When the Options Market Disagrees*

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Abstract

We construct a new measure of investor disagreement from signed equity options trading volumes. Options disagreement negatively predicts stock returns over various horizons. The high disagreement stock portfolio underperforms the low disagreement portfolio by about 5% per year after standard risk adjustments. Options disagreement increases around news releases but its predictive power for stock returns does not depend on the news content. Higher short-selling costs in the stock market result in higher disagreement and increase its impact on expected stock returns. Overall, our results are consistent with differences of opinion theories where investors "agree to disagree" in the options market.

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Keywords: Option-implied disagreement; stock return predictability; news; short-sale constraints.

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1 Introduction

The importance of the heterogeneity of investors' beliefs for asset pricing has been recognized since Williams (1977). In rational expectations models with asymmetric information, agents use prices to infer the valuations of others and the heterogeneity of beliefs increases expected stock returns (Wang, 1993; Naik, 1997). When investors with heterogeneous priors agree to disagree, as in standard disagreement models, disagreement and expected stock returns are negatively related (Harrison and Kreps, 1978; Scheinkman and Xiong, 2003). So far, the empirical literature has mostly focused on studying heterogeneity of beliefs by analyzing measures of disagreement such as analyst forecast dispersion (Diether et al. 2002), breadth of institutional ownership (Chen, Hong and Stein, 2002), institutional ownership (Nagel, 2005), or dealers disagreement about payments on mortgage backed securities (Carlin et al 2014). Not only are these empirical results controversial, but interpretations of similar results often diverge in the literature. Overall, to the date, there is no clear differentiation between the two competing hypotheses.

In this paper we construct a novel measure of disagreement based on customer trades in the options market. Besides an increasing popularity and large trading volumes in equity options, there are several advantages of our measure compared to others. First, it is based on actual investors' trades which is the best testament of their opinion about the underlying.[1] Second, unlike in the stock market, where the participation of pessimists crucially depends on the absence of short-sale constraints (Miller, 1977), pessimists in the options market can always obtain negative exposure to the underlying by buying put or selling call options. Thus, the options market offers an ideal environment to infer opinions of both optimists and pessimists from their actual trades. Third, while trading in the stock market can be motivated by liquidity needs, trading in the options market by customer accounts is largely driven by betting on directional price changes of underlying stocks (Lakonishok et al., 2007). Fourth, while other proxies can be constructed monthly (e.g., analyst forecast dispersion) or quarterly (e.g., institutional ownership), our measure can be constructed daily. This provides a unique opportunity to study the sources and determinants of disagreement associated with daily scheduled or unscheduled corporate news releases, and how this information is transmitted into subsequent stock returns. Finally, it is conventionally accepted in the literature that options are not a redundant asset class (Bollen and Whaley, 2004; Garleanu et al. 2009; Christoffersen et al. 2017).

Our main results can be summarized as follows. First, consistent with agree to disagree models, we find that options disagreement negatively predicts stock returns. The results are

[1] See Goetzmann and Massa (2005) for discussion of advantages of inferring differences in opinions from actual investors' trades compared to all other measures.

economically and statistically significant and robust to the inclusion of existing proxies for disagreement, as well as options and stock order imbalances, proxies for informed trading and investors' attention, and other stock characteristics which can affect expected returns. The results are also robust to multi-period forecasting: options disagreement predicts stock returns up to five weeks ahead. Importantly, the magnitude of this effect is economically large. Sorting stocks on options disagreement into quintile portfolios, a zero investment strategy that buys the high disagreement portfolio and sells the low portfolio yields the future annualized four-factors alphas ranging from -6% to -3% depending on the sample period and the horizon considered. These results are not driven by the recent financial crisis.

Second, we analyze how news releases are transmitted into future stock returns. Using a comprehensive news database we show that new public information releases are associated with higher disagreement. Disagreement increases regardless of whether the news are positive or negative. This evidence is consistent with the literature convincingly arguing that exposure to the same information leads to higher investors' disagreement about asset valuations while interpreting this information (Harris and Raviv, 1993; Kandel and Pearson, 1995; Cao and Ou-Yang, 2009; Hong and Stein, 2007; Banerjee and Kremer, 2010). Consequently, options disagreement negatively predicts stock returns covered by either positive or negative news.

Third, we analyze whether the negative predictive effect of disagreement for future stock returns is associated with temporary stock over valuations due to short-sale impediments (Hong and Stein, 2007) or whether it reflects a risk based explanation (Banerjee, 2011). Based on stock short-sale borrowing and lending costs data, we find evidence for both. Supporting the first argument, we find that the negative impact of disagreement on stock returns is about five times bigger for stocks with higher short-sale constraints (higher loan fees or harder-to-borrow stocks) than for stocks with lower constraints. Moreover, consistent with D'Avalio (2002) and Duffie, Garleanu and Pedersen (2002), we also show that options disagreement increases with loan fees and lower availability of stocks on loans. Supporting the second argument, we also find a negative and significant predictability of disagreement for stock returns when short-selling is less expensive. Here, investors disagree more when they are more confident about their own (private) signal, and hence the perceived risk of asymmetric information is low. As a result, they require lower expected returns.

Fourth, options disagreement strongly predicts stock volume for multiple forecasting periods. This suggests that our measure captures well the stock market disagreement, which is also consistent with theoretical predictions in the literature (Hong and Stein, 2007; Banerjee and Kremer, 2010).

Overall, our results not only provide an overwhelming support to the heterogeneous beliefs

theories where investors agree to disagree, but also help to understand the underlying economic forces driving investors disagreement, and asset valuations.

Our disagreement measure uses signed trading volume data from the Chicago Board Options Exchange (CBOE) and the International Securities Exchange (ISE). Combined, these datasets capture more than 60% of overall equity options trading volume in the US. The data allow us to construct a stock-level measure of disagreement from customer accounts for all stocks with traded options. Our measure is the highest when the number of traded contracts providing positive exposure to the underlying stocks equals to those with negative exposure. It is the lowest when trading activity shifts towards contracts with only positive or only negative exposure to the underlying.

Our study is related to a large empirical literature on disagreement. Diether, Malloy, and Scherbina (2002), Chen, Hong, and Stein (2002), and Goetzmann and Massa (2005) document a negative relationship between disagreement and future stock returns. They attribute their results to the optimistic pricing model of Miller (1977). Sadka and Sherbina (2007) support this explanation by showing that the disagreement effect is more prominent among illiquid firms, where costs of short-selling are higher. In contrast, Johnson (2004) argues that Diether et al. (2002) results are due to higher idiosyncratic risks of leveraged firm, and Avramov et al. (2009) explain the negative dispersion-return relationship by financial distress proxied by credit ratings downgrades. Neither of them supports overpricing by optimists explanation.

In contrast, Anderson et al. (2005), Banerjee (2011), Jiang and Sun (2014), and Carlin et al (2014) report that the positive relation between disagreement and expected asset returns dominates, and favor rational expectation theories.

We complement this literature in several important ways. First, similar to Carlin et al. (2014) we study disagreement in the market without short-sale constraints, but unlike Carlin et al. (2014) we find an overwhelming support to the theories where investors agree to disagree. Perhaps the difference in the results is driven by considering different investor types. Carlin et al. (2014) analyze disagreement among mortgage dealers about prepayment speed forecasts on mortgage-backed securities. While their measure reflects disagreement among a limited number of financial intermediaries, i.e. dealers, we exclusively focus on disagreement of much broader clientile of customer accounts.

Second, we provide clear interpretations of our findings and economic mechanisms behind disagreement-returns relations. The disagreement increases with positive or negative news releases, as investors agree to disagree (Harris and Raviv, 1993; Kandel and Pearson, 1995). This leads to lower expected returns even in the absence of short-sale constraints (Banerjee, 2011). These effects are especially pronounced around earnings announcements. We, however, cannot

completely overrule the overpricing story associated with difficulty to short-sell stocks due to either higher borrowing costs or low availability of loanable securities (Nagel, 2005).

At the same time as our research, Cookson and Niessner (2016) also come to similar conclusions about the sources of disagreement. The authors use StockTwits platform where users report their investment profiles and philosophies, and twit their opinions about the same stocks. They find that most of disagreement is attributed to private model-based disagreement or different investment philosophies rather than information asymmetry. Using a panel of 100 stocks the authors report a strong disagreement-volume relations. Using a larger cross-section of all stocks with listed options and longer sample period we also find a strong link between our disagreement measure and sock volume. Our analysis however is mostly focused on the disagreement – stock returns relations and identifying how the information environment of firms interacts with disagreement to influence stock expected returns. Moreover, we are also able to quantify an economic impact of disagreement for asset prices.

The remainder of the paper is organized as follows. Section 2 presents our hypotheses. Section 3 describes the data and discusses the main variables used in our empirical analysis. Section 4 presents cross-sectional and portfolio sorting results. Section 5 discusses the factors influencing option-implied disagreement. Finally, Section 6 concludes.

2 Hypotheses and Related Literature

Differences in opinions arise due to different information sets or different ways of updating beliefs. Subsequently they have different pricing implications for expected stock returns.

If differences in opinions reflect information asymmetry then an increase in disagreement lowers current stock prices, and positively predicts expected stock returns (Kraus and Smith, 1989; Wang, 1993; Harris and Raviv, 1993; He and Wang, 1995; Naik, 1997). In these models, the expected return on an asset is driven by investors' perceived risk from holding that asset. When investors have heterogeneous beliefs about a stock's future dividends and realize that others also have relevant information, they condition more aggressively on prices to infer the valuation of others. As a result, disagreement and perceived information risk are positively related and higher disagreement is compensated by a higher expected return in equilibrium.

In contrast, when investors have heterogeneous beliefs and agree to disagree (Banerjee, 2011), they rely solely on their personal interpretations of incoming news, and update their valuation of an asset according to their private models. As these private valuations diverge, the higher disagreement is associated with more certainty of these investors about their own assessment of

asset prices. As their perception of information risk and uncertainty decreases, higher disagreement leads to lower future stock returns. This negative relation between disagreement and future returns is also consistent with standard disagreement models relying on the presence of shorting constraints (Harrison and Kreps, 1978; Scheinkman and Xiong, 2003; Hong, Scheinkman, and Xiong, 2006). Banerjee (2011), however, shows that this negative relation can theoretically be also obtained without short-sale restrictions.

Ex-ante, the nature of disagreement captured by options trades is not obvious. On the one hand, the options literature convincingly argues that informed trading aggressively takes place in the options market (Pan and Poteshman 2006; Easley et al., 1998; Cremers and Weinbaum, 2010). If options markets largely disagree about asymmetric information, then we should expect positive predictability for stock returns. On the other hand some literature argues in favor of disagreement driven trading in options (Vijh, 1990; Cho and Engle, 1999; and Choy and Wei, 2012). In the latter case, disagreement should have negative predictability for stock returns. Overall, which effect dominates is an empirical question. We answer it in our first hypothesis:

H1. *If the options market is the venue where investors "agree to disagree" about the value of the underlying, we should observe negative disagreement-return predictive relations. If options trades are dominated by disagreement about private information, a positive relations should prevail. Finally, if options disagreement is irrelevant, we should find no predictive effect for stock returns.*

Not only do we find that the options market disagreement is not irrelevant, but we also provide compelling evidence that options disagreement captures the trading behavior of investors who agree to disagree.

In what follows, we use this result to further test and understand empirical properties and economic determinants of disagreement suggested by the theories. This, in turn, allows us to contribute to the literature in understanding the sources of disagreement.

In agree to disagree models, investors disagree even if they have the same information (Harrison and Kreps, 1978; Harris and Raviv, 1993; Kandel and Pearson, 1995; Scheinkman and Xiong, 2003; and Cao and Ou-Yang, 2009). This outcome occurs when investors use different models to update their beliefs and forecast firm values. Therefore, as news arrival increases disagreement, its subsequent effect on stock returns should be higher for firms with new public releases compared to those without. Further, since traders equally disagree about either positive or negative news (Kandel and Pearson, 1995), for the news sample, the predictive effect of disagreement should be qualitatively similar for stock with positive or negative information releases. The testable implications of these theories are summarized in the following hypotheses:

H2.1. *As option investors agree to disagree, the predictive ability of disagreement in the*

cross-section of stocks covered by news releases should be stronger compared to no-news cross-section.

H2.2.: *The impact of disagreement on future stock returns should remain negative regardless of whether stocks are experiencing positive or negative news.*

H2.3. *Disagreement should increase with public news releases.*

Short selling costs can be a serious impediment for pessimistic investors in the stock market. However in order to overcome these costs, short-sellers can trade in the options market. As short-sellers start taking synthetic short positions using options, our disagreement measure should increase, as sidelined Miller (1977) type pessimists now have a venue to short stocks.

To capture the expensiveness of short selling in the stock market and an increased demand for options by pessimists we use explicit costs of short-selling: short-selling fees and availability of shares on loans. D'Avalio (2002) and Duffie, Garleanu and Pedersen (2002) argue that short-selling fees and share availability on loans are a function of differences of opinions. D'Avalio (2002) documents that the cost of borrowing a stock is positively predicted by turnover and dispersion of analyst forecasts, which are empirical proxies for disagreement. Duffie, Garleanu and Pedersen (2002) formalize this idea and show that lending fees and demand for loanable securities are endogenously increasing in differences of opinions. In Duffie, Garleanu and Pedersen (2002)'s model, lending fees reflect the expectations of future shorting demand and future price declines. By anticipating higher future lending fees caused by higher future shorting demand, optimists are willing to pay higher prices for stocks today expecting to lend them in the future. This inflates current prices and lowers future returns. Thus, disagreement is positively related to lending fees and negatively related to future stock returns. We directly test the theoretical predictions of Duffie, Garleanu and Pedersen (2002) in the following hypothesis:

H3.1: *The predictive power of option-implied disagreement for stock returns is more pronounced among stocks with higher loan fees or that are harder-to-borrow.*

H3.2: *Disagreement should increase with the costs of short-selling.*

The dynamic models of disagreement and short sale constraints (Harrison and Kreps, 1978; Scheinkman and Xiong, 2003; and Hong, Scheinkman, and Xiong, 2006) strongly suggest a positive relation between disagreement and volume. Abstracting from short-sale constraints, when investors use different economic models and interpret the same news differently, i.e., agree to disagree (Harris and Raviv, 1993; Kandel and Pearson, 1995; and Banerjee, 2011), we should also observe an increase in volume. Hong and Stein (2007) also advocate an overpricing of glamour stocks due to investors' different conclusions about the same public news, and re-emphasize an increase in subsequent trading volume. Theoretically, Banerjee and Kremer (2010) show that

when investors agree to disagree, an increase in trading volume should also be accompanied by an increase in volatility. This leads us to the final set of hypotheses:

H4.1. *Disagreement positively predicts stock trading activity*

H4.2. *Disagreement positively predicts stock volatility*

3 Data

We first describe the data sources and the construction of the variables used in the empirical analysis. We then present descriptive statistics.

