Differences in Expectations and the Cross Section of Stock Returns*

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This draft: January 2016

Abstract

This paper constructs a new firm-level measure for differences in expectations (DiE) about future stock returns, which is obtained from the dispersion of equity options trading volume across strike prices. We demonstrate that stocks with higher differences in expectations consistently earn lower returns, with high DiE firms underperforming low DiE firms by 1.25 percent per month. Moreover, the relationship is more pronounced for small, illiquid, value, short-sale constrained, more volatile, lottery-type stocks and is the strongest following high sentiment times. We further show that the DiE effect cannot be subsumed by previously documented cross-sectional return predictors and is distinct to the effect of the dispersion in analysts' forecasts.

JEL Classification: G10, G11, G12, G14

Keywords: Dispersion of beliefs; Heterogeneity; Cross Section of Stock Returns; Equity options; Trading volume

*We would like to thank Yakov Amihud, Anurag Banerjee, Jie Cao, Ray Chou, Piet Sercu and participants at Durham Finance workshop 2014, Spring 2015 Multinational Finance Society, and 2015 OptionMetrics Research conference for helpful comments. All errors are our own responsibility.

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1 Introduction

The bet-like nature of option payoffs combined with the embedded leverage make options an ideal instrument for traders with clear expectations about the future direction of the underlying asset price. Motivated by this, a series of recent papers (Pan and Poteshman, 2006; Han, 2008; Johnson and So, 2012; Chen, Joslin and Ni, 2015) assume that options trading reflects investors' expectations and hence they construct measures of aggregate investors' beliefs that are based on the trading activity in the options market. While prior literature has exploited the information incorporated in the options trading volume and open interest of different classes of options, the information embedded in the exact strike price at which the trades take place is rather unexplored. Andreou, Kagkadis, Maio and Philip (2015) use volume information across strike prices to measure market-wide differences in opinions among options traders. However, whether this disagreement in the options market is priced in the cross section of expected stock returns remains an open question.

In this study, we propose a firm-level differences in expectations (hereafter, DiE) measure from the options market and examine its cross sectional predictability. The DiE proxy is constructed as the dispersion of trading volume across different strike prices. Our proposed measure is motivated by the notion that the selected strike prices reflect traders' expected stock returns. The rationale is that options end-users engage in different trading strategies with market makers based on their views about the future asset price and the expected payoffs from such strategies are intrinsically reflected in the strike prices at which transactions occur. For example, investors with more optimistic views will purchase deeper out-of-the-money (OTM) call options since contracts with higher strike prices have lower premium and higher leverage whereas less optimistic traders will invest in sufficiently low strikes to guarantee positive profits from a small upward price movement. Alternatively, optimistic investors with more positive expectations can sell deep in-the-money (ITM) put contracts to benefit from higher premium, while less optimistic agents will select less ITM put options to ensure that contracts expire worthless. Moreover, due to put-call parity, the payoffs from the above strategies can be replicated by purchasing ITM put contracts (selling OTM call contracts), along with a long position in the underlying asset and a short position in the risk-free asset. By utilizing a similar argument, pessimistic investors can also reveal their views via options trades at certain strike prices, for example trading at ITM calls or OTM puts.[1] Overall, the above arguments suggest that the selected strike prices at which different trades are implemented will reveal the positive and negative views of options traders about expected asset payoffs. Hence, using the dispersion in volume across strikes will naturally reflect the divergence in opinions among options market participants.

The existing literature on opinion dispersion measures can be classified into two major categories. The first group includes studies that use trading volume or traders' holdings information to capture differences in beliefs. For example, Goetzmann and Massa (2005) construct an opinion dispersion index using investors' trading account information. Chen, Hong and Stein (2002) and Jiang and Sun (2014) estimate a proxy of disagreement from active portfolio holdings across mutual funds. Garfinkel and Sokobin (2006) and Garfinkel (2009) create a measure of diverse beliefs from trading volume that is not attributable to liquidity or informedness effects. Sarkar and Schwartz (2009) compute a sidedness measure based on buyer- and seller-initiated trades. The second category represents a series of papers which explore the information content of dispersion variables based on the predictions of professional forecasters (Diether, Malloy and Scherbina, 2002; Park, 2005; Anderson, Ghysels and Juergens, 2009; Yu, 2011; Choy and Wei, 2012; Carlin, Longstaff and Matoba, 2014).

Compared to previously constructed measures, our proposed differences in expectations proxy exhibits several advantageous properties. First, unlike survey-type proxies that represent only a restricted subset of opinions, our measure emerges directly from the transactions in the options market which represents a perfect venue for a massive pool of investors to explicitly express their opinions. Second, most of the divergence proxies that are based on forecasts are influenced by uncertainty, herding and close-to-earnings-expectations biases (see, for example, Trueman, 1994; Barron et al., 1998; De Bondt and Forbes, 1999; Doukas, Kim and Pantzalis, 2006) and are mainly related to earnings or firm-specific information. On the contrary, DiE measure is unlikely to be affected by such biases and directly relates to expected stock payoffs. Third, unlike dispersion proxies that rely on aggregate volume or portfolio holdings data, our measure can equally incorporate

[1] If investors with positive or negative opinions prefer to exploit more complex trading strategies such as bull/bear call/put spreads, backspreads or butterfly spreads, then the selected strikes of the different combinations of put-call pairs will ultimately reflect the traders' expected asset payoffs since the aggregate expectations expressed by complicated strategies can be seen as a composition of different beliefs implied by single strikes at which simple put/call contracts are traded.

different levels of both optimistic and pessimistic expectations. Finally, in comparison to forecasts that are typically released monthly or quarterly, our measure is easily computable at any frequency and benefits traders with direct access to the information about the belief dispersion level for any optioned stock at any time.

Based on the estimated proxy for differences of traders' opinions, we document that stocks with higher differences in expectations earn considerably lower returns. Portfolio-level analysis indicates that firms sorted into the highest DiE decile underperform otherwise similar firms in the lowest DiE decile by 1.25% per month (15% per annum) for equally-weighted returns and by 0.87% per month (10.44% per annum) for value-weighted returns. After adjusting for asset pricing risk factors, the equally-weighted (value-weighted) return differential between highest and lowest DiE stocks remains highly significant and more than 1.23% (0.89%) per month in absolute terms.

The finding that DiE is negatively priced in the cross section of stock returns is consistent with Miller's (1977) hypothesis and is also documented by other studies such as Diether, Malloy and Scherbina (2002), Chen, Hong and Stein (2002), Goetzmann and Massa (2005) and Boehme, Danielsen and Sorescu (2006), among others. The notion of negative DiE-return relationship implies that differences in expectations are priced at a premium in a sense that investors appear to pay extra money for holding more dispersed stocks thus earning a negative premium for risk. Miller (1977), Harrison and Kreps (1978), Morris (1996) and Scheinkman and Xiong (2003), in static and dynamic theoretical frameworks, suggest that binding short-sale constraints in the presence of high differences of beliefs prevent pessimistic agents from revealing their negative valuations and the equilibrium price will exhibit an upward bias leading to lower subsequent returns. Consequently, due to limited market participation, optimists hold overvalued stocks and high differences in expectations are associated with negative risk premium. We empirically support this hypothesis by showing that the return forecasting power of dispersion in beliefs is the strongest for stocks that have lower level of residual institutional ownership i.e. higher short-sale costs.

Further, we examine the characteristics of stocks with various levels of differences in expectations and explore the economic nature of the DiE effect. The results provide several important implications for the cross section of expected stock returns. First, we observe that high DiE firms have high beta and are highly volatile implying a generally greater level of risk or uncertainty. High dispersion stocks are also past losers, small, illiquid, incur higher short-sale costs and exhibit lottery-type characteristics in the sense that they tend to experience extreme returns. Second, we establish that the underperformance of high DiE relative to low DiE stocks is the strongest for firms with small market capitalization, high volatility and low liquidity implying that abnormally low returns of high DiE stocks are particularly pronounced when limits to arbitrage are assumed to be high (see, for instance, Pontiff, 2006; Gromb and Vayanos, 2010; Conrad, Kapadia and Xing, 2015; Stambaugh, Yu and Yuan, 2015).[2] Third, we document a more evident dispersion effect for stocks that are prone to lottery-like payoffs i.e. stocks with a small chance of extreme positive or negative return over the past month. Fourth, this paper reports that high dispersion stocks underperform more significantly low dispersion stocks when they are also value firms. Overall, these findings can be explained by high arbitrage risk of the stocks with above characteristics. In particular, highly divergent stocks become overpriced since optimists bid the prices up, pessimists' views are restricted due to short-sale constraints and price-correcting positions of arbitrageurs for the stocks with aforementioned characteristics involve too high arbitrage risk that cannot be perfectly hedged leading to the difficulty in arbitraging the DiE effect away. Moreover, De Long et al. (1990), Edelen, Kalec and Ince (2014) show that arbitrageurs perceiving an overpricing are more likely to execute contrary-to-arbitrage trades i.e. buy high DiE stocks and sell low DiE stocks, thus contributing more to mispricing of highly dispersed stocks.

Finally, we test the robustness of DiE in the portfolio, component-based as well as two-stage regression settings and find that its predictability for expected returns remains strongly significant after both simultaneous and sequential inclusion of other factors such as beta, momentum, risk-neutral skewness, volatility spread, etc. We also establish the sentiment-driven nature of DiE effect and document a strong return predictability following high sentiment times. The additional comparative analysis of DiE and analysts' forecast dispersion concludes that the cross-sectional effects of both opinion-divergence proxies are robust to each other, hence the informational content of our DiE measure for future returns is distinct from that of forecast dispersion.

Our findings contribute to the existing literature in several ways. First, to the best of our knowledge, this is the first paper that investigates the role of differences of beliefs

[2] The results on idiosyncratic volatility are suppressed as they are quantitatively similar to the ones obtained from total volatility.

among options traders in explaining the cross section of stock returns. Second, this study constructs an option-implied stock-level measure of differences in expectations that directly stems from options trading activity, contains a firm-specific degree of opinion divergence and is conceptually distinct from all other volume- and forecasts-based disagreement proxies. Third, we present empirical evidence supporting Miller's (1977) hypothesis using opinion dispersion stemming from the options market. In particular, opinion dispersion is priced at a premium and the negative relation between the suggested diversion in beliefs measure and future stock returns is particularly pronounced for high limits-to-arbitrage, short-sale constrained, value, illiquid, lottery-type stocks and when investor sentiment is high.

The remainder of the paper is organized as follows. Section 2 introduces the measure and describes the data used in the study. Section 3 presents the empirical results on how DiE is associated with expected returns and other firm-specific characteristics as well as reports robustness checks and two-stage regressions tests. Finally, section 4 concludes.

2 Data and Methodology

In this section, we first show how the primary variable, the differences in investors' expectations, is constructed and then, we present a description of the data and key screening criteria applied in the study.

2.1 DiE Measure Construction

In constructing a dispersion measure for the opinions reflected in the options market, we build on the notion that a high dispersion of trading volume across the range of available strike prices implies high disagreement among traders about the future underlying asset price, while a low dispersion shows that traders' expectations are rather similar. As a result, we define a firm-level DiE measure for each stock i and each month t as the volume-weighted mean absolute deviation of strike prices. For comparability of strike prices across different firms in month t, we scale a dispersion estimate by the volume-weighted average strike. As a result, we obtain the following empirical proxy for differences in expectations:

$$DiE_{i,t} = \frac{\sum_{j=1}^{K} w_j |X_j - \sum_{j=1}^{K} w_j X_j|}{\sum_{j=1}^{K} w_j X_j} \tag{1}$$

where w_j is a proportion of trading volume attached to strike price X_j and K is the total number of available strikes.

