Ambiguity, Investor Disagreement, and Expected Stock Returns

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Abstract

Based on the implication of a disagreement model, I measure investor disagreement (ID) as the correlation coefficient between trading volume and absolute price change, multiplied by -1. The model along with traders being ambiguity-averse predicts a positive relation between ID and expected stock return. I find that stocks in the highest ID decile outperform stocks in the lowest ID decile by 9.24 percent annually, adjusted for exposures to the market return as well as size, value, momentum, and liquidity factors. In addition, stocks in the highest ID decile prior to earnings announcements earn significantly higher earnings announcement returns. ID increases after earnings announcements and increases more following bad earnings news.

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1 Introduction

People always disagree. In financial markets, investors have different interpretations of public information all the time. A famous example would be Carl Icahn and Bill Ackman's epic fight over their opposing views on Herbalife: they remain publicly entrenched on either side of the Herbalife trade for years. Many theoretical models in economics and finance also assume that investors can differ in how to interpret fundamentals or information.[1] Empirically, however, it is extremely difficult to directly measure investor disagreement. The most commonly used investor disagreement measure in the literature is perhaps analyst forecast dispersion (Diether et al. (2002), Doukas et al. (2006), Sadka and Scherbina (2007), and Barinov (2013)), which, however, captures disagreement in earnings forecasts among "analysts" instead of "investors".[2]

In this paper, I focus on two issues. First, how is investor disagreement (ID) related to the cross-section of expected stock returns? Second, how do we measure ID? Based on the implication of Kandel and Pearson (1995) model, I use the correlation coefficient between trading volume and absolute price change, multiplied by -1, to measure ID. I further incorporate ambiguity aversion into the model and show that there exists a postive relation between ID and expected stock returns. I find that a portfolio of stocks in the highest decile of ID outperforms a portfolio of stocks in the highest decile of ID by 65 basis points per month with a Newey and West (1987) t-statistic of 3.91. The corresponding return monthly differences in CAPM, three-, four-, and five-factor alphas are 0.87% (t-statistic = 5.64), 0.71% (t-statistic = 5.47), 0.75% (t-statistic = 5.94), and 0.77% (t-statistic = 6.28), respectively.[3] In addition, stocks in the highest ID decile prior to earnings asnnouncements outperform stocks in the lowest ID decile by 65 pasis points in the 3-day window around earnings announcements.

In the model, there are two types of traders that have different interpretations of a public signal. Traders are uncertain about the other type's interpretation of information and thus assign a range of instead of a single information precision to it. Unlike most models studying ambiguity (Epstein and Schneider (2007), Epstein and Schneider (2008), Easley and O'HARA (2010), and Illeditsch (2011)) where ambiguity refers to the ambiguous information quality

[1]See, for example, Harrison and Kreps (1978), Harris and Raviv (1993), Scheinkman and Xiong (2003), Cao and Ou-Yang (2008), and Banerjee and Kremer (2010)

[2]Investor disagreement is the degree to which investors' estimated values on assets differ. For example, Varian (1985) defines it as an increase in the "spread" of the probability beliefs on asset prices, and Miller (1977) defines it as the extent to which the investors' estimated returns differ. In this paper, investor disagreement is defined as the absolute difference between the two types of interpretations.

[3]The returns reported here are equal-weighted as in Table 1. I also present value-weighted returns in Table 2. For robustness checks, I also use DGTW-adjusted returns following Daniel et al. (1997) and Wermers (2003), and the results remain the same. The results are available upon request.

of a signal, in this paper ambiguity occurs as traders don't know how to correctly interpret the other type's interpretation of information. In other words, although traders realize that the expected values of both types of interpretations are equal, they are uncertain about the information quality of the other type's intepretation in a sense that it can range from being less precise to more precise than their own interpretation.

The important behavioral assumption is that, traders are ambiguity-averse when facing ambiguity.[4] In order to characterize ambiguity-averse behavior, various forms of preferences are introduced in the literature, including "smooth ambiguity" by Klibanoff et al. (2005), "kinked preference" by Bossaerts et al. (2010), and "robust control" by Hansen and Sargent (2007). For tractability, I follow the approach of Gilboa and Schmeidler (1989), with investors preferences represented by the maxmin expected utility to capture investors' aversion to ambiguity as recent papers studying ambiguity aversion also follow this approach.[5] Under the maxmin expected utility, agents evaluate any action using the conditional probability that minimizes the utility of that action.

The intuition is that ambiguity aversion induces traders to assign an information precision to the other type's interpretation that generates the highest posterior interpretation of the public signal, which by setup leads to lower expected utility before maximization. As a result, traders take into account the other type's interpretation asymmetrically, i.e., traders give more (less) weight to the other type's interpretation if it is higher (lower) than their own interpretation. That is, traders are "conservative" under ambiguity. As time goes by, the fraction of traders facing ambiguity decrease and thus price increases. It can be shown that the price increase is strictly increasing in investor disagreement.

In addition, I use simulation to show that the relation between volume and absolute price change is weaker when the level of disagreement among investors is higher. When there's no investor disagreement, volume should be perfectly proportional to absolute price change (Kim and Verrecchia (1991) and Harris and Raviv (1993)). Intuitively, if investors actively trade in the exact opposite ways (high investor disagreement), large trading volume can be well accompanied by a small price change (correlation between volume and absolute price change is low). In other words, the contemporaneous correlation coefficient of daily trading volume and absolute price change serves as a negative indicator for investor disagreement (ID). Empirically, ID for a stock at the end a given month is defined as the correlation coefficient of daily trading volume and absolute price change over the past two months,

[4]The concept of ambiguity aversion can be traced back to the Ellsberg Paradox (Ellsberg (1961)), which suggests that individuals are adverse to vague probabilities and may not act as if they have a single prior.