3.1 Data Sources

Our sample period is from January 2005 to December 2013. We adopt a weekly measurement frequency where a week is defined from Monday market open to Friday market close.[2] Our sample is composed of 470 weeks in total.

Option-Implied Disagreement

We obtain Open/Close trading volume data from CBOE and ISE. Together, these data account for more than sixty percent of the total trading activity in the US equity options market. Both exchanges provide information on daily trading volumes of individual equity options with buy and sell order identifiers for firms and customers. For each investor category, volumes are further categorized into open buy, close buy, open sell, and close sell orders by option series. Firm orders are exclusively initiated by proprietary trading desks. Customer orders correspond to the remaining orders not submitted by proprietary trading desks. Option market-makers' trading volume is not included in these data. Because our main objective is to study disagreement among investors rather than the strategic trading of prop-desks we focus on customer order flows. This is consistent with several other papers which also use customer orders when studying the relation between options volume and stock returns (Pan and Poteshman, 2006; Ni, Pan and Poteshman, 2008).

We merge the CBOE and ISE customer order flow data with OptionMetrics to obtain option deltas. To avoid rollover trades around contract expirations, we eliminate options with less than 10 days to maturity. We also filter out options with missing implied volatilities or deltas and

[2] We adopt a weekly frequency to avoid market microstructure biases in daily returns documented by previous studies. The results we document in Section 4 below are robust to a daily measurement frequency.

with absolute deltas greater than 0.98 or lower than 0.02.[3]

Based on equity option customer order flows, we construct two weekly measures of disagreement. For the first measure, we compute disagreement on each day d from call and put option order flows separately, and then aggregate them. This allows controlling for stylized facts that calls trade more actively than puts (Cristoffersen et al 2017). We denote call disagreement for stock i on day d, $DIS^C_{i,d}$. $DIS^P_{i,d}$ corresponds to put disagreement. For a given payoff category $Z \in \{C, P\}$, disagreement is given by

$$DIS^Z_{i,d} \equiv \frac{\sum_j^{N^Z_{i,d}} abs(\Delta^Z_{i,j,d}) \left[BO^Z_{i,j,d} + SO^Z_{i,j,d} - abs\left(BO^Z_{i,j,d} - SO^Z_{i,j,d}\right)\right]}{\sum_j^{N^Z_{i,d}} \left(BO^Z_{i,j,d} + SO^Z_{i,j,d}\right)}, \tag{3.1}$$

where j identifies a particular call option when $Z = C$ or put option when $Z = P$, $N^Z_{i,d}$ denotes the total number of puts or calls quoted on day d and written on stock i, $\Delta^Z_{i,j,d}$ is the option delta, and $abs(\cdot)$ is the absolute value operator. Based on this notation, the combination $\{j, Z, i\}$ identifies one particular option written on stock i. In (3.1), $BO^Z_{i,j,d}$ denotes customer total buy orders for option $\{j, Z, i\}$ on day d, which is the sum of customer open and close buy orders. Similarly, $SO^Z_{i,j,d}$ is customer total sell orders, the sum of customer open and close sell orders.

To see why our measure captures disagreement, consider the following example using call order flows. Suppose that on day d options end-users disagree and take equal positive and negative exposures to the underlying stock i by trading calls, such that $BO^C_{i,j,d} = SO^C_{i,j,d}$ for all $j \in \left\{1, ..., N^C_{i,d}\right\}$. Then, $abs\left(BO^C_{i,j,d} - SO^C_{i,j,d}\right) = 0$ for all j, the numerator in (3.1) is large due to significant trading dispersion, and $DIS^C_{i,d}$ is high. In contrast, if on day d options end-users only send buy orders for calls (i.e. $BO^C_{i,j,d} > 0$ and $SO^C_{i,j,d} = 0$) then the sum of trading dispersion is 0 and $DIS^C_{i,d} = 0$.[4]

Note that we weigh order-flows by absolute deltas in (3.1). The delta-weighting converts raw option orders into units of exposure to the underlying stock i. Because put deltas are negative, taking the absolute value of deltas allows put- and call-implied disagreements to be symmetric.

For a given payoff category and underlying stock, we divide the sum of delta-weighted trading dispersion by total customer-initiated trading volume. We perform these calculations daily for each stock to obtain $DIS^C_{i,d}$ and $DIS^P_{i,d}$. We require at least one order per day to compute the daily disagreement measures.

In the second step, we calculate the average of call- and put-implied disagreements. Trading activity in equity calls is substantially higher than in equity puts (see, among others, Cao and

[3] The results we document are not sensitive to this filter.

[4] $DIS^C_{i,d}$ is also equal to 0 when $BO^C_{i,j,d} = 0$ and $SO^C_{i,j,d} > 0$ across calls.

Han, 2013; Christoffersen, Goyenko, Jacobs, and Karoui, 2015; Christoffersen, Fournier, and Jacobs, 2016). We account for this stylized fact by volume-weighting call- and put-implied disagreements.[5] More specifically, we compute disagreement on day d as

$$DIS_{i,d} \equiv DIS^C_{i,d} \cdot w^C_{i,d} + DIS^P_{i,d} \cdot w^P_{i,d}, \tag{3.2}$$

where $w^Z_{i,d}$ with $Z \in \{C, P\}$ is given by

$$w^Z_{i,d} = \frac{\sum_j^{N^Z_{i,d}} \left(BO^Z_{i,j,d} + SO^Z_{i,j,d}\right)}{\sum_j^{N^C_{i,d}} \left(BO^C_{i,j,d} + SO^C_{i,j,d}\right) + \sum_j^{N^P_{i,d}} \left(BO^P_{i,j,d} + SO^P_{i,j,d}\right)}. \tag{3.3}$$

In the third step, we average the daily measures for each week t to obtain $DIS_{i,t}$.[6]

Our second measure of disagreement jointly combines the volume of calls and puts. While the sum $BO^C_{i,j,d} + SO^P_{i,j,d}$ provides positive exposure to the price of stock i, $SO^C_{i,j,d} + BO^P_{i,j,d}$ provides negative exposure to the underlying stock price. Defining $Pos_{i,j,d} \equiv \Delta^C_{i,j,d} \cdot BO^C_{i,j,d} + abs(\Delta^P_{i,j,d}) \cdot SO^P_{i,j,d}$ and $Neg_{i,j,d} \equiv \Delta^C_{i,j,d} \cdot SO^C_{i,j,d} + abs(\Delta^P_{i,j,d}) \cdot BO^P_{i,j,d}$, the delta-weighted positive and negative exposures, respectively, our second measure satisfies on each day d and underlying stock i

$$DIS\text{-}CP_{i,d} \equiv \frac{\sum_j^{N_{i,d}} \left[Pos_{i,j,d} + Neg_{i,j,d} - abs\left(Pos_{i,j,d} - Neg_{i,j,d}\right)\right]}{\sum_j^{N_{i,d}} \left(BO^C_{i,j,d} + SO^P_{i,j,d} + SO^C_{i,j,d} + BO^P_{i,j,d}\right)}, \tag{3.4}$$

where $N_{i,d} = \max(N^C_{i,d}, N^P_{i,d})$ is the maximum number of calls or puts quoted on day d. Unlike our first proxy, this measure does not explicitly account for differences between call and put trading volumes. Similarly to our first proxy, $DIS\text{-}CP_{i,d}$ is high whenever $Pos_{i,j,d} = Neg_{i,j,d}$. In contrast, it will be low whenever $Pos_{i,j,d} > 0$ and $Neg_{i,j,d} = 0$ or $Pos_{i,j,d} = 0$ and $Neg_{i,j,d} > 0$. For consistency with the construction of our first proxy, we require at least one order per day to compute $DIS\text{-}CP_{i,d}$.

In the second step, we average the daily measures for each week t and underlying stock i to obtain $DIS\text{-}CP_{i,t}$.[7]

[5] Our results are robust to an equal-weighting scheme.

[6] The numerator in (3.1) is weighted by options deltas where the maximum observable delta is 0.98 given our filter. Thus, $DIS_{i,t}$ can take any value between 0 (i.e. no disagreement) and 0.98 (i.e. maximum disagreement).

[7] A potential concern when constructing disagreement measures from equity option order flows is that these measures may capture disagreement about underlying stock volatility. To investigate this, we constructed disagreement measures from straddles only. Straddle-disagreements have low correlation with our disagreement measures and have no predictive power for stock returns.

Stock-Based Disagreement: Analyst Dispersion and Turnover

Following Diether, Malloy, and Scherbina (2002) among many others, we construct a measure of analyst forecast dispersion using analyst forecasts from IBES data. At the end of each trading week t, we compute the standard deviation and the average of analyst forecasts for the next year's earnings per share of stock i. We define analyst forecast dispersion as the ratio of analyst forecasts' standard deviation divided by the average of analyst forecasts. We require a minimum of two forecasts to construct this variable. Because the average earnings forecasts are close to zero for some stocks, it creates significant outliers when computing analyst dispersion. Consequently, we winsorize the variable at the 99th percentile and denote it $Analyst\text{-}Disp_{i,t}$.

Following Hong and Stein (2007) and D'Avalio (2002), we also use stock turnover as a proxy for disagreement. We compute the daily ratio of stock volume to shares outstanding and take the average over each week to obtain a weekly stock-level estimate of turnover. We denote this variable $Turnover_{i,t}$.

Stock Market Control Variables

Our analysis focuses on all common stocks listed on NYSE, AMEX, and NASDAQ with options traded on CBOE and/or ISE. We use various stock market variables throughout our analysis. Variables obtained from the Center for Research on Securities Prices' (CRSP) daily stock files include stock returns, prices, volume, and shares outstanding. We denote stock weekly market capitalization $Size_{i,t}$. It is defined as the logarithm of stock i's market capitalization observed on the last trading day on any given week. We further control for stock volatility by including $\sigma(Ret_{i,t})$, which equals the standard deviation of the most recent 60 daily returns.

We complement these variables with information obtained from the Trade and Quote (TAQ) database. On each day, stock order imbalance, $StockIMB_{i,d}$, is defined as the total daily dollar buy volume minus the total dollar sell volume divided by the sum of both. To identify buys and sells, we sign intraday volume using Lee and Ready (1991) algorithm. Stock illiquidity, $ILS_{i,d}$, is the average daily dollar-volume-weighted relative effective spread. We average these variables over each week t to obtain $StockIMB_{i,t}$ and $ILS_{i,t}$.

News

The analyst literature has provided extensive evidence on the way earning announcements influence analyst recommendations in an attempt to explain the post-earnings-announcement drift.[8]

[8] See, among many others, Abarbanell and Bernard (1992) for a discussion of analyst over- and under-reaction to earning announcements.

However, little evidence exists on the way news arrival impacts investor disagreement.

To investigate this, we obtain firm-specific news data from RavenPack Analytics DowJones and Press Release files (RPA). One key advantage of RPA data is that it covers a wide range of news categories not only limited to earning announcements. Because RPA data are rich and have not yet been used by previous studies on disagreement, it offers a unique opportunity to analyze the way public information and dispersion of investor beliefs interact with each other.

RPA converts unstructured news into a set of standardized variables describing the content of the news. RPA identifies the company affected by the news story and provides a relevance score that indicates how important the news is for the firm covered by the news. RPA also provides a novelty score which reflects whether a news story is related to previously released news. We restrict our analysis to the most relevant and novel news identified by relevance and novelty scores equal to 100.

When studying the interaction of disagreement with news, we rely on RPA's event sentiment score (ESS). ESS is provided by RPA on a firm-news level basis. A higher score should have a more positive impact on the firm's stock price.

For each firm, we calculate a daily news index as follows. We first compute the average of ESS of all news observed between the previous trading day's market close and the current trading day's close. News released during non-trading hours are assigned to the next trading day. In a second step, we average the daily ESS over each week to obtain $ESS_{i,t}$.

Short-Sale Constraints and Hard-to-Borrow Stocks

In most disagreement models, the pricing implications of disagreement rely on the existence of short-sale constraints which are usually assumed to be exogenous. This assumption is relaxed by Duffie, Garleanu and Pedersen (2002) who derive the equilibrium relation between disagreement, lending fees, and the supply of lendable shares.

To analyze how option-implied disagreement and short-sale constraints interact to influence future stock returns we obtain data on loan fees and loan supply from the Markit Security Finance. Our key variables to measure short-selling restrictions are the indicative fee and the utilization rate. The indicative fee is the expected cost of borrowing a stock on a given day. The utilization rate is the value of assets on loan from lenders divided by the total lendable value. It is thus negatively related to the availability of lendable shares for a given stock. We average the daily variables weekly and denote them $LoanFee_{i,t}$ and $UtilizationRate_{i,t}$, respectively. Note that we use indicative instead of actual loan fees to proxy for current short-sale constraints. The advantages of doing so are twofold. First, indicative fees capture the expected

costs of new borrowers while actual loan fees reflect the fees paid for loans already outstanding. Second, indicative fees are updated daily while actual loan fees are not. Actual loan fees are thus backward-looking and outdated when no borrowing has occurred for an extended period of time.

Options Market Control Variables

We include a series of control variables to assess the robustness of our results. We use options order imbalances to control for the impact of demand pressures and directional trading in options may have on stock prices. Following Bollen and Whaley (2004), we compute daily imbalances for customer order flows for each stock i as

$$IMB\text{-}Option_{i,d} \equiv \frac{\sum_j^{N_{i,d}^C} \Delta_{i,j,d}^C \left(BO_{i,j,d}^C - SO_{i,j,d}^C\right) + \sum_j^{N_{i,d}^P} abs(\Delta_{i,j,d}^P) \left(BO_{i,j,d}^P - SO_{i,j,d}^P\right)}{\sum_j^{N_{i,d}^C} \left(BO_{i,j,d}^C + SO_{i,j,d}^C\right) + \sum_j^{N_{i,d}^P} \left(BO_{i,j,d}^P + SO_{i,j,d}^P\right)}, \quad (3.5)$$

where $\Delta_{i,j,d}^Z$ is the option $\{j, Z, i\}$'s delta, and $BO_{i,j,d}^Z$ and $SO_{i,j,d}^Z$ denote customer total buy and sell orders for option $\{j, Z, i\}$ on day d, respectively.

To control for informed trading activity in options, we use Pan and Poteshman (2006)'s put-to-call volume ratio. On day d for stock i, it is defined as

$$PP_{i,d} = \frac{\sum_j^{N_{i,d}^P} OBO_{i,j,d}^P}{\sum_j^{N_{i,d}^P} OBO_{i,j,d}^P + \sum_j^{N_{i,d}^C} OBO_{i,j,d}^C}, \quad (3.6)$$

where $OBO_{i,j,d}^Z$ denotes customer open buy orders for the option $\{j, Z, i\}$. Note that $PP_{i,d}$ is constructed from customer open buy orders only. This specification is motivated by the strongest predictability results documented in Pan and Poteshman (2006).

