0 and P_0 are the Black-Scholes call and put prices respectively, S_T is the terminal stock price whose distribution depends on μ_i and v_i, W_0 is the initial wealth, $V_{0,d}$ is the wealth that is allocated to options and rf is the risk-free rate. In essence, the investor allocates a fixed amount $V_{0,d} < W_0$ either to call options if she is optimistic $(\mu_i > 0)$, or to put options if she is pessimistic $(\mu_i < 0)$, and the remainder $W_0 - V_{0,d}$ to the risk-free asset. The strike price of the purchased options is selected in a way that maximizes the investor's expected utility.

Similarly, in the case of selling options the problem takes the form:

$$\max_K E_0 \left[U \left(\left(W_0 + V_{0,d} \right) R_{f,T} - V_{0,d} R_{d,T} \right) \right]. \tag{6}$$

In this scenario, the investor allocates to the risk-free asset her initial wealth W_0 and the proceedings $V_{0,d}$ from selling a fixed amount of either put options in the case where she is optimistic $(\mu_i > 0)$, or call options in the case where she is pessimistic $(\mu_i < 0)$. The strike price of the options sold is the one that maximizes the investor's expected utility.

Given the above expected utility maximization problems, we investigate the optimal strike price for the case of an optimistic investor with expected return $\mu_i \in [0.05, 0.10, ..., 0.50]$ and a pessimistic investor with expected return $\mu_i \in [-0.05, -0.10, ..., -0.50]$. The conditional volatility of the posterior v_i is assumed to be either 1% or 5% in both scenarios. For a given μ_i and v_i, the optimal strike price is found by simulating 10,000 normally distributed two-month returns. Option prices are calculated assuming a current stock price equal to 30 USD, risk-free rate equal to 2%, annualized volatility equal to 30% and time to maturity equal to two months. Risk aversion is assumed to be equal to 3, $\bar{\mu} = 0\%$ and $\frac{1}{u}$ is inferred from the stock volatility used for option prices calculations. The levels of W_0 and $V_{0,d}$ are selected in such a way that the terminal wealth is always non-negative.

The results for the case of an optimistic investor are presented in the first two panels of Figure 1, while those for the case of a pessimistic investor are shown in the final two panels of Figure 1. It can be seen that, irrespective of whether the investor selects to buy or sell options, the optimal strike price increases monotonically with the level of her optimism. This means that the more optimistic the investor, the higher the strike price chosen. Similarly, the optimal strike price decreases monotonically with the level of the investor's pessimism, meaning that the more pessimistic the investor, the lower the strike price chosen. The above monotonic relations hold for different levels of conditional volatility v_i.[21] In essence, the above analysis shows that more optimistic investors will elect either to buy more OTM call options or sell more ITM put options, while more pessimistic investors will choose either to buy more OTM put options or sell more ITM call options. Intuitively, option buyers benefit from the higher leverage offered by more OTM options, while option sellers benefit from the higher premium provided by more ITM options. Overall, we observe that, within our framework, the strike prices (or moneyness levels, represented by the strike prices scaled by the current stock price) chosen are reflective of investors' expectations about future stock price movements. As a result, it is natural to consider the dispersion in trading volume across moneyness levels as a proxy for dispersion in investors' expectations.

[21] As expected, a higher v_i moves the optimal strike price further away from the expected terminal stock price. Similarly, different parameter values for risk aversion, stock volatility, etc. generate different optimal strike prices for the same μ_i. In all cases, however, the monotonic pattern of optimal strikes across μ_is remains intact. It is also notable that when puts are traded the optimal strike price is always slightly higher compared to the case where calls are traded. Further, we observe that in some cases, when μ_i is close to zero and the investor purchases options, the optimal position is comprised of slightly ITM rather than OTM options. Intuitively, this is because the posterior distribution of the investor does not allow for a clear distinction between optimism and pessimism since it covers a wide range of both positive and negative outcomes.

It is important to note that, while the above framework highlights one type of trading behavior that has been shown to be prevalent in stock options markets, other factors, such as the liquidity of the option contracts, and other trading behaviors, such as hedging activity, might also play a role in determining options investors' behavior. As long as investors' selected strike prices are *mainly* driven by their expectations, it is reasonable to view the dispersion in options trading volume across moneynesses as a proxy for the dispersion in options investors' beliefs. Furthermore, while our framework considers an environment where investors take naked call or put option positions, it can be easily extended to cases where investors synthetically create one of the option positions described above by relying on the put-call parity. The main theoretical result which is that more optimistic (pessimistic) investors will choose higher (lower) strike price options remains unaffected.

B Description of Variables

This appendix provides a detailed definition of all the stock- and option-related variables used in the paper. All variables are computed for each stock i at the end of month t to predict stock returns in month $t+1$. The abbreviation of each variable is specified in *italic* face.

IO (Nagel, 2005): Residual institutional ownership is the residual from cross-sectional regressions of the logit transformation of institutional ownership (fraction of shares outstanding held by institutional investors, as recorded on Thomson Financial's CDA/Spectrum Institutional (13f) Holdings) on log of market capitalization and its squared term. If the stock is listed in the CRSP database, but is missing in Thomson Financial's Institutional (13f) database, its institutional ownership is assumed to be zero.

Size (Banz, 1981): A firm's size is the natural logarithm of the firm's monthly market capitalization (stock price multiplied by the number of shares outstanding), measured in millions of dollars.

IdV (Ang, Hodrick, Xing and Zhang, 2006): Idiosyncratic volatility is the standard deviation of the residuals obtained from Fama and French's (1993) three-factor model.[22] We run time-series regressions of excess stock returns on the market, SMB and HML factors using one month of daily returns and requiring a minimum of 15 days of non-missing return data. Idiosyncratic volatility is the standard deviation of the residuals obtained from this model. We multiply the monthly estimates by $\sqrt{252}$ to obtain annualized figures.

Illiq (Amihud, 2002): Amihud's illiquidity measure is computed as the ratio of the absolute value of the daily returns to the daily dollar trading volume (stock price multiplied by the trading volume), averaged over all days within the annual rolling windows including month t. We require a minimum of 225 non-missing daily observations within an estimation year. Daily dollar trading volume is divided by one million to measure the percentage price impact of trading one million dollars.

MAX (Bali, Cakici and Whitelaw, 2011): Maximum return is the maximum daily return within a given month t.

STR (Jegadeesh, 1990; Lehmann, 1990): Short-term reversal is the stock return during month t.

Beta (Fama and MacBeth, 1973): Beta is the slope coefficient estimated from the time-series regression of excess stock returns on the excess market returns using one year of daily excess return data on a rolling basis including month t. We require a minimum of 225 non-missing daily observations within an estimation year.

BM (Diether, Malloy and Scherbina, 2002): Book-to-market is the ratio of a firm's book equity to its market capitalization. Book equity is the book value of shareholders' equity, plus investment tax credit and balance sheet deferred taxes, minus the book value of preferred stock. If book value of shareholders' equity is missing, we use either total common equity plus stock par value or total assets minus total liabilities, whichever is available in such an order. If nothing is available, then book value of shareholders' equity is considered as missing (Daniel and Titman, 2006). The book value of a preferred stock is either redemption, liquidation or par value, whichever is available in

[22]Market, SMB, HML portfolio returns and the risk-free rate are taken from Kenneth French's data library.

such an order. Next, to ensure that the book equity is known to the investors before the returns that it is assumed to explain, we match year-by-year book equity values ending in the past calendar year with stock returns from July of this year until June of the subsequent year. Finally, book equity values are divided by the monthly market capitalization.

Mom (Jegadeesh and Titman, 1993): Momentum is the cumulative stock return over the last twelve months, skipping the last month, i.e., from month $t-12$ to $t-1$. We require a minimum of 9 non-missing monthly returns during the estimation period.

Vliq (Chordia, Subrahmanyam, and Anshuman, 2001): Volatility of liquidity is the natural logarithm of the standard deviation of monthly turnover (number of shares traded divided by the number of shares outstanding), estimated over the past 36 months beginning in the second-to-last-month. We require a minimum of 30 non-missing monthly turnover data during the estimation period.

AFD (Diether, Malloy and Scherbina, 2002): Dispersion in analysts' earnings forecasts is the standard deviation of analysts' earnings forecasts for the next fiscal year, scaled by the absolute value of the mean earnings forecast.

