Essays on Asset Return Predictability Using Options Market Information

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by

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Abstract

In this dissertation, I study the effects of option-type measures of investors' beliefs on expected asset returns. The key contribution of the thesis lies in exploiting options trading information to summarize a wide range of traders' directional beliefs via the measures of investor sentiment and differences in investors' expectations and showing their superior forecasting power for future asset payoffs. Chapter 1 constructs the proxy for investor sentiment in the options market, using the volume-weighted average moneyness level, and explores its market-wide predictability. Consistent with the existing literature, I find that option-implied sentiment is a strong in- and out-of-sample predictor of stock market returns, both at short and long investment horizons. Chapter 2 proposes a firm-level measure for differences in expectations among options traders, obtained from the dispersion of equity options trading volume across various moneyness levels, and examines its cross-sectional profitability. In line with the theoretical predictions of Miller (1977), I demonstrate that stocks with high differences in expectations consistently earn lower returns than otherwise similar stocks. Moreover, this underperformance pattern is more pronounced for firms that incur higher short-sale costs and relatively high arbitrage risk and is robustly distinct from that shown by previously revealed cross-sectional return predictors. Finally, in Chapter 3, I extend the prior analysis and investigate the mechanism and timing of the Miller (1977) hypothesis, using the option-implied measure of belief dispersion. In particular, I document that stocks with high differences in expectations exhibit a clearly pronounced overvaluation in the earnings pre-announcement period and a more severe subsequent price correction upon the release of new information. Additionally, I show that the differences in expectations among options traders tend to better capture the Miller (1977) predictions, relative to analysts' forecasts dispersion, for stocks with listed options.

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To my parents and family

Introduction

The forward-looking bet-type nature of derivative markets and their informational implications for underlying asset prices have long been a subject of widespread interest for academics and practitioners. Since the seminal work of Black (1975), the main focus of the subsequent studies has been on the informational role of options for the price discovery process in the stock market.[1] For example, Manaster and Rendleman (1982), Bhattacharya (1987), Anthony (1988), Kumar, Sarin and Shastri (1992), Easley, O'Hara and Srinivas (1998), Chakravarty, Gulen and Mayhew (2004), Pan and Poteshman (2006) show, both theoretically and empirically, that options market is a venue for information-based trading and specific options trades carry a strong predictive power for future stock movements.[2] Further, a series of recent studies establish a strong stock return predictability with the various indirect proxies for informed trading based on option prices. Dennis and Mayhew (2002), Bali and Hovakimian (2009), Cremers and Weinbaum (2010), Xing, Zhang and Zhao (2010), An et al. (2014) demonstrate that the risk-neutral skewness, the spread between realized and implied volatilities, put-call parity deviations, the volatility smirk and call/put

[1] Black (1975) suggests that, due to the higher leverage embedded in option contracts, options trades may first reveal information that is relevant to, but not yet incorporated into, the stock price.

[2] In a similar vein, Cao, Chen and Griffin (2005) document that call option volume is positively associated with takeover premia prior to merger announcements. Figlewski and Webb (1993), Ge, Lin and Pearson (2016) report that options play an important role in reducing the impact of short sale constraints and improving the informational efficiency of the stock market. Roll, Schwartz and Subrahmanyam (2010) establish that some of earnings pre-announcement trading volume is informed, Johnson and So (2012) investigate the presence of informed traders when short-selling is costly, whereas Cremers, Fodor and Weinbaum (2015) find a rich information content of signed options trading volume for stock prices around various news releases.

volatility innovations predict the cross-section of expected stock returns.[3,4] Additionally, in line with the sequential trade models of Glosten and Milgrom (1985) and Easley and O'Hara (1987), options markets can also be extensively used for other non-speculative reasons such as hedging background, stochastic volatility and jump risks (Franke, Stapleton and Subrahmanyam, 1998; Bates, 2001; Liu and Pan, 2003; Chen, Joslin and Ni, 2016) and mimicking the dynamic portfolio strategies (Haugh and Lo, 2001).[5]

In this thesis, we complement the aforementioned literature by exploiting options trading information to investigate the effects of investors' beliefs in the options market on expected stock returns. In this regard, our results also contribute to another strand of literature, that explores the asset pricing implications and volume formation in the context of speculative trading models developed by Harrison and Kreps (1978), De Long et al. (1990), Harris and Raviv (1993), Kim and Verrecchia (1994), Barberis, Shleifer and Vishny (1998), Hong and Stein (2003), Shefrin (2005).[6] More specifically, we capture a wide range of options traders' beliefs using two sufficient measures, the average bias in beliefs i.e. investor sentiment and differences in expectations about future asset payoff, and explore their information content for stock return predictability in three chapters.

[3]Supporting this evidence, Jin, Livnat and Zhang (2012), Lin, Lu and Driessen (2012), Chan, Ge and Lin (2015) discover a return predictability, using volatility spreads and volatility skews around earnings, acquirer, client and product announcements, analysts' recommendations and forecast updates.

[4]Needless to say, there is also an extensive literature, documenting that options market is led by stock market and has no or little predictive power for expected asset payoffs (see, for instance, Stephan and Whaley, 1990; Vijh, 1990; Chan, Chung and Johnson, 1993; Muravyev, Pearson and Broussard, 2013).

[5]However, the recent studies of Lakonishok et al. (2007), Ge, Lin and Pearson (2016) find that the highest proportion of total stock options trading volume is the covered call writing and new bought call positions, which are unlikely to be associated with hedging demand. Searching for alternative rationale behind options trading, Kraus and Smith (1996), Buraschi and Jiltsov (2006), Cao and Ou-Yang (2008) build theoretical models based on differences of opinion and document important implications for option prices, volatility smile and trading volume. Empirically, Choy and Wei (2012) suggest that options trading is mainly driven by small speculative retail investors with diverse beliefs, however researchers do not propose any measure of belief dispersion and do not investigate its potential effect on stock prices.

[6]In such models, agents hold diverse beliefs, are subject to various psychological biases and not fully rational, causing a stock mispricing that cannot be instantly eliminated by rational arbitrageurs due to the limits to arbitrage (Shleifer and Vishny, 1997).

The first chapter constructs a measure of investor sentiment, using the volume-weighted average moneyness level across all options series, and examines its market-wide predictive power. The seminal study of Keynes (1936) suggests that the waves of optimism and pessimism change the individual risk preferences, judgements and choices, leading to an increased level of speculation and a significant impact of psychological biases on asset prices.[7] Looking closely at the financial markets, Hardy (1939), Wiesenberger (1946), Malkiel (1977) first posit that discounts on closed-end funds, odd-lot sale-purchase ratio and net mutual fund redemptions tend to reflect investor sentiment, while later Neal and Wheatley (1998) provide supportive evidence that such sentiment proxies predict stock returns.[8] Further, a series of recent papers discover new investor sentiment proxies such as the equity share in new issues (Baker and Wurgler, 2000), share turnover and liquidity (Baker and Stein, 2004), dividend premium (Baker and Wurgler, 2004), the average return on IPOs and the number of IPOs (Stigler, 1964; Ritter, 1991) and report their strong predictability for future returns. Finally, a highly influential study of Baker and Wurgler (2006) applies a principal component analysis to estimate a sentiment index that captures a common variation across all previously mentioned individual sentiment proxies, while a new paper by Huang et al. (2015) improves the Baker and Wurgler index by using a partial least squares method to eliminate noise from individual proxies. Both studies document a strong negative relation between sentiment and future stock market returns, however Huang et al. (2015) aligned investor sentiment index generates superior short- and long-run return predictability.[9] Consistent with the above literature, our key results reveal that option-implied sentiment predicts negative fu-

[7]The theoretical explanation of a significant sentiment-return relation has been proposed later by a series of "limits to arbitrage" models. For example, De Long et al. (1990), Shleifer and Vishny (1997) show that sentiment-driven investors push prices further away from fundamental values and smart-money short-horizon arbitrageurs cannot instantaneously correct the mispricing due to a high risk of more severe short-term adverse stock fluctuations. This risk can also be escalated given various transactional (high short-sale costs), liquidity and capital constraints.

[8]Particularly, Neal and Wheatley (1998) show that the discount on closed-end funds and net redemptions explain the return differential between small and large firms, whereas odd-lot ratio exhibits a weak predictive power for stock returns. Similarly, Lee, Shleifer and Thaler (1991) demonstrate that changes in discounts of closed-end funds are positively related to investor sentiment.

[9]In this chapter, we exploit both sentiment indices and compare their forecasting performance with that of option-implied sentiment.

ture excess market returns, both in the short- and long-run, that have a similar in-sample economic magnitude compared to that of alternative sentiment trading strategies, while its out-of-sample performance is consistently superior to that shown by other sentiment proxies.

The second chapter proposes a firm-level measure for differences in expectations (DiE) among options traders, that is obtained from the dispersion of stock options trading volume across different moneyness levels, and analyzes its cross-sectional asset pricing implications. The effect of dispersion in investors' beliefs on stock prices has initially been studied within the static theoretical frameworks developed by Miller (1977), Jarrow (1980), Chen, Hong and Stein (2002) and has further been explored in dynamic models by Harrison and Kreps (1978), Morris (1996), Scheinkman and Xiong (2003). The key prediction of these models is that, whenever investors strongly differ in their beliefs about the value of the firm, asset price will either equal to or exceed the valuation of the most optimistic investor since high short-sale costs or other market frictions will prevent pessimistic agents from revealing their negative valuations. As a result, the price will exhibit an upward bias, leading to lower subsequent returns. Empirically, utilizing various proxies for differences of opinion such as analysts' forecasts dispersion, breadth of ownership, mutual funds' active holdings or dispersion of investors' trades, Diether, Malloy and Scherbina (2002), Chen, Hong and Stein (2002), Goetzmann and Massa (2005), Park (2005), Boehme, Danielsen and Sorescu (2006), Yu (2011), Jiang and Sun (2014) document a strong, both time-series and cross-sectional, negative relationship between belief dispersion and future asset returns.[10] An alternative strand of literature, building on the theoretical models of Williams (1977), Cho (1992), Harris and Raviv (1993), Varian (1985), He and Wang (1995), asserts that investors tend to price disagreement at a discount, requiring additional compensation for keeping more diver-

[10]A series of recent studies provide several alternative explanations of a negative relation between disagreement and stock returns. For example, Johnson (2004) suggests that differences of opinion is a proxy for unpriced information risk and should negatively predict future stock returns only for leveraged firms. Avramov et al. (2009) document that a dispersion effect is particularly pronounced for worst-rated firms at times of high default risk. Barinov (2013) extends Johnson (2004) hypothesis and attributes disagreement effect to real options theory.

gent stocks in their portfolios due to a high risk of adverse selection when opinions in the market are notably different. In line with these predictions, Anderson, Ghysels and Juergens (2005), Doukas, Kim and Pantzalis (2006), Garfinkel and Sokobin (2006), Banerjee and Kremer (2010), Carlin, Longstaff and Matoba (2014) report a positive dispersion-return relation and suggest that differences of opinion represent an idiosyncratic risk for poorly diversified investors.[11] In this chapter, we find supportive evidence for Miller (1977) hypothesis, using the option-implied measure of differences of opinion, and reveal a strong negative relation between differences in expectations and stock returns, that is particularly pronounced for stocks that are more costly to short sell and difficult to value, more persistent during the periods of excessive optimism and unlikely to be explained by previously documented return predictors.

Finally, in the third chapter, we extend the previous analysis and investigate the main driving forces behind the DiE effect, exploiting the scheduled earnings announcement events. Since the early studies of Ball and Brown (1968), Bamber (1986), earnings announcements are shown to generate price drifts (Bernard and Thomas, 1989), increase event-period trading volume (Cready and Mynatt, 1991; Barron, Harris and Stanford, 2005), create an informational efficiency through derivative and bond markets (Skinner, 1990; Amin and Lee, 1997; Easton, Monahan and Vasvari, 2009). Additionally, several recent studies explore the information content of earnings announcements for the differences of investors' opinion and the expected effect on stock prices. In particular, Berkman et al. (2009) demonstrate that earnings releases tend to reduce the uncertainty and belief dispersion among investors, leading to substantially lower announcement returns for the stocks that exhibit a more severe Miller (1977) overvaluation in the pre-announcement period.[12] Consistent with this evidence, we

[11]There are also studies that establish no relationship between belief dispersion and stock returns (see, for example, Diamond and Verrecchia, 1987; Hong and Stein, 2003). In such models, rational arbitrageurs can precisely estimate the unbiased asset value, based on public information, and eliminate the mispricing, that is caused by the actions of speculative investors. However, in the presence of limits to arbitrage, such models seem to be quite unrealistic.

[12]However, Keskek, Rees and Thomas (2013) find that the relationship between differences of opinion and asset returns either disappears or is opposite from that hypothesized by Miller (1977) after accounting for the level of earnings news.

show that firms with high differences in expectations among options traders, being more overvalued over the earnings pre-announcement period, experience a subsequent price correction once new information is disclosed to the market. Hence, our results illustrate that overvalued stocks based on the DiE measure become even more overpriced prior to earnings disclosures, earning significantly lower returns following the release of corporate information.

A negative return predictability of option-implied measures for investors' beliefs, documented in the thesis, may potentially have a dual explanatory mechanism. First, it can be interpreted in the context of an options market where investors receive different signals and rely only on their own private information when updating their posterior beliefs. In such a case, the main source of predictability is the differential (asymmetric) information. This environment is in line with theoretical models of Kim and Verrecchia (1991), He and Wang (1995), Banerjee (2011) and is also consistent with recent studies that support the presence of informed (e.g. Pan and Poteshman, 2006) as well as uninformed (e.g. Lemmon and Ni, 2015) investors in the stock options market. Therefore, given that at least some market participants are informed, various measures of investors' beliefs in the options market will carry predictive information for expected returns in the stock market. Second, a driving force behind the observed predictability can be limits to arbitrage, affecting both stock and options markets. Investors, who want to speculate on the positive (negative) movement of the underlying asset, may induce a strong demand pressure on high (low)-strike call (put) options. Market makers, absorbing this demand and being unable to perfectly hedge their positions (Bollen and Whaley, 2004; Garleanu, Pedersen and Poteshman, 2009), are forced to increase call (put) option prices. In this case, if the price of a call (put) becomes disproportionately higher relative to the price of the corresponding put (call) and the underlying asset, then put-call parity implies an arbitrage strategy that involves a long (short) position in the underlying asset because option-implied price is above (below) the stock price. As a result, the mispricings in the options market will carry through to the stock market since, due to short-sales constraints or other frictions, arbitrageurs are more likely to long the stock than to short sell it, leading to a potential stock overpricing and lower subsequent returns. In line with the above argument, Ofek, Richardson and Whitelaw (2004) document negative future abnormal returns for stocks with relatively expensive puts.

Overall, this thesis contributes to the literature in several ways. First, we propose two new measures, investor sentiment and differences in expectations, that capture a wide range of investors' beliefs in the options market and help shed more light on the sensitivity of asset prices to the behavioural biases of options traders. These measures are based on the idea that the moneyness levels at which different options are traded reflect positive and negative investors' beliefs. Hence, these proxies stem from actual trades executed by a massive pool of investors, are directly related to stock returns, less likely to be affected by different biases (relative to analysts' forecast dispersion) and easy to construct at any frequency, providing a real-time instrument for asset allocation decisions. Second, we present new empirical evidence on the effect of investor sentiment in the options market on the stock market returns. More specifically, we demonstrate that the predictive power of option-implied sentiment for future market returns is economically tantamount in case of the in-sample forecasts and is consistently superior in case of the out-of-sample performance compared to the predictability generated by the well-known alternative sentiment proxies. Finally, we perform a comprehensive analysis of the Miller (1977) hypothesis, using a firm-level measure for differences in expectations among options investors. We report a strong negative and economically large relation between differences in expectations and future returns, which is more pronounced for stocks with high short-sale costs and arbitrage risk, more persistent during high sentiment periods and robustly distinct from that shown by other cross-sectional return predictors. Furthermore, we investigate the timing of the Miller (1977) effect and find that stocks with high differences in expectations earn substantially lower returns around earnings disclosure periods and exhibit a more severe overvaluation prior to the release of earnings information.

Chapter 1

Option-Implied Investor Sentiment and Stock Market Predictability

1.1 Introduction

The directional bets on the future states of the underlying asset placed by investors via trading at various option contracts contain valuable information about the traders' expectations and hence, about the average mood in the market. In this context, several studies exploit options trading activity to construct the measures of informed trading (Pan and Poteshman, 2006; Johnson and So, 2012), demand for crash insurance (Chen, Joslin and Ni, 2016) or disagreement (Andreou et al., 2016). While all these studies ultimately incapsulate traders' expectations about future asset payoffs, the ability of options to capture the average investor mood in the market remains mostly unexamined.[1] Therefore, in this chapter, we build a market-wide measure of investor sentiment (ISent) in the options market, defined as the volume-weighted average moneyness level across all options series, and explore its in- and out-of-sample predictive power for stock market returns.

[1]A recent study of Lemmon and Ni (2015) document a positive relationship between newly established net call and put option positions and survey-based investor sentiment, however researchers do not measure sentiment directly in the options market.

The fact that high (low) sentiment leads to excessive optimism (pessimism) in investors' beliefs about the value of the stock has been known a long time ago (since the works of Keynes, 1936), however the empirical studies on the direct effect of sentiment on stock prices have proliferated only recently. A series of papers construct various proxies of sentiment based on investor surveys, mutual fund flows, retail investor trades, trading volume, option-implied information and establish a negative relationship between sentiment and expected returns. For example, Brown and Cliff (2005) use Investors Intelligence surveys as a proxy of investor sentiment to examine its effect on market returns. Brown et al. (2005) employ mutual fund flows in and out of bonds, stocks to build an overall market sentiment measure and investigate whether it is priced in the US and Japan markets. In a similar vein, Frazzini and Lamont (2008) document that if stock experiences a sufficient fund inflow, it tends to perform poorly in the future. Barber, Odean and Zhu (2006) explore the trading behaviour of retail investors and show that they tend to buy and sell in concert, which implies the existence of systematic sentiment. Baker and Stein (2004) suggest that the trading volume may reflect investor sentiment especially when short-selling costs are higher than opening and closing long positions leading to a more pronounced trading activity of irrational optimistic investors. The studies of Han (2008), Lemmon and Ni (2015) document that option prices, pricing kernel and demand for stock options, that is mainly driven by individual unsophisticated investors, are affected by investor sentiment.[2] Complementing the above literature, this chapter proposes a new market-based measure of investor sentiment from the trades in stock options and investigates its effect on asset prices at the stock market level.

To analyze the relative magnitude of the return predictability with our sentiment measure, we construct two widely known sentiment indices introduced by Baker and Wurgler (2006) and Huang et al. (2015). The first study applies principal component analysis to six individ-

[2]Furthermore, a series of recent papers analyze the effect of sentiment in international markets (Baker, Wurgler and Yuan, 2012), mean-variance tradeoff (Yu and Yuan, 2011) and stock market anomalies (Stambaugh, Yu and Yuan, 2012).

ual sentiment proxies and measures the investor sentiment as the first principal component of the proxies. The main idea is that the first principal component, representing a linear combination of the six proxies, captures the common variation across all proxies that is related to investor sentiment. Based on this sentiment index, Baker and Wurgler (2006) find that high sentiment is associated with low future returns of small, young, more volatile, unprofitable, growth and distressed stocks. Although the main focus of Baker and Wurgler (2006) is on the cross-section of stock returns, a later study of Baker and Wurgler (2007) finds a strong negative relationship between sentiment index and market returns. Hence, we also compare our findings relative to those obtained with Baker and Wurgler (2006) sentiment index. The second study, using the same six individual sentiment proxies, constructs the aligned sentiment index by applying partial least squares method to eliminate the approximation error or noise from the six proxies, that affect the predictive power of Baker and Wurgler (2006) sentiment index, and retain the most relevant component for forecasting market returns. The findings of Huang et al. (2015) suggest that the aligned sentiment index substantially improves the forecasting performance of Baker and Wurgler (2006) sentiment measure and exhibits strong negative short- and long-run stock market return predictability.[3]

In contrast to the above sentiment indices, our measure emerges directly from the investors' trading activity and is free of any econometric estimations. More specifically, the proposed sentiment proxy can be rationalized within the typical options market, where trading at various option contracts occurs mostly between end-users and market makers and represents the directional expectations of the end-users about the future asset payoff. In this case, the trading activity at different option moneyness levels can naturally reflect the positive and negative investors' views about expected returns. For example, trades at high-strike call and put options tend to reveal optimistic investors' expectations. Out-of-the-money calls are mainly purchased by optimistic traders who are willing to benefit from the high lever-

[3]The detailed discussion of the construction of both sentiment indices is provided in the next section.

age, while in-the-money puts are typically sold by investors with positive expectations, who are willing to benefit from a higher option premium. Due to put-call parity, the synthetic payoffs from the above strategies can be created by purchasing in-the-money put contracts (selling out-of-the-money call contracts), taking a long position in the underlying asset and a short position in the risk-free asset. As a result, both buyer- and seller-motivated trades at high-strike puts and calls reflect positive traders' expectations about the future movement of underlying asset. By utilizing a similar argument, pessimistic investors can also express their negative views via trades at low-strike options and synthetic put-call parity strategies. Hence, trading volume at out-of-the-money puts or in-the-money calls is assumed to reveal negative traders' expectations. Motivated by the above discussion, since trading at options with high (low) strike prices captures optimistic (pessimistic) investors' expectations, a natural method to extract sentiment i.e. the aggregate error in traders' beliefs is to compute the volume-weighted average moneyness level across all options series. We utilize the total trading volume attached to each moneyness level, however we also exploit signed volume data, keeping only the buy-side volume of OTM options and the sell-side volume of ITM options.

By definition, the true investor sentiment is unobservable and can only be approximated either by using survey-type proxies (such as AAII, Conference Board or University of Michigan Consumer sentiment indices) or, as shown above, by applying a relevant econometric technique to extract the average bias in beliefs from other individual sentiment proxies. In contrast, this study contributes to the literature by exploiting the bet-like nature of options and suggesting a conceptually different way of estimating investor sentiment, that has several advantageous characteristics. First, survey-based proxies show the sentiment based on the restricted number of consumers/investors, while options markets become an increasingly popular venue for traders, thus allowing to capture the aggregate sentiment from the transactions of the massive pool of investors. Second, investors with positive or negative opinion about the future stock return can reliably use options market since it is not affected by any trading restrictions (for example, short-sale constraints) or high transaction fees, thus making our measure unbiased towards either optimistic or pessimistic views. Finally, our option-implied sentiment measure is easy to construct at any frequency, is free of any statistical estimation techniques and can be easily exploited by practitioners for building profitable trading strategies.

The empirical results demonstrate several important implications. First, to verify that the information content of our option-implied sentiment measure is similar to that of Baker and Wurgler (2006) and Huang et al. (2015) sentiment indices, we perform contemporaneous regression analysis and find that the ISent measure has the strongest (less pronounced) positive relationship with the Huang et al. (2015) sentiment index (Baker and Wurgler (2006) sentiment measure), that is not driven by various option-related characteristics. Second, consistent with the theory that, due to the limits to arbitrage, high optimism creates overpricing and leads to lower subsequent returns, we document that ISent is a strong negative predictor of market excess profitability both in the short- and long-run. The forecasting power of the ISent measure is economically comparable to that generated by other sentiment indices and is robustly distinct from the predictability shown by alternative economic drivers. For example, a one-standard-deviation positive shock to the ISent measure (Huang et al. (2015) aligned sentiment index) leads to the statistically significant negative market excess return of 0.78% (0.89%) for monthly horizon, 2.42% (2.68%) for quarterly horizon and 3.29% (5.50%) for half-year horizon. Additionally, we demonstrate that a significantly negative relationship between the ISent measure and future market returns is robust to various ISent specifications and cannot be mechanically driven by the moneyness level, that is based on the current asset price. For instance, the ISent measure based on signed volume data generates a negative monthly (quarterly) market excess return of 1% (2.51%). This finding supports the main rationale behind our measure, that trading at high (low) strikes is related to optimistic (pessimistic) expectations, and hence, the signed-volume sentiment measure can be seen as a robust version of the main sentiment index used in the analysis.

Third, due to the potential over-fitting issues, we also examine the out-of-sample performance of all sentiment indices and report that the return forecasts produced by the ISent predictive model are consistently superior to those made by other sentiment trading strategies. For example, ISent exhibits the out-of-sample $\widetilde{R}^2$, which is more than twice greater for monthly horizon and six times greater for quarterly horizon than the $\widetilde{R}^2$ generated by Huang et al. (2015) sentiment trading strategy. Finally, we explore the economic value of the return forecasts based on the sentiment proxies and historical model and document that the mean-variance investor will hugely benefit from investing his funds on the basis of the forecasts produced by the ISent strategy, whereas an investor with binary portfolio weights will obtain an economically significant gain in utility (relative to historical average model) from investing either with the ISent or Baker and Wurgler (2006) sentiment predictive model.

The remainder of the chapter is organized as follows. Section 1.2 outlines the construction of the ISent measure and describes the data, key filters and variables used in the study. Section 1.3 presents the in- and out-of-sample test results of the ISent predictability for stock market excess returns as well as asset allocation implications. We also examine the contemporaneous relation between the ISent measure and other sentiment indices. Finally, Section 1.4 concludes.

1.2 Option-Implied Sentiment and Alternative Predictors

In this section, we first discuss the construction of the option-implied sentiment measure

(ISent). Next, we provide a description of the data, main screening criteria and key variables used in the study. Finally, we present descriptive statistics and correlation matrix.

1.2.1 Construction of the ISent Measure

The proposed sentiment measure can be rationalized within an options market where most trades occur between end-users and market makers and are driven by the directional expectations of end-users about the future price of the underlying asset. Recent empirical evidence suggests that options demand from end-users is mainly accommodated by market makers (Ge, Lin and Pearson, 2016) and such demand tends to reflect directional underlying price bets of end-users since trades that exhibit volatility expectations represent less than 2% of total trading volume (Lakonishok et al., 2007).

Motivated by the above evidence, our sentiment measure is based on the idea that the moneyness levels at which different trades are implemented can naturally mirror the positive and negative expectations of options traders about future asset returns. For example, trading volume associated with high call or put strike prices is assumed to reflect positive investors' expectations. To benefit from higher leverage, an optimistic call buyer will select the highest possible strike price conditional on the option being exercised at maturity, thus increasing the buyer-initiated volume of OTM call options. To maximize the option premium, an optimistic put seller will select the highest possible strike price conditional on the option expiring worthless, thus contributing to the seller-initiated volume of ITM put options. Furthermore, by virtue of put-call parity, an optimistic trader can synthetically replicate the expected payoffs from buying OTM call options (selling ITM put options) by purchasing ITM put contracts (selling OTM call contracts), taking a long position in the underlying asset and a short position in the risk-free asset. As a result, the total trading volume at ITM put or OTM call options tends to reveal the positive directional investor's bets on the future movement of underlying asset. On the other hand, a pessimistic investor can reveal his views by taking a long position in OTM puts or short position in ITM calls. Further, the put-call parity implies that the same investor can replicate payoffs from the above strategies by purchasing ITM calls (selling OTM puts), taking a short position in underlying asset and a long position in risk-free asset. Hence, the total trading activity at low-strike-price options is likely to express the negative trader's expectations about expected asset returns.[4]

It is likely, however, that from the above synthetic strategies some are more frequently used by options investors, whereas others may be difficult to implement due to various transactional, liquidity or capital constraints. For example, an ITM put purchase is associated with an optimistic expectation if it is a part of a synthetic OTM call position. Since it is unclear how many traders actually implement such complicated synthetic put-call parity strategies, we additionally construct a measure of investor sentiment utilizing only the buy-side trades of OTM options and the sell-side trades of ITM options, which can be certainly linked to positive and negative expectations. The results with the signed volume ISent proxy support the key rationale behind our measure that a wide range of trades at OTM and ITM options can be intrinsically associated with a specific optimistic or pessimistic expectation about asset return, depending on the selected moneyness level. However, these results are only valid for a short sample period and can only be obtained by investors who have private access to signed volume database. Hence, it is natural that our analysis is conducted with unsigned volume data that can be relatively easier acquired by an actual investor.

In light of the above discussion, since trading at high-strike (low-strike) contracts tends to reflect optimistic (pessimistic) investors' beliefs, a natural way to measure the average bias i.e. investor sentiment is to estimate the volume-weighted average moneyness level across all

[4]If investors with positive or negative opinions wish to utilize more complex strategies such as bull/bear call/put spreads, backspreads or butterfly spreads, then the selected moneyness levels 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 decomposed into expectations implied by single moneyness levels at which simple put/call contracts are traded.

options series. The higher the volume-weighted average moneyness level, the more positive the investors' expectations about the future state of the underlying asset and hence, the higher the sentiment in the options market. Therefore, given the range of strike prices X_j for $j = 1, .., K$ and a stock price S, we propose the following measure of option-implied investor sentiment:

$$ISent = \sum_{j=1}^{K} w_j M_j, \tag{1.1}$$

where w_j is the proportion of trading volume attached to the moneyness level $M_j = \frac{X_j}{S}$. Since the ISent computation is based on moneyness levels, our sentiment proxy is comparable across stocks and over time.

To construct the ISent measure, we use stock call and put options daily data from Ivy DB's OptionMetrics over the period from January 1996 to August 2014.[5] Next, we select options with time to maturity between 5 and 60 calendar days, since these contracts tend to have more liquidity. Further, we exclude near-the-money options (moneyness between 0.975 and 1.025) because trading activity at such contracts is more likely to reflect volatility expectations (Bakshi and Kapadia, 2003; Ni, Pan and Poteshman, 2008). As a robustness check, we construct the ISent measure including near-the-money options (ISent^F). To exclude days when options are not actively traded, we consider only those days when there are at least 5 contracts with positive trading volume. After applying the above filters, we estimate a daily firm-level ISent measure using Equation (1.1). To obtain reliable and accurate monthly estimates of investor sentiment for each stock, we average daily ISent values within a month, requiring a minimum of 10 non-missing daily observations and excluding the last trading day of the 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

[5]This chapter selects options written on ordinary shares (share codes 10 and 11) listed on NYSE, AMEX and NASDAQ excluding closed-end funds and REITs.

of exchanges (Battalio and Schultz, 2006; Baltussen, Van Bekkum, and Van Der Grient, 2015).

Since the proposed option-implied sentiment measure involves moneyness level, that is based on the current stock price, it is possible that the observed predictability for equity premium is mechanically driven by the current level of asset price. To mitigate such concerns, we obtain a stock-level option-implied investor sentiment utilizing the previous-day stock price in the estimation of moneyness level (ISent^{PD}). Additionally, we derive a sentiment index in the options market by calculating the monthly volume-weighted average strike price for each stock and scaling it with the average stock price computed over the previous month (ISent^{PM}). Furthermore, as discussed above, the measurement of investor sentiment implicitly assumes that synthetic option positions via put-call parity are frequently used in the market. However, in reality such synthetic option positions might not be particularly popular among investors. Therefore, utilizing signed volume data, we create the ISent measure exploiting only the buy-side trading volume of out-of-the-money options and the sell-side trading volume of in-the-money options (ISent^{SV}).[6] Trades at such moneyness levels can be undoubtedly linked to pessimistic or optimistic expectations.

Finally, to obtain a market-wide measure of investor sentiment, this chapter employs a bottom-up methodology by value-weighting monthly ISent values across all stocks in our sample. We focus on a bottom-up sentiment index for at least three reasons. First, the bottom-up estimates tend to produce a better signal-to-noise ratio than the top-down measures (i.e. sentiment proxies based on S&P-500 index options) since our sentiment index is constructed using thousands of individual sentiment proxies extracted from relatively large and liquid optioned stocks, while the stock market index contains a limited number of big

[6] We obtain signed volume data from the International Securities Exchange (ISE) Trade Profile, which contains all end-users' trades decomposed into a buy or sell order. However, due to a shorter sample coverage (from May 2005 onwards), the results with signed volume ISent measure are considered as complementary to those produced with the main ISent proxy.

stocks which are less likely to be affected by investor sentiment (Baker and Wurgler, 2006). Hence, a bottom-up composite index may exhibit a strong overall sentiment in the market which is not fully reflected in the top-down proxies. Second, in the spirit of theoretical investor sentiment models introduced by Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyman (1998), the bottom-up sentiment better incorporates various psychological biases since most investors focus naturally on individual stocks (Yu, 2011) and provides important microfoundations for the sentiment variation that the top-down approach treats as exogenous (Baker and Wurgler, 2007). Finally, since the alternative optimism indices of Baker and Wurgler (2006) and Huang et al. (2015) exploit stock-level individual sentiment proxies such as equity share in new issues, dividend premium, etc. to gauge the aggregate mood in the market, this study also extracts the market-wide sentiment measure from individual stocks that have listed options. Additionally, we value-weight each stock's sentiment value in the aggregate ISent measure since any small fluctuations in the sentiment for big firms are more likely to have a larger impact on overall market sentiment and hence, on the future stock market movements. However, for comparison purposes, we also estimate a naïve option-implied sentiment measure (ISent^{EW}, hereafter) by taking a simple average of the monthly sentiment values across all stocks. The empirical results with ISent^{EW} are presented in Appendix A.1.

1.2.2 Other Stock Market Predictors

To investigate the relationship between the ISent measure and other sentiment indices, this chapter constructs two well-known proxies of investor sentiment. The first proxy is Huang et al. (2015) aligned investor sentiment index (PLS, hereafter) constructed from five individual sentiment proxies by applying the partial least squares method. Five individual sentiment proxies are proposed by Baker and Wurgler (2006) and include the closed-end fund discount rate, the number of IPOs, the 12-month lagged first-day returns of IPOs, the 12-month lagged dividend premium and the equity share in new issues.[7] The partial least squares method consists of two steps. In the first step, for each of the five individual sentiment proxies, a time-series regression of lagged proxy on a constant and current stock market return is run in order to capture each proxy's sensitivity (coefficient on current stock market return) to true-but-unobserved sentiment that is instrumented by future stock market return. In the second step, for each month, we run cross-sectional regressions of current sentiment proxies on sensitivities of each proxy to sentiment obtained from the first step. As a result, PLS index is the slope coefficient from the second-step regressions. The second proxy is Baker and Wurgler (2006) investor sentiment index (BW, hereafter) computed as the first principle component of the cross-section of each of the five individual sentiment proxies mentioned above. The first principal component is the linear combination of the sentiment proxies that captures the largest part of total variation. In this study, PLS index is the main comparative sentiment measure because, as noted by Huang et al. (2015), principal component analysis, used to extract BW index, may lead to the insignificant forecasts of future market returns in case when these returns are in fact strongly predictable by the true sentiment. In contrast, PLS index is specifically designed to eliminate components that are irrelevant to forecasting market returns.[8]

In addition to PLS and BW indices, that are calculated by utilizing the full sample information, we also construct two additional sentiment measures (PLS^{BF} and BW^{BF}, hereafter) that are free of look-forward bias. As discussed by Huang et al. (2015), the first-step regression for PLS estimation involves a look-ahead bias because it employs future information,

[7]The most recent data on these variables are collected from Jeffrey Wurgler website. According to the recent update, the sixth sentiment proxy, share turnover, is dropped from index estimation because it is no longer driven by investors' sentiment due to the explosion of institutional high-frequency trading. One-year lags of average first-day return of IPOs and dividend premium are estimated to reflect the fact that these variables take more time to reflect sentiment. Following Huang et al. (2015), before applying partial least squares method, we estimate six-month moving average for each of the five individual sentiment proxies and standardize them.

[8]It is important to note that both PLS and BW indices are estimated over same sample period as the ISent measure, hence options investors, willing to exploit any of the three indices in their trading strategies, have the same information set for an adequate comparative analysis.

thus making some inferences about the forecasting power of PLS index potentially spurious. To eliminate look-ahead bias, the first-step time-series regression is run using information up to time t only (the time when forecasts are formed). Then, the second-step cross-sectional regressions are performed as before and the slope coefficient from these regressions is the aligned sentiment at time t. Implementing this two-stage procedure recursively, we estimate look-forward bias-free PLS index. BW sentiment measure is computed analogously by applying principal component analysis to five individual sentiment proxies known up to time t and repeating this procedure recursively. Following Huang et al. (2015), we use the first 56 months of data (one fourth of the full sample size) i.e. from January 1996 until August 2000 as the initial sample to start the recursive estimations.

The alternative predictor variables can be classified into two categories. The first category represents option-based characteristics that can potentially be more related to investor sentiment than the ISent measure. These variables include the second S&P 500 index risk-neutral moment (VIX), the variance risk premium (VRP; Bollerslev, Tauchen and Zhou, 2009), the hedging pressure (Hedge; Han, 2008), the slope of the implied volatility smirk (Smirk; Xing, Zhang and Zhao, 2010), the third and fourth S&P 500 index risk-neutral moments (Skew and Kurt; Bakshi, Kapadia and Madan, 2003; Chang, Christoffersen and Jacobs, 2013; Conrad, Dittmar and Ghysels, 2013). The data on VIX are downloaded from CBOE website. VRP is the difference between 1-month ahead risk-neutral variance of stock market returns and 1-month ahead realized variance of S&P 500 index returns under the physical measure. Hedge is defined as the ratio of the open interest of out-of-the-money (OTM) S&P 500 index puts to the open interest of at-the-money (ATM) S&P 500 index calls. Smirk is constructed as the difference between the volume-weighted implied volatilities of OTM S&P 500 index puts and ATM S&P 500 index calls. Skew and Kurt are estimated using the methodology of Bakshi, Kapadia and Madan (2003). Monthly VRP data are downloaded from Hao Zhou website. The options data on S&P 500 index come from Ivy DB's OptionMetrics.

The second category contains alternative economic predictors that are previously shown in the literature to significantly predict stock market returns. These variables include the dividend-payout ratio (D/E; Campbell and Shiller, 1988; Lamont, 1998), the earnings-price ratio (E/P; Campbell and Shiller, 1988), the yield gap (YGap; Maio, 2013), the yield term spread (YSpr; Campbell, 1987; Fama and French, 1989), the default spread (DSpr; Keim and Stambaugh, 1986; Fama and French, 1989), the analysts' forecasts dispersion (Dis; Yu, 2011), the consumption-wealth ratio (C/W; Lettau and Ludvigson, 2001), the stock market illiquidity (Illiq; Amihud, 2002), the idiosyncratic volatility (IdV; Goyal and Santa-Clara, 2003), and the tail risk (TRisk; Kelly and Jiang, 2014). D/E is the difference between the aggregate yearly dividends and the aggregate yearly earnings, in logs. E/P is the difference between the aggregate yearly earnings and the log value of the S&P 500 index. YGap is the difference between E/P and 10-year bond yield, in logs. YSpr is the yield differential between the 10-year and 1-year bond. DSpr is the yield differential between BAA and AAA corporate bonds from Moody's. Dis is the value-weighted average of the dispersion in analysts' long-term forecasts about growth rate of stock's earnings per share across NYSE/AMEX/NASDAQ stocks with share codes 10 and 11. C/W is obtained from estimating the cointegrating relationship between consumption, labor income and asset wealth and identifying the trend deviation between these variables. Illiq is the monthly average of stock illiquidity values defined as the average of the daily ratio of the absolute return to dollar trading volume in a given month across all stocks. IdV is the monthly average of stock return variance computed from daily return data in a given month across all stocks. TRisk is the probability of extreme negative market returns, computed by applying Hill (1975) estimator to the cross-section of daily stock returns in a given month. The monthly data on market prices, dividends and earnings are downloaded from Robert Shiller website. Yield data are collected from the FRED database of the Federal Reserve Bank of St. Louis. The data on analysts' earnings forecasts are obtained from I/B/E/S. The monthly data on C/W are from Martin Lettau website. To estimate Illiq, IdV and TRisk, we obtain NYSE/AMEX/NASDAQ (with share codes 10 and 11) stock returns and volume data from the Center for Research in Security Prices (CRSP).

Finally, this study employs the value-weighted index from CRSP to proxy for the stock market return and 1-month Treasury bill rate, collected from Kenneth French website, to proxy for the return on risk-free asset. Monthly excess market return is the difference between monthly log-return and log of Treasury bill. In order to calculate continuously compounded excess market returns for a horizon greater than one month, we estimate the cumulative sum of monthly excess market returns.