To account for trading activity in equity options, we also construct a daily measure of log-option volume, $log(OptVolume)_{i,d}$. It is defined as the log of total option volume where total option volume is obtained from OptionMetrics.

For each stock, the daily variables discussed above are then averaged over each week.

3.2 Descriptive Statistics

Table 1 presents the mean, standard deviation, and the 1st, 50th, and 99th percentiles of the variables of interest. Panel A reports these statistics for the two measures of disagreement constructed from option order flow as well as for analyst dispersion and turnover. The means of $DIS_{i,t}$ and $DIS\text{-}CP_{i,t}$ are comparable in magnitude with their respective standard deviation.

Thus, the signal to noise ratio of these measures is relatively high. Similar observations can be made about stock turnover. Unlike option-implied disagreements and turnover, the standard deviation of $Analyst\text{-}Disp_{i,t}$ is about three times bigger than its sample mean. Arguably, this low signal to noise ratio indicates the difficulty to precisely measure disagreement from analyst forecast data. Moreover, the 99th percentile of $Analyst\text{-}Disp_{i,t}$ is about 20 times its sample average even after winsorizing. This suggests significant outliers in the cross-sectional distribution of this variable.

Panel B presents the results for the news and short-selling variables. The average ESS is 54.82 and its median is 52.45. The average of utilization rate and loan fee are 22.92% and 1.39%, respectively. As one would expect, both measures are positively skewed (as the mean is greater than the median).

Panel C presents the statistics for the remaining variables. Average customer imbalances are negative similar to the evidence reported in Lakonishok et al. (2007) among others. Note that the mean and standard deviation of the remaining variables compare well to what has been reported in previous studies.

Table 2 presents the cross-sectional correlations of option-implied disagreements with some key variables. For any pair of variables, the correlations are first computed across stocks on a weekly basis and then averaged over time. Panel A shows correlations between different measures of disagreement. We document the correlations of option disagreement with news and short-sale constraint proxies in Panel B, and with the remaining control variables in Panel C.

The reported correlations provide a few important insights. The two option-implied disagreement measures are highly correlated with a correlation coefficient of 0.94. This suggests that the differences in constructions between the two measures should have little effect on our empirical results.

Theoretically, disagreement models predict a strong and positive relation between disagreement, volume, and turnover (see, Hong and Stein, 2007). The high correlations of option-implied disagreement with turnover in Panel A and log-option volume in Panel C are consistent with these predictions. This is in stark contrast with analyst dispersion which has a low correlation with turnover and log-option volume in our sample. Moreover, the correlation between $Analyst\text{-}Disp_{i,t}$ and option-implied disagreement is almost zero in both cases which indicates the novelty of our measures relative to analyst dispersion.

The correlations between our measures and Pan and Poteshman (2006)'s put-to-call volume ratio ($PP_{i,t}$) as well as option imbalances ($IMB\text{-}Option_{i,t}$) are small in absolute value. This demonstrates that option-implied disagreement variables are not related to informed and directional trading activity in options.

$DIS_{i,t}$ and $DIS\text{-}CP_{i,t}$ are negatively correlated with stock illiquidity and positively with size. This can be explained by the fact that bigger and more liquid companies have a richer news environment. These firms may thus face a higher level of investor disagreement. This is consistent with the small but positive correlations between ESS and the two disagreement measures in Panel B.

We conclude that option-implied disagreement embeds information that is not already captured by $Analyst\text{-}Disp_{i,t}$, and various option- and stock-based variables. We now analyze the pricing implications of disagreement in the options market for stock returns.

4 Option-Implied Disagreement and the Cross-Section of Stock Returns

Guided by the hypotheses in Section 2, we study the pricing of option-implied disagreement in the cross-section of equities. We first investigate the risk-adjusted return properties of portfolios sorted on disagreement. We then analyze its predictive power for future stock returns based on cross-sectional regressions controlling for various stock and option-based characteristics. Finally, we study the way disagreement interacts with news and short-sale constraints.

4.1 Portfolio Sorting on Option-Implied Disagreement

To study the economic impact of option-implied disagreement on stock returns, we adopt a portfolio sorting methodology. On each week we sort stocks on $DIS_{i,t}$ or $DIS\text{-}CP_{i,t}$ into quintile portfolios and compute both equally- and value-weighted returns of these portfolios for the following weeks. We then estimate the risk-adjusted alphas of these portfolios and of high minus low zero investment trading strategies based on Fama-French-Carhart risk factors. We consider five predictive investment horizons of one, two, three, four, and five weeks ahead. The statistical significance of the alphas is evaluated based on Newey-West standard errors adjusted for three autocorrelation lags. Table 3 reports the results obtained.

Consider Panels A and B of Table 3 first in which we present the portfolio sorting results for our benchmark measure of disagreement, $DIS_{i,t}$. Independently of the weighting scheme and forecast horizon considered, the highest DIS portfolios in Panels A and B always obtain the most negative alphas. For a horizon of one week, the highest DIS equally-weighted portfolio obtains a negative alpha of -3.12% annualized ($t = -1.66$). When using value-weighted portfolio returns, the alpha is smaller in absolute value, -1.44% annualized, but its statistical significance increases ($t = -2.12$). Let us now consider the high minus low strategy which buys the high disagreement

portfolio and shorts the low disagreement portfolio in week t and then unwinds the position the following weeks. For a horizon of one week, this zero cost strategy produces annualized alphas of -4.92% ($t = -2.58$) for the equally-weighted portfolios and of -2.89% ($t = -1.98$) for the value-weighted portfolios. Note also the way the economic magnitudes of the high minus low DIS strategy, and its statistical significance, increases with the horizon. For a forecast horizon of five weeks, the alpha increases, in absolute values, to -6.03% per year ($t = -2.97$) for the equally-weighted portfolios and to -5.14% ($t = -3.14$) for the value-weighted ones. These results provide evidence of the substantial economic impact of option-implied disagreement on future stock returns after standard risk adjustments. Panels C and D of Table 3 present the portfolios sorting results for the alternative measure of disagreement, $DIS\text{-}CP_{i,t}$. Overall, the results are qualitatively and quantitatively similar to those reported in Panel A.

We conclude that the negative predictability of disagreement for stock returns is economically meaningful and is robust to the specification used to measure disagreement in the options market. In the next section, we test the predictive power of disagreement using multivariate cross-sectional regressions controlling for various stock and options characteristics.

4.2 Multivariate Predictive Regressions

The previous section provides first evidence of the negative impact of disagreement on future stock returns. In this section, we directly test **H1** controlling for relevant predictors introduced by previous studies. Our main regression specification is as follows

$$CAR_{i,t+1} = \alpha_t + \beta_t^{Dis} \times DIS_{i,t} + \beta_t^{Cont.} \times Controls_{i,t} + \varepsilon_{i,t+1}, \tag{4.1}$$

where $DIS_{i,t}$ (or $DIS\text{-}CP_{i,t}$) is the option-implied disagreement measure, $Controls_{i,t}$ is the matrix of control variables, and $\beta_t^{Cont.}$ denotes the vector of factor loadings of the control variables. We denote weekly cumulative abnormal returns by $CAR_{i,t+1}$. They correspond to the difference between weekly compounded returns on stocks and CRSP value-weighted market portfolio returns. We run (4.1) on each week to obtain the time-series of coefficients, $\left\{\alpha_t, \beta_t^{Dis}, \beta_t^{Cont.}\right\}_{t\in\{1,\ldots,470\}}$. In the tables, we report the average of the weekly coefficients, and the t-statistics below the coefficients are computed using Newey-West methodology allowing for three autocorrelation lags. In the last two rows we also report the average adjusted R-squared and the average number of stocks per week, N, respectively.

Table 4 presents the Fama-MacBeth regressions estimation results for our benchmark specification when we include three return lags to control for price run-ups and reversals. Several studies argue that volatility and disagreement are positively related (Harris and Raviv, 1993;

Banerjee and Kremer, 2010). To understand whether the predictive ability of our measures is related to volatility, we also control for $\sigma(Ret_{i,t})$ in the regressions. Our sample includes the recent financial crisis. To assess the sensitivity of our results to the 2008-2009 crisis, we present the results for the whole sample (e.g., 2005-2013) in columns 1 and 2 and for the post-crisis period (e.g., 2010-2013) in columns 3 and 4. Note that we estimate (4.1) using $DIS_{i,t}$ and $DIS\text{-}CP_{i,t}$, separately.

Regardless of the disagreement measure and sample considered, disagreement always negatively and significantly predicts next week abnormal stock returns. Comparing the coefficients for disagreement in columns 1 and 2 with the ones in columns 3 and 4, we see that the coefficients estimated for the post-crisis period are slightly bigger in absolute value than the ones obtained for the full sample. Not only their economic magnitude increases in absolute value after the crisis but their t-statistics are also larger in absolute value. We conclude that the negative impact of disagreement on future stock returns is not driven by the financial crisis.

The coefficient estimated for the first lag of stock returns, $Ret_{i,t}$, is negative and statistically significant in all regressions. In contrast, the coefficient for $\sigma(Ret_{i,t})$ is negative but only statistically significant for the 2005-2013 sample period. The negative predictive power of $\sigma(Ret_{i,t})$ is consistent with the evidence reported by Ang et al. (2006). Because controlling for $\sigma(Ret_{i,t})$ in the regressions has no impact on the predictive ability of disagreement, we conclude that option-implied disagreement is not related to the idiosyncratic variance puzzle of Ang et al. (2006).

Building on Nagel (2005), we further control in (4.1) for two alternative measures of disagreement constructed from stock market data only: stock turnover (D'Avalio, 2002) and analyst forecast dispersion (Diether, Malloy, and Scherbina, 2002). We present the results in Table 5.

As readily apparent from the results in column 1 of Table 5, analyst disagreement is not a significant predictor of stock returns in our sample even though it has the expected negative sign. $Turnover_{i,t}$ obtains also a negative coefficient which is not statistically significant. Interestingly, once $Analyst\text{-}Disp_{i,t}$ or $Turnover_{i,t}$ are included in the regressions $\sigma(Ret_{i,t})$ becomes insignificant. Moreover, the sign of the coefficient for $\sigma(Ret_{i,t})$ switches when stock turnover is included in the regressions. Consistent with Buraschi, Trojani and Vedolin (2014), this evidence indicates a tight link between volatility and stock market-based disagreement measures.

Columns 3 and 4 present the key results of Table 5. Option-implied disagreements negatively predict future stock returns at conventional statistical levels even after controlling for commonly used stock market disagreement proxies. We conclude that disagreement in the options market not only wins a horse race between various disagreement measures but also captures novel information not related to that of conventional proxies.

Overall, the results documented so far provide support to the models where agents agree to disagree. More specifically, traders in these models use different likelihood functions to interpret public news (Kandel and Pearson, 1995). To explain the negative relation between disagreement and expected returns, other models explicitly rely on short-sale constraints and heterogeneity of beliefs (Miller, 1977; Harrison and Kreps, 1978; Scheinkman and Xiong, 2003). Empirically, using analyst forecast dispersion, Diether, Malloy, and Scherbina (2002) find evidence of a negative relationship between disagreement and stock returns. They attribute their results to the optimistic investor model of Miller (1977). Banerjee (2011) shows that when investors agree to disagree, disagreement negatively impacts stock expected returns even in the absence of short-sale constraints. Since the existence of options markets alleviates the impact of short-selling constraints, our results are also consistent with Banerjee (2011) theoretical predictions.

In the subsequent analysis, we further explore the robustness of our results for multi-horizon return forecasts, and shed light on the information content of option-implied disagreement.

Robustness Analysis

In the rest of our analysis we use our benchmark measure $DIS_{i,t}$, and the results for our alternative measure, $DIS\text{-}CP_{i,t}$, are reported in to the Appendix.

Table 6 presents the results of multivariate predictive regressions. We consider five horizons ranging from one to five week-ahead. Motivated by previous studies we also include relevant option- and stock-based control variables: $IMB\text{-}Option_{i,t}$, $PP_{i,t}$, $log(OptVolume)_{i,t}$, $ILS_{i,t}$, $Size_{i,t}$, and $StockIMB_{i,t}$ (see, among others, Pan and Poteshman, 2006; Kelley and Tetlock, 2013; Hu, 2014).

$DIS_{i,t}$ obtains a negative coefficient independently of the horizon considered. The variable is highly statistically significant to predict stock returns up to four weeks ahead and still remains marginally significant when forecasting five weeks ahead returns. Interestingly, the coefficients estimated for $DIS_{i,t}$ are relatively stable across horizons. They range from -0.395 ($t = -3.83$) for the one-week ahead forecast to -0.223 ($t = -1.86$) for a forecasting horizon of five weeks. The economic magnitude of the impact of option-implied disagreement on next week abnormal returns is large. A one standard deviation increase in $DIS_{i,t}$ leads to a -0.05% abnormal stock returns in the next week. This corresponds to an annual abnormal returns of -2.34%. Thus, the economic magnitude estimated through the lance of cross-sectional predictive regressions is consistent with the risk-adjusted alphas reported in Table 3.

Among other control variables, $PP_{i,t}$ is statistically significant and negatively predicts stock returns independently of the horizon. This result is consistent with Pan and Poteshman (2006).

However, the economic magnitude of the impact $PP_{i,t}$ on future stock returns is not as persistent as the one of $DIS_{i,t}$. For example, when forecasting three weeks ahead returns the coefficient estimated for $PP_{i,t}$ decreases by a factor of three relative to the one estimated when forecasting one week ahead returns. Unlike $DIS_{i,t}$, the coefficient estimated for $PP_{i,t}$ tend to converge toward 0 as the horizon increases. Arguably, the transitory impact of $PP_{i,t}$ can be explained by the fast dissemination of private information in stock prices (Pan and Poteshman, 2006). This highlights important discrepancies in the persistence of the impact that $DIS_{i,t}$ and $PP_{i,t}$ have on future stock returns.

Hu (2014) documents that option order imbalances capture the hedging needs of option market makers and help predict stock returns. Consistent with Hu (2014), we find positive predictive effect of $IMB\text{-}Option_{i,t}$ for next week stock returns. However, its coefficient becomes insignificant beyond one week horizon and changes sign depending on the horizon considered.

$ILS_{i,t}$ negatively predicts future stock returns while size is insignificant in all regressions. The negative predictive effect of $ILS_{i,t}$ for stock returns is consistent with stock market under-reaction to stock-level liquidity shocks documented in Bali et al. (2013). Kelley and Tetlock (2013) show that stock order imbalances are positively related to future stock returns. Consistent with this study, we also find that $StockIMB_{i,t}$ has a positive impact on abnormal stock returns but is only significant when forecasting two weeks ahead returns.