Turn (Bali, Engle and Tang, 2017): Share turnover is the daily ratio of the total number of shares traded to the total number of shares outstanding, averaged over all days within a month. We require a minimum of 15 non-missing daily observations to obtain monthly turnover values.

DRisk (Bharath and Shumway, 2008): Distress risk is estimated from the "naive" distance to default of Merton (1974), which has the same structural form as the standard model, but does not require solving for the market value of the firm's equity and its volatility. The inputs of the model are: the firm's asset value, which is estimated as the sum of market value of equity (price times the number of shares outstanding) plus the face value of debt (next-year debt plus half long-term debt), the firm's face value of debt and the firm's volatility, which is estimated as a weighted average of the debt and equity volatilities. The volatility of debt is equal to $0.05 + 0.25\times$the volatility of equity.

RNS, RNK (Conrad, Dittmar and Ghysels, 2013; Stilger, Kostakis and Poon, 2017): Risk-neutral skewness (kurtosis) is the Bakshi, Kapadia and Madan (2003) model-free estimate of risk-neutral skewness (kurtosis) of a stock's log return spanning the period up to the maturity day of the options. We use volatility surface data with maturity of 30 days. Out-of-the-money put and call options are those with deltas above -0.5 and below 0.5 respectively.

VolSpr (Bali and Hovakimian, 2009): Realized-implied volatility spread is defined as the difference between monthly realized volatility and the average of at-the-money call and put implied volatilities. We use volatility surface data with maturity of 30 days. At-the-money options have a delta (in absolute value) equal to 0.5.

QSkew (Xing, Zhang and Zhao, 2010): Out-of-the-money skew is defined as the difference between the implied volatility of an out-of-the-money put option and the average implied volatility of an at-the-money call and an at-the-money put option. We use volatility surface data with a maturity of 30 days. The out-of-the-money and at-the-money options are those with deltas (in absolute values) of 0.2 and 0.5 respectively.

VS (Cremers and Weinbaum, 2010): Call-put volatility spread is computed as the open-interest-weighted (average open interest in the call and put) difference in implied volatilities between call options and put options with the same strike price and maturity. We use raw options data with maturities between 10 and 360 calendar days and require at least one available option pair. We eliminate option pairs that violate basic no-arbitrage bounds and where either the call or the put has zero open interest or bid price.

O/S (Johnson and So, 2012): Option-to-stock-trading-volume ratio is estimated as the total monthly equity volume divided by the total monthly volume in option contracts across all strikes. We use raw options data with maturities between 5 and 30 trading days. To obtain total monthly volume in option contracts, we first sum trading volumes across all strike prices within a day, then sum daily trading volumes within a month.

InnCall, InnPut (An, Ang, Bali and Cakici, 2014): Call (Put) implied volatility innovations is defined as the monthly first-difference of at-the-money call (put) implied volatilities, i.e. from month $t-1$ to t. We use volatility surface data with a maturity of 30 days. At-the-money options are those with a delta (in absolute value) of 0.5.

VoV (Baltussen, Van Bekkum and Van Der Grient, 2015): Volatility of volatility is defined as the standard deviation of daily at-the-money implied volatilities within a month, scaled by the average at-the-money implied volatility in the same month. We use raw options data with maturities between 10 and 52 trading days. At-the-money options have a ratio of strike price to stock price varying between 0.95 and 1.05 inclusive. If multiple at-the-money options are eligible, the option closest to 1 is chosen. To obtain reliable implied volatility estimates, we follow the screening criteria introduced by the original paper.

OVlm (Xing, Zhang and Zhao, 2010): The level of the options trading volume is the logarithm of the monthly total trading volume, which is computed as the sum of daily trading volume across all option contracts.

Figure 1: Optimal strike prices for an optimistic or pessimistic investor

This figure plots the optimal strike ($\widetilde{K}$) for either an optimistic investor with an expected return μ_i ranging from 0.05 to 0.50 (first two panels) or a pessimistic investor with an expected return μ_i ranging from -0.05 to -0.50 (final two panels). The investor either buys options (first and third panel) or sells options (second and fourth panel). The current stock price is equal to 30, risk-free rate equal to 2%, stock volatility equal to 30%, time to maturity equal to two months, risk aversion coefficient equal to 3 and the volatility of the posterior is either $v_i = 1\%$ (solid lines) or $v_i = 5\%$ (dashed lines).

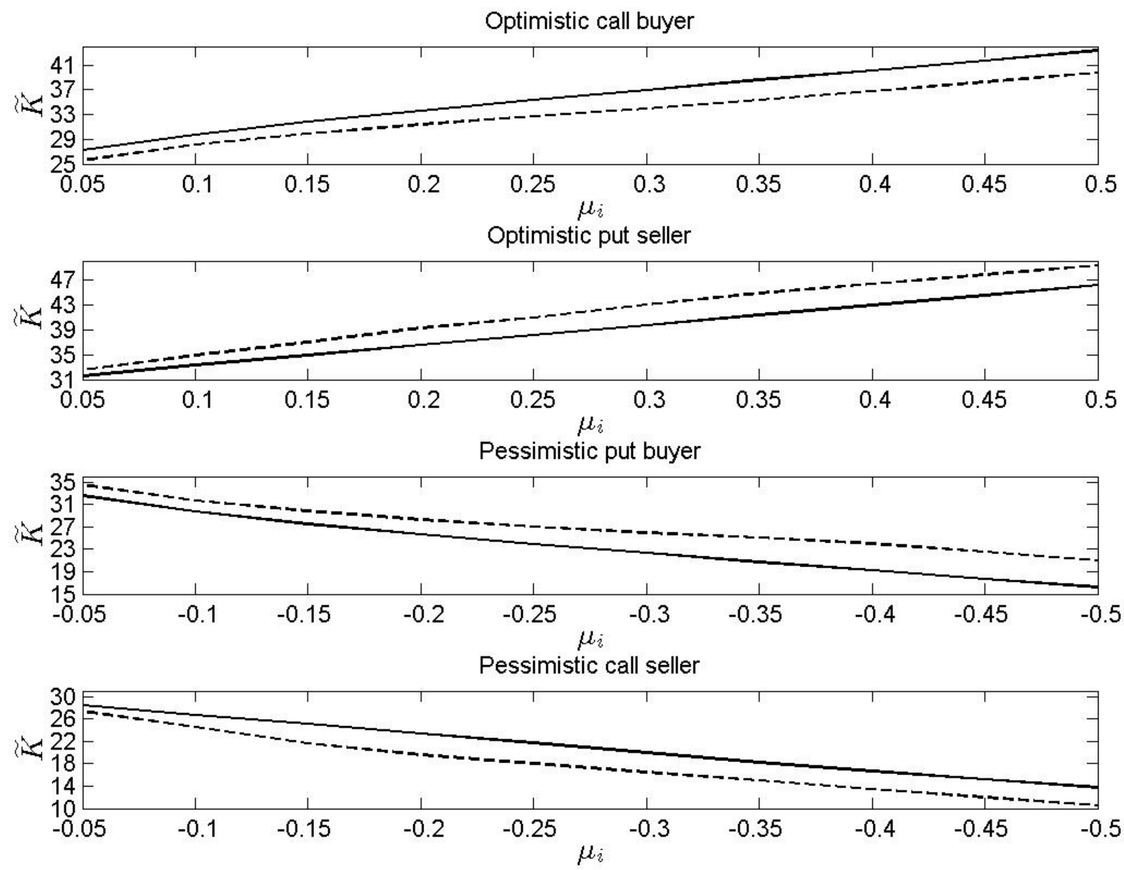

Figure 2: Average IDISP across industries

This figure plots the yearly average values of the individual stock options dispersion (IDISP) measure for ten industries based on the Fama-French classification over the sample period from January 1996 to September 2015. Each month, stocks are grouped into ten industries and IDISP is the monthly average dispersion of individual stock options trading volume across moneyness levels for each industry. Industry classifications are provided in the graph below.