1.2.3 Descriptive Statistics

Figure 1.1 shows a time-series plot of the various specifications of the ISent measure, PLS and BW indices. To examine the relative dynamics, all sentiment measures are standardized to have zero mean and unit variance. Of all sentiment proxies, PLS and ISent fluctuate similarly across the full sample, capturing the common patterns in investors' mood during the periods of market boom and downturn, although PLS index tends to be smoother. Option-based sentiment drops to a trough during the Latin America financial crisis in January 1999, dotcom bubble in 2001 and at the end of global financial crisis in 2009. Similar to a positive sentiment captured by PLS index, the upward spikes in the ISent measure are observed right before the dotcom bubble, however, in contrast to the alternative sentiment proxies, the ISent values increase substantially in the middle of global financial crisis, implying a huge overreaction caused by individual speculative investors during the 2007-2009 recession period. As shown in the second graph, this surprising upward spike of the ISent measure in the middle of global financial crisis still exists when we calculate ISent using the moneyness level, that is computed relative to the average stock price estimated over the previous month

(ISent(PM)), or exploiting the signed volume data (ISent(SV)). These findings suggest that the time-series dynamics of ISent is unlikely to be mechanically driven by the presence of the current stock price in its estimation or usage of total trading volume. Overall, the figures clearly illustrate that unlike PLS or BW index, the ISent measure seems to effectively capture the short-term investor mood since the average bias in investors' beliefs varies substantially over short periods of time reflecting a more active reaction of options traders to news or changing economic conditions.

Further, we provide summary statistics and correlation coefficients of three sentiment measures and alternative predictors in Table 1.1 and 1.2, respectively. First, over our sample period, both the naïve and ISent measures have an average value of one meaning that the average bias in options traders' beliefs is zero. The ISent and ISent^{EW} proxies exhibit positive skewness, excess kurtosis and first-order autocorrelation coefficients of 0.74 and 0.68, respectively. In contrast, PLS and BW indices have less skewness and kurtosis, but tend to be more persistent, with a first-order autocorrelation coefficient of 0.97. This means that ISent tends to better capture variations in the short-term equity premium compared to the alternative sentiment indices. Of all other variables, alternative economic predictors are highly persistent (apart from IdV and TRisk), having an AR(1) of almost one, whereas first-order correlation coefficients of option-based characteristics are close to 0.5 (apart from VIX). Second, as shown in Table 1.2, the ISent measure is strongly positively correlated with the naïve option-implied sentiment proxy (0.89) as well as with PLS and BW sentiment indices, with correlation coefficients of 0.54 and 0.24, respectively. Additionally, ISent is negatively correlated with VRP (-0.17), Hedge (-0.23), Smirk (-0.25) and Kurt (-0.38), but positively related to VIX (0.51) and Skew (0.36). Considering all economic predictors, ISent has the strongest positive relationship with IdV (0.50) and negative relationship with TRisk (-0.49).

1.3 Empirical Results

1.3.1 Contemporaneous Analysis of Sentiment Measures

We begin the empirical analysis by examining the contemporaneous relationship between the ISent measure and PLS and BW sentiment indices after controlling for other option-related characteristics. If the ISent measure indeed captures a certain dimension of investor sentiment, then the comovement between the previously established sentiment indices and our proxy should be the strongest among all option-related variables. To test this proposition, we run contemporaneous time-series regressions of PLS and BW indices on the ISent measure and a list of option-based variables in univariate, bivariate and multivariate settings. To compare the relative strength of the regressors, the slope coefficients are standardized to show the change in standard deviation of PLS and BW indices for a one standard deviation increase in the explanatory variable. We also report adjusted R^2s from the regressions. Furthermore, since all sentiment proxies are relatively persistent, we provide Newey-West adjusted t-statistics with four lags obtained from Newey-West (1994) plug-in procedure to account for serial correlation. OLS and Newey-West adjusted t-statistics are documented in round and square parentheses, respectively.[9]

Table 1.3 reports the estimation results for PLS (Panel A) and BW (Panel B) indices. First, the ISent measure has the strongest positive contemporaneous relationship with PLS index. One standard deviation increase in the ISent measure leads to a 0.539 standard deviation increase in PLS in univariate model and a 0.698 standard deviation increase in multivariate model. After a sequential inclusion of option-related controls, the slope coefficient on ISent varies from 0.481 (when Smirk is added) to 0.706 (when VIX is included). The coefficient on the ISent measure is highly statistically significant across all model specifications, with

[9] We also carry out the same analysis with the ISent^{EW} measure and the main results, presented in Appendix A.1, demonstrate that the naïve option-implied sentiment is strongly related to PLS index, but has a less pronounced relationship with BW index, when considering both look-ahead biased and unbiased sentiment proxies.

t-statistics (Newey-West t-statistics) of greater than 8 (3). Of all option-related predictors, the strongest positive relationship with PLS index is observed with Skew (0.295 with a Newey-West t-statistic of 2.38 in univariate model) and VRP (0.135 with a Newey-West t-statistic of 2.21 in multivariate model), however the economic magnitude of Skew and VRP coefficients is substantially lower than that of the ISent measure. Second, our proxy exhibits a strongly positive relationship with BW index. One standard deviation rise in the ISent measure causes the standard deviation of BW index to increase by 0.236 in univariate model and 0.479 in multivariate model. Similar magnitude is also documented in bivariate models, where the slope coefficient on the ISent proxy ranges between 0.178 (when Smirk is added) and 0.491 (when VIX is included). However, the statistical significance across all BW models drops substantially after controlling for serial correlation. This implies that the ISent proxy has a weak relationship with BW index possibly due to the lower correlation of the option-implied measure, that directly relates to stock returns, with noise and idiosyncratic component of the BW index, that are irrelevant for forecasting returns. It is also important to note that the $\widetilde{R}^2$s increase substantially after including ISent in various models. Overall, these findings demonstrate that the ISent measure exhibits the strongest (less pronounced) contemporaneous explanatory power for PLS (BW) sentiment index, that is not driven and subsumed by various option-related characteristics.

To alleviate any concerns about the strength of the relationship between the ISent measure, PLS and BW proxies established above, we repeat the contemporaneous regression analysis with look-ahead bias-free sentiment indices. Table 1.4 illustrates the main findings for PLS^{BF} (Panel A) and BW^{BF} (Panel B) indices over the sample period from September 2000 to August 2014. First, taking a closer look at univariate and multivariate models, one standard deviation boost in option-implied sentiment leads to a 0.505 standard deviation increase in PLS index (with a t-statistic of 11.87), a 0.218 standard deviation rise in BW index (with a t-statistic of 2.84) for single-variable regressions and a 0.527 standard deviation increase in PLS index (with a t-statistic of 9.58), a 0.422 standard deviation rise in BW index (with a t-statistic of 4.80) when all variables are added to the model. Equally significant results, both economically and statistically, are also documented for bivariate models. However, after accounting for serial correlation, a positive and statistically significant relation between PLS^{BF} and ISent measures still persists, whereas ISent tends to exhibit a weak relationship with BW^{BF} as it is likely to be less correlated with common component of BW index, that is not relevant for predicting returns. These findings clearly indicate that the greatest (less pronounced) explanatory power of the ISent measure for PLS (BW) index among all option-related variables is robust to the existence of look-forward bias in sentiment estimates.

1.3.2 In-sample Market Forecasts

In the previous section, we have established that the information content of the ISent measure is robustly similar to that of PLS and BW indices. Thus, in this section, this study performs the comparative analysis of the predictive power of our proposed sentiment measure, PLS and BW indices for short- and long-run equity premium. We consider long-horizon predictability of the ISent measure because, as documented by Huang et al. (2015), short-run mispricing, generated by investor sentiment, may persist due to the limits to arbitrage, hence several studies find a strong relation between sentiment and long-term returns (Brown and Cliff, 2005; Baker, Wurgler and Yuan, 2012). To this end, we run univariate time-series regressions of the 1-, 2-, 3- and 6-month-ahead CRSP value-weighted index excess returns on the investor sentiment proxies (various ISent specifications, PLS and BW) included separately in model specifications. We also perform bivariate regression analysis by adding sequentially each alternative predictor to the ISent-return model to explore whether the forecasting power of the ISent measure is driven by economic characteristics that are related to business-cycle fluctuations or economic fundamentals. To avoid spurious t-statistics due to overlapping observations, we use Newey and West (1987) standard errors with lag length equal to the forecasting horizon. To compare the relative strength of the regressors, the slope coefficients are standardized to show the monthly excess return resulting from a one standard deviation increase in the explanatory variable. We also report adjusted R^2s from the regressions.[10]

Table 1.5 reports the results for univariate predictive regressions. First, consistent with the literature, the ISent measure is a negative stock market excess return predictor for short and long horizons. One standard deviation rise in the option-implied sentiment forecasts a market excess return of -0.78% for monthly horizon, -2.42% for quarterly horizon and -3.29% for half-year horizon. All coefficients are statistically significant at 5% level. The adjusted R^2 is 2.23% in monthly regression, then it peaks at 7.14% in quarterly regression and drops slightly to 5.88% when predicting half-year market excess returns. Second, the predictive power of a similar economic magnitude and statistical significance is documented by PLS index. For example, in line with the findings of Huang et al. (2015), high PLS index generates market excess profitability of -0.89% for monthly horizon, -2.68% for quarterly horizon and -5.50% for half-year horizon. Observed $\widetilde{R}^2$s are of similar magnitude to those generated by the ISent measure up to quarterly horizon: $\widetilde{R}^2$ equals to 3.07% for monthly regression and it escalates to 8.89% for quarterly regression. In contrast to PLS index, BW sentiment proxy is not statistically significant up to quarterly horizon, but then it generates negative market excess returns that are economically comparable to those predicted by PLS and ISent. Finally, we also examine the market excess return forecasts generated by look-ahead bias-free indices over the out-of-sample period from September 2000 to August 2014. For a 1-standard-deviation positive shock to PLS^{BF} index, the market excess return varies from -1.80% for 1-month horizon to -5.47% for half-year horizon. All slope coefficients are statistically significant at 1% level, whereas $\widetilde{R}^2$s are of similar magnitude to those generated by PLS index and the ISent measure (apart from monthly horizon). The market excess returns predicted by look-forward bias-free BW index are lower than those forecasted by BW sentiment proxy and are not statistically significant up to half-year horizon. Overall, these

[10] The univariate and bivariate results with the naïve sentiment measure are quantitatively similar to those presented in this section and are reported in Appendix A.1.

findings reveal that our suggested option-implied sentiment measure generates the negative stock market profitability at short and long horizons that is of close economic magnitude to, and comparable with, that predicted by well-known PLS and BW sentiment indices.

The observed predictability for future market excess returns, that is generated by the ISent measure, can be potentially related to the moneyness level, that is computed relative to the current-day stock price, to the usage of total trading volume or to the exclusion of near-the-money options in the sentiment estimation. To alleviate all potential concerns, we test the in-sample forecasting power for equity premium using various ISent specifications. First, one standard deviation rise in the ISent^{F} measure, that is based on all available moneyness levels, predicts a negative monthly market excess return of 0.76% (with a t-statistic of -2.10) and a negative quarterly market excess return of 2.36% (with a t-statistic of -2.82). Second, the estimation of option moneyness on the basis of the previous-day stock price or average stock price computed over the previous month does not alter the main findings — the equity premium, predicted by ISent^{PD} (ISent^{PM}), is statistically significant at 5% level and escalates in absolute terms from 0.70% (0.75%) for monthly horizon to 2.44% (2.30%) for quarterly horizon. Finally, considering only the buy-side of out-of-the-money options and the sell-side of in-the-money options, one standard deviation increase in the ISent^{SV} measure leads to a monthly (quarterly) market excess return of -1% with a t-statistic of -1.88 (-2.51% with a t-statistic of -2.17). Overall, these results reveal that the strong and negative in-sample predictive power of the ISent measure for future market returns cannot be mechanically driven by the exclusion of near-the-money options, the presence of current stock price in moneyness computation or the usage of total options trading volume.

The short- and long-run effect of the ISent measure on market excess returns, shown above, can still be driven by alternative economic stock market predictors. To examine the incremental predictive power of ISent and to avoid highly parameterized non-parsimonious models, that may bring extra noise and lead to in-sample overfitting and misleading inferences (Rapach and Zhou, 2013), we follow Huang et al. (2015) and implement bivariate regression analysis. In Table 1.6, we report the slope coefficient on the ISent measure and verify that none of the economic or stock-related characteristics can explain the negative ISent-return relationship. The ISent measure retains its strong negative short- and long-run predictive power for market excess returns, with the slope coefficient varying from -0.94% (when IdV is added) to -0.75% (when Dis is included) for monthly horizon, from -3.24% (after controlling for TRisk) to -2.33% (when Dis is included) for quarterly horizon and from -4.52% (when IdV is added) to -3.09% (after controlling for Dis) for half-year horizon. All coefficients on ISent are statistically significant at 5% level, except for the 1-month-horizon model where ISent is significant at 10% level when TRisk is added. With few exceptions, $\widetilde{R}^2$s exhibit increasing pattern when we increase the forecasting horizon, reaching its lowest value of 1.78% when we control for YGap, YSpr and DSpr in 1-month-horizon models and peaking at 9.99% after adding C/W variable to 6-month-horizon regression. Summing up, it is clearly revealed that the negative relationship between stock market excess returns and the ISent measure is robust to the inclusion of various economic forecasters.

1.3.3 Out-of-sample Market Forecasts

In-sample predictability tests implemented in the previous section possess higher statistical power (Inoue and Kilian, 2004) and generate more efficient return forecasts (Huang at al., 2015), however they may suffer from over-fitting issues (Goyal and Welch, 2008) and are unable to provide any estimates of the real-time investor's performance. Hence, in this section, we carry out out-of-sample predictability tests of the ISent measure by focusing on the horizons up to a quarter since the in-sample forecasting power of the ISent measure attains its peak at 3-month horizon.

Following Lettau and Ludvigson (2001), Goyal and Welch (2008), Ferreira and Santa-Clara (2011), Huang et al. (2015), among many others, we estimate 1-, 2- and 3-month-ahead regression models recursively using information up time t to predict market excess returns at time $t{+}k$,

$$\hat{R}^{M}_{t+k} = \hat{\alpha}_t + \hat{\beta}_t \cdot Z_{1:t;t}, \tag{1.2}$$

where k is 1-, 2- or 3-month horizon, $\hat{\alpha}_t$ and $\hat{\beta}_t$ are OLS estimates from time-series regression of excess market return $\{R^{M}_{j+k}\}_{j=1}^{t-k}$ on a constant and one of sentiment proxies $\{Z_{1:t;j}\}_{j=1}^{t-k}$ (Z = ISent, PLS^{BF} or BW^{BF}).

Given the initial sample $t = 1, ..., N$ and using the estimates from the above model, we generate excess market return forecasts for $t = N+1, ..., T-k$, where T is the size of the full sample. In total, we produce $T-k-N$ out-of-sample forecasts of future stock market returns from the sentiment predictive model (Equation 1.2 with different sentiment measures), that will be compared to the returns generated by recursively estimating the historical average model (Equation 1.2 with only a constant parameter). Following Huang et al. (2015), we use the first 56 months (one fourth of the full sample) as the initial sample to start the recursive estimation procedure and the first forecast is generated for September 2000. In order to assess the out-of-sample performance of the ISent measure, we exploit four different statistics.

The first performance measure is the out-of-sample $\widetilde{R}^2$, that compares the mean squared prediction error of the sentiment predictive model and the historical average model,

$$\widetilde{R}^2 = 1 - \frac{\sum_{t=N+1}^{T-k}(R^{M}_{t+k} - \hat{R}^{M}_{t+k})^2}{\sum_{t=N+1}^{T-k}(R^{M}_{t+k} - \widetilde{R}^{M}_{t+k})^2}, \tag{1.3}$$

where $\widetilde{R}^{M}_{t+k}$ is the returns generated by recursively estimating the historical average model.

The out-of-sample $\widetilde{R}^2$ is positive when the sentiment predictive model outperforms the historical average model in terms of the mean squared prediction error.

The second performance statistic that we exploit is McCracken's (2007) F-statistic (MSE-F),

$$\text{MSE-F} = (T - N - 2k + 1) \cdot \frac{\sum_{t=N+1}^{T-k}(R_{t+k}^M - \widetilde{R}_{t+k}^M)^2 - \sum_{t=N+1}^{T-k}(R_{t+k}^M - \hat{R}_{t+k}^M)^2}{\sum_{t=N+1}^{T-k}(R_{t+k}^M - \hat{R}_{t+k}^M)^2}. \quad (1.4)$$

This statistic tests for the equality of mean squared prediction error of the sentiment predictive model and the historical average model. The resulting F-statistic follows a non-standard normal distribution and McCracken (2007) reports corresponding critical values.

The third measure is the encompassing test introduced by Clark and McCracken (2001),

$$\text{ENC-NEW} = (T - N - 2k + 1) \cdot \frac{\sum_{t=N+1}^{T-k}\left[(R_{t+k}^M - \hat{R}_{t+k}^M)^2 - (R_{t+k}^M - \hat{R}_{t+k}^M) \cdot (R_{t+k}^M - \widetilde{R}_{t+k}^M)\right]}{\sum_{t=N+1}^{T-k}(R_{t+k}^M - \hat{R}_{t+k}^M)^2}. \quad (1.5)$$

This test examines whether the sentiment predictive model improves the predictive power of the historical average model. The critical values are also reported by the original paper.

The final performance measure is the restricted $\widetilde{R}^2$ ($\widetilde{R}^2_C$) proposed by Campbell and Thompson (2008). This statistic is identical to the out-of-sample $\widetilde{R}^2$ with the following difference: if the return forecasts made by the sentiment predictive model are negative, then, consistent with the predictions from standard asset pricing theory, they become zero.

Table 1.7 reports the results for the ISent measure, PLS^{BF} and BW^{BF} indices that are estimated recursively to eliminate look-ahead bias in out-of-sample forecasts.[11] First, the

[11] The naïve option-implied sentiment proxy exhibits quantitatively similar out-of-sample results, that we

ISent measure generates positive out-of-sample $\widetilde{R}^2$s across all horizons, implying that mean squared prediction error of the ISent model is lower than that of the historical average model. Further, these out-of-sample $\widetilde{R}^2$s are substantially higher than those produced by PLS^{BF} predictive model, reaching the maximum difference at 3-month horizon (6.70% - ISent, 1.12% - PLS^{BF}). The out-of-sample $\widetilde{R}^2$s from BW^{BF} trading strategy are negative across all horizons. Second, the outperformance of the models based on the ISent measure, relative to the historical average strategy, is statistically significant at 5% level across all horizons, with the obtained statistics being substantially greater than those produced by PLS^{BF} index. PLS^{BF} models consistently outperform the historical average only based on MSE-F statistic, which shows a significance at 1% level across all horizons, and generate statistically insignificant out-of-sample return forecasts based on ENC-NEW statistic. For example, MSE-F for ISent (PLS^{BF}) model is 3.83 (1.58) for 1-month horizon and 11.70 (1.85) for quarterly horizon. The outperformance of BW^{BF} index, relative to the historical average model, is statistically insignificant across all horizons. Finally, considering the restricted $\widetilde{R}^2$, it can be seen that $\widetilde{R}^2_C$s from ISent models remain almost the same as the unrestricted $\widetilde{R}^2$s (they even slightly decrease in 2- and 3-month-horizon models), whereas PLS^{BF} generates the restricted $\widetilde{R}^2$s that are substantially higher than the unrestricted coefficients of determination. This evidence suggests that the proposed option-implied measure exhibits stronger predictability during market declines. Overall, in contrast to findings from the in-sample forecasts, these results explicitly show that the ISent measure outperforms both PLS^{BF} and BW^{BF} sentiment indices in terms of the out-of-sample market excess return predictability.

In Figure 1.2, in addition to test statistics presented above, we also illustrate the time-series plots of the differences in the 1-, 2- and 3-month-horizon cumulative squared prediction error based on each of sentiment proxies and the historical average model. To interpret the graphs, consider the beginning and the end of the out-of-sample period. If the overall slope of the

report in Appendix A.1.

curve between these two points is positive i.e. the difference in error increases over time, then a certain sentiment model performs better than the historical average model. Across all forecasting horizons, the error curve of the ISent measure has a strongly positive slope during NBER-dated recession periods (especially during 2007-2009 financial crisis) and after 2009. Over the years between two recessions, the ISent measure exhibits a relatively flat pattern. In contrast, the out-of-sample performance of PLS^{BF} is better than the historical average in the first years of the forecasting sample, however it deteriorates during and after the 2007-2009 financial crisis. Furthermore, if we increase the forecasting horizon, the slope of the PLS^{BF} error curve becomes more negative. Overall, Figure 1.2 shows that the ISent measure exhibits a strong out-of-sample predictive power for market excess returns, especially during the periods of market turbulence.

1.3.4 Asset Allocation

In this section, we conclude the empirical analysis by examining the economic importance of the forecasted market excess returns based on the ISent, PLS^{BF} and BW^{BF} indices. Following Kandel and Stambaugh (1996), Campbell and Thompson (2008), Ferreira and Santa-Clara (2011), Huang et al. (2015), among many others, we evaluate the portfolio performance of the mean-variance risk-averse investor, who optimally allocates his wealth between the market index and the risk-free asset, exploiting 1-month-ahead market excess return forecasts made by the out-of-sample sentiment predictive models. As a result, the 1-month-ahead market excess return forecasts are generated at the end of forecasting sample N and the realized portfolio return at time $N+1$ is

$$R^P_{N+1} = w_t R^m_{N+1} + R^F_{N+1} \tag{1.6}$$

where the weight allocated to the market index is $w_t = \frac{1}{\gamma} \cdot \frac{\hat{R}^m_{N+1}}{\hat{\sigma}^2_{N+1}}$, γ is the risk-aversion coefficient (equals to 3), $\hat{R}^m_{N+1}$ is the 1-month-ahead forecasted simple market excess return (not logarithmic), $\hat{\sigma}^2_{N+1}$ is the variance of market returns estimated over initial period $t = 1, ..., N$ (56 months) and R^F_{N+1} is the return of one-month Treasury bill. We also restrict the weights, assigned to the market index, to be between 0 and 1.5 to allow the maximum of 50% leverage (Campbell and Thompson, 2008).

Additionally, we also assess the profitability of the "binary" portfolio, where weights are assigned by either allowing or disallowing short sales. In particular, investor with the right to short sell allocates $w_t = 1.5$ to the market index if $\hat{R}^m_{N+1}$ is greater or equal than zero; otherwise, $w_t = -0.5$. Further, if short sales are banned, then investor assigns $w_t = 1$ to the market index if $\hat{R}^m_{N+1}$ is greater or equal than zero; otherwise, $w_t = 0$.

In this study, we employ several portfolio performance measures. The first measure is the Sharpe ratio (Sharpe), estimated as the average monthly excess portfolio returns divided by standard deviation of the monthly excess portfolio returns. The second statistic is the percentage gain in a certainty equivalent return (CE). A certainty equivalent return of the portfolio is computed as follows

$$\text{CER}^P = E(R^P_{N+1}) - \frac{1}{2} \cdot \gamma \cdot Var(R^P_{N+1}), \tag{1.7}$$

where $E(R^P_{N+1})$ and $Var(R^P_{N+1})$ are mean and variance of investor's portfolio returns, respectively, generated by the predictive model over the forecasting period. The gain in a certainty equivalent return is the difference between certainty equivalent portfolio return forecasts made by the sentiment predictive model (Equation 1.2) and certainty equivalent return forecasts produced by the historical average model (Equation 1.2 with only a constant parameter). This measure essentially shows the effect on investor's utility function from exploiting the sentiment predictive regression rather than the historical average model to make the return forecasts. The third portfolio performance indicator is the maximum drawdown (MDD), calculated as the maximum loss of the portfolio if investor decides to use the sentiment predictive strategy at any time during the forecasting period. Finally, we calculate the fraction of months (Long) when investor takes a long position in the market index based on the sentiment predictive model. All measures (apart from MDD and Long) are annualized.

Table 1.8 reports the results from asset allocation decisions.[12] First, the investor with mean-variance portfolio weights, who allocates his wealth based on the option-implied sentiment measure, will gain much higher expected return per unit of risk than that predicted by the historical average model: a Sharpe ratio, generated by ISent strategy is 0.60, whereas the historical average model produces a Sharpe ratio of 0.12. Moreover, the same investor will hugely benefit from investing his funds based on ISent rather than PLS^{BF} and BW^{BF} indices, that exhibit annualized Sharpe ratios of 0.32 and 0.05, respectively. These results are further supported by CE statistic. The utility of mean-variance investor is much higher in case of investing with the ISent measure rather than with the PLS^{BF} or BW^{BF} indices when comparing the returns predicted by each sentiment trading strategy with the historical average model. CE generated by ISent is 5.68% compared to 2.31% and -1.91% for PLS^{BF} and BW^{BF} sentiment indices, respectively. Looking at the maximum drawdown figures, ISent exhibits a maximum loss that is of similar magnitude to the historical average (-39% for the historical average and -41% for ISent) and is slightly higher in absolute terms than that shown by PLS^{BF} (-33%). Overall, these findings demonstrate that the portfolios constructed on the return predictions of ISent model clearly dominate those created on the basis of historical average, PLS^{BF} or BW^{BF} trading models in terms of the gain in utility and Sharpe ratios.

Second, if the risk-averse investor decides to short sell the market index when the forecasted

[12] In Appendix A.1, we also report quantitatively similar asset allocation results based on the naïve option-implied sentiment measure.

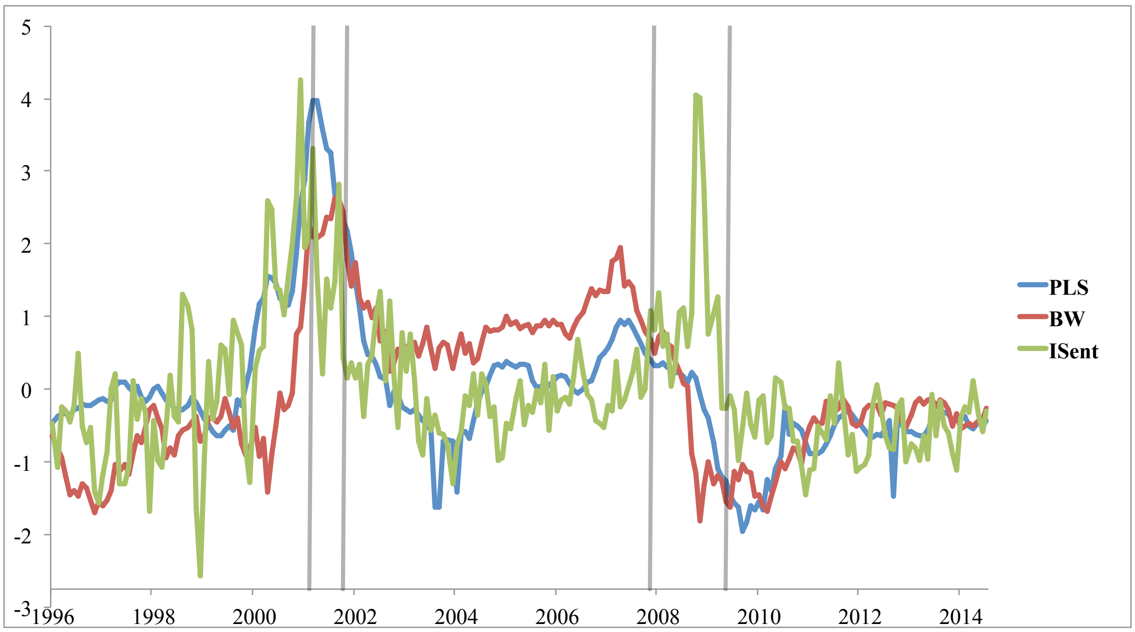
return is negative, he will obtain higher expected return-risk trade-off investing with the ISent measure and, surprisingly, with the BW^{BF} index. In particular, the Sharpe ratios generated by ISent and BW^{BF} predictive models are 0.39 and 0.44, respectively, compared to 0.35 and 0.18 shown by the historical predictive model and PLS^{BF} trading strategy, respectively. Taking a closer look at CE, the gains in utility obtained from investing with the ISent and BW^{BF} measures rather than with the historical average model are 1.93% and 2.52%, respectively, whereas PLS^{BF} cannot beat the historical average, showing the negative CE value. MDD numbers are quite similar across all four strategies, ranging around -70%. Finally, we consider the case when investor is not allowed to short sell the market index, if she wishes to do so. The Sharpe ratios associated with the ISent and BW^{BF} index trading strategies are 0.44 and 0.46, that are clearly higher than those produced by the historical average model and PLS^{BF} index (0.38 and 0.27, respectively). CE figures are of similar economic significance for the ISent and BW^{BF} measures (0.97% and 1.26%, respectively), whereas PLS^{BF} index generates lower utility than the historical average model. MDD displays similar values across four trading strategies, fluctuating around -50%. Overall, the results for binary portfolios indicate that the ISent measure exhibits an economic value that is of close magnitude to BW^{BF} index and substantially outperforms PLS^{BF} sentiment proxy in terms of economic significance.

1.4 Conclusion

In this chapter, consistent with the theoretical predictions, we demonstrate that the option-implied sentiment measure, constructed as the volume-weighted average moneyness level across all options series, is a strong negative predictor of stock market excess returns. Our suggested measure of investor sentiment can be rationalized within a typical options market, in which end-users' trading strategies at various moneyness levels reflect positive and negative directional traders' bets on the future price of the underlying asset and such strategies are accommodated by the options market makers. The key findings of the chapter illustrate that (1), among all option-related characteristics, our measure has the strongest contemporaneous relationship with existing sentiment proxies such as PLS and BW indices, (2) a one-standard-deviation shock to the ISent measure is associated with an in-sample market excess return of -0.78% for monthly horizon, -2.42% for quarterly horizon and -3.29% for half-year horizon, and (3) the out-of-sample performance of the ISent measure is clearly superior to that shown by PLS^{BF} and BW^{BF} sentiment indices. The in-sample market forecasts are statistically significant and economically similar to those made by PLS^{BF} and BW^{BF} indices. Furthermore, the investor's portfolio constructed from the ISent predictive model produces an economic value that is higher in case of the mean-variance weights and is tantamount in case of the binary weights relative to the economic value of the portfolios created on the basis of PLS^{BF} or BW^{BF} sentiment indices. Overall, although the origin of the ISent predictability for stock market returns requires further empirical investigation, the proposed option-implied sentiment measure, which is easy to construct at any frequency and whose effect is not subsumed by various economic drivers, can be of particular interest both to academics and practitioners.

Figure 1.1: Time-Series Plot of Sentiment Indices

This figure plots the monthly time series of various specifications of the option-implied sentiment measure, Huang et al. (2015) aligned investor sentiment index (PLS), constructed from five individual sentiment proxies by applying partial least squares methodology, and Baker and Wurgler (2006) investor sentiment index (BW), derived as the first principal component of five individual sentiment proxies. ISent and ISent(PM) are defined as the volume-weighted average moneyness level, where moneyness is estimated relative to a current-day stock price and average stock price over the previous month, respectively. ISent(SV) is the signed volume-weighted average moneyness level. The estimated sentiment measures are standardized to have zero mean and unit variance. The vertical bars designate NBER-dated recession periods. Our sample period is from January 1996 to August 2014.



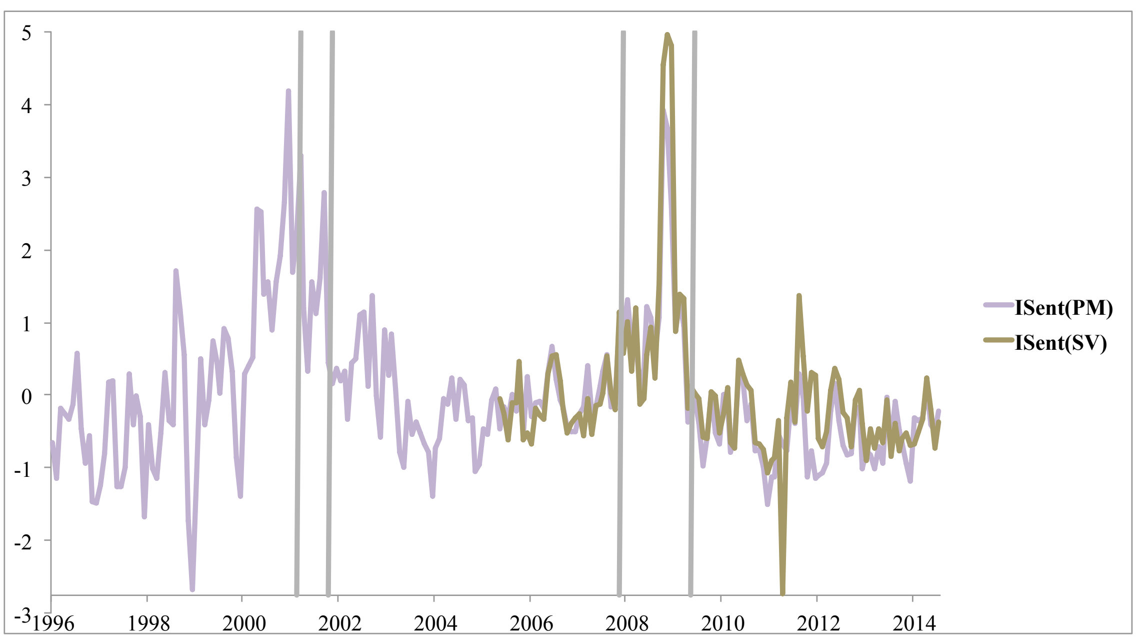


Figure 1.2: Difference in Cumulative Squared Prediction Error (CSPE)

This figure shows the differences in the cumulative squared prediction error (CSPE) based on the option-implied sentiment measure (ISent), defined as the volume-weighted average moneyness level, Huang et al. (2015) aligned investor sentiment index (PLS), constructed from five individual sentiment proxies by applying partial least squares methodology, Baker and Wurgler (2006) investor sentiment index (BW), derived as the first principal component of five individual sentiment proxies, and the historical average model. PLS and BW are constructed recursively using information up to the period of forecast formation, that starts in September 2000 and ends in August 2014. The vertical bars designate NBER-dated recession periods.

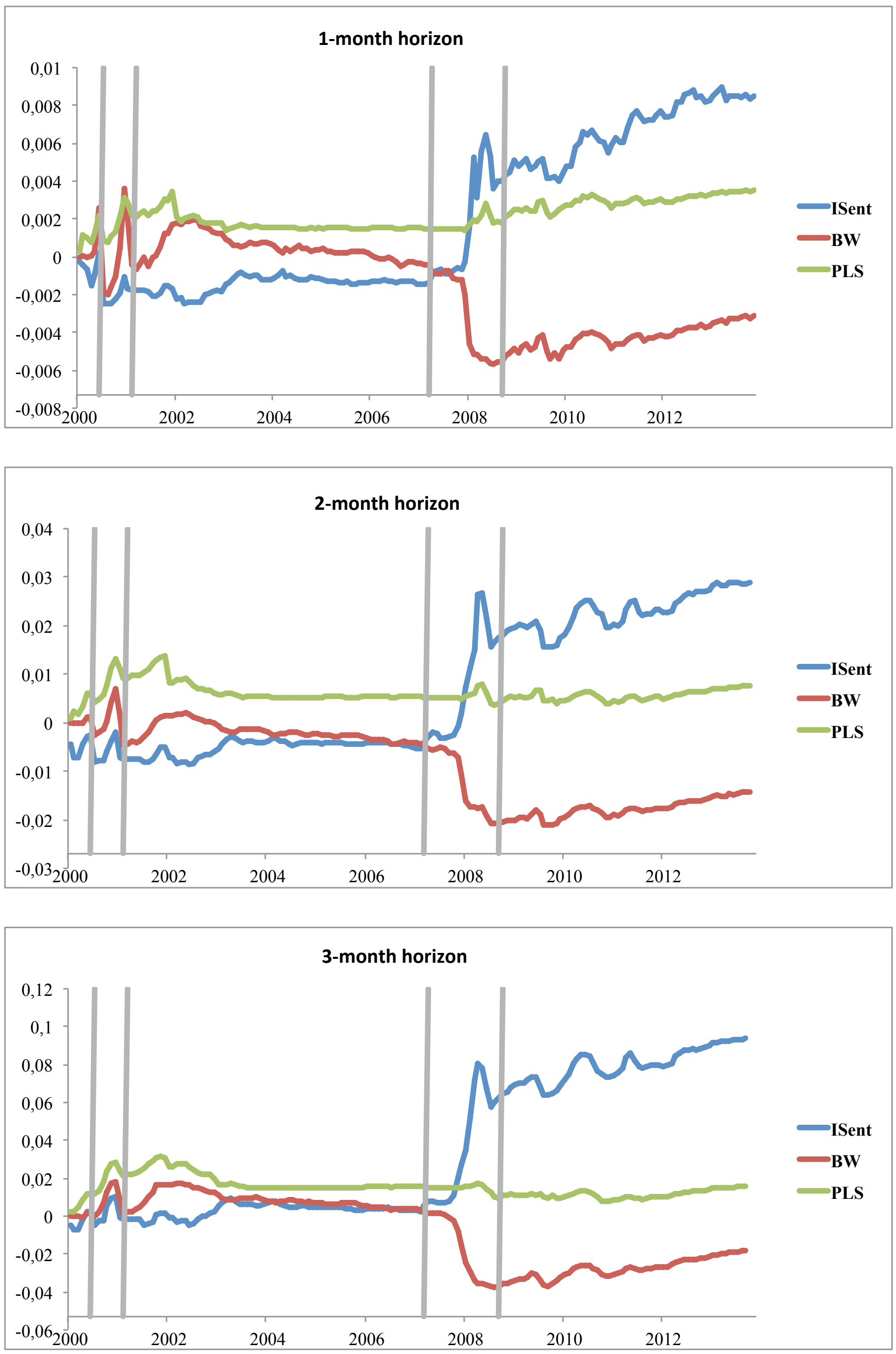


Table 1.1: Summary Statistics

This table reports summary statistics for three groups of variables. The first group includes sentiment proxies such as the option-implied sentiment measure (ISent), defined as the volume-weighted average moneyness level, the naïve option-implied sentiment measure (ISent^{EW}), Huang et al. (2015) aligned investor sentiment index (PLS), constructed from five individual sentiment proxies by applying partial least squares methodology, and Baker and Wurgler (2006) investor sentiment index (BW), derived as the first principal component of five individual sentiment proxies. The second group represents option-based characteristics i.e. second risk-neutral moment (VIX), variance risk premium (VRP), hedging pressure (Hedge), slope of implied volatility smirk (Smirk), third risk-neutral moment (Skew) and fourth risk-neutral moment (Kurt). The third group contains other predictor variables such as dividend-payout ratio (D/E), earnings-price ratio (E/P), yield gap (YGap), yield term spread (YSpr), default spread (DSpr), disagreement (Dis), consumption-wealth ratio (C/W), illiquidity (Illiq), idiosyncratic volatility (IdV) and tail risk (TRisk). Our sample period is from January 1996 to August 2014. AR(1) is the first-order autocorrelation coefficient.