Table A.1 reports the results obtained when using our alternative measure of option-implied disagreement, $DIS\text{-}CP_{i,t}$. Overall, the results documented in this section are robust to the disagreement measure specification used.

Several important conclusions can be drawn from the analysis in this section. The results demonstrate that option-implied measures of divergence of opinions capture patterns in the cross-section of future stock returns better than other known predictors. The sign of the estimated coefficients for these variable are broadly consistent with the prediction of disagreement models where investors agree to disagree. We find that the predictive ability of these measures is not related to various option- and stock-based variables. Unlike other predictors, the impact of disagreement in the options market is pervasive and is robust across horizons. We next study the interactions between disagreement and firm specific news, and their impact on future stock returns.

4.3 Option-Implied Disagreement and Firm-Specific News

As new public information arrives to financial markets, investors form opinions about firms' outlook which should increase disagreement when investors have heterogeneous priors and agree to

disagree (Kandel and Pearson, 1995; Hong and Stein, 2007; Cao and Ou-Yang, 2009). Consequently, the predictive ability of disagreement in the cross-section of stocks with news releases should be stronger, compared to stocks without public news.

Kandel and Pearson (1995) argue that disagreement should increase with positive and negative news about the firm. The pricing implication of this argument is that the negative impact of disagreement on future stock returns should be observed for firms covered by both positive and negative news releases. We also empirically test and confirm Kandel and Pearson (1995) hypothesis that disagreement does increase with public news.

To test these predictions, each week we construct the following variables. The first variable is a dummy indicator which is equal to 1 for stock i on a week t whenever a news has been released for that stock on that week. We denote it $IndicNews_{i,t}$. We then multiply the news indicators and $1 - IndicNews_{i,t}$ by disagreement for each stock on each week. We denote these interaction variables $DIS\text{-}News_{i,t}$, and $DIS\text{-}NoNews_{i,t}$, respectively.[9]

We also construct two dummy variables informative about the direction of the news. The first dummy indicates whether the news are positive on average for stock i on week t. It takes the value of 1 whenever $ESS_{i,t} \geqslant median(ESS)$ and is set to 0 otherwise. Reciprocally, the second dummy indicates whether the news are negative for stock i on week t (i.e. it is is equal to 1 whenever $ESS_{i,t} < median(ESS)$ and 0 otherwise). Note that we use the pooled median of ESS of 54.82 in the construction of these dummy variables. We then multiply the positive and negative news indicators by disagreement for each stock on each week. We denote these interaction variables $DIS\text{-}P_{i,t}$, and $DIS\text{-}N_{i,t}$, respectively.

We further construct a proxy for investor attention. The $NewsCount_{i,t}$ variable reflects the total number of news for each firm for a week t. Investors' attention has been argued to be a key determinant of asset prices (Da, Engelberg, and Gao, 2011; Andrei and Hasler, 2015). Da et al. (2011) suggest a positive predictive impact of investors' attention on next week stock returns. Andrei and Hasler (2015) provide evidence of an increase in aggregate volatility due to higher attention. This literature uses the search frequency in Google to measure investors attention. We hypothesize that the frequency of public news releases can be another direct proxy for investors attention. Obviously, attention and disagreement can be related since more attention to news can cause more disagreement. Therefore, controlling for attention can be important. It allows to separate the effect of disagreement on stock returns due to an increase in existing heterogeneous priors versus an increase in attention or learning about stocks (Andrei and Hasler, 2015).

Finally, we construct an earnings announcement dummy indicator. This variable takes the

[9] $DIS\text{-}News_{i,t}$ is equal to disagreement if a firm has news on a week t and to zero otherwise. Reciprocally, $DIS\text{-}NoNews_{i,t}$ equals disagreement whenever a firm does not have any news on a week t and to zero otherwise.

value 1 whenever a stock has an earnings announcement on a given week. We then multiply the earnings indicators and one minus the earnings indicators (i.e., indicator of no earnings announcement) by disagreement for each stock on each week. We denote these interaction variables $DIS\text{-}E_{i,t}$, and $DIS\text{-}NoE_{i,t}$, respectively.[10]

Based on these variables we run predictive cross-sectional Fama-MacBeth regressions. We report the average coefficients estimated and their Newey-West t-statistics in Table 7. Our first regression specification investigates the way news releases and disagreement interact with each other to influence next week stock abnormal returns. Each week, we regress $CAR_{i,t+1}$ on $IndicNews_{i,t}$, $DIS\text{-}News_{i,t}$, $DIS\text{-}NoNews_{i,t}$, and the control variables. If disagreement increases due to news arrival, its impact on the expected return of stock with news should be greater compared to the way disagreement will influence the returns of firms not covered by news. From the results in column 1, the coefficient of $DIS\text{-}News_{i,t}$ is -0.49 ($t = -3.34$) which is 40% bigger in absolute value compared to the coefficient estimated for $DIS\text{-}NoNews_{i,t}$, -0.36 ($t = -2.71$). While news do increase disagreement and amplify its impact on stock returns, we see that the impact of disagreement is not purely concentrated around news releases. For example, the coefficient of $DIS\text{-}NoNews_{i,t}$ is close in magnitude to the one reported in column 1 of Table 6 for the whole sample. Qualitatively similar results are reported for the alternative measure of disagreement in Table A.2, where the difference between the two coefficients of $DIS\text{-}CP\text{-}News_{i,t}$ and $DIS\text{-}CP\text{-}NoNews_{i,t}$ is even bigger. We conclude that the predictive ability of disagreement in the cross-section of stocks with news releases is stronger due to the increase in disagreement induced by information arrival. This confirms our *H2.1*.

One key advantage of having news data is that it allows us to relate disagreement to the informational environment of firms and study their joint effect on expected returns. According to agree to disagree theories, disagreement should increase with respect to both positive and negative public information. The empirical implications of these theories, as stated in *H2.2*, is that we should observe the negative impact of disagreement on the expected returns of firms covered by both negative and positive news releases. To test this, we focus exclusively on stocks with weekly news observations available which results in a smaller cross-section of stocks.

We first regress $CAR_{i,t+1}$ on $ESS_{i,t}$, $NewsCount_{i,t}$, $DIS_{i,t}$, and the control variables. The results are reported in column 2. The coefficient of $DIS_{i,t}$ for the news sample, -0.375 ($t = -2.46$), is comparable in magnitude to the one reported for the whole sample in column 1 of Table 6. We then regress $CAR_{i,t+1}$ on the disagreement conditioned on positive and negative news, $DIS\text{-}P_{i,t}$ and $DIS\text{-}N_{i,t}$ respectively, including the same control variables. Column 3 presents the results.

[10] $DIS\text{-}E_{i,t}$ corresponds to disagreement when firm i has an earnings announcement on week t and is zero otherwise. $DIS\text{-}NE_{i,t}$ is equal to disagreement when a firm has no earnings announcement, and is 0 otherwise.

Comparing the coefficients in columns 2 and 3 uncovers new insights about the relation between news and disagreement. As expected, $ESS_{i,t}$ obtains a positive coefficient in all specifications as the more positive the news is (i.e. higher ESS score) the higher the returns should be. However, these coefficients are not statistically significant. $NewsCount_{i,t}$ is also not significant in our sample. Both $DIS\text{-}P_{i,t}$ and $DIS\text{-}N_{i,t}$ are negatively related to future returns, and their coefficients have similar economic magnitudes. Table A.2 provides the regression results when using $DIS\text{-}CP\text{-}P_{i,t}$ and $DIS\text{-}CP\text{-}N_{i,t}$. Here, the coefficients of positive and negative disagreement are almost identical and are not statistically different one from another. Together, the results in Table 7 and Table A.2 provide a direct support to "agree to disagree" theories. As more information arrives to the market, regardless of its content, the larger the dispersion of beliefs is. As current disagreement increases, subsequent stock returns decrease. These results are consistent with *H2.2*.

Corporate news releases can be anticipated (e.g., scheduled) or unanticipated (e.g., non-scheduled). Anticipated corporate news releases such as earnings announcements are accompanied by various press-releases before, during and after the announcements. Quarterly earnings reports are used by investors to update their views about a company performance. We therefore expect that earnings announcements should increase disagreement among investors. As a result, the impact of disagreement on future stock returns around earnings releases should be large.

Column 4 of Table 7 reports the results of regressing $CAR_{i,t+1}$ on $DIS\text{-}E_{i,t}$, $DIS\text{-}NoE_{i,t}$, and the control variables. While both of the coefficients of $DIS\text{-}E_{i,t}$ and $DIS\text{-}NE_{i,t}$ are negative and statistically significant, the coefficient of $DIS\text{-}E_{i,t}$ is twice as large in absolute value compared to that of $DIS\text{-}NoE_{i,t}$ (i.e., -0.91 versus -0.41). This results is consistent with the idea that investors used earnings releases to update their valuation of the firm which increases, rather than decreases, the heterogeneity of their beliefs. Interestingly, the coefficient of $DIS\text{-}NoE_{i,t}$ is almost identical to the coefficient of $DIS_{i,t}$ in column 2. This suggests that our results for the news sub-sample are not entirely driven by earnings announcements.

The results in this section provide overwhelming evidence about the sources of disagreement and how news and disagreement interact to influence asset prices. Three main conclusions can be drawn from our analysis. First, the predictive ability of disagreement in the cross-section of stocks with news releases is stronger due to the increase in disagreement induced by public information arrival. Second, the more information about the firm arrives to the market, regardless of its content, the more disperse investor beliefs become which in turn lowers the expected return of the firm. Finally, the increase in disagreement is larger for scheduled than for non-scheduled news releases. This in turn result in a stronger impact of disagreement on the expected return of stocks following scheduled news announcements. Overall, these results are broadly consistent

with heterogeneous belief models where investors agree to disagree.

4.4 Option-Implied Disagreement and Stocks' Short-Sale Constraints

So far, we have introduced new measures of disagreement in the options market and analyzed their empirical properties. We have established the robustness of the predictive power of these measures for future stock returns and study the way these measures interact with news releases to influence stock returns. We now turn to an analysis of the relationship between disagreement, short-sale constraints in the stock market, and stock expected returns.

Duffie, Garleanu and Pedersen (2002) show that lending fees and demand for loanable securities are endogenously increasing in differences of opinion. Their model predicts that lending fees endogenously depend on the level of disagreement. As a result, stocks with higher lending fees should be earning lower returns ex-post and the predictability of disagreement should be stronger for stocks that have higher short-selling costs or that are harder-to-borrow. Our third hypothesis (*H3.1*) builds on the idea that short-selling costs for the underlying and option-implied disagreement should be positively related.

We use Markit utilization rates and loan fees to identify short-sale constraints. Note that the utilization rate is usually considered to be a better proxy for short-sale constraints than loan fees. Higher loan fees, for example, do not necessarily mean that short-sale constraints are high if those fees are accompanied by a larger lending supply of shares (see, among others, Cohen, Diether, and Malloy, 2007; Suffi and Sigurdsson, 2011). In contrast, the utilization rate accounts for both effects, the short-selling demand and lending supply.

We first describe our methodology when using utilization rates as a proxy of short-sale constraints. Each week, we construct two dummy variables that reflect the level of utilization rates for each stock. For stock i on week t, the first variable takes the value of 1 whenever the utilization rate for that week satisfies $UtilizationRate_{i,t} \geqslant 90^{th}(UtilizationRate)$ and is set to 0 otherwise.[11] Note that $90^{th}(UtilizationRate)$ corresponds to the 90th percentile of the pooled utilization rates across stocks for each week. Reciprocally, stock i's low short-sale constraint indicator is equal to 1 on a given week whenever $UtilizationRate_{i,t} < 90^{th}(UtilizationRate)$ and to 0 otherwise. Adopting a similar methodology using loan fees, we construct high and low loan fees dummy variables on a stock-week level. We then multiply the high and low short-sale indicators by $DIS_{i,t}$. We denote the product of these variables $DIS\text{-}SSCH_{i,t}$, and $DIS\text{-}SSCL_{i,t}$, respectively.

We then run cross-sectional Fama-MacBeth regressions for the next week $CAR_{i,t}$ on the short-

[11] Our results are not sensitive to the percentile cutoff value.

sale constraint variables, high and low short-sale constraints disagreement, and other control variables. Table 8 presents the results for $DIS_{i,t}$ and Table A.3 presents the results when using $DIS\text{-}CP_{i,t}$. Independently of the proxy used and the specification considered, the short-sale constraint variables are negatively related to subsequent stock returns. The estimated coefficients for these variables are highly statistically significant. This is consistent with Jones and Lamont (2002) who find that stocks that are expensive to short-sell have high current valuations and low subsequent returns. $DIS_{i,t}$ obtains a negative coefficient which is statistically significant (columns 1 and 3) even after controlling for short-selling costs.

As apparent from columns 2 and 4, the impact of disagreement on future stock returns is more pronounced among hard-to-borrow and high lending fee stocks. In column 2, the coefficient estimate for $DIS\text{-}SSCH_{i,t}$, -0.895 ($t = -3.29$) is almost 4 times bigger in absolute value than the one obtained for $DIS\text{-}SSCL_{i,t}$, -0.227 ($t = -2.09$). In column 4, where we use loan fees as a proxy for short-sale constraints, the difference between the two coefficients is even more pronounced. The coefficient estimated for $DIS\text{-}SSCH_{i,t}$ is almost 5 times the one of $DIS\text{-}SSCL_{i,t}$. Quantitatively similar results are obtained for the alternative disagreement measure specification in Table A.3.

Overall, the results for disagreement are consistent with the predictions of Duffie, Garleanu and Pedersen (2002) and support *H3.1*. This in turn provides further evidence that options market disagreement is a direct measure of disagreement about the underlying.

4.5 Option-Implied Disagreement and Stocks' Trading Activity and Volatility

Tables 9 and 10 provide a direct tests for our *H4.1* and *H4.2* hypotheses respectively using $DIS_{i,t}$ measure and Tables A.4 and A.5 use an alternative $DIS\text{-}CP$ specification.

All disagreement theories predict that disagreement should be positively associated with trading activity. Following Hong and Stein (2007) we measure trading activity in the stock market with *turnover*. As a proxy for volatility we simply use a squared weekly stock return.[12]

The results of these two tables can be summarized as follows. Not only disagreement is positively associated with current *turnover* (see Table 2) but it also predicts higher stock turnover for all forecasting periods we consider (Table 9 and Table A.4).

Further, it also positively predicts stock market volatility for all forecasting periods as well (Table 10, and Table A.5). This provides support for our *H4.1* and *H4.2* and suggests that

[12] We cannot use rolling volatility similar to the one in control variables since it will create overlapping rolling windows and spurious relations between left and right hand-side variable.

options disagreement is a good measure of disagreement in the stock market. It also implies that investors often prefer to disagree first in the options market before trading activity and volatility spike in the stock market.

5 Determinants of Option-Implied Disagreement

The empirical literature investigating the pricing implications of disagreement is extensive. However, the empirical analysis of the determinants of disagreement is rather limited.