The computational advantages of our measure of belief dispersion are fivefold. First, compared to market-wide belief dispersion estimate that is constructed by Andreou et al. (2015), a DiE proxy directly refers to firm-level information and avoids any market aggregation of divergent opinions. Second, due to a forward-looking nature of options, we capture the diverse expectations *ex ante*. Third, a DiE estimate is completely computationally-free of implied volatilities and option prices making it less prone to unreliable estimates and measurement errors. Fourth, under the assumption that options trading is driven by traders' expected asset payoffs, our DiE measure can be seen as a close approximation of a true level of opinion divergence among traders since it intrinsically aggregates the subjective beliefs of all investors who trade options. Finally, our belief dispersion proxy is not related to any accounting information, macroeconomic indicators or firm-specific characteristics, but entirely refers to stock expected returns.

2.2 Data

We obtain options data including volume, strike prices, the best bid and ask prices, open interest, delta and implied volatilities for individual stocks from Ivy DB's OptionMetrics over the sample period from January 1996 to December 2012. Additionally, we use a 30-days-to-maturity standardized volatility surface to estimate risk-neutral moments and several option-related characteristics. In the main analysis, American-style options written on stocks traded on NYSE, AMEX and NASDAQ with maturities between 5 and 60 calendar days are selected. We classify the call and put contracts into three moneyness (the ratio of strike price to the stock price) levels. A put option is called in-the-money (ITM) if the strike-spot ratio is between 1.05 and 1.20 and out-of-the-money (OTM) if the ratio lies between 0.8 and 0.95. A call option is defined as ITM if the strike-spot ratio is higher than 0.8 and lower than 0.95 and OTM if the ratio is between 1.05 and 1.20. All options with moneyness between 0.95 and 1.05 are considered as at-the-money (ATM).

To construct a measure of differences in expectations, we use calls and puts series for each stock i at the end of month t. To exclude days when options are thinly traded and to avoid unreliable DiE estimates, we take only those days when there are at least four contracts with positive trading volume. Further, we discard near-the-money options (moneyness between 0.975 and 1.025) since they exhibit the highest sensitivity to volatility changes and hence their trading is more likely to be related to volatility expectations.[3]

To estimate option-related control variables, we follow a series of filtering rules similar to those imposed by Neumann and Skiadopoulos (2013). First, we remove non-standard options that do not mature on the third Friday of a month. Second, we eliminate options contracts with zero bid prices, zero open interest and missing implied volatility values. Third, we delete options with bid-ask spread exceeding 50% of the midpoint of best bid and offer to remove illiquid contracts. Finally, we retain only those options that have implied volatility values in a range between 3% and 200%.

The data on monthly closing prices, stock returns, shares outstanding, trading volume is obtained from CRSP. We use this information to compute firm-specific characteristics that are used in bivariate portfolio-level analysis and robustness tests. From the entire universe of securities, we select ordinary shares only (share codes 10 and 11), exclude closed-end funds and REITs, and deal with stocks listed on NYSE, AMEX and NASDAQ. 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, 520-584). Finally, to compute the dispersion in analysts' forecasts, we use I/B/E/S summary data file with calculated summary statistics. The detailed description of all variables constructed in the study is provided in the Appendix.

Once the stock and options data are cleaned, we select options for each stock on the one-but-last trading day of a month and match them to corresponding stock data from CRSP over the next month. 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, 2014).

Table 1 presents the coverage statistics of our sample. Specifically, we report the total yearly number of firms for which we can obtain DiE estimates and that survives our screening criteria. Additionally, we compute the yearly average of monthly mean, median, 25^{th}

[3] Our results are quantitatively similar with the DiE measure that is estimated from the full set of available options.

and 75^{th} percentile values of DiE measure. First, we find that the number of firms with sufficient trading activity to produce DiE estimates increases during the times of economic recessions in 2001 and 2007-2009. Second, the average and median DiE estimates tend to escalate around the periods of market turbulence. For instance, before 2001-2002 "Dot-com bubble" and "2008-2009 recession period", the average and 75^{th} percentile are highest across all years reaching the values of 0.115 and 0.147 in 2000 and 0.107 and 0.134 in 2008, respectively. Low levels of DiE are documented during the economic recovery periods.

Figure 1 shows a time-series plot of yearly averages of DiE estimates across twelve industries based on Fama and French classification. Each month, we sort stocks into twelve industries and compute monthly means of DiE values for each industry. Next, we average monthly mean values for each year and each industry. The graph illustrates that differences in expectations are especially high for HiTech industry during "Dotcom" bubble in 2001-2002 and for Money and Finance industry during "2008-2009 recession period". For all other industries, investors' expectations also simultaneously diverge during market downturns and relatively converge during the normal times. This figure clearly demonstrates that a DiE proxy seems to effectively incapsulate the traders' opinions about expected stock returns in those industries that are excessively turbulent during market declines.

3 DiE and Expected Stock Returns

In this section, we examine the characteristics of DiE portfolios and investigate the DiE-return relation using both portfolio-level and regression approaches. Finally, we provide a comparative analysis of DiE and analysts' forecast dispersion (hereafter, AFD) effects on cross section of stock returns.

3.1 Stock Characteristics Analysis

We begin the empirical analysis by examining the composition of high and low differences in expectations portfolios. Particularly, at the end of each month, we group stocks into ten portfolios (1-10) on the basis of DiE and compute monthly averages and median values of stock characteristics in each decile. Then, we estimate mean values of monthly averages and medians across all months in our sample. In addition to DiE estimates for each decile, we present the values of log of market capitalization (Size), total volatility (Vol), illiquidity (Illiq), book-to-market ratio (BM), maximum return over the previous month (MAX), the return over the last month (STR), institutional ownership (IO), stock beta (Beta), the return over the last eleven months (Mom), and idiosyncratic volatility (IdV).

Table 2 shows the average and median values of characteristics for each DiE decile. First, the disagreement values are almost fifteen times higher for high DiE decile (0.203 - average, 0.191 - median) compared to low DiE decile (0.014 - average, 0.013 - median). Second, high DiE stocks are much riskier both systematically (as represented by beta) and idiosyncratically (as shown by idiosyncratic volatility) compared to the stocks in the lowest DiE portfolio. For example, idiosyncratic volatility increases monotonically from the average (median) value of 37.6% (33.2%) for low DiE decile to 64.8% (61.3%) for high DiE decile. Third, high DiE stocks tend to be strongly illiquid with the mean (median) illiquidity values of 0.441 (0.067) for low DiE portfolio and 2.968 (0.363) for high DiE stocks.[4] Fourth, high-disagreement stocks are generally small-sized with the average and median values of market capitalization decreasing gradually as we increase DiE across the deciles. Fifth, high DiE stocks have a higher propensity to exhibit lottery-like payoffs since MAX is monotonically rising from low DiE to high DiE portfolio. The average (median) MAX value in low-disagreement decile is 5.6% (4.6%) whereas high DiE portfolio exhibits striking extreme return patterns reaching the average (median) MAX value of 9.9% (8.4%). Unreported results for minimum return over the past month are in line with MAX findings. Additionally, high-disagreement stocks have a negative cumulative return over the past twelve months (-5.9% - average, -4.5% - median), while a strong positive performance is demonstrated by low dispersed stocks (9.7% - average, 10.7% - median). Finally, high DiE stocks have lower level of institutional ownership. As we move from low DiE to high DiE decile, the average (median) ownership declines from 0.704 (0.731) to 0.588 (0.614). Overall, high DiE stocks are small, illiquid, riskier, value, past losers, short-sale constrained stocks and are likely to be preferred by investors with lottery-type preferences.

3.2 Univariate Portfolio-level Analysis

In this section, we examine the profitability of portfolios that are formed on the basis of firm-level differences-in-expectations measure. For each of the ten decile portfolios sorted

[4] The difference between mean and median values of illiquidity for each DiE portfolio is the highest among all characteristics suggesting that our sample is largely dominated by illiquid stocks since the time-series distribution of illiquidity is skewed to the right.

on DiE, we calculate equally-weighted and value-weighted monthly excess returns. We also test a simple trading strategy of selling lowest DiE portfolio of stocks and buying highest DiE portfolio of stocks (*H-L*). In addition to excess returns (R), we document the alphas from Fama-French Three Factor ($FF3\alpha$) and Fama-French-Carhart Four Factor ($FFC4\alpha$) regressions.

Table 3 presents the results for the time-series average of equally- and value-weighted excess returns computed for each decile and alphas from aforementioned asset pricing models. In Panel A, analyzing the profitability of each decile, it becomes clear that the decline in average excess returns is almost uniform and monotonic as DiE increases. The largest rise in disagreement levels shown from decile 9 to 10 (from 0.132 to 0.203) corresponds to the most significant drop in the average excess returns across all deciles (from 0.40% for decile 9 to -0.36% for decile 10). The identical pattern is also pronounced for alphas from three- and four-factor models. This evidence suggests that investors prefer, and are consistently paying more for, holding high DiE stocks accepting lower future returns. The results on average profitability indicate that stocks in the highest firm-level DiE portfolio earn -0.36% per month in excess of risk free rate (-4.32% annually) whereas the lowest DiE portfolio generates a monthly profit of 0.89% which is equivalent to 10.68% on an annual basis. The trading strategy of buying highest and selling lowest DiE stocks results in an economically large and statistically significant monthly return of -1.25% (-15% annually). Alphas from two asset pricing models further show strong underperformance patterns of high DiE stocks compared to the portfolio of low DiE stocks which are unlikely to be driven by market, size, value or momentum factors. For example, the three-factor alpha difference between the high DiE and low DiE deciles is -1.55% per month with t-statistic of -4.84 whereas four-factor alpha differential is -1.23% per month with t-statistic -3.54. These findings validate our hypothesis that high DiE stocks exhibit more overpricing indicating that differences in expectations are priced at a premium.

Panel B reports the findings for the value-weighted average monthly excess returns of each DiE decile portfolio. The underperformance patterns of High DiE firms compared to the otherwise similar stocks are also preserved in case of value-weighted returns. The lowest DiE portfolio benefits investors with a monthly return of 0.61% (7.32% per annum) in excess of risk free rate per month, whereas the highest DiE stocks earn -0.26% per month (3.12% per annum). The High-Low portfolio generates an economically substantial and statistically significant loss of -0.87% per month (with t-statistics -1.66). When we control for systematic risk factors, high DiE stocks still earn considerably lower returns than low DiE stocks and this evidence remains to be both economically and statistically significant, with alpha differentials varying from -1.13% (with t-statistic of -3.14) to -0.89% (with t-statistic of -2.31) per month. Overall, our findings suggest that a negative DiE-return relation is both economically and statistically significant (in case of both equally- and value-weighted portfolios) and is robust to market, size, value, and momentum factors.

The notion that investors may hold overpriced high DiE stocks and earn lower subsequent returns can presumably be attributed to the persistency of different levels of dispersion in beliefs across time and firms. Figure 2 examines this issue by presenting the time-series average of monthly mean DiE values for each of five quantile portfolios eleven months before and eleven months after portfolio formation.[5] The results clearly indicate that the cross-sectional dispersion in DiE is fairly flat, with the highest DiE value observed at the time of portfolio formation, and portfolio sortings exhibit striking persistent patterns both in the months before and after portfolio construction, with clear differences between DiE portfolios. For example, the average DiE in Quantile 5 varies from 0.10 to 0.11 before and after portfolio formation with a large spike at 0.17 at time zero, whereas low DiE portfolio shows even less variation over time with a big drop to 0.025 in the month when portfolios are created.