[5]See, for example, Epstein and Schneider (2007), Epstein and Schneider (2008), Easley and O'HARA (2010), and Illeditsch (2011).

multiplied by -1.[6]

In addition to univariate portfolio analysis, I perform bivariate portfolio analysis to ensure that the significant return differences are not driven by well-known stock characteristics or risk factors. The results are robust to sorts on including firm size (SIZE), book-to-market (BM) ratio, the cumulative return over the 11 months prior to the portfolio formation month (MOM), the return in the portfolio formation month (REV), average turnover ratio (TURN), idiosyncratic volatility (IVOL) as defined in Ang et al. (2006), Amihud (2002) illiquidity ratio (ILLIQ), demand for lottery stocks with extreme positive returns (MAX) as defined in Bali et al. (2011), institutional owernship ratio (IOR), the stock beta (BETA), co-skewness (COSKEW) as defined in Harvey and Siddique (2000), and analyst forecast dispersion (DISP).

Also, I implement Fama and MacBeth (1973) regressions to examine the cross-sectional relation at the stock level. The positive relation between ID and future stock returns remains highly significant when a large set of control variables is included. I also perform a battery of robustness checks. The positive relation persists in high and low sentiment periods (Baker and Wurgler (2006)), NBER recessions and expansions, high and low economic uncertainty periods (Jurado et al. (2015), Ludvigson et al. (2015), and Baker et al. (2016)), different formation periods, and different holding months. All the results provide strong evidence for a positive and highly statistically significant relation between ID and future stock returns.

I also examine whether the positive relation between investor disagreement and future stock returns holds in the earnings announcement setting, as firms typically use earnings announcements to effectively communicate relevant information to the market (DellaVigna and Pollet (2009) and Pevzner et al. (2015)). In particular, Ball and Brown (1968), Krinsky and Lee (1996), Back et al. (2018), and Yang et al. (2020) argue that the leaking of information are pervasive prior to earnings announcements. Hence, there typically exists a sudden increase of information prior to the earnings announcement for investors to disagree on. Using portfolio sorts and stock level cross-sectional regressions, I provide evidence that stocks with high ID prior to the earnings announcement experience significantly higher cumulative abnormal returns around the earnings announcement period compared to stocks with low ID stocks.

Another interesting question is to examine whether earnings announcement resolve investor disagreement (ID). Theoretical papers typically assume that investors are uncertain about the parameter of the distribution of the firm's underlying earnings.[7] However, whether

[6] The number of trading days is around 44 in two months. Using only one trading month to compute correlation coefficient may be subject to lack of statistical power.

[7] See, for example,Verrecchia (1983), Lewellen and Shanken (2002), and Pástor and Pietro (2003).

more available information increases or decreases investor disagreement is still in doubt. For example, Bailey et al. (2003) finds that analyst forecast dispersion increases following the adoption of Regulation Fair Disclosure (Reg FD), which aims to prevent firms from doing selective disclosure. Chang et al. (2020), on the other hand, finds that analyst forecast dispersion decreases following the staggered implementation of Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system.

I provide evidence that earnings announcements on average increase ID and this effect is attributable to those that convey bad earnings news. That is, bad earnings news trigger a larger increase in ID than good earnings news. I also obtain firm-specific public news stories from RavenPack and classify them into six different news categories (Financial, Legal, M&A, Operational, Ratings, and Others). It turns out that ID also increases after these firm-specific news stories. In contrast, ID before and after macroeconomic announcements like FOMC meetings remain virtually the same.

The paper is organized as follows. Section 2 introduces the literature on disagreement. Section 3 set ups the model. Section 4 describes the data, variables, and the main empirical tests. Section 5 examines the relation between investor disagreement and future stock returns in the earnings announcement setting, and the evolution of ID from before to after earnings announcements, firm-specific news stories, and FOMC announcements. Section 6 provides a summary and concludes.

2 Literature on Investor Disagreement

The literature has not yet reached a consensus on how disagreement should be related to expected stock returns. Miller (1977) posits that in the presence of short-sales constraints, stock prices are biased upward (and, hence, lower future returns) when disagreement among investors is high. This occurs since asset prices are set by optimists as pessimists can't freely trade on the negative information. Miller (1977) further predicts that the negative relation between divergence of opinion and future returns should be more pronounced when short-sales constraints become more binding.

In particular, Diether et al. (2002) and Goetzmann and Massa (2005) both document a negative relation between dispersion in beliefs and future returns. However, Diamond and Verrecchia (1987) claim that short-sales constraints only eliminate some informative traders but do not lead to biased prices if traders have rational expectations. This is because in their model the competitive market maker can estimate the unbiased stock price instantaneously conditional on all publicly available information.

On the other hand, some papers view heterogeneous beliefs as a source of risk and hence thus posit a positive relation between investor disagreement and expected stock returns. Varian (1985) analyzes the effect of divergence of opinion on asset prices in an Arrow-Debreu economy and conclude that as long as risk aversion is not abnormally high, higher differences in beliefs is associated with decreased asset prices (and, hence, higher future returns). Merton (1987) suggests that investors should be compensated for the idiosyncratic risk from holding undiversified portfolios and since dispersion in beliefs indicates higher variation in earning streams, stocks with high divergence of opinion should earn higher future returns.

David (2008) constructs a general equilibrium model in which two types of agents have heterogeneous beliefs about the future growth and interpret even the same information differently. In particular, less risk-averse agents speculate more while demanding higher risk premiums. The model implies that equity premium is higher when dispersion among agents' expectations of future growth is high.

In addition, Gao et al. (2019) shows that assets with high disagreement beta should have higher expected returns. Finally, Clark (1973) regards dispersion in beliefs as a risk factor but finds evidence of a negative (positive) relation between short-term (long-term) disagreement among analysts about expected earnings and returns.

This paper, on the other hand, views investor disagreement as ambiguity faced by market participants as traders are uncertain about the sources of conflicting interpretations at first glance. Along with ambiguity aversion, the disagreement model in this paper generates a positive relation between investor disagreement and expected stock returns.