	Mean	**Median**	**Std**	**Min**	**Max**	**Skewness**	**Kurtosis**	**AR(1)**
ISent	1.00	1.00	0.01	0.97	1.06	1.48	6.57	0.74
ISent^{EW}	1.02	1.01	0.03	0.99	1.18	2.48	10.88	0.68
PLS	0.00	-0.19	1.00	-1.96	3.98	1.59	6.81	0.97
BW	0.00	-0.22	1.00	-1.82	2.64	0.40	2.52	0.97
VIX	21.45	20.06	7.94	10.42	59.89	1.56	6.79	0.84
VRP	17.82	14.96	23.68	-218.60	115.90	-3.81	47.62	0.23
Hedge	2.05	1.97	0.56	0.87	4.42	1.01	4.61	0.30
Smirk	0.11	0.11	0.04	0.03	0.24	0.79	3.65	0.50
Skew	-1.58	-1.61	0.40	-3.02	-0.59	-0.21	2.94	0.64
Kurt	7.23	6.96	1.91	4.12	16.00	0.93	4.34	0.64
D/E	-0.87	-1.01	0.47	-1.24	1.38	3.12	13.34	0.98
E/P	-3.16	-3.02	0.41	-4.82	-2.60	-1.81	7.15	0.98
YGap	-3.58	-3.55	0.46	-5.18	-2.80	-0.90	4.34	0.98
YSpr	0.01	0.02	0.01	-0.00	0.03	-0.05	1.64	0.99
DSpr	0.01	0.01	0.00	0.01	0.03	2.89	13.27	0.96
Dis	3.71	3.60	0.57	2.80	5.13	0.53	2.35	0.95
C/W	-0.00	-0.01	0.01	-0.03	0.03	0.41	2.40	0.94
Illiq	0.01	0.01	0.01	0.00	0.05	0.72	2.05	0.96
IdV	0.04	0.03	0.03	0.01	0.36	4.23	33.07	0.62
TRisk	0.41	0.42	0.04	0.29	0.51	-0.49	3.38	0.57

Table 1.2: Correlation Matrix

This table reports Pearson's correlation coefficients for three groups of variables. The first group includes sentiment proxies such as the option-implied sentiment measure (ISent), defined as the volume-weighted average moneyness level, the naïve option-implied sentiment measure (ISent^{EW}), Huang et al. (2015) aligned investor sentiment index (PLS), constructed from five individual sentiment proxies by applying partial least squares methodology, and Baker and Wurgler (2006) investor sentiment index (BW), derived as the first principal component of five individual sentiment proxies. The second group represents option-based characteristics i.e. second risk-neutral moment (VIX), variance risk premium (VRP), hedging pressure (Hedge), slope of implied volatility smirk (Smirk), third risk-neutral moment (Skew) and fourth risk-neutral moment (Kurt). The third group contains other predictor variables such as dividend-payout ratio (D/E), earnings-price ratio (E/P), yield gap (YGap), yield term spread (YSpr), default spread (DSpr), disagreement (Dis), consumption-wealth ratio (C/W), illiquidity (Illiq), idiosyncratic volatility (IdV) and tail risk (TRisk). Our sample period is from January 1996 to August 2014.

	ISent	**ISent^{EW}**	**PLS**	**BW**	**VIX**	**VRP**	**Hedge**	**Smirk**	**Skew**	**Kurt**	**D/E**	**E/P**	**YGap**	**YSpr**	**DSpr**	**Dis**	**C/W**	**Illiq**	**IdV**	**TRisk**
ISent	1.00																			
ISent^{EW}	0.89	1.00																		
PLS	0.54	0.53	1.00																	
BW	0.24	0.10	0.64	1.00																
VIX	0.51	0.54	0.03	-0.25	1.00															
VRP	-0.17	-0.12	-0.05	-0.07	0.19	1.00														
Hedge	-0.23	-0.16	-0.09	-0.08	-0.08	0.09	1.00													
Smirk	-0.25	-0.18	-0.35	-0.28	0.04	0.09	0.05	1.00												
Skew	0.36	0.31	0.29	0.10	0.32	0.10	-0.15	-0.61	1.00											
Kurt	-0.38	-0.33	-0.26	-0.05	-0.40	-0.11	0.10	0.54	-0.97	1.00										
D/E	0.20	0.17	-0.20	-0.23	0.54	0.15	-0.04	0.00	0.25	-0.26	1.00									
E/P	-0.30	-0.27	-0.06	0.06	-0.51	-0.25	0.18	0.14	-0.36	0.34	-0.88	1.00								
YGap	-0.32	-0.30	-0.17	0.05	-0.46	-0.26	0.14	0.26	-0.41	0.38	-0.77	0.96	1.00							
YSpr	-0.17	-0.20	-0.43	-0.17	0.15	-0.01	-0.12	0.29	-0.05	0.07	0.33	-0.16	0.01	1.00						
DSpr	0.29	0.26	-0.20	-0.16	0.58	-0.09	-0.08	0.06	0.19	-0.22	0.74	-0.52	-0.34	0.35	1.00					
Dis	0.12	0.11	-0.08	-0.20	0.18	0.03	-0.23	0.27	-0.07	0.06	0.01	-0.02	0.11	0.27	0.25	1.00				
C/W	0.03	0.17	0.02	-0.28	0.41	0.19	0.10	-0.23	0.38	-0.40	0.27	-0.25	-0.33	0.09	0.14	-0.32	1.00			
Illiq	0.27	0.39	0.33	-0.18	0.32	0.24	-0.08	-0.29	0.30	-0.32	0.02	-0.31	-0.49	-0.40	-0.25	-0.20	0.59	1.00		
IdV	0.50	0.54	0.20	-0.17	0.66	-0.03	-0.19	-0.11	0.31	-0.32	0.53	-0.60	-0.59	-0.07	0.47	0.07	0.35	0.45	1.00	
TRisk	-0.49	-0.43	-0.06	0.04	-0.43	0.12	0.12	-0.04	-0.01	0.07	-0.10	0.09	0.05	-0.00	-0.29	-0.41	0.23	0.05	-0.24	1.00

Table 1.3: Contemporaneous Analysis of Sentiment Indices

This table reports in-sample estimation results from univariate, bivariate and multivariate contemporaneous regressions of Huang et al. (2015) aligned investor sentiment index (PLS), constructed from five individual sentiment proxies by applying partial least squares methodology (Panel A), and Baker and Wurgler (2006) investor sentiment index (BW), derived as the first principal component of five individual sentiment proxies (Panel B), on the option-implied sentiment measure (ISent), defined as the volume-weighted average moneyness level, and option-based characteristics such as second risk-neutral moment (VIX), variance risk premium (VRP), hedging pressure (Hedge), slope of implied volatility smirk (Smirk), third risk-neutral moment (Skew) and fourth risk-neutral moment (Kurt). The obtained slope coefficients are standardized to show the change in standard deviation of sentiment indices for a one standard deviation increase in each predictor. OLS and Newey-West adjusted (with four lags) t-statistics are reported in round and square parentheses, respectively. Our sample period is from January 1996 to August 2014.

Panel A: PLS Index

	Univariate Models		**Bivariate Models**			**Multivariate Model**	
		$\widetilde{R}^2$	**ISent**	**X**	$\widetilde{R}^2$		$\widetilde{R}^2$
ISent	0.539	0.287				0.698	0.408
	(9.51) [3.41]					(10.30) [4.95]	
VIX	0.0282	-0.004	0.706	-0.330	0.366	-0.362	
	(0.42) [0.32]		(11.39) [5.02]	(-5.32) [-3.59]		(-5.36) [-3.83]	
VRP	-0.0548	-0.002	0.546	0.0394	0.285	0.135	
	(-0.82) [-0.91]		(9.47) [3.52]	(0.68) [0.39]		(2.40) [2.21]	
Hedge	-0.0917	0.004	0.547	0.0356	0.285	0.0471	
	(-1.37) [-1.15]		(9.38) [3.35]	(0.61) [0.56]		(0.88) [0.85]	
Smirk	-0.354	0.122	0.481	-0.235	0.336	-0.142	
	(-5.63) [-3.91]		(8.51) [3.22]	(-4.17) [-3.53]		(-2.01) [-1.90]	
Skew	0.295	0.083	0.497	0.115	0.295	0.0649	
	(4.58) [2.38]		(8.23) [3.28]	(1.90) [1.52]		(0.88) [0.71]	
Kurt	-0.257	0.062	0.515	-0.0636	0.287		
	(-3.95) [-2.38]		(8.42) [3.29]	(-1.04) [-1.04]			

Panel B: BW Index

	Univariate Models		**Bivariate Models**			**Multivariate Model**	
		$\widetilde{R}^2$	**ISent**	**X**	$\widetilde{R}^2$		$\widetilde{R}^2$
ISent	0.236	0.051				0.479	0.256
	(3.60) [1.48]					(6.29) [3.33]	
VIX	-0.254	0.060	0.491	-0.503	0.235	-0.502	
	(-3.89) [-2.63]		(7.19) [3.64]	(-7.36) [-4.70]		(-6.61) [-4.96]	
VRP	-0.0722	0.001	0.230	-0.0325	0.048	0.124	
	(-1.07) [-0.65]		(3.45) [1.45]	(-0.49) [-0.25]		(1.97) [1.95]	
Hedge	-0.0806	0.002	0.229	-0.0272	0.047	-0.0162	
	(-1.20) [-0.65]		(3.40) [1.41]	(-0.40) [-0.22]		(-0.27) [-0.14]	
Smirk	-0.278	0.073	0.178	-0.234	0.098	-0.171	
	(-4.29) [-3.43]		(2.70) [1.11]	(-3.55) [-2.68]		(-2.17) [-2.31]	
Skew	0.0960	0.005	0.231	0.0125	0.047	-0.0364	
	(1.43) [0.89]		(3.28) [1.40]	(0.18) [0.13]		(-0.44) [-0.36]	
Kurt	-0.0490	-0.002	0.253	0.0460	0.049		
	(-0.73) [-0.49]		(3.57) [1.53]	(0.65) [0.50]			

Table 1.4: Contemporaneous Analysis of Sentiment Indices: Look-ahead Bias-free Approach

This table reports in-sample estimation results from univariate, bivariate and multivariate contemporaneous regressions of look-ahead bias-free Huang et al. (2015) aligned investor sentiment index (PLS^{BF}), constructed from five individual sentiment proxies by applying partial least squares methodology and using information up to the period of forecast formation (Panel A), and look-ahead bias-free Baker and Wurgler (2006) investor sentiment index (BW^{BF}), derived as the first principal component of five individual sentiment proxies using information up to the period of forecast formation (Panel B), on the option-implied sentiment measure (ISent), defined as the volume-weighted average moneyness level, and option-based characteristics such as second risk-neutral moment (VIX), variance risk premium (VRP), hedging pressure (Hedge), slope of implied volatility smirk (Smirk), third risk-neutral moment (Skew) and fourth risk-neutral moment (Kurt). The obtained slope coefficients are standardized to show the change in standard deviation of sentiment indices for a one standard deviation increase in each predictor. OLS and Newey-West adjusted (with four lags) t-statistics are reported in round and square parentheses, respectively. Our forecast formation period is from September 2000 to August 2014.

Panel A: PLS^{BF} Index

	Univariate Models		**Bivariate Models**			**Multivariate Model**	
		$\widetilde{R}^2$	**ISent**	**X**	$\widetilde{R}^2$		$\widetilde{R}^2$
ISent	0.505	0.456				0.527	0.532
	(11.87) [6.12]					(9.58) [7.80]	
VIX	0.242	0.118	0.530	-0.0391	0.455	-0.0697	
	(4.84) [3.76]		(10.16) [6.86]	(-0.81) [-0.57]		(-1.39) [-1.17]	
VRP	0.0719	0.004	0.537	0.166	0.505	0.170	
	(1.30) [0.76]		(13.01) [9.00]	(4.20) [4.34]		(4.16) [3.51]	
Hedge	-0.0692	0.000	0.504	-0.0368	0.454	-0.0381	
	(-1.04) [-0.95]		(11.79) [6.12]	(-0.74) [-0.67]		(-0.81) [-0.68]	
Smirk	-0.286	0.153	0.458	-0.135	0.484	-0.0920	
	(-5.58) [-4.39]		(10.37) [5.90]	(-3.19) [-3.18]		(-1.78) [-1.68]	
Skew	0.316	0.187	0.447	0.133	0.481	0.0448	
	(6.28) [3.76]		(9.73) [5.51]	(2.99) [2.40]		(0.81) [0.65]	
Kurt	-0.276	0.154	0.463	-0.0914	0.467		
	(-5.59) [-3.68]		(9.93) [5.48]	(-2.11) [-1.87]			

Panel B: BW^{BF} Index

	Univariate Models		**Bivariate Models**			**Multivariate Model**	
		$\widetilde{R}^2$	**ISent**	**X**	$\widetilde{R}^2$		$\widetilde{R}^2$
ISent	0.218	0.041				0.422	0.353
	(2.84) [0.99]					(4.80) [2.04]	
VIX	-0.216	0.048	0.527	-0.496	0.225	-0.489	
	(-3.06) [-1.93]		(6.24) [2.77]	(-6.36) [-4.13]		(-6.11) [-4.10]	
VRP	0.0674	-0.001	0.239	0.109	0.047	0.173	
	(0.90) [0.69]		(3.07) [1.14]	(1.47) [0.91]		(2.65) [1.70]	
Hedge	0.0154	-0.006	0.220	0.0295	0.035	0.0494	
	(0.17) [0.16]		(2.84) [0.99]	(0.33) [0.30]		(0.66) [0.58]	
Smirk	-0.447	0.205	0.0677	-0.425	0.204	-0.286	
	(-6.63) [-6.03]		(0.91) [0.33]	(-5.92) [-5.72]		(-3.46) [-4.68]	
Skew	0.236	0.052	0.140	0.179	0.062	0.0805	
	(3.20) [1.98]		(1.66) [0.64]	(2.20) [1.90]		(0.91) [0.82]	
Kurt	-0.166	0.025	0.173	-0.0972	0.044		
	(-2.31) [-1.55]		(2.04) [0.77]	(-1.23) [-1.17]			

Table 1.5: In-Sample Predictability: Univariate Analysis

This table reports in-sample estimation results from univariate predictive regressions of the CRSP value-weighted index excess return on various specifications of option-implied sentiment measure, full-sample and look-ahead bias-free (PLS and PLS^{BF}, respectively) Huang et al. (2015) aligned investor sentiment index, constructed from five individual sentiment proxies by applying partial least squares methodology, and full-sample and look-ahead bias-free (BW and BW^{BF}, respectively) Baker and Wurgler (2006) investor sentiment index, derived as the first principal component of five individual sentiment proxies. ISent and ISent^{F} are defined as the volume-weighted average moneyness level, excluding and utilizing near-the-money options, respectively. ISent^{PD} and ISent^{PM} are the volume-weighted average moneyness level, where moneyness is estimated relative to a previous-day stock price and average stock price over the previous month, respectively. ISent^{SV} is the signed volume-weighted average moneyness level. The obtained coefficients are standardized to indicate the monthly excess return for a one standard deviation increase in each predictor. Newey-West adjusted (the lag length equals to forecasting horizon) t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Look-ahead bias-free sentiment measures are constructed from September 2000 to August 2014. Our full sample period is from January 1996 to August 2014.

	1 month	**2 month**	**3 month**	**6 month**
ISent	-0.0078**	-0.0145**	-0.0242***	-0.0329***
	(-2.15)	(-2.56)	(-3.06)	(-2.65)
$\widetilde{\mathbf{R}}^2$	0.0223	0.0375	0.0714	0.0588
$\mathbf{ISent}^{F}$	-0.0076**	-0.0143**	-0.0236***	-0.0338**
	(-2.10)	(-2.39)	(-2.82)	(-2.58)
$\widetilde{\mathbf{R}}^2$	0.0210	0.0360	0.0675	0.0621
$\mathbf{ISent}^{PD}$	-0.0070**	-0.0146**	-0.0244***	-0.0336**
	(-1.98)	(-2.55)	(-3.08)	(-2.58)
$\widetilde{\mathbf{R}}^2$	0.0173	0.0380	0.0731	0.0615
$\mathbf{ISent}^{PM}$	-0.0075**	-0.0137**	-0.0230***	-0.0318**
	(-2.08)	(-2.39)	(-2.85)	(-2.56)
$\widetilde{\mathbf{R}}^2$	0.0207	0.0330	0.0647	0.0547
$\mathbf{ISent}^{SV}$	-0.0100*	-0.0170**	-0.0251**	-0.0064
	(-1.88)	(-2.09)	(-2.17)	(-0.38)
$\widetilde{\mathbf{R}}^2$	0.0370	0.0465	0.0665	-0.0077
PLS	-0.0089**	-0.0177***	-0.0268***	-0.0550***
	(-2.40)	(-3.10)	(-3.87)	(-4.67)
$\widetilde{\mathbf{R}}^2$	0.0307	0.0580	0.0889	0.1727
$\mathbf{PLS}^{BF}$	-0.0180***	-0.0248***	-0.0341***	-0.0547***
	(-3.08)	(-2.68)	(-3.05)	(-3.18)
$\widetilde{\mathbf{R}}^2$	0.0740	0.0578	0.0713	0.0778
BW	-0.0049	-0.0095	-0.0157*	-0.0395***
	(-1.37)	(-1.58)	(-1.96)	(-3.44)
$\widetilde{\mathbf{R}}^2$	0.0061	0.0137	0.0278	0.0874
$\mathbf{BW}^{BF}$	-0.0038	-0.0057	-0.0099	-0.0326**
	(-0.81)	(-0.70)	(-0.89)	(-2.22)
$\widetilde{\mathbf{R}}^2$	0.0007	0.0003	0.0060	0.0484

Table 1.6: In-Sample Predictability: Bivariate Analysis

This table reports in-sample estimation results from bivariate predictive regressions of the CRSP value-weighted index excess return on the option-implied sentiment measure (ISent), defined as the volume-weighted average moneyness level, and each of stock market return predictors. These variables include dividend-payout ratio (D/E), earnings-price ratio (E/P), yield gap (YGap), yield term spread (YSpr), default spread (DSpr), analysts' forecasts dispersion (Dis), consumption-wealth ratio (C/W), market illiquidity (Illiq), idiosyncratic volatility (IdV) and tail risk (TRisk). The obtained coefficients are standardized to indicate the monthly excess return for a one standard deviation increase in each predictor. Newey-West adjusted (the lag length equals to forecasting horizon) *t*-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our sample period is from January 1996 to August 2014.

	1 month		2 month		3 month		6 month	
	ISent	$\widetilde{\mathbf{R}}^2$	**ISent**	$\widetilde{\mathbf{R}}^2$	**ISent**	$\widetilde{\mathbf{R}}^2$	**ISent**	$\widetilde{\mathbf{R}}^2$
D/E	-0.0083**	0.0211	-0.0159***	0.0417	-0.0265***	0.0857	-0.0379***	0.0914
	(-2.32)		(-2.87)		(-3.38)		(-3.93)	
E/P	-0.0079**	0.0180	-0.0152***	0.0340	-0.0259***	0.0713	-0.0358***	0.0594
	(-2.17)		(-2.75)		(-3.26)		(-3.19)	
YGap	-0.0077**	0.0178	-0.0147***	0.0331	-0.0251***	0.0682	-0.0339***	0.0550
	(-2.08)		(-2.60)		(-3.10)		(-2.89)	
YSpr	-0.0077**	0.0178	-0.0145**	0.0331	-0.0241***	0.0671	-0.0318**	0.0567
	(-2.09)		(-2.46)		(-2.94)		(-2.53)	
DSpr	-0.0077**	0.0178	-0.0149***	0.0333	-0.0258***	0.0711	-0.0386***	0.0764
	(-2.17)		(-2.73)		(-3.28)		(-3.86)	
Dis	-0.0075**	0.0198	-0.0139**	0.0390	-0.0233***	0.0734	-0.0309***	0.0707
	(-2.07)		(-2.41)		(-2.89)		(-2.65)	
C/W	-0.0079**	0.0231	-0.0148**	0.0458	-0.0245***	0.0866	-0.0335***	0.0999
	(-2.19)		(-2.55)		(-2.99)		(-2.85)	
Illiq	-0.0087**	0.0224	-0.0165***	0.0431	-0.0268***	0.0789	-0.0354**	0.0591
	(-2.28)		(-2.80)		(-3.22)		(-2.49)	
IdV	-0.0094**	0.0215	-0.0172***	0.0373	-0.0279***	0.0728	-0.0452***	0.0821
	(-2.34)		(-2.65)		(-3.17)		(-3.32)	
TRisk	-0.0079*	0.0179	-0.0193***	0.0471	-0.0324***	0.0945	-0.0448***	0.0804
	(-1.92)		(-2.87)		(-3.40)		(-3.12)	

Table 1.7: Out-of-Sample Predictability

This table reports out-of-sample predictability results for the CRSP value-weighted index excess return based on the option-implied sentiment measure (ISent), defined as the volume-weighted average moneyness level, look-ahead bias-free (PLS^{BF}) Huang et al. (2015) aligned investor sentiment index, constructed from five individual sentiment proxies by applying partial least squares methodology, and look-ahead bias-free (BW^{BF}) Baker and Wurgler (2006) investor sentiment index, derived as the first principal component of five individual sentiment proxies. $\widetilde{R}^2$ is the out-of-sample coefficient of determination, MSE-F is the McCracken (2007) F-statistic, ENC-NEW is the encompassing test of Clark and McCracken (2001), and $\widetilde{R}^2_C$ is the out-of-sample coefficient of determination with positive prediction restriction. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our out-of-sample forecasting period is from September 2000 to August 2014.

1-month horizon			
	ISent	**PLS^{BF}**	**BW^{BF}**
$\widetilde{\mathbf{R}}^2$	0.0224	0.0094	-0.0082
MSE-F	3.8329***	1.5784***	-1.3629
ENC-NEW	3.0579**	0.9938	0.0796
$\widetilde{\mathbf{R}}^2_C$	0.0246	0.0160	-0.0008

2-month horizon			
	ISent	**PLS^{BF}**	**BW^{BF}**
$\widetilde{\mathbf{R}}^2$	0.0317	0.0083	-0.0158
MSE-F	5.4001***	1.3821***	-2.5672
ENC-NEW	4.3539**	1.0190	-0.7652
$\widetilde{\mathbf{R}}^2_C$	0.0309	0.0201	-0.0009

3-month horizon			
	ISent	**PLS^{BF}**	**BW^{BF}**
$\widetilde{\mathbf{R}}^2$	0.0670	0.0112	-0.0129
MSE-F	11.7011***	1.8542***	-2.0750
ENC-NEW	8.9046**	1.3785	-0.1841
$\widetilde{\mathbf{R}}^2_C$	0.0595	0.0240	-0.0037

Table 1.8: Asset Allocation

This table reports the performance results of investor's portfolio with mean-variance weights (Mean-Variance Strategy), binary weights with short sales (Binary Strategy With Short Sales), and binary weights without short sales (Binary Strategy Without Short Sales). This investor is risk-averse (with risk-averse coefficient of 3) and allocates his wealth between risky and risk-free assets using one-month-ahead out-of-sample forecasts of the CRSP value-weighted index excess return based on the option-implied sentiment measure (ISent), defined as the volume-weighted average moneyness level, look-ahead bias-free (PLS^{BF}) Huang et al. (2015) aligned investor sentiment index, constructed from five individual sentiment proxies by applying partial least squares methodology, and look-ahead bias-free (BW^{BF}) Baker and Wurgler (2006) investor sentiment index, derived as the first principal component of five individual sentiment proxies. Mean indicates the average return, St. Dev. stands for the standard deviation of returns, Sharpe denotes the Sharpe ratio, CE is the certainty equivalent return in excess of the historical average (HAV), MDD is the maximum drawdown, and Long is the fraction of months when the strategy takes long position in the market index. All measures except for MDD and Long are annualized. Our out-of-sample forecasting period is from September 2000 to August 2014.

Mean-Variance Strategy				
	HAV	**ISent**	**PLS^{BF}**	**BW^{BF}**
Mean	0.0133	0.0747	0.0347	0.0069
St. Dev.	0.1120	0.1248	0.1068	0.1448
Sharpe	0.1189	0.5982	0.3247	0.0473
CE		0.0568	0.0231	-0.0191
MDD	-0.3899	-0.4131	-0.3257	-0.5900
Long	1	0.9222	0.9581	0.9162

Binary Strategy With Short Sales				
	HAV	**ISent**	**PLS^{BF}**	**BW^{BF}**
Mean	0.0843	0.0835	0.0416	0.0991
St. Dev.	0.2412	0.2117	0.2288	0.2263
Sharpe	0.3493	0.3945	0.1819	0.4377
CE		0.0193	-0.0339	0.0252
MDD	-0.6785	-0.7132	-0.6797	-0.6923
Long	1	0.9222	0.9581	0.9162

Binary Strategy Without Short Sales				
	HAV	**ISent**	**PLS^{BF}**	**BW^{BF}**
Mean	0.0617	0.0614	0.0404	0.0691
St. Dev.	0.1606	0.1382	0.1511	0.1495
Sharpe	0.3845	0.4440	0.2675	0.4626
CE		0.0097	-0.0169	0.0126
MDD	-0.5144	-0.5075	-0.4795	-0.5144
Long	1	0.9222	0.9581	0.9162

Chapter 2

Differences in Expectations and the Cross-Section of Stock Returns

2.1 Introduction

The bet-like nature of option payoffs combined with their embedded leverage make options an ideal instrument for investors with clear expectations about the future direction of the underlying asset price. In line with this, Bali and Hovakimian (2009), Xing, Zhang and Zhao (2010), Cremers and Weinbaum (2010) and An et al. (2014), among others, show that various option-implied measures encapsulate valuable information about the cross-section of expected stock returns. Motivated by the notion that options trading provides information about investors' expectations, a series of recent papers (Pan and Poteshman, 2006; Johnson and So, 2012; Chen, Joslin and Ni, 2016) aggregate trading volume or open interest in order to capture investors' beliefs. However, the information embedded in the exact moneyness levels at which the trades take place remains largely unexplored. To this end, in this chapter we propose a firm-level measure of differences in expectations (DiE) among options investors, which is constructed as the dispersion of stock options trading volume across different moneyness levels, and examine its cross-sectional predictability.

The proposed measure is supported in the context of the typical options market, where most trades take place between end-users and market makers, and are driven by the directional expectations of the end-users about the future price of the underlying asset. In this context, the selected moneyness level at which a wide range of options trades are implemented can naturally reflect the end-users' expected returns. As an illustration, deep out-of-the-money (OTM) calls are typically bought by highly optimistic investors who want to benefit from the high leverage of those contracts, while less OTM calls are typically bought by investors who want to secure a positive payoff even with a small upward price movement. In the same spirit, deep in-the-money (ITM) puts are typically sold by investors with highly positive expectations, who want to benefit from a higher premium, while less ITM puts are typically sold by investors whose priority is to ensure that the option will expire worthless even with a relatively small increase in the underlying asset price. Motivated by the above arguments, we construct the DiE measure as the volume-weighted mean absolute deviation of moneyness levels. To this end, we utilize the trading volume attributed to each moneyness level, while we also consider the case of using signed volume data, keeping for example only the buy-side volume of OTM calls and the sell-side volume of ITM puts.

The literature on various proxies for dispersion in beliefs and their asset pricing implications is vast and expansive. Exploiting mutual fund data, Chen, Hong and Stein (2002), Jiang and Sun (2014) propose a breadth of ownership and dispersion in active portfolio holdings as proxies for differences of opinions and document a negative disagreement-return relation. Goetzmann and Massa (2005) utilize the trading accounts of retail investors and construct a proxy for dispersion in beliefs, which is shown to negatively predict stock returns. On the other hand, Carlin, Longstaff and Matoba (2014) report a positive relationship between stock returns and disagreement that is constructed from mortgage prepayment speeds. Garfinkel and Sokobin (2006) and Garfinkel (2009) measure the diverse beliefs via the trading volume, that is not attributable liquidity or informedness effects, and demonstrate a positive predictive power of this proxy for expected stock returns. Perhaps, the most controversial measure in terms of the effect on expected asset returns is the dispersion in analysts' earnings forecasts. Diether, Malloy and Scherbina (2002), Park (2005), Yu (2011) document a negative relation between analysts' forecasts dispersion and expected asset returns, whereas Anderson, Ghysels and Juergens (2005), Doukas, Kim and Pantzalis (2006) establish a positive relationship. In this chapter, our main contribution to the above literature is the construction of a new option-implied proxy for differences in beliefs, that appears to be negatively related to the cross-section of stock returns.

Compared to previously proposed measures, the suggested DiE measure exhibits several advantageous properties. First, unlike survey-type proxies that represent only a restricted subset of opinions, our measure emerges directly from 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 based on forecasts are influenced by uncertainty, herding and close-to-earnings-expectations biases (see, for example, Trueman, 1994; Barron, Kim, Lim and Stevens, 1998; De Bondt and Forbes, 1999; Doukas, Kim and Pantzalis, 2006) and are mainly related to earnings or other corporate information. By contrast, our DiE measure is unlikely to be affected by such biases and directly relates to expected stock payoffs. 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 hardly influenced by the short-sale constraints that are present in the equity market (Lakonishok et al., 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.

Our empirical results show that stocks with high differences in options investors' expectations earn substantially lower returns than stocks that exhibit low differences in expectations. In particular, a portfolio-level analysis indicates that stocks sorted into the highest DiE decile consistently underperform stocks in the lowest DiE decile, by 1.51% per month (18.1% per annum) for equal-weighted returns and by 1.39% per month (16.7% per annum) for value-weighted returns. After adjusting for common risk factors, the equal-weighted (value-weighted) Carhart four-factor alpha of a strategy that buys high DiE stocks and sells low DiE stocks remains economically substantial and statistically significant, earning -1.59% (-1.57%) per month, with associated t-statistics of -4.20 (-3.45). The underperformance of high DiE stocks relative to low DiE stocks is also confirmed when utilizing signed volume data, even though this analysis covers a smaller sample period since the respective data are first recorded in 2005. For example, in this case, the equal-weighted (value-weighted) four-factor alpha of a high minus low DiE portfolio is -1.72% (-1.72%) per month with associated t-statistics of -4.69 (-3.84). Furthermore, the observed negative predictability for stock returns is robust to alternative DiE specifications, especially to the case where the differences in expectations are estimated without incorporating any stock-price information. In this case, we rule out the possibility that the documented DiE-return relation is mechanically driven by the price pressure in stock market, that tends to affect the predictability of various option-implied measures.

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 for an investor holding high DiE stocks would also require differences in expectations 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 DiE stocks in one month remain high in the subsequent month with an almost 60% probability. Furthermore, the risk-adjusted return of a strategy that buys low DiE stocks and sells high DiE stocks remains economically and statistically significant even when considering a

12-month holding period.

The finding that DiE is negatively priced in the cross-section of stock returns is consistent with the theoretical mechanism described by Miller (1977) and the empirical evidence provided by studies such as Diether, Malloy and Scherbina (2002), Chen, Hong and Stein (2002), Goetzmann and Massa (2005) and Boehme, Danielsen and Sorescu (2006). The notion of the negative relationship between differences in expectations and subsequent returns implies that high DiE firms are priced at a premium, indicating that investors appear to pay extra money for holding more opinion dispersed stocks, thus earning a negative risk premium in the future. Miller (1977), Harrison and Kreps (1978), Morris (1996) and Scheinkman and Xiong (2003) 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 further explore the economic nature of the documented negative relation between differences in expectations and future stock returns. In particular, we show that the DiE effect is strongest for those stocks in our sample with lower levels of residual institutional ownership (higher short-sale costs). This result provides further support for Miller's (1977) hypothesis, rationalizing the existence of overpriced stocks that earn lower future returns. In addition, we observe that stocks with relatively small market capitalization, low liquidity and high idiosyncratic volatility portray the highest DiE effect. These results reveal that the mispricing of high DiE stocks tends to persist more in the case of stocks exhibiting higher limits to arbitrage. Intuitively, such characteristics deter arbitrageurs from instantly eliminating the mispricing, leading to a slow correction within the subsequent months (see, for instance, Conrad, Kapadia and Xing, 2014; Edelen, Ince and Kadlec, 2016). Furthermore, we demonstrate that the return predictability of DiE mainly stems from relatively optimistic periods. This is consistent with the idea that the overpricing generated by the difference in expectations in the presence of short-sales constraints is more severe when the optimistic investors who end up holding the stock are excessively optimistic (see also Stambaugh, Yu and Yuan, 2012).

Finally, we investigate the robustness of the DiE effect using a bivariate-portfolio analysis and Fama and MacBeth (1973) regressions, as well as the component decomposition of Hou and Loh (2016). The results of the portfolio analysis and the Fama and MacBeth (1973) regressions demonstrate that the predictability of DiE for stock returns remains strongly significant even after controlling for twenty alternative stock-related and option-related characteristics such as beta, momentum, maximum return, risk-neutral skewness, volatility spread, volatility of volatility, among others. In addition, the results of the Hou and Loh (2016) component decomposition show that none of the alternative variables can adequately explain the negative relation between DiE and future stock returns. More importantly, we show that the DiE predictability remains robust in all specifications that control for the dispersion in analysts' forecasts, while the component decomposition results indicate that the dispersion in analysts' forecasts can account for only 4.41% of the DiE-return relation. This means that the information embedded in the suggested DiE measure is unique and therefore different from that embedded in the dispersion in analysts' forecasts, implying that the two variables capture different aspects of the overall divergence of investors' opinions.[1]

Overall, our study contributes to the existing literature in a number of ways. First, it proposes an option-implied firm-level measure of differences in expectations that directly stems from options trading activity, is distinct from all other disagreement measures that rely on surveys, portfolio holdings or aggregate stock trading volume, and exhibits several advanta-

[1] In a contemporaneous study, Andreou et al. (2016) use volume information across different moneyness levels to measure market-wide differences in opinions among options investors. Similar to this chapter, they show that their measure is similar to, but different from, a market-wide measure of dispersion in analysts' forecasts and provides stronger predictability for the equity premium.

geous characteristics. Second, we present empirical evidence showing that there is a strong negative and economically significant relation between dispersion in beliefs in the options market and future stock returns, which is particularly pronounced during periods of high optimism in the market and for stocks with relatively high short-sale constraints and high limits to arbitrage. Finally, we document a highly persistent, easy-to-construct return predictor, which can be profitably used by actual investors who hold high disagreement stocks, and whose effect is not subsumed by a broad set of previously documented return predictors.

The remainder of the chapter is organized as follows. Section 2.2 outlines the construction of the DiE measure and describes the data used in the study. Section 2.3 presents the empirical test results of DiE predictability for expected returns and investigates the economic drivers behind the DiE-return predictability. In this section, we also present a series of robustness checks and additional analyses, confirming the stability of the findings. Finally, Section 2.4 concludes.

2.2 Measurement of DiE and Data

In this section, we first present the construction of the differences in options investors' expectations measure, following which we discuss the description of the data and key screening criteria applied in the study, and finally we provide sample descriptive statistics.

2.2.1 Construction of the DiE Measure

The proposed dispersion in beliefs measure can be understood 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. Ge, Lin and Pearson (2016) examine the options exchange trading activity and advocate that the norm is for a market maker to be on the other side of the trade made by an end-user. Furthermore, Lakonishok et al. (2007) show that, despite the common belief, trading strategies that reflect volatility expectations constitute only a very small fraction of the total trading activity (typically less than 2% of the total volume) and most trades are driven by expectations about directional movements in the underlying asset price.

Given the above evidence, our measure is based on the notion that the moneyness levels at which a wide range of options trading strategies are implemented can naturally be associated with different expectations. To see this, consider the case of an investor with a positive expectation about the future price of the underlying asset. The obvious choices for such an investor is to either buy a call option or sell a put option. Moreover, the more positive the expectation of the investor, the higher the strike price that she will typically choose. This is because more OTM options exhibit higher leverage, while more ITM options have a higher premium. Therefore, a call buyer will be inclined to select a strike price that is as high as possible, conditional on the option being exercised at maturity, to benefit from the high leverage. Similarly, a put seller will be inclined to select a strike price that is as high as possible, conditional on the option expiring worthless at maturity, to maximize the premium that she will receive. Moreover, due to put-call parity, the payoffs from buying OTM call options (selling ITM put options) 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 similar arguments, pessimistic investors can also reveal their views via options trades at certain moneyness levels, for example trading at OTM puts or ITM calls (or implementing the respective put-call parity strategies).[2]

[2] 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 moneyness levels 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 moneyness levels at which simple put/call contracts are traded.

Overall, the above arguments suggest that the selected moneyness levels at which different trades are implemented can naturally reveal the positive and negative views of options investors about expected asset payoffs. It is true, though, that from the above strategies some might be more likely to be used by investors, while others, such as the strategies that utilize the put-call parity, might be rarer. It is possible, for example, that part of the trading activity includes selling OTM calls and puts, or buying ITM puts and calls, without these trades being associated with put-call parity strategies and thus not necessarily reflecting investors' expectations in the way described above. Therefore, in this study we additionally consider the case of using only the buy-side volume of OTM options and the sell-side volume of ITM options, thus keeping only the fraction of the total options' trading activity that can be undoubtedly linked to certain positive or negative expectations.

Motivated by the above discussion, we build on the idea that a high dispersion of trading volume across the range of various moneyness levels implies high disagreement among options investors about the future underlying asset price, while a low dispersion shows that investors' expectations are rather similar. As a result, we define a firm-level DiE 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 X_j for $j = 1, .., K$ and a stock price S, we propose the following measure of differences in expectations:

$$DiE = \sum_{j=1}^{K} w_j \left| M_j - \sum_{j=1}^{K} w_j M_j \right|, \tag{2.1}$$

where w_j is the proportion of trading volume attached to the moneyness level $M_j = \frac{X_j}{S}$. Since we employ moneyness levels in the DiE computation, our measure is comparable across stocks and over time. In extreme cases, the belief dispersion measure takes the minimum value of zero if all the trading volume is concentrated on only one strike price, while it reaches the maximum value either when investors trade identically at the two extreme strike prices, holding the range of available strikes fixed, or when the set of strike prices becomes infinite, holding the distribution of trading volume fixed.

2.2.2 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 the DiE measure, we use raw options data to construct three option-related characteristics – call-put volatility spread (VS), option to stock trading volume ratio (O/S), and volatility of volatility (VoV). Further, we use the 30-days-to-maturity standardized volatility surface file to estimate several 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).

To construct the DiE measure, we use calls and puts series for each stock on a given day 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). To exclude days when options are thinly traded, we use only those days when 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. Using the filtered options data, we estimate DiE on a daily frequency using Equation (2.1). Finally, to encapsulate adequate information about investors' dispersion in expectations, we create the monthly DiE measure by averaging daily DiE values within a month, excluding the last trading day of the month. Therefore, the monthly values of DiE (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 DiE 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), 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, 505-588). We use this information to compute firm-specific characteristics such as log of 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), and volatility of liquidity (Vliq). Data required for the estimations of residual institutional ownership (IO) and book-to-market ratio (BM) are obtained from the Thomson Financial 13f database and Compustat, respectively. Finally, to compute the dispersion in analysts' earnings forecasts (AFD), we use the I/B/E/S summary data file with calculated summary statistics. The detailed description of all stock- and option-related characteristics as well as the applied filtering rules are provided in the Appendix B.1.[3]

[3]For a detailed explanation of the methodologies used for constructing the various cross-sectional predictors, see Bali, Engle and Murray (2016).

2.2.3 Summary Statistics

Table 2.1 presents the descriptive statistics of our sample. Specifically, we report the total yearly number of common stocks in CRSP universe traded on NYSE, AMEX and NASDAQ, the total number of firms and the percentage of such firms (relative to the full CRSP universe) for which we can obtain DiE 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 DiE across all firms in our sample. First, we show that in the first year of our sample about 23% of the firms in the CRSP universe have DiE estimates and sufficient options listed, while this number increases to almost 50% during the last years. Second, we observe that the average and median DiE estimates tend to escalate before periods of market turbulence. For instance, during the 2001-2002 dotcom bubble and 2008-2009 recession period, the average and 75^{th} percentile are highest across all years, reaching values of 0.126 and 0.147 in 2000 and 0.125 and 0.133 in 2008, respectively. Low levels of DiE are documented during the economic recovery periods.

Figure 2.1 shows a time-series plot of yearly DiE 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 DiE values across all years in the sample. Interestingly and as expected, we observe that DiE peaks for the HiTech industry during the dotcom bubble in 2001-2002 and for the Money industry during the financial crisis period in 2008-2009. Additionally, the graph highlights the nature of the differences in expectations that existed during the two crises — we observe that, while DiE across the various industries is rather dispersed during the dotcom bubble, the financial crisis has a systemic impact, with DiE concurrently peaking across all the various industries. Overall, the figure clearly illustrates that the DiE 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.

2.3 Empirical Tests

2.3.1 Returns on DiE Portfolios

We start the empirical analysis by examining the average monthly profitability of DiE portfolios. Each month, we sort stocks in ascending order into ten portfolios based on DiE, from low DiE (decile 1) to high DiE (decile 10). Next, for each DiE decile portfolio, we estimate the time-series averages of monthly mean DiE values, equal-weighted and value-weighted average future monthly returns in excess of the risk-free rate and alphas from the Fama and French (1993) three-factor and Carhart (1997) four-factor models. Finally, we compute returns for the strategy that buys the high DiE portfolio and sells the low DiE portfolio (H-L).