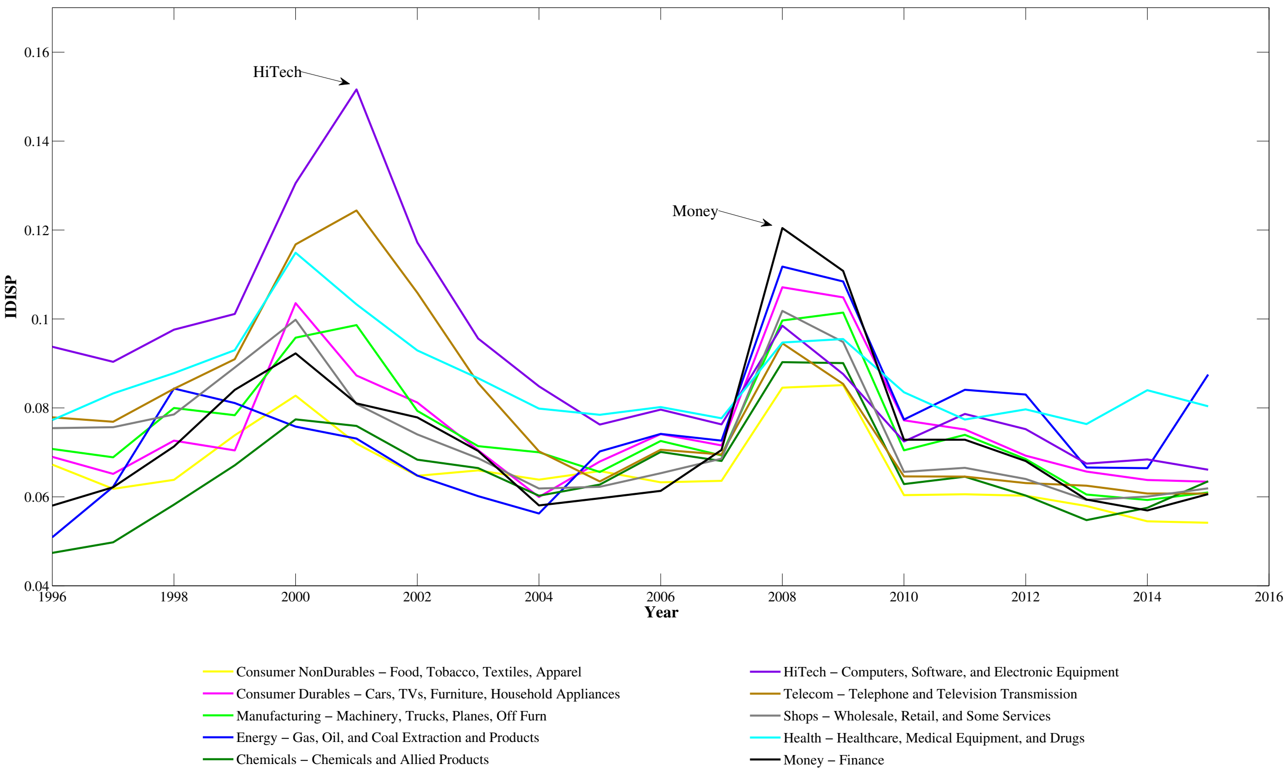

Figure 3: IDISP Portfolios across months

This figure plots the individual stock options monthly dispersion (IDISP) measure averages for each of the IDISP quintile portfolios, eleven months before and eleven months after the formation month. IDISP is the monthly average dispersion of individual stock options trading volume across moneyness levels. Each month, stocks are grouped into portfolios in ascending order from quintile 1 (low IDISP) to quintile 5 (high IDISP).

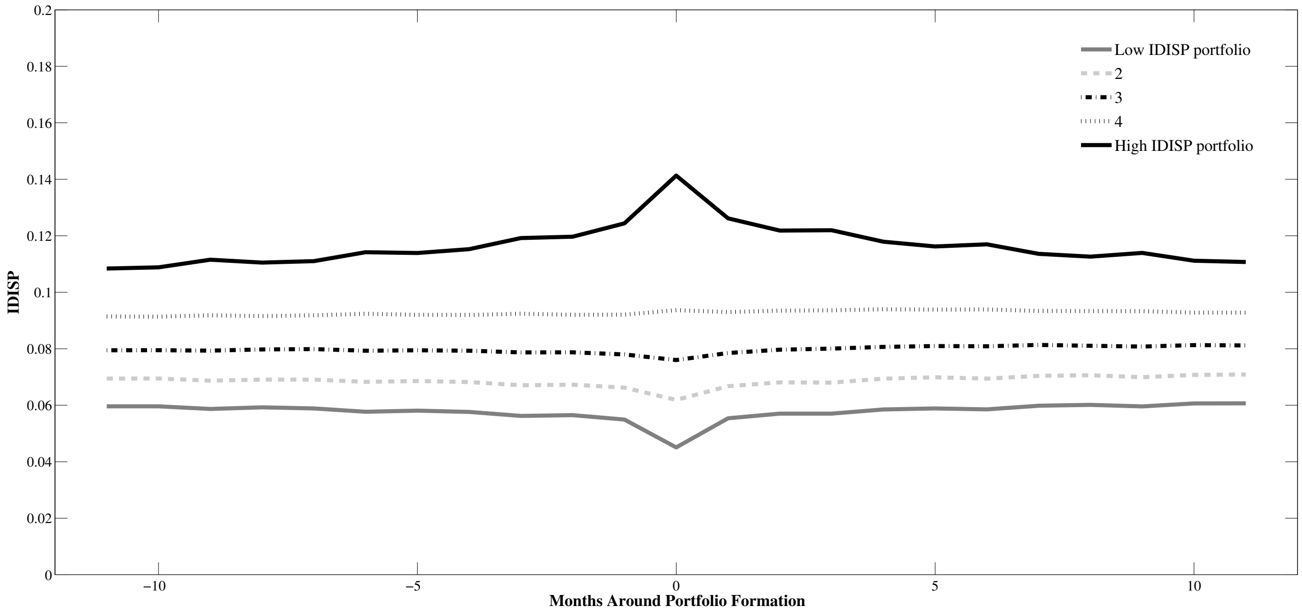

Figure 4: Average IDISP Around Earnings Announcements and Pseudo-Events

This figure illustrates the dynamics of the average IDISP across firms and announcements for a period of 15 trading days (from -7 to 7) around the event date (day 0). The solid line corresponds to the actual earnings announcement date, while the dotted line corresponds to a pseudo-event date that is selected randomly from the one-month period starting one month after the actual announcement date. IDISP is the dispersion of individual stock options trading volume across moneyness levels. On each occasion, the daily IDISP values are scaled by the average IDISP over the event period. We consider those firms' announcements for which IDISP values exist for all the 15 days under examination. Our sample period is from 1996:Q1 to 2015:Q3.

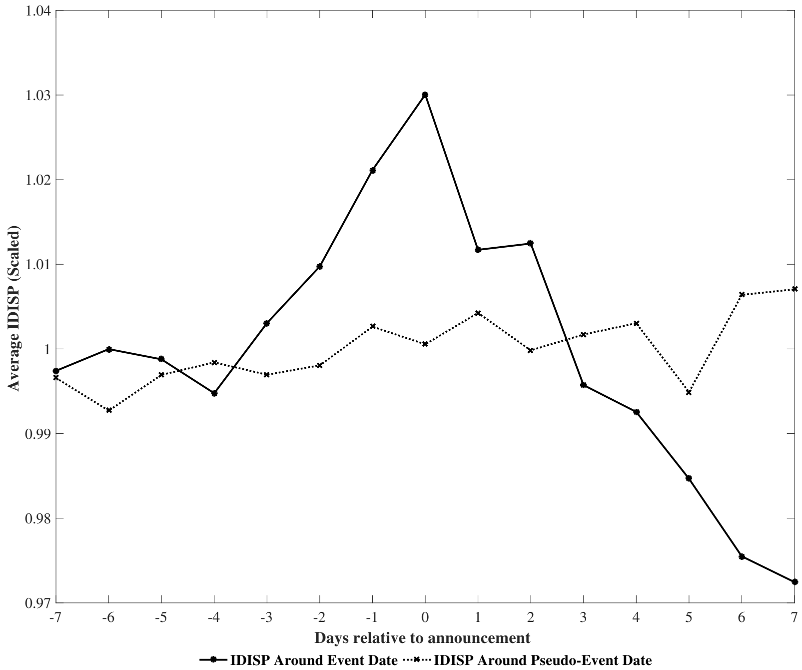

Figure 5: Returns of $H - L$ IDISP Portfolios Around Earnings Announcements

This figure shows the cumulative excess returns of the $H-L$ portfolio that buys high IDISP stocks and sells low IDISP stocks over the 15 trading days (from -7 to 7) around the earnings announcement date (day 0). IDISP is the dispersion of individual stock options trading volume across moneyness levels, estimated over the month ending two trading days, five trading days or ten trading days prior to the earnings announcement ($\text{IDISP}_{(-23,-2)}$, $\text{IDISP}_{(-26,-5)}$ and $\text{IDISP}_{(-31,-10)}$ respectively). In each calendar quarter, we sort firms that report earnings into quintile portfolios based on each of the IDISP proxies and estimate the average buy-hold excess returns of the $H - L$ portfolio. The buy-hold returns start cumulating from day -7, relative to the announcement date, until day +7. The returns are expressed as percentages. Our sample period is from 1996:Q1 to 2015:Q3.