3 The Model

Following the basic setup in Kandel and Pearson (1995), there are two assets in a competitive market: a risk-free asset with a zero rate of return and a risky security with an uncertain payoff X. The risky asset is assumed to be in zero net supply. There are three time periods and Figure 1 presents the model timeline.

There is a continuum of type 1 traders and a continuum of type 2 traders in the market, with each type constituting half of the total traders. Traders strive to maximize their final wealth W, and are endowed with negative exponential utility functions $U(W) = -e^{-\lambda W}$, where λ is the coefficient of absolute risk aversion. In addition, traders are ambiguity-averse with preferences represented by maxmin expected utility of Gilboa and Schmeidler (1989).

At $t = 0$, traders can have different prior beliefs on X. In particular, type i traders' prior beliefs of X are given by normal distributions of mean X_i and precision Z_i, where $i \in \{1, 2\}$. Traders are assumed to be "naive" so that they don't know others' beliefs and likelihood functions. Hence, prices are set by market clearing conditions and since there is no private information, traders have nothing to learn from market price.

At $t = 1$, a public signal S arrives and traders observe S. The informative while imprecise signal is given by $S = X + \eta$, where η is independent of X and $\eta \sim N(\mu_\eta, \sigma_\eta^2)$. Everything about S is common knowledge except for the mean μ_η. In particular, two type of traders differ in how to interpret S and form their beliefs on μ_η accordingly. That is, type i traders believe that

$$\mu_\eta \sim N(\mu_i, \sigma^2), \tag{1}$$

where μ_i denotes type i traders' interpretation of S. Hence, from type i traders' point of view,

$$S \sim N(X + \mu_i, \sigma^2 + \sigma_\eta^2). \tag{2}$$

In other words, type i traders think that S is higher than X if $\mu_i > 0$, and higher μ_i implies a more negative view of the same signal.

At $t = 1'$ (shortly after $t = 1$), type 1 traders observe μ_2, and type 2 traders observe μ_1. The assumption that traders do not observe the other type's interpretation until $t = 1$ aims to capture the existence of information acquisition costs and traders' limited attention (Hirshleifer and Teoh (2003), Peng and Xiong (2006), and Corwin and Coughenour (2008)), which delays the information transmission process. To simplify notations, let μ_{-i} denote the other type's interpretation from type i traders' point of view. In other words, type i traders observe μ_{-i} at $t = 1'$. In addition, since traders don't observe the beliefs and likelihood functions of the other type, they can not infer μ_{-i} at $t = 1$ from market price.

The key assumption is that, traders have a hard time interpreting the other type's interpretation at first glance when it contradicts with their interpretation. As a result, traders are assumed to treat the other type's interpretation as an ambiguous signal that can be less or more informative than their own interpretation. In particular, type i traders have multiple likelihoods in mind when processing μ_{-i} at $t = 1'$:

$$\mu_{-i} = \mu_\eta + \epsilon, \quad \mu_\eta \perp \epsilon, \quad \epsilon \sim N(0, \sigma_\epsilon^2), \quad \sigma_\epsilon^2 \in [\underline{\sigma_\epsilon^2}, \overline{\sigma_\epsilon^2}], \tag{3}$$

where $0 < \underline{\sigma_\epsilon^2} < \overline{\sigma_\epsilon^2} < \infty$. When σ_ϵ^2 is higher (lower) than σ^2, type i traders believe that compared to their own interpretation μ_i, the other type's interpretation μ_{-i} is more imprecise (precise).[8] The information quality of μ_{-i} is thus captured by the range of precisions $[1/\overline{\sigma_\epsilon^2}, 1/\underline{\sigma_\epsilon^2}]$.

Hence, in order to update their priors on μ_η, type i traders apply Bayes's rule to obtain a family of posteriors:

$$\mu_\eta \sim N(\mu_i + \frac{\sigma^2}{\sigma^2+\sigma_\epsilon^2}(\mu_{-i}-\mu_i), \frac{\sigma^2\sigma_\epsilon^2}{\sigma^2+\sigma_\epsilon^2}), \quad \sigma_\epsilon^2 \in [\underline{\sigma_\epsilon^2}, \overline{\sigma_\epsilon^2}]. \tag{4}$$

For tractability, let $\underline{\sigma_\epsilon^2} = \sigma^2(1-\beta_1)$, $\overline{\sigma_\epsilon^2} = \sigma^2(1+\beta_2)$, $0 < \beta_1 < 1$, and $0 < \beta_2 < \infty$.

At $t = 2$, some traders finalize their evaluation of the contradicting interpretations. Without loss of generality, let α_1 and α_2 denote the fraction of type i traders, $i \in \{1, 2\}$, that believe in μ_i and μ_{-i}, respectively at $t = 2$. If type i traders eventually still believe in their own interpretation μ_i, then μ_{-i} is considered as completely uninformative and thus type i traders' belief on μ_η follows (1). If, on the other hand, type i traders think that μ_{-i} is the correct interpretation of S, then they believe that $\mu_\eta \sim N(\mu_{-i}, \phi^2)$, where $\phi^2 \approx 0$. Third, $(1-\alpha_1-\alpha_2)$ of fraction of traders within each type still treat the other type's interpretation as an ambiguous signal. Hence, their posterior belief on μ_η follows (4).

At $t = 3$, X is realized and agents consume their wealth. Next, I introduce trade at each time. Let $m_{i,t}$ denote the position held by a type i trader at time t.