Table 2.2 presents the results for equal-weighted (Panel A) and value-weighted (Panel B) portfolios. In Panel A, the profitability of the decile portfolios declines in terms of the average monthly excess returns as DiE increases, although this decline is not monotonic. Strikingly, the largest jumps in dispersion levels observed from deciles 8 to 9, and 9 to 10 (from 0.101 to 0.120, and then to 0.186) correspond to the most dramatic declines in the average monthly excess returns across those deciles (from 0.64% for decile 8 to 0.15% for decile 9, and then to -0.56% for decile 10). A similar pattern is also found for risk-adjusted returns, with the four-factor alpha showing the largest reductions in monthly profitability from -0.30% for decile 8 to -0.74% for decile 9, and then to -1.41% for decile 10. This evidence suggests that investors holding higher DiE 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 DiE stocks on average underperforming low DiE stocks by 1.51% per month (18.12% per annum) in terms of raw returns, by 2.19% per month (26.28% per annum) after adjusting for risk from the three-factor model, and by 1.59% per month (19.08% per annum) after adjusting for risk from the four-factor model. Both the H-L return, and the three-factor and four-factor alpha differentials are statistically significant, with Newey and West (1987)

t-statistics (with six lags) of -2.57, -5.63, and -4.20, respectively.

Equally significant results, both economically and statistically, are observed with value-weighted average returns, in Panel B. The underperformance of high DiE, compared to low DiE, stocks is economically large and statistically significant, generating a negative return on the H-L portfolio of -1.39% per month (-16.68% per annum), with a t-statistic of -2.24. High DiE stocks continue to earn considerably lower future risk-adjusted returns than low DiE stocks. Three-factor and four-factor alpha differentials between high DiE and low DiE portfolios are -2.01% per month, with a t-statistic of -4.91, and -1.57% per month, with a t-statistic of -3.45, respectively. Overall, our results suggest that negative DiE 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 or momentum factors, indicating that differences in expectations are priced at a premium.

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 the price of a stock with more diverse investors' valuations and binding short-sale constraints will largely reflect the views of optimistic traders, leading to more overpricing and lower subsequent returns. If differences in expectations is a persistent rather than a random stock characteristic, it will be easy for an investor, who holds high disagreement stocks, to exploit the generated overpricing following a strategy that will require low rebalancing and hence 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 DiE. In Table 2.3, we observe that all the diagonal elements of the transition probability matrix exceed 10%, with stocks in high (low) DiE portfolio having a huge almost 60% (41%) likelihood of remaining in the same portfolio next month. The results indicate that DiE is a persistent stock characteristic and far from being random. Further, stocks in the higher DiE deciles 8-10 have an almost 90% chance of staying in those deciles – deciles that exhibit the most significant declines in average excess returns over the next month (as shown in Table 2.2).

Additionally, in Figure 2.2, we take a closer look at the persistency of the DiE measure at the aggregate quintile portfolio level. Each month, we group stocks into quintile portfolios based on their DiE values (from low DiE, quintile 1 to high DiE, quintile 5), and plot the average monthly DiE for each of the portfolios, for the eleven months before and after portfolio formation. The highest (lowest) DiE value of 0.154 (0.045) is observed at the time of portfolio construction. Moreover, the results show a clear difference across the DiE quintile portfolios, with a strong persistent ranking of the DiE portfolios across each of the eleven months around portfolio formation.[4] Overall, the above findings establish strongly persistent DiE dynamics over time, suggesting that stocks with a high DiE characteristic in one month also tend to exhibit more dispersed opinions in the following months.

2.3.2 Characteristics of DiE Portfolios

In this section, we examine the firm characteristics of stocks across the DiE portfolios. For each month, we construct decile portfolios based on DiE, and for each decile portfolio, we report the time-series averages of monthly mean values of numerous stock-related characteristics. Specifically, we present the average values for residual institutional ownership (IO), log of market capitalization (Size), idiosyncratic volatility (IdV), illiquidity (Illiq), maximum return within a month (MAX), stock return within a month (STR), stock beta (Beta), book-

[4] Additionally, we conduct a cross-sectional regression analysis, which confirms that DiE exhibits strong persistent patterns after controlling for various stock- and option-related characteristics. The results are reported in the Appendix B.2.

to-market ratio (BM), momentum (Mom), volatility of liquidity (Vliq), and the dispersion in analysts' forecasts (AFD).[5]

Table 2.4 reports some interesting results. First, high DiE stocks are less likely to be held by institutional investors, as suggested by almost uniformly decreasing patterns for IO as we move from the low DiE decile (with average IO of 2.246) to the high DiE decile (with average IO of 1.376). The results, therefore, imply that high DiE stocks are more difficult to short sell (see Nagel, 2005). Second, as DiE 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.[6] Conrad, Kapadia and Xing (2014) and Edelen, Ince and Kadlec (2016) postulate that stocks with such characteristics are likely to be hard to value. Hence, it is expected that such stocks generate a high dispersion in beliefs among investors. Third, high DiE stocks show a greater propensity to exhibit lottery-type payoffs, with MAX values monotonically rising from the low DiE to the high DiE portfolio. The average MAX value in the lowest DiE portfolio is 4.0%, whereas stocks in the highest DiE portfolio have the maximum daily return over the past month of 11.7%. 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 to almost double from decile 9 (0.463) to decile 10 (0.802). This indicates a strong dominance of value stocks in the high DiE portfolio. Finally, comparing DiE 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 DiE increases, the average values of AFD gradually rise from 0.050 in the low DiE portfolio to 0.287 in the high DiE portfolio. Overall, our findings suggest

[5] The median values for the firm characteristics of stocks in the various DiE portfolios displays a qualitatively similar pattern to those reported for the mean values and hence are provided in the Appendix B.2.

[6] It is noteworthy that small and illiquid stocks in our sample are still relatively large and liquid when compared with the full universe of stocks, since the optioned firms tend to be generally big and more liquid.

that high DiE stocks, as compared to low DiE stocks, are relatively small, riskier, relatively illiquid, value- (rather than growth-) oriented, with less institutional ownership, preferred by investors with lottery-type preferences, and have higher analysts' forecast dispersion.

2.3.3 DiE Effect: Short-Sale Constraints and Limits to Arbitrage

In this section, we delve into understanding the economic nature of the persistent negative firm-level DiE effect observed in the univariate analysis. Specifically, we examine whether short-sale constraints and limits to arbitrage play a role in explaining the DiE effect. To this end, we perform a dependent bivariate portfolio-level analysis at the quintile-level, instead of the decile-level for ease of presentation and interpretation. For each month, stocks are firstly sorted in ascending order into quintile portfolios on the basis of key firm characteristic variables measuring short-sale constraints and limits to arbitrage, and next, within each characteristic portfolio, the same stocks are further sorted into quintile portfolios based on DiE values. Finally, for the resulting twenty-five characteristic-DiE 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.[7] We also evaluate the average returns, and Fama-French three-factor and Carhart four-factor alphas for the strategy that buys high DiE stocks and sells low DiE stocks within each characteristic portfolio quintile.

Short-Sale Constraints

Miller's (1977) theory predicts that stocks with high dispersion of opinions tend to be overpriced and are expected to earn negative subsequent returns in the presence of binding short-sale constraints. To test this prediction, we use the level of residual institutional ownership (IO) as a proxy for the cost of short-selling. Intuitively, the lower the level of institutional ownership, the lower the supply for loanable shares by institutions (Nagel, 2005) and hence

[7] Quantitatively similar results for value-weighted portfolios are provided in the Appendix B.2.

the higher the short-sale costs. Table 2.5 reports the results. We document that the high DiE portfolio underperforms the low DiE portfolio by 2.04% per month (with a t-statistic of -3.13) if these firms have a lower level of IO, whereas the return differential between high DiE and low DiE portfolios is -0.73% per month (with a t-statistic of -1.64) for high IO firms. It is important to note that the H-L portfolio results are in line with Miller's (1977) theory, since the negative profitability is mainly driven by high DiE and low IO (higher short-sale costs) portfolio stocks that earn on average -1.14% per month in excess of the risk-free rate, while other high DiE stocks with various levels of IO in H-L portfolio earn instead a return premium. After controlling for asset-pricing risk factors, both three- and four-factor model alpha spreads between high DiE and low DiE portfolios are larger and more statistically significant for low IO firms. The risk-adjusted monthly profitability of the H-L portfolio is -2.77% (-1.17%), with a t-statistic of -5.62 (-4.13), controlling for risk from the three-factor model and -2.09% (-0.80%), with a t-statistic of -4.17 (-2.78), controlling for risk from the four-factor model if this portfolio is dominated by low IO (high IO) stocks. Overall, our results provide supportive evidence for the role of short-sale constraints in explaining the substantial return variations in high and low DiE portfolios.

Limits to Arbitrage

While the existence of an overpricing for high DiE stocks can be rationalized within Miller's (1977) theoretical framework, the reason this mispricing is not eliminated instantly by arbitrageurs should be related to limits to arbitrage. In the spirit of Shleifer and Vishny (1997), Pontiff (2006), Gromb and Vayanos (2010), Conrad, Kapadia and Xing (2014) and Edelen, Ince and Kadlec (2016), we test this prediction utilizing market capitalization (Size), idiosyncratic volatility (IdV) and illiquidity (Illiq) as the dimensions commonly associated with limits to arbitrage. Intuitively, relatively small, volatile and illiquid stocks are not desirable by arbitrageurs and hence any mispricing persists and is only slowly corrected. As a result, we expect to find that the DiE-return relationship is stronger among firms that exhibit high limits to arbitrage.

Tables 2.5 and 2.6 present the results of the analysis. First, we observe that relatively small, more volatile and less liquid stocks with high DiE earn average monthly excess returns of -0.85%, -1.38% and -1.00%, respectively, while high DiE stocks with high size, low volatility and high liquidity earn instead a large return premium. The result indicates that the underperformance of high DiE stocks is pronounced for stocks that arbitrageurs are less likely to hold in their portfolios due to high arbitrage risk. This can further be observed in the abnormally lower returns of high DiE relative to low DiE stocks in the case of stock portfolios with low capitalization (-1.76% per month with a t-statistic of -3.03), high idiosyncratic risk (-2.09% per month with a t-statistic of -3.54) and low liquidity (-1.81% per month with a t-statistic of -3.12). On the other hand, the returns on the H-L portfolio are negligible and statistically insignificant for big, less risky and more liquid firms. Second, after controlling DiE profitability for asset-pricing risk factors, the three-factor and four-factor alphas remain economically substantial and statistically significant for small, more volatile and illiquid stocks. For example, the four-factor alpha differential between high DiE and low DiE portfolios is equal to -1.61% per month (with a t-statistic of -3.18) for low Size, -2.00% per month (with a t-statistic of -3.88) for high IdV and -1.60% per month (with a t-statistic of -2.88) for high Illiq stocks. By contrast, the risk-adjusted (by the four-factor model) monthly average returns on the H-L portfolio are -0.32% (with a t-statistic of -1.23) for high Size, 0.11% (with a t-statistic of 0.59) for low IdV and -0.20% (with a t-statistic of -0.64) for low Illiq portfolios. Overall, our findings confirm that the persistent DiE effect is generally more difficult to be arbitraged away for stocks that are likely to exhibit higher limits to arbitrage.

2.3.4 Controlling for Other Cross-Sectional Characteristics

In this section, we analyze the interaction of the negative DiE-return relationship with various stock- and option-related characteristics using dependent bivariate portfolio-level analysis. Each month, we sort stocks in ascending order into decile portfolios based on one of the alternative stock characteristics, and next, within each characteristic portfolio, we further sort stocks into decile portfolios on the basis of DiE values. Finally, we compute the time-series averages of equal-weighted average future monthly excess returns for each of the DiE deciles across the ten characteristic portfolios obtained from the first sort. This procedure of accounting for non-DiE effects does not involve any regression-based tests and helps track the persistence of the negative DiE effect across all characteristic deciles. Additionally, we estimate the average raw returns, and the Fama-French three-factor and Carhart four-factor alphas for the strategy that buys a high DiE portfolio and sells a low DiE portfolio.[8]

Table 2.7 reports the profitability results of the DiE portfolios after controlling for stock- and option-related characteristics. We control for all the stock characteristic variables considered in Table 2.4. The results are summarized as follows. First, complementary to the bivariate sorting results presented in Tables 2.5 and 2.6, we observe that the DiE effect is not driven by short-sale costs or limits to arbitrage when averaging returns across the IO, Size, IdV or Illiq deciles. For example, the average raw return and the four-factor alpha differences between the high and low DiE portfolios are -1.08% and -1.19% per month (with t-statistics of -4.14 and -5.22) respectively when controlling for IO, or -0.55% and -0.44% per month (with t-statistics of -2.43 and -2.06) respectively when controlling for IdV. Second, the results demonstrate that preferences for lottery-type payoffs cannot explain the negative DiE-return relationship. After controlling for MAX, the average raw and risk-adjusted (by the four-factor model) monthly returns on the H-L portfolio are -0.61% (with a t-statistic of -2.58) and -0.51% (with a t-statistic of -2.21), respectively. Third, we observe a decrease in

[8]Similar results with value-weighted portfolios are provided in the Appendix B.2.

portfolio returns as DiE increases, after accounting for return reversals (STR) and momentum (MOM) effects, with a steeper decline observed from DiE decile portfolio 9 to 10. In this regard, the return differentials between high and low DiE portfolios remain statistically significant. Fourth, we establish that the underperformance of high DiE relative to low DiE stocks is robust to Beta, BM and Vliq, with significant four-factor alpha differences between the high DiE and low DiE deciles of -1.28% per month for Beta, -1.20% per month for BM and -0.77% per month for Vliq, respectively. Finally, examining the informational content of the DiE measure and AFD, our findings indicate that the DiE proxy contains predictive information for stock payoffs that cannot be subsumed by the analysts' forecast dispersion. Both the average raw return as well as the four-factor alpha spreads between the high DiE and low DiE portfolios are highly statistically significant, earning -1.21% and -1.19% per month, respectively.

In terms of option-related characteristics, we verify that the information content of the DiE measure is unique and not captured by previously documented option-based return predictors. First, we investigate the hedging-demand-based explanation for the DiE phenomenon by controlling for the implied higher moments of the risk-neutral distribution, skewness (RNS) and kurtosis (RNK) (Bali and Murray, 2013; Conrad, Dittmar and Ghysels, 2013; Stilger, Kostakis and Poon, 2016). We observe that the DiE effect is not subsumed by the implied higher moments, with H-L portfolio trading strategies generating highly statistically and economically significant average monthly returns. Second, we control for volatility and downside risk as captured by the realized-implied volatility spread, VolSpr (Bali and Hovakimian, 2009) and volatility skew, QSkew (Xing, Zhang and Zhao, 2010), respectively. Our results clearly show that the return and four-factor alpha differentials between high DiE and low DiE stocks cannot be explained by the dimensions of risk, showing an average profitability of -1.24% (-1.32%) per month after controlling for VolSpr and -1.31% (-1.38%) per month after controlling for QSkew on the raw return (four-factor alpha) basis. Third, we test whether the abnormally low returns of high DiE compared to low DiE stocks are potentially related to informed trading in options markets. We employ the call-put volatility spread (VS) suggested by Cremers and Weinbaum (2010), and call and put implied volatility innovations (InnCall and InnPut) introduced by An et al. (2014), as the proxies for informed and news trading. After controlling for VS, high DiE stocks still underperform low DiE stocks by 1.03% per month (with a t-statistic of -4.18) on a raw return basis and by 1.09% per month (with a t-statistic of -5.37) on a risk-adjusted return (four-factor alpha) basis. Similar highly significant average returns are observed when controlling for InnCall and InnPut, with four-factor alpha differences between high DiE and low DiE stocks of -1.02% per month for InnCall and -1.11% per month for InnPut, respectively. Further, the results do not show support for any relationship between the asymmetric information measure of option to stock trading volume (O/S) ratio and DiE, thus rejecting the private-information-based origin of the DiE effect. Finally, we confirm that the predictability of DiE for future stock returns is not associated with investors' uncertainty about the volatility of asset payoffs (Baltussen, Van Bekkum and Van Der Grient, 2015). By controlling for volatility of volatility (VoV) as a proxy for uncertainty, we document that the H-L DiE portfolio still earns highly significant average raw and risk-adjusted (by the four-factor model) returns of -1.10% and -1.22% per month, respectively. To summarize, the findings indicate that the negative relationship between the DiE 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.

2.3.5 Fama-MacBeth Regressions

The bivariate portfolio-level analyses demonstrate that a stock portfolio with high DiE, as compared to low DiE, 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 DiE-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 DiE measure and a variety 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.

Tables 2.8 and 2.9 present the results for all the stock- and option-related characteristics considered in the previous section. In Panel A, we estimate univariate/multivariate models with different control variables and thirteen cross-sectional regression specifications of excess returns on DiE and various stock characteristic variables. First, the univariate model shows that the coefficient on DiE is negative (-0.1395) and statistically significant (with a t-statistic of -3.35). The economic magnitude of the DiE effect is similar to that presented in univariate portfolio-level analysis. In particular, multiplying the difference in mean values between high DiE and low DiE deciles (from Table 2.2) by the slope coefficient yields a monthly risk premium differential between the high and low DiE portfolio of -2.05%. Second, estimating bivariate regressions with DiE and stock-related characteristics, the average slope coefficient on DiE remains negative, statistically significant at the 1% level and economically large, with values ranging between -0.1388 and -0.1002. Of all stock-related characteristics, only idiosyncratic volatility of Ang et al. (2006), and monthly maximum return of Bali, Cakici and Whitelaw (2011) exhibit a negative and statistically significant predictability for future stock returns in our sample period. Interestingly, AFD does not exhibit any significant cross-sectional predictability after controlling for DiE, even though it is significant (at the 5% level) in the multivariate model when DiE is excluded. This result may suggest that our proxy for disagreement carries a superior or distinct information content for stock returns relative to that of AFD. Considering the same multivariate model, the coefficients on

Size, IdV, Illiq and STR are of expected sign and statistically significant, whereas the same coefficients across all model specifications with the DiE measure lose their significance and economic magnitude. This finding may indicate that the firms with available DiE estimates constitute a relatively small fraction of the entire CRSP universe, where such characteristics as Size, Illiq or STR are shown to be strongly related to expected stock returns (see also Table 2.1). Finally, in the multivariate model specification that includes all the control variables, we observe that DiE retains its strong significance (t-statistic of -3.43), with a slope coefficient value of -0.0760. In economic terms, this coefficient translates to a return differential of -1.11%.

In Panel B, we provide the predictability results from ten cross-sectional regression specifications involving DiE and other option-related characteristic variables which were considered in the previous section. We observe that in bivariate regressions, the coefficient on DiE 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 -0.1378 and -0.1030. From the remainder of the variables, RNS and VS exhibit a positive and significant effect, consistent with the papers of Stilger, Kostakis and Poon (2016) 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 et al. (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 DiE remains negative (-0.0738) and retains its statistical significance (t-statistic of -2.21). In economic terms, this coefficient translates to a return differential of -1.08%. Overall, our findings indicate that the DiE 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.

2.3.6 Decomposition of the DiE Effect

To supplement the previous results suggesting that a negative DiE effect remains unexplained by any of the stock- or option-related characteristics, we examine what percentage of DiE's return predictability is explained, and how much remains unexplained, by each of the other candidate control variables. More specifically, we use Hou and Loh's (2016) component decomposition methodology to decompose the DiE-return predictability into the fraction that is also explained by a candidate variable and the remaining fraction that can only be explained by DiE. In the first stage, we regress excess stock returns at the end of month t+1 ($Exret_{it+1}$) on DiE measured in month t (DiE_{it}) to obtain a time-series average of the cross-sectional slope coefficients, with the total DiE effect expressed as β_{t+1}:

$$Exret_{it+1} = \alpha_{t+1} + \beta_{t+1} \times DiE_{it} + \epsilon_{it+1}. \tag{2.2}$$

Next, in stage 2, we run monthly regressions of DiE_{it} on the candidate control variable ($candidate_{it}$), both measured at the end of month t:

$$DiE_{it} = a_t + \gamma_t \times candidate_{it} + \omega_{it}. \tag{2.3}$$

Finally, using coefficient 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. The time-series averages of β_{t+1}^{Exp} and β_{t+1}^{Unexp} are used to measure the explained and unexplained fractions, respectively. Thus,

$$\beta_{t+1} = \frac{Cov[Exret_{it+1}, DiE_{it}]}{Var[DiE_{it}]} = \frac{Cov[Exret_{it+1}, \gamma_t \times candidate_{it}]}{Var[DiE_{it}]} + \tag{2.4}$$

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

It is important to note that even if a candidate variable is highly correlated with DiE, it may not explain a substantial fraction of the DiE-return relation. This is because it is possible for the DiE-return relation to stem from the component of DiE that is uncorrelated with the candidate variable, while the component of DiE that is correlated with the candidate variable exhibits low or even opposite explanatory power for future returns. Therefore, as Hou and Loh (2016) show, it is possible that the candidate variable contributes even negatively to the DiE effect.

Tables 2.10 and 2.11 present the results from component decomposition for stock- (Panel A) and option-related (Panel B) characteristic candidate variables. All slope and intercept coefficients, except for realized-implied volatility spread, and call and put implied volatility innovations, are statistically significant at the 1% level, implying a strong interaction between DiE and the various candidate variables. In Panel A, the results clearly indicate that almost none of the potential stock-related or option-based candidate variables is able to explain any substantial part of the negative DiE-return predictability. The strongest explanatory power is documented for idiosyncratic volatility, with about 52% of the total DiE effect being explained. This, however, does not diminish the DiE effect, as observed in the strong significance of the DiE coefficient in the Fama-MacBeth regression (in Table 2.8) after inclusion of idiosyncratic volatility. The next largest explanatory power is observed for size, maximum return and volatility of liquidity, which account for 34%, 33% and 26% of the negative DiE-return relationship, respectively. By contrast, all the remaining stock-related characteristics each contribute no more than 10% to the explained component of the DiE anomaly. Interestingly, only 4.41% of the total DiE effect can be attributed to the explanatory power of analysts' forecast dispersion, implying a distinct information content of the DiE measure. In Panel B, only the call-put volatility spread exhibits some predictive power for the DiE profitability, accounting for about 21% of the total DiE effect. None of the other option-related candidates can capture even one-tenth of the total DiE effect, whereas risk-neutral skewness contributes even more to the unexplained part of dispersion effect, with

103.1% being unexplained. The uncertainty proxy, volatility of volatility, explains only 7.6% of the total DiE-return relationship. Overall, our findings further suggest that the negative DiE-return relationship cannot be significantly attributed to any of the potential stock- or option-related candidate variables.

2.3.7 DiE and Investor Sentiment

The negative relation between differences in expectations and stock returns, presented in the previous sections, can be rationalized in the context of a market with binding short-sale constraints. In particular, in such cases the pessimistic investors sit out of the market and prices reflect only the views of the relatively more 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 DiE and stock returns is expected to be more pronounced during periods of high sentiment in the market.[9] In this section, we test this premise and investigate the asymmetric DiE effect during times of high and low investor sentiment. In particular, we estimate monthly cross-sectional Fama and MacBeth (1973) regressions 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 2.12 presents the Fama and MacBeth (1973) slope coefficients for DiE from the various

[9] Atmaz and Basak (2016) 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.

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 DiE, Models (2)-(12) show bivariate regressions with DiE and the stock characteristic variable listed in the column header and Model (13) is the multivariate regression with DiE and all the stock characteristic variables. Similarly, in the panel with option characteristics results, Models (1)-(9) show bivariate regressions with DiE and an option characteristic variable, and Model (10) is the multivariate regression with DiE and all the option variables. The results provide a consistent picture across all the regression specifications. Following periods of high sentiment, we observe that the slope coefficients for DiE are economically large, with strong statistical significance. The univariate analysis produces a significant (at the 1% level) slope coefficient of -0.1041 following the high sentiment period, compared to -0.0354 (and insignificant) for the low sentiment period. After controlling for various stock and option characteristics, DiE retains its strong negative predictability for excess returns in high sentiment months. The effect is negligible following times of low sentiment, where the negative DiE-return relationship remains statistically insignificant in most specifications. Overall, the findings confirm that the DiE effect stemming from overpricing is pronounced following periods of high investor sentiment.

2.3.8 Additional Analysis

This section complements the main findings in the chapter by, first, examining the robustness of DiE-return predictability using signed volume data and various alternative constructions of the DiE measure, and second, testing whether the DiE-return predictability persists for longer horizons.

Construction of the DiE Measure with Signed Volume Information

As discussed in Section 2.2.1, the suggested DiE measure relies on the notion that moneyness levels at which various options strategies are implemented can naturally reflect the expectations of the end-users who initiate the trades. For example, investors with more optimistic views will end up buying more OTM calls or selling more ITM puts. While the above strategies can be replicated via put-call parity by purchasing matched-strike ITM puts and selling matched-strike OTM calls respectively, it is unclear how many investors actually implement such complicated put-call parity strategies. Therefore, it is important to check the validity of our previously presented results using an alternative DiE measure that utilizes only the buy-side trading volume of OTM options and the sell-side trading volume of ITM options. More specifically, for robustness, we measure DiE using only signed trading volume across different moneyness levels that reflect expectations more clearly; i.e., in constructing DiE, 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 DiE measure constructed from signed volume can be seen as a robust version of the original measure presented in the chapter.

Table 2.13 displays equal- and value-weighted return predictability results for the new DiE 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 2.2. Moreover, we observe striking resemblance in the return properties of the higher decile portfolios sorted on the new DiE measure, with largest declines observed from DiE decile 8 to 9 and then from decile 9 to 10 in the average monthly excess returns. Further, the H-L portfolio return is -1.41% per month for equal-weighted portfolios and -1.31% per month for value-weighted portfolios, both significant at the 10% level. In line with Table 2.2, the results become stronger when considering risk-adjusted returns. For example, the four-factor alpha differential between high DiE and low DiE stocks is -1.72% per month for both equal- and value-weighted portfolios, with t-statistics of -4.69 and -3.84 respectively. Overall, the findings suggest that the DiE measure, capturing the trading behavior at various moneyness levels, exhibits consistent negative predictability for the cross-section of returns, irrespective of whether we use unsigned or signed trading volume data.

Alternative Constructions of the DiE Measure

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

Thus, we construct nine alternative DiE measures. DiE 1 is the standard deviation of stock options trading volume across moneyness levels. DiE 2 and DiE 3 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. DiE 4 and DiE

5 are similar to the original DiE measure and to DiE 1 respectively, but we use alternative filtering criteria requiring within a month at least ten days of non-missing DiE values. DiE 6 and DiE 7 are similar to the original DiE measure and to the DiE 1 respectively, but we include near-the-money options in calculating the measures. DiE 8 and DiE 9 are similar to the original DiE measure and to DiE 1 respectively, but are measured at the penultimate day of a month (instead of averaged within a month excluding the last trading day).

Table 2.14 reports the equal-weighted average monthly profitability of portfolios with the lowest and highest DiE in the previous month.[10] For all nine alternative DiE measures, we observe that portfolios with the highest DiE values consistently underperform the lowest DiE portfolios, both on a raw return as well as a risk-adjusted return basis. For instance, the four-factor alpha differential between high DiE and low DiE portfolios ranges between -1.70% per month with a t-statistic of -4.67 (for DiE 1) and -1.28% per month with a t-statistic of -3.89 (for DiE 8). The finding that the DiE profitability remains strong in the cases of DiE 2 and DiE 3 can be of particular interest. It is true that the option-based predictors of stock returns, such as implied-realized volatility spreads, skews, can be significantly affected by price pressure in the stock market. Since both DiE 2 and DiE 3 are free of any stock-level information, we mitigate any potential concerns that the DiE predictability is mechanically driven by price pressure in the stock market. Overall, these results indicate that the strong negative dispersion-return predictability is robust to various alternative specifications for DiE.

Long-term DiE Predictability

In the main analysis, we document a strong predictive relationship between DiE and next-month stock returns. Since the DiE measure is persistent across time, a natural question

[10]The value-weighted average profitability analysis portray similar results and hence is reported in the Appendix B.2.

that arises is whether DiE 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 DiE, and construct a trading strategy that buys high DiE and sells low DiE 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. Finally, for each investment horizon, equal-weighted average raw returns, and Fama-French three-factor and Carhart four-factor alphas are estimated for the above strategy.[11]

Table 2.15 demonstrates the DiE-based 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 significant predictability patterns up to six months holding periods for raw returns. For instance, we observe that a portfolio holding high DiE and sells low DiE stocks for two, three and six months will incur an average monthly return of -1.40%, -1.29% and -1.16%, respectively. When adjusting for market, size, value and momentum risk factors, the statistical significance of the H-L DiE portfolios seems to extend to twelve-month horizons. The results indicate that the DiE effect undergoes a long-term price correction rather than having a short-run temporal effect.

2.4 Conclusion

In this chapter, we explore the effect of differences in expectations (DiE) in the options market on subsequent equity returns. Our measure, which is constructed as the disper-

[11]The results for value-weighted average returns are provided in the Appendix B.2.

sion of stock options trading volume across various moneyness levels, can be rationalized within a theoretical framework wherein investors with divergent expectations about future asset returns trade options with different strike prices and such trades are accommodated by the market makers. Hence, high trading dispersion across moneyness levels indicates that investors' expectations are diverse, while a low dispersion implies that options investors' beliefs are rather similar. The key results of the chapter are obtained with a dispersion proxy that is based on total trading volume for each moneyness level. Additionally, we show that a similar measure of belief dispersion that reflects expectations more clearly, by incorporating only the buy- and sell-side volumes of out-of-the-money and in-the-money options respectively, reveals a remarkably similar pricing impact in the cross-section of stock returns.

We document that high DiE stocks consistently underperform low DiE stocks by 1.51% (1.39%) per month on a raw return basis and by 1.59% (1.57%) after adjusting for four asset pricing factors for 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 DiE measure exhibits strong persistent patterns in the future, since stocks with the highest DiE in one month tend to exhibit similar features in the subsequent month with an almost 60% chance. Moreover, the portfolio that buys high DiE and sells low DiE 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 DiE effect by showing that, in line with Miller (1977), the negative relation between differences in expectations and stock returns is more pronounced for stocks that are apt to be held by individual investors rather than institutions and hence are more difficult to short sell. Furthermore, the relation is stronger for stocks that exhibit relatively small market capitalization, lower liquidity and higher idiosyncratic volatility, consistent with the idea that the overpricing of high DiE stocks is not instantaneously eliminated by investors, due to high limits to arbitrage. We also establish that the DiE predictability mainly emerges from times of high investor sentiment, supporting the conjecture that the overpricing of high DiE stocks is more severe when the optimistic investors, who end up holding high disagreement stocks, are excessively optimistic.

Performing a series of robustness checks, we observe that the negative DiE-return relationship cannot be fully subsumed by previously documented stock-related return predictors and is distinct from the effect of various option-related return drivers. For example, using Hou and Loh's (2016) component decomposition, none of the characteristics can adequately explain the total DiE profitability. Of particular interest, analysts' forecast dispersion can account for only 4.41% of the DiE-return relation, meaning that the two disagreement proxies reflect different aspects of the overall level of belief divergence in the equity market. Finally, this chapter demonstrates that the DiE effect is robust to various alternative DiE specifications and screening criteria.

Figure 2.1: Average DiE across industries

This figure plots the yearly average values of the differences in expectations (DiE) 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 DiE is the monthly average dispersion of stock options trading volume across moneyness levels for each industry. Industry classifications are provided in the graph below.

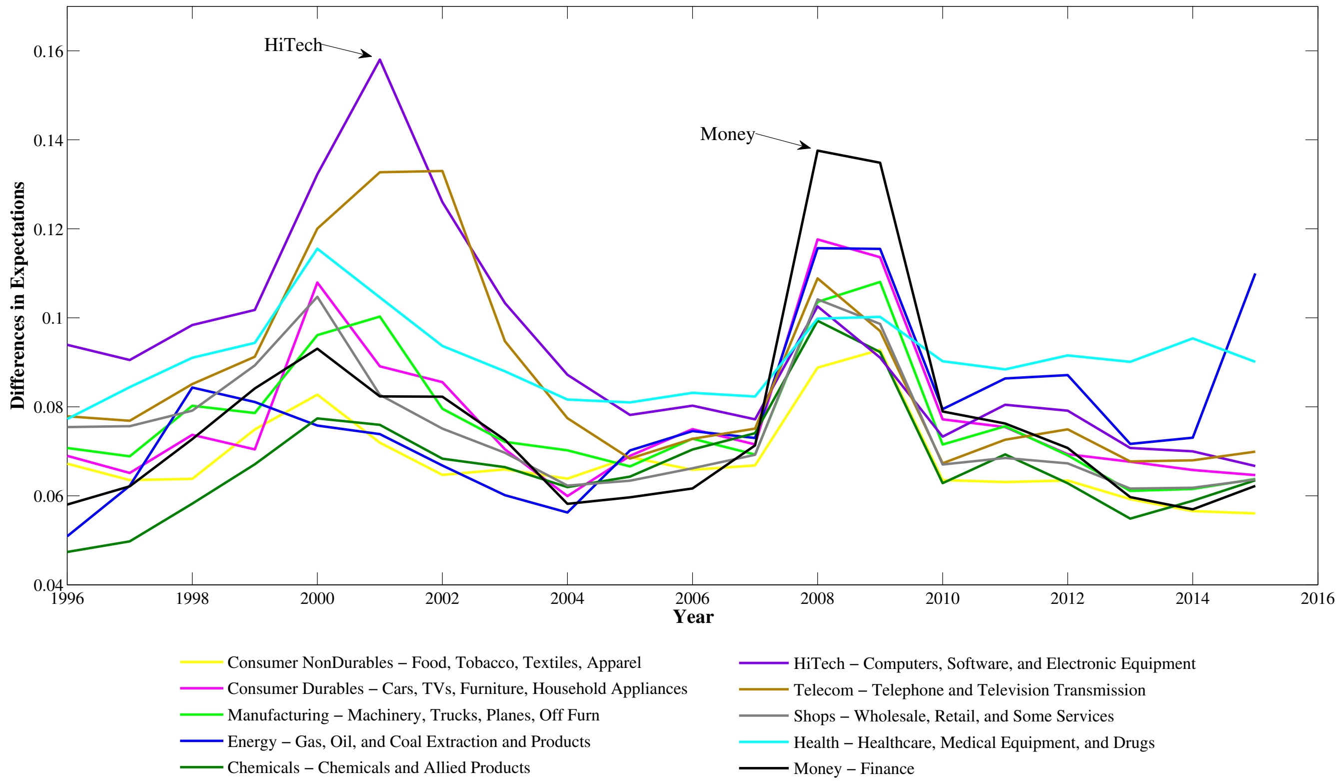


Figure 2.2: DiE Portfolios across months

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

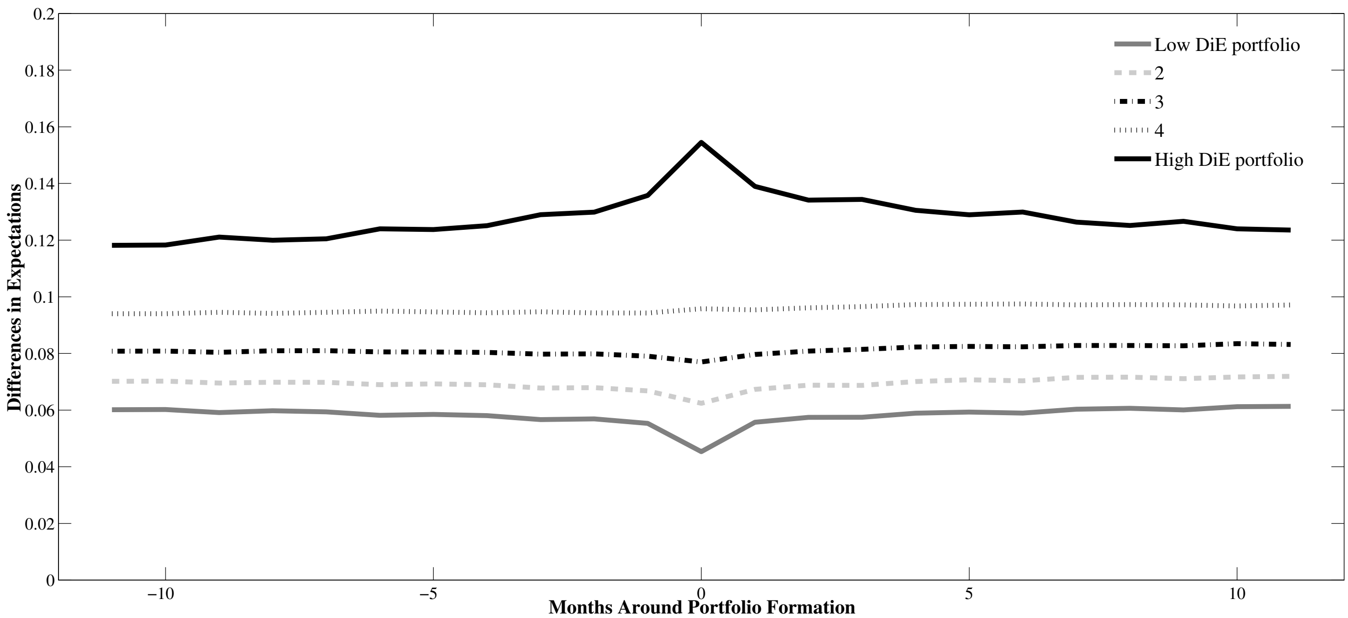


Table 2.1: Descriptive Statistics for DiE Measure

This table reports the yearly descriptive statistics for differences in expectations (DiE) over the sample period from January 1996 to September 2015. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. The column "Num. of CRSP stocks" displays the total number of common stocks in CRSP universe, that are traded on NYSE, AMEX and NASDAQ. The column "Num. of stocks with DiE" displays the number of firms for which we can estimate the DiE measure and that survive the screening criteria. The column "% of stocks with DiE" displays the percentage of firms for which we can estimate the DiE measure relative to the total number of stocks in CRSP universe. The subsequent four columns report the mean, median, 25^{th} and 75^{th} percentile values of average DiE across all firms in our sample.

Year	Num. of CRSP stocks	Num. of stocks with DiE	% of stocks with DiE	Mean	Median	25^{th} perc.	75^{th} perc.
1996	3447	779	22.60	0.081	0.077	0.057	0.098
1997	3632	1002	27.59	0.080	0.075	0.056	0.096
1998	3677	1122	30.51	0.088	0.079	0.061	0.104
1999	3824	1264	33.05	0.094	0.087	0.067	0.112
2000	3806	1483	38.96	0.126	0.109	0.080	0.147
2001	3612	1186	32.83	0.121	0.097	0.069	0.136
2002	3424	1048	30.61	0.105	0.083	0.063	0.115
2003	3323	992	29.85	0.082	0.073	0.057	0.094
2004	3340	1165	34.88	0.076	0.067	0.052	0.088
2005	3385	1253	37.02	0.072	0.065	0.051	0.082
2006	3378	1406	41.62	0.075	0.068	0.053	0.087
2007	3400	1572	46.24	0.078	0.068	0.054	0.087
2008	3244	1543	47.56	0.125	0.098	0.075	0.133
2009	3146	1404	44.63	0.098	0.086	0.068	0.110
2010	3111	1380	44.36	0.076	0.067	0.053	0.085
2011	3060	1439	47.03	0.082	0.071	0.055	0.092
2012	2995	1278	42.67	0.078	0.066	0.051	0.088
2013	3000	1361	45.37	0.071	0.060	0.047	0.080
2014	3015	1480	49.09	0.074	0.060	0.046	0.084
2015	2944	1395	47.38	0.075	0.061	0.047	0.084

Table 2.2: Profitability of DiE Portfolios

This table reports equal-weighted (in Panel A) and value-weighted (in Panel B) monthly profitability results for the decile portfolios sorted on differences in expectations (DiE) (in ascending order from decile 1, low DiE to decile 10, high DiE) over the sample period from January 1996 to September 2015. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. For each decile portfolio, we report the average DiE over the last month (Average DiE), equal- and value-weighted average monthly returns in excess of the risk-free rate (R) and alphas from the Fama-French three-factor ($FF3\alpha$) and Carhart four-factor ($C4\alpha$) models. The $H-L$ row reports the average raw returns and alphas for the strategy that buys a high DiE portfolio and sells a low DiE portfolio. Newey-West adjusted (with six lags) t-statistics are reported in parentheses. *,**,*** denote statistical significance at 10%, 5% and 1%, respectively. Equal- and value-weighted average raw returns and risk-adjusted returns are expressed as percentages.