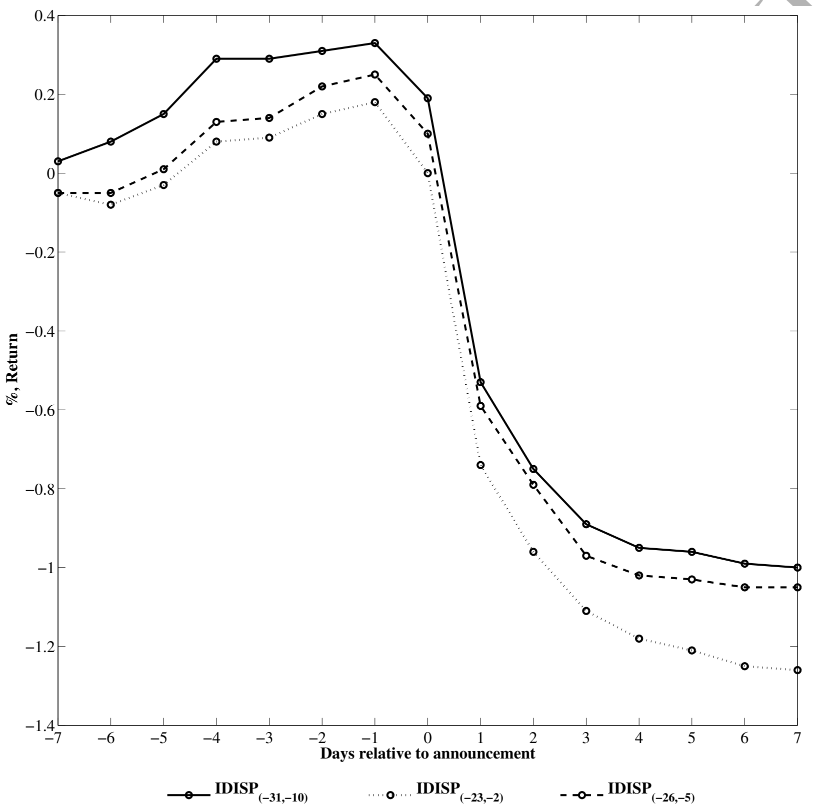

Table 1: Descriptive Statistics for IDISP Measure

This table reports the yearly descriptive statistics for the individual stock options dispersion (IDISP) measure over the sample period from January 1996 to September 2015. IDISP is the monthly average dispersion of individual stock options trading volume across moneyness levels. The column "Num. of IDISP stocks" displays the number of firms for which we can estimate the IDISP measure and that survive the screening criteria. The subsequent four columns report the yearly averages of monthly mean, median, 25^{th} and 75^{th} percentile values of IDISP across all firms in our sample. The last four columns present the yearly averages of monthly mean proportions of calls (Calls, %), puts (Puts, %), out-of-the-money (OTM, %) and in-the-money (ITM, %) options traded relative to the total trading volume.

Year	Num. of IDISP stocks	Mean	Median	25^{th} perc.	75^{th} perc.	Calls, %	Puts, %	OTM, %	ITM, %
1996	763	0.080	0.076	0.056	0.097	72.0	28.0	59.3	40.7
1997	999	0.080	0.075	0.056	0.096	72.3	27.7	58.9	41.1
1998	1117	0.087	0.079	0.061	0.103	70.4	29.6	60.3	39.7
1999	1262	0.094	0.087	0.067	0.111	71.9	28.1	63.1	36.9
2000	1475	0.124	0.109	0.080	0.146	71.7	28.3	67.4	32.6
2001	1170	0.112	0.096	0.068	0.133	64.3	35.7	68.0	32.0
2002	1036	0.095	0.082	0.063	0.112	59.7	40.3	66.6	33.4
2003	977	0.079	0.073	0.057	0.093	61.7	38.3	64.3	35.7
2004	1153	0.074	0.067	0.052	0.086	62.1	37.9	64.8	35.2
2005	1234	0.070	0.064	0.051	0.081	61.6	38.4	63.9	36.1
2006	1393	0.074	0.068	0.053	0.087	61.3	38.7	63.4	36.6
2007	1552	0.075	0.067	0.054	0.086	60.5	39.5	67.1	32.9
2008	1517	0.111	0.096	0.074	0.127	57.5	42.5	71.7	28.3
2009	1356	0.091	0.084	0.067	0.105	58.3	41.7	72.7	27.3
2010	1328	0.072	0.066	0.053	0.084	59.7	40.3	73.2	26.8
2011	1387	0.076	0.069	0.055	0.089	59.2	40.8	75.2	24.8
2012	1217	0.071	0.065	0.050	0.084	58.1	41.9	75.3	24.7
2013	1292	0.066	0.059	0.046	0.077	58.7	41.3	74.0	26.0
2014	1413	0.069	0.059	0.046	0.080	59.7	40.3	74.5	25.5
2015	1345	0.069	0.060	0.047	0.081	58.7	41.3	76.9	23.1

Table 2: Returns and Characteristics of IDISP Portfolios

This table reports the average IDISP estimates, equal-weighted and value-weighted monthly returns and alphas as well as the average stock-related characteristics for the decile portfolios sorted on the individual stock options dispersion (IDISP) measure (in ascending order from decile 1, low IDISP to decile 10, high IDISP) over the sample period from January 1996 to September 2015. IDISP is the monthly average dispersion of individual stock options trading volume across moneyness levels. For each decile portfolio, we report average equal- and value-weighted monthly returns in excess of the risk-free rate (R) and alphas from the Carhart four-factor model ($C4\alpha$) and the Carhart four-factor model augmented by the Pastor and Stambaugh liquidity factor ($C4PS\alpha$). The $H-L$ column reports the difference in IDISP, other characteristics as well as in raw returns and alphas between the high IDISP portfolio and the low IDISP portfolio. Column 13 ("t-stat") reports corresponding Newey-West adjusted t-statistics (with six lags). *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. All raw and risk-adjusted returns are expressed as percentages. The definitions of all the variables are detailed in the Appendix B.