3.1 Trade at $t = 0$

At $t = 0$, type i traders solve the following problem

$$\max_{m_{i,0}} E_{i,0} \; - e^{-\lambda m_{i,0}(X-P_0)}, \tag{5}$$

where $E_{i,0}$ denotes expectation with respect to X of trader i trader at $t = 0$. The resulting demand is

$$m_{i,0}(P_0) = (X_i - P_0)\frac{Z_i}{\lambda}. \tag{6}$$

Using the market-clearing condition $(\frac{1}{2}m_{1,0} + \frac{1}{2}m_{2,0} = 0)$, the equilibrium price at $t = 0$ is v

$$P_0^* = \frac{Z_1X_1 + Z_2X_2}{Z_1+Z_2}, \tag{7}$$

[8] Since $\mu_{-i} = \mu_\eta + \epsilon$, $\mu_\eta = \mu_{-i} - \epsilon$. Hence, $\mu_\eta \sim N(\mu_{-i}, \sigma_\epsilon^2)$. From (1) we know that $\mu_\eta \sim N(\mu_i, \sigma^2)$.

and the equilibrium holdings are $m_{1,0}(P_0^*)$ and $m_{2,0}(P_0^*)$, respectively.

3.2 Trade at $t = 1$

After observing the public signal S at $t = 1$, type i traders form their interpretations of S, i.e, μ_i. The posterior beliefs of type i traders on X are represented by

$$X \sim N(\frac{Z_i X_i + b(S - \mu_i)}{Z_i + b}, (Z_i + b)^{-1}), \tag{8}$$

where $b = (\sigma^2 + \sigma_\eta^2)^{-1}$. At $t = 1$, type i traders solve the following problem

$$\max_{m_{i,1}} E_{i,1} \ - e^{-\lambda m_{i,1}(X - P_1)}, \tag{9}$$

where $E_{i,1}$ denotes expectation with respect to X of type i traders at $t = 1$. The resulting demand is

$$m_{i,1}(P_1) = (\frac{Z_i X_i + b(S - \mu_i)}{Z_i + b} - P_1)\frac{(Z_i + b)}{\lambda}. \tag{10}$$

Using the market-clearing condition ($\frac{1}{2}m_{1,1} + \frac{1}{2}m_{2,1} = 0$), the equilibrium price at $t = 1$ is given by

$$P_1^* = \frac{Z_1 X_1 + Z_2 X_2 + b(S - \mu_1) + b(S - \mu_2)}{Z_1 + Z_2 + 2b}. \tag{11}$$

The demand $m_{1,1}(P_1^*)$ and $m_{2,1}(P_1^*)$ can be computed accordingly.

3.3 Trade at $t = 1'$

Following Gilboa and Schmeidler (1989), ambiguity-averse traders maximize expected utility under the worst-case belief chosen from the family of posteriors. In particular, at $t = 1'$ type i traders solve the following problem

$$\max_{m_{i,1'}} \min_{\sigma_\epsilon^2 \in [\underline{\sigma_\epsilon^2}, \overline{\sigma_\epsilon^2}]} E_{i,1'} \ - e^{-\lambda m_{i,1'}(X - P_{1'})}, \tag{12}$$

where $E_{i,1'}$ denotes expectation with respect to X of type i attentive traders at $t = 1'$.

Note that traders' posterior mean on μ_η is negatively related to the expected utility before maximization. Hence, traders select an information quality $\sigma_\epsilon^2 \in [\underline{\sigma_\epsilon^2}, \overline{\sigma_\epsilon^2}]$ that generates the highest posterior mean on μ_η. In other words, if the other type's interpretation is higher ($\mu_{-i} - \mu_i > 0$), type i attentive traders act as if μ_{-i} is precise ($\sigma_\epsilon^2 = \underline{\sigma_\epsilon^2}$). In contrast, if the other type's interpretation is lower ($\mu_{-i} - \mu_i < 0$), type i traders act as if μ_{-i} is imprecise ($\sigma_\epsilon^2 = \overline{\sigma_\epsilon^2}$).

Formally, at $t = 1'$, type i traders' posterior belief on μ_η is given by

$$\begin{cases} \mu_\eta \sim N(\mu_i + \frac{\sigma^2}{\sigma^2 + \underline{\sigma_\epsilon^2}}(\mu_{-i} - \mu_i), \frac{\sigma^2 \underline{\sigma_\epsilon^2}}{\sigma^2 + \underline{\sigma_\epsilon^2}}) & \text{, if } \mu_{-i} - \mu_i > 0 \\ \mu_\eta \sim N(\mu_i + \frac{\sigma^2}{\sigma^2 + \overline{\sigma_\epsilon^2}}(\mu_{-i} - \mu_i), \frac{\sigma^2 \overline{\sigma_\epsilon^2}}{\sigma^2 + \overline{\sigma_\epsilon^2}}) & \text{, if } \mu_{-i} - \mu_i < 0. \end{cases} \tag{13}$$

Plugging in $\underline{\sigma_\epsilon^2} = \sigma^2(1 - \beta_1)$ and $\overline{\sigma_\epsilon^2} = \sigma^2(1 + \beta_2)$, we have

$$\begin{cases} \mu_\eta \sim N(\frac{(1-\beta_1)\mu_i + \mu_{-i}}{2-\beta_1}, \frac{1-\beta_1}{2-\beta_1}\sigma^2) & \text{, if } \mu_{-i} - \mu_i > 0 \\ \mu_\eta \sim N(\frac{(1+\beta_2)\mu_i + \mu_{-i}}{2+\beta_2}, \frac{1+\beta_2}{2+\beta_2}\sigma^2) & \text{, if } \mu_{-i} - \mu_i < 0. \end{cases} \tag{14}$$

The market-clearing condition is $\frac{1}{2} m_{1,1'} + \frac{1}{2} m_{2,1'} = 0$.

3.4 Trade at $t = 2$

At $t = 2$, type i traders' beliefs on μ_η are as follows:

1. α_1 fraction of traders believe that $\mu_\eta \sim N(\mu_i, \sigma^2)$.
2. α_2 fraction of traders believe that $\mu_\eta \sim N(\mu_{-i}, \phi^2)$, where $\phi^2 \approx 0$
3. $(1 - \alpha_1 - \alpha_2)$ fraction of traders treat μ_{-i} as an ambiguous signal and thus think $\mu_\eta \sim N(\mu_i + \frac{\sigma^2}{\sigma^2 + \sigma_\epsilon^2}(\mu_{-i} - \mu_i), \frac{\sigma^2 \sigma_\epsilon^2}{\sigma^2 + \sigma_\epsilon^2})$, $\quad \sigma_\epsilon^2 \in [\underline{\sigma_\epsilon^2}, \overline{\sigma_\epsilon^2}]$.