Panel A: Equal-Weighted Portfolios

Portfolio	Average DiE	R	$FF3\alpha$	$C4\alpha$
Low DiE	0.039	0.95	0.23	0.18
2	0.051	0.94	0.14	0.07
3	0.058	1.04	0.22	0.15
4	0.065	1.00	0.12	0.08
5	0.072	0.67	-0.26	-0.24
6	0.080	0.96	-0.02	0.00
7	0.089	0.76	-0.27	-0.18
8	0.101	0.64	-0.46	-0.30
9	0.120	0.15	-1.11	-0.74
High DiE	0.186	-0.56	-1.97	-1.41
$H-L$		-1.51**	-2.19***	-1.59***
		(-2.57)	(-5.63)	(-4.20)

Panel B: Value-Weighted Portfolios

Portfolio	R	$FF3\alpha$	$C4\alpha$
Low DiE	0.90	0.31	0.26
2	0.75	0.14	0.07
3	0.75	0.16	0.06
4	0.89	0.19	0.15
5	0.47	-0.27	-0.28
6	0.60	-0.20	-0.25
7	0.96	0.09	0.11
8	0.78	-0.14	-0.06
9	0.73	-0.34	-0.16
High DiE	-0.48	-1.71	-1.31
$H-L$	-1.39**	-2.01***	-1.57***
	(-2.24)	(-4.91)	(-3.45)

Table 2.3: Transition Matrix

This table reports the average month-to-month transition probabilities for the decile portfolios sorted on differences in expectations (DiE) (in ascending order from decile 1, low DiE to decile 10, high DiE) over our sample period from January 1996 to September 2015. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. The reported values are 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 DiE	2	3	4	5	6	7	8	9	High DiE
Low DiE	0.406	0.247	0.143	0.084	0.052	0.028	0.018	0.010	0.008	0.005
2	0.224	0.242	0.194	0.134	0.088	0.052	0.033	0.019	0.010	0.005
3	0.127	0.192	0.198	0.170	0.126	0.084	0.051	0.029	0.016	0.007
4	0.073	0.130	0.162	0.182	0.157	0.127	0.082	0.051	0.027	0.010
5	0.044	0.083	0.124	0.155	0.172	0.162	0.123	0.078	0.042	0.016
6	0.028	0.049	0.086	0.118	0.158	0.178	0.167	0.119	0.073	0.024
7	0.014	0.031	0.051	0.081	0.116	0.165	0.201	0.184	0.115	0.040
8	0.008	0.018	0.031	0.046	0.080	0.121	0.180	0.224	0.204	0.088
9	0.005	0.009	0.014	0.024	0.042	0.066	0.118	0.206	0.306	0.211
High DiE	0.004	0.003	0.005	0.010	0.016	0.026	0.042	0.085	0.213	0.597

Table 2.4: Characteristics of Portfolios sorted on DiE

This table reports the average stock-related characteristics for the decile portfolios sorted on differences in expectations (DiE) (in ascending order from decile 1, low DiE to decile 10, high DiE) over the sample period from January 1996 to September 2015. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. The definitions of all the variables are detailed in the Appendix B.1.

	Low DiE	2	3	4	5	6	7	8	9	High DiE
IO	2.246	2.410	2.425	2.429	2.408	2.379	2.301	2.187	1.951	1.376
Size	9.081	8.968	8.799	8.569	8.371	8.146	7.904	7.613	7.261	6.603
IdV	0.221	0.252	0.279	0.312	0.343	0.378	0.414	0.463	0.529	0.683
Illiq	0.001	0.001	0.002	0.002	0.003	0.004	0.005	0.006	0.013	0.028
MAX	0.040	0.046	0.051	0.057	0.063	0.069	0.076	0.084	0.094	0.117
STR	0.020	0.021	0.022	0.022	0.023	0.020	0.019	0.013	0.005	-0.024
Beta	0.888	0.994	1.084	1.180	1.270	1.358	1.457	1.544	1.603	1.619
BM	0.406	0.382	0.373	0.373	0.368	0.372	0.383	0.402	0.463	0.802
Mom	0.200	0.235	0.266	0.297	0.317	0.337	0.354	0.361	0.333	0.143
Vliq	1.448	1.635	1.802	1.985	2.157	2.317	2.496	2.654	2.812	3.016
AFD	0.050	0.057	0.068	0.078	0.096	0.108	0.134	0.163	0.214	0.287

Table 2.5: DiE, Short-sale Constraints and Limits to Arbitrage

This table presents the average monthly profitability of twenty-five portfolios sorted on one of the four stock characteristics variables and the differences in expectations (DiE) measure over the sample period from January 1996 to September 2015. We use residual institutional ownership (IO) as a proxy for short-sale constraints and firm's size (Size), idiosyncratic volatility (IdV) and Amihud illiquidity (Illiq) as proxies for limits to arbitrage. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. Each month, we sort stocks in ascending order into quintile portfolios (column vector, from quintile 1 to 5) based on one of the four characteristics. Next, within each characteristic portfolio, we further sort stocks into five extra portfolios based on DiE (row vector, from quintile 1 to 5). Finally, for each characteristic-DiE portfolio, we compute equal-weighted average 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 Fama-French three-factor ($FF3\alpha$) and Carhart four-factor ($C4\alpha$) alphas for the strategy that buys a high DiE portfolio and sells a low DiE portfolio. Newey-West adjusted (with six lags) t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. The definitions of all the variables are detailed in the Appendix B.1. Average raw and risk-adjusted returns are expressed as percentages.

Residual Institutional Ownership

	Low DiE	2	3	4	High DiE	$H-L$	$FF3\alpha$	$C4\alpha$
Low IO	0.90	0.41	0.30	-0.02	-1.14	-2.04***	-2.77***	-2.09***
						(-3.13)	(-5.62)	(-4.17)
2	0.81	0.92	0.65	0.13	0.19	-0.61	-1.31**	-0.66
						(-0.98)	(-2.39)	(-1.20)
3	0.90	1.02	0.90	1.22	0.53	-0.37	-0.91**	-0.42
						(-0.71)	(-2.56)	(-1.47)
4	1.16	0.95	1.09	0.82	0.65	-0.51	-0.95***	-0.59*
						(-1.16)	(-2.80)	(-1.91)
High IO	0.89	1.27	1.14	0.95	0.16	-0.73	-1.17***	-0.80***
						(-1.64)	(-4.13)	(-2.78)

Size

	Low DiE	2	3	4	High DiE	$H-L$	$FF3\alpha$	$C4\alpha$
Low Size	0.90	0.62	0.26	-0.48	-0.85	-1.76***	-2.19***	-1.61***
						(-3.03)	(-4.15)	(-3.18)
2	0.91	0.86	0.87	0.58	0.01	-0.90**	-1.26***	-0.71**
						(-2.00)	(-3.41)	(-2.13)
3	1.19	1.03	1.05	0.69	0.45	-0.74	-1.14***	-0.64*
						(-1.55)	(-3.44)	(-1.91)
4	0.88	1.08	0.91	0.98	0.52	-0.36	-0.76**	-0.53
						(-0.66)	(-2.10)	(-1.43)
High Size	0.83	0.90	0.77	0.67	0.71	-0.12	-0.45*	-0.32
						(-0.26)	(-1.77)	(-1.23)

Table 2.6: DiE, Short-sale Constraints and Limits to Arbitrage (continued)

Idiosyncratic Volatility

	Low DiE	2	3	4	High DiE	$H-L$	$FF3\alpha$	$C4\alpha$
Low IdV	0.94	0.89	0.86	1.02	1.12	0.18	-0.01	0.11
						(0.72)	(-0.06)	(0.59)
2	0.90	1.20	0.72	0.92	1.19	0.29	0.04	0.33
						(0.88)	(0.17)	(1.22)
3	0.95	1.03	1.14	0.81	0.39	-0.56*	-0.85***	-0.50*
						(-1.71)	(-3.01)	(-1.86)
4	0.86	0.74	0.73	0.32	0.13	-0.74	-1.04**	-0.49
						(-1.63)	(-2.57)	(-1.22)
High IdV	0.71	0.53	0.20	-0.57	-1.38	-2.09***	-2.58***	-2.00***
						(-3.54)	(-4.65)	(-3.88)

Amihud Illiquidity

	Low DiE	2	3	4	High DiE	$H-L$	$FF3\alpha$	$C4\alpha$
Low Illiq	0.85	0.79	0.77	0.66	0.74	-0.11	-0.53*	-0.20
						(-0.19)	(-1.91)	(-0.64)
2	0.99	0.93	1.09	0.93	0.37	-0.62	-1.06***	-0.63*
						(-1.18)	(-2.92)	(-1.68)
3	1.19	1.19	1.12	0.93	0.36	-0.83	-1.32***	-0.70*
						(-1.65)	(-3.81)	(-1.86)
4	0.87	0.85	0.44	0.45	0.17	-0.69	-1.21***	-0.47
						(-1.32)	(-2.74)	(-1.35)
High Illiq	0.81	0.77	0.84	-0.03	-1.00	-1.81***	-2.19***	-1.60***
						(-3.12)	(-3.98)	(-2.88)

Table 2.7: Controlling for Other Cross-Sectional Characteristics

This table presents the average monthly profitability of portfolios sorted on one of the stock- or option-related characteristics and the differences in expectations (DiE) measure over our sample period from January 1996 to September 2015. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. Each month, we sort stocks in ascending order into decile portfolios (from decile 1, low DiE to decile 10, high DiE) based on one of the characteristics. Next, within each characteristic portfolio, we further sort stocks into ten extra portfolios in ascending order on the basis of DiE. Finally, we calculate the time-series averages of equal-weighted average monthly excess returns for each of the DiE deciles across the ten characteristic portfolios obtained from the first sort. Additionally, we report the average raw returns ($H-L$) as well as the Fama-French three-factor ($FF3\alpha$) and Carhart four-factor ($C4\alpha$) alphas for the strategy that buys a high DiE portfolio and sells a low DiE portfolio. Newey-West adjusted (with six lags) t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. The definitions of all the variables are detailed in the Appendix B.1. Average raw and risk-adjusted returns are expressed as percentages.

Stock-related Characteristics

	IO	**Size**	**IdV**	**Illiq**	**MAX**	**STR**	**Beta**	**BM**	**Mom**	**Vliq**	**AFD**
Low DiE	1.00	0.95	0.83	0.87	0.83	0.84	0.86	0.90	0.93	0.94	1.06
2	0.98	0.95	0.95	0.99	0.98	0.94	0.81	1.03	1.05	1.09	0.93
3	0.99	0.92	0.82	0.92	0.78	0.99	0.97	1.03	0.93	0.90	0.89
4	0.73	0.88	1.00	0.89	0.78	0.92	0.91	0.98	0.90	0.91	0.90
5	0.94	0.80	0.71	0.97	0.69	0.88	0.91	0.97	0.84	1.06	1.00
6	0.80	0.62	0.59	0.75	0.92	0.79	0.74	0.65	0.81	0.92	0.79
7	0.54	0.59	0.43	0.63	0.67	0.64	0.86	0.77	0.67	0.71	0.82
8	0.56	0.40	0.61	0.57	0.51	0.54	0.94	0.64	0.43	0.54	0.64
9	0.71	0.26	0.31	0.32	0.16	0.33	0.14	0.24	0.28	0.54	0.10
High DiE	-0.13	0.20	0.28	-0.06	0.22	-0.39	-0.34	-0.25	-0.05	0.13	-0.15
$H-L$	-1.08***	-0.74***	-0.55**	-0.93***	-0.61***	-1.22***	-1.20***	-1.15***	-0.98***	-0.82***	-1.21***
	(-4.14)	(-3.05)	(-2.43)	(-3.66)	(-2.58)	(-5.01)	(-5.27)	(-4.44)	(-4.01)	(-3.61)	(-4.81)
$FF3\alpha$	-1.75***	-1.22***	-0.92***	-1.49***	-1.00***	-1.79***	-1.59***	-1.74***	-1.42***	-1.30***	-1.71***
	(-7.63)	(-5.67)	(-4.36)	(-6.49)	(-4.37)	(-8.45)	(-7.35)	(-7.72)	(-6.32)	(-5.96)	(-8.12)
$C4\alpha$	-1.19***	-0.71***	-0.44**	-0.79***	-0.51**	-1.27***	-1.28***	-1.20***	-1.14***	-0.77***	-1.19***
	(-5.22)	(-3.37)	(-2.06)	(-3.46)	(-2.21)	(-6.08)	(-5.95)	(-5.24)	(-5.07)	(-3.60)	(-5.48)

Option-related Characteristics

	RNS	**RNK**	**VolSpr**	**QSkew**	**VS**	**O/S**	**InnCall**	**InnPut**	**VoV**
Low DiE	1.03	0.99	0.90	1.01	1.00	0.97	0.83	0.81	0.97
2	0.90	0.93	0.93	0.82	0.87	0.96	0.98	0.99	0.84
3	1.06	1.03	0.89	0.97	0.91	0.98	0.96	0.97	0.97
4	1.10	0.93	0.85	0.87	0.77	0.73	0.99	0.84	0.96
5	0.81	0.87	0.78	0.65	0.84	0.90	0.72	0.74	0.88
6	0.86	0.71	0.87	0.84	0.97	0.85	0.65	0.78	0.79
7	0.71	0.69	0.73	0.83	0.75	0.79	0.60	0.69	0.79
8	0.57	0.53	0.52	0.52	0.34	0.51	0.62	0.69	0.67
9	0.22	0.43	0.50	0.41	0.24	0.31	0.38	0.35	0.31
High DiE	-0.58	-0.41	-0.34	-0.30	-0.03	-0.51	-0.15	-0.26	-0.12
$H-L$	-1.61***	-1.40***	-1.24***	-1.31***	-1.03***	-1.48***	-0.98***	-1.07***	-1.10***
	(-6.25)	(-5.92)	(-4.98)	(-5.26)	(-4.18)	(-5.74)	(-4.04)	(-4.22)	(-4.26)
$FF3\alpha$	-2.24***	-1.93***	-1.84***	-1.89***	-1.63***	-2.17***	-1.55***	-1.64***	-1.56***
	(-10.43)	(-9.14)	(-8.52)	(-8.85)	(-8.02)	(-10.13)	(-7.42)	(-7.33)	(-6.91)
$C4\alpha$	-1.75***	-1.46***	-1.32***	-1.38***	-1.09***	-1.60***	-1.02***	-1.11***	-1.22***
	(-8.17)	(-6.96)	(-6.14)	(-6.64)	(-5.37)	(-7.31)	(-4.81)	(-4.96)	(-5.32)

Table 2.8: 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 differences in expectations (DiE) 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. DiE is the monthly average dispersion of 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 findings with option-related characteristics. The definitions of all the variables are detailed in the Appendix B.1. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

Panel A: Stock-related Characteristics

Univariate Analysis

	IO	**Size**	**IdV**	**Illiq**	**MAX**	**STR**	**Beta**	**BM**	**Mom**	**Vliq**	**AFD**
	-0.0011	-0.0026***	-0.0037	0.0047***	-0.0294	-0.0040	-0.0044	-0.0002	0.0013	-0.0016	-0.0031
	(-1.48)	(-2.62)	(-0.51)	(3.51)	(-0.97)	(-0.56)	(-1.45)	(-0.08)	(0.26)	(-0.85)	(-1.23)
$\mathbf{R^2}$	0.004	0.013	0.023	0.005	0.017	0.012	0.024	0.011	0.016	0.022	0.004

Multivariate Model: No DiE

	IO	**Size**	**IdV**	**Illiq**	**MAX**	**STR**	**Beta**	**BM**	**Mom**	**Vliq**	**AFD**	$\mathbf{R^2}$
	0.0001	-0.0020***	-0.0074*	0.0086**	-0.0125	-0.0141**	-0.0011	-0.0003	0.0013	-0.0009	-0.0031**	0.088
	(0.33)	(-3.45)	(-1.85)	(2.43)	(-0.83)	(-2.36)	(-0.39)	(-0.19)	(0.35)	(-0.90)	(-2.40)	

Multivariate Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
DiE	-0.1395***	-0.1337***	-0.1158***	-0.1002***	-0.1312***	-0.1160***	-0.1388***	-0.1387***	-0.1251***	-0.1294***	-0.1351***	-0.1223***	-0.0760***
	(-3.35)	(-3.32)	(-3.29)	(-3.11)	(-3.21)	(-3.45)	(-3.31)	(-4.20)	(-3.04)	(-3.32)	(-4.13)	(-2.83)	(-3.43)
IO		0.0004											0.0001
		(0.63)											(0.45)
Size			0.0003										-0.0011
			(0.43)										(-1.16)
IdV				-0.0114**									-0.0037
				(-2.49)									(-0.73)
Illiq					-0.0481								-0.2404*
					(-0.68)								(-1.77)
MAX						-0.0453*							-0.0093
						(-1.96)							(-0.40)
STR							-0.0027						-0.0027
							(-0.35)						(-0.34)
Beta								0.0029					0.0011
								(0.83)					(0.34)
BM									-0.0044				0.0001
									(-1.05)				(0.02)
Mom										0.0040			0.0004
										(1.09)			(0.13)
Vliq											0.0007		-0.0004
											(0.40)		(-0.41)
AFD												0.0011	0.0012
												(0.50)	(0.57)
$\mathbf{R^2}$	0.035	0.039	0.046	0.045	0.042	0.044	0.048	0.064	0.052	0.056	0.053	0.039	0.132

Table 2.9: Fama-MacBeth Regressions (continued)

Panel B: Option-related Characteristics

Univariate Analysis

	RNS	**RNK**	**VolSpr**	**QSkew**	**VS**	**O/S**	**InnCall**	**InnPut**	**VoV**
	0.0049**	0.0005	-0.0051*	-0.0240***	0.0666***	-0.0655**	0.0077	0.0011	-0.0429**
	(2.24)	(0.21)	(-1.69)	(-3.71)	(7.55)	(-2.00)	(1.43)	(0.20)	(-2.16)
$\mathbf{R^2}$	0.004	0.010	0.005	0.002	0.003	0.004	0.004	0.004	0.005

Multivariate Model: No DiE

	RNS	**RNK**	**VolSpr**	**QSkew**	**VS**	**O/S**	**InnCall**	**InnPut**	**VoV**	$\mathbf{R^2}$
	-0.0007	0.0007	-0.0067	-0.0339	0.0330*	-0.0023	-0.0022	-0.0048	-0.0179	0.0624
	(-0.14)	(0.16)	(-1.50)	(-0.86)	(1.89)	(-0.10)	(-0.15)	(-0.33)	(-1.35)	

Multivariate Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DiE	-0.1378***	-0.1324***	-0.1300***	-0.1230***	-0.1164***	-0.1373***	-0.1256***	-0.1227***	-0.1030**	-0.0738**
	(-3.42)	(-3.43)	(-3.12)	(-2.94)	(-2.77)	(-3.29)	(-3.01)	(-2.91)	(-2.10)	(-2.21)
RNS	0.0083***									-0.0017
	(3.22)									(-0.36)
RNK		-0.0019								-0.0026
		(-0.52)								(-0.50)
VolSpr			-0.0010							-0.0029
			(-0.25)							(-0.67)
QSkew				-0.0587***						-0.0298
				(-5.55)						(-0.88)
VS					0.0615***					0.0125
					(3.99)					(0.56)
O/S						-0.0293*				0.0064
						(-1.78)				(0.38)
InnCall							-0.0070			0.0120
							(-0.96)			(0.66)
InnPut								-0.0125*		-0.0220
								(-1.70)		(-1.23)
VoV									-0.0337**	-0.0257
									(-2.18)	(-1.54)
$\mathbf{R^2}$	0.038	0.041	0.040	0.038	0.038	0.039	0.040	0.040	0.040	0.085

Table 2.10: Component Decomposition

This table presents univariate cross-sectional regressions and the decomposition of the negative differences in expectations (DiE)-return relationship into explained and unexplained components using Hou and Loh's (2016) methodology over the sample period from January 1996 to September 2015. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. In stage 1, we run monthly regressions of excess returns (Exret) at the end of month *t+1* on the DiE measure at the end of month t ($Exret_{it+1} = \alpha_{t+1} + \beta_{t+1} \times DiE_{it} + \epsilon_{it+1}$). The total DiE effect reflected by β_{t+1} is reported in the rows "Total". In stage 2, we run monthly regressions of DiE on the candidate control variable, both measured at the end of month t, ($DiE_{it} = a_t + \gamma_t \times candidate_{it} + \omega_{it}$). a_t and γ_t are reported as Inter. and Slope, respectively. Finally, β_{t+1} coefficient from stage 1 is decomposed into two orthogonal components from stage 2: $\beta_{t+1} = \frac{Cov[Exret_{it+1}, DiE_{it}]}{Var[DiE_{it}]} = \frac{Cov[Exret_{it+1}, \gamma_t \times candidate_{it}]}{Var[DiE_{it}]} + \frac{Cov[Exret_{it+1}, a_t + \omega_{it}]}{Var[DiE_{it}]} = \beta_{t+1}^{Exp} + \beta_{t+1}^{Unexp}$. The time-series averages of β_{t+1}, β_{t+1}^{Exp} (Exp.), β_{t+1}^{Unexp} (Unexp.) are used to measure the percentage of the DiE-return relationship that is explained (%, Exp.) and unexplained (%, Unexp.) by the candidate variable. Panel A shows the results with stock-related variables, while Panel B reports the findings with option-related characteristics. The definitions of all the variables are detailed in the Appendix B.1. The slope and intercept are statistically significant at the 1% level (except for VolSpr, InnCall and InnPut).

Panel A: Stock-related Characteristics

Cand.	Var.	Coeff.	Cand.	Var.	Coeff.	Cand.	Var.	Coeff.
IO	Slope	-0.0057	**Size**	Slope	-0.0129	**IdV**	Slope	0.1087
	Inter.	0.0965		Inter.	0.1906		Inter.	0.0443
	Exp.	-0.0158		Exp.	-0.0520		Exp.	-0.0793
	%, Exp.	**10.47**		%, Exp.	**33.94**		%, Exp.	**51.63**
	Unexp.	-0.1351		Unexp.	-0.1012		Unexp.	-0.0743
	%, Unexp.	**89.53**		%, Unexp.	**66.06**		%, Unexp.	**48.37**
	Total	-0.1509		Total	-0.1532		Total	-0.1536
		(100%)			(100%)			(100%)
Illiq	Slope	0.7924	**MAX**	Slope	0.4200	**STR**	Slope	-0.0431
	Inter.	0.0837		Inter.	0.0567		Inter.	0.0820
	Exp.	-0.0097		Exp.	-0.0509		Exp.	-0.0125
	%, Exp.	**6.65**		%, Exp.	**33.16**		%, Exp.	**8.15**
	Unexp.	-0.1362		Unexp.	-0.1026		Unexp.	-0.1408
	%, Unexp.	**93.35**		%, Unexp.	**66.84**		%, Unexp.	**91.85**
	Total	-0.1458		Total	-0.1535		Total	-0.1533
		(100%)			(100%)			(100%)
Beta	Slope	0.0317	**BM**	Slope	0.0135	**Mom**	Slope	-0.0164
	Inter.	0.0451		Inter.	0.0785		Inter.	0.0834
	Exp.	-0.0130		Exp.	-0.0083		Exp.	-0.0057
	%, Exp.	**8.90**		%, Exp.	**5.70**		%, Exp.	**3.91**
	Unexp.	-0.1330		Unexp.	-0.1373		Unexp.	-0.1401
	%, Unexp.	**91.10**		%, Unexp.	**94.30**		%, Unexp.	**96.09**
	Total	-0.1460		Total	-0.1456		Total	-0.1458
		(100%)			(100%)			(100%)

Table 2.11: Component Decomposition (continued)

Vliq	Slope	0.0239	**AFD**	Slope	0.0338
	Inter.	0.0301		Inter.	0.0812
	Exp.	-0.0368		Exp.	-0.0059
	%, Exp.	**26.46**		%, Exp.	**4.41**
	Unexp.	-0.1023		Unexp.	-0.1278
	%, Unexp.	**73.54**		%, Unexp.	**95.59**
	Total	-0.1391		Total	-0.1337
		(100%)			(100%)

Panel B: Option-related Characteristics

Cand.	Var.	Coeff.	Cand.	Var.	Coeff.	Cand.	Var.	Coeff.
RNS	Slope	0.0373	**RNK**	Slope	-0.0288	**VolSpr**	Slope	-0.0032
	Inter.	0.0979		Inter.	0.1815		Inter.	0.0837
	Exp.	0.0044		Exp.	-0.0022		Exp.	-0.0060
	%, Exp.	**-3.09**		%, Exp.	**1.55**		%, Exp.	**4.10**
	Unexp.	-0.1467		Unexp.	-0.1401		Unexp.	-0.1403
	%, Unexp.	**103.09**		%, Unexp.	**98.45**		%, Unexp.	**95.90**
	Total	-0.1423		Total	-0.1423		Total	-0.1464
		(100%)			(100%)			(100%)
QSkew	Slope	0.0973	**VS**	Slope	-0.1772	**O/S**	Slope	0.0628
	Inter.	0.0805		Inter.	0.0825		Inter.	0.0821
	Exp.	-0.0152		Exp.	-0.0304		Exp.	-0.0083
	%, Exp	**10.40**		%, Exp.	**20.91**		%, Exp.	**5.42**
	Unexp.	-0.1310		Unexp.	-0.1150		Unexp.	-0.1447
	%, Unexp.	**89.60**		%, Unexp.	**79.09**		%, Unexp.	**94.58**
	Total	-0.1462		Total	-0.1454		Total	-0.1530
		(100%)			(100%)			(100%)
InnCall	Slope	0.0045	**InnPut**	Slope	0.0068	**VoV**	Slope	0.0911
	Inter.	0.0828		Inter.	0.0829		Inter.	0.0697
	Exp.	-0.0085		Exp.	-0.0115		Exp.	-0.0099
	%, Exp.	**5.98**		%, Exp.	**8.10**		%, Exp.	**7.60**
	Unexp.	-0.1336		Unexp.	-0.1305		Unexp.	-0.1203
	%, Unexp.	**94.02**		%, Unexp.	**91.90**		%, Unexp.	**92.40**
	Total	-0.1421		Total	-0.1421		Total	-0.1301
		(100%)			(100%)			(100%)

Table 2.12: DiE 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 differences in expectations (DiE) measure and a list of stock- and option-related characteristics computed at the end of month *t* over high and low investor sentiment periods across the sample period from January 1996 to September 2015. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. A high (low) sentiment month is one where Baker and Wurgler's (2006) index value in the previous month 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. The first column in the stock-related characteristics panel reports the coefficient of DiE from univariate models, while all other columns with control variable abbreviations report the coefficients of DiE from bivariate regressions after controlling for the relevant characteristic. The final column (Full) reports the DiE coefficient from the multivariate model with all control variables. The definitions of all the variables are detailed in the Appendix B.1. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

High Sentiment

Stock-related Characteristics

	(1)	(2) IO	(3) Size	(4) IdV	(5) Illiq	(6) MAX	(7) STR	(8) Beta	(9) BM	(10) Mom	(11) Vliq	(12) AFD	(13) Full
DiE	-0.1041***	-0.0964***	-0.0791***	-0.0676***	-0.0988***	-0.0780***	-0.1071***	-0.0946***	-0.0940***	-0.0946***	-0.0801***	-0.1000***	-0.0422***
	(-3.48)	(-3.37)	(-3.30)	(-3.24)	(-3.30)	(-3.38)	(-3.76)	(-3.90)	(-3.20)	(-3.22)	(-3.97)	(-3.35)	(-3.49)
$\mathbf{R^2}$	0.021	0.023	0.027	0.027	0.024	0.026	0.027	0.035	0.030	0.033	0.032	0.023	0.071

Option-related Characteristics

	(1) RNS	(2) RNK	(3) VolSpr	(4) QSkew	(5) VS	(6) O/S	(7) InnCall	(8) InnPut	(9) VoV	(10) Full
DiE	-0.1032***	-0.0964***	-0.1017***	-0.0996***	-0.1001***	-0.1032***	-0.0999***	-0.1001***	-0.1097***	-0.0736***
	(-3.52)	(-3.43)	(-3.52)	(-3.44)	(-3.39)	(-3.45)	(-3.46)	(-3.43)	(-3.16)	(-3.02)
$\mathbf{R^2}$	0.022	0.023	0.022	0.022	0.022	0.022	0.023	0.023	0.024	0.046

Low Sentiment

Stock-related Characteristics

	(1)	(2) IO	(3) Size	(4) IdV	(5) Illiq	(6) MAX	(7) STR	(8) Beta	(9) BM	(10) Mom	(11) Vliq	(12) AFD	(13) Full
DiE	-0.0354	-0.0374	-0.0367	-0.0326	-0.0324	-0.0380	-0.0317	-0.0440*	-0.0311	-0.0348	-0.0550*	-0.0223	-0.0338*
	(-1.10)	(-1.19)	(-1.32)	(-1.25)	(-1.04)	(-1.40)	(-0.96)	(-1.69)	(-1.00)	(-1.21)	(-1.85)	(-0.68)	(-1.69)
$\mathbf{R^2}$	0.015	0.016	0.019	0.018	0.018	0.019	0.021	0.029	0.023	0.024	0.021	0.017	0.061

Option-related Characteristics

	(1) RNS	(2) RNK	(3) VolSpr	(4) QSkew	(5) VS	(6) O/S	(7) InnCall	(8) InnPut	(9) VoV	(10) Full
DiE	-0.0345	-0.0360	-0.0283	-0.0234	-0.0163	-0.0341	-0.0258	-0.0226	0.0067	-0.0002
	(-1.12)	(-1.21)	(-0.88)	(-0.73)	(-0.52)	(-1.06)	(-0.80)	(-0.70)	(0.20)	(-0.01)
$\mathbf{R^2}$	0.016	0.018	0.018	0.017	0.017	0.017	0.017	0.017	0.016	0.039

Table 2.13: The DiE Measure with Signed Volume

This table presents equal-weighted (Panel A) and value-weighted (Panel B) average monthly profitability results for decile portfolios sorted on differences in expectations (DiE) (in ascending order from decile 1, low DiE to decile 10, high DiE) over the sample period from May 2005 to September 2015. DiE is the monthly average dispersion of signed options trading volume across moneyness levels, where we utilize only trading volume of buyer-motivated out-of-the-money options and seller-motivated in-the-money options. For each decile portfolio, we report the average DiE over the last month (Average DiE), equal- and value-weighted average monthly returns in excess of the risk-free rate (R) and alphas from the Fama-French three-factor ($FF3\alpha$) and Carhart four-factor ($C4\alpha$) models. The $H-L$ row reports the average raw returns and alphas for the strategy that buys a high DiE portfolio and sells a low DiE portfolio. Newey-West adjusted (with six lags) t-statistics are reported in parentheses. *,**,*** denote statistical significance at 10%, 5% and 1%, respectively. Equal- and value-weighted average raw and risk-adjusted returns are expressed as percentages.

Panel A: Equal-Weighted Portfolios

Portfolio	Average DiE	R	$FF3\alpha$	$C4\alpha$
Low DiE	0.026	0.96	0.36	0.36
2	0.034	0.62	-0.06	-0.06
3	0.040	0.76	0.02	0.03
4	0.045	0.69	-0.09	-0.08
5	0.050	0.81	-0.04	-0.02
6	0.056	0.73	-0.16	-0.14
7	0.063	0.53	-0.42	-0.41
8	0.073	0.73	-0.26	-0.24
9	0.088	0.09	-0.99	-0.91
High DiE	0.140	-0.45	-1.54	-1.36
$H-L$		-1.41*	-1.91***	-1.72***
		(-1.95)	(-3.43)	(-4.69)

Panel B: Value-Weighted Portfolios

Portfolio	R	$FF3\alpha$	$C4\alpha$
Low DiE	0.88	0.36	0.36
2	0.54	-0.03	-0.04
3	0.76	0.17	0.15
4	0.54	-0.13	-0.14
5	0.24	-0.48	-0.50
6	0.62	-0.20	-0.18
7	0.78	-0.05	-0.06
8	1.00	0.11	0.10
9	0.49	-0.54	-0.50
High DiE	-0.44	-1.49	-1.36
$H-L$	-1.31*	-1.85***	-1.72***
	(-1.74)	(-3.81)	(-3.84)

Table 2.14: Alternative DiE Specifications

This table presents the average monthly profitability of portfolios with the lowest (Low DiE) and highest (High DiE) DiE, as well as the average raw ($H - L$) and risk-adjusted ($FF3\alpha$ and $C4\alpha$) returns on the strategy that buys a high DiE portfolio and sells a low DiE portfolio over the sample period from January 1996 to September 2015. We use nine alternative DiE specifications. DiE 1 is the standard deviation measure of stock options trading volume across moneyness levels. DiE 2 and DiE 3 are mean absolute and standard deviation measures respectively, of options trading volume across strike prices (rather than moneyness), scaled by the volume-weighted average strike. DiE 4 and DiE 5 are similar to the original DiE measure and DiE 1 respectively, but we use alternative filtering criteria, which requires within a month at least ten days of non-missing DiE values. DiE 6 and DiE 7 are similar to the original DiE measure and DiE 1 respectively, but we include near-the-money options in calculating the measures. DiE 8 and DiE 9 are similar to the original DiE measure and DiE 1 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. Average raw and risk-adjusted returns are expressed as percentages.

	DiE 1	**DiE 2**	**DiE 3**	**DiE 4**	**DiE 5**	**DiE 6**	**DiE 7**	**DiE 8**	**DiE 9**
Low DiE	0.97	0.96	0.97	0.92	0.93	0.92	0.91	0.89	0.87
	(3.34)	(3.16)	(3.34)	(3.18)	(3.23)	(3.30)	(3.31)	(2.15)	(2.39)
High DiE	-0.65	-0.43	-0.54	-0.75	-0.61	-0.46	-0.52	-0.42	-0.54
	(-0.85)	(-0.58)	(-0.71)	(-0.98)	(-0.77)	(-0.64)	(-0.71)	(-0.59)	(-0.78)
$H - L$	-1.62***	-1.39**	-1.52**	-1.67***	-1.54**	-1.38**	-1.43**	-1.31***	-1.42***
	(-2.67)	(-2.35)	(-2.44)	(-2.60)	(-2.40)	(-2.35)	(-2.39)	(-3.15)	(-3.13)
$FF3\alpha$	-2.33***	-2.04***	-2.22***	-2.40***	-2.29***	-2.10***	-2.18***	-1.69***	-1.90***
	(-6.03)	(-5.60)	(-6.07)	(-5.48)	(-5.23)	(-5.71)	(-5.73)	(-5.61)	(-5.74)
$C4\alpha$	-1.70***	-1.48***	-1.61***	-1.70***	-1.57***	-1.51***	-1.56***	-1.28***	-1.38***
	(-4.67)	(-3.95)	(-4.44)	(-4.01)	(-3.80)	(-4.18)	(-4.18)	(-3.89)	(-4.05)

Table 2.15: Long-term Profitability of DiE Portfolios

This table reports long-term profitability results for differences in expectations (DiE) portfolios. DiE is the monthly dispersion of stock options trading volume across moneyness levels. Each month, we sort stocks in ascending order into decile portfolios on the basis of DiE (from decile 1, low DiE to decile 10, high DiE) and construct a strategy that buys a high DiE portfolio and sells a low DiE 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, and at the same time closing out the previously-initiated positions that expire. As a result, for each investment horizon, we estimate a time-series average of equal-weighted average raw returns ($H-L$), as well as the Fama-French three-factor ($FF3\alpha$) and Carhart four-factor ($C4\alpha$) alphas for a strategy that involves overlapping holding periods. Newey-West adjusted (with six lags) t-statistics are reported in parentheses. *,**,*** denote statistical significance at 10%, 5% and 1%, respectively. Average raw and risk-adjusted returns are expressed as percentages.

	2m	**3m**	**4m**	**5m**	**6m**	**9m**	**12m**
$H-L$	-1.40**	-1.29**	-1.24**	-1.20**	-1.16*	-0.97	-0.91
	(-2.41)	(-2.25)	(-2.13)	(-2.05)	(-1.96)	(-1.64)	(-1.55)
$FF3\alpha$	-2.08***	-1.96***	-1.92***	-1.87***	-1.83***	-1.63***	-1.55***
	(-5.55)	(-5.70)	(-5.61)	(-5.36)	(-5.20)	(-4.50)	(-4.32)
$C4\alpha$	-1.44***	-1.31***	-1.24***	-1.17***	-1.10***	-0.92**	-0.88**
	(-3.91)	(-3.73)	(-3.58)	(-3.25)	(-3.00)	(-2.32)	(-2.25)

Chapter 3

Differences in Expectations and Stock Returns Around Earnings Announcements

3.1 Introduction

The disclosure of corporate company earnings conveys a rich information content for analyzing the price and trading formation in the stock market (Ball and Brown, 1968; Bamber, 1986; Bernard and Thomas, 1989; 1990; Grundy and McNichols, 1989), the price discovery process through derivative and bond markets (Skinner, 1990; Amin and Lee, 1997; Easton, Monahan and Vasvari, 2009; Truong, Corrado and Chen, 2012) and other announcement-related characteristics such as excess realized and option-implied volatilities (Beaver, 1968; Patell and Wolfson, 1979; 1981; 1984), inventory risk (Johnson and So, 2015), investor earnings expectations (Battalio and Mendenhall, 2005). In a similar vein, a series of recent studies document important implications of earnings announcements for the differences of investors' opinion and their subsequent impact on stock prices (see, for example, Berkman et al., 2009; Keskek, Rees and Thomas, 2013). In this chapter, complementing the above literature, we provide new empirical evidence on the effect of differences in expectations in the options market on underlying asset prices around earnings disclosures.[1]

The literature on the responses of various options market characteristics to the earnings announcements is vast and expansive. Skinner (1990), Ho (1993), Mendenhall and Fehrs (1999), among many others, find that stocks with listed options tend to incorporate new earnings information faster and exhibit smaller average surprises than stocks without options. In line with this evidence, Amin and Lee (1997) report a more than 10% increase in the options trading activity over the several days prior to earnings releases and a less than 5% rise in the stock volume. While it is mostly agreed that the options trading activity escalates before earnings announcements, the evidence on the origin of such trading volume is mixed. The most popular explanation is the informed trading prior to firm-specific events (Pan and Poteshman, 2006; Roll, Schwartz and Subrahmanyam, 2010; Cremers, Fodor and Weinbaum, 2015, among many others), which is also reflected in the increase of implied volatilities (Patell and Wolfson, 1984; Donders and Vorst, 1996), implied higher-order moments (Xing, Zhang and Zhao, 2010; Diavatopoulos et al., 2012) and open interest (Schachter, 1988).[2] An alternative explanation of the escalated options transactions around earnings releases is the diverse beliefs held by investors. In the spirit of speculative trading models developed by Kim and Verecchia (1991) and He and Wang (1995), Choy and Wei (2012) find that options trading around earnings releases is mostly initiated by small retail speculative investors and is mainly driven by opinion dispersion.

In this study, we investigate a new dimension of options market reactions to earnings information by examining the effect of differences in expectations among options traders on the

[1]Following the aforementioned literature, we select scheduled earnings announcements for the analysis because these events bring a substantial amount of information to the market and are specifically designed to reduce uncertainty about earnings, revenues, growth potential and other firm-relevant indicators.

[2]Needless to say, there is also an extensive literature that documents a non-existence of informed traders in the options market (see, for example, Vijh, 1990; Muravyev, Pearson and Broussard, 2013).

stock returns around earnings announcements. To this end, we construct a firm-level measure of differences in expectations (DiE) from the dispersion of individual stock options trading volume across different moneyness levels. The proposed measure can be rationalized within an options market, where end-users trade with market makers (Ge, Lin and Pearson, 2016) and reveal their directional expectations about the future underlying price (Lakonishok et al., 2007). In such markets, the moneyness levels at which different trades are executed can naturally reflect the positive and negative expectations of options traders about future asset returns. For example, an optimistic investor will purchase high-strike call or sell high-strike put and, by the virtue of put-call parity, may also synthetically replicate the expected payoffs from these strategies by purchasing high-strike puts or selling high-strike calls, respectively, along with a long position in the underlying asset and a short position in the risk-free asset. A similar argument applies to the pessimistic investor, who wishes to reveal his views via options trading. However, it may be argued that some of the above trading strategies may be difficult to implement due to the extra capital involved, hence we also consider a DiE measure, constructed from the trading volume that can be certainly attributed to either positive or negative expectations i.e. buyer-initiated volume of out-of-the-money options and seller-initiated volume of in-the-money options.[3]

Based on the suggested DiE measure, we report several important implications for firm profitability around earnings announcements. In terms of the empirical design, our analysis resembles the study of Berkman et al. (2009), hence our key findings for optioned stocks can be directly compared to the overall belief dispersion effect documented by Berkman et al. (2009). First, Miller (1977) predicts that stocks with high differences in expectations and binding short-sale constraints (lower (IO) institutional ownership) are overvalued since the price mostly reflects the views of optimistic agents.[4] Extending the Miller (1977)

[3]The detailed explanation of the DiE measures, constructed in this study, and their advantageous characteristics (relative to the other proxies for differences of opinion) are provided in the previous chapter.