Portfolio	Low IDISP	2	3	4	5	6	7	8	9	High IDISP	$H-L$	t-stat
Average IDISP												
	0.039	0.050	0.058	0.065	0.072	0.079	0.087	0.098	0.115	0.165	0.13***	(20.11)
Equal-Weighted Results												
R	0.96	0.95	1.02	0.98	0.71	0.94	0.72	0.68	0.17	-0.52	-1.49***	(-2.77)
$C4\alpha$	0.19	0.09	0.12	0.08	-0.21	-0.01	-0.25	-0.25	-0.72	-1.43	-1.62***	(-5.27)
$C4PS\alpha$	0.16	0.05	0.09	0.07	-0.24	-0.02	-0.29	-0.28	-0.69	-1.38	-1.54***	(-4.88)
Value-Weighted Results												
R	0.89	0.75	0.74	0.94	0.39	0.65	0.96	0.71	0.93	-0.61	-1.50**	(-2.52)
$C4\alpha$	0.25	0.08	0.05	0.19	-0.37	-0.22	0.13	-0.12	0.08	-1.45	-1.70***	(-4.39)
$C4PS\alpha$	0.22	0.08	0.06	0.18	-0.36	-0.21	0.18	-0.09	0.14	-1.37	-1.59***	(-4.23)
Average of Other Characteristics												
IO	0.176	0.398	0.429	0.457	0.500	0.452	0.363	0.271	-0.005	-0.574	-0.75***	(-5.48)
Size	9.090	8.974	8.807	8.595	8.389	8.174	7.957	7.692	7.368	6.844	-2.25***	(-22.98)
IdV	0.219	0.250	0.277	0.310	0.340	0.373	0.408	0.450	0.510	0.627	0.41***	(21.62)
Illiq	0.001	0.001	0.002	0.002	0.003	0.004	0.005	0.006	0.012	0.024	0.02***	(4.37)
MAX	0.040	0.046	0.051	0.056	0.062	0.068	0.075	0.082	0.092	0.109	0.07***	(17.88)
STR	0.020	0.021	0.022	0.022	0.023	0.021	0.020	0.014	0.009	-0.010	-0.03***	(-3.33)
Beta	0.883	0.991	1.077	1.171	1.258	1.350	1.437	1.528	1.591	1.612	0.73***	(10.15)
BM	0.405	0.382	0.375	0.372	0.369	0.370	0.375	0.389	0.420	0.563	0.16***	(3.44)
Mom	0.201	0.235	0.265	0.297	0.316	0.336	0.358	0.365	0.347	0.229	0.03	(0.36)
Vliq	1.442	1.629	1.794	1.966	2.144	2.298	2.465	2.615	2.772	2.964	1.52***	(22.51)
AFD	0.076	0.088	0.102	0.118	0.145	0.168	0.204	0.257	0.339	0.497	0.42***	(19.12)
Turn	0.008	0.009	0.011	0.012	0.014	0.015	0.017	0.019	0.022	0.025	0.02***	(37.29)
DRisk	0.004	0.005	0.009	0.012	0.015	0.020	0.030	0.042	0.066	0.137	0.13***	(8.54)

Table 3: Transition Matrix

This table reports the average month-to-month transition probabilities for the decile portfolios sorted on the individual stock options dispersion (IDISP) measure (in ascending order from decile 1, low IDISP to decile 10, high IDISP) over our sample period from January 1996 to September 2015. IDISP is the monthly average dispersion of individual stock options trading volume across moneyness levels. The reported values represent the average probability that a stock in decile i (the rows of the matrix) in one month will be in decile j (the columns of the matrix) in the next month.

i/j	Low IDISP	2	3	4	5	6	7	8	9	High IDISP
Low IDISP	0.402	0.246	0.144	0.085	0.053	0.030	0.019	0.011	0.007	0.004
2	0.221	0.238	0.194	0.133	0.089	0.054	0.036	0.019	0.011	0.005
3	0.128	0.192	0.193	0.168	0.125	0.085	0.051	0.032	0.018	0.008
4	0.074	0.129	0.159	0.180	0.152	0.126	0.086	0.053	0.029	0.012
5	0.045	0.083	0.124	0.150	0.174	0.156	0.122	0.082	0.044	0.020
6	0.029	0.050	0.086	0.120	0.152	0.173	0.165	0.120	0.075	0.029
7	0.015	0.032	0.054	0.083	0.116	0.158	0.192	0.177	0.123	0.050
8	0.009	0.019	0.032	0.050	0.081	0.125	0.173	0.219	0.198	0.095
9	0.005	0.010	0.016	0.025	0.047	0.071	0.122	0.200	0.284	0.219
High IDISP	0.003	0.004	0.006	0.010	0.018	0.031	0.051	0.097	0.224	0.556

Table 4: Next-month IDISP Predictability

This table presents the results from Fama and MacBeth (1973) cross-sectional regressions of the individual stock options dispersion (IDISP) measure over month *t+1* on the IDISP measure and a list of firm characteristics computed at the end of month t over the sample period from January 1996 to September 2015. IDISP is the monthly average dispersion of individual stock options trading volume across moneyness levels. We obtain coefficient estimates from monthly cross-sectional regressions, and report their time-series averages, Newey-West adjusted t-statistics (with six lags) in parentheses and the R^2. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. The definitions of the variables are detailed in the Appendix B.

IDISP	IO	Size	IdV	Illiq	MAX	STR	Beta	BM	Mom	Vliq	AFD	Turn	DRisk	R^2
0.571***	-0.0001**	0.0007**	0.0237***	0.564***	-0.0197**	-0.0205***	0.0044***	0.0009	-0.0013**	0.0037***	0.0045***	0.0230	0.0376***	0.588
(28.41)	(-3.75)	(2.52)	(10.27)	(5.88)	(-2.44)	(-5.67)	(7.58)	(1.24)	(-2.33)	(7.64)	(7.77)	(0.84)	(6.03)	

Table 5: Controlling for Other Cross-Sectional Characteristics

This table presents the average monthly returns of portfolios sorted on one of the stock- or option-related characteristics and the individual stock options dispersion (IDISP) measure over our sample period from January 1996 to September 2015. IDISP is the monthly average dispersion of individual stock options trading volume across moneyness levels. Each month, we sort stocks in ascending order into quintile portfolios based on one of the characteristics. Next, within each characteristic portfolio, we further sort stocks into five extra portfolios in ascending order on the basis of IDISP (from quintile 1, low IDISP to quintile 5, high IDISP). Finally, we calculate the time-series averages of equal-weighted monthly excess returns for each of the IDISP quintiles across the five characteristic portfolios obtained from the first sort. Additionally, we report the average raw returns ($H-L$), as well as the alphas from the Carhart four-factor model ($C4\alpha$) and the Carhart four-factor model augmented by the Pastor and Stambaugh liquidity factor ($C4PS\alpha$), for a strategy that buys the high IDISP portfolio and sells the low IDISP portfolio. Columns 8, 10 and 12 ("t-stat") report the corresponding Newey-West adjusted t-statistics (with six lags). *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. All raw and risk-adjusted returns are expressed as percentages. The definitions of all the variables are detailed in the Appendix B.

Stock-related Characteristics

	Low IDISP	2	3	4	High IDISP	$H-L$	t-stat	$C4\alpha$	t-stat	$C4PS\alpha$	t-stat
IO	0.96	0.95	0.82	0.62	-0.04	-1.00***	(-4.27)	-1.07***	(-6.56)	-1.02***	(-6.24)
Size	0.93	0.97	0.72	0.52	0.16	-0.77***	(-3.64)	-0.79***	(-4.83)	-0.72***	(-4.42)
IdV	0.90	0.86	0.70	0.52	0.32	-0.58***	(-3.24)	-0.54***	(-3.42)	-0.52***	(-3.28)
Illiq	0.97	0.87	0.88	0.59	0.14	-0.83***	(-3.66)	-0.78***	(-4.49)	-0.73***	(-4.16)
MAX	0.92	0.80	0.83	0.50	0.25	-0.66***	(-3.54)	-0.65***	(-3.84)	-0.61***	(-3.64)
STR	0.89	0.93	0.87	0.63	-0.01	-0.90***	(-4.03)	-0.97***	(-6.36)	-0.91***	(-5.91)
Beta	0.86	0.92	0.77	0.88	0.01	-0.85***	(-4.88)	-0.90***	(-6.08)	-0.87***	(-5.81)
BM	0.95	1.01	0.80	0.68	-0.00	-0.95***	(-4.01)	-1.00***	(-5.71)	-0.98***	(-5.57)
Mom	0.97	0.93	0.85	0.68	0.02	-0.96***	(-4.06)	-1.13***	(-5.90)	-1.06***	(-5.37)
Vliq	1.00	0.95	0.95	0.73	0.28	-0.72***	(-4.07)	-0.69***	(-4.09)	-0.67***	(-3.94)
AFD	1.05	0.81	0.93	0.68	-0.01	-1.06***	(-5.32)	-1.06***	(-7.01)	-1.00***	(-6.66)
Turn	1.02	0.84	0.87	0.56	0.01	-1.02***	(-5.27)	-0.96***	(-5.82)	-0.93***	(-5.70)
DRisk	0.94	0.99	0.88	0.74	0.32	-0.63***	(-2.78)	-0.77***	(-3.95)	-0.71***	(-3.61)