3.5 Trade at $t = 3$

At $t = 3$, the equilibrium price P_3^* is equal to X trivially since X is revealed. The following proposition presents the main results of the model.

Proposition 1. *Suppose $\sigma^2 << \sigma_\eta^2$, then the market-clearing price at $t = 1'$, $P_{1'}^*$, is given by*

$$P_{1'}^* = \frac{Z_1 X_1 + Z_2 X_2 + \sigma_\eta^{-2}\{(S - \mu_1) + (S - \mu_2) - \frac{(\beta_1 + \beta_2)}{(2-\beta_1)(2+\beta_2)}|\mu_1 - \mu_2|\}}{Z_1 + Z_2 + 2\sigma_\eta^{-2}}, \tag{15}$$

and the market-clearing price at $t = 2$*,* P_2^**, is given by*

$$P_2^* = \frac{Z_1 X_1 + Z_2 X_2 + \sigma_\eta^{-2}\{(S - \mu_1) + (S - \mu_2) - \frac{(1-\alpha_1-\alpha_2)(\beta_1+\beta_2)}{(2-\beta_1)(2+\beta_2)}|\mu_1 - \mu_2|\}}{Z_1 + Z_2 + 2\sigma_\eta^{-2}}. \tag{16}$$

Let $R = P_2^* - P_{1'}^*$*. Then,* $R = \frac{(\alpha_1+\alpha_2)(\beta_1+\beta_2)}{(2-\beta_1)(2+\beta_2)(Z_1+Z_2+2\sigma_\eta^{-2})}|\mu_1 - \mu_2|$ *and is increasing in investor disagreement,* $|\mu_1 - \mu_2|$*.*

Proof. See Appendix II. □

The intuition is as follows. At $t = 1'$, traders view the other type's interpretation as uncertain and since they are ambiguity-averse, they choose an information quality $\sigma_\epsilon^2 \in [\underline{\sigma_\epsilon^2}, \overline{\sigma_\epsilon^2}]$ that generates the highest posterior mean on μ_η before maximization. That is, traders place more emphasis on the larger of the two interpretations. In other words, ambiguity aversion always motivates traders to form a more negative view on S after observing the other type's interpretation.

At $t = 2$, α_1 fraction of traders within each type stick to their original interpretation, while α_2 fraction of traders within each type turn to the other type's interpretation. In other words, the fraction of traders within each type that suffer from ambiguity aversion decrease from 1 at $t = 1'$ to $(1 - \alpha_1 - \alpha_2)$ at $t = 2$, given $\alpha_1\alpha_2 \neq 0$. Hence, the average posterior mean on μ_η of all traders in the market is lower at $t = 2$ than at $t = 1'$, which means that the price increases from $t = 1'$ to $t = 2$.

The assumption of $\sigma^2 << \sigma_\eta^2$ requires that the public signal S is extremely imprecise. This is consistent with that fact that in reality, firms do not communicate with investors on a daily basis, so most of the time publicly available information reveals very less about the true value of the stock. In addition, an imprecise signal is also more likely to trigger different interpretations among investors.

3.6 Measuring investor disagreement

The model in the previous section predicts that when traders exhibit ambiguity aversion, future return is increasing in investor disagreement. In this section, I show that investor disagreement, $|\mu_1 - \mu_2|$, can be measured at $t = 1$ using the relation between trading volume and absolute price change. Since there are only two types of traders in the market, the equilibrium trading volume from $t = 0$ to $t = 1$, $V_{0,1}^*$, is the absolute change in traders' respective equilibrium holdings. In particular,

$$V_{0,1}^* = |\frac{1}{2}m_{1,1}(P_1^*) - \frac{1}{2}m_{1,0}(P_0^*)| = |\frac{1}{2}m_{2,1}(P_1^*) - \frac{1}{2}m_{2,0}(P_0^*)|. \tag{17}$$

Using (5) to (11), it can be shown that

$$V_{0,1}^* = |A + B\Delta P_{0,1}^*|, \tag{18}$$

where $\Delta P_{0,1}^* = (P_1^* - P_0^*)$,

$$A = \frac{b(\mu_1 - \mu_2)}{4\lambda}, \tag{19}$$

and

$$B = \frac{(Z_1 - Z_2)}{4\lambda}. \tag{20}$$

Note that when there is no disagreement in the market, i.e., $\mu_1 = \mu_2$, equilibrium trading volume is perfectly proportional to absolute price change (Kim and Verrecchia (1991) and Harris and Raviv (1993)), and there exists no trading volume given zero price change. However, when disagreement exists so that $\mu_1 \neq \mu_2$, there can exist trading volume given zero price change (Kandel and Pearson (1995)).[9]

In addition, when investor disagreement, $|\mu_1 - \mu_2|$, is higher, the relation between the equilibrium trading volume ($V_{0,1}^*$) and absolute price change ($|\Delta P_{0,1}^*|$) is weaker. To illustrate this idea, Figure 2 plots the correlation between equilibrium trading volume and absolute price change over different values of $(\mu_1 - \mu_2)$. Without loss of generality, μ_1 is fixed to 0, so $(\mu_1 - \mu_2)$ varies under different values of μ_2. For a given value of $(\mu_1 - \mu_2)$, I draw 100,000 observations from the distribution of $\eta \sim N(\mu_\eta = 0, \sigma_\eta^2 = 2,000)$ and thus acquire 100,000 observations of S since $S = X + \eta$. In particular, σ_η^2 is set to be very large in order to be consistent with the requirement of Proposition 1, i.e, $\sigma^2 << \sigma_\eta^2$. The equilibrium trading volume, absolute price change, and the correlation between the two can be computed

[9] According to the no-trade theorem (Milgrom and Stokey (1982)), trade should not exist under asymmetric information with three assumptions: Pareto-efficiency of the initial allocation, commonly knowledge of rationality, and agents exhibiting same interpretations over the same information. In particular, even if agents have different priors, speculative trade is still impossible when the three assumptions are satisfied (Gizatulina and Hellman (2019)). However, when the third assumption is relaxed so that Bayesian agents interpret information in a dissimilar fashion, there can be trade in the market. Indeed, it is difficult to explain why investors would trade in the first place without some source of investor disagreement involved.

accordingly.