[4]Diether, Malloy and Scherbina (2002), Chen, Hong and Stein (2002), Goetzmann and Massa (2005), Jiang and Sun (2014) empirically support the Miller (1977) hypothesis, using monthly or quarterly full

theory, Berkman et al. (2009) present new evidence, suggesting that differences of opinion and stock overvaluation are reduced once earnings information is disclosed, leading to lower earnings announcement period returns. Consistent with this evidence, we document that high DiE (low IO) stocks underperform low DiE (high IO) stocks by an economically large and statistically significant average excess return of 0.82% (0.65%) over the three days around earnings announcements. Moreover, the underperformance of high DiE relative to low DiE firms is mostly unaffected by alternative DiE specifications, computed over different time windows, with the returns varying from -0.91% to -0.77%, and is more pronounced for stocks with higher short-sale costs (lower IO), producing an average earnings announcement period excess return of -1.11%. Interestingly, the economic magnitude of the analysts' forecast dispersion (AFD) effect among optioned stocks, both in univariate case (-0.81%) and when considered jointly with low IO (-0.83%), is substantially larger than the magnitude of a similar effect, documented by Berkman et al. (2009), for entire universe of stocks (-0.39% and -0.53%, respectively).

Second, in light of theoretical models on speculative trading, which show an increase in trading volume prior to earnings announcements, Berkman et al. (2009) reveal the mechanism and timing of the Miller (1977) overvaluation and following price correction. In line with their findings, we demonstrate that high DiE (and low IO) stocks exhibit a large price run-up of 0.42% (0.43%) over the seven days preceding the earnings releases and a subsequent price reversal of even higher magnitude upon the release of new information. The underperformance of high DiE (and low IO) relative to low DiE (and high IO) firms escalates from -0.46% (-1.07%) on day 1 to -0.98% (-1.80%) on day 7. In contrast, high AFD stocks also become overpriced prior to earnings announcements, however this effect is less pronounced than for high DiE stocks, but experience a more severe price correction following earnings disclosures. For example, when considered jointly with IO, more overvalued stocks

cross-sectional information.

(high AFD and low IO) earn 0.13% on day -7, then 0.17% on day -1 and -2.07% on day 7, compared to less overvalued stocks (low AFD and high IO). Furthermore, taking a closer look at the profitability of overvalued firms based on IO-DiE or IO-AFD double sorting, we present supportive evidence that optioned companies tend to react to new information more quickly. The cumulative excess return from the day, when earnings are released, to the next day decreases by about 1.30% for either high DiE or high AFD and low IO stocks, whereas across all five proxies, used by Berkman et al. (2009), the excess return over the same period declines by maximum 1% (for AFD, the price drop is equal to 0.68%).

Finally, implementing a series of regression-based tests, we show that size, value, leverage, post-announcement drift, and price momentum anomalies cannot explain the negative relation between DiE and earnings announcement period excess returns. Further, the regression analysis reveals that the information content conveyed by the DiE measure for earnings announcement period excess returns tends to be both economically and statistically superior relative to that of AFD. Additionally, consistent with the Miller (1977) hypothesis, our results illustrate that the DiE effect around earnings releases is more pronounced within the subsample of low IO firms, and is also robustly distinct from informed trading or uncertainty-based alternative explanations.

The remainder of the chapter is organized as follows. Section 3.2 outlines the construction of the DiE measure and describes the data, key filters and variables used in the study. Section 3.3 presents the empirical results on the profitability of overpriced relative to underpriced stocks based on DiE, AFD and IO measures before and after earnings announcements. We also perform a series of robustness tests for the DiE effect around earnings releases. Finally, Section 3.4 concludes.

3.2 DiE and Other Characteristics

To test the Miller (1977) hypothesis around firm-specific events, we start the analysis with the construction of a firm-level measure for differences in options investors' expectations. Next, we provide the description of the sample and data, employed to estimate key variables used in the study, and present descriptive statistics with cross-sectional correlation matrix.

3.2.1 DiE Measure

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 moneynesses implies high disagreement among options traders about the future underlying asset price, while a low dispersion shows that traders' expectations are rather similar.[5] As a result, we define a firm-level DiE measure as the volume-weighted mean absolute deviation of moneyness levels around the volume-weighted average moneyness level. Given the range of strike prices X_j for $j = 1, .., K$ and a stock price S, we estimate the following measure of differences in expectations:

$$DiE = \sum_{j=1}^{K} w_j \left| M_j - \sum_{j=1}^{K} w_j M_j \right|, \tag{3.1}$$

where w_j is the proportion of trading volume attached to the moneyness level $M_j = \frac{X_j}{S}$. Since the DiE computation is based on moneyness levels, our proxy for differences in expectations is comparable across stocks and over time.

To construct various specifications of the DiE measure, we use call and put options daily data for individual stocks from Ivy DB's OptionMetrics over the period from 1996:Q1 to 2015:Q3 and apply the following screening criteria. First, we select options with time to maturity between 5 and 60 calendar days, since these contracts tend to have more liquidity.

[5] A detailed motivation behind the proposed DiE measure is provided in the previous chapter.

Second, we exclude near-the-money options (moneyness between 0.975 and 1.025) because trading activity at such contracts is more likely to reflect volatility expectations (Bakshi and Kapadia, 2003; Ni, Pan and Poteshman, 2008). Third, to exclude days when options are not actively traded, we consider only those days when there are at least 4 contracts with non-zero trading volume. Finally, after applying the above filters, we estimate a daily firm-level DiE measure using Equation (3.1).

To examine the DiE effect around earnings announcements and verify that it is not sensitive to a particular time window over which DiE is calculated, we estimate several measures for differences in expectations. First, to acquire reliable and accurate DiE estimates for each stock, the main measure, that will be used throughout the entire analysis, is obtained by averaging daily DiE values within a trading month two days prior to the earnings announcement date.[6] We also consider a DiE specification, that is computed within a trading month ending five days prior to the earnings announcement date ($\text{DiE}_{(-26,-5)}$). Second, to alleviate potential concerns that the observed DiE effect around earnings releases may be caused by other firm-related news in the first days of the estimation month, we exploit alternative DiE measures by averaging daily DiE values over the weekly time window ending two ($\text{DiE}_{(-7,-2)}$) and five ($\text{DiE}_{(-10,-5)}$) days prior to the earnings announcement date. Finally, we estimate the main DiE measure using only the buy-side volume of out-of-the-money options and the sell-side volume of in-the-money options (DiE^{SV}). In our explanation, we rely on the notion that investors with positive or negative views about the expected asset returns can exploit a put-call parity to create synthetic payoffs reflecting certain expectations. However, such strategies may be rarely used in real trading activity, hence, it is important to compute the DiE measure by considering only those trades that can be certainly linked to particular positive or negative expectations.[7]

[6]We do not include the DiE value on the second day before announcement as the different closing hours of exchanges may lead to spurious results due to the effect of non-synchronous trading between stocks and options (Battalio and Schultz, 2006; Baltussen, Van Bekkum, and Van Der Grient, 2015).

[7]We also estimate the average monthly DiE measures ending two and five days before the earnings

3.2.2 Sample Description and Variable Definitions

Our sample consists of firms listed on NYSE, AMEX and NASDAQ that have options written on their stock and make quarterly earnings announcements over the period from the first calendar quarter of 1996 (1996:Q1) to the third quarter of 2015 (2015:Q3). We collect the data on earnings announcement dates from Compustat Quarterly file. From the entire universe of stocks, we select ordinary shares (share codes 10 and 11), exclude closed-end funds and REITs. Additionally, following Berkman et al. (2009), to mitigate the potentially adverse effects of bid-ask bounce, stale prices and tick sizes, we keep earnings announcements of firms with the market capitalization and total assets of $10 million or greater, or with a price of greater than $1 per share at the beginning of the current fiscal quarter.

To measure the firm profitability around earnings announcements, we estimate the abnormal return (ABRET) as the difference between three-day buy-and-hold stock and value-weighted CRSP index returns, centered at the earnings announcement date. We consider a three-day event window in order to attenuate the potential effect of systematic risk factors on our results. As a proxy for short-sale constraints and alternative measure of differences of opinion, we use the level of institutional ownership (IO) and dispersion in analysts' earnings forecasts (AFD), respectively. Data required for the estimations of IO and AFD are collected from Thomson Financial's CDA/Spectrum Institutional (13f) Holdings and I/B/E/S summary data file with calculated summary statistics, respectively. Finally, we utilize a series of various characteristics to control for differences in company size (Size), market-to-book ratio (MB), financial firm leverage (Lev), post-earnings-announcement drift (SUE) and price momentum (Mom). To estimate the first four control variables, we obtain the data from Compustat Quarterly file, whereas the stock and index return data, employed to measure ABRET and Mom, are from the CRSP. Additionally, we use raw options data from Ivy DB's

announcement date by requiring a minimum of 5 non-missing daily observations within a certain month. The results with these measures are quantitatively similar to those presented in the main body and are reported in the Appendix C.2.

OptionMetrics to construct option-related characteristics, controlling for informed trading (O/S) and uncertainty about return volatility (VoV). The detailed description of the estimation methodology for all variables is provided in the Appendix C.1.

3.2.3 Descriptive Statistics

Table 3.1 shows the summary statistics (Panel A) and correlation matrix (Panel B) for all characteristics used in the chapter, considering only firms that report quarterly earnings. In Panel A, we report a time-series average of quarterly mean, median, 25^{th}, 75^{th} percentile, minimum and maximum values for all variables across 79 quarters in our sample. First, the mean DiE and AFD are 0.09 and 0.24, respectively, whereas the median value is the same for both measures (0.07). Second, consistent with the studies that establish a presence of earnings announcement premium (Chari, Jagannathan and Ofer, 1988), we document a positive mean (median) cumulative three-day excess return of 0.11% (0.07%) around earnings announcements. Third, the average (maximum) market capitalization of the firms with listed options is \$651.97 million (\$358.61 billion). Finally, firms that report earnings exhibit a relatively high average momentum (8.54%) before announcements and have, on average, about 52% of their total shares held in the portfolios of institutional investors.

In Panel B, we document a time-series average of quarterly Pearson correlation coefficients between all variables. First, the DiE measure has the strongest positive correlation with AFD (0.11) and VoV (0.13), suggesting that our measure carries a similar information content as that of AFD and captures some dimension of uncertainty among options traders before earnings releases. Second, high DiE stocks tend to be small (correlation with Size is -0.30) and have higher short-sale constraints (correlation with IO is -0.25). Finally, as predicted by Miller (1977) hypothesis, high DiE and AFD stocks and firms with higher short-sale costs (lower IO) have lower buy-and-hold three-day excess returns around earnings announcements, although the correlation coefficient in all cases is not very high.

3.3 Empirical Results

In this section, we first examine the profitability of various DiE and AFD portfolios around quarterly earnings announcements. Next, we empirically test whether stocks with high differences in expectations and binding short-sale constraints are overpriced, earning negative excess returns following the release of earnings information and whether such overvaluation is particularly amplified several days prior to the earnings announcement date. Finally, we perform a series of Fama-MacBeth (1973) cross-sectional regressions to verify that the economically significant negative DiE-return relationship around earnings announcements cannot be subsumed by previously revealed return anomalies.

3.3.1 Differences of Opinion, Short-sale Constraints and Earnings Announcement Period Returns

We start the empirical analysis by exploring the average excess profitability of DiE, AFD and IO portfolios around earnings announcement period. Each calendar year-quarter, firms that report earnings in that quarter are sorted into quantile portfolios (portfolio 1-5) based on DiE, AFD or IO. Next, for each DiE/AFD/IO quantile portfolio, we calculate a time-series average of the quarterly mean cumulative three-day excess returns around earnings releases. Finally, we compute the average buy-and-hold excess returns for the portfolio (H-L) that buys high DiE, AFD or IO stocks (portfolio 5) and sells low DiE, AFD or IO stocks (portfolio 1).[8]

[8] In the main analysis, we use a simple time-series average across quarters to obtain the excess returns for each portfolio. However, Berkman et al. (2009) exploit a precision-weighted average of the quarterly means, where the precision is approximated by the number of available observations each quarter, since it gives more accurate weights to quarters with few observations and avoids noisy estimates. The results with a precision-weighted procedure are quantitatively similar to those presented in the main analysis and are

Table 3.2 illustrates the profitability of various DiE, AFD and IO portfolios around earnings announcements. It is important to notice that, due to the earnings announcement premium, that is equal to 0.11% in our sample (Table 3.1, Panel A), the mean excess returns for each of the quantile portfolios will be larger by that amount. Hence, our main empirical focus will be on the strategy that buys portfolio 5 and sells portfolio 1, that is not influenced by the announcement premium. First, based on the main measure of differences in expectations, high DiE stocks underperform low DiE stocks by economically large and statistically significant average three-day buy-and-hold excess return of 0.82%.[9] Interestingly, an almost identical, both economically and statistically, pattern is observed with the dispersion in analysts' forecasts. The average excess return differential between high AFD and low AFD stocks is -0.81% with a t-statistic of -5.94. Second, the underperformance of high DiE relative to low DiE stocks exhibits a very similar economic magnitude, when portfolios are formed using alternative DiE specifications. For example, for all three DiE measures, estimated over different time windows before earnings announcements, we observe that firms with the highest DiE values consistently underperform the lowest DiE firms, with the average buy-and-hold three-day excess return on H-L portfolio varying from -0.84% both for $\text{DiE}_{(-7,-2)}$ and $\text{DiE}_{(-10,-5)}$ to -0.77% for $\text{DiE}_{(-26,-5)}$. Moreover, the mean excess return spread on H-L portfolio, formed on the DiE measure that is constructed from signed volume data, is -0.91% with a t-statistic of -4.04. Finally, consistent with the Miller (1977) hypothesis, we demonstrate that stocks with higher short-sale costs (lower IO) earn significantly lower average cumulative three-day announcement period excess returns than stocks with lower short-sale costs (higher IO). The average excess return on H-L IO portfolio is statistically significant at 1% level and equal to 0.65%.

reported in the Appendix C.2.

[9] In the previous chapter, performing a quantile portfolio analysis, we find that the average monthly return on H-L DiE quantile portfolio is -1.15%, which translates to a daily return of -0.055% and three-day return of -0.165%. Apparently, focusing on the returns around earnings announcements, we obtain a profitability of H-L portfolio that is almost five times higher than a similar profitability generated by average monthly H-L portfolio.

In addition to univariate analysis, we also examine the quarterly distribution of the average excess returns on H-L portfolio based on DiE and AFD over the 79 quarters in our sample (Figure 3.1). In Panel A, we show that high DiE stocks earn lower average earnings announcement period excess returns than low DiE stocks over 61 quarters (77%), whereas, in Panel B, the average excess return differential between high AFD and low AFD stocks is negative for 58 quarters (73%). Furthermore, both DiE and AFD H-L portfolios generate a positive excess return around the periods of market downturn i.e. dotcom bubble and 2007-2009 financial crisis, whereas the negative average excess returns on H-L DiE portfolio are more pronounced (relative to H-L AFD portfolio) at the times of economic recovery or high investor sentiment. Overall, the results obtained in this section reveal that the release of earnings information consistently reduces the differences of opinion not only among professional forecasters, but also among options investors, leading to the underlying price correction and the average negative announcement period excess returns on H-L portfolios.

3.3.2 Testing Miller Hypothesis

In this section, we perform a direct empirical test of Miller (1977) hypothesis around earnings announcements. To this end, each calendar year-quarter, we sort firms that report earnings into three portfolios based on the level of institutional ownership and next, within each IO portfolio, we further group the same stocks into three DiE or AFD portfolios. Next, for each of the nine IO-DiE or IO-AFD portfolios, we estimate a time-series average of the quarterly mean cumulative three-day excess returns around earnings releases. Finally, we also report the average excess returns for the strategy that buys high DiE or AFD stocks and sells low DiE or AFD stocks within each IO portfolio quantile (H-L). Following recent studies (Chen, Hong and Stein, 2002; Nagel, 2005; Berkman et al., 2009), we use the level of institutional ownership as a proxy for short-sale constraints. Institutional investors tend to be the main supplier of loanable shares to the market, hence stocks with low institutional supply are more costly to short sell.

Miller (1977) theory predicts that stock prices exhibit an optimistic bias when differences of opinion are high and binding short-sale constraints prevent pessimistic investors to short sell the stock and drive prices back to fundamental value. As a result, such stocks become overpriced and earn lower subsequent returns. Complementing the results of Berkman et al. (2009), we provide new evidence on the timing of Miller (1977) effect for stocks with listed options. In particular, we demonstrate that earnings announcements play an important role in reducing the Miller's overvaluation for optioned stocks since the disclosure of new information about firm's earnings attenuates the differences in investors' expectations, leading to lower average excess returns for high DiE relative to low DiE stocks with the same short-sale costs upon the release of company earnings. For example, as shown in Table 3.3, the high DiE portfolio underperforms the low DiE portfolio by an economically large and statistically significant average excess return of 1.11% over the three days around announcement, if these stocks have a low level of IO. Consistent with the Miller (1977) predictions, this profitability is mainly driven by high DiE and low IO stocks that earn an average announcement period excess return of -1.04% (with a t-statistic of -5.59). In contrast, the average three-day excess return differential between high AFD and low AFD stocks has a lower economic magnitude and is equal to -0.83% within the subsample of low IO firms. Moreover, the average excess returns on H-L portfolios exhibit a monotonically decreasing pattern (in absolute terms) for DiE portfolios as we move from low IO to high IO portfolios (from -1.11% to -0.09%), while this return pattern is not very uniform for AFD portfolios (from -0.83% to -0.47% both for medium and high IO terciles).

3.3.3 Overvaluation Before Earnings Announcements

In the previous sections, we provide strong supportive evidence for the Miller (1977) hypothesis and reveal that the stock overvaluation is significantly reduced following earnings announcements. In this section, we make a further extension of the Miller (1977) theory for optioned stocks by suggesting that, given the binding short-sale constraints, differences in options investors' expectations tend to be particularly high over the pre-announcement period, resulting in a more pronounced stock overvaluation.[10] To test this proposition and to compare the relative magnitude of overpricing before with the following price reversal after the earnings release date, we examine the profitability of the mispriced portfolios around earnings announcements, constructed using two trading strategies. In the first strategy, we perform the same univariate sorting procedure as in Section 3.3.1 and stocks that are more (less) prone to overpricing are in the highest (lowest) DiE or AFD quantile portfolio. In the second strategy, we perform the same bivariate sorting procedure as in Section 3.3.2 and stocks that are more (less) prone to overvaluation are in the lowest (highest) IO tercile portfolio and highest (lowest) DiE or AFD tercile portfolio. Finally, for each day and each trading strategy, we estimate a time-series average of the quarterly mean cumulative excess returns for the portfolio that buys stocks that are more prone to overvaluation and sells stocks that tend to be less overvalued, over the 15-day earnings announcement period. The average excess returns start cumulating from day -7, relative to the earnings announcement date, until day +7.

Table 3.4 and Figure 3.2 present the results for two trading strategies that help to identify

[10]The reason why differences in expectations are likely to increase prior to earnings announcements may be partially explained in the context of speculative trading models of Kim and Verrecchia (1991), He and Wang (1995). These models predict that speculative trading over the pre-announcement periods tends to rise because of lower costs and risks since the portfolio positions are held over short time windows. On the other hand, according to the Miller (1977) model, the increase in speculative trading is expected to have a positive price net impact as more investors with optimistic views engage in speculative positions, while pessimists are less likely to short sell due to high costs. As a result, stocks with higher differences of opinion are expected to be more overvalued prior to earnings announcements.

more and less overvalued stocks. First, conditional on univariate sorting based on DiE and AFD, the price run-up for high DiE stocks prior to announcements is positive up to day 0 and exhibits a higher economic magnitude than the price run-up for high AFD stocks. For example, the average excess return spread between high DiE and low DiE stocks increases from 0.07% on day -7 to 0.42% on day -1 and to 0.35% on the day when earnings are released, whereas H-L AFD portfolios start generating an average excess return of 0.05% on day -7, then increasing to 0.10% on day -4 and dropping to -0.09% on the day of earnings announcement. Second, using a double sorting procedure based on IO and DiE or AFD, we document a similar price boost, that is more pronounced for high DiE than for high AFD stocks. The outperformance of low IO and high DiE relative to high IO and low DiE firms escalates from 0.15% on day -7 to 0.43% on day -1, while the same return pattern generated by IO-AFD H-L portfolios is less evident, varying from 0.13% on day -7 to 0.17% on day -1. It is important to note that the cumulative returns on H-L portfolios are not statistically significant prior to the earnings announcement date probably due to the idiosyncratic noise in the stock price variation across time, that is induced by pre-announcement uncertainty. Nevertheless, the pattern of stock overvaluation, experienced by high disagreement and low IO firms, is quite pronounced and robust. Also, the abnormal returns on H-L DiE stocks prior to announcement behave similarly to the ones documented for AFD by Berkman et al. (2009). Finally, consistent with prior results and supporting the Miller (1977) hypothesis, we document substantially negative cumulative average excess returns on H-L portfolios following the release of new information. For instance, the largest price correction for overvalued stocks based on IO and DiE occurs on the next day after earnings announcements[11] (from 0.19% on day 0 to -1.07% on day 1) and the price for such stocks continues its reversal, showing an average decline of -1.80% on day 7 relative to day -7. IO-AFD H-L portfolios generate similar return dynamics after earnings announcements, earning a cumulative aver-

[11] This evidence may suggest that most earnings are announced when the market is already closed on day 0 (Berkman and Truong, 2009).

age excess return of -1.30% on day 0 and -2.07% on day 7.[12] Overall, these findings clearly demonstrate that the overpricing of optioned stocks is more pronounced in the periods prior to earnings announcements and high DiE portfolios exhibit a more severe overvaluation relative to similar AFD portfolios.

3.3.4 Controlling for Other Characteristics

In this section, we perform a series of robustness tests to verify that the DiE effect (and Miller (1977) effect in general) around earnings announcements, documented in the previous section, is not driven by other previously revealed return anomalies. To this end, we execute Fama and MacBeth (1973) cross-sectional regressions after a simultaneous inclusion of other stock- and option-related variables. Since the abnormal returns are estimated over short time windows, Fama and MacBeth (1973) procedure yields unbiased estimates of standard errors (Petersen, 2009).[13] Each calendar year-quarter, using all firms that report earnings, we obtain coefficient estimates from cross-sectional regressions of ABRET on DiE and other various characteristics and document a time-series average of slope coefficients, corresponding Newey-West adjusted t-statistics (with four lags) and adjusted R^2s. All explanatory variables are calculated prior to the earnings announcement period returns to alleviate re-

[12] It is also important to mention that the magnitude of price run-up before announcements is lower than that of price correction after announcements (see, Figure 3.2). As pointed out by Berkman et al. (2009), such observation may be explained by the fact that overvaluation is not fully revealed during earnings announcement periods and may also exist over earlier periods.

[13] In particular, Petersen (2009) point out that Fama and MacBeth (1973) procedure is designed to account for cross-correlation (i.e. the correlation between observations on different companies in the same year) or time effect, that is frequently observed in equity returns and earnings surprises, but it does not control for serial correlation or firm effect (i.e. the correlation between observations on the same company in different years). In case of event study, it accounts for the fact that $Cov(\widehat{ABRET}_{i,t}, \widehat{ABRET}_{j,t}) \neq 0$ for any company $i \neq j$, but it does not deal with the situation when $Cov(\widehat{ABRET}_{i,t}, \widehat{ABRET}_{i,t+s}) \neq 0$ for any time $t+s>t$. This may result in spurious findings if there are long event windows, for example 5-year post-IPO cumulative abnormal returns for 1998 and the same returns for 1999 will both include the returns in year 2000 that will covary. Since we focus on short event windows, Fama and MacBeth (1973) procedure leads to unbiased estimates of standard errors.

verse causality concerns.[14]

Size and Market-to-book Ratio

The well-known small cap premium, established by Banz (1981), Fama and French (1992), and value anomaly, documented by Fama and French (1992), Lakonishok, Shleifer and Vishny (1994), may potentially explain the negative DiE-return relationship and Miller (1977) effect around earnings announcements. We empirically test this prediction and report the key findings in Table 3.5. Panel A shows that the coefficient on DiE is negative and statistically significant at 1% level, reaching the values of -0.0479 in univariate and -0.0233 in multivariate settings after controlling for Size and MB simultaneously. Also, considering DiE and AFD in the same model specifications, the coefficient on DiE retains its statistical and economic significance, while the coefficient on AFD becomes positive and statistically significant at the 5% level in the full regression model. Further, the positive IO-return relationship is also unlikely to be driven by size or value anomalies as the coefficient on IO is positive (0.0193) and highly statistically significant (with a t-statistic of 9.77). In contrast, although high AFD stocks are shown to earn a negative average cumulative three-day excess return, the coefficient is only significant at 5% level in univariate and at 10% level in full models, generating lower R^2s than in the models with the DiE measure. In Panel B, we test the joint effect of DiE or AFD and IO on the returns around earnings announcements. In particular, each year-quarter, we, first, sort stocks into tercile portfolios based on IO and, next, within each IO portfolio, we run cross-sectional regressions and obtain the corresponding coefficient estimates. The results indicate that the effect of DiE is stronger for stocks that are more costly to short sell (low IO) and is uniformly decreasing, both in terms of economic magnitude and statistical significance, across IO portfolios (from low IO to high IO). Furthermore, the Miller (1977)

[14] The results from the regression analysis with precision-weighted coefficient estimates, where weights equal to the number of available observations each year-quarter, are similar and reported in the Appendix C.2.

effect based on DiE measure seems to be more pronounced and statistically significant than the same effect based on AFD proxy. The coefficient on DiE, within the subsample of low IO stocks, is -0.0458 with a t-statistic of -3.88, whereas the AFD coefficient is -0.0017 with a t-statistic of -2.62. Overall, the findings reveal that the DiE effect is robustly distinct from size or value anomalies, is more economically pronounced than the AFD effect and generates a higher predictability within the IO portfolios than a similar effect of the AFD measure.

Financial Leverage

Johnson (2004) develops a simple theoretical framework and explains that the negative effect of differences of opinion on future returns may not reflect persistent stock overpricing, but instead it can be rationalized within a standard option-pricing theory that implies a negative relationship between expected return on levered stock and idiosyncratic asset risk, where such risk is proxied by differences of opinion. Hence, the financial leverage of the firm is assumed to be the key driver of the negative relation between differences of opinion and subsequent stock returns. We test this proposition with earnings announcement period returns, using the leverage ratio and multiplicative variable of DiE or AFD and leverage (Lev$\times$Dis), and report the findings in Table 3.6, Panel A. Contradicting the predictions from Johnson (2004) model, we find that the coefficient on DiE is negative (-0.0379) and statistically significant at 1% level. Furthermore, the leverage cannot capture the effect of short-sale costs on earnings announcement period returns as the coefficient on IO is positive and highly statistically significant. A similar result, although less pronounced and not significant at 5% level, is observed with AFD. The slope coefficient is -0.0010 with a t-statistic of -1.94. Interestingly, when considered with DiE measure, the leverage effect becomes more pronounced than in the similar model with AFD, but it does not diminish the marginal effect of DiE on excess returns. The coefficients on Lev and Lev$\times$Dis are -0.0064 and 0.0773, respectively, and are statistically significant at 5% level. Summing up, our results provide evidence, that supports the Miller (1977) hypothesis around earnings announcements and contradicts the leverage explanation introduced by Johnson (2004).

Post-announcement Drift and Momentum

In this section, we examine whether the negative relation between differences in expectations and excess returns can be interpreted within previously established earnings announcements return anomalies. First, Bernard and Thomas (1989, 1990) find that post-earnings announcement cumulative returns tend to drift in the direction of a recent earnings surprise for several weeks, while Chen and Jiambalvo (2004) argue that this anomaly explains the negative dispersion-return relation, documented by Diether, Malloy and Scherbina (2002). Following Chan, Jegadeesh and Lakonishok (1996), Livnat and Mendenhall (2006), Berkman et al. (2009), we use the standardized earnings surprise (SUE) on which the drift is based as a proxy for post-announcement price drift. Livnat and Mendenhall (2006) point out that post-earnings announcement drift, that is reflected in the higher subsequent abnormal returns following a positive earnings news surprise, is also known as the SUE effect, hence it is important to adequately gauge the earnings surprise as a measure of drift. Second, Jegadeesh and Titman (1993) document that stocks with higher price momentum earn higher returns around earnings announcements. We measure the price momentum (Mom) as the cumulative returns over the last year prior to the announcement date. Finally, we analyze the robustness of the DiE effect around earnings announcements to above anomalies in a regression framework and present the results in Table 3.6, Panel B. Similar to the previous findings, we document that neither SUE nor Mom can account for the marginal effect of DiE on earnings announcement period returns. The coefficient on DiE is negative and statistically significant at 1% level. In line with the findings of Berkman et al. (2009), we find that the AFD effect also remains economically large and statistically significant after controlling for SUE and Mom. Moreover, the estimated positive relation between SUE and earnings announcement period excess returns is consistent with the post-announcement drift anomaly, however the coefficient on Mom is negative and statistically insignificant. Overall, we find that the DiE effect is robustly distinct from post-earnings announcement and momentum return patterns.

Informed Trading and Uncertainty in the Options Market

Finally, we conclude the empirical analysis with a few more robustness checks that aim to account for option-related return predictability, documented in the literature. More specifically, since differences in expectations are closely related to some dimension of uncertainty in the market, it is important to test the DiE effect in the presence of various uncertainty proxies. We exploit the volatility-of-volatility measure (VoV), introduced by Baltussen, Van Bekkum and Van der Grient (2015), that is shown to be negatively associated with future stock returns. Additionally, our results may also contribute to the big strand of literature on the informed trading in the options markets (see, for example, Easley, O'Hara and Srinivas (1998), Pan and Poteshman (2006), An et al. (2014), among many others). We control for the effect of informed trading using an option-to-stock-trading-volume ratio (O/S) of Roll, Schwartz and Subrahmanyam (2010). Researchers find that high O/S and high cumulative returns before earnings announcements lead to lower cumulative returns following the announcements. Table 3.7 presents two separate sets of results for VoV and O/S. First, after controlling for O/S, the negative relation between DiE and three-day cumulative excess returns persists and is statistically significant at 5% level. The coefficient on O/S is of expected sign, implying lower cumulative abnormal returns for high O/S stocks. Second, we report an economically large and statistically significant slope coefficient on DiE (-0.0413 with a t-statistic of -1.99) after controlling for VoV, meaning that the differences in expectations capture a distinct information content relative to the uncertainty for the earnings announcement period excess returns. Surprisingly, the AFD effect no longer exists, when we account for either O/S or VoV, which may suggest that the negative AFD-return relation does not hold for stocks that have non-missing O/S and VoV values. To sum up, it becomes clear that the information content of the DiE measure for cumulative excess returns around earnings announcements is distinct from that implied by O/S or VoV.

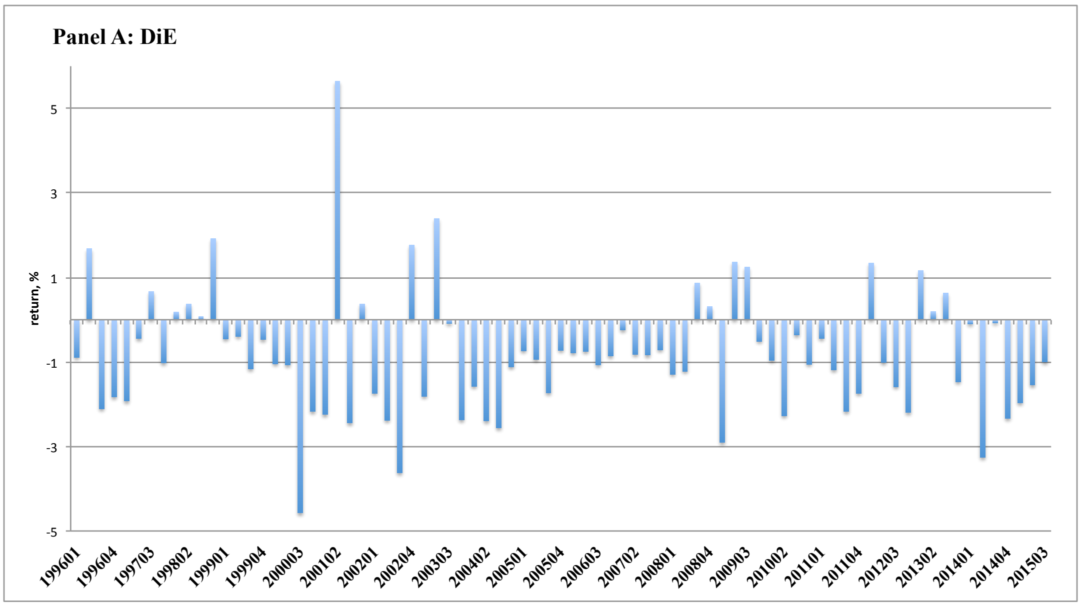
3.4 Conclusion

In this chapter, we demonstrate that the release of earnings information plays a vital role in reducing the differences in investors' expectations and following company overvaluation not only in the stock, but also in the options market. Using the dispersion of equity options trading volume across various moneyness levels as a measure of differences in expectations among options traders, we document several important implications for stock performance around earnings announcements. First, we empirically support the Miller (1977) hypothesis for companies with listed options by showing that stocks with high differences in expectations earn lower buy-and-hold three-day earnings announcement period excess returns than stocks with low DiE and that this effect is more pronounced for firms that are more difficult to short sell. For example, conditional on higher short-sale costs, high DiE stocks earn a negative average excess return of -1.11% relative to low DiE firms. Second, our findings are consistent with those of Berkman et al. (2009), who find a negative relation between AFD and returns around earnings announcements, however we show that this relation appears to be weak for optioned stocks and is less pronounced than the DiE effect. Third, this chapter suggests that more optimistic investors tend to induce a higher upward bias on the prices of stocks, that have high DiE and low IO, during the pre-announcement period, leading to a substantial price overshooting prior to announcements and subsequent price reversal upon the release of new information. In particular, we document a price run-up of about 0.45% up to day 0 and even a bigger following price correction of -1.80% ending on day 7 for high DiE and low

IO stocks compared to low DiE and high IO stocks. Finally, after controlling for well-known stock- and option-related return effects, our study reveals that the Miller (1977) effect based on the DiE measure cannot be fully subsumed by alternative explanations such as small cap premium, value anomaly, financial leverage, post-earnings-announcement drift, price momentum, informed trading and option-related uncertainty. Overall, our results imply that the revelation of earnings reports not only provides an insight into a price or volume formation and contains valuable corporate information, but also helps to attenuate the optimistic bias induced via options market.

Figure 3.1: Excess Returns on High-Low DiE and AFD Portfolios Around Earnings Announcements

This figure plots the quarterly distribution of the cumulative three-day earnings announcement period excess returns on High-Low DiE (Panel A) and AFD (Panel B) portfolios. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. AFD is the standard deviation of analysts' earnings forecasts for the current fiscal quarter, scaled by the absolute value of the mean earnings forecast. Each year-quarter, we sort firms that report earnings into quantile portfolios on the basis of DiE or AFD and report average cumulative three-day earnings announcement period returns in excess of the market return for the portfolio that buys highest DiE or AFD stocks (portfolio 5) and sells lowest DiE or AFD stocks (portfolio 1) before earnings announcements. The returns are expressed as percentages. Our sample period is from 1996:Q1 to 2015:Q3.



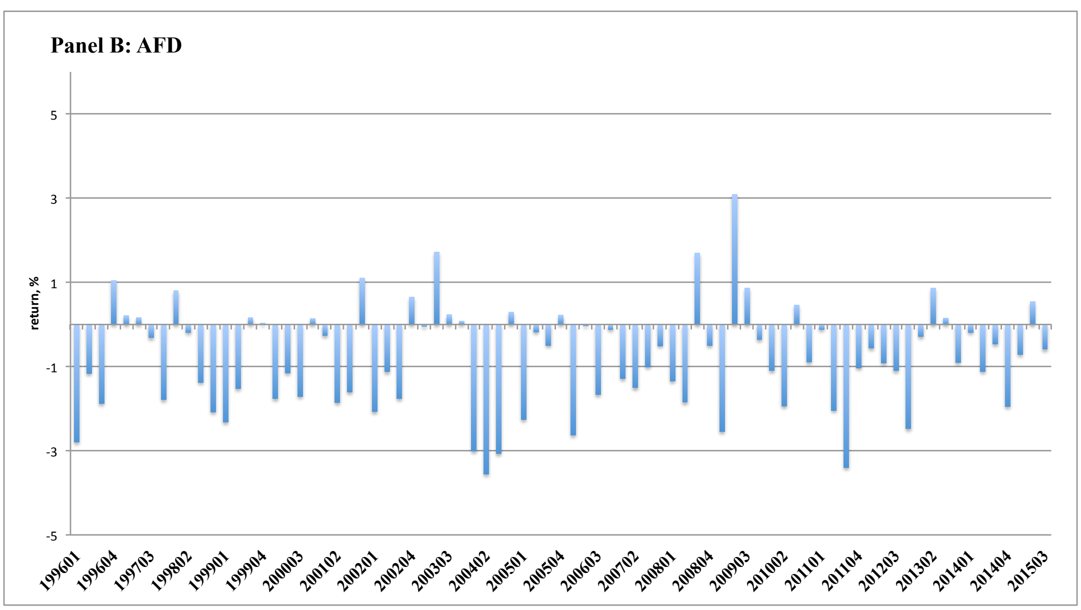
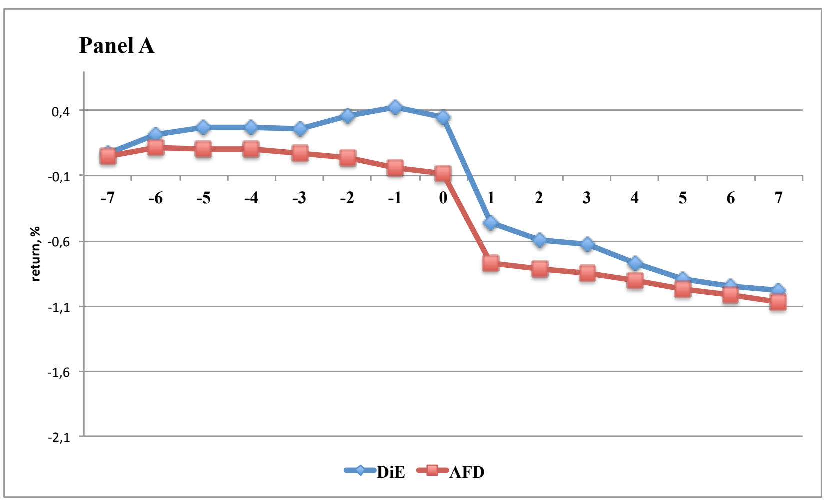


Figure 3.2: Returns on Mispriced Portfolios Around Announcement Date

This figure shows the cumulative buy-and-hold excess returns on the portfolio that buys more overvalued stocks and sells less overvalued stocks over the 15 days (from -7 to 7) around earnings announcements. In Panel A, we define stocks that are more (less) prone to overvaluation as those that have highest (lowest) DiE or AFD, whereas, in Panel B, stocks that are more (less) prone to overvaluation have lowest (highest) level of institutional ownership and highest (lowest) DiE or AFD. To find stocks which have the highest or lowest DiE, AFD and IO, in Panel A, each year-quarter, we sort firms that report earnings into quantile portfolios based on DiE or AFD, while in Panel B, we first sort stocks into three portfolios based on the level of institutional ownership (IO) and next, within each IO portfolio, we further sort stocks into three DiE or AFD portfolios. Finally, for each day, we estimate a time-series average of the quarterly mean buy-and-hold returns in excess of the market return for the portfolio that buys stocks that are more prone to overvaluation and sells stocks that tend to be less overvalued before earnings announcements. The buy-and-hold returns start cumulating from day -7. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. AFD is the standard deviation of analysts' earnings forecasts for the current fiscal quarter, scaled by the absolute value of the mean earnings forecast. IO is the total fraction of shares outstanding held by institutional investors. The returns are expressed as percentages. Our sample period is from 1996:Q1 to 2015:Q3.