To analyze the factors influencing disagreement in the options market, we build on several theoretical studies. Harris and Raviv (1993), Kandel and Pearson (1995), and Cao and Ou-Yang (2009) argue that disagreement should increase as new information arrives. Heterogeneity of beliefs and the different likelihood functions used by investors to interpret public information further increase the dispersion of opinions in these models as information is released (Kandel and Pearson, 1995). This prediction is also directly related to the pricing implications of disagreement conditioning on news arrival as stated in *H2.3*. In addition to be influenced by information arrival, Harris and Raviv (1993) argue that disagreement and return volatility should be positively related. Finally, the predictions of the model of Duffie, Garleanu and Pedersen (2002) and the empirical evidence of D'Avalio (2002) suggest that short-sale constraints should be positively correlated with disagreement (*H3.3*).

To test these predictions we run weekly contemporaneous Fama-MacBeth regressions of option-implied disagreement on various explanatory variables. Our benchmark specification investigates the dependence of disagreement on stock and option imbalances, current and lagged returns and return volatility, Pan and Poteshman (2006)'s put-to-call volume ratio, log-option volume, stock illiquidity, and size. Table 11, column 1 presents the results. The average adjusted R-Squared is about 31%. This demonstrates the relevance of the explanatory variables used to explain the cross-sectional variations in divergence of opinions in the options market.

The recent stock performance as captured by current and lagged stock returns over the previous three weeks is highly statistically significant. Disagreement in the options market is higher following periods of increase in prices.

Consistent with theoretical predictions of Harris and Raviv (1993), stock return volatility is positively related to disagreement. This relation is statistically significant at conventional levels. Option order imbalances are positive but not statistically significant in this regression. It is negative and significant in Table A.4 for the alternative measure of disagreement. By construction, disagreement and imbalances should either not be related or be negatively correlated. This relation is confirmed in our benchmark regression specification. Moreover, stock imbalances are also

negatively related to disagreement. This is to be expected as higher buying or selling pressures in the stock market are consistent with lower disagreement overall.

Furthermore, $PP_{i,t}$ is negatively and significantly associated with disagreement. This suggests that disagreement is lower when informed trading increases.

Not surprisingly, the log of options volume is positively related to disagreement. The positive relations between volume and disagreement suggests that a substantial part of the trading activity in the options market is attributed to disagreement. This has also been argued by previous literature (Vijh, 1990; Cho and Engle, 1999; Choy and Wei, 2012). The economic magnitude of the relation between volume and disagreement is large: when log-option volume increases by one standard deviation, disagreement increases by 37%.

$Size_{i,t}$ positively explains cross-sectional variations in disagreement. This can be due to the fact that large firms also have a richer news environment, and more publicly available information which may cause more disagreement. Unlike $Size_{i,t}$, the results for stock illiquidity are no consistent across disagreement measures. It is positive and significant in columns 1 to 3 in Table 9, and negative and significant in Table A.6.

Column 2, Table 11 presents the results when we control for news arrival using news dummy. This variable takes the value one for stocks covered by news and is set to zero otherwise. Consistent with the implications of models where agents agree to disagree, we see that news and disagreement are positively correlated. Instead of reducing uncertainty about the firm valuation, news tend to increase investors' divergence of opinions. This result is consistent with the pricing implications of disagreement conditioning on news documented in Table 7. Note that the coefficient for earnings announcements dummy is positive. Not only disagreement increases on average with news releases but also the increase in disagreement during earnings announcements is higher than the increase incurred following other types of news releases.

In columns 3 and 4, we study the relation between disagreement and short-sale constraints. Both lending fees and utilization rates positively explain disagreement and yield statistically significant coefficients. This demonstrates that high short-sale constraints stocks are also the ones having a higher level of disagreement. This result is consistent with the model of Duffie, Garleanu and Pedersen (2002), and the empirical results documented in D'Avalio (2002). Both argue that short-sale constraints are increasing in the divergence of opinions among investors. It thus supports the idea that options disagreement directly reflects the divergence of opinions among stock market investors.

6 Conclusion

We study customer disagreement in the equity options market. We develop a high-frequency measures designed to capture dispersion of opinions in the underlying stocks implied by end-user equity options order flows. We analyze the predictive ability of these variables for stock returns, and find that customer disagreement strongly negatively predicts future stock returns. These results are economically and statistically significant and robust for multiple forecasting periods.

We show that the predictive power of options disagreement is consistent with standard disagreement theories where investors agree to disagree. Consistent with theoretical predictions of Harris and Raviv (1993) and Kandel and Pearson (1995), we find that options disagreement increases with public news. Moreover, the predictive effect of disagreement for future stock returns remains strong for both positive and negative news about the underlying.

Furthermore, consistent with Duffie, Garleanu and Pedersen (2002), and D'Avalio (2002) we find positive association between short-sale costs in the stock market and our disagreement measure. This suggests that options market disagreement mirrors the disagreement in the stock market. However, the richness of the options data, i.e. signed trading volumes by investor type, allows us to compute a better measure of disagreement.

Overall, our results provide evidence that disagreement in options has important pricing implications for the stock market.

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Table 1: Mean, Standard Deviation, 1st, 50th, and 99th Percentiles

Panel A. Disagreement Variables

	Mean	Std.	1st	50th	99th
DIS	0.1412	0.1151	0.0000	0.1362	0.4182
DIS-CP	0.1684	0.1229	0.0000	0.1728	0.4415
Turnover	13.7639	16.2653	1.9031	9.7942	69.7987
Analyst-Disp	0.1905	0.5131	0.0000	0.0439	3.8099

Panel B. News and Short Selling Variables

	Mean	Std.	1st	50th	99th
ESS	54.8220	10.4571	24.0000	52.4524	78.0000
Utilization Rate	0.2292	0.2298	0.0018	0.1445	0.8915
Loan Fee	0.0139	0.0550	0.0025	0.0038	0.2500

Panel C. Control Variables

	Mean	Std.	1st	50th	99th
IMB-Custom	-0.0721	0.2329	-0.6757	-0.0625	0.6307
PP	0.3135	0.3024	0.0000	0.2568	1.0000
Log(OptVolume)	9.4213	2.5314	3.6889	9.4788	14.8684
ILS (%)	0.1711	0.3711	0.0257	0.1073	0.9371
Size	14.5414	1.5833	11.3790	14.4200	18.6629
StockIMB	0.0077	0.0943	-0.2379	0.0036	0.2784
σ(Ret) (%)	2.7530	1.8336	0.7192	2.3226	9.4266

The table presents the mean, standard deviation (Std.), and the 1st, 50th, and 99th percentiles of the variables used in the subsequent empirical analysis. For a given variable, the statistics are calculated based on the pooled variables across firms and weeks. Panel A reports the summary statistics for DIS (Proxy 1) and DIS-CP (Proxy 2) which are option-implied disagreement measures constructed from customer-order flows, respectively. We also include stock turnover (turnover) and the Diether, Malloy, and Scherbina (2002)'s analyst dispersion measure (Analyst-Disp) as alternative proxies for disagreement. In Panel B, we report the summary statistics for news and short-sale variables. The variable capturing news is Ravenpack's ESS. Variables reflecting short-sale constraints include utilization rates and loan fees. We further report statistics of some important control variables in Panel C. IMB-Custom refers to option imbalances calculated from customer order flows. We also report statistics for Pan and Poteshman (2006)'s put-to-call volume ratio (PP), log-option volume (Log(OptVolume)), the dollar-volume weighted effective spreads of stocks (ILS), the log of market capitalization (Size), stock order imbalances (StockIMB), and stock volatility (σ(Ret)). We refer to Section (3.1) for additional information about the construction of these variables. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.

Table 2: Descriptive Statistics on the Correlation of Disagreement Measures

Panel A. Correlation Matrix of Disagreement

	DIS	DIS-CP	Turnover	Analyst-Disp
DIS	1			
DIS-CP	0.9404	1		
Turnover	0.2552	0.2443	1	
Analyst-Disp	-0.0147	-0.0204	0.0961	1

Panel B. Correlation of Option-Implied Disagreements with News and Short-Sale Constraints

	DIS	DIS-CP
ESS	0.0467	0.0430
Utilization Rate	-0.0031	-0.0049
Loan Fee	0.0261	0.0187

Panel C. Correlation of Option-Implied Disagreements with Control Variables

	DIS	DIS-CP
IMB-Custom	0.1480	0.1155
PP	-0.0458	-0.0116
Log(OptVolume)	0.5772	0.5923
ILS	-0.1539	-0.1811
Size	0.3629	0.3786
StockIMB	0.0307	0.0320
σ(Ret)	0.0434	0.0272

The table presents the correlations between the main variables used in our empirical analysis. To obtain one single measure of correlation for any pair of variables, we first compute the correlations of the two variables considered across stocks for each week. Based on the weekly estimates, we then calculate the time-series average and report it in the table. We refer to Table 1 and Section (3.1) for additional information about the labelling and construction of these variables. Panel A reports the correlation matrix of various disagreement measures. Panel B reports the correlation of option-implied disagreements with news and short-sale constraint measures. In Panel C, we report the correlation of option-implied disagreements with some important control variables. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.

Table 3: Alphas of Equally- and Value-Weighted Single Sorted Portfolios on Customer Disagreement. Various Horizons

Panel A: Alphas of Equally-Weighted Portfolios Sorted on DIS

Rank	$Alpha_{t+1}$	*t-Stat.*	$Alpha_{t+2}$	*t-Stat.*	$Alpha_{t+3}$	*t-Stat.*	$Alpha_{t+4}$	*t-Stat.*	$Alpha_{t+5}$	*t-Stat.*
1. Low	1.80	*1.45*	2.24	*1.85*	1.64	*1.43*	1.72	*1.53*	2.42	*2.13*
2	1.42	*1.16*	0.92	*0.76*	1.93	*1.60*	1.85	*1.45*	0.95	*0.79*
3	1.19	*0.99*	0.29	*0.23*	-0.56	*-0.43*	0.26	*0.20*	0.50	*0.38*
4	-1.37	*-1.02*	-0.55	*-0.39*	-0.95	*-0.72*	-1.63	*-1.13*	-1.15	*-0.81*
5. High	-3.12	*-1.66*	-3.30	*-1.68*	-3.02	*-1.49*	-3.43	*-1.74*	-3.61	*-1.79*
H-L	-4.92	*-2.58*	-5.54	*-2.72*	-4.66	*-2.22*	-5.15	*-2.55*	-6.03	*-2.97*

Panel B: Alphas of Value-Weighted Portfolios Sorted on DIS

Rank	$Alpha_{t+1}$	*t-Stat.*	$Alpha_{t+2}$	*t-Stat.*	$Alpha_{t+3}$	*t-Stat.*	$Alpha_{t+4}$	*t-Stat.*	$Alpha_{t+5}$	*t-Stat.*
1. Low	1.45	*1.30*	2.39	*2.15*	1.58	*1.40*	2.43	*2.16*	3.70	*3.11*
2	2.99	*2.58*	1.72	*1.54*	2.75	*2.48*	2.30	*2.11*	1.14	*1.04*
3	2.11	*2.02*	2.37	*2.24*	1.05	*0.95*	2.42	*2.32*	1.52	*1.22*
4	0.42	*0.48*	0.28	*0.30*	1.50	*1.57*	1.49	*1.54*	1.05	*0.99*
5. High	-1.44	*-2.12*	-1.55	*-2.01*	-1.57	*-2.02*	-1.93	*-2.50*	-1.44	*-1.80*
H-L	-2.89	*-1.98*	-3.94	*-2.56*	-3.15	*-2.01*	-4.37	*-2.80*	-5.14	*-3.14*

Panel C: Alphas of Equally-Weighted Portfolios Sorted on DIS-CP

Rank	$Alpha_{t+1}$	*t-Stat.*	$Alpha_{t+2}$	*t-Stat.*	$Alpha_{t+3}$	*t-Stat.*	$Alpha_{t+4}$	*t-Stat.*	$Alpha_{t+5}$	*t-Stat.*
1. Low	2.13	*1.67*	1.24	*1.02*	1.52	*1.28*	1.86	*1.63*	1.99	*1.69*
2	0.80	*0.64*	1.47	*1.22*	2.15	*1.78*	1.14	*0.90*	2.06	*1.74*
3	1.18	*0.96*	-0.13	*-0.10*	-0.35	*-0.27*	0.67	*0.52*	-0.75	*-0.57*
4	-1.09	*-0.84*	-0.35	*-0.24*	-1.96	*-1.48*	-1.66	*-1.17*	-0.55	*-0.37*
5. High	-2.82	*-1.53*	-2.59	*-1.37*	-2.02	*-1.04*	-3.17	*-1.68*	-3.59	*-1.86*
H-L	-4.94	*-2.61*	-3.83	*-1.93*	-3.54	*-1.77*	-5.03	*-2.70*	-5.58	*-2.81*

Panel D: Alphas of Value-Weighted Portfolios Sorted on DIS-CP

Rank	$Alpha_{t+1}$	*t-Stat.*	$Alpha_{t+2}$	*t-Stat.*	$Alpha_{t+3}$	*t-Stat.*	$Alpha_{t+4}$	*t-Stat.*	$Alpha_{t+5}$	*t-Stat.*
1. Low	2.05	*1.79*	1.26	*1.12*	1.82	*1.58*	2.14	*1.92*	3.75	*3.32*
2	2.85	*2.47*	1.99	*1.86*	2.81	*2.46*	2.32	*2.08*	1.99	*1.72*
3	2.99	*2.77*	2.30	*2.08*	0.89	*0.80*	3.32	*3.13*	1.06	*0.90*
4	-0.19	*-0.20*	0.54	*0.55*	0.46	*0.47*	0.95	*1.08*	1.83	*1.78*
5. High	-1.16	*-1.55*	-1.69	*-2.03*	-1.11	*-1.32*	-2.26	*-2.85*	-2.00	*-2.25*
H-L	-3.21	*-2.19*	-2.95	*-1.91*	-2.92	*-1.86*	-4.41	*-2.95*	-5.75	*-3.53*

The table presents the annualized alphas expressed in percentage of equally- and value-weighted quintile portfolios. The quintile portfolios are sorted every week on customer disagreement. Based on that sorting, we compute the abnormal returns of each portfolio one week, two weeks, three weeks, four weeks, and five weeks ahead, respectively. We use Fama-French-Carhart factors to estimate the alphas. The time period is from January 2005 to December 2013. The t-statistics reported beside the alphas are adjusted for 3 autocorrelation lags in the residuals using Newey-West methodology.