[Insert Figure 2 about here]

Figure 2 suggests that, the correlation coefficient between equilibrium trading volume and absolute price change is decreasing in investor disagreement, $|\mu_1 - \mu_2|$. When there is no disagreement, equilibrium trading volume and absolute price change are perfectly correlated. In addition, as long as investor disagreement is not too high, the correlation coefficient of trading volume and absolute price change is positive, which is consistent with the findings in the past literature.[10]

Hence, the contemporaneous correlation coefficient of daily trading volume and absolute price change appears to serve as a negative indicator for investor disagreement (ID).[11] When the correlation coefficient between the two is smaller, it is more likely that disagreement among investors is higher.

4 Data and variable definitions

This section contains detail of the sample selection and empirical analysis.

4.1 Data

The stock sample includes all common stocks (share code 10 or 11) traded on NYSE, AMEX, and Nasdaq from the Center for Research in Security Prices (CRSP) for the period from January 1983 to December 2019. The second data set is Compustat, which is used to obtain the equity book values for computing the book-to-market ratios of individual firms. Stocks are required to have non-missing firm size (SIZE), book-to-market (BM) ratio, and momentum (MOM), which are defined in detail in Appendix I.

4.2 Estimating investor disagreement

The first step involves estimating investor disagreement (ID) for each stock-month. The model predicts that in equilibrium, when the relation between trading volume and absolute price change is weaker, it is more likely that investor disagreement is higher. Hence, I define ID at the end of a given month as the contemporaneous correlation coefficient of daily

[10]Past literature has documented a positive contemporaneous relation of volume and volatility. See for example, Clark (1973), Tauchen and Pitts (1983), Karpoff (1987), Gallant et al. (1992), and Andersen (1996).

[11]In cross-section asset pricing, the implicit assumption is that b and $|Z_1 - Z_2|$ are virtually the same across assets.

trading volume and absolute price change over the past two months (around 44 trading days), multiplied by -1. For example, investor disagreement of a stock at the end of October is defined as the correlation coefficient between its daily trading volume and absolute price change over September and October, multiplied by -1.

A stock trading day t is eligible if the price per share on $t-31$ is at least 5 dollars[12] and has non-missing return and volume. All returns are delisting-adjusted. Stocks are required to have at least 30 eligible trading days to compute ID. Figure 3 plots the time-series distribution of all CRSP common stocks and eligible stocks.

[Insert Figure 3 about here]

4.3 Univariate portfolio-level analysis

I first perform univariate portfolio-level analysis. In each month, I sort stocks into ten decile portfolios based on investor disagreement (ID) at the end of the previous month. Decile 1 (low ID) is the portfolio of stocks with the lowest investor disagreement at the end of the previous month, and decile 10 (high ID) is the portfolio of stocks with the highest investor disagreement. Stocks are held for one month after being assigned into ID decile portfolios. If investor disagreement is positively related to future stock returns, then we should see significant differences in the average returns of ID-sorted decile portfolios.

Table 1 presents the equal-weighted monthly average returns of ID-sorted decile portfolios. When moving from the lowest to highest ID decile, the next-month average excess return increases almost monotonically from 0.18% to 0.82%. The average excess return difference between decile 10 (high ID) and decile (low ID) is 0.65% with a corresponding Newey and West (1987) t-statistic of 3.91.

[Insert Table 1 about here]

In addition to the average excess returns, Table 1 also presents the risk-adjusted returns (alphas) from regressing monthly excess return on contemporaneous risk factors. CAPM alpha is the intercept from the regression of excess portfolio returns on a constant and excess market return (MKT). Three-factor alpha is the intercept from the regression of excess portfolio returns on a constant, the excess market return (MKT), a size factor (SMB), and a book-to-market factor (HML). Four-factor alpha is the intercept from the regression of excess portfolio returns on a constant, the excess market return (MKT), a size factor (SMB), a book-to-market factor (HML), and a momentum factor (UMD) of Carhart (1997). Five-factor

[12] This is to ensure the results are not driven by small, illiquid stocks or by bid-ask bounce.

alpha is the intercept from the regression of excess portfolio returns on a constant, the excess market return (MKT), a size factor (SMB), a book-to-market factor (HML), a momentum factor (UMD), and a liquidity factor (LIQ) of Pástor and Stambaugh (2003). If the factor model can capture the cross-sectional variation in stock returns, then the corresponding alpha should be statistically indistinguishable from zero.

As shown in the third column in Table 1, CAPM alpha increases from −0.63% to 0.23% per month when moving from the lowest to highest ID decile. The difference in CAPM alphas between the high and low ID portfolios is 0.87% per month with a Newey and West (1987) t-statistic of 5.64. The next three columns present similar alpha results from the three-factor, four-factor, and five-factor models. When moving from the lowest to the highest ID decile, the three-factor alpha increases from −0.57% to 0.14%, the four-factor alpha increases from −0.50% to 0.25%, and the five-factor alpha increases from −0.51% to 0.26%. The difference in alphas between the high ID and low ID portfolios is 0.71% (t-statistic=5.47), 0.75% (t-statistic=5.94), and 0.77% (t-statistic=6.28) per month for the three-factor, four-factor, and five-factor model, respectively.