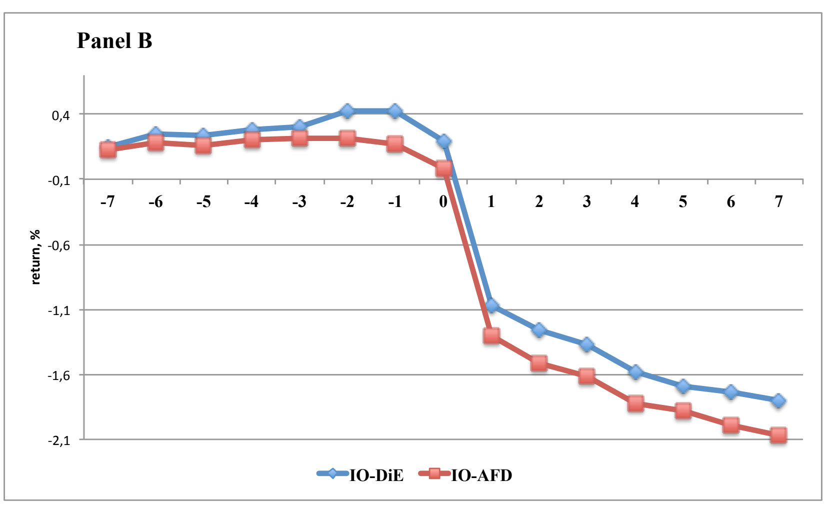


Table 3.1: Descriptive Statistics

This table reports the descriptive statistics for our sample that consists of ordinary firms with listed option contracts that report quarterly earnings and trade on NYSE, AMEX and NASDAQ. We exclude earnings announcements of firms with market capitalization and total assets less than $10 million or with price less than $1 dollar in the current fiscal quarter. Panel A shows summary statistics for all variables used in the study, whereas Panel B displays Pearson cross-sectional correlation coefficients between these variables across quarters. Our sample period is from 1996:Q1 to 2015:Q3. The variable definitions are provided in the Appendix C.1.

Panel A: Summary Statistics

	Mean	**Median**	**Q1**	**Q3**	**Min**	**Max**
ABRET, %	0.11	0.07	-3.76	4.04	-65.52	88.19
DiE	0.09	0.07	0.05	0.10	0.00	1.23
AFD	0.24	0.07	0.03	0.18	0.00	27.51
Size	6.48	6.35	5.21	7.57	1.39	12.79
MB	3.39	2.10	1.36	3.58	0.15	89.66
IO, %	51.89	54.93	30.88	73.70	0.00	99.65
Lev	0.21	0.17	0.02	0.33	0.00	0.99
SUE	0.01	0.00	-0.01	0.01	-24.44	63.38
Mom, %	8.54	4.64	-17.41	28.80	-111.30	464.62
O/S	0.03	0.01	0.00	0.04	0.00	0.84
VoV	0.07	0.06	0.04	0.08	0.01	0.40

Panel B: Correlation Matrix

	ABRET	**DiE**	**AFD**	**Size**	**MB**	**IO**	**Lev**	**SUE**	**Mom**	**O/S**	**VoV**
ABRET	1										
DiE	-0.03	1									
AFD	-0.01	0.11	1								
Size	0.01	-0.30	-0.10	1							
MB	-0.01	0.06	-0.02	0.14	1						
IO	0.03	-0.25	-0.06	0.42	0.02	1					
Lev	0.00	-0.05	0.03	0.13	0.05	0.08	1				
SUE	0.03	-0.05	-0.01	-0.01	0.01	-0.01	-0.01	1			
Mom	0.01	-0.04	-0.05	0.06	0.16	0.05	-0.03	0.07	1		
O/S	-0.01	0.07	-0.01	0.24	0.14	0.01	-0.03	0.00	0.12	1	
VoV	-0.01	0.13	0.01	0.09	0.05	-0.03	0.00	-0.01	0.01	0.21	1

Table 3.2: Profitability of DiE, AFD and IO Portfolios Around Earnings Announcements

This table reports the average excess profitability around earnings announcements for the quantile portfolios sorted on various specifications of DiE measure, AFD and IO. The main measure for differences in expectations (DiE) is the average dispersion of stock options trading volume across moneyness levels, estimated over one month two days prior to earnings announcement date. We also consider DiE measures, estimated over monthly time window five days prior to earnings release date ($\text{DiE}_{(-26,-5)}$) and over weekly time window two ($\text{DiE}_{(-7,-2)}$) and five ($\text{DiE}_{(-10,-5)}$) days prior to earnings announcement date. Additionally, we compute the main DiE measure, but utilizing only trading volume of buyer-motivated out-of-the-money options and seller-motivated in-the-money options (DiE^{SV}). AFD is the standard deviation of analysts' earnings forecasts for the current fiscal quarter, scaled by the absolute value of the mean earnings forecast, estimated during 45-day period ending two days prior to announcement date. IO is the total fraction of shares outstanding held by institutional investors prior to the earnings announcement date. Each year-quarter, we sort firms that report earnings into quantile portfolios (Portfolio 1-5) based on each of the DiE measures, AFD or IO and report a time-series average of the quarterly mean cumulative three-day earnings announcement period returns in excess of the market return for each portfolio. Finally, we report the average cumulative three-day excess returns for the strategy that buys highest DiE, AFD or IO stocks and sells lowest DiE, AFD or IO stocks ($H - L$) before earnings announcements. The returns are expressed as percentages. t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our sample period is from 1996:Q1 to 2015:Q3.

Portfolio	**DiE**	$\textbf{DiE}_{(-7,-2)}$	$\textbf{DiE}_{(-26,-5)}$	$\textbf{DiE}_{(-10,-5)}$	$\textbf{DiE}^{SV}$	**AFD**	**IO**
1	0.30***	0.18**	0.25***	0.20**	0.16	0.52***	-0.25***
	(5.14)	(2.28)	(4.57)	(2.34)	(1.48)	(4.62)	(-2.74)
2	0.25***	0.18**	0.31***	0.21**	0.12	0.22***	-0.06
	(2.91)	(1.99)	(3.75)	(2.32)	(1.11)	(3.85)	(-0.81)
3	0.32***	0.27**	0.30***	0.21**	-0.01	-0.01	0.16*
	(3.72)	(2.49)	(3.32)	(2.46)	(-0.06)	(-0.06)	(1.96)
4	-0.03	0.02	-0.03	0.04	-0.03	-0.11	0.28***
	(-0.28)	(0.19)	(-0.31)	(0.27)	(-0.14)	(-1.00)	(3.95)
5	-0.52***	-0.66***	-0.52***	-0.65***	-0.75***	-0.28*	0.40***
	(-3.30)	(-3.82)	(-3.08)	(-4.23)	(-2.75)	(-1.95)	(5.99)
$H - L$	-0.82***	-0.84***	-0.77***	-0.84***	-0.91***	-0.81***	0.65***
	(-5.51)	(-5.20)	(-4.43)	(-5.87)	(-4.04)	(-5.94)	(10.54)

Table 3.3: DiE, Short-sale Constraints and Excess Returns Around Earnings Announcements

This table presents the average excess profitability around quarterly earnings announcements for nine portfolios sorted on the level of institutional ownership (IO) and the differences in expectations (DiE) measure or analysts' forecasts dispersion (AFD). We use the level of institutional ownership as a proxy for short-sale constraints. Each year-quarter, we sort firms that report earnings into three portfolios based on IO (Low IO - High IO) and, within each IO portfolio, we further sort stocks into three extra portfolios based on DiE or AFD (Low DiE or AFD - High DiE or AFD). For each of the resulting portfolios, we report a time-series average of the quarterly mean cumulative three-day earnings announcement period returns in excess of the market return. Finally, we compute the average cumulative three-day excess returns for the strategy that buys highest DiE or AFD stocks and sells lowest DiE or AFD stocks within each IO portfolio ($H-L$) before earnings announcements. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. AFD is the standard deviation of analysts' earnings forecasts for the current fiscal quarter, scaled by the absolute value of the mean earnings forecast. IO is the total fraction of shares outstanding held by institutional investors. The returns are expressed as percentages. t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our sample period is from 1996:Q1 to 2015:Q3.

	Low DiE	Medium DiE	High DiE	$H-L$
Low IO	0.07	-0.35**	-1.04***	-1.11***
	(0.74)	(-2.60)	(-5.59)	(-6.24)
Medium IO	0.28***	0.29***	0.01	-0.27*
	(3.27)	(3.11)	(0.10)	(-1.81)
High IO	0.45***	0.54***	0.36**	-0.09
	(4.68)	(5.99)	(2.39)	(-0.65)

	Low AFD	Medium AFD	High AFD	$H-L$
Low IO	0.06	-0.49***	-0.76***	-0.83***
	(0.50)	(-3.83)	(-5.34)	(-6.17)
Medium IO	0.44***	0.18**	-0.02	-0.47***
	(5.42)	(2.56)	(-0.16)	(-2.97)
High IO	0.76***	0.32***	0.29*	-0.47***
	(6.86)	(2.81)	(1.79)	(-2.77)

Table 3.4: Returns on Mispriced Portfolios Around Announcement Date

This table shows the cumulative buy-and-hold excess returns on the portfolio that buys more overvalued stocks and sells less overvalued stocks over the 15-day period (from day -7 to 7), centered at announcement date (day 0). In DiE and AFD columns, we define stocks that are more (less) prone to overvaluation as those that have highest (lowest) DiE or AFD based on univariate sorting of firms that report earnings into quantile DiE or AFD portfolios each year-quarter. In IO-DiE and IO-AFD columns, stocks that are more (less) prone to overvaluation have lowest (highest) level of institutional ownership and highest (lowest) DiE or AFD based on bivariate sorting of firms that report earnings into three institutional ownership (IO) portfolios and next, within each IO portfolio, into extra three DiE or AFD portfolios. Finally, for each day, we estimate a time-series average of the quarterly mean buy-and-hold returns in excess of the market return for the portfolio that buys stocks that are more prone to overvaluation and sells stocks that tend to be less overvalued before earnings announcements. The buy-and-hold returns start cumulating from day -7. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. AFD is the standard deviation of analysts' earnings forecasts for the current fiscal quarter, scaled by the absolute value of the mean earnings forecast. IO is the total fraction of shares outstanding held by institutional investors. The returns are expressed as percentages. t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our sample period is from 1996:Q1 to 2015:Q3.

Day	**DiE**		**AFD**		**IO-DiE**		**IO-AFD**	
-7	0.07	(0.67)	0.05	(0.74)	0.15	(1.24)	0.13	(1.37)
-6	0.21	(1.29)	0.12	(1.23)	0.25	(1.39)	0.18	(1.60)
-5	0.27	(1.23)	0.10	(0.88)	0.24	(1.05)	0.16	(1.21)
-4	0.27	(1.16)	0.10	(0.84)	0.28	(1.10)	0.20	(1.20)
-3	0.26	(1.12)	0.07	(0.58)	0.30	(1.14)	0.22	(1.26)
-2	0.36	(1.52)	0.04	(0.37)	0.42	(1.54)	0.22	(1.24)
-1	0.42	(1.58)	-0.04	(-0.30)	0.43	(1.44)	0.17	(0.91)
0	0.35	(1.11)	-0.09	(-0.55)	0.19	(0.55)	-0.02	(-0.06)
1	-0.46	(-1.36)	-0.77***	(-3.47)	-1.07***	(-3.05)	-1.30***	(-5.31)
2	-0.59*	(-1.68)	-0.82***	(-3.58)	-1.26***	(-3.44)	-1.51***	(-6.06)
3	-0.63*	(-1.73)	-0.85***	(-3.61)	-1.37***	(-3.60)	-1.61***	(-5.99)
4	-0.77**	(-2.07)	-0.91***	(-3.56)	-1.58***	(-4.06)	-1.83***	(-6.48)
5	-0.89**	(-2.33)	-0.97***	(-3.83)	-1.69***	(-4.30)	-1.88***	(-6.38)
6	-0.95**	(-2.41)	-1.02***	(-3.83)	-1.74***	(-4.36)	-1.99***	(-6.27)
7	-0.98**	(-2.40)	-1.07***	(-3.91)	-1.80***	(-4.17)	-2.07***	(-6.07)

Table 3.5: Fama-MacBeth Regressions

This table reports the results from Fama and MacBeth (1973) quarterly cross-sectional regressions of the cumulative three-day earnings announcement period returns in excess of the market return on the differences in expectations (DiE) measure, analysts' forecasts dispersion (AFD), log of market capitalization (Size), log of market-to-book ratio (MB) and the level of institutional ownership (IO). Considering only the firms that report earnings, we obtain coefficient estimates from year-quarter cross-sectional regressions and document their time-series averages, corresponding t-statistics (with four lags), presented in parentheses, and adjusted R2s ($\widetilde{R}^2$). Panel A presents the results for the main model specification, while Panel B reports the findings for each IO portfolio, obtained by sorting firms that report earnings into three portfolios on the basis of IO each year-quarter. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our sample period is from 1996:Q1 to 2015:Q3. The detailed definitions of all the variables are provided in the Appendix C.1.

Panel A:

	(1)	(2)	(3)	(4)	(5)	(6)
DiE	-0.0479***		-0.0501***	-0.0233***		-0.0297***
	(-5.49)		(-6.05)	(-2.74)		(-3.64)
AFD		-0.0009**	0.0012		-0.0007*	0.0021**
		(-2.36)	(1.38)		(-1.87)	(2.18)
Size				0.0010***	0.0002	0.0009**
				(2.72)	(0.61)	(2.36)
MB				0.0003	-0.0004	0.0003
				(0.40)	(-0.83)	(0.42)
IO				0.0193***	0.0096***	0.0198***
				(9.77)	(7.77)	(9.66)
$\widetilde{\mathbf{R}}^2$	0.003	0.001	0.005	0.011	0.005	0.013

Panel B:

	IO Portfolio				**IO Portfolio**		
	Low IO	Med IO	High IO		Low IO	Med IO	High IO
DiE	-0.0458***	-0.0381**	0.0159	**AFD**	-0.0017**	-0.0008	-0.0007
	(-3.88)	(-2.54)	(0.61)		(-2.62)	(-1.22)	(-1.11)
Size	0.0015***	0.0004	0.0007	**Size**	0.0006	0.0001	-0.0000
	(3.47)	(0.78)	(1.43)		(1.46)	(0.34)	(-0.11)
MB	-0.0006	0.0003	0.0005	**MB**	-0.0017**	-0.0004	0.0006
	(-0.49)	(0.37)	(0.49)		(-2.47)	(-0.64)	(1.16)
$\widetilde{\mathbf{R}}^2$	0.018	0.016	0.017	$\widetilde{\mathbf{R}}^2$	0.008	0.007	0.006

Table 3.6: Fama-MacBeth Regressions: Leverage, Post-announcement Drift and Momentum

This table reports the results from Fama and MacBeth (1973) quarterly cross-sectional regressions of the cumulative three-day earnings announcement period returns in excess of the market return on the differences in expectations (DiE) measure, analysts' forecasts dispersion (AFD), log of market capitalization (Size), log of market-to-book ratio (MB) and the level of institutional ownership (IO). We also control for leverage, using the ratio of total debt to total assets (Lev) and multiplicative variable of Lev and Dis (Lev×Dis), where Dis is either DiE or AFD, in Panel A as well as post-earnings-announcement drift (SUE), using standardized unexpected earnings, and price momentum (Mom) in Panel B. Considering only the firms that report earnings, we obtain coefficient estimates from year-quarter cross-sectional regressions and document their time-series averages, corresponding *t*-statistics (with four lags), presented in parentheses, and adjusted R2s ($\widetilde{R}^2$). *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our sample period is from 1996:Q1 to 2015:Q3. The detailed definitions of all the variables are provided in the Appendix C.1.

Panel A: Leverage			**Panel B: Drift and Momentum**		
	(1)	(2)		(1)	(2)
DiE	-0.0379***		**DiE**	-0.0266***	
	(-3.22)			(-2.66)	
AFD		-0.0010*	**AFD**		-0.0009**
		(-1.94)			(-2.26)
Size	0.0010***	0.0002	**Size**	0.0008***	0.0002
	(2.69)	(0.52)		(2.95)	(0.67)
MB	0.0001	-0.0004	**MB**	-0.0006	-0.0013***
	(0.18)	(-1.16)		(-0.84)	(-2.84)
IO	0.0189***	0.0100***	**IO**	0.0166***	0.0089***
	(9.75)	(8.15)		(8.20)	(7.04)
Lev	-0.0064**	-0.0011	**SUE**	0.0771***	0.0552***
	(-2.06)	(-0.59)		(6.50)	(6.86)
Lev×Dis	0.0773**	0.0003	**Mom**	-0.0020	-0.0000
	(2.23)	(0.27)		(-1.56)	(-0.03)
$\widetilde{\mathbf{R}}^2$	0.014	0.007	$\widetilde{\mathbf{R}}^2$	0.019	0.012

Table 3.7: Fama-MacBeth Regressions: Informed Trading and Uncertainty

This table reports the results from Fama and MacBeth (1973) quarterly cross-sectional regressions of the cumulative three-day earnings announcement period returns in excess of the market return on the differences in expectations (DiE) measure, analysts' forecasts dispersion (AFD), log of market capitalization (Size), log of market-to-book ratio (MB) and the level of institutional ownership (IO). We also control for informed trading in the options market (O/S), using the ratio of option to stock trading volume, and uncertainty about return volatility (VoV), using the standard deviation of option implied volatilities. Considering only the firms that report earnings, we obtain coefficient estimates from year-quarter cross-sectional regressions and document their time-series averages, corresponding t-statistics (with four lags), presented in parentheses, and adjusted R2s ($\widetilde{R}^2$). *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our sample period is from 1996:Q1 to 2015:Q3. The detailed definitions of all the variables are provided in the Appendix C.1.

	(1)	(2)	(3)	(4)
DiE	-0.0216**		-0.0413**	
	(-2.48)		(-1.99)	
AFD		0.0002		-0.0002
		(0.31)		(-0.16)
Size	0.0011***	0.0008**	0.0010**	0.0010**
	(2.87)	(2.11)	(2.17)	(2.24)
MB	0.0005	0.0001	0.0001	-0.0004
	(0.68)	(0.18)	(0.08)	(-0.53)
IO	0.0190***	0.0154***	0.0192***	0.0173***
	(9.47)	(10.21)	(6.29)	(5.94)
O/S	-0.0123*	-0.0228***		
	(-1.79)	(-3.57)		
VoV			-0.0114	-0.0157
			(-1.06)	(-1.46)
$\widetilde{\mathbf{R}}^2$	0.012	0.009	0.019	0.016

Conclusion

In this thesis, we explore the effects of investor sentiment and differences in expectations in the options market on asset prices in time-series, cross-sectional and event-based settings. To this end, we construct two measures of options traders' beliefs, investor sentiment, obtained from the volume-weighted average moneyness level across all options series, and differences in expectations, constructed from the dispersion of stock options trading volume across different moneyness levels. Both measures can be rationalized within a theoretical framework, wherein investors with different directional expectations about the future state of the underlying asset trade options with various strike prices and market makers serve as a counterparty to such trades. The key results of the thesis are as follows.

In the first chapter, consistent with prior studies, we document that option-implied sentiment is a strong negative predictor of excess stock market returns both at short and long investment horizons. The in-sample forecasting power of the sentiment measure and investor sentiment indices of Huang et al. (2015) and Baker and Wurgler (2006) has a similar economic magnitude, whereas the out-of-sample predictability of the option-implied investor sentiment is clearly superior to that exhibited by alternative sentiment proxies. For example, a one-standard-deviation positive shock to option-implied sentiment leads to the statistically significant negative market excess return of 0.78 percent for monthly horizon and 3.29 percent for half-year horizon, while the out-of-sample coefficients of determination generated by option-implied sentiment measure are more than twice greater relative to those produced by alternative sentiment proxies. Further, applying various asset allocation techniques, we demonstrate that the proposed option-implied sentiment measure carries an important economic value for a risk-averse investor, which is either higher than or tantamount to that shown by existing sentiment indices.

In the second chapter, we provide new strong evidence that the measure of differences in options investors' expectations (DiE) contains valuable information about future stock returns. Performing univariate portfolio-level analysis, we demonstrate that stocks with higher differences in expectations consistently earn lower returns, with high DiE firms underperforming low DiE firms by 1.51 percent per month. These findings support the theoretical predictions of Miller's (1977) model that high differences of opinion generate stock overpricing and a following negative risk premium in the presence of binding short-sale constraints. Further, in line with Miller (1977), we show that the negative DiE-return relationship is the strongest for stocks that are more likely to be held by individual investors and thus, more difficult to short sell. Additionally, the relation is more pronounced for small, more volatile and less liquid firms i.e. stocks that tend to incur higher arbitrage risk. Finally, this chapter documents that the differences-in-expectations effect is persistent up to 12 months, pronounced in high sentiment periods, and is robustly distinct from that shown by a large array of previously documented cross-sectional return predictors.

In the third chapter, we investigate the mechanism and timing of the previously documented DiE effect (and the Miller (1977) effect in general). Consistent with the study of Berkman et al. (2009), we find that stocks with high differences in investors' expectations, experiencing a large price run-up of 0.42 percent over the seven days preceding the earnings releases, exhibit a substantial price reversal upon the disclosure of new information, underperforming low DiE stocks by an economically large buy-and-hold three-day abnormal return of 0.82 percent. Moreover, the DiE effect around earnings releases is more pronounced for stocks with higher short-sale costs, tends to better reflect the Miller (1977) predictions for stocks with listed options (relative to the effect from analysts' forecasts dispersion) and is robustly distinct from size, market-to-book, post-announcement drift and other previously revealed return anomalies.

Limitations and Further Research

Despite the comprehensive and thorough empirical analysis, conducted in this thesis, our findings are subject to several important limitations. As any study in the options literature, our main conclusions are valid only for a certain subset of the whole universe of securities, which are shown to be large-sized and more liquid, and for a short time period relative to the similar inferences that are based on the entire set of stocks. Unlike various fixed income or macroeconomic observations, the options data become available from 1996, spanning the period for the last nineteen years only. Nevertheless, although the time coverage of the analysis is relatively small, our results still incorporate the periods of economic booms and recessions and two major financial downturns. Moreover, the computation of the measures for investors' beliefs involves trading volume information, both across different moneyness levels and maturities, however options markets exhibit a large proliferation of the trading activity and gain its popularity only from 2000s, thus a relatively low liquidity, that is reflected both in trading volume and availability of strike prices, in the late nineties may result in the belief measures that are based on the trades of a restricted pool of investors. Additionally, the empirical results, presented in this thesis, can potentially be examined for the robustness and can also be extended in the future research to acquire an in-depth understanding of the key inferences drawn in this work. Below, I suggest several ideas for further investigation.

In all chapters, our empirical findings provide supportive evidence for theoretical models, that are either developed to explain the dynamics of a certain market characteristic i.e.

trading volume or created generally for stock markets. For example, in the first chapter, we compare our results with those from the studies of Baker and Wurgler (2006) and Huang et al. (2015), which estimate the sentiment indices from firm-specific information and hence, draw key conclusions based on the predictions made particularly for equity markets. Similarly, the findings in the second chapter are consistent with the models of Miller (1977), Chen, Hong and Stein (2002) that consider the disagreement effect solely in the stock market. In this regard, a theoretical framework, that is specifically designed to take into account the specifics of the options market and to rationalize the effect of options traders' expectations or sentiment on stock prices, can shed more light on the key empirical findings of the thesis and provide new and deeper understanding of the sentiment or differences-in-expectations effects. Furthermore, such theoretical model may also establish the link between investor sentiment in stock and derivative markets and explain the driving forces behind the waves of optimism and pessimism as well as the divergence in beliefs in the options market. For instance, there is a wide literature on the mechanisms that can generate disagreement in the stock market including overconfidence (Scheinkman and Xiong, 2003), gradual information flow (Hong and Stein, 1999) or heterogeneous priors (Harris and Raviv, 1993), however whether such mechanisms can also generate differences of opinion in the options market remains an open question.

Looking at the potential areas of further research in each of the chapters, there are a few suggestions for consideration. First, Chapter 1 constructs a market-wide sentiment measure from the volume-weighted average moneynesses of individual stocks and compares its forecasting power with that of alternative sentiment proxies. Since the option-implied sentiment is shown to strongly predict market returns, it would be interesting to augment the existing sentiment indices with options trading information, in principal component analysis or partial least squares settings, and test the predictive power of new index for future market returns. Second, Chapter 2 investigates the cross-sectional pricing of the differences in expectations among options traders, dealing with stocks listed on NYSE, AMEX and NASDAQ. To test the international differences-in-expectations effect and to examine its strength in other markets, it would be interesting to consider European markets and options markets on other underlying assets such as currencies or treasuries. Also, in regression-based and component decomposition settings, we find that the analysts' forecasts dispersion, a popular measure for differences of opinion, carries insignificant economic value for future stock returns. A more careful investigation of this finding can shed more light on the relationship between two belief divergence measures. Additionally, the differences-in-expectations effect is observed for monthly stock profitability, however an interested researcher can also test the dispersion-return relation on a daily (or even intraday) frequency and examine the hedging properties of the dispersion effect. Finally, Chapter 3 provides a further understanding of the negative relation between differences in expectations and stock returns, using the scheduled earnings announcement events. It would be intriguing to examine this effect around other public events such as dividend announcements, company announcements of earnings forecasts or releases of interest rate information by central banks. These tests may additionally enhance the understanding of the Miller (1977) hypothesis for stocks with listed options.

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Appendix A

Appendix to Chapter 1

A.1 Supplementary Results

In this section, using a naïve option-implied sentiment measure, we present the empirical results that are complementary to those discussed in the main body of the Chapter 1. The main sentiment proxy is obtained by value-weighting monthly ISent values across all stocks in our sample, whereas a naïve sentiment measure (ISent^{EW}) is estimated by taking a simple average of the monthly ISent values across all stocks. The key results with the ISent^{EW} measure are discussed below.

First, Table A.1 and A.2 explore the contemporaneous relationship between Huang et al. (2015), Baker and Wurgler (2006) sentiment indices, that are estimated from the full information set and using information up to the period of forecast formation (look-ahead bias-free approach), and a naïve option-implied sentiment measure. The results show that ISent^{EW} is strongly positively related to the PLS and PLS^{BF} indices among various option-related characteristics, with highly statistically significant slope coefficients across all model specifications, however it tends to exhibit a weaker or no relationship with BW and BW^{BF} sentiment indices. Unreported findings indicate that even after controlling for serial correlation, the relationship between ISent^{EW} and PLS (BW) index remains strong (less pronounced). For example, in Table A.1, Panel B, the coefficient on ISent^{EW} is statistically insignificant in univariate and bivariate models, after controlling for VRP, Hedge and other option-related variables. The similar patterns are also observed in case of the look-ahead bias-free BW index (Table A.2, Panel B). Second, examining the in-sample predictability in Table A.3, market return forecasts generated by ISent^{EW} are economically and statistically similar to those produced by the main sentiment measure and cannot be explained by other previously documented economic return drivers. For instance, one standard deviation increase in the ISent^{EW} measure forecasts a market excess return of -0.85% for monthly horizon, -2.19% for quarterly horizon, -2.85% for half-year horizon. Third, Table A.4 presents the results on the out-of-sample performance of the ISent^{EW} measure and documents that the out-of-sample forecasting power of a naïve option-implied sentiment measure is economically comparable for 1-, 2-month-ahead horizon and is clearly inferior for quarterly horizon, relative to that generated by the main ISent measure. In particular, the out-of-sample $\tilde{R}^2$s are positive across all investment horizons, however experiencing a substantial decline when forecasting market excess returns for the next quarter. Finally, we investigate the economic significance of the portfolio returns generated by the ISent^{EW} trading strategy in Table A.5. Surprisingly, this table illustrates that the investor with mean-variance and binary (with and without short sales) portfolio weights will gain a higher expected rate of return per unit of risk and will have a higher utility in case of investing his funds with the ISent^{EW} measure, relative to the Sharpe ratios and increase in utility generated by the main sentiment trading model. Overall, the key findings reveal that the forecasting performance of both option-implied sentiment measures has a similar magnitude and hence, carry a higher economic value to the investor, compared to that produced by alternative sentiment indices.

Table A.1: Contemporaneous Analysis of Sentiment Indices

This table reports in-sample estimation results from univariate, bivariate and multivariate contemporaneous regressions of Huang et al. (2015) aligned investor sentiment index (PLS) constructed from five individual sentiment proxies by applying partial least squares methodology (Panel A) and Baker and Wurgler (2006) investor sentiment index (BW) derived as the first principal component of five individual sentiment proxies (Panel B) on the naïve option-implied sentiment measure (ISent^{EW}) and option-based characteristics such as second risk-neutral moment (VIX), variance risk premium (VRP), hedging pressure (Hedge), slope of implied volatility smirk (Smirk), third risk-neutral moment (Skew) and fourth risk-neutral moment (Kurt). The obtained slope coefficients are standardized to show the change in standard deviation of sentiment indices for a one standard deviation increase in each predictor. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our sample period is from January 1996 to August 2014.

Panel A: PLS Index

	Univariate Models		Bivariate Models			Multivariate Model	
		$\widetilde{R}^2$	**ISent^{EW}**	**X**	$\widetilde{R}^2$		$\widetilde{R}^2$
ISent^{EW}	0.527***	0.274				0.690***	0.418
	(9.22)					(10.56)	
VIX	0.0282	-0.004	0.725***	-0.365***	0.366	-0.391***	
	(0.42)		(11.39)	(-5.73)		(-5.73)	
VRP	-0.0548	-0.002	0.528***	0.00608	0.271	0.101*	
	(-0.82)		(9.15)	(0.11)		(1.85)	
Hedge	-0.0917	0.004	0.526***	-0.00824	0.271	0.0013	
	(-1.37)		(9.06)	(-0.14)		(0.03)	
Smirk	-0.354***	0.122	0.478***	-0.266***	0.340	-0.159**	
	(-5.63)		(8.61)	(-4.80)		(-2.28)	
Skew	0.295***	0.083	0.482***	0.148**	0.291	0.102	
	(4.58)		(8.12)	(2.49)		(1.40)	
Kurt	-0.257***	0.062	0.496***	-0.0913	0.279		
	(-3.95)		(8.21)	(-1.51)			

Panel B: BW Index

	Univariate Models		Bivariate Models			Multivariate Model	
		$\widetilde{R}^2$	**ISent^{EW}**	**X**	$\widetilde{R}^2$		$\widetilde{R}^2$
ISent^{EW}	0.103	0.006				0.288***	0.172
	(1.54)					(3.69)	
VIX	-0.254***	0.060	0.341***	-0.438***	0.138	-0.416***	
	(-3.89)		(4.59)	(-5.90)		(-5.11)	
VRP	-0.0722	0.001	0.0961	-0.0611	0.005	0.0637	
	(-1.07)		(1.42)	(-0.90)		(0.97)	
Hedge	-0.0806	0.002	0.0927	-0.0658	0.006	-0.0631	
	(-1.20)		(1.37)	(-0.97)		(-1.00)	
Smirk	-0.278***	0.073	0.0538	-0.268***	0.071	-0.214**	
	(-4.29)		(0.82)	(-4.06)		(-2.58)	
Skew	0.0960	0.005	0.0815	0.0711	0.006	-0.0054	
	(1.43)		(1.16)	(1.01)		(-0.06)	
Kurt	-0.0490	-0.002	0.0977	-0.0164	0.002		
	(-0.73)		(1.37)	(-0.23)			

Table A.2: Contemporaneous Analysis of Sentiment Indices: Look-ahead Bias-free Approach

This table reports in-sample estimation results from univariate, bivariate and multivariate contemporaneous regressions of look-ahead bias-free Huang et al. (2015) aligned investor sentiment index (PLS^{BF}) constructed from five individual sentiment proxies by applying partial least squares methodology and using information up to the period of forecast formation (Panel A) and look-ahead bias-free Baker and Wurgler (2006) investor sentiment index (BW^{BF}) derived as the first principal component of five individual sentiment proxies using information up to the period of forecast formation (Panel B) on the naïve option-implied sentiment measure (ISent^{EW}) and option-based characteristics such as second risk-neutral moment (VIX), variance risk premium (VRP), hedging pressure (Hedge), slope of implied volatility smirk (Smirk), third risk-neutral moment (Skew) and fourth risk-neutral moment (Kurt). The obtained slope coefficients are standardized to show the change in standard deviation of sentiment indices for a one standard deviation increase in each predictor. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our forecast formation period is from September 2000 to August 2014.

Panel A: PLS^{BF} Index

	Univariate Models		Bivariate Models			Multivariate Model	
		$\widetilde{R}^2$	ISent^{EW}	X	$\widetilde{R}^2$	X	$\widetilde{R}^2$
ISent^{EW}	0.446***	0.393				0.428***	0.485
	(10.45)					(8.30)	
VIX	0.242***	0.118	0.455***	-0.0143	0.390	-0.0368	
	(4.84)		(8.65)	(-0.28)		(-0.71)	
VRP	0.0719	0.004	0.465***	0.137***	0.426	0.131***	
	(1.30)		(11.09)	(3.24)		(3.14)	
Hedge	-0.0692	0.000	0.445***	-0.0160	0.390	-0.0050	
	(-1.04)		(10.34)	(-0.31)		(-0.10)	
Smirk	-0.286***	0.153	0.402***	-0.190***	0.456	-0.151***	
	(-5.58)		(9.67)	(-4.50)		(-2.85)	
Skew	0.316***	0.187	0.384***	0.174***	0.441	0.0652	
	(6.28)		(8.74)	(3.90)		(1.12)	
Kurt	-0.276***	0.154	0.396***	-0.129***	0.420		
	(-5.59)		(8.78)	(-2.94)			

Panel B: BW^{BF} Index

	Univariate Models		Bivariate Models			Multivariate Model	
		$\widetilde{R}^2$	ISent^{EW}	X	$\widetilde{R}^2$		$\widetilde{R}^2$
ISent^{EW}	0.127*	0.011				0.299***	0.319
	(1.71)					(3.71)	
VIX	-0.216***	0.048	0.386***	-0.434***	0.150	-0.439***	
	(-3.06)		(4.57)	(-5.29)		(-5.40)	
VRP	0.0674	-0.001	0.139*	0.0868	0.013	0.134**	
	(0.90)		(1.86)	(1.15)		(2.05)	
Hedge	0.0154	-0.006	0.129*	0.0308	0.006	0.0738	
	(0.17)		(1.73)	(0.34)		(0.96)	
Smirk	-0.447***	0.205	0.0244	-0.442***	0.201	-0.341***	
	(-6.63)		(0.36)	(-6.35)		(-4.12)	
Skew	0.236***	0.052	0.0493	0.218***	0.049	0.0989	
	(3.20)		(0.63)	(2.75)		(1.09)	
Kurt	-0.166**	0.025	0.0730	-0.139*	0.024		
	(-2.31)		(0.92)	(-1.79)			

Table A.3: In-Sample Predictability: Univariate and Bivariate Analyses

This table reports in-sample estimation results from univariate and bivariate predictive regressions of the CRSP value-weighted index excess return on the naïve option-implied sentiment measure (ISent^{EW}) and each of other market return predictors. These variables include dividend-payout ratio (D/E), earnings-price ratio (E/P), yield gap (YGap), yield term spread (YSpr), default spread (DSpr), analysts' forecasts dispersion (Dis), consumption-wealth ratio (C/W), market illiquidity (Illiq), idiosyncratic volatility (IdV) and tail risk (TRisk). The obtained coefficients are standardized to indicate the monthly excess return for a one standard deviation increase in each predictor. Newey-West adjusted (the lag length equals to forecasting horizon) t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our full sample period is from January 1996 to August 2014.

Univariate Models

	1 month	**2 month**	**3 month**	**6 month**
ISent^{EW}	-0.0085**	-0.0152***	-0.0219***	-0.0285***
	(-2.18)	(-2.79)	(-2.94)	(-2.99)
$\widetilde{\mathbf{R}}^2$	0.0276	0.0414	0.0578	0.0431

Bivariate Models

	1 month		**2 month**		**3 month**		**6 month**	
	ISent^{EW}	$\widetilde{\mathbf{R}}^2$	**ISent^{EW}**	$\widetilde{\mathbf{R}}^2$	**ISent^{EW}**	$\widetilde{\mathbf{R}}^2$	**ISent^{EW}**	$\widetilde{\mathbf{R}}^2$
D/E	-0.0089**	0.0262	-0.0163***	0.0448	-0.0237***	0.0687	-0.0324***	0.0703
	(-2.24)		(-2.92)		(-3.07)		(-4.53)	
E/P	-0.0086**	0.0233	-0.0157***	0.0377	-0.0231***	0.0559	-0.0304***	0.0414
	(-2.12)		(-2.84)		(-2.93)		(-3.47)	
YGap	-0.0085**	0.0232	-0.0153***	0.0371	-0.0224***	0.0539	-0.0288***	0.0387
	(-2.05)		(-2.71)		(-2.78)		(-3.14)	
YSpr	-0.0085**	0.0232	-0.0152***	0.0371	-0.0219***	0.0535	-0.0273***	0.0410
	(-2.14)		(-2.73)		(-2.86)		(-2.92)	
DSpr	-0.0085**	0.0232	-0.0154***	0.0372	-0.0230***	0.0557	-0.0329***	0.0553
	(-2.14)		(-2.87)		(-2.96)		(-4.03)	
Dis	-0.0083**	0.0250	-0.0146***	0.0429	-0.0211***	0.0604	-0.0265***	0.0561
	(-2.10)		(-2.61)		(-2.74)		(-2.94)	
C/W	-0.0093**	0.0331	-0.0170***	0.0581	-0.0245***	0.0845	-0.0338***	0.0993
	(-2.38)		(-3.02)		(-3.16)		(-4.00)	
Illiq	-0.0103**	0.0326	-0.0192***	0.0548	-0.0269***	0.0720	-0.0333***	0.0465
	(-2.34)		(-3.30)		(-3.34)		(-2.82)	
IdV	-0.0109**	0.0296	-0.0189***	0.0439	-0.0261***	0.0591	-0.0419***	0.0649
	(-2.31)		(-2.71)		(-2.93)		(-4.42)	
TRisk	-0.0086**	0.0232	-0.0188***	0.0481	-0.0273***	0.0701	-0.0362***	0.0537
	(-1.99)		(-3.04)		(-3.23)		(-3.66)	

Table A.4: Out-of-Sample Predictability

This table reports out-of-sample predictability results for the CRSP value-weighted index excess return based on the naïve option-implied sentiment measure (ISent^{EW}). $\widetilde{R}^2$ is the out-of-sample coefficient of determination, MSE-F is the McCracken (2007) F-statistic, ENC-NEW is the encompassing test of Clark and McCracken (2001), and $\widetilde{R}^2_C$ is the out-of-sample coefficient of determination with positive prediction restriction. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our out-of-sample forecasting period is from September 2000 to August 2014.

1-month horizon	
	ISent^{EW}
$\widetilde{\mathbf{R}}^2$	0.0238
MSE-F	4.0631***
ENC-NEW	4.0671**
$\widetilde{\mathbf{R}}^2_C$	0.0301

2-month horizon	
	ISent^{EW}
$\widetilde{\mathbf{R}}^2$	0.0384
MSE-F	6.5853***
ENC-NEW	4.8779**
$\widetilde{\mathbf{R}}^2_C$	0.0222

3-month horizon	
	ISent^{EW}
$\widetilde{\mathbf{R}}^2$	0.0266
MSE-F	4.4474***
ENC-NEW	4.3717**
$\widetilde{\mathbf{R}}^2_C$	0.0106

Table A.5: Asset Allocation

This table reports the performance results of investor's portfolio with mean-variance weights (Mean-Variance Strategy), binary weights with short sales (Binary Strategy With Short Sales), and binary weights without short sales (Binary Strategy Without Short Sales). This investor is risk-averse (with risk-averse coefficient of 3) and allocates his wealth between risky and risk-free assets using one-month-ahead out-of-sample forecasts of the CRSP value-weighted index excess return based on the naïve option-implied sentiment measure (ISent^{EW}). Mean indicates the average return, St. Dev. stands for the standard deviation of returns, Sharpe denotes the Sharpe ratio, CE is the certainty equivalent return in excess of the historical average (HAV), MDD is the maximum drawdown, and Long is the fraction of months when the strategy takes long position in the market index. All measures except for MDD and Long are annualized. Our out-of-sample forecasting period is from September 2000 to August 2014.