Table 4: Option-Implied Disagreement and the Cross-Section of Next Week Abnormal Stock Returns. Various Sample Periods

	Dependent Variable: $CAR_{i,t+1}$ (%)			
	Sample: 2005-2013		Sample: 2010-2013	
	(1)	*(2)*	*(3)*	*(4)*
$DIS_{i,t}$	-0.2651		-0.3417	
	-2.39		*-2.75*	
$DIS\text{-}CP_{i,t}$		-0.2303		-0.2844
		-2.22		*-2.42*
$Ret_{i,t}$ (%)	-0.0091	-0.0092	-0.0147	-0.0148
	-2.14	*-2.16*	*-2.60*	*-2.61*
$Ret_{i,t-1}$ (%)	-0.0014	-0.0015	-0.0007	-0.0008
	-0.37	*-0.39*	*-0.16*	*-0.19*
$Ret_{i,t-2}$ (%)	-0.0014	-0.0014	-0.0004	-0.0004
	-0.40	*-0.39*	*-0.09*	*-0.08*
$Ret_{i,t-3}$ (%)	0.0025	0.0024	0.0002	0.0001
	0.71	*0.69*	*0.04*	*0.03*
$\sigma(Ret_{i,t})$ (%)	-0.0523	-0.0526	-0.0487	-0.0492
	-1.90	*-1.91*	*-1.35*	*-1.36*
Adj. R^2	4.38	4.38	3.61	3.62
N	1 599	1 599	1 665	1 665

The table presents the results of predictive Fama-MacBeth cross-sectional regressions. Each week, we regress the cross-section of next week abnormal stock returns (CAR) on various explanatory variables. CAR corresponds to the difference between next week stock excess return and the excess return on the market portfolio. In columns 1 and 3, we analyze the predictive ability of DIS. In columns 2 and 4, we analyze the predictive ability of DIS-CP. In all specifications, we control for three return lags as well as lagged return volatility. We refer to Section (3.1) and the previous tables for additional details about the construction of these variables. The coefficients reported are the sample average of the weekly coefficient estimates. The t-statistics below the coefficient estimates are Newey-West t-statistics calculated using 3 autocorrelation lags. The sample period is from January 2005 to December 2013 in the first two columns. It is from January 2010 to December 2013 in the two last columns. The measurement frequency is weekly.

Table 5: Disagreement Measures and the Cross-Section of Next Week Abnormal Stock Returns

	Dependent Variable: $CAR_{i,t+1}$ (%) Sample: 2005-2013			
	(1)	*(2)*	*(3)*	*(4)*
$DIS_{i,t}$			-0.2631	
			-2.24	
$DIS\text{-}CP_{i,t}$				-0.2400
				-2.11
$Turnover_{i,t}$		-0.0017	-0.0011	-0.0012
		-1.21	*-0.78*	*-0.82*
$Analyst\text{-}Disp_{i,t}$	-0.0481	-0.0466	-0.0482	-0.0564
	-0.51	*-0.48*	*-0.50*	*-0.57*
$Ret_{i,t}$ (%)	-0.0094	-0.0088	-0.0083	-0.0083
	-2.08	*-1.93*	*-1.84*	*-1.82*
$Ret_{i,t-1}$ (%)	-0.0042	-0.0039	-0.0034	-0.0034
	-0.98	*-0.91*	*-0.80*	*-0.80*
$Ret_{i,t-2}$ (%)	-0.0025	-0.0027	-0.0022	-0.0022
	-0.64	*-0.69*	*-0.57*	*-0.57*
$Ret_{i,t-3}$ (%)	-0.0017	-0.0019	-0.0016	-0.0018
	-0.43	*-0.47*	*-0.42*	*-0.45*
$\sigma(Ret_{i,t})$ (%)	-0.0040	0.0081	0.0067	0.0069
	-0.12	*0.26*	*0.21*	*0.22*
Adj. R^2	5.20	5.63	5.77	5.78
N	1 314	1 314	1 314	1 314

The table presents the results of predictive Fama-MacBeth cross-sectional regressions. Each week, we regress the cross-section of next week stock abnormal returns (CAR) on various explanatory variables. CAR corresponds to the difference between next week stock excess return and the excess return on the market portfolio. In column 1 we analyze the predictive ability of analyst forecast dispersion. In column 2, we further control for the impact of stock turnover. In columns 3 and 4, we analyze the predictive ability of DIS and DIS-CP, respectively, controlling for analyst dispersion and turnover. In all specifications, we include three return lags and lagged return volatility. We refer to Section (3.1) and the previous tables for additional details about the construction of these variables. The coefficients reported are the sample average of the weekly coefficient estimates. The t-statistics below the coefficient estimates are Newey-West t-statistics calculated using 3 autocorrelation lags. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.

Table 6: The Predictive Ability of Option-Implied Disagreement. Various Horizons

	Dependent Variable: $CAR_{i,t+h}$ (%)				
	h=1	*h=2*	*h=3*	*h=4*	*h=5*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
$DIS_{i,t}$	-0.3951	-0.2340	-0.2423	-0.3339	-0.2226
	-3.83	*-2.13*	*-2.26*	*-2.98*	*-1.86*
Option-$IMB_{i,t}$	0.2540	-0.0035	0.0774	0.0371	-0.0198
	5.79	*-0.08*	*1.55*	*0.85*	*-0.42*
$PP_{i,t}$	-0.2863	-0.2025	-0.0966	-0.1214	-0.0927
	-6.17	*-4.36*	*-2.19*	*-2.91*	*-2.10*
$Log(OptVolume)_{i,t}$	-0.0059	-0.0167	-0.0099	-0.0147	-0.0097
	-0.70	*-2.16*	*-1.22*	*-1.72*	*-1.22*
$ILS_{i,t}$ (%)	-0.4280	-0.3540	-0.1024	-0.1837	-0.2499
	-3.03	*-2.71*	*-0.77*	*-1.52*	*-1.79*
$Size_{i,t}$	-0.0118	0.0095	0.0115	0.0221	0.0129
	-0.58	*0.48*	*0.60*	*1.05*	*0.65*
Stock-$IMB_{i,t}$	0.1398	0.2780	0.1712	0.0358	0.1040
	0.89	*1.88*	*1.15*	*0.24*	*0.66*
$Ret_{i,t}$ (%)	-0.0085	-0.0034	-0.0025	0.0046	-0.0024
	-1.98	*-0.87*	*-0.69*	*1.19*	*-0.67*
$Ret_{i,t-1}$ (%)	-0.0008	-0.0016	0.0036	-0.0025	-0.0043
	-0.22	*-0.44*	*0.97*	*-0.68*	*-1.19*
$Ret_{i,t-2}$ (%)	-0.0001	0.0013	-0.0008	-0.0033	-0.0033
	-0.02	*0.37*	*-0.22*	*-0.94*	*-0.95*
$Ret_{i,t-3}$ (%)	0.0025	-0.0015	-0.0025	-0.0019	0.0043
	0.72	*-0.42*	*-0.72*	*-0.55*	*1.33*
$\sigma(Ret_{i,t})$ (%)	-0.0439	-0.0319	-0.0241	-0.0078	-0.0128
	-1.92	*-1.37*	*-1.01*	*-0.33*	*-0.54*
Adj. R^2	5.55	5.43	5.38	5.29	5.20
N	1 386	1 385	1 384	1 382	1 381

We report results of predictive Fama-MacBeth cross-sectional regressions. On each week, we regress the cross-section of future abnormal stock returns (CAR) on various explanatory variables. We consider five horizons of one-, two-, three-, four-, and five-weeks. On each week, we regress abnormal stock return for a given horizon against lagged DIS. We further control for various option-volume based measures, ILS, size, and stock imbalances. We also include lagged stock returns and volatility. The coefficients reported correspond to the sample average of the weekly coefficient estimates. The t-statistics below the coefficient estimates correspond to Newey-West t-statistics computed using 3 autocorrelation lags. CAR corresponds to the difference between stock weekly excess return and the weekly excess return on the market portfolio. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.

Table 7: Positive and Negative News, Earnings Announcements, Disagreement, and the Cross-Section of Next Week Abnormal Stock Returns

	Dependent Variable: $CAR_{i,t+1}$ (%)			
	(1)	*(2)*	*(3)*	*(4)*
$IndicNews_{i,t}$	*0.0866*			
	2.37			
$DIS\text{-}News_{i,t}$	*-0.4876*			
	-3.34			
$DIS\text{-}NoNews_{i,t}$	*-0.3556*			
	-2.71			
$ESS_{i,t}$		*0.0016*	*0.0011*	*0.0015*
		1.24	*0.72*	*1.14*
$NewsCount_{i,t}$		*-0.0204*	*-0.0198*	*-0.0173*
		-1.16	*-1.14*	*-0.98*
$DIS_{i,t}$		*-0.3752*		
		-2.46		
$DIS\text{-}P_{i,t}$			*-0.3453*	
			-1.94	
$DIS\text{-}N_{i,t}$			*-0.4281*	
			-2.44	
$DIS\text{-}E_{i,t}$				*-0.9075*
				-2.30
$DIS\text{-}NoE_{i,t}$				*-0.4146*
				-2.65
$Option\text{-}IMB_{i,t}$	*0.2519*	*0.3396*	*0.3376*	*0.3400*
	5.74	*5.03*	*4.95*	*5.02*
$PP_{i,t}$	*-0.2851*	*-0.2788*	*-0.2791*	*-0.2744*
	-6.11	*-4.98*	*-4.99*	*-4.93*
$Log(OptVolume)_{i,t}$	*-0.0077*	*-0.0074*	*-0.0073*	*-0.0050*
	-0.91	*-0.73*	*-0.72*	*-0.48*
$ILS_{i,t}$ (%)	*-0.4277*	*-0.4627*	*-0.4583*	*-0.4822*
	-3.03	*-2.38*	*-2.35*	*-2.48*
$Size_{i,t}$	*-0.0134*	*-0.0208*	*-0.0216*	*-0.0248*
	-0.66	*-0.98*	*-1.01*	*-1.14*
$Stock\text{-}IMB_{i,t}$	*0.1330*	*0.2090*	*0.2109*	*0.1948*
	0.84	*0.94*	*0.95*	*0.88*
$Ret_{i,t}$ (%)	*-0.0085*	*-0.0054*	*-0.0055*	*-0.0047*
	-1.97	*-1.25*	*-1.26*	*-1.09*
$Ret_{i,t-1}$ (%)	*-0.0006*	*-0.0016*	*-0.0017*	*-0.0018*
	-0.18	*-0.35*	*-0.38*	*-0.39*
$Ret_{i,t-2}$ (%)	*-0.0001*	*0.0017*	*0.0019*	*0.0020*
	-0.04	*0.38*	*0.44*	*0.47*
$Ret_{i,t-3}$ (%)	*0.0025*	*0.0062*	*0.0061*	*0.0062*
	0.73	*1.40*	*1.36*	*1.41*
$\sigma(Ret_{i,t})$ (%)	*-0.0446*	*-0.0206*	*-0.0199*	*-0.0238*
	-1.95	*-0.70*	*-0.68*	*-0.82*
Adj. R^2	5.60	7.14	7.18	7.24
N	1 386	646	646	647

In column 1, we present the results of regressing CAR on a news dummy indicator and the decomposition of DIS into a news and non-news disagreement variables, DIS-News and DIS-NoNews. In column 2, we present the results of regressing CAR on ESS, news count, and DIS. In column 3, we present the results of regressing CAR on ESS, news count, and the decomposition of DIS into a negative news and positive news disagreement variables, DIS-N and DIS-P. In column 4, we present the results of regressing CAR on ESS, news count, and the decomposition of DIS into an earning and non-earning disagreement variables, DIS-E and DIS-NoE. We report the sample average of the weekly coefficient estimates and their Newey-West t-statistics adjusted for 3 autocorrelation lags. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.

Table 8: Short-Sale Constraints, Option-Implied Disagreement, and Next Week CAR

	Dependent Variable: $CAR_{i,t+1}$ (%)			
	SSConstraint = Utilization Rate		SSConstraint = Loan Fee	
	(1)	*(2)*	*(3)*	*(4)*
$SSConstraint_{i,t}$	-0.3667	-0.2501	-2.4184	-1.8534
	-4.01	*-2.64*	*-5.17*	*-3.63*
$DIS_{i,t}$	-0.2991		-0.2940	
	-2.81		*-2.77*	
$DIS\text{-}SSCH_{i,t}$		-0.8954		-1.0137
		-3.29		*-3.57*
$DIS\text{-}SSCL_{i,t}$		-0.2265		-0.1913
		-2.09		*-1.78*
$Option\text{-}IMB_{i,t}$	0.2485	0.2491	0.2475	0.2481
	5.73	*5.77*	*5.70*	*5.73*
$PP_{i,t}$	-0.2727	-0.2760	-0.2794	-0.2771
	-6.25	*-6.35*	*-6.21*	*-6.18*
$Log(OptVolume)_{i,t}$	0.0070	0.0073	0.0021	0.0036
	0.82	*0.85*	*0.24*	*0.42*
$ILS_{i,t}$ (%)	-0.2309	-0.2197	-0.0234	-0.0143
	-1.51	*-1.44*	*-0.16*	*-0.10*
$Size_{i,t}$	-0.0438	-0.0415	-0.0151	-0.0215
	-2.06	*-1.94*	*-0.74*	*-1.07*
$Stock\text{-}IMB_{i,t}$	0.2138	0.2065	0.1595	0.1632
	1.34	*1.30*	*1.00*	*1.03*
$Ret_{i,t}$ (%)	-0.0089	-0.0089	-0.0093	-0.0094
	-2.08	*-2.07*	*-2.16*	*-2.17*
$Ret_{i,t-1}$ (%)	-0.0014	-0.0015	-0.0017	-0.0016
	-0.39	*-0.42*	*-0.46*	*-0.43*
$Ret_{i,t-2}$ (%)	0.0005	0.0005	0.0002	0.0002
	0.14	*0.13*	*0.07*	*0.07*
$Ret_{i,t-3}$ (%)	0.0015	0.0014	0.0013	0.0013
	0.41	*0.38*	*0.37*	*0.37*
$\sigma(Ret_{i,t})$ (%)	-0.0367	-0.0358	-0.0318	-0.0296
	-1.60	*-1.55*	*-1.37*	*-1.27*
Adj. R^2	5.77	5.89	5.88	6.03
N	1 301	1 301	1 300	1 300

The table presents results of predictive cross-sectional regressions where short-sales constraints are proxy by utilization rates in columns 1 and 2, and by loan fees in columns 3 and 4. High short-sale constraint disagreement, DIS-SSCH, corresponds to the interaction of disagreement with a dummy variable that takes the value one when utilization rates or loan fees are above or equal to their 90th percentile on a given week. Low short-sale constraint disagreement, DIS-SSCL, is equal to disagreement when utilization rate or loan fee are below their 90th percentile on a given week. The coefficients reported correspond to the sample average of the weekly coefficient estimates. The t-statistics below the coefficient estimates are Newey-West t-statistics calculated using 3 autocorrelation lags. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.