3.3 Bivariate Portfolio-level Analysis

In this section, we investigate the economic origin of a negative firm-level disagreement effect across seven stock-related characteristics. In particular, we examine the profitability of high dispersed relative to low dispersed stocks among small (Size), more volatile (Vol), illiquid (Illiq), value (BM), lottery-type (MAX, STR) and short-sale constrained (IO) firms. To this end, we perform a bivariate portfolio-level analysis where each month stocks are firstly sorted into five quantile portfolios on the basis of a certain characteristic and then, within each characteristic category, the stocks are further sorted into five portfolios based on differences in expectations. Next, for the resulting twenty five portfolios at the end of each month t, we obtain average monthly excess returns and present a time-series average of these figures over all months in our sample. In addition, we show the average returns on the trading strategy that buys high DiE stocks and sells low DiE stocks, compute Newey-West corrected t-statistic and estimate alpha differentials between high

[5]Our results are quantitatively similar when we use decile portfolios.

DiE portfolio and low DiE portfolio from Fama-French Three Factor (*FF3α*) and Fama-French-Carhart Four Factor (*FFC4α*) regressions.

Table 4 reports the results. Panel (a) starts the analysis with examining the predictive power of differences in expectations in the presence of short-sale constraints. In particular, we proxy the cost of short-selling using the level of residual institutional ownership (IO) after accounting for size effects in cross-sectional regression setting. Intuitively, the higher the short-sale costs, the lower the supply for loanable shares (Nagel, 2005), hence the lower the level of institutional ownership. Empirically, we show that high DiE stocks underperform low DiE stocks by 1.98% per month (with t-statistic of -3.01) if these stocks have lower level of IO whereas the return differential between high DiE and low DiE stocks is 0.41% per month (with t-statistic of 0.98) for high IO firms. When controlling for risk factors, both three- and four-factor models demonstrate significant underperformance patterns of high DiE compared to low DiE stocks given a low level of institutional ownership. Overall, our results provide supportive empirical evidence for Miller (1977) hypothesis that higher differences in beliefs lead to lower subsequent returns for stocks that experience higher short-sale costs.

Next, Panels (b), (c) and (d) examine whether the underperformance of high DiE relative to low DiE stocks is more evident for small, more volatile and less liquid companies.[6] First, small and high (low) disagreement stocks earn -0.96% (0.79%) per month, while large and high (low) DiE firms exhibit a positive monthly return of 0.69% (0.59%). It becomes clear that the dispersion effect is more pronounced for small-sized firms, with statistically significant negative returns of higher magnitude on H-L portfolio for low Size firms (-1.75% per month with t-statistic of -3.77) compared to high Size firms (0.10% per month with t-statistic of 0.25). Second, the negative profitability of high DiE compared to low DiE firms is more preserved for highly volatile stocks. The return differential between high DiE and low DiE stocks is 0.10% (with t-statistic of 0.63) for low Vol firms relative to -1.39% (with t-statistic of -2.62) for high Vol firms. Third, constructing Amihud illiquidity measure, we document that the return spread between high DiE and low DiE portfolios has a larger economic magnitude for high Illiq stocks (-1.51% per month with t-statistic of -2.62) relative to low Illiq stocks (-0.18% per month with t-statistic of -0.41). Addi-

[6]We use total volatility in main analysis because both fundamental and idiosyncratic volatility is less likely to be hedged, hence both types of risk matter for investors (Shleifer and Vishny, 1997; Gromb and Vayanos, 2010).

tionally, as we decrease the size of the firms, increase volatility and decrease liquidity, the underperformance of high DiE relative to low DiE stocks becomes more statistically significant and economically large. Furthermore, after controlling for standard risk factors, the alphas spread for H-L portfolio remains more economically pronounced for low Size, high Vol and high Illiq firms. For instance, four-alpha model shows that the abnormal return on H-L DiE portfolio is -1.68% with t-statistic of -4.03 (-1.25% with t-statistic of -2.05) per month for low Size (high Vol) stocks whereas the monthly return differential between high-disagreement and low-disagreement stocks is 0.06% with t-statistic of 0.24 (0.05% with t-statistic of 0.30) for high Size (low Vol) firms. At the same time, the monthly abnormal return on H-L portfolio is -0.13% (with t-statistic of -0.44) for low Illiq quantile whereas the alpha spread between high and low DiE portfolios is -1.35% per month (with t-statistic of -2.26) for high Illiq stocks.

These findings can be explained by the notion that small, highly volatile and less liquid firms tend to exhibit higher limits to arbitrage. These stocks are less likely to be held in arbitrageur's portfolio since the potential profit from arbitrage strategy incurs too high both fundamental and arbitrage risk that cannot be perfectly hedged due to too few close substitutes and that lowers the reward-to-risk ratio forcing arbitrageurs to close the position with losses. Given that rational agents are expected to provide liquidity to the market thus mitigating the "Miller effect" of a big price rise, limits to arbitrage imply that the abnormally low returns to buying high DiE stocks tend to be more pronounced for less liquid firms since DiE effect and overpricing continue to exist.

Additionally, Panels (e) and (f) explore the lottery-type characteristics of stocks for which the dispersion effect is more evident. First, the firms in high DiE quantile underperform the similar firms in low DiE quantile by -1.64% per month with t-statistic of -3.04 for high MAX stocks whereas the monthly return spread between high and low DiE firms is 0.35% with t-statistic of 1.41 for low MAX stocks. This evidence is further supported when we account for risk factors. The alpha differentials between high-disagreement and low-disagreement firms remain economically large and statistically significant for high MAX relative to low MAX stocks. Unreported findings for stocks that are prone to extreme negative return also reveal that the dispersion effect is the strongest for high MIN firms. Second, to underpin above findings, we examine the relationship between short-term reversal (STR) and the DiE effect. The underperformance patterns of high DiE stocks compared to low DiE stocks are equally pronounced for low STR and high STR quantiles.

The return on H-L DiE portfolio of low STR stocks is -1.77% (with t-statistic of -4.05) whereas high DiE stocks underperform low DiE stocks by 1.28% (with t-statistic of -2.69) if these stocks have a high STR. These findings are robust to systematic risk factors and further support evidence that the DiE effect is more preserved for stocks with a small chance of extreme returns (either negative or positive) over the last month. There exists a dual interpretation of above results. Lottery-type stocks tend to exhibit a high arbitrage risk leading to deterrence of arbitrage activity and persistent overpricing in such stocks (Conrad, Kapadia and Xing, 2014). On the other hand, overpricing that is partly caused by high demand of optimistic agents who hold high DiE stocks is more dominant for firms with lottery-type characteristics because optimism tends to generate a preference for skewed and lottery-like payoffs among irrational agents (Brunnermeier, Gollier and Parker, 2007; Conrad, Kapadia and Xing, 2014; Avramov, Cheng and Hameed, 2015).

Finally, the analysis of a negative profitability of high disagreement stocks among different book-to-market ratios is presented in Panel (g). We report that high DiE stocks underperform low DiE stocks more strongly for high BM ratios (-1.08% with t-statistic of -2.33) compared to low BM ratios (-0.67% with t-statistic of -1.46). This evidence suggests that value stocks exhibit a more pronounced DiE effect relative to growth stocks. Furthermore, after adjusting for canonical risk factors, the alpha differential between high DiE and low DiE firms is more evident for value than for growth stocks. For example, four-factor model demonstrates that high BM stocks in the H-L DiE portfolio earn consistently lower returns (-1.06% with t-statistic of -2.55) than low BM stocks in the same DiE portfolio (-0.71% with t-statistic of -1.75). Overall, a possible explanation for this result can be related to the assertion of Zhang (2005) that value stocks are riskier than growth stocks during recessions. In such a case, this additional source of risk makes it difficult for arbitrageurs to profitably exploit the overpricing especially during turbulent periods.

3.4 Controlling for Other Cross-Sectional Characteristics

This section presents bivariate portfolio-level sorts to verify that the DiE effect is not driven by any single option- or stock-related characteristic when we control for each of these variables sequentially. Specifically, each month we first sort stocks into ten decile portfolios based on one of the control variables. Next, within each characteristic decile, we further rank stocks into ten extra decile portfolios on the basis of DiE. As a result, we prepare one hundred portfolios at the end of month t. Finally, we compute time-series average of monthly excess returns for each of the DiE deciles across ten characteristic portfolios that are obtained from the first sort. This procedure of accounting for non-DiE effects does not involve any regression-based tests and helps to track the persistence of a negative DiE effect across all characteristic deciles. Additionally, we create a High-Low DiE portfolio which buys high DiE portfolio and sells low DiE portfolio and document the average returns (H-L) as well as the alpha differentials from Fama-French Three Factor ($FF3\alpha$) and Fama-French-Carhart Four Factor ($FFC4\alpha$) models.

Table 5 reports the results. The negative DiE-return relation remains economically and statistically robust to stock-related characteristics such as market beta (Beta), the return over the previous eleven months (Mom), idiosyncratic volatility (IdV). For instance, the trading strategy that buys high DiE stocks and sells low DiE stocks earns statistically significant and economically large average monthly returns of -0.83% when controlled for Beta, -0.85% when controlled for Mom, and -0.59% when controlled for IdV. This effect within H-L portfolio is preserved after adjusting for standard risk factors, with statistically significant monthly alpha differentials varying from -1.05% to -0.90% when controlled for Beta, from -1.06% to -0.91% when controlled for Mom, and from -0.67% to -0.49% when controlled for IdV. These results clearly reject the hypothesis that DiE can be a proxy for arbitrage costs as captured by idiosyncratic volatility or for a price continuation anomaly as identified by momentum.

Since the computation of DiE measure involves option-related information, it is conceivable that the dispersion of options volume across strike prices can capture the same effect as that of previously documented option-based return predictors. First, we control for implied moments of risk-neutral distribution i.e. skewness (RNS) and kurtosis (RNK) and find that the DiE effect is still highly pronounced generating a negative monthly return on H-L portfolio of -1.08% (RNS) and -0.85% (RNK). Second, it is possible that the DiE effect can be attributed to deviations of call-put parity or volatility spread. However, after controlling for volatility spread (VolSpr) and price pressure (VS), we notice that high DiE stocks still underperform low DiE stocks, with monthly returns of -0.88% (VolSpr) and -0.71% (VS). Both figures are highly statistically significant. Third, DiE measure can be a proxy for a particular dimension of information-based trading that is reflected in call (InnPut) and put (InnPut) volatility innovations. We reject this hypothesis since high DiE stocks exhibit strong underperformance patterns compared to otherwise similar stocks in low DiE portfolio, earning a monthly return of -0.86% when controlled for

InnCall and -0.88% when controlled for InnPut. These findings are also supported after accounting for another proxy for asymmetric information such as the option to stock trading volume (O/S) ratio. The return spread is -1.13% per month with t-statistic of -4.47. Finally, the alpha differentials across all characteristics and all asset pricing models remain economically large and statistically significant indicating that the DiE effect is not only unexplained by any of the control variables, but also is robust to canonical risk factors within each characteristic sort.

3.5 Fama-MacBeth Regressions

The portfolio-level analysis clearly demonstrates that portfolios sorted on DiE generate economically substantial profits that survive any of the control variable sorts. However, despite the non-parametric nature of portfolio analysis, this method suffers from some disadvantages. First, the aggregation of excess returns is likely to discard important information in cross section. Second, using portfolio sorts, we are able to control for one particular characteristic only, hence ignoring complex multiple effects. Hence, in this section we perform Fama and MacBeth (1973) regression tests to control for a wide range of control variables simultaneously. Specifically, for each month t, we estimate cross-sectional OLS regressions of excess stock returns in month $t+1$ on firm-level differences-in-expectations measure in month t and previously-documented return drivers in month t. Next, we compute a time-series average of coefficients from cross-sectional regressions and provide Newey-West (1987) corrected t-statistics on the basis of standard deviation of slope coefficients. To mitigate the potential effect of outliers, we winsorize each control variable at the 1^{st} and 99^{th} percentile. Table 6 presents the results classified into two groups: stock- and option-related characteristics.