In addition, I examine the source of the risk-adjusted return difference between high ID and low ID portfolios. Is it generated by outperformance of high ID stocks or underperformance of low ID stocks? The last column of Table 1 indicates the strongly significant five-factor alpha spread (t-statistic=6.28) is driven by both the outperformance of high ID stocks (significantly positive with a t-statistic of 2.69) and the underperformance of low ID stocks (significantly negative with a t-statistic of −6.43).

Table 2 presents evidence from the value-weighted decile portfolios of ID. The results are slightly weaker but in general consistent with the equal-weighted portfolio results.

[Insert Table 2 about here]

Stocks in decile 1 (low ID) generate a value-weighted average excess return of 0.50% per month, while stocks in decile 10 (high ID) generate higher value-weighted average excess return of 0.91% per month. The average return differential is 0.50% per month with a Newey and West (1987) t-statistic of 2.78. The difference in alphas between the high ID and low ID portfolios is 0.52% (t-statistic=3.56), 0.40% (t-statistic=3.20), 0.37% (t-statistic=2.95), and 0.36% (t-statistic=2.84) per month for the CAPM, three-factor, four-factor, and five-factor model, respectively.

In Table 1 and Table 2, I also report betas with respect to MKT, SMB, HML, UMD, and LIQ risk factors. In both cases, MKT betas and HML betas are significantly negative and significantly positive, respectively, suggesting that compared to stocks in the lowest ID decile, stocks in the highest ID decile are less exposed to market risk and have a tilt towards value stocks. To test the hypothesis that all 10 alphas are jointly equal to zero, I implement GRS test of Gibbons et al. (1989). For both equal-weighted and value-weighted and for all regression models, the GRS test rejects at 1% level.[13]

Overall, the univariate portfolio analysis is consistent with the model prediction, which suggests a positive relation between investor disagreement and expected stock returns.

4.4 Average stock characteristics

Next, I examine the stock composition of investor disagreement (ID) decile portfolios. In particular, Table 3 presents for each ID decile, the time-series average of mean values of stock characteristics, including firm size (SIZE), book-to-market (BM) ratio, the cumulative return (in percent) over the 11 months prior to the portfolio formation month (MOM), the return (in percent) in the portfolio formation month (REV), average turnover ratio (TURN), idiosyncratic volatility (IVOL) as defined in Ang et al. (2006), Amihud (2002) illiquidity ratio (ILLIQ), lottery demand (MAX) as defined in Bali et al. (2011), institutional owernship ratio (IOR) defined the ratio of shares owned by institutions as reported in 13F filings in the last quarter, the stock beta (BETA), and co-skewness (COSKEW) as defined in Harvey and Siddique (2000). Definitions of these variables are given in the Appendix. The weights are based on the number of observations in each portfolio in each month and there is an average of 306 stocks per decile portfolio.

The first row of Table 3 reports that the average investor disagreement (ID) increases from -0.77 to 0.07 when moving from the lowest to highest ID decile. The average ID in the subsequent month increases monotonically from -0.58 to -0.12 from the lowest to highest ID decile, which sheds light on the persistence of investor disagreement.

[Insert Table 3 about here]

Fama and French (1992) and Fama and French (1993) report that on average, small stocks earn higher future returns than large stocks. The third row of Table 3 indicates the average market capitalization (SIZE) slightly increases and then decreases when moving from the low ID decile to high ID decile. In fact, SIZE is relatively large around middle ID deciles. This is perhaps because large firms benefit more from their disclosure policy compared to small firms (Diamond and Verrecchia (1991)) due to lower information and proprietary costs. As large firms on average tend to be more transparent, investors disagree less.

This result provides further support for the return differences between high and low ID decile in Table 2 and Table 3 since if small stocks do earn higher subsequent returns, then low ID decile should earn higher returns than middle ID decile.

[13]For brevity I didn't report the results here. However, all the test statistics are available upon request.

The average book-to-market (BM) ratio for each investor disagreement (ID) decile is reported in the fourth row. As ID increases across the deciles, BM increases monotonically. The concentration of high book-to-market stocks in the high ID deciles casts doubt on the positive relation between ID and expected stock returns, as Fama and French (1992) and Fama and French (1993) document that stocks with high BM ratio stocks (value stocks) earn higher subsequent returns than stocks with low BM ratio (growth stock).

Looking at the fifth and sixth row of Table 3, one observes that as ID increases across the deciles, both momentum (MOM) and short-term reversal (REV) decrease. The decrease in MOM is good news as Jegadeesh and Titman (1993) shows that stocks that perform the best (worst) over intermediate horizons tend to do well (poorly) in the future. If past losers do continue to perform badly in the future, high ID stocks should experience low instead of high returns. However, the decrease in REV across ID deciles casts doubt on the significance of the long-short ID strategy, as stocks tend to exhibit return reversal due to initial price overreaction to good news and bid-ask bounce (Jegadeesh (1990) and Lehmann (1990)).

Gervais et al. (2001) find that stocks withe higher volume earn higher returns, which is known as the high volume return premium. Looking at the seventh row of Table 3, stock turnover ratio (TURN) decreases monotonically when ID increases. The pattern is good news for the positive relation between ID and expected stock returns, as the concentration of high trading volume stocks in low ID deciles would suggest these portfolios earn higher instead of lower returns observed in the data.

Next, the eight row of Table 3 indicates that as ID increases across deciles, average idiosyncratic volatility (IVOL) decreases. As Ang et al. (2006) present evidence that stocks with high idiosyncratic volatility generate lower future returns, the negative relation between ID and idiosyncratic volatility raises concern on the positive relation between ID and future stock returns. On the other hand, Amihud (2002) suggests that expected stock returns increase in illiquidity. Looking at the ninth row of Table 3, there exists no striking pattern of illiquidity across ID deciles.

As shown in the tenth row of Table 3, the average demand for lottery stocks with extreme positive returns (MAX) is lower for stocks in high ID deciles. Since Bali et al. (2011) and Bali et al. (2017) document that low MAX stocks earn higher expected returns than high MAX stocks, the negative relation between ID and MAX casts doubt on the positive relation between ID and future stock returns.