Mean-Variance Strategy	
	ISent^{EW}
Mean	0.0958
St. Dev.	0.1285
Sharpe	0.7455
CE	0.0765
MDD	-0.3327
Long	0.9102
Binary Strategy With Short Sales	
	ISent^{EW}
Mean	0.0945
St. Dev.	0.2105
Sharpe	0.4490
CE	0.0311
MDD	-0.6533
Long	0.9102
Binary Strategy Without Short Sales	
	ISent^{EW}
Mean	0.0669
St. Dev.	0.1374
Sharpe	0.4867
CE	0.0155
MDD	-0.4585
Long	0.9102

Appendix B

Appendix to Chapter 2

B.1 Description of Variables

In this section, we provide a detailed definition of all the stock- and option-related variables used in the chapter. 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 residuals constitutes quarterly 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. The procedure of winsorizing the fraction of shares outstanding held by institutional investors is identical to that of Nagel (2005). Finally, we match previous-quarter values of residual institutional ownership with stock returns in month t to insure that the residual institutional ownership is known to investors before the returns that it is assumed to explain.

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 et al., 2006): Idiosyncratic volatility is the standard deviation of the residuals from Fama and French's (1993) three-factor model.[1] We run daily time-series regressions of excess stock returns on the excess market returns, Value-minus-Growth (HML) portfolio returns, and Small-minus-Big (SMB) portfolio returns 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 residuals obtained from this model. We multiply obtained 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.

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

Beta (Fama and MacBeth, 1973): Beta is the slope coefficient estimated from the daily 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 such an order. Next, to insure 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 in July of this year. Finally, we divide these book equity values by market capitalization over the previous month to update book-to-market ratio monthly.

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.

RNS, RNK (Bakshi, Kapadia and Madan, 2003): Risk-neutral skewness (kurtosis) is an annualized model-free estimate of skewness (kurtosis) of the risk-neutral distribution of a stock's log return from time t until 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; An et al., 2014): 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 a maturity of 30 days. At-the-money options have a delta (in absolute value) equal to 0.5.

QSkew (Xing, Zhang and Zhao, 2010; An et al., 2014): 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. We use volatility surface data with a maturity of 30 days. Out-of-the-money put option 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) across all available option pairs. 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 call or 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 et al., 2014): Call (Put) implied volatility innovations are defined as 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 during month t, scaled by the average at-the-money implied volatility over month t. 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.

B.2 Supplementary Results

B.2.1 Cross-sectional Predictability of Next-month DiE

In the main body of the chapter, we demonstrate the persistence in the differences in expectations measure by constructing a probability transition matrix for portfolios sorted according to DiE and plotting a time-series graph of the DiE measure eleven months before and eleven months after portfolio formation. In this section, we verify the results presented in the main empirical analysis by investigating the persistency of the DiE measure in Fama and MacBeth (1973) monthly cross-sectional regressions of DiE at the end of month $t+1$ on DiE and other stock- and option-related characteristics, measured at the end of month t. Table B.1 presents the time-series average of monthly cross-sectional coefficient estimates and corresponding t-statistics. The coefficient on DiE is positive, has a large magnitude and is highly statistically significant both in univariate regression and after simultaneous inclusion of various stock- and option-related variables. R^2s are high (greater than 50% across all models), indicating a strong explanatory power for the next-month DiE measure. Overall, the above findings support the main results reported in the chapter and establish the persistent DiE dynamics over time after controlling for numerous characteristics, suggesting that stocks with a high DiE characteristic in one month also tend to exhibit more dispersed opinions in the following month.

B.2.2 Median Characteristics of DiE Portfolios

To supplement the mean characteristics of DiE portfolios reported in Table 2.4 of the main chapter, we report the median characteristics of stocks in the various DiE deciles. In particular, we sort stocks into decile portfolios based on DiE and estimate the time-series averages of monthly median values of various stock-related variables across the DiE deciles. Table B.2 illustrates the results. First, as we move from the low DiE to the high DiE portfolio, the median values of DiE exhibit an almost identical magnitude to that documented for average values. Second, high DiE stocks remain to be more difficult to short sell, with median residual institutional ownership values decreasing from the 2.262 in low DiE portfolio to 0.862 in the high DiE portfolio. Also, these stocks tend to exhibit higher limits to arbitrage, in sense that they are relatively small, more volatile and more illiquid. One of the biggest differences between mean and median values is observed with illiquidity. The median illiquidity for the low DiE portfolio is almost at zero level, while it increases to 0.004 (compared to 0.028 when considering the average value) in the portfolio with the highest DiE. This evidence demonstrates a highly skewed distribution of illiquidity values (see also, Bali, Engle and Murray, 2016). Consistent with the findings from mean characteristics, high DiE stocks also tend to be value-oriented, systematically riskier and show a greater propensity to exhibit lottery-type payoffs. When examining the dispersion in analysts' forecasts, we observe that the monotonically increasing pattern across DiE portfolios is preserved when utilizing median rather than average values. The main difference is that the median AFD value for the high DiE portfolio is 0.117 (compared to 0.287 when considering the average value), implying a highly skewed distribution of AFD values. Overall, the findings with median characteristics confirm the results from the average composition of DiE portfolios, suggesting that high DiE firms are relatively small, riskier, relatively illiquid, value-oriented, with less institutional ownership, preferred by investors with lottery-type preferences, and have higher analysts' forecast dispersion.

B.2.3 Results for Value-weighted Portfolios

In this section, we complement the equal-weighted portfolios analyses in the main chapter by examining the results for value-weighted average returns.

First, we investigate the economic origin of the DiE effect in the presence of short-sale costs (proxied by the residual of institutional ownership) and limits to arbitrage (proxied by size, idiosyncratic volatility and illiquidity) using value-weighted portfolios. Similar to Tables

2.5 and 2.6 in the main chapter, we double-sort stocks into quintile portfolios and for each characteristic-DiE portfolio, compute value-weighted average monthly excess returns and present a time-series average of these excess returns over all months in our sample. We also compute value-weighted average raw returns and factor alphas for the strategy that buys the high DiE portfolio and sells the low DiE portfolio. As shown in Tables B.3 and B.4, the findings for value-weighted portfolios exhibit similar features relative to those documented for equal-weighted average returns. For example, high DiE stocks underperform low DiE stocks by 1.89% per month (with a t-statistic of -2.50) if these stocks have a lower level of institutional ownership, whereas the value-weighted average return differential between high DiE and low DiE portfolios is -0.60% per month (with a t-statistic of -1.04) for high institutional ownership firms. Further, we report that the underperformance of high DiE compared to low DiE stocks is more pronounced for low size (-1.25% per month with a t-statistic of -2.10), high idiosyncratic volatility (-1.56% per month with a t-statistic of -2.31) and high illiquidity (-1.11% per month with a t-statistic of -1.90) portfolios. These predictability patterns are robust to the inclusion of asset pricing factors. Overall, consistent with the results presented in the main body of the chapter, these findings indicate that the DiE effect is the strongest for stocks that are more difficult to short sell and tend to have higher limits to arbitrage.

Second, we verify that the DiE predictability is not driven by previously documented return predictors, using value-weighted portfolios in bivariate dependent sorts. Similar to Table 2.7 in the main chapter, we use double decile sortings and we compute the time-series averages of value-weighted average monthly excess returns for each of the DiE deciles across the various characteristics portfolios. Further, we estimate value-weighted average raw returns and factor alphas for the strategy that buys the high DiE portfolio and sells the low DiE portfolio. As presented in Table B.5, we observe that after controlling for the stock-related characteristics, the profitability of the H-L DiE portfolio still remains significant in almost all cases, except for marginally insignificance reported for short-term reversal, with a value-weighted average return of -0.45% per month (and a t-statistic of -1.59); however, when we risk-adjust the returns for the various asset pricing factors, the return differential between the high and low DiE stocks is statistically significant and economically large, irrespective of the stock-related characteristic we control for. Across all option-related variables, the value-weighted average raw (risk-adjusted) results of the H-L portfolio are statistically significant, with returns varying from -1.43% (-1.56%) per month after controlling for risk-neutral kurtosis to -0.72% (-0.82%) per month when the call option implied volatility innovation is considered. Overall, the series of bivariate sorts with value-weighted average returns provides quantitatively similar results to those reported for equal-weighted average returns, suggesting that none of the stock- or option-related characteristics can adequately explain the DiE effect.

Third, we test whether the results of the value-weighted portfolio analyses are robust to alternative definitions of dispersion and alternative data screening criteria. We construct nine different DiE measures and report univariate portfolio-level analysis, similar to Table 2.14 in the main chapter. The results are reported in Table B.6. We document that, consistent with the equal-weighted findings, the predictive power of DiE for future value-weighted average stock returns is robust to utilizing standard deviation rather than mean absolute deviation, as well as to utilizing strike prices rather than moneynesses. We also find that the DiE predictability results are robust to using alternative screening criteria on the minimum number of days within a month with non-missing DiE values and inclusion of near-the-money options in the DiE computation. Similar results are obtained when considering DiE estimation using information from the penultimate day of a month (rather than averaged within a month excluding the last trading day). For instance, Table B.6 shows that the value-weighted average raw and risk-adjusted returns on the H-L portfolio are statistically significant and do not vary dramatically across different DiE measures, with average raw returns ranging between -1.43% per month with a t-statistic of -2.21 for DiE 4 and -1.07% per month with a t-statistic of -1.67 for DiE 2. Moreover, after adjusting for asset pricing factors, the negative relation between DiE and future returns is economically substantial and highly significant across all the DiE specifications, indicating the robustness of the DiE effect to alternative DiE definitions.

Finally, Table B.7 illustrates the results for value-weighted long-term DiE profitability. Following Jegadeesh and Titman (1993), we examine the long-term DiE profitability using value-weighted portfolios with overlapping holding periods, where we hold a portfolio that buys high DiE stocks and sells low DiE stocks for T months, where T is equal to two (2m), three (3m), four (4m), five (5m), six (6m), nine (9m), and twelve (12m), and at the same time, each month, we close out any previously-initiated positions that expire. As a result, using this trading strategy, we allocate new weights on $1/T$ of the stocks in the entire portfolio for a certain month and carry over the rest from the past month. All open portfolios in a given month receive equal weights. For each investment horizon, value-weighted average raw returns and factor alphas are estimated for the above strategy. The results indicate that the H-L DiE portfolio predictability lasts up to 3 months (compared to 6 months with equal-weighted portfolios), while the alpha (based on the four-factor model) differentials between high DiE and low DiE stocks are economically large and statistically significant up to 12 months, with the values varying from -1.25% per month with a t-statistic of -2.99 for the 2-month horizon to -0.87% per month with a t-statistic of -2.40 for the 12-month horizon. Overall, the findings from value-weighted portfolios are quantitatively similar to those presented for equal-weighted average returns, indicating that the DiE effect persists for the horizons longer than just one-month ahead.

Table B.1: Next-month DiE Predictability

This table presents the results from Fama and MacBeth (1973) cross-sectional regressions of differences in expectations (DiE) over month *t+1* on a DiE measure and a list of stock- and option-related characteristics computed at the end of month t over the sample period from January 1996 to September 2015. DiE is the monthly average dispersion of 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 R^2s. The definitions of the variables are detailed in the Appendix B.1. *,**,*** denote statistical significance at 10%, 5% and 1%, respectively.

Stock-related Characteristics

DiE	IO	Size	IdV	Illiq	MAX	STR	Beta	BM	Mom	Vliq	AFD	R^2
0.7837***												0.554
(65.05)												
0.5544***	-0.0009***	0.0001	0.0212***	0.3550***	-0.0074	-0.0218***	0.0043***	0.0045***	-0.0023***	0.0050***	0.0042***	0.623
(31.41)	(-6.70)	(0.43)	(16.61)	(3.72)	(-1.14)	(-6.99)	(7.77)	(4.77)	(-4.33)	(9.22)	(8.37)	

Option-related Characteristics

DiE	RNS	RNK	VolSpr	QSkew	VS	O/S	InnCall	InnPut	VoV	R^2
0.6056***	0.0226***	-0.0124***	0.0006	0.1651***	-0.0434***	0.0329***	0.0222***	0.0094***	0.0008	0.585
(45.48)	(11.32)	(-10.94)	(0.65)	(16.70)	(-7.98)	(9.16)	(6.36)	(2.83)	(0.24)	

Table B.2: Median Characteristics of Portfolios sorted on DiE

This table reports the median stock-related characteristics for the decile portfolios sorted on differences in expectations (DiE) (in ascending order from decile 1, low DiE to decile 10, high DiE) over the sample period from January 1996 to September 2015. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. The definitions of the variables are detailed in the Appendix B.1.

	Low DiE	2	3	4	5	6	7	8	9	High DiE
DiE	0.040	0.051	0.058	0.065	0.072	0.080	0.089	0.100	0.119	0.167
IO	2.262	2.357	2.331	2.278	2.225	2.158	2.027	1.868	1.540	0.862
Size	9.189	8.991	8.764	8.473	8.243	7.989	7.726	7.436	7.100	6.442
IdV	0.197	0.225	0.251	0.282	0.313	0.344	0.380	0.424	0.484	0.607
Illiq	0.000	0.000	0.000	0.001	0.001	0.001	0.001	0.002	0.002	0.004
MAX	0.034	0.039	0.044	0.049	0.055	0.060	0.066	0.073	0.082	0.099
STR	0.016	0.016	0.017	0.016	0.015	0.011	0.010	0.002	-0.009	-0.041
Beta	0.852	0.953	1.041	1.142	1.247	1.346	1.454	1.548	1.609	1.632
BM	0.321	0.301	0.295	0.288	0.282	0.277	0.277	0.276	0.288	0.417
Mom	0.161	0.171	0.182	0.193	0.198	0.201	0.186	0.178	0.114	-0.108
Vliq	1.409	1.623	1.815	2.021	2.200	2.361	2.529	2.674	2.825	3.044
AFD	0.019	0.021	0.023	0.028	0.033	0.039	0.047	0.059	0.078	0.117

Table B.3: DiE, Short-sale Constraints and Limits to Arbitrage

This table presents the value-weighted average monthly profitability of twenty five portfolios sorted on one of the four stock characteristic variables and the differences in expectations (DiE) measure over the sample period from January 1996 to September 2015. We use residual institutional ownership (IO) as a proxy for short-sale constraints and firm's size (Size), idiosyncratic volatility (IdV) and Amihud illiquidity (Illiq) as the proxies for limits to arbitrage. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. Each month, we sort stocks in ascending order into quintile portfolios (column vector, from quintile 1 to 5) based on one of the four characteristics. Next, within each characteristic portfolio, we further sort stocks into five extra portfolios based on DiE (row vector, from quintile 1 to 5). Finally, for each characteristic-DiE portfolio, we compute value-weighted average monthly excess returns and present a time-series average of these excess returns over all the months in our sample. Also, we report the value-weighted average raw returns ($H-L$) as well as the Fama-French three-factor ($FF3\alpha$) and Carhart four-factor ($C4\alpha$) alphas for the strategy that buys a high DiE portfolio and sells a low DiE portfolio. Newey-West adjusted (with six lags) t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. The definitions of all the variables are detailed in the Appendix B.1. Value-weighted average raw and risk-adjusted returns are expressed as percentages.

Residual Institutional Ownership

	Low DiE	2	3	4	High DiE	$H-L$	$FF3\alpha$	$C4\alpha$
Low IO	0.73	0.19	0.29	0.67	-1.16	-1.89**	-2.80***	-2.26***
						(-2.50)	(-4.80)	(-3.68)
2	0.46	0.88	0.77	0.57	0.01	-0.45	-1.01*	-0.54
						(-0.72)	(-1.91)	(-0.97)
3	0.93	0.93	0.85	1.08	0.89	-0.04	-0.45	-0.15
						(-0.06)	(-1.04)	(-0.38)
4	1.02	0.84	0.93	0.45	0.92	-0.11	-0.62	-0.38
						(-0.20)	(-1.32)	(-0.73)
High IO	0.64	0.76	0.67	1.09	0.04	-0.60	-1.05***	-0.73**
						(-1.04)	(-2.92)	(-2.18)

Size

	Low DiE	2	3	4	High DiE	$H-L$	$FF3\alpha$	$C4\alpha$
Low Size	0.93	0.68	0.24	-0.27	-0.32	-1.25**	-1.71***	-1.13**
						(-2.10)	(-3.18)	(-2.11)
2	0.90	0.89	0.86	0.61	-0.06	-0.96**	-1.32***	-0.78**
						(-2.11)	(-3.54)	(-2.36)
3	1.20	1.05	1.10	0.67	0.45	-0.75	-1.14***	-0.63*
						(-1.55)	(-3.38)	(-1.83)
4	0.87	1.08	0.89	1.00	0.49	-0.38	-0.79**	-0.55
						(-0.67)	(-2.20)	(-1.47)
High Size	0.83	0.83	0.62	0.43	0.84	0.01	-0.31	-0.15
						(0.03)	(-1.21)	(-0.53)

Table B.4: DiE, Short-sale Constraints and Limits to Arbitrage (continued)

Idiosyncratic Volatility

	Low DiE	2	3	4	High DiE	$H-L$	$FF3\alpha$	$C4\alpha$
Low IdV	0.95	0.87	0.69	0.75	0.91	-0.04	-0.19	-0.16
						(-0.14)	(-0.86)	(-0.77)
2	0.75	0.92	0.60	0.81	0.96	0.20	0.01	0.18
						(0.38)	(0.02)	(0.50)
3	0.88	0.65	0.80	0.95	0.32	-0.56	-0.76**	-0.52
						(-1.47)	(-2.25)	(-1.53)
4	0.60	1.10	0.22	0.35	0.09	-0.51	-0.93**	-0.59
						(-0.89)	(-2.06)	(-1.14)
High IdV	0.24	0.86	0.10	-0.41	-1.32	-1.56**	-2.10***	-1.50***
						(-2.31)	(-3.49)	(-2.74)

Amihud Illiquidity

	Low DiE	2	3	4	High DiE	$H-L$	$FF3\alpha$	$C4\alpha$
Low Illiq	0.87	0.73	0.57	0.49	0.93	0.06	-0.33	-0.07
						(0.12)	(-1.10)	(-0.19)
2	0.90	0.88	0.91	0.99	0.50	-0.40	-0.80**	-0.52
						(-0.78)	(-2.36)	(-1.59)
3	1.17	1.07	1.10	1.03	0.63	-0.54	-1.01***	-0.54
						(-1.06)	(-2.93)	(-1.37)
4	0.70	0.82	0.47	0.59	0.22	-0.48	-0.90**	-0.28
						(-0.95)	(-2.27)	(-0.82)
High Illiq	0.82	0.72	1.11	0.39	-0.29	-1.11*	-1.45**	-0.85
						(-1.90)	(-2.53)	(-1.35)

Table B.5: Controlling for Other Cross-Sectional Characteristics

This table presents the value-weighted average monthly profitability of portfolios sorted on one of the stock- or option-related characteristics and the differences in expectations (DiE) measure over the sample period from January 1996 to September 2015. DiE is the monthly average dispersion of stock options trading volume across moneyness levels. Each month, we sort stocks in ascending order into decile portfolios (from decile 1, low DiE to decile 10, high DiE) based on one of the characteristics. Next, within each characteristic portfolio, we further sort stocks into ten extra portfolios in ascending order on the basis of DiE. Finally, we calculate the time-series averages of value-weighted average monthly excess returns for each of the DiE deciles across the ten characteristic portfolios that are obtained from the first sort. Also, we report the value-weighted average raw returns ($H-L$) as well as the Fama-French three-factor ($FF3\alpha$) and Carhart four-factor ($C4\alpha$) alphas for the strategy that buys high a DiE portfolio and sells a low DiE portfolio. Newey-West adjusted (with six lags) t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. The definitions of all the variables are detailed in the Appendix B.1. Value-weighted average raw and risk-adjusted returns are expressed as percentages.

Stock-related Characteristics

	IO	**Size**	**IdV**	**Illiq**	**MAX**	**STR**	**Beta**	**BM**	**Mom**	**Vliq**	**AFD**
Low DiE	0.88	0.96	0.74	0.87	0.77	0.68	0.85	0.82	0.85	0.96	0.89
2	0.94	0.93	0.83	0.93	0.93	0.85	0.75	0.82	1.01	1.11	0.80
3	0.73	0.94	0.83	0.86	0.81	0.89	0.79	1.00	0.88	0.88	0.74
4	0.73	0.87	0.85	0.86	0.82	0.78	0.89	0.85	0.88	0.91	0.63
5	0.97	0.80	0.52	0.93	0.50	0.58	0.71	0.82	0.81	1.10	0.91
6	0.65	0.66	0.47	0.68	0.80	0.74	0.69	0.59	0.77	0.87	1.01
7	0.64	0.62	0.34	0.78	0.85	0.77	0.69	0.67	0.45	0.63	0.90
8	0.56	0.39	0.58	0.66	0.59	0.38	0.90	0.62	0.33	0.48	0.69
9	0.70	0.31	0.29	0.53	0.20	0.47	0.38	0.36	0.29	0.58	0.32
High DiE	-0.12	0.26	0.04	0.08	0.20	0.23	-0.06	0.19	-0.09	0.21	-0.19
$H-L$	-0.95***	-0.70***	-0.70***	-0.79***	-0.58**	-0.45	-0.91***	-0.63**	-0.94***	-0.75***	-1.08***
	(-3.35)	(-2.71)	(-2.80)	(-3.05)	(-2.17)	(-1.59)	(-3.70)	(-2.19)	(-3.74)	(-3.12)	(-3.86)
$FF3\alpha$	-1.64***	-1.21***	-1.07***	-1.32***	-0.99***	-1.00***	-1.26***	-1.27***	-1.37***	-1.21***	-1.57***
	(-6.45)	(-5.33)	(-4.51)	(-5.53)	(-3.97)	(-3.96)	(-5.26)	(-5.14)	(-5.80)	(-5.31)	(-6.68)
$C4\alpha$	-1.16***	-0.68***	-0.70***	-0.74***	-0.58**	-0.56**	-0.99***	-0.79***	-1.17***	-0.70***	-1.17***
	(-4.52)	(-3.00)	(-2.92)	(-3.10)	(-2.31)	(-2.28)	(-4.17)	(-3.12)	(-4.78)	(-3.09)	(-4.91)

Option-related Characteristics

	RNS	**RNK**	**VolSpr**	**QSkew**	**VS**	**O/S**	**InnCall**	**InnPut**	**VoV**
Low DiE	0.99	0.99	0.82	0.92	0.92	0.91	0.85	0.79	0.88
2	0.82	0.86	0.93	0.74	0.81	0.86	0.91	0.82	0.86
3	0.81	0.97	0.88	0.88	0.68	0.78	0.84	0.79	0.78
4	0.89	0.79	0.68	0.87	0.69	0.74	0.89	0.77	0.69
5	0.72	0.78	0.86	0.50	0.75	0.99	0.68	0.68	0.92
6	0.77	0.70	1.00	0.82	0.86	0.99	0.75	0.76	0.71
7	0.76	0.63	0.71	0.74	0.61	0.73	0.68	0.72	0.79
8	0.89	0.83	0.35	0.47	0.48	0.55	0.57	0.74	0.73
9	0.21	0.31	0.73	0.62	0.37	0.49	0.42	0.30	0.54
High DiE	-0.22	-0.44	-0.00	-0.09	-0.03	0.01	0.12	-0.04	0.12
$H-L$	-1.21***	-1.43***	-0.82***	-1.01***	-0.96***	-0.90***	-0.72***	-0.83***	-0.76***
	(-4.11)	(-5.47)	(-2.86)	(-3.61)	(-3.33)	(-3.31)	(-2.76)	(-2.94)	(-2.58)
$FF3\alpha$	-1.84***	-1.96***	-1.37***	-1.59***	-1.55***	-1.62***	-1.27***	-1.42***	-1.27***
	(-7.51)	(-8.05)	(-5.36)	(-6.63)	(-6.66)	(-7.05)	(-5.46)	(-5.74)	(-4.96)
$C4\alpha$	-1.43***	-1.56***	-0.93***	-1.19***	-1.12***	-1.09***	-0.82***	-0.95***	-0.94***
	(-5.79)	(-6.32)	(-3.64)	(-4.92)	(-4.85)	(-4.64)	(-3.47)	(-3.86)	(-3.68)

Table B.6: Alternative DiE Specifications

This table presents value-weighted average monthly profitability of portfolios with the lowest (Low DiE) and highest (high DiE) DiE in the previous month as well as value-weighted average raw ($H-L$) and risk-adjusted ($FF3\alpha$ and $C4\alpha$) returns on the strategy that buys a high DiE portfolio and a sells low DiE portfolio over the sample period from January 1996 to September 2015. We use nine alternative DiE specifications. DiE 1 is the standard deviation of stock options trading volume across moneyness levels. DiE 2 and DiE 3 are mean absolute and standard deviation measures respectively, of options trading volume across strike prices (rather than moneyness), scaled by the volume-weighted average strike. DiE 4 and DiE 5 are similar to the original DiE measure and DiE 1 respectively, but we use alternative filtering criteria, which requires within a month at least ten days of non-missing DiE values. DiE 6 and DiE 7 are similar to the original DiE measure and DiE 1 respectively, but we include near-the-money options in calculating the measures. DiE 8 and DiE 9 are similar to the original DiE measure and DiE 1 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. Value-weighted average raw and risk-adjusted returns are expressed as percentages.

	DiE 1	**DiE 2**	**DiE 3**	**DiE 4**	**DiE 5**	**DiE 6**	**DiE 7**	**DiE 8**	**DiE 9**
Low DiE	0.98	0.94	0.98	0.83	0.81	0.86	0.88	0.89	0.86
	(3.92)	(3.57)	(3.85)	(3.18)	(3.19)	(3.57)	(3.72)	(2.91)	(2.99)
High DiE	-0.39	-0.13	-0.17	-0.60	-0.31	-0.35	-0.31	-0.22	-0.26
	(-0.54)	(-0.17)	(-0.23)	(-0.78)	(-0.40)	(-0.49)	(-0.43)	(-0.36)	(-0.43)
$H-L$	-1.37**	-1.07*	-1.16*	-1.43**	-1.12*	-1.22**	-1.19**	-1.11**	-1.12**
	(-2.23)	(-1.67)	(-1.79)	(-2.21)	(-1.71)	(-2.01)	(-1.99)	(-2.52)	(-2.59)
$FF3\alpha$	-2.03***	-1.69***	-1.83***	-2.07***	-1.77***	-1.90***	-1.89***	-1.47***	-1.57***
	(-5.26)	(-4.88)	(-5.24)	(-4.67)	(-4.10)	(-4.79)	(-5.23)	(-4.94)	(-4.86)
$C4\alpha$	-1.57***	-1.34***	-1.45***	-1.61***	-1.33***	-1.47***	-1.43***	-1.17***	-1.23***
	(-3.53)	(-3.52)	(-3.57)	(-3.33)	(-2.69)	(-3.41)	(-3.41)	(-3.50)	(-3.30)

Table B.7: Long-term Profitability of DiE Portfolios

This table reports the long-term value-weighted average profitability results for differences in expectations (DiE) portfolios. DiE is the monthly dispersion of stock options trading volume across moneyness levels. Each month, we sort stocks in ascending order into decile portfolios on the basis of DiE (from decile 1, low DiE to decile 10, high DiE) and construct a strategy that buys a high DiE portfolio and sells a low DiE 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, and at the same time closing out the previously-initiated positions that expire. As a result, for each investment horizon, we estimate a time-series average of value-weighted average raw returns ($H-L$), as well as the Fama-French three-factor ($FF3\alpha$) and Carhart four-factor ($C4\alpha$) alphas for a strategy that involves overlapping holding periods. Newey-West adjusted (with six lags) t-statistics are reported in parentheses. *,**,*** denote statistical significance at 10%, 5% and 1%, respectively. Value-weighted average raw and risk-adjusted returns are expressed as percentages.

	2m	**3m**	**4m**	**5m**	**6m**	**9m**	**12m**
$H-L$	-1.06*	-0.99*	-0.84	-0.76	-0.71	-0.57	-0.59
	(-1.75)	(-1.73)	(-1.50)	(-1.36)	(-1.23)	(-1.01)	(-1.05)
$FF3\alpha$	-1.74***	-1.66***	-1.48***	-1.41***	-1.34***	-1.20***	-1.21***
	(-4.55)	(-4.86)	(-4.45)	(-4.31)	(-4.18)	(-3.73)	(-3.82)
$C4\alpha$	-1.25***	-1.19***	-1.00***	-0.93***	-0.90**	-0.81**	-0.87**
	(-2.99)	(-3.28)	(-2.82)	(-2.65)	(-2.55)	(-2.25)	(-2.40)

Appendix C

Appendix to Chapter 3

C.1 Description of Variables

In this section, we provide a detailed definition of all the explanatory variables used in the chapter. The definition of the DiE measures is discussed in the main body of the chapter. The abbreviation of each variable is specified in *italic* face.

ABRET (Berkman et al., 2009): Abnormal return is the difference between buy-and-hold stock and value-weighted (VW) Center for Research in Security Prices (CRSP) index returns, estimated over the three days centered at the quarterly earnings announcement date. We exclude cases when the returns are missing for any of the three days around announcements.

AFD (Diether, Malloy and Scherbina, 2002): Dispersion in analysts' earnings forecasts is the standard deviation of analysts' earnings-per-share forecasts for the current fiscal year, scaled by the absolute value of the mean earnings forecast, estimated during the 45-day period ending two days prior to the earnings announcement date.

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

MB (Fama and French, 1992): Market-to-book ratio is the firm's quarterly market capitalization divided by book value of common stock, estimated at the end of prior fiscal quarter. MB is missing if it is less than 0.01 or greater than 100.

IO (Nagel, 2005): Institutional ownership is the fraction of firm's shares outstanding held by institutional investors prior to the earnings announcement date. IO is zero if no institutional ownership is reported during the 180 days prior to the earnings announcement date. IO is missing if it is greater than or equal to one.

Lev (Johnson, 2004): Financial leverage is the ratio of total debt (long-term debt plus debt in current liabilities) to total assets, measured at the end of the prior fiscal quarter. Lev is missing if it is less than zero or greater than one.

SUE (Bernard and Thomas, 1989): Standardized unexpected earnings is the fiscal-year difference (assuming a seasonally adjusted random-walk model) in quarterly basic earnings per share excluding extraordinary items (adjusted for stock splits and stock dividends), scaled by the price per share measured at the beginning of the current fiscal quarter.

Mom (Jegadeesh and Titman, 1993): Price momentum is the cumulative stock return in excess of the CRSP VW index return over the last 12 months prior to the earnings announcement date.

O/S (Roll, Schwartz and Subrahmanyam, 2010; Johnson and So, 2012): Option-to-stock-trading-volume ratio is the total monthly equity volume divided by the total monthly volume in option contracts across all strikes, estimated over the month ending two days prior to the earnings announcement date. 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.

VoV (Baltussen, Van Bekkum and Van Der Grient, 2015): Volatility of volatility is the standard deviation of daily at-the-money implied volatilities, scaled by the average at-the-money implied volatility, estimated over the last month prior to the earnings announcement 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.

C.2 Supplementary Results

In this section, we show a series of findings that verify the robustness of the results, presented in the main body of the Chapter 3. More specifically, we investigate the cross-sectional profitability of the DiE measures, estimated over one month two and five days prior to earnings announcement date, however, unlike in the main body of the chapter, we also impose a restriction, requiring a minimum of five non-missing daily DiE values to estimate the average monthly dispersion measure. Additionally, we replicate some of the results in the chapter by calculating the precision-weighted average (instead of the simple time-series average) of the quarterly mean cumulative three-day excess returns around earnings announcements, where the precision is the number of available observations in each quarter. The primary results are discussed below.

First, Table C.1 reports the average excess profitability around earnings announcements for the quantile portfolios formed on alternative DiE specifications (the first two columns) as well as on DiE, AFD and IO measures, where the returns are calculated with precision weights (the last three columns). The results indicate that stocks in the highest DiE or AFD quantile consistently underperform stocks in the lowest DiE or AFD quantile, earning a cumulative three-day earnings announcement period abnormal return of greater than -0.80% (in absolute terms). Similarly, in line with the main predictions, low IO stocks underperform high IO stocks by 0.64% over the three days around earnings releases. Second, Table C.2 demonstrates that our empirical evidence, supporting Miller (1977) hypothesis, is robust to the precision-weighted method of estimating excess returns. In particular, stocks in high DiE and low IO terciles earn substantially lower returns than stocks in low DiE and low IO portfolio, whereas this return pattern disappears when considering stocks in high IO terciles. The return on H-L DiE portfolio for low IO firms is -1.13% with a t-statistic of -6.20, while the return on the same portfolio, but for high IO stocks is -0.10% with a t-statistic of -0.63. The findings for AFD measure are also similar to those established in the main body of the chapter. Finally, in Table C.3, we perform a series of Fama and MacBeth (1973) regressions, where the coefficient estimates from cross-sectional models are precision-weighted over all quarters in our sample. The key findings show that the coefficient on DiE remains negative and highly statistically significant, after controlling for size, market-to-book ratio and institutional ownership. Overall, our results demonstrate that the DiE effect, documented in the main analysis, is robust to alternative DiE specifications and different methods of estimating the excess profitability across quarters.

Table C.1: Profitability of DiE, AFD and IO Portfolios Around Earnings Announcements

This table reports the average excess profitability around earnings announcements for the quantile portfolios sorted on various specifications of DiE measure and AFD. DiE and $\text{DiE}_{(-26,-5)}$ are the average dispersions of stock options trading volume across moneyness levels, estimated over one month two and five days prior to earnings announcement date, respectively. We also require a minimum of five non-missing daily DiE values to estimate the average monthly dispersion. Each year-quarter, we sort firms that report earnings into quantile portfolios (Portfolios 1-5) based on each of the DiE measures and report a time-series average of the quarterly mean cumulative three-day earnings announcement period returns in excess of the market return for each portfolio. Additionally, for the main DiE (DiE^{PW}), AFD (AFD^{PW}) and IO (IO^{PW}) measures, used in the main body of the chapter, we also compute a precision-weighted average of the quarterly mean cumulative three-day excess returns for each portfolio, where the precision of the quarterly average is the number of available observations each quarter. Finally, we also report the excess returns for the strategy that buys highest DiE stocks and sells lowest DiE stocks ($H - L$) before earnings announcements. The abbreviation PW stands for the precision-weighted procedure, applied to estimate excess returns for the portfolios sorted on DiE, AFD or IO. The returns are expressed as percentages. t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our sample period is from 1996:Q1 to 2015:Q3.

Portfolio	**DiE**	$\mathbf{DiE}_{(-26,-5)}$	$\mathbf{DiE}^{PW}$	$\mathbf{AFD}^{PW}$	$\mathbf{IO}^{PW}$
1	0.23***	0.31***	0.29***	0.50***	-0.24**
	(2.85)	(3.68)	(4.79)	(4.41)	(-2.56)
2	0.29***	0.29**	0.23***	0.24***	-0.05
	(3.06)	(2.52)	(2.77)	(4.04)	(-0.67)
3	0.32**	0.25**	0.29***	0.01	0.17**
	(2.19)	(2.26)	(3.39)	(0.10)	(2.04)
4	-0.03	-0.04	-0.04	-0.11	0.28***
	(-0.22)	(-0.30)	(-0.34)	(-0.98)	(4.05)
5	-0.65***	-0.63***	-0.54***	-0.32**	0.40***
	(-3.30)	(-3.25)	(-3.32)	(-2.24)	(6.12)
$H - L$	-0.89***	-0.95***	-0.83***	-0.81***	0.64***
	(-4.53)	(-4.61)	(-5.66)	(-6.06)	(10.49)

Table C.2: DiE, Short-sale Constraints and Excess Returns Around Earnings Announcements

This table presents the average excess profitability around quarterly earnings announcements for nine portfolios sorted on the level of institutional ownership (IO^{PW}) and the differences in expectations (DiE^{PW}) measure or analysts' forecasts dispersion (AFD^{PW}). We use the level of institutional ownership as a proxy for short-sale constraints. Each year-quarter, we sort firms that report earnings into three portfolios based on IO^{PW} (Low IO^{PW} - High IO^{PW}) and, within each IO^{PW} portfolio, we further sort stocks into three extra portfolios based on DiE^{PW} or AFD^{PW} (Low DiE^{PW} or AFD^{PW} - High DiE^{PW} or AFD^{PW}). For each of the resulting portfolios, we report a precision-weighted average of the quarterly mean cumulative three-day earnings announcement period returns in excess of the market return, where the precision of the quarterly average is the number of available observations each quarter. Finally, we also compute the excess returns for the strategy that buys highest DiE^{PW} or AFD^{PW} stocks and sells lowest DiE^{PW} or AFD^{PW} stocks within each IO^{PW} portfolio ($H - L$) before earnings announcements. DiE^{PW} is the monthly average dispersion of stock options trading volume across moneyness levels. AFD^{PW} is the standard deviation of analysts' earnings forecasts for the current fiscal quarter, scaled by the absolute value of the mean earnings forecast. The abbreviation PW stands for the precision-weighted procedure, applied to estimate excess returns for the portfolios sorted on IO and DiE or AFD. IO is the total fraction of shares outstanding held by institutional investors. The returns are expressed as percentages. t-statistics are reported in parentheses. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our sample period is from 1996:Q1 to 2015:Q3.

	Low DiE^{PW}	Medium DiE^{PW}	High DiE^{PW}	$H - L$
Low IO^{PW}	0.06	-0.36**	-1.07***	-1.13***
	(0.59)	(-2.63)	(-5.70)	(-6.20)
Medium IO^{PW}	0.28***	0.29***	0.00	-0.28*
	(3.26)	(3.03)	(0.02)	(-1.89)
High IO^{PW}	0.42***	0.52***	0.33**	-0.10
	(4.25)	(6.01)	(2.08)	(-0.63)

	Low AFD^{PW}	Medium AFD^{PW}	High AFD^{PW}	$H - L$
Low IO^{PW}	0.04	-0.48***	-0.79***	-0.83***
	(0.30)	(-3.71)	(-5.54)	(-6.41)
Medium IO^{PW}	0.42***	0.19**	-0.03	-0.45***
	(5.33)	(2.64)	(-0.17)	(-2.68)
High IO^{PW}	0.75***	0.31**	0.23	-0.52***
	(6.77)	(2.61)	(1.46)	(-3.32)

Table C.3: Weighted Fama-MacBeth Regressions

This table reports the results from Fama and MacBeth (1973) quarterly cross-sectional regressions of the cumulative three-day earnings announcement period returns in excess of the market return on the differences in expectations (DiE) measure, analysts' forecasts dispersion (AFD), log of market capitalization (Size), log of market-to-book ratio (MB) and the level of institutional ownership (IO). Considering only the firms that report earnings, we obtain coefficient estimates from year-quarter cross-sectional regressions and document their precision-weighted averages, where precision equals to the number of available observations each quarter, corresponding t-statistics (with four lags), presented in parentheses, and adjusted R2s ($\widetilde{R}^2$). *, **, *** denote statistical significance at 10%, 5% and 1%, respectively. Our sample period is from 1996:Q1 to 2015:Q3. The detailed definitions of all the variables are provided in the Appendix C.1.

	(1)	(2)	(3)	(4)
DiE	-0.0552***		-0.0291***	
	(-5.92)		(-3.02)	
AFD		-0.0008**		-0.0007
		(-2.10)		(-1.61)
Size			0.0012***	0.0004
			(3.15)	(0.92)
MB			0.0005	-0.0003
			(0.56)	(-0.66)
IO			0.0184***	0.0092***
			(7.95)	(7.05)
$\widetilde{\mathbf{R}}^2$	0.004	0.001	0.012	0.005