In Panel (i), we estimate eleven Fama-MacBeth regressions of stock excess returns on log of market capitalization (Size), total volatility (Vol), illiquidity (Illiq), the book-to-market ratio (BM), maximum daily return over the past month (MAX), the return over the past month (STR), beta (Beta), the cumulative return over the past eleven months (Mom), and idiosyncratic volatility (IdV). The first model (1) shows a univariate regression of one-period-ahead excess stock returns on current values of firm-level DiE. The coefficient on differences in expectations is negative (-0.0821) and statistically significant (t-statistic equals to -3.26). The economic magnitude of the DiE effect is similar to those provided in double portfolio sorts. If we multiply the difference in median values between high DiE decile and low DiE decile that is about 0.18 (See Table 1) by the slope coefficient, we obtain that the monthly risk premium differential is -1.46%. When each of the potential explanatory characteristics is added to univariate regression, the coefficient on DiE remains negative and economically large ranging between -0.0908 (t-statistic of -3.78) when STR is added (Model 5) and -0.0413 (t-statistic of -3.00) when IdV is added (Model 5). When controlling for all firm-specific variables simultaneously, the coefficient on DiE is -0.0238 with t-statistic of -2.14. The coefficients on most of the control variables are significantly different from zero and exhibit a small economic magnitude.

In Panel (ii), we test whether the negative DiE effect can be explained by option-related control variables. In particular, we consider that risk-neutral skewness (RNS), risk-neutral kurtosis (RNK), volatility spread (VolSpr), OTM Skew (QSkew), the price pressure (VS), option-to-stock-volume ratio (O/S), and call and put implied volatility innovations (InnCall and InnPut) can explain DiE-return phenomenon. The coefficient on DiE is economically substantial, with the values ranging between -0.0790 with t-statistic of -3.20 when DiE is considered together with risk-neutral skewness and -0.0626 with t-statistics of -2.56 after controlling for VS. When all option-based characteristics are included into the model, the coefficient on firm-level DiE measure becomes economically smaller (-0.0419), but remains significantly different from zero (t-statistic is -2.38). Of all the option-specific characteristics, QSkew and VS tend to be important variables explaining one-period-ahead stock returns both in single and multiple asset pricing models. Overall, our findings provide a strong evidence that a DiE measure has an explanatory power for future returns, which is robust to that of a wide range of control characteristics.

3.6 Component Decomposition

Although the previous results suggest that a negative DiE effect is unlikely to be fully explained by any of stock- or option-related characteristics, monthly cross-sectional regressions remain silent on the magnitude of explanatory power of any single variable for negative DiE-return relationship. Therefore, to examine the potential candidate explanations of this relation and precisely estimate the percentages of the DiE effect that are explained and unexplained by each characteristic, we use Hou and Loh (2015) decomposition methodology. Specifically, in the first stage, we regress monthly excess returns at $t+1$ on DiE at t to obtain a time-series average of all cross-sectional slope coefficients.

$$Exret_{it+1} = \alpha_{t+1} + \beta_{t+1} \times DiE_{it} + \epsilon_{it+1} \tag{2}$$

Next, in stage 2, we run regressions of DiE_{it} on candidate variable in month t that can potentially explain the DiE effect. In order for candidate variable to capture a substantial fraction of negative DiE-return relation, we expect to document a high correlation of DiE with this explanatory variable.

$$DiE_{it} = a_t + \gamma_t \times candidate_{it} + \omega_{it} \tag{3}$$

Finally, using coefficients estimates from stage 2 and decomposing DiE_{it} into two orthogonal components ($\gamma_t \times candidate_{it}$ and $a_t + \omega_{it}$), we perform the total decomposition of estimated β_{t+1} into the percentages that are explained (β_{t+1}^{Exp}) and unexplained (β_{t+1}^{Unexp}) by the candidate variable.

$$\beta_{t+1} = \frac{Cov[Exret_{it+1}, DiE_{it}]}{Var[DiE_{it}]} = \frac{Cov[Exret_{it+1}, \gamma_t \times candidate_{it}]}{Var[DiE_{it}]} + \tag{4}$$

$$+\frac{Cov[Exret_{it+1}, a_t + \omega_{it}]}{Var[DiE_{it}]} = \beta_{t+1}^{Exp} + \beta_{t+1}^{Unexp} \tag{5}$$

Table 7 shows the results from component decomposition. All slope and intercept coefficients are statistically significant at 1% level implying a strong relationship between DiE and the candidate variable. Panel A indicates that almost none of the potential stock-related candidates are able to explain the substantial part of DiE-return relation. The strongest explanatory power is documented by idiosyncratic volatility, with about 55% of the total DiE effect being explained. Also, the relatively strong explanation candidates are Size, MAX and Vol capturing 24.6%, 31.8% and 39% of a negative DiE-return relationship, respectively. On the contrary, the characteristics such as STR and BM contribute more to the unexplained component of DiE anomaly, with overall percentages being 109.11% and 101%, respectively. Panel B reports the decomposition results for option-related variables. None of the potential candidates are likely to capture even one-fifth of the total DiE effect. The highest explanation fractions are shown by VS (15.33%), InnPut (10.53%) whereas the weakest explanatory performance is demonstrated by RNS (-4.70%), RNK (2.78%) and O/S (0.37%). Overall, our findings further suggest that a negative DiE-return relationship cannot be substantially subsumed by any of the potential explanation candidates.

3.7 DiE vs Dispersion in Analysts' Earnings Forecasts

This section performs a comparative analysis of our measure of differences in beliefs that is estimated from the options market and a well-known proxy for opinion divergence that is the dispersion in analysts' earnings forecasts (AFD). A large number of studies including Diether, Malloy and Scherbina (2002), Park (2005), Anderson, Ghysels and Juergens (2009), Yu (2011) and Choy and Wei (2012), among many others, construct forecast dispersion measures and establish its strong cross sectional return predictability. In such a case, investigating the relationship between DiE and AFD effects is of paramount importance and helps to extract the salient features of both proxies for belief dispersion in the cross section of stock returns. To this end, we perform bivariate portfolio sorts similar to those reported in Table 5 (where stocks are first grouped into ten decile portfolios based on AFD and then within each AFD portfolio, further sorted into ten extra decile portfolios on the basis of DiE), but we also carry out reverse stock rankings to examine the profitability of the AFD effect in the presence of DiE. We compute a time-series average of monthly excess returns for each of the DiE (AFD) deciles across ten AFD (DiE) portfolios and estimate alphas from three- and four-factor models. Additionally, we run regression-based tests to examine the predictive power of AFD for negative DiE-return relation. Finally, to obtain the precise percentage estimates of the total DiE (AFD) effect that can be explained and unexplained by AFD (DiE), we utilize a component decomposition methodology.

Table 7 presents three sets of results. Panel A shows two-way portfolio-level analysis and reports the average AFD values for each decile. "AFD-DiE" column reports the findings for the portfolios first sorted on AFD, then on DiE, whereas "DiE-AFD" column shows the profitability of reversely-sorted portfolios. First, it is clear that for each DiE decile portfolio, the average values of AFD exhibit almost monotonically increasing patterns as we move from low DiE (1) to high DiE (10). Second, when we control for AFD, high DiE stocks still underperform low DiE stocks by statistically significant and economically substantial 0.90% per month. This DiE effect is also robust to systematic factors as alpha spread remains significant at all conventional levels across all factor models. However, after controlling for DiE and examining the AFD effect, we establish a distinct nature of the underperformance of high AFD relative to low AFD stocks in the presence of DiE. In particular, the return spread between high AFD firms and low AFD firms is -0.84% per month with t-statistic -3.40. The alpha differentials across all models are still highly significant and economically large with the values ranging from -1.31% to -1.07% per month.

Panels B and C investigate the robustness of DiE effect to AFD in regression- and component-based settings. The results from Fama and MacBeth regressions demonstrate that the predictability of DiE for the future stock returns is economically pronounced and statistically significant before (-0.0821 with t-statistic of -3.26) and after (-0.0566 with t-statistic of -2.24) the inclusion of AFD. However, the coefficient on AFD appears to be not significantly different from zero. Finally, based on component decomposition, it can be seen that only 6.67% of the total DiE effect can be attributed to the explanatory power of AFD whereas DiE can explain about 39% of the AFD-return relationship. Overall, the comparative analysis of a negative DiE and AFD relation with future returns reveals that both effects are robust to each other indicating that DiE measure contains predictive information for stock payoffs that cannot be substantially explained by AFD.

3.8 DiE and Investor Sentiment

A negative relationship between DiE and future excess returns that originates from optimist-driven overpricing is expected to be particularly pronounced during the periods of high investor sentiment. Intuitively, traders with positive beliefs become even more optimistic at the times of high sentiment, pessimists cannot reveal their views due to short-sale impediments, and stock price exhibits more severe overpricing according to Miller (1977). A theoretical belief dispersion model of Atmaz and Basak (2015) supports this argument and establishes that, due to convexity in cash-flow news, stock price increases with dispersion of opinions in optimistic economy. In this section, we provide empirical test of above hypothesis and examine the asymmetric DiE effect during the times of high and low investor sentiment. In particular, we run monthly cross-sectional Fama-MacBeth regressions for each sentiment period. High (low) sentiment months are those when the Baker and Wurgler (2006) index in the previous month is above (below) the median value over the preceding twelve months. In the similar vein, Stambaugh, Yu and Yuan (2012), Jiang et al. (2015) discover that well-known asset pricing anomalies reflect sentiment-driven overpricing and abnormal returns are generated following the times of high investor sentiment.

Table 9 provides the results in two panels. Panel A shows the coefficient estimates from Fama-MacBeth regressions with stock- and option-related characteristics in high sentiment period, whereas Panel B presents similar findings in low sentiment months. First, looking at univariate analysis across both panels, the return predictability of DiE is shown to be more economically large and statistically significant for high sentiment (-0.062 with t-statistic -3.56) compared to low sentiment (-0.020 with t-statistic -1.01) period. Second, considering bivariate regressions, DiE has a strong negative effect on future stock returns that is robust to the inclusion of any stock- or option-related characteristic following high sentiment months. For example, DiE measure exhibits strong predictive power for stock returns at the times of high sentiment, with values varying from -0.066 (with t-statistic -3.59) when short-term reversal is added to -0.023 (with t-statistic -2.74) when idiosyncratic volatility is included, whereas it has no or a little (when volatility and beta are added) effect over the periods of low sentiment. Finally, a strong high-sentiment-driven negative relation between DiE and future stock returns persists when we perform multivariate tests. The loadings on DiE remain economically and statistically significant both in stock-related (-0.015 with t-statistic -2.08) and option-related (-0.032 with t-statistic -2.59) regressions in high sentiment times compared to the DiE coefficient in stock-related (-0.008 with t-statistic -0.99) and option-related (-0.010 with t-statistic -0.79) regressions over low sentiment period. Additionally, our results are consistent with the findings of Stambaugh, Yu and Yuan (2012, 2015) that momentum and idiosyncratic volatility anomalies are particularly strong when sentiment is high. Overall, investor sentiment analysis reveals that the DiE effect stemming from overpricing is especially pronounced following high investor sentiment.