Option-related Characteristics

	Low IDISP	2	3	4	High IDISP	$H-L$	t-stat	$C4\alpha$	t-stat	$C4PS\alpha$	t-stat
RNS	0.97	1.04	0.82	0.62	-0.10	-1.07***	(-4.48)	-1.18***	(-7.27)	-1.10***	(-6.86)
RNK	0.99	0.96	0.80	0.56	0.04	-0.95***	(-4.69)	-1.02***	(-6.56)	-0.95***	(-6.13)
VolSpr	0.95	0.82	0.85	0.70	0.02	-0.93***	(-4.16)	-1.00***	(-6.12)	-0.98***	(-5.95)
QSkew	0.91	0.93	0.75	0.70	0.03	-0.88***	(-3.85)	-0.94***	(-5.68)	-0.91***	(-5.40)
VS	0.92	0.96	0.76	0.65	0.04	-0.88***	(-3.81)	-0.95***	(-5.99)	-0.89***	(-5.55)
O/S	0.96	0.92	0.82	0.65	-0.04	-1.00***	(-4.22)	-1.08***	(-6.63)	-1.01***	(-6.28)
InnCall	0.93	0.91	0.80	0.59	0.07	-0.86***	(-3.94)	-0.96***	(-5.81)	-0.91***	(-5.51)
InnPut	0.91	0.94	0.79	0.74	-0.08	-0.99***	(-4.45)	-1.07***	(-6.63)	-1.01***	(-6.24)
VoV	0.90	0.96	0.84	0.74	0.10	-0.80***	(-3.38)	-0.92***	(-5.34)	-0.86***	(-5.10)
OVlm	0.92	1.02	0.80	0.69	-0.13	-1.05***	(-4.34)	-1.16***	(-7.10)	-1.10***	(-6.81)

Table 6: Fama-MacBeth Regressions

This table reports the results from Fama and MacBeth (1973) cross-sectional regressions of excess stock returns over month *t+1* on the individual stock options dispersion (IDISP) measure and a list of stock- and option-related characteristics computed at the end of month t over our sample period from January 1996 to September 2015. IDISP is the monthly average dispersion of individual stock options trading volume across moneyness levels. We obtain coefficient estimates from monthly cross-sectional regressions and report their time-series averages, Newey-West adjusted t-statistics (six lags) in parentheses, and R^2s. Panel A presents the results with stock-related variables, while Panel B reports the results with option-related variables. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. The definitions of all the variables are detailed in the Appendix B.

Panel A: Stock-related Characteristics

Univariate Analysis

	IDISP	IO	Size	IdV	Illiq	MAX	STR	Beta	BM	Mom	Vliq	AFD	Turn	DRisk
	-0.1360***	0.0003*	-0.0017***	-0.0055	0.0060***	-0.0280	-0.0009	-0.0026	0.0001	0.0046	-0.0012	-0.0043**	-0.1190	-0.0256***
	(-3.24)	(1.88)	(-2.76)	(-0.82)	(3.80)	(-0.96)	(-0.12)	(-0.74)	(0.03)	(1.30)	(-0.69)	(-1.97)	(-0.70)	(-3.09)
R^2	0.032	0.002	0.009	0.023	0.003	0.018	0.013	0.034	0.011	0.019	0.025	0.007	0.019	0.012

Multivariate Analysis

IDISP	IO	Size	IdV	Illiq	MAX	STR	Beta	BM	Mom	Vliq	AFD	Turn	DRisk	R^2
-0.1326***	0.0004**													0.035
(-3.20)	(2.59)													
-0.1130***		0.0003												0.043
(-3.18)		(0.34)												
-0.1040***			-0.0088*											0.042
(-3.20)			(-1.89)											
-0.1249***				-0.0258										0.039
(-3.02)				(-0.31)										
-0.1198***					-0.0323									0.041
(-3.55)					(-1.44)									
-0.1336***						-0.0007								0.045
(-3.14)						(-0.08)								
-0.1338***							0.0029							0.062
(-4.35)							(0.82)							
-0.1244***								-0.0030						0.048
(-2.97)								(-0.67)						
-0.1299***									0.0035					0.053
(-3.26)									(0.93)					
-0.1293***										0.0007				0.049
(-4.19)										(0.42)				
-0.1290***											0.0004			0.039
(-3.13)											(0.23)			
-0.1300***												0.0242		0.045
(-3.67)												(0.21)		
-0.1070***													-0.0351***	0.050
(-2.61)													(-2.99)	
-0.0543**	0.0004***	-0.0011	-0.0066	0.0154	0.0092	0.0009	0.0015	0.0033	-0.0003	-0.0006	0.0025	-0.0182	-0.0391***	0.163
(-2.31)	(3.88)	(-1.00)	(-1.21)	(0.06)	(0.44)	(0.11)	(0.41)	(1.20)	(-0.07)	(-0.49)	(1.20)	(-0.18)	(-3.28)	

Table 6: Fama-MacBeth Regressions (continued)

Panel B: Option-related Characteristics

Univariate Analysis

	IDISP	RNS	RNK	VolSpr	QSkew	VS	O/S	InnCall	InnPut	VoV	OVlm
	-0.1360***	0.0037***	0.0006	-0.0053	-0.0186***	0.0552***	-0.0564*	0.0032	-0.0009	-0.0437**	-0.0007
	(-3.24)	(2.74)	(0.28)	(-1.59)	(-3.18)	(6.57)	(-1.74)	(0.60)	(-0.17)	(-2.21)	(-1.40)
R^2	0.032	0.003	0.010	0.005	0.002	0.003	0.005	0.004	0.004	0.005	0.008

Multivariate Analysis

IDISP	RNS	RNK	VolSpr	QSkew	VS	O/S	InnCall	InnPut	VoV	OVlm	R^2
-0.1366***	0.0065***										0.036
(-3.33)	(2.81)										
-0.1352***		-0.0023									0.039
(-3.56)		(-0.63)									
-0.1323***			0.0017								0.037
(-3.18)			(0.40)								
-0.1231***				-0.0448***							0.036
(-2.96)				(-3.76)							
-0.1211***					0.0491***						0.037
(-2.89)					(3.10)						
-0.1329***						-0.0224					0.036
(-3.14)						(-1.44)					
-0.1302***							-0.0091				0.038
(-3.14)							(-1.23)				
-0.1277***								-0.0137*			0.038
(-3.06)								(-1.88)			
-0.1025**									-0.0341**		0.040
(-2.09)									(-2.22)		
-0.1330***										-0.0005	0.036
(-3.17)										(-0.91)	
-0.0697**	-0.0013	-0.0027	-0.0036	-0.0323	0.0150	0.0027	0.0109	-0.0220	-0.0229	0.0003	0.091
(-2.10)	(-0.29)	(-0.54)	(-0.87)	(-0.95)	(0.69)	(0.12)	(0.58)	(-1.18)	(-1.34)	(0.35)	

Table 7: IDISP and Short-Selling Impediments

This table presents the average monthly returns of portfolios sorted on one of the short-selling impediments proxies and the individual stock options dispersion (IDISP) measure over the sample period from January 1996 to September 2015. We use residual institutional ownership (IO) as a proxy for short-sale costs and firm's size (Size), idiosyncratic volatility (IdV) and Amihud illiquidity (Illiq) as proxies for limits to arbitrage. IDISP is the monthly average dispersion of individual stock options trading volume across moneyness levels. Each month, we sort stocks in ascending order into tercile portfolios (column vector, from tercile 1 to 3) based on one of the four characteristics. Next, within each characteristic portfolio, we further sort stocks into five extra portfolios based on IDISP (row vector, from quintile 1 to 5). Finally, for each characteristic-IDISP portfolio, we compute equal-weighted monthly excess returns and present a time-series average of these excess returns over all months in our sample. We also report the average raw returns ($H - L$), as well as the alphas from the Carhart four-factor model ($C4\alpha$) and the Carhart four-factor model augmented by the Pastor and Stambaugh liquidity factor ($C4PS\alpha$), for a strategy that buys the high IDISP portfolio and sells the low IDISP portfolio. Columns 8, 10 and 12 ("t-stat") report corresponding Newey-West adjusted t-statistics (with six lags). *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. All raw and risk-adjusted returns are expressed as percentages. The definitions of all the variables are detailed in the Appendix B.