Table 9: The Predictive Ability of Option-Implied Disagreement for Stock Turnover. Various Horizons

	Dependent Variable: $Turnover_{i,t+h}$				
	h=1	*h=2*	*h=3*	*h=4*	*h=5*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
$DIS_{i,t}$	5.4251	6.9382	7.5572	7.8653	7.8175
	21.84	*26.27*	*26.95*	*26.24*	*26.96*
$Option\text{-}IMB_{i,t}$	1.2850	0.9124	0.6735	0.6175	0.6429
	14.97	*10.62*	*7.49*	*6.42*	*6.31*
$PP_{i,t}$	0.4716	0.6111	0.6536	0.6381	0.6285
	8.48	*8.50*	*7.68*	*6.92*	*6.83*
$Log(OptVolume)_{i,t}$	0.9517	1.1125	1.1817	1.1978	1.2089
	37.14	*38.68*	*38.78*	*39.06*	*38.18*
$ILS_{i,t}$ (%)	-8.8421	-10.5963	-11.1425	-11.3079	-11.5203
	-22.66	*-23.00*	*-21.90*	*-20.89*	*-20.62*
$Size_{i,t}$	-1.7249	-2.0341	-2.1605	-2.1929	-2.1782
	-33.65	*-35.62*	*-34.72*	*-33.73*	*-32.19*
$Stock\text{-}IMB_{i,t}$	1.8100	1.9094	1.9029	1.6037	1.7583
	5.90	*5.59*	*5.30*	*4.28*	*4.70*
$Ret_{i,t}$ (%)	-0.0766	-0.0927	-0.0899	-0.0975	-0.0850
	-9.01	*-9.76*	*-9.48*	*-10.20*	*-8.60*
$Ret_{i,t-1}$ (%)	-0.0282	-0.0376	-0.0416	-0.0334	-0.0321
	-4.90	*-5.53*	*-6.57*	*-5.07*	*-3.97*
$Ret_{i,t-2}$ (%)	-0.0094	-0.0185	-0.0117	-0.0113	-0.0172
	-1.59	*-2.93*	*-1.92*	*-1.48*	*-2.48*
$Ret_{i,t-3}$ (%)	-0.0050	-0.0033	-0.0050	-0.0082	-0.0043
	-0.79	*-0.48*	*-0.58*	*-1.15*	*-0.57*
$\sigma(Ret_{i,t})$ (%)	0.5086	0.6437	0.6584	0.6465	0.7508
	12.33	*13.74*	*12.40*	*11.25*	*13.09*
$Turnover_{i,t}$	0.5669	0.4650	0.4214	0.4030	0.3831
	61.54	*49.81*	*44.74*	*40.66*	*38.66*
Adj. R^2	47.38	38.12	34.59	32.91	31.42
N	1 387	1 387	1 387	1 388	1 388

We present results of predictive Fama-MacBeth cross-sectional regressions. On each week, we regress the cross-section of stock turnover on various explanatory variables. We consider five horizons of one-, two-, three-, four-, and five-weeks. On each week, we regress stock turnover for a given horizon against lagged DIS. We further control for various option-volume based measures, ILS, size, and stock imbalances. We also include lagged stock returns, stock volatility, and turnover. The coefficients reported correspond to the sample average of the weekly coefficient estimates. The t-statistics below the coefficient estimates correspond to Newey-West t-statistics computed using 3 autocorrelation lags. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.

Table 10: The Predictive Ability of Option-Implied Disagreement for Stock Volatility. Various Horizons

	Dependent Variable: Squared-$Ret_{i,t+h}$ in %				
	h=1	*h=2*	*h=3*	*h=4*	*h=5*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
$DIS_{i,t}$	0.1905	0.3590	0.3570	0.2609	0.3908
	3.95	*5.06*	*4.92*	*4.19*	*5.03*
Option-$IMB_{i,t}$	0.1416	0.0464	0.0726	0.0698	0.0359
	5.09	*3.36*	*2.66*	*2.82*	*1.51*
$PP_{i,t}$	0.0126	0.0098	0.0362	0.0178	0.0297
	1.28	*0.84*	*2.29*	*1.14*	*2.35*
$Log(OptVolume)_{i,t}$	0.0485	0.0381	0.0391	0.0363	0.0324
	13.29	*13.67*	*11.20*	*8.43*	*10.96*
$ILS_{i,t}$ (%)	0.7995	0.5941	0.7356	0.6957	0.6804
	6.75	*12.30*	*8.08*	*8.74*	*9.10*
$Size_{i,t}$	-0.0835	-0.0824	-0.0781	-0.0716	-0.0707
	-10.57	*-10.84*	*-8.17*	*-7.26*	*-7.88*
Stock-$IMB_{i,t}$	0.2103	0.2171	-0.0142	0.0340	0.0848
	2.16	*3.28*	*-0.09*	*0.36*	*0.77*
$Ret_{i,t}$ (%)	-0.0080	-0.0074	-0.0069	-0.0061	-0.0076
	-3.73	*-4.75*	*-4.90*	*-3.25*	*-2.67*
$Ret_{i,t-1}$ (%)	-0.0050	-0.0055	-0.0052	-0.0060	-0.0069
	-3.72	*-4.12*	*-2.66*	*-2.12*	*-4.05*
$Ret_{i,t-2}$ (%)	-0.0042	-0.0062	-0.0049	-0.0052	-0.0048
	-3.14	*-4.98*	*-1.79*	*-3.74*	*-2.48*
$Ret_{i,t-3}$ (%)	-0.0050	-0.0037	-0.0042	-0.0037	-0.0042
	-3.81	*-3.04*	*-3.11*	*-1.79*	*-3.23*
$\sigma(Ret_{i,t})$ (%)	0.1249	0.1328	0.1373	0.1434	0.1484
	11.25	*10.54*	*9.33*	*8.55*	*8.61*
Adj. R^2	7.56	7.12	6.99	6.95	6.85
N	1 387	1 387	1 387	1 387	1 387

We present results of predictive Fama-MacBeth cross-sectional regressions. On each week, we regress the cross-section of stock squared-returns on various explanatory variables. We consider five horizons of one-, two-, three-, four-, and five-weeks. On each week, we regress stock squared-returns for a given horizon against lagged DIS. We further control for various option-volume based measures, ILS, size, and stock imbalances. We also include lagged stock returns volatility, and turnover. The coefficients reported correspond to the sample average of the weekly coefficient estimates. The t-statistics below the coefficient estimates correspond to Newey-West t-statistics computed using 3 autocorrelation lags. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.

Table 11: Explaining the Cross-Section of Option-Implied Disagreement

	Dependent Variable: $DIS_{i,t}$			
	(1)	*(2)*	*(3)*	*(4)*
News-Dummy$_{i,t}$		0.0007	0.0009	0.0009
		2.82	*3.67*	*3.49*
Earnings-Dummy$_{i,t}$		0.0035	0.0038	0.0033
		3.42	*3.77*	*3.24*
UtilizationRate$_{i,t}$			0.0223	
			22.37	
LoanFee$_{i,t}$				0.0788
				15.32
Option-IMB$_{i,t}$	0.0017	0.0016	0.0036	0.0034
	0.96	*0.93*	*2.03*	*1.89*
PP$_{i,t}$	-0.0352	-0.0352	-0.0361	-0.0353
	-25.78	*-25.80*	*-26.23*	*-25.77*
Log(OptVolume)$_{i,t}$	0.0215	0.0215	0.0207	0.0212
	79.47	*79.30*	*78.14*	*77.99*
ILS$_{i,t}$ (%)	0.0151	0.0149	0.0077	0.0025
	8.58	*8.47*	*4.06*	*1.25*
Size$_{i,t}$	0.0106	0.0106	0.0125	0.0108
	37.11	*37.48*	*43.17*	*37.82*
Stock-IMB$_{i,t}$	-0.0055	-0.0056	-0.0065	-0.0044
	-2.52	*-2.57*	*-2.81*	*-1.90*
Ret$_{i,t}$ (%)	0.0009	0.0009	0.0009	0.0009
	18.04	*17.85*	*16.97*	*16.90*
Ret$_{i,t-1}$ (%)	0.0009	0.0009	0.0009	0.0009
	20.77	*20.75*	*20.90*	*20.93*
Ret$_{i,t-2}$ (%)	0.0006	0.0006	0.0007	0.0007
	17.20	*17.11*	*16.56*	*16.49*
Ret$_{i,t-3}$ (%)	0.0005	0.0005	0.0005	0.0005
	13.31	*13.28*	*13.39*	*13.27*
σ(Ret$_{i,t}$) (%)	0.0080	0.0081	0.0080	0.0081
	25.93	*25.96*	*23.31*	*23.67*
Adj. R^2	31.03	31.05	31.54	31.45
N	1 387	1 387	1 302	1 301

The table presents results of cotemporaneous cross-sectional regressions. On each week, we regress DIS on various explanatory variables including option imbalances, Pan and Poteshman (2006)'s put-to-call volume ratio, and log-option volume. We also consider stock illiquidity, size, stock imbalances, lagged stock returns and volatility. In column 1, we present the results of the benchmark specification. In column 2, we control for the impact of news arrival and earnings announcements using news/earning announcement dummy variables equal to one for stocks covered by news release/earning announcement and set to zero otherwise. In columns 3 and 4, we analyze the impact of loan fees and utilization rates on DIS. The coefficients reported correspond to the sample average of the weekly coefficient estimates. The t-statistics below the coefficient estimates are Newey-West t-statistics calculated using 3 autocorrelation lags. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.

Table A.1: The Predictive Ability of Option-Implied Disagreement. Various Horizons

	Dependent Variable: $CAR_{i,t+h}$ (%)				
	h=1	*h=2*	*h=3*	*h=4*	*h=5*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
$DIS\text{-}CP_{i,t}$	-0.3006	-0.1424	-0.1864	-0.2273	-0.1295
	-3.23	*-1.48*	*-1.97*	*-2.18*	*-1.22*
$IMB_{i,t}$	0.2468	-0.0092	0.0701	0.0323	-0.0190
	5.59	*-0.20*	*1.41*	*0.74*	*-0.40*
$PP_{i,t}$	-0.2794	-0.1978	-0.0927	-0.1163	-0.0891
	-5.99	*-4.24*	*-2.09*	*-2.77*	*-2.00*
$Log(OptVolume)_{i,t}$	-0.0078	-0.0185	-0.0107	-0.0165	-0.0115
	-0.92	*-2.39*	*-1.31*	*-1.94*	*-1.43*
$ILS_{i,t}$ (%)	-0.4356	-0.3598	-0.1077	-0.1907	-0.2537
	-3.08	*-2.75*	*-0.81*	*-1.57*	*-1.82*
$Size_{i,t}$	-0.0129	0.0084	0.0104	0.0207	0.0117
	-0.63	*0.43*	*0.54*	*0.98*	*0.59*
$StockIMB_{i,t}$	0.1392	0.2814	0.1748	0.0355	0.1055
	0.88	*1.90*	*1.17*	*0.23*	*0.67*
$Ret_{i,t}$ (%)	-0.0087	-0.0035	-0.0026	0.0045	-0.0025
	-2.01	*-0.89*	*-0.72*	*1.16*	*-0.69*
$Ret_{i,t-1}$ (%)	-0.0009	-0.0016	0.0035	-0.0026	-0.0043
	-0.25	*-0.46*	*0.95*	*-0.71*	*-1.21*
$Ret_{i,t-2}$ (%)	-0.0001	0.0012	-0.0009	-0.0034	-0.0034
	-0.04	*0.35*	*-0.24*	*-0.97*	*-0.98*
$Ret_{i,t-3}$ (%)	0.0024	-0.0016	-0.0025	-0.0020	0.0043
	0.70	*-0.44*	*-0.73*	*-0.57*	*1.31*
$\sigma(Ret_{i,t})$ (%)	-0.0449	-0.0328	-0.0248	-0.0088	-0.0134
	-1.96	*-1.41*	*-1.04*	*-0.37*	*-0.57*
Adj. R^2	5.54	5.42	5.37	5.28	5.19
N	1 386	1 385	1 384	1 382	1 381

We report results of predictive Fama-MacBeth cross-sectional regressions. On each week, we regress the cross-section of future abnormal stock returns (CAR) on various explanatory variables. We consider five horizons of one-, two-, three-, four-, and five-weeks. On each week, we regress abnormal stock return for a given horizon against lagged DIS-CP (Proxy 2). We further control for various option-volume based measures, ILS, size, and stock imbalances. We also include lagged stock returns and volatility. The coefficients reported correspond to the sample average of the weekly coefficient estimates. The t-statistics below the coefficient estimates correspond to Newey-West t-statistics computed using 3 autocorrelation lags. CAR corresponds to the difference between stock weekly excess return and the weekly excess return on the market portfolio. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.

Table A.2: Positive and Negative News, Earnings Announcements, Disagreement, and the Cross-Section of Next Week Abnormal Stock Returns

	Dependent Variable: $CAR_{i,t+1}$ (%)			
	(1)	*(2)*	*(3)*	*(4)*
$IndicNews_{i,t}$	*0.0930*			
	2.43			
$DIS\text{-}CP\text{-}News_{i,t}$	*-0.4029*			
	-3.12			
$DIS\text{-}CP\text{-}NoNews_{i,t}$	*-0.2575*			
	-2.11			
$ESS_{i,t}$		*0.0016*	*0.0015*	*0.0015*
		1.20	*0.95*	*1.11*
$NewsCount_{i,t}$		*-0.0200*	*-0.0188*	*-0.0170*
		-1.13	*-1.08*	*-0.96*
$DIS\text{-}CP_{i,t}$		*-0.2956*		
		-2.25		
$DIS\text{-}CP\text{-}P_{i,t}$			*-0.2994*	
			-1.90	
$DIS\text{-}CP\text{-}N_{i,t}$			*-0.3144*	
			-2.06	
$DIS\text{-}CP\text{-}E_{i,t}$				*-0.7577*
				-2.35
$DIS\text{-}CP\text{-}NoE_{i,t}$				*-0.3287*
				-2.42
$Option\text{-}IMB_{i,t}$	*0.2439*	*0.3294*	*0.3277*	*0.3320*
	5.51	*4.93*	*4.86*	*4.95*
$PP_{i,t}$	*-0.2786*	*-0.2723*	*-0.2729*	*-0.2673*
	-5.95	*-4.84*	*-4.85*	*-4.78*
$Log(OptVolume)_{i,t}$	*-0.0094*	*-0.0090*	*-0.0088*	*-0.0063*
	-1.11	*-0.89*	*-0.87*	*-0.61*
$ILS_{i,t}$ (%)	*-0.4361*	*-0.4750*	*-0.4702*	*-0.4961*
	-3.09	*-2.44*	*-2.42*	*-2.56*
$Size_{i,t}$	*-0.0146*	*-0.0226*	*-0.0228*	*-0.0272*
	-0.72	*-1.06*	*-1.08*	*-1.25*
$Stock\text{-}IMB_{i,t}$	*0.1337*	*0.2096*	*0.2153*	*0.2009*
	0.85	*0.95*	*0.98*	*0.92*
$Ret_{i,t}$ (%)	*-0.0086*	*-0.0054*	*-0.0054*	*-0.0048*
	-1.99	*-1.25*	*-1.25*	*-1.11*
$Ret_{i,t-1}$ (%)	*-0.0008*	*-0.0017*	*-0.0018*	*-0.0018*
	-0.22	*-0.37*	*-0.39*	*-0.40*
$Ret_{i,t-2}$ (%)	*-0.0002*	*0.0016*	*0.0019*	*0.0020*
	-0.05	*0.37*	*0.44*	*0.45*
$Ret_{i,t-3}$ (%)	*0.0025*	*0.0061*	*0.0060*	*0.0061*
	0.71	*1.38*	*1.35*	*1.38*
$\sigma(Ret_{i,t})$ (%)	*-0.0455*	*-0.0217*	*-0.0211*	*-0.0253*
	-1.99	*-0.74*	*-0.72*	*-0.87*
Adj. R^2	5.59	7.12	7.15	7.22
N	1 386	646	646	647

In column 1, we present the results of regressing CAR on a news dummy indicator and the decomposition of DIS-CP into a news and non-news disagreement variables, DIS-CP-News and DIS-CP-NoNews. In column 2, we present the results of regressing CAR on ESS, news count, and DIS-CP. In column 3, we present the results of regressing CAR on ESS, news count, and the decomposition of DIS into a negative news and positive news disagreement variables, DIS-CP-N and DIS-CP-P. In column 4, we present the results of regressing CAR on ESS, news count, and the decomposition of DIS into an earning and non-earning disagreement variables, DIS-CP-E and DIS-CP-NoE. We report the sample average of the weekly coefficient estimates and their Newey-West t-statistics adjusted for 3 autocorrelation lags. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.