4 Conclusion

In this paper, we explore the effect of differences in expectations in the options market on subsequent equity returns. First, given that options trading activity at specific strike prices is driven by investors' beliefs about expected returns, we explicitly show that a measure of disagreement, that is estimated from the dispersion of options trading volume across strike exhibits several attractive features. In particular, it is easy to compute, can be estimated at any frequency, and more importantly can intrinsically incorporate the different levels of both optimistic and pessimistic beliefs of a large pool of option traders. Second, our results support the Miller (1977) hypothesis that differences in expectations are associated with stock overpricing and a negative risk premium. Third, we provide evidence showing that the negative relation between differences in expectations and stock returns is more pronounced for stocks which have high limits to arbitrage, are short-sale constrained, illiquid, tend to experience extreme returns, have high book-to-market ratio, and is the strongest following high sentiment times.

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Appendix

Variables Description

This section 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. The variables abbreviation is specified in *italic* face.

Size (Banz, 1981): Firm's size is the natural logarithm of the firm's market capitalization (stock price times the number of shares outstanding in millions dollars).

Vol (Zhang, 2006): Volatility is the standard deviation of returns over the last year using weekly returns series.

Illiq (Amihud, 2002): Amihud illiquidity measure is computed as the average ratio of absolute value of daily returns to daily dollar trading volume (in $ thousands) estimated from annual rolling windows including month t. To account for inter-dealer double count, volume is divided by 2 for NASDAQ firms.

BM (Diether, Malloy and Scherbina, 2002): Book-to-market is the ratio of firm's book equity to its market capitalization. Book equity is the COMPUSTAT book value of stockholders' equity, plus investment tax credit and balance sheet deferred taxes, minus the book value of preferred stock. The book value of preferred stock is either redemption, liquidation or par value, whichever is available. Next, me match book equity ending in calendar year t - 1 with stock returns in July of year t. Finally, we divide July book equity value by market capitalization at month t - 1 to update book-to-market ratio monthly.

MAX (Bali, Cakici and Whitelaw, 2011): Maximum return is the maximum daily return over the previous month i.e. from t - 2 to t - 1.

STR (Jegadeesh, 1990; Lehmann, 1990): Short-term reversal is the stock return over the previous month i.e. from t - 2 to t - 1.

IO (Nagel, 2005): Residual institutional ownership is the residual from cross-sectional regressions of the log of institutional ownership (fraction of number of shares held by 13F institutional investors) on log of market capitalization.

Beta (Fama and MacBeth, 1973): Beta is estimated from the time-series regression of monthly excess stock returns on excess market portfolio return using prior one year of daily return data including month t on a rolling basis. The market excess return is the value-weighted return of all CRSP common stocks. The risk-free rate is proxied by Ibbotson and Associates.

Mom (Jegadeesh and Titman, 1993): Momentum is the stock cumulative return over previous eleven months i.e. the sum of log returns from t - 12 to t - 2.

IdV[7] (Ang et al., 2006): Idiosyncratic volatility is the standard deviation of the residuals from Fama-French (1993) three-factor model. We run daily time-series regressions of excess stock return on market excess return, Value-minus-Growth (HML) portfolio return, Small-minus-Big (SMB) portfolio return, and idiosyncratic stock return, which is represented by the regression error, using annual rolling window including month t. The residuals from this model are used to compute idiosyncratic volatility. Additionally, we multiply obtained daily estimates by $\sqrt{252}$ to obtain annualized figures.

RNS, RNK (Bakshi, Kapadia and Madan, 2003): Risk-neutral skewness (kurtosis) is an annualized model-free estimate of skewness (kurtosis) of risk-neutral distribution of a stock's log return from time t until the maturity day of the options.

VolSpr (Bali and Hovakimian, 2009; An et al., 2014): 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 a delta of 0.5 and maturity of 30 days.

QSkew (Xing, Zhang and Zhao, 2010): Out-of-the-money skew is defined as the difference between implied volatilities of out-of-the-money put option and the average of at-the-money call and put implied volatilities. Out-of-the-money put option has a delta of 0.2, the maturity is 30 days.

[7] Market, SMB, HML portfolio returns and risk-free rate are taken from Kenneth French website.

VS (Cremers and Weinbaum, 2010): Volatility spread or a measure of price pressure is computed as the open-interest weighted difference in implied volatilities between call options and put options (with the same strike price and maturity) across all available option pairs.

O/S (Johnson and So, 2012): Option-to-stock-trading-volume ratio is estimated as the total equity volume at month t divided by the total volume in option contracts across all strikes. The maturity is approximately 30 trading days.

InnCall, InnPut (An et al., 2014): Call (Put) implied volatility innovations are defined as monthly difference between at-the-money call (put) implied volatilities in month t and month t-1.

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

Figure 1: Average DiE across industries

This figure illustrates the yearly averages of DiE values across twelve industries based on Fama and French classification. Each month, we group stocks into twelve industries and compute average DiE values for each industry. Next, we estimate time-series yearly averages of monthly mean values over our sample period from January 1996 to December 2012. Firm-level Differences-In-Expectations ("DiE") measure is the dispersion of stock options trading volume across the strike prices scaled by the volume-weighted average strike at the end of month t. NBER recession periods and the names of all industries are presented underneath and on the right hand side of the graph, respectively.

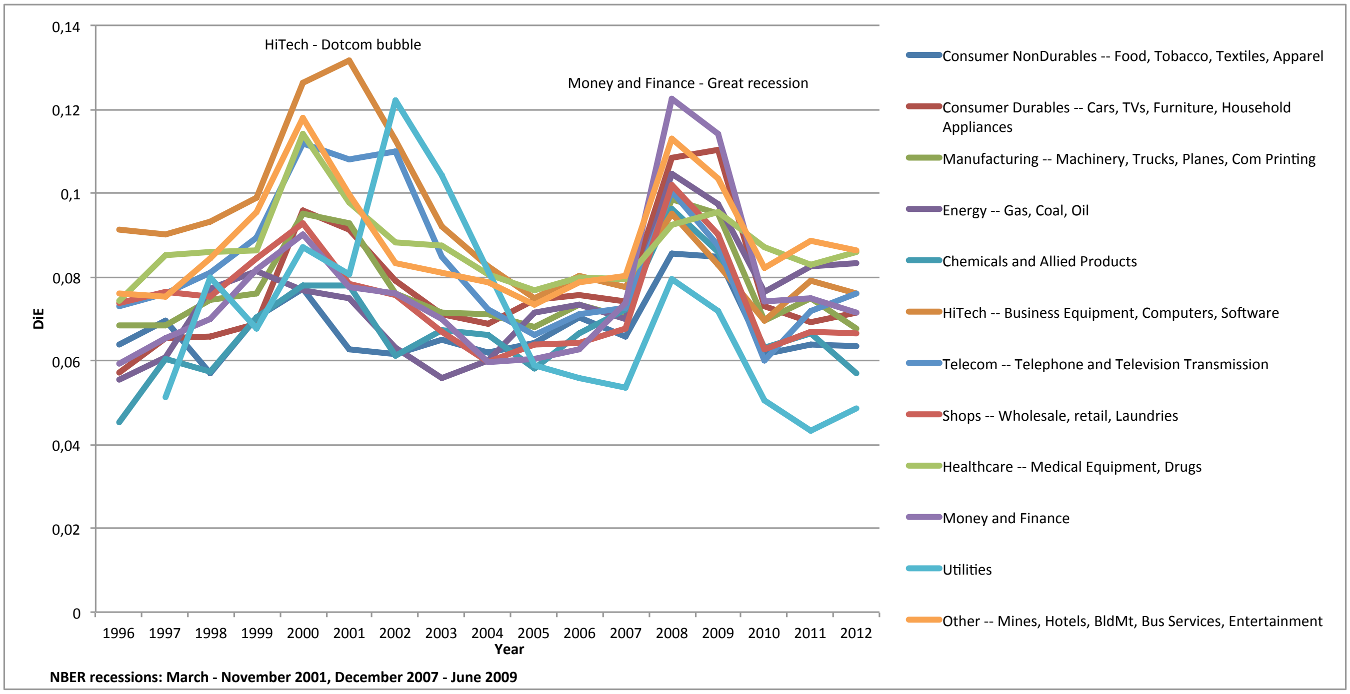

Figure 2: DiE Portfolios across months

This figure plots the time-series average of monthly mean values of DiE for each of five quantile portfolios sorted on DiE from eleven months before $(t-11)$ until eleven months $(t+11)$ after portfolio formation (time 0). Each month, we sort stocks into five quantile DiE portfolios and estimate average DiE for each portfolio each month. Our sample period is from January 1996 to December 2012. Firm-level Differences-In-Expectations ("DiE") measure is the dispersion of stock options trading volume across the strike prices scaled by the volume-weighted average strike at the end of month t.

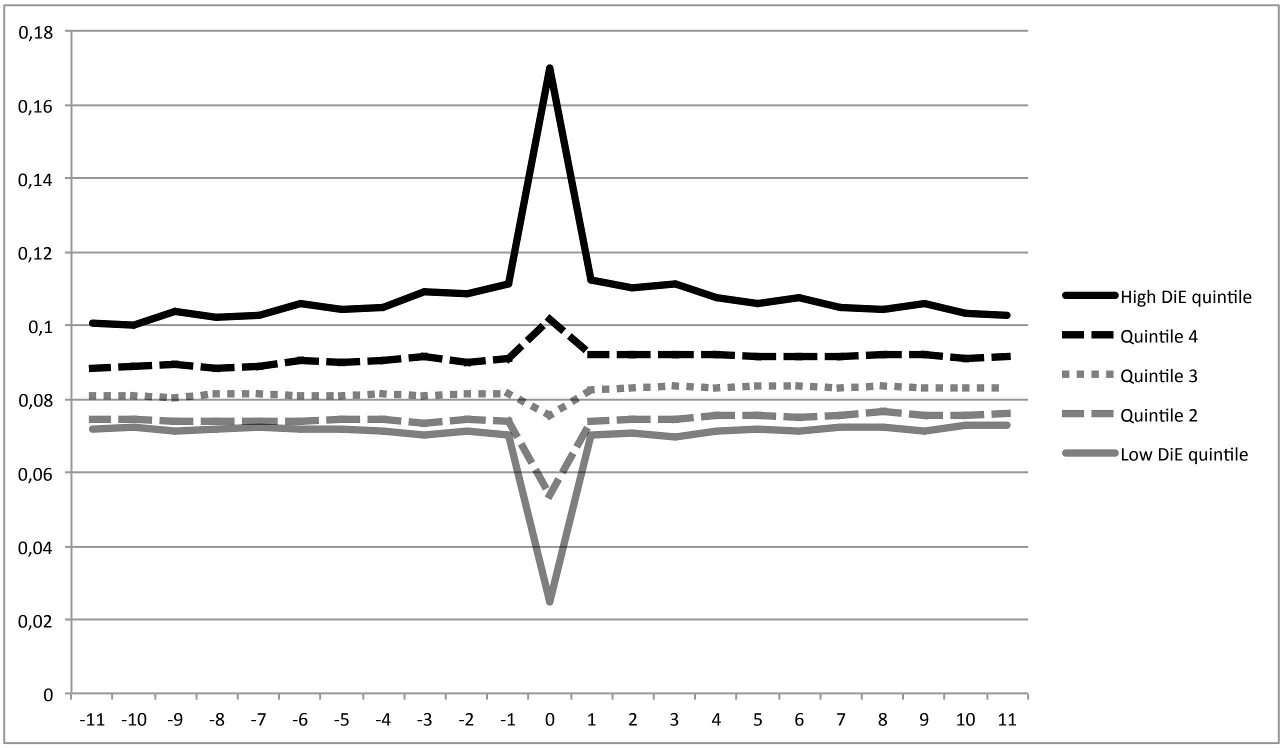

Table 1: Descriptive Statistics of DiE

This table contains the yearly coverage statistics of the optioned and differences-in-expectations ("DiE") sample over our sample period from January 1996 to December 2012. Firm-level Differences-In-Expectations ("DiE") measure is the dispersion of stock options trading volume across the strike prices scaled by the volume-weighted average strike at the end of month t. "Num. of stocks with DiE" column presents the number of firms for which we can estimate DiE measure and that survives our screening criteria. "Mean", "Median", "25^{th} perc.", and "75^{th} perc." columns report the yearly averages of monthly mean, median, 25^{th} and 75^{th} percentile values of DiE for all firms in our sample, respectively.