Residual Institutional Ownership

	Low IDISP	2	3	4	High IDISP	$H-L$	t-stat	$C4\alpha$	t-stat	$C4PS\alpha$	t-stat
Low IO	0.93	0.71	0.55	0.24	-0.83	-1.77***	(-3.06)	-1.89***	(-4.97)	-1.83***	(-4.82)
2	1.08	0.94	0.99	0.79	0.35	-0.73	(-1.59)	-0.75**	(-2.53)	-0.72**	(-2.43)
High IO	0.99	1.09	1.01	0.67	0.38	-0.61	(-1.41)	-0.62**	(-2.13)	-0.54*	(-1.85)
$H-L$						1.16***	(2.61)	1.27***	(2.97)	1.28***	(2.95)

Size

	Low IDISP	2	3	4	High IDISP	$H-L$	t-stat	$C4\alpha$	t-stat	$C4PS\alpha$	t-stat
Low Size	1.02	0.63	0.51	-0.10	-0.40	-1.42***	(-3.33)	-1.27***	(-3.07)	-1.25***	(-2.94)
2	1.07	1.01	0.94	0.77	0.43	-0.65	(-1.34)	-0.58	(-1.58)	-0.49	(-1.37)
High Size	0.84	0.99	0.81	0.77	0.62	-0.22	(-0.44)	-0.40	(-1.33)	-0.34	(-1.12)
$H-L$						1.21**	(2.26)	0.87**	(2.03)	0.92**	(2.06)

Idiosyncratic Volatility

	Low IDISP	2	3	4	High IDISP	$H-L$	t-stat	$C4\alpha$	t-stat	$C4PS\alpha$	t-stat
Low IdV	0.92	0.95	0.99	0.86	1.11	0.19	(0.68)	0.11	(0.59)	0.12	(0.60)
2	1.00	0.85	1.14	0.90	0.56	-0.45	(-1.30)	-0.40	(-1.62)	-0.38	(-1.46)
High IdV	0.75	0.58	0.31	0.09	-1.11	-1.86***	(-4.34)	-1.77***	(-4.46)	-1.69***	(-4.14)
$H-L$						-2.05***	(-4.53)	-1.88***	(-4.40)	-1.80***	(-4.07)

Amihud Illiquidity

	Low IDISP	2	3	4	High IDISP	$H-L$	t-stat	$C4\alpha$	t-stat	$C4PS\alpha$	t-stat
Low Illiq	0.91	0.91	0.89	0.75	0.50	-0.41	(-0.76)	-0.48	(-1.44)	-0.44	(-1.30)
2	0.96	1.07	1.08	0.92	0.18	-0.77*	(-1.72)	-0.67*	(-1.94)	-0.57*	(-1.70)
High Illiq	0.94	0.69	0.68	0.35	-0.48	-1.42***	(-3.24)	-1.27***	(-3.34)	-1.25***	(-3.22)
$H-L$						-1.01*	(-1.84)	-0.79*	(-1.76)	-0.82*	(-1.72)

Table 8: IDISP and Earnings Announcements

This table reports the average excess returns around earnings announcements for quintile portfolios sorted on the individual stock options dispersion (IDISP) measure. IDISP is the average dispersion of individual stock options trading volume across moneyness levels, estimated over the trading month ending two days, five days or ten days prior to the earnings announcement (IDISP$_{(-23,-2)}$, IDISP$_{(-26,-5)}$ and IDISP$_{(-31,-10)}$ respectively). Each calendar quarter, we sort firms that report earnings into quintile portfolios (Portfolio 1, Low IDISP - Portfolio 5, High IDISP) based on each of the IDISP proxies and report for each portfolio the time-series average of the quarterly mean cumulative three-day earnings announcement period returns in excess of the market return. Finally, we report the average cumulative three-day excess returns for a strategy that buys the high IDISP portfolio and sells the low IDISP portfolio ($H-L$). The returns are expressed as percentages. Newey-West adjusted t-statistics (with four lags) are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our sample period is from 1996:Q1 to 2015:Q3.

Portfolio	IDISP$_{(-23,-2)}$	IDISP$_{(-26,-5)}$	IDISP$_{(-31,-10)}$
Low IDISP	0.33	0.30	0.32
2	0.29	0.33	0.34
3	0.38	0.29	0.28
4	-0.04	-0.03	0.09
High IDISP	-0.47	-0.43	-0.45
$H-L$	-0.80***	-0.73***	-0.77***
	(-4.85)	(-4.07)	(-4.39)

Table 9: IDISP and Investor Sentiment

This table presents the results from Fama and MacBeth (1973) cross-sectional regressions of excess stock returns over month *t+1* on the individual stock options dispersion (IDISP) measure and a list of stock- and option-related characteristics computed at the end of month *t*. The analysis is run separately for high and low investor sentiment months over the sample period from January 1996 to September 2015. IDISP is the monthly average dispersion of individual stock options trading volume across moneyness levels. A high (low) sentiment month *t+1* is one in which the value of the Baker and Wurgler (2006) index in month *t* is above (below) the sample median. We obtain coefficient estimates from monthly cross-sectional regressions, and report their time-series averages, Newey-West adjusted t-statistics (with six lags) in parentheses, and R^2s. Additionally, we report the p-values from a t-test of equal IDISP slope coefficients between high and low sentiment periods. The first column in the stock-related characteristics panel reports the coefficient of IDISP from univariate models, while all other columns with control variable abbreviations report the coefficients of IDISP from bivariate regressions after controlling for the relevant characteristic. The final column (Full) reports the IDISP coefficient from the multivariate model with all control variables. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. The definitions of all the variables are detailed in the Appendix B.

Stock-related Characteristics

High Sentiment

	(1)	(2) IO	(3) Size	(4) IdV	(5) Illiq	(6) MAX	(7) STR	(8) Beta	(9) BM	(10) Mom	(11) Vliq	(12) AFD	(13) Turn	(14) DRisk	(15) Full
IDISP	-0.2147***	-0.2073***	-0.1654***	-0.1429***	-0.2072***	-0.1670***	-0.2206***	-0.1929***	-0.1964***	-0.2006***	-0.1598***	-0.2089***	-0.1821***	-0.1762***	-0.0628**
	(-4.54)	(-4.49)	(-3.92)	(-4.20)	(-4.28)	(-4.61)	(-5.08)	(-5.91)	(-3.95)	(-4.07)	(-5.67)	(-4.53)	(-4.48)	(-3.54)	(-2.01)
R^2	0.037	0.040	0.051	0.051	0.045	0.048	0.051	0.067	0.054	0.062	0.059	0.045	0.053	0.056	0.176

Low Sentiment

	(1)	(2) IO	(3) Size	(4) IdV	(5) Illiq	(6) MAX	(7) STR	(8) Beta	(9) BM	(10) Mom	(11) Vliq	(12) AFD	(13) Turn	(14) DRisk	(15) Full
IDISP	-0.0573	-0.0579	-0.0607	-0.0650	-0.0427	-0.0726	-0.0466	-0.0746	-0.0523	-0.0593	-0.0987*	-0.0490	-0.0774	-0.0384	-0.0457
	(-0.86)	(-0.87)	(-1.10)	(-1.19)	(-0.67)	(-1.28)	(-0.68)	(-1.52)	(-0.79)	(-0.97)	(-1.72)	(-0.76)	(-1.35)	(-0.59)	(-1.32)
R^2	0.027	0.029	0.036	0.033	0.033	0.034	0.039	0.057	0.042	0.045	0.038	0.034	0.036	0.045	0.150

Difference test (High-Low Sentiment)

	(1)	(2) IO	(3) Size	(4) IdV	(5) Illiq	(6) MAX	(7) STR	(8) Beta	(9) BM	(10) Mom	(11) Vliq	(12) AFD	(13) Turn	(14) DRisk	(15) Full
p-value	0.056	0.067	0.133	0.229	0.041	0.162	0.033	0.047	0.084	0.074	0.341	0.044	0.137	0.095	0.715

Table 9: IDISP and Investor Sentiment (continued)

Option-related Characteristics

High Sentiment

	(1) RNS	(2) RNK	(3) VolSpr	(4) QSkew	(5) VS	(6) O/S	(7) InnCall	(8) InnPut	(9) VoV	(10) OVlm	(11) Full
IDISP	-0.2146***	-0.1998***	-0.2115***	-0.2026***	-0.2058***	-0.2128***	-0.2083***	-0.2086***	-0.2203***	-0.2094***	-0.1424***
	(-4.59)	(-4.46)	(-4.63)	(-4.36)	(-4.30)	(-4.48)	(-4.53)	(-4.47)	(-3.93)	(-4.39)	(-3.46)
R^2	0.042	0.045	0.042	0.041	0.041	0.040	0.044	0.043	0.048	0.042	0.100