Table A.3: Short-Sale Constraints, Option-Implied Disagreement, and Next Week CAR

	Dependent Variable: $CAR_{i,t+1}$ (%)			
	SSConstraint = Utilization Rate		SSConstraint = Loan Fee	
	(1)	*(2)*	*(3)*	*(4)*
$SSConstraint_{i,t}$	-0.3692	-0.2640	-2.4247	-1.8647
	-4.04	*-2.85*	*-5.19*	*-3.71*
$DIS\text{-}CP_{i,t}$	-0.2264		-0.2204	
	-2.33		*-2.27*	
$DIS\text{-}CP\text{-}SSCH_{i,t}$		-0.7145		-0.8735
		-3.07		*-3.47*
$DIS\text{-}CP\text{-}SSCL_{i,t}$		-0.1754		-0.1272
		-1.78		*-1.29*
$Option\text{-}IMB_{i,t}$	0.2422	0.2430	0.2413	0.2427
	5.55	*5.59*	*5.52*	*5.57*
$PP_{i,t}$	-0.2670	-0.2711	-0.2740	-0.2717
	-6.08	*-6.19*	*-6.06*	*-6.03*
$Log(OptVolume)_{i,t}$	0.0056	0.0060	0.0006	0.0024
	0.66	*0.70*	*0.07*	*0.28*
$ILS_{i,t}$ (%)	-0.2367	-0.2279	-0.0284	-0.0200
	-1.55	*-1.50*	*-0.19*	*-0.13*
$Size_{i,t}$	-0.0448	-0.0430	-0.0159	-0.0229
	-2.10	*-2.01*	*-0.78*	*-1.14*
$Stock\text{-}IMB_{i,t}$	0.2125	0.2050	0.1578	0.1592
	1.33	*1.29*	*0.99*	*1.00*
$Ret_{i,t}$ (%)	-0.0091	-0.0091	-0.0095	-0.0095
	-2.11	*-2.10*	*-2.19*	*-2.20*
$Ret_{i,t-1}$ (%)	-0.0015	-0.0016	-0.0018	-0.0017
	-0.42	*-0.45*	*-0.48*	*-0.46*
$Ret_{i,t-2}$ (%)	0.0005	0.0004	0.0002	0.0002
	0.13	*0.12*	*0.06*	*0.05*
$Ret_{i,t-3}$ (%)	0.0014	0.0013	0.0013	0.0013
	0.39	*0.36*	*0.35*	*0.35*
$\sigma(Ret_{i,t})$ (%)	-0.0373	-0.0367	-0.0325	-0.0302
	-1.63	*-1.59*	*-1.41*	*-1.30*
Adj. R^2	5.76	5.86	5.87	6.02
N	1 301	1 301	1 300	1 300

The table presents results of predictive cross-sectional regressions where short-sales constraints are proxy by utilization rates in columns 1 and 2, and by loan fees in columns 3 and 4. High short-sale constraint disagreement, DIS-CP-SSCH, corresponds to the interaction of disagreement with a dummy variable that takes the value one when utilization rates or loan fees are above or equal to their 90th percentile on a given week. Low short-sale constraint disagreement, DIS-CP-SSCL, is equal to disagreement when utilization rate or loan fee are below their 90th percentile on a given week. The coefficients reported correspond to the sample average of the weekly coefficient estimates. The t-statistics below the coefficient estimates are Newey-West t-statistics calculated using 3 autocorrelation lags. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.

Table A.4: The Predictive Ability of Option-Implied Disagreement for Stock Turnover. Various Horizons

	Dependent Variable: $Turnover_{i,t+h}$				
	h=1	*h=2*	*h=3*	*h=4*	*h=5*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
$DIS\text{-}CP_{i,t}$	4.7214	6.2168	6.8187	7.1130	7.0014
	21.10	*26.22*	*26.19*	*25.79*	*25.40*
$Option\text{-}IMB_{i,t}$	1.4077	1.0721	0.8443	0.8006	0.8247
	16.18	*12.23*	*9.23*	*8.34*	*7.96*
$PP_{i,t}$	0.4018	0.5277	0.5639	0.5448	0.5335
	7.32	*7.39*	*6.69*	*5.93*	*5.83*
$Log(OptVolume)_{i,t}$	0.9585	1.1173	1.1859	1.2023	1.2144
	36.64	*38.32*	*38.26*	*38.64*	*37.62*
$ILS_{i,t}$ (%)	-8.7249	-10.4468	-10.9835	-11.1456	-11.3574
	-22.47	*-22.75*	*-21.64*	*-20.62*	*-20.35*
$Size_{i,t}$	-1.7126	-2.0204	-2.1465	-2.1788	-2.1629
	-33.61	*-35.55*	*-34.59*	*-33.61*	*-32.04*
$Stock\text{-}IMB_{i,t}$	1.8020	1.9169	1.9037	1.6101	1.7623
	5.86	*5.60*	*5.29*	*4.30*	*4.71*
$Ret_{i,t}$ (%)	-0.0752	-0.0911	-0.0881	-0.0956	-0.0830
	-8.85	*-9.59*	*-9.32*	*-10.01*	*-8.41*
$Ret_{i,t-1}$ (%)	-0.0269	-0.0359	-0.0401	-0.0317	-0.0304
	-4.67	*-5.30*	*-6.32*	*-4.82*	*-3.76*
$Ret_{i,t-2}$ (%)	-0.0086	-0.0176	-0.0107	-0.0103	-0.0163
	-1.45	*-2.78*	*-1.75*	*-1.36*	*-2.34*
$Ret_{i,t-3}$ (%)	-0.0044	-0.0026	-0.0042	-0.0073	-0.0034
	-0.70	*-0.38*	*-0.49*	*-1.01*	*-0.45*
$\sigma(Ret_{i,t})$ (%)	0.5111	0.6461	0.6604	0.6487	0.7534
	12.38	*13.78*	*12.44*	*11.30*	*13.14*
$Turnover_{i,t}$	0.5677	0.4658	0.4223	0.4039	0.3841
	61.76	*49.98*	*44.87*	*40.80*	*38.81*
Adj. R^2	47.37	38.10	34.57	32.89	31.40
N	1 387	1 387	1 387	1 388	1 388

We present results of predictive Fama-MacBeth cross-sectional regressions. On each week, we regress the cross-section of stock turnover on various explanatory variables. We consider five horizons of one-, two-, three-, four-, and five-weeks. On each week, we regress stock turnover for a given horizon against lagged DIS-CP. We further control for various option-volume based measures, ILS, size, and stock imbalances. We also include lagged stock returns, stock volatility, and turnover. The coefficients reported correspond to the sample average of the weekly coefficient estimates. The t-statistics below the coefficient estimates correspond to Newey-West t-statistics computed using 3 autocorrelation lags. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.

Table A.5: The Predictive Ability of Option-Implied Disagreement for Stock Volatility. Various Horizons

	Dependent Variable: Squared-$Ret_{i,t+h}$ in %				
	h=1	*h=2*	*h=3*	*h=4*	*h=5*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
$DIS\text{-}CP_{i,t}$	0.1380	0.2974	0.2968	0.2103	0.3328
	3.06	*4.54*	*4.93*	*3.77*	*5.14*
$Option\text{-}IMB_{i,t}$	0.1451	0.0525	0.0787	0.0743	0.0441
	5.29	*3.80*	*2.92*	*3.03*	*1.82*
$PP_{i,t}$	0.0098	0.0055	0.0312	0.0146	0.0249
	0.99	*0.47*	*1.96*	*0.93*	*1.97*
$Log(OptVolume)_{i,t}$	0.0495	0.0390	0.0399	0.0372	0.0332
	13.12	*13.38*	*10.91*	*8.51*	*10.97*
$ILS_{i,t}$ (%)	0.8023	0.6011	0.7415	0.7000	0.6873
	6.78	*12.24*	*8.16*	*8.82*	*9.11*
$Size_{i,t}$	-0.0830	-0.0817	-0.0773	-0.0711	-0.0700
	-10.55	*-10.85*	*-8.16*	*-7.20*	*-7.78*
$Stock\text{-}IMB_{i,t}$	0.2100	0.2183	-0.0126	0.0334	0.0842
	2.15	*3.30*	*-0.08*	*0.36*	*0.76*
$Ret_{i,t}$ (%)	-0.0079	-0.0073	-0.0069	-0.0061	-0.0075
	-3.70	*-4.71*	*-4.85*	*-3.21*	*-2.63*
$Ret_{i,t-1}$ (%)	-0.0049	-0.0054	-0.0051	-0.0059	-0.0068
	-3.69	*-4.08*	*-2.60*	*-2.11*	*-4.01*
$Ret_{i,t-2}$ (%)	-0.0042	-0.0061	-0.0049	-0.0052	-0.0047
	-3.11	*-4.94*	*-1.78*	*-3.72*	*-2.46*
$Ret_{i,t-3}$ (%)	-0.0050	-0.0037	-0.0041	-0.0037	-0.0042
	-3.79	*-2.99*	*-3.07*	*-1.78*	*-3.21*
$\sigma(Ret_{i,t})$ (%)	0.1253	0.1332	0.1377	0.1436	0.1488
	11.28	*10.55*	*9.35*	*8.56*	*8.63*
Adj. R^2	7.55	7.11	6.98	6.94	6.84
N	1 387	1 387	1 387	1 387	1 387

We present results of predictive Fama-MacBeth cross-sectional regressions. On each week, we regress the cross-section of stock squared-returns on various explanatory variables. We consider five horizons of one-, two-, three-, four-, and five-weeks. On each week, we regress stock squared-returns for a given horizon against lagged DIS-CP. We further control for various option-volume based measures, ILS, size, and stock imbalances. We also include lagged stock returns volatility, and turnover. The coefficients reported correspond to the sample average of the weekly coefficient estimates. The t-statistics below the coefficient estimates correspond to Newey-West t-statistics computed using 3 autocorrelation lags. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.

Table A.6: Explaining the Cross-Section of Option Disagreement

	Dependent Variable: DIS-CP$_{i,t}$			
	(1)	*(2)*	*(3)*	*(4)*
News-Dummy$_{i,t}$		0.0004	0.0007	0.0007
		1.71	*2.81*	*2.63*
Earnings-Dummy$_{i,t}$		0.0067	0.0071	0.0065
		6.01	*6.32*	*5.77*
UtilizationRate$_{i,t}$			0.0250	
			22.82	
LoanFee$_{i,t}$				0.0875
				16.64
Option-IMB$_{i,t}$	-0.0237	-0.0238	-0.0218	-0.0220
	-16.76	*-16.73*	*-14.55*	*-14.60*
PP$_{i,t}$	-0.0259	-0.0260	-0.0271	-0.0262
	-21.53	*-21.59*	*-22.23*	*-21.69*
Log(OptVolume)$_{i,t}$	0.0229	0.0228	0.0220	0.0225
	87.75	*87.42*	*85.94*	*85.33*
ILS$_{i,t}$ (%)	-0.0037	-0.0040	-0.0118	-0.0178
	-2.03	*-2.18*	*-5.78*	*-8.22*
Size$_{i,t}$	0.0101	0.0101	0.0122	0.0103
	36.33	*37.14*	*43.36*	*37.42*
Stock-IMB$_{i,t}$	-0.0055	-0.0056	-0.0064	-0.0041
	-2.51	*-2.56*	*-2.81*	*-1.78*
Ret$_{i,t}$ (%)	0.0007	0.0007	0.0007	0.0007
	16.27	*16.10*	*15.26*	*15.18*
Ret$_{i,t-1}$ (%)	0.0007	0.0007	0.0008	0.0008
	18.84	*18.85*	*18.93*	*18.93*
Ret$_{i,t-2}$ (%)	0.0006	0.0006	0.0006	0.0006
	15.59	*15.48*	*14.95*	*14.96*
Ret$_{i,t-3}$ (%)	0.0004	0.0004	0.0004	0.0004
	11.30	*11.27*	*11.34*	*11.24*
σ(Ret$_{i,t}$) (%)	0.0080	0.0081	0.0080	0.0081
	26.08	*26.18*	*23.30*	*23.63*
Adj. R^2	31.41	31.45	31.88	31.77
N	1 387	1 387	1 302	1 301

The table presents results of cotemporaneous cross-sectional regressions. On each week, we regress DIS-CP on various explanatory variables including option imbalances, Pan and Poteshman (2006)'s put-to-call volume ratio, and log-option volume. We also consider stock illiquidity, size, stock imbalances, lagged stock returns and volatility. In column 1, we present the results of the benchmark specification. In column 2, we control for the impact of news arrival and earnings announcements using news/earning announcement dummy variables equal to one for stocks covered by news release/earning announcement and set to zero otherwise. In columns 3 and 4, we analyze the impact of loan fees and utilization rates on DIS. The coefficients reported correspond to the sample average of the weekly coefficient estimates. The t-statistics below the coefficient estimates are Newey-West t-statistics calculated using 3 autocorrelation lags. The sample period is from January 2005 to December 2013. The measurement frequency is weekly.