Year	Num. of stocks with DiE	Mean	Median	25^{th} perc.	75^{th} perc.
1996	955	0.079	0.072	0.046	0.103
1997	1240	0.079	0.070	0.046	0.101
1998	1377	0.082	0.074	0.048	0.106
1999	1527	0.091	0.082	0.054	0.116
2000	1739	0.115	0.101	0.066	0.147
2001	1418	0.102	0.087	0.054	0.132
2002	1276	0.091	0.078	0.049	0.115
2003	1294	0.079	0.069	0.044	0.101
2004	1504	0.073	0.065	0.040	0.094
2005	1627	0.070	0.061	0.038	0.090
2006	1921	0.074	0.065	0.041	0.095
2007	2211	0.075	0.066	0.042	0.095
2008	2179	0.107	0.092	0.060	0.134
2009	1909	0.092	0.079	0.052	0.114
2010	1949	0.073	0.064	0.041	0.091
2011	1969	0.079	0.068	0.045	0.098
2012	1762	0.074	0.063	0.040	0.093

Table 2: Characteristics of Portfolios sorted on DiE

This table presents mean and median values of firm-related characteristics at the end of month t for portfolios sorted on DiE over our sample period from January 1996 to December 2012. Firm-level Differences-in-Expectations ("DiE") measure is the dispersion of stock options trading volume across the strike prices scaled by the volume-weighted average strike at the end of month t. Each month we sort stocks into ten portfolios (1-10) based on DiE and calculate characteristic averages and median values across ten DiE portfolios. Panel A reports the averages of firm-related characteristics whereas Panel B provides median values. The variables description is provided in Appendix.

Panel A: Average Characteristics:

	Low DiE	2	3	4	5	6	7	8	9	High DiE
DiE	0.014	0.034	0.048	0.059	0.069	0.080	0.092	0.108	0.132	0.203
Size	15.237	15.460	15.507	15.451	15.338	15.213	15.050	14.818	14.541	13.982
Vol	0.470	0.467	0.481	0.502	0.531	0.562	0.595	0.636	0.685	0.776
Illiq	0.441	0.467	0.468	0.482	0.813	0.615	0.800	1.105	1.606	2.968
BM	0.468	0.433	0.422	0.419	0.411	0.419	0.416	0.430	0.456	0.561
MAX	0.056	0.055	0.057	0.059	0.063	0.068	0.073	0.078	0.086	0.099
STR	0.008	0.012	0.012	0.011	0.012	0.009	0.005	0.003	-0.003	-0.025
IO	0.704	0.703	0.701	0.699	0.695	0.690	0.680	0.670	0.648	0.588
Beta	1.102	1.109	1.150	1.198	1.269	1.328	1.403	1.460	1.519	1.559
Mom	0.097	0.124	0.133	0.140	0.154	0.141	0.141	0.116	0.078	-0.059
IdV	0.376	0.366	0.375	0.391	0.415	0.439	0.472	0.509	0.557	0.648

Panel B: Median Characteristics:

	Low DiE	2	3	4	5	6	7	8	9	High DiE
DiE	0.013	0.033	0.046	0.056	0.066	0.076	0.088	0.103	0.126	0.191
Size	15.236	15.491	15.514	15.429	15.278	15.140	14.954	14.686	14.417	13.820
Vol	0.414	0.407	0.426	0.455	0.491	0.527	0.564	0.604	0.651	0.732
Illiq	0.067	0.054	0.054	0.061	0.080	0.101	0.121	0.164	0.213	0.363
BM	0.372	0.346	0.333	0.331	0.321	0.326	0.320	0.331	0.335	0.389
MAX	0.046	0.046	0.048	0.050	0.055	0.059	0.064	0.068	0.075	0.084
STR	0.010	0.012	0.014	0.013	0.013	0.011	0.007	0.005	-0.003	-0.023
IO	0.731	0.726	0.720	0.719	0.714	0.711	0.702	0.693	0.677	0.614
Beta	1.025	1.032	1.081	1.137	1.219	1.290	1.381	1.442	1.508	1.556
Mom	0.107	0.131	0.141	0.136	0.157	0.140	0.140	0.121	0.086	-0.045
IdV	0.332	0.325	0.338	0.359	0.387	0.416	0.449	0.487	0.532	0.613

Table 3: Univariate Portfolio Sorts on DiE

This table presents the average excess returns ("R") and alphas for ten portfolios sorted on DiE over the sample period from January 1996 to December 2012. Each month we divide stocks in ascending order into decile portfolios from (1-Low DiE) to (10-High DiE) on the basis of DiE, estimate Fama and French (1993) three-factor and Fama, French, and Carhart (1997) four-factor models, and obtain the intercepts ("$FF3\alpha$" and "$FFC4\alpha$", respectively) for each of ten portfolios. Panel A shows the equally-weighted excess returns and alphas at the end of month *t+1* for each decile portfolio. Panel B reports the findings for value-weighted portfolios. We also show the average returns and alphas for portfolio High minus Low ("H-L"), that is the difference in returns/alphas between High DiE and Low DiE portfolios. "Average DiE" presents the mean DiE value for each decile across months. Standard errors are Newey-West corrected (six lags) with t-values reported in parentheses. *,**,*** denote the statistical significance at 10%, 5% and 1%, respectively.

Panel A: Equally-Weighted Returns

Portfolio	Average DiE	R	$FF3\alpha$	$FFC4\alpha$
Low DiE	0.014	0.89	0.02	0.06
2	0.034	0.87	0.07	0.06
3	0.048	0.86	0.03	0.03
4	0.059	0.79	-0.03	-0.03
5	0.069	0.64	-0.21	-0.19
6	0.080	0.70	-0.16	-0.15
7	0.092	0.69	-0.21	-0.15
8	0.108	0.50	-0.44	-0.27
9	0.132	0.40	-0.59	-0.40
High DiE	0.203	-0.36	-1.53	-1.17
H-L		-1.25***	-1.55***	-1.23***
		(-2.69)	(-4.84)	(-3.54)

Panel B: Value-Weighted Returns

Portfolio	R	$FF3\alpha$	$FFC4\alpha$
Low DiE	0.61	-0.07	-0.05
2	0.83	0.26	0.22
3	0.55	-0.02	-0.10
4	0.74	0.11	0.07
5	0.47	-0.15	-0.22
6	0.63	-0.01	-0.05
7	1.01	0.37	0.41
8	0.65	-0.12	-0.11
9	0.65	-0.16	-0.10
High DiE	-0.26	-1.20	-0.94
H-L	-0.87*	-1.13***	-0.89**
	(-1.66)	(-3.14)	(-2.31)

Table 4: Bivariate Portfolio Sorts on Characteristic and DiE

This table presents the average and risk-adjusted profitability for more than twenty five portfolios ranked on stock characteristic and DiE over our sample period from January 1996 to December 2012. Each month we divide stocks in ascending order into quantile portfolios (column vector, from 1 to 5) based on one of the control variables. Next, within each stock characteristic quantile portfolio, we further divide stocks into five extra quantile portfolios (row vector, from 1 to 5) on the basis of DiE. As a result, we obtain 25 portfolios at the end of month *t*. Finally, for each stock characteristic-DiE quantile portfolio, we compute monthly equally-weighted excess returns at the end of month *t+1* and present a time-series average of these excess returns over all months in our sample. Additionally, we show the average returns on High minus Low DiE portfolio ("H-L"), that is the difference in average returns between High DiE and Low DiE portfolios. We also estimate three-factor ("$FF3\alpha$") and four-factor ("$FFC4\alpha$") alphas for "H-L" portfolio, that is an alpha differential between High DiE and Low DiE portfolios. Standard errors are Newey-West corrected (six lags) with t-values reported in parentheses. *, **, *** denote the statistical significance at 10%, 5% and 1%, respectively. The variables description is provided in Appendix.

(a) Institutional Ownership

IO-DiE Sorts

	Low DiE	2	3	4	High DiE	H-L	$FF3\alpha$	$FFC4\alpha$
Low IO	0.28	0.46	-0.00	-0.09	-1.70	-1.98***	-2.39***	-2.19***
						(-3.01)	(-4.82)	(-4.29)
2	0.46	0.77	0.29	0.23	-0.45	-0.91*	-1.09***	-0.85**
						(-1.81)	(-3.13)	(-2.17)
3	1.07	0.72	0.87	0.62	-0.16	-1.23***	-1.42***	-1.16***
						(-2.66)	(-4.23)	(-3.28)
4	1.02	0.92	1.12	1.01	0.83	-0.19	-0.43	-0.15
						(-0.45)	(-1.08)	(-0.34)
High IO	1.20	1.63	1.17	0.99	1.60	0.41	0.21	0.37
						(0.98)	(0.57)	(0.99)

(b) Size

Size-DiE Sorts

	Low DiE	2	3	4	High DiE	H-L	$FF3\alpha$	$FFC4\alpha$
Low Size	0.79	0.40	0.01	0.05	-0.96	-1.75***	-2.04***	-1.68***
						(-3.77)	(-4.77)	(-4.03)
2	0.83	0.66	0.72	0.53	-0.06	-0.89**	-0.95***	-0.73*
						(-2.20)	(-2.66)	(-1.84)
3	1.16	0.77	0.80	1.16	0.55	-0.61	-0.85***	-0.55**
						(-1.46)	(-3.00)	(-2.09)
4	0.89	0.95	0.94	0.97	0.31	-0.58	-0.70**	-0.60*
						(-1.26)	(-2.19)	(-1.82)
High Size	0.59	0.71	0.78	0.73	0.69	0.10	-0.02	0.06
						(0.25)	(-0.07)	(0.24)

(c) Volatility

Volatility-DiE Sorts

	Low DiE	2	3	4	High DiE	H-L	$FF3\alpha$	$FFC4\alpha$
Low Vol	0.71	0.89	0.91	0.90	0.80	0.10	0.04	0.05
						(0.63)	(0.24)	(0.30)
2	0.97	0.89	0.75	1.12	1.17	0.20	0.14	0.34
						(0.75)	(0.52)	(1.12)
3	0.64	0.47	0.47	0.77	0.36	-0.28	-0.30	-0.16
						(-0.81)	(-0.92)	(-0.46)
4	0.87	1.10	0.84	0.39	0.29	-0.59	-0.76**	-0.59*
						(-1.61)	(-2.15)	(-1.72)
High Vol	0.53	0.33	-0.08	0.38	-0.87	-1.39***	-1.46**	-1.25**
						(-2.62)	(-2.53)	(-2.05)

Table 4: Bivariate Portfolio Sorts on Characteristic and DiE (Continued)

(d) Amihud Illiquidity

Illiquidity-DiE Sorts

	Low DiE	2	3	4	High DiE	H-L	$FF3\alpha$	$FFC4\alpha$
Low Illiq	0.74	0.68	0.77	0.95	0.55	-0.18	-0.32	-0.13
						(-0.41)	(-1.30)	(-0.44)
2	0.72	1.06	0.58	0.83	0.14	-0.57	-0.74***	-0.49*
						(-1.22)	(-2.63)	(-1.68)
3	1.03	1.05	0.99	1.45	0.36	-0.66*	-0.81**	-0.53
						(-1.69)	(-2.49)	(-1.44)
4	0.67	0.62	0.42	0.64	0.15	-0.52	-0.80**	-0.49
						(-1.22)	(-2.32)	(-1.32)
High Illiq	1.06	0.29	0.13	0.11	-0.45	-1.51***	-1.69***	-1.35**
						(-2.62)	(-2.91)	(-2.26)