Low Sentiment

	(1) RNS	(2) RNK	(3) VolSpr	(4) QSkew	(5) VS	(6) O/S	(7) InnCall	(8) InnPut	(9) VoV	(10) OVlm	(11) Full
IDISP	-0.0586	-0.0706	-0.0530	-0.0437	-0.0364	-0.0531	-0.0527	-0.0476	0.0153	-0.0570	0.0024
	(-0.90)	(-1.17)	(-0.80)	(-0.66)	(-0.56)	(-0.79)	(-0.80)	(-0.73)	(0.22)	(-0.85)	(0.05)
R^2	0.030	0.033	0.033	0.031	0.032	0.031	0.033	0.033	0.032	0.031	0.081

Difference test (High-Low Sentiment)

	(1) RNS	(2) RNK	(3) VolSpr	(4) QSkew	(5) VS	(6) O/S	(7) InnCall	(8) InnPut	(9) VoV	(10) OVlm	(11) Full
p-value	0.052	0.087	0.050	0.050	0.037	0.054	0.054	0.047	0.009	0.066	0.019

Table 10: The IDISP Measure with Signed Volume

This table reports the average IDISP estimates as well as average equal- and value-weighted monthly returns and alphas for decile portfolios sorted on the individual stock options dispersion (IDISP) measure (in ascending order from decile 1, low IDISP to decile 10, high IDISP) over the sample period from May 2005 to September 2015. IDISP is the monthly average dispersion of signed individual stock options trading volume across moneyness levels, where we utilize only trading volume of buyer-initiated out-of-the-money options and seller-initiated in-the-money options. For each decile portfolio, we report average equal- and value-weighted monthly returns in excess of the risk-free rate (R) and alphas from the Carhart four-factor model ($C4\alpha$) and the Carhart four-factor model augmented by the Pastor and Stambaugh liquidity factor ($C4PS\alpha$). The $H-L$ column reports the difference in IDISP as well as in raw returns and alphas between the high IDISP portfolio and the low IDISP portfolio. Column 13 ("t-stat") reports corresponding Newey-West adjusted t-statistics (with six lags). *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. All raw and risk-adjusted returns are expressed as percentages.

Portfolio	Low IDISP	2	3	4	5	6	7	8	9	High IDISP	$H-L$	t-stat
Average IDISP												
	0.026	0.034	0.039	0.044	0.050	0.055	0.062	0.071	0.085	0.128	0.10***	(18.41)
Equal-Weighted Results												
R	0.96	0.62	0.80	0.69	0.81	0.71	0.50	0.75	0.12	-0.32	-1.28**	(-2.12)
$C4\alpha$	0.36	-0.05	0.08	-0.08	-0.01	-0.17	-0.44	-0.22	-0.89	-1.30	-1.66***	(-5.74)
$C4PS\alpha$	0.36	-0.06	0.06	-0.12	-0.03	-0.23	-0.49	-0.27	-0.94	-1.30	-1.66***	(-5.74)
Value-Weighted Results												
R	0.87	0.53	0.81	0.46	0.37	0.41	0.87	0.96	0.62	-0.35	-1.21*	(-1.77)
$C4\alpha$	0.35	-0.05	0.19	-0.21	-0.35	-0.40	0.03	0.06	-0.38	-1.31	-1.66***	(-4.80)
$C4PS\alpha$	0.36	-0.02	0.20	-0.23	-0.35	-0.45	0.02	0.04	-0.38	-1.31	-1.67***	(-4.99)

Table 11: Alternative IDISP Specifications

This table reports the average equal-weighted monthly returns of portfolios with the lowest (Low IDISP) and highest (High IDISP) IDISP, as well as the average returns ($H-L$) and alphas ($C4\alpha$ and $C4PS\alpha$) of a strategy that buys the high IDISP portfolio and sells the low IDISP portfolio over the sample period from January 1996 to September 2015. We use nine alternative IDISP specifications. IDISP1 is the standard deviation measure of individual stock options trading volume across moneyness levels. IDISP2 and IDISP3 are mean absolute and standard deviation measures respectively, of individual stock options trading volume across strike prices (rather than moneyness), scaled by the volume-weighted average strike. IDISP4 and IDISP5 are similar to the original IDISP measure and IDISP1 respectively, but we use an alternative filtering criterion that requires at least ten days of non-missing IDISP values within a month. IDISP6 and IDISP7 are similar to the original IDISP measure and IDISP1 respectively, but we include near-the-money options in calculating the measures. IDISP8 and IDISP9 are similar to the original IDISP measure and IDISP1 respectively, but measured at the penultimate day of a month (instead of averaged within a month excluding the last trading day). Newey-West adjusted (with six lags) t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. All raw and risk-adjusted returns are expressed as percentages.

	IDISP1	IDISP2	IDISP3	IDISP4	IDISP5	IDISP6	IDISP7	IDISP8	IDISP9
Low IDISP	0.98	0.98	0.98	0.92	0.91	0.94	0.91	0.89	0.83
	(3.36)	(3.29)	(3.38)	(3.22)	(3.37)	(3.39)	(3.31)	(2.27)	(2.32)
High IDISP	-0.55	-0.33	-0.45	-0.68	-0.60	-0.45	-0.45	-0.32	-0.51
	(-0.80)	(-0.46)	(-0.63)	(-0.94)	(-0.84)	(-0.65)	(-0.64)	(-0.47)	(-0.76)
$H-L$	-1.53***	-1.32**	-1.44**	-1.60***	-1.51**	-1.39**	-1.36**	-1.21***	-1.34***
	(-2.85)	(-2.38)	(-2.50)	(-2.73)	(-2.58)	(-2.53)	(-2.45)	(-3.03)	(-3.23)
$C4\alpha$	-1.65***	-1.47***	-1.59***	-1.72***	-1.63***	-1.57***	-1.54***	-1.22***	-1.35***
	(-5.21)	(-4.56)	(-4.95)	(-4.71)	(-4.33)	(-5.36)	(-5.02)	(-4.57)	(-4.82)
$C4PS\alpha$	-1.58***	-1.35***	-1.48***	-1.63***	-1.55***	-1.49***	-1.48***	-1.15***	-1.29***
	(-4.94)	(-4.18)	(-4.65)	(-4.38)	(-4.09)	(-5.07)	(-4.86)	(-4.44)	(-4.67)

Table 12: Long-term Performance of IDISP Portfolios

This table reports the long-term performance results of a strategy that buys the high IDISP portfolio and sells the low IDISP portfolio. IDISP is the monthly dispersion of individual stock options trading volume across moneyness levels. Each month, we sort stocks in ascending order into decile portfolios on the basis of IDISP (from decile 1, low IDISP to decile 10, high IDISP) and form a long-short IDISP portfolio holding this position for T months, where T is equal to two (2m), three (3m), four (4m), five (5m), six (6m), nine (9m), and twelve (12m) months, while at the same time closing out the previously-initiated positions that expire. For each investment horizon, we estimate average equal-weighted raw returns ($H-L$), alphas from the Carhart four-factor model ($C4\alpha$) and alphas from the Carhart four-factor model augmented by the Pastor and Stambaugh liquidity factor ($C4PS\alpha$). Newey-West adjusted (with six lags) t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. All raw and risk-adjusted returns are expressed as percentages.

	2m	3m	4m	5m	6m	9m	12m
$H-L$	-1.39***	-1.26**	-1.22**	-1.17**	-1.11**	-0.93*	-0.88*
	(-2.64)	(-2.42)	(-2.34)	(-2.26)	(-2.09)	(-1.76)	(-1.68)
$C4\alpha$	-1.50***	-1.33***	-1.27***	-1.19***	-1.09***	-0.91**	-0.87**
	(-4.76)	(-4.34)	(-4.25)	(-3.78)	(-3.32)	(-2.52)	(-2.44)
$C4PS\alpha$	-1.42***	-1.27***	-1.22***	-1.14***	-1.05***	-0.87**	-0.84**
	(-4.51)	(-4.21)	(-4.18)	(-3.82)	(-3.36)	(-2.56)	(-2.49)