(e) Maximum Return

Maximum-Return-DiE Sorts

	Low DiE	2	3	4	High DiE	H-L	$FF3\alpha$	$FFC4\alpha$
Low MAX	0.90	0.90	0.93	0.97	1.24	0.35	0.27	0.30
						(1.41)	(1.10)	(1.15)
2	1.09	0.95	0.96	1.24	0.80	-0.29	-0.37	-0.26
						(-1.07)	(-1.55)	(-0.96)
3	0.84	0.73	0.99	0.56	0.26	-0.57*	-0.70**	-0.52
						(-1.88)	(-2.47)	(-1.54)
4	0.52	0.85	0.32	0.15	0.16	-0.36	-0.50	-0.29
						(-0.97)	(-1.32)	(-0.72)
High MAX	0.38	0.15	0.42	-0.05	-1.26	-1.64***	-1.85***	-1.60***
						(-3.04)	(-3.62)	(-3.27)

(f) Short-term Reversal

Short-term-Reversal-DiE Sorts

	Low DiE	2	3	4	High DiE	H-L	$FF3\alpha$	$FFC4\alpha$
Low STR	1.02	0.72	0.76	-0.01	-0.74	-1.77***	-2.00***	-1.76***
						(-4.05)	(-4.62)	(-3.99)
2	0.99	0.92	0.66	0.85	0.38	-0.61	-0.79**	-0.66*
						(-1.50)	(-2.32)	(-1.90)
3	0.79	0.96	0.79	0.78	0.38	-0.41	-0.59*	-0.41
						(-0.87)	(-1.90)	(-1.20)
4	0.84	0.88	0.71	0.58	0.21	-0.64	-0.83**	-0.69**
						(-1.23)	(-2.52)	(-2.02)
High STR	0.94	0.92	0.50	0.47	-0.33	-1.28***	-1.41***	-1.26***
						(-2.69)	(-3.48)	(-3.11)

(g) Book-to-Market Ratio

Book-To-Market-DiE Sorts

	Low DiE	2	3	4	High DiE	H-L	$FF3\alpha$	$FFC4\alpha$
Low BM	0.44	0.36	0.74	0.24	-0.22	-0.67	-0.89**	-0.71*
						(-1.46)	(-2.33)	(-1.75)
2	0.62	0.85	0.41	0.57	0.09	-0.54	-0.68***	-0.51*
						(-1.37)	(-2.63)	(-1.78)
3	0.82	0.65	0.59	0.50	0.08	-0.74	-0.90**	-0.67*
						(-1.46)	(-2.56)	(-1.74)
4	0.86	0.87	0.82	0.77	0.56	-0.29	-0.51	-0.23
						(-0.75)	(-1.39)	(-0.52)
High BM	1.43	1.02	1.12	0.74	0.35	-1.08**	-1.40***	-1.06**
						(-2.33)	(-3.46)	(-2.55)

Table 5: Bivariate Portfolio Sorts on Characteristics and DiE

Table 5 presents the average excess returns, mean return differentials as well as alphas from three- and four-factor models for ten portfolios that are ranked by stock- or option-related characteristic and DiE over our sample period from January 1996 to December 2012. Each month, we divide stocks into hundred portfolios based on one of the control variables and then on DiE. This table presents time-series averages of monthly excess returns for each of the DiE portfolios across the ten characteristic decile portfolios that are obtained from the first sort. Finally, for each characteristic-DiE sort, we compute the average returns on High minus Low DiE portfolio ("H-L"), that is the spread in average returns between High DiE and Low DiE portfolios and estimate three-factor ("$FF3\alpha$") and four-factor ("$FFC4\alpha$") alphas for "H-L" portfolio, that is an alpha differential between High DiE and Low DiE portfolios. Standard errors are Newey-West corrected (six lags) with t-values reported in parentheses. *, **, *** denote the statistical significance at 10%, 5% and 1%, respectively. The variables description is provided in Appendix.

Average Portfolio Returns

	Beta	Mom	IdV	RNS	RNK	VolSpr	QSkew	VS	O/S	InnCall	InnPut
Low DiE	0.64	0.84	0.80	0.88	0.77	0.77	0.75	0.75	0.78	0.76	0.77
2	0.84	0.79	0.57	0.84	0.95	0.90	0.83	0.86	0.91	0.78	0.86
3	0.91	0.88	0.62	0.98	0.97	0.80	0.66	0.66	0.76	0.75	0.88
4	0.66	0.93	0.94	0.72	0.71	0.61	0.90	0.68	0.86	0.52	0.51
5	0.85	0.64	0.58	0.75	0.85	0.58	0.70	0.73	0.71	0.86	0.49
6	0.58	0.60	0.72	0.63	0.36	0.61	0.71	0.63	0.68	0.61	0.72
7	0.71	0.54	0.64	0.81	0.74	0.80	0.51	0.66	0.70	0.83	0.71
8	0.65	0.78	0.69	0.47	0.60	0.70	0.65	0.76	0.52	0.51	0.63
9	0.51	0.31	0.46	0.20	0.16	0.39	0.26	0.24	0.39	0.44	0.49
High DiE	-0.19	-0.02	0.21	-0.20	-0.08	-0.12	0.03	0.03	-0.34	-0.10	-0.11
$H-L$	-0.83***	-0.85***	-0.59***	-1.08***	-0.85***	-0.88***	-0.72***	-0.71***	-1.13***	-0.86***	-0.88***
	(-3.40)	(-3.04)	(-2.90)	(-4.36)	(-3.15)	(-3.75)	(-2.86)	(-2.93)	(-4.47)	(-3.56)	(-3.38)
$FF3\alpha$	-1.05***	-1.06***	-0.67***	-1.32***	-1.08***	-1.10***	-0.94***	-0.92***	-1.35***	-1.11***	-1.05***
	(-4.40)	(-3.92)	(-3.19)	(-5.89)	(-4.23)	(-5.00)	(-3.99)	(-4.11)	(-5.82)	(-4.74)	(-4.26)
$FFC4\alpha$	-0.90***	-0.91***	-0.49**	-1.09***	-0.87***	-0.83***	-0.75***	-0.70***	-1.12***	-0.86***	-0.80***
	(-3.69)	(-3.33)	(-2.24)	(-4.77)	(-3.37)	(-3.63)	(-3.14)	(-3.01)	(-4.68)	(-3.59)	(-3.13)

Table 6: Fama-MacBeth Regressions

Table 6 contains coefficient estimates from Fama and MacBeth (1973) monthly cross-sectional regressions using our sample period from January 1996 to December 2012. We run regressions of excess stock returns over month *t+1* on a constant, differences-in-expectations ("DiE") estimate, and a list of different control variables computed at the end of month *t*. We employ one-day implementation lag technique to eliminate potential spurious findings caused by non-synchronous trading. Firm-level Differences-in-Expectations ("DiE") measure is the dispersion of stock options trading volume across the strike prices scaled by the volume-weighted average strike at the end of month *t*. The variables description is provided in Appendix. Newey-West corrected *t*-statistics (six lags) are presented in parentheses. Coefficients that are significant at 1%, 5% and 10% are denoted by ***, **, *, respectively. The monthly average R^2 from cross-sectional regressions is reported underneath the tables.

(i) Stock-related Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
DiE	-0.0821***	-0.0683***	-0.0649***	-0.0714***	-0.0908***	-0.0620***	-0.0413***	-0.0759***	-0.0609***	-0.0569***	-0.0238**
	(-3.26)	(-3.40)	(-3.17)	(-3.03)	(-3.78)	(-2.64)	(-3.00)	(-3.11)	(-3.55)	(-3.39)	(-2.14)
Size		0.00102									-0.000595
		(1.07)									(-0.70)
Vol			-0.00891								-0.00338
			(-1.12)								(-0.94)
Illiq				-0.0856							-0.114
				(-0.87)							(-1.57)
BM					0.00333						0.00622**
					(0.76)						(2.33)
MAX						-0.0743**					-0.0128
						(-2.07)					(-0.68)
STR							0.00580				0.00634
							(0.54)				(0.78)
Beta								0.00238			0.000248
								(0.54)			(0.07)
Mom									0.00676		0.00685**
									(1.64)		(1.99)
IdV										-0.0187*	-0.00938
										(-1.86)	(-1.50)
R^2	0.018	0.060	0.038	0.044	0.034	0.034	0.056	0.026	0.037	0.052	0.129

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Fama-MacBeth Regressions (continued)

(ii) Option-related Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DiE	-0.0790***	-0.0749***	-0.0744***	-0.0686***	-0.0626**	-0.0759***	-0.0705***	-0.0721***	-0.0419**
	(-3.20)	(-3.26)	(-3.02)	(-2.77)	(-2.56)	(-3.11)	(-2.82)	(-2.90)	(-2.38)
RNS	0.00769*								-0.00368
	(1.90)								(-0.67)
RNK		-0.00153							-0.000308
		(-0.33)							(-0.06)
VolSpr			0.00269						-0.00138
			(0.50)						(-0.26)
QSkew				-0.0629***					-0.0641**
				(-4.32)					(-2.08)
VS					0.0683***				0.0496**
					(3.71)				(2.44)
O/S						-0.296**			-0.216
						(-2.12)			(-1.40)
InnCall							-0.0193**		-0.0146
							(-2.18)		(-0.96)
InnPut								-0.0125	-0.00574
								(-1.46)	(-0.36)
R^2	0.024	0.029	0.025	0.024	0.023	0.020	0.025	0.025	0.070

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Component Decomposition

This table presents univariate cross sectional regressions over our sample period from January 1996 to December 2012 and the decomposition of total DiE effect into explained and unexplained components using Hou and Loh (2015) methodology. In stage 1, for each month t we regress excess returns ($Exret$) at the end of month t+*1* on DiE measured at t ($Exret_{it+1} = \alpha_{t+1} + \beta_{t+1} \times DiE_{it} + \epsilon_{it+1}$). The total DiE effect estimated by β_{t+1} is reported in *Total* section. In stage 2, we run monthly regressions of DiE_{it} on the candidate variable at t that can explain negative DiE-return relationship ($DiE_{it} = a_t + \gamma_t \times candidate_{it} + \omega_{it}$). a_t and γ_t are shown under *Inter.* and *Slope* sections, respectively. Finally, the total β_{t+1} effect is decomposed into two orthogonal components as follows: $\beta_{t+1} = \frac{Cov[Exret_{it+1}, DiE_{it}]}{Var[DiE_{it}]} = \frac{Cov[Exret_{it+1}, \gamma_t \times candidate_{it}]}{Var[DiE_{it}]} + \frac{Cov[Exret_{it+1}, a_t + \omega_{it}]}{Var[DiE_{it}]} = \beta^{Exp}_{t+1} + \beta^{Unexp}_{t+1}$. Time-series averages of β_{t+1}, β^{Exp}_{t+1} (*Exp.*), β^{Unexp}_{t+1} (*Unexp.*) are used to measure the percentage of the DiE-return relationship that is explained (*%, Exp.*) and unexplained (*%, Unexp.*) by candidate variable. Firm-level Differences-In-Expectations ("DiE") measure is the dispersion of stock options trading volume across the strike prices scaled by the volume-weighted average strike at the end of month t. The variables description is provided in Appendix. The slope, intercept and total coefficients are statistically significant at 1% level. Standard errors are Newey-West corrected (six lags).

Panel A: Stock-related Characteristics

Candidate Variable		Coeff.	Candidate Variable		Coeff.	Candidate Variable		Coeff.
Size	Slope	-0.0094	**Vol**	Slope	0.0734	**Illiq**	Slope	0.3823
	Inter.	0.2262		Inter.	0.0420		Inter.	0.0823
	Exp.	-0.0213		Exp.	-0.0319		Exp.	-0.0023
	%, Exp.	**24.57**		%, Exp.	**39.00**		%, Exp.	**2.81**
	Unexp.	-0.0654		Unexp.	-0.0499		Unexp.	-0.0796
	%, Unexp.	**75.43**		%, Unexp.	**61.00**		%, Unexp.	**97.19**
	Total	-0.0867		Total	-0.0818		Total	-0.0819
		(100%)			(100%)			(100%)
BM	Slope	0.0054	**MAX**	Slope	0.3769	**STR**	Slope	-0.0266
	Inter.	0.0801		Inter.	0.0582		Inter.	0.0804
	Exp.	0.0006		Exp.	-0.0276		Exp.	0.0079
	%, Exp.	**-1.00**		%, Exp.	**31.83**		%, Exp.	**-9.11**
	Unexp.	-0.0663		Unexp.	-0.0591		Unexp.	-0.0946
	%, Unexp.	**101.00**		%, Unexp.	**68.17**		%, Unexp.	**109.11**
	Total	-0.0657		Total	-0.0867		Total	-0.0867
		(100%)			(100%)			(100%)
Beta	Slope	0.0262	**Mom**	Slope	-0.0124	**IdV**	Slope	0.1101
	Inter.	0.0499		Inter.	0.0809		Inter.	0.0350
	Exp.	-0.0153		Exp.	-0.0037		Exp.	-0.0447
	%, Exp.	**18.66**		%, Exp.	**4.56**		%, Exp.	**54.51**
	Unexp.	-0.0667		Unexp.	-0.0775		Unexp.	-0.0373
	%, Unexp.	**81.34**		%, Unexp.	**95.44**		%, Unexp.	**45.49**
	Total	-0.082		Total	-0.0812		Total	-0.0820
		(100%)			(100%)			(100%)

Table 7: Component Decomposition (continued)

Panel B: Option-related Characteristics

Candidate Variable		Coeff.	Candidate Variable		Coeff.	Candidate Variable		Coeff.
RNS	Slope	0.0219	**RNK**	Slope	-0.0207	**VolSpr**	Slope	-0.0022
	Inter.	0.0905		Inter.	0.1524		Inter.	0.0825
	Exp.	0.0037		Exp.	-0.0022		Exp.	-0.0054
	%, Exp.	**-4.70**		%, Exp.	**2.78**		%, Exp.	**6.55**
	Unexp.	-0.0827		Unexp.	-0.0768		Unexp.	-0.0771
	%, Unexp.	**104.70**		%, Unexp.	**97.22**		%, Unexp.	**93.45**
	Total	-0.0790		Total	-0.079		Total	-0.0825
		(100%)			(100%)			(100%)
QSkew	Slope	0.1436	**VS**	Slope	-0.1394	**O/S**	Slope	-0.3061
	Inter.	0.0760		Inter.	0.0808		Inter.	0.0832
	Exp.	-0.0122		Exp.	-0.0115		Exp.	-0.0003
	%, Exp.	**14.79**		%, Exp.	**15.33**		%, Exp.	**0.37**
	Unexp.	-0.0703		Unexp.	-0.0635		Unexp.	-0.0798
	%, Unexp.	**85.21**		%, Unexp.	**84.67**		%, Unexp.	**99.63**
	Total	-0.0825		Total	-0.0750		Total	-0.0801
		(100%)			(100%)			(100%)
InnCall	Slope	0.0289	**InnPut**	Slope	0.0314			
	Inter.	0.0811		Inter.	0.0810			
	Exp.	-0.0064		Exp.	-0.0086			
	%, Exp.	**7.83**		%, Exp.	**10.53**			
	Unexp.	-0.0753		Unexp.	-0.0731			
	%, Unexp.	**92.17**		%, Unexp.	**89.47**			
	Total	-0.0817		Total	-0.0817			
		(100%)			(100%)			

Table 8: Bivariate Portfolio Sorts on DiE and AFD (Analyst Forecast Dispersion)

Table 8 shows the results from comparative analysis of DiE and AFD. Panel A presents the average excess returns, mean return differentials, and alphas from three- and four-factor models for ten portfolios that are ranked by DiE and AFD (and vice versa) over our sample period from January 1996 to December 2012. Each month, we divide stocks into hundred portfolios based on AFD and then on DiE (and vice versa) and report time-series averages of equally-weighted excess returns for each of the DiE (AFD) portfolios across ten AFD (DiE) decile portfolios. Column "AFD-DiE" presents average excess returns for portfolios, first sorted on AFD, then on DiE, whereas column "DiE-AFD" reports the profitability of portfolios, first sorted on DiE, then on AFD. Finally, for each portfolio we compute the average returns on High minus Low DiE portfolio ("H-L"), that is the difference in average returns between High DiE and Low DiE portfolios and estimate three-factor ("$FF3\alpha$") and four-factor ("$FFC4\alpha$") alphas for "H-L" portfolio, that is an alpha differential between High DiE and Low DiE portfolios. Panel B shows the results from monthly cross-sectional Fama-MacBeth regressions of excess stock returns over month *t+1* on a constant, DiE, and AFD computed at the end of month *t*. Panel C presents the findings of DiE (AFD) effect decomposition and percentage estimates of a DiE(AFD)-return relation that are (un)explained by AFD (DiE). Standard errors are Newey-West corrected (six lags) with t-values reported in parentheses. *, **, *** denote the statistical significance at 10%, 5% and 1%, respectively. The variables description is provided in Appendix.

Panel A: Average Portfolio Returns

	Average AFD	AFD-DiE	DiE-AFD
1	0.096	0.90	1.32
2	0.085	0.68	0.38
3	0.086	0.95	0.53
4	0.088	0.77	0.43
5	0.094	0.52	0.73
6	0.107	0.74	0.45
7	0.120	0.82	0.70
8	0.146	0.49	0.67
9	0.169	0.56	0.74
10	0.222	-0.00	0.49
$H-L$		-0.90***	-0.84***
		(-3.63)	(-3.40)
$FF3\alpha$		-1.06***	-1.31***
		(-4.57)	(-5.85)
$FFC4\alpha$		-0.82***	-1.07***
		(-3.34)	(-4.73)

Panel B: Fama-MacBeth Regressions

	(1)	(2)	(3)
DiE	-0.0821***		-0.0566**
	(-3.26)		(-2.24)
AFD		-0.00285	-0.00348
		(-0.94)	(-1.15)
R^2	0.018	0.005	0.023

Panel C: Component Decomposition

Candidate	Variable	Coeff.	Candidate	Variable	Coeff.
AFD	Slope	0.0264	**DiE**	Slope	0.7879
	Inter.	0.0802		Inter.	0.0571
	Exp.	-0.0043		Exp.	-0.0018
	%, Exp.	**6.67**		%, Exp.	**39.13**
	Unexp.	-0.0602		Unexp.	-0.0028
	%, Unexp.	**93.33**		%, Unexp.	**60.87**
	Total	-0.0645		Total	-0.0046
		(100%)			(100%)

Table 9: DiE and Investor Sentiment

Table 9 contains coefficient estimates from Fama and MacBeth (1973) monthly cross-sectional regressions of excess stock returns over month *t+1* on a constant, DiE measure, and a list of different control variables computed at the end of month t over high and low sentiment periods from January 1996 to December 2012. Panel A shows the results for high sentiment months, while Panel B displays the findings for low sentiment periods. High (low) sentiment month is the one when Baker and Wurgler (2006) index value in the previous month is above (below) the median over the past twelve months. The variables description is provided in Appendix. Newey-West corrected t-statistics (six lags) are presented in parentheses. Coefficients that are significant at 1%, 5% and 10% are denoted by ***, **, *, respectively.

Panel A: High Sentiment

(i) Stock-related Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
DiE	-0.062***	-0.049***	-0.033***	-0.057***	-0.054***	-0.041***	-0.066***	-0.041***	-0.049***	-0.023***	-0.015**
	(-3.56)	(-3.55)	(-2.90)	(-3.41)	(-3.15)	(-3.69)	(-3.59)	(-2.96)	(-2.97)	(-2.74)	(-2.08)
Size		0.001*									-0.000
		(1.93)									(-0.95)
Vol			-0.011**								-0.001
			(-2.32)								(-0.65)
Illiq				-0.048							-0.070
				(-0.93)							(-1.46)
BM					0.004						0.003
					(1.37)						(1.57)
MAX						-0.071***					-0.011
						(-2.89)					(-0.79)
STR							0.000				0.001
							(0.07)				(0.36)
Beta								-0.002			-0.001
								(-1.06)			(-0.57)
Mom									0.004*		0.004***
									(1.79)		(2.90)
IdV										-0.019***	-0.012***
										(-2.94)	(-3.00)

(ii) Option-related Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DiE	-0.060***	-0.057***	-0.057***	-0.056***	-0.050***	-0.056***	-0.057***	-0.057***	-0.032***
	(-3.44)	(-3.53)	(-3.52)	(-3.36)	(-2.79)	(-3.19)	(-3.47)	(-3.50)	(-2.59)
RNS	-0.000								-0.007*
	(-0.25)								(-1.83)
RNK		0.002							0.003
		(0.62)							(0.74)
VolSpr			0.002						0.000
			(0.68)						(0.29)
QSkew				-0.028**					-0.052**
				(-2.20)					(-2.21)
VS					0.032**				0.025**
					(2.33)				(2.01)
O/S						-0.160			-0.096
						(-1.64)			(-0.88)
InnCall							-0.001		0.006
							(-0.28)		(0.67)
InnPut								-0.005	-0.006
								(-1.00)	(-0.63)

Table 9: DiE and Investor Sentiment (continued)

Panel B: Low Sentiment

(i) Stock-related Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
DiE	-0.020	-0.016	-0.024*	-0.019	-0.008	-0.020	-0.025	-0.027*	-0.022	-0.018	-0.008
	(-1.01)	(-0.98)	(-1.81)	(-0.96)	(-0.47)	(-1.38)	(-1.43)	(-1.83)	(-1.28)	(-1.60)	(-0.99)
Size		-0.000									-0.000
		(-0.20)									(-0.07)
Vol			0.002								-0.002
			(0.34)								(-0.69)
Illiq				-0.037							-0.044
				(-0.45)							(-0.88)
BM					-0.001						0.003*
					(-0.23)						(1.81)
MAX						-0.003					-0.002
						(-0.12)					(-0.14)
STR							0.005				0.005
							(0.63)				(0.73)
Beta								0.005			0.001
								(1.33)			(0.46)
Mom									0.003		0.002
									(0.88)		(0.79)
IdV										0.000	0.002
										(0.04)	(0.53)

(ii) Option-related Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DiE	-0.019	-0.018	-0.017	-0.013	-0.013	-0.019	-0.015	-0.013	-0.010
	(-1.02)	(-1.00)	(-0.86)	(-0.65)	(-0.72)	(-1.07)	(-0.79)	(-0.66)	(-0.79)
RNS	0.008**								0.004
	(2.20)								(0.95)
RNK		-0.003							-0.003
		(-1.04)							(-0.89)
VolSpr			0.000						-0.002
			(0.12)						(-0.57)
QSkew				-0.034***					-0.012
				(-3.50)					(-0.50)
VS					0.037***				0.024*
					(2.91)				(1.66)
O/S						-0.136			-0.119
						(-1.36)			(-1.16)
InnCall							-0.011		-0.012
							(-1.62)		(-0.94)
InnPut								-0.014*	-0.008
								(-1.84)	(-0.70)