Looking at the eleventh row of Table 3, institutional ownership ratio (IOR) decreases as ID increases. This negative relation between ID and IOR provides support of the positive relation between ID and expected stock returns, as Asquith et al. (2005) find that short-sale constrained stocks with low institutional ownership significantly underperform than high institutional ownership stocks.

Next, the twelfth row of Table 3 indicates that when ID increases across deciles, average stock beta (BETA) decreases monotonically. This pattern suggests that high ID stocks are less exposed to market risk. If stocks are compensated more for bearing more exposure to market risk, stocks with higher ID should instead earn lower future returns. Hence, the negative relation between ID and BETA is good news for the return differences between the high and low ID decile as reported in Table 1 and Table 2.

On the other hand, in the thirteenth row of Table 3, average co-skewness (COSKEW) first increases then decreases when moving from the lowest to the highest ID decile. Compared to low ID deciles, high ID deciles on average have lower co-skewness, which further provides support for the positive relation between ID and future stock returns, since Harvey and Siddique (2000) report that stocks with high co-skewness generate lower one-month-ahead returns.

In sum, Table 3 indicates that compared to low ID stocks, high ID stocks on average have high book-to-market (BM) ratio, low intermediate-horizon momentum (MOM), low short-term reversal (REV), low turnover ratio (TURN), low idiosyncratic volatility (IVOL), low demand for lottery stocks (MAX), and low exposure to market risk (BETA). In particular, the fact that high ID stocks having high BM, low REV, low IVOL, and low MAX seems to dampen the validity of the positive relation between ID and expected stock returns. In the next section, I use bivariate portfolio sorts to show that the positive relation between ID and expected stock returns is not driven by the above return predictors.

4.5 Bivariate portfolio-level analysis

The section studies whether the relation between investor disagreement (ID) and expected stocks returns still holds after controlling for the well-known cross-sectional return predictors: market capitalization (SIZE), book-to-market (BM) ratio, momentum (MOM), short-term reversal (REV), turnover ratio (TURN), idiosyncratic volatility (IVOL), illiquidity (ILILQ), demand for lottery stocks with extreme positive returns (MAX), institutional ownership ratio (IOR), the stock beta (BETA), co-skewness (COSKEW), and anaylst forecast dispersion (DISP).

I first examine whether the results in Table 1 and Table 2 are simply capturing a size effect. Each month, I assign stocks to one of five quintiles based on firm size (SIZE).[14] Within each size quintile, stocks are further sorted into deciles based on ID in the previous month. I then

[14]As a robustness check, I also form portfolios using NYSE-based market capitalization. The results are similar and are available upon request.

examine the next month returns in each portfolio. Table 4 shows that the return differential is positive and highly significant in all size quintiles. In addition, the average equal-weighted monthly return differential between high ID and low ID stocks decreases when moving from the smallest to the largest size quintile (except when going from the second to the third size quintile).

[Insert Table 4 about here]

In particular, the long-short ID strategy for the smallest and the largest size quintile on average generates a return of 1.07% and 0.28% per month, with a Newey and West (1987) t-statistic of 3.75 and 2.14, respectively. In addition, the corresponding CAPM, three-factor, four-factor, and five-factor alphas are all significantly positive. Specifically, the five-factor alpha differences are in the range of 0.29% to 1.32% per month with t-statistics ranging from 2.29 to 4.57. The above results indicate that the strongly positive relation between ID and expected stock returns is not driven by size effect.

Table 5 presents the results of two-way cuts on book-to-market (BM) ratio and ID. The return differential and corresponding CAPM, three-factor, four-factor, and five-factor alphas between low and high ID stocks are highly significant in all book-to-market quintiles, indicating that the positive relation between ID and expected stock returns is not simply capturing a book-to-market effect. In addition, compared to other BM quintiles, the long-short ID strategy in the lowest BM quintile generates the highest return of 0.97% per month with a Newey and West (1987) t-statistic of 5.33.

[Insert Table 5 about here]

Table 6 presents the double sorts results on momentum (MOM) and ID. Again, the return differential and CAPM, three-factor, four-factor, and five-factor alphas between high and low ID stocks remain highly significant across all momentum quintiles. In particular, the return differential between high and low ID stocks is the highest in the stocks that are past losers. In particular, the long-short ID strategy generates a five-factor alpha of 1.54% with a Newey and West (1987) t-statistic of 6.57 in the lowest momentum quintile.

[Insert Table 6 about here]

Overall, Table 5, Table 6, and Table 7 indicate that the significantly positive relation between ID and future stock returns cannot be explained by the well-known size, value, or momentum effect. In addition, the return differential between high and low ID stocks is most pronounced in small stocks, growth stocks, and stocks that perform poorly over the past year.

I proceed to control for other commonly used return-predicting stock characteristics. In each month, stocks are first sorted into deciles based on a control variable and then, within each decile I sort stocks into deciles based on ID. Stocks are held for month and portfolio returns are equal-weighted. For brevity, I do not report returns for all 100 (10×10) portfolios. Instead, the ten investor disagreement decile portfolios are averaged over each of the ten control variable decile portfolios. Table 8 reports for each control variable the time-series average of excess returns, high-minus-low excess returns, and corresponding five-factor alphas, together with Newey and West (1987) t-statistics to examine their statistical significance.

[Insert Table 8 about here]

Table 8 shows that after controlling for many cross-sectional return predictors, the return differences between high ID and low ID decile portfolios are in the range of 0.34% and 0.68% per month with Newey and West (1987) t-statistics ranging from 3.41 to 6.78. The corresponding 5-factor alpha differences are in the range of 0.45% to 0.72% and are all highly significant. The results in this section indicate that well-known firm characteristics or risk factors cannot explain the significantly positive relation between ID and expected stock returns.

4.6 Firm-level cross-sectional regressions

So far, the significance of investor disagreement (ID) as a determinant of the cross-section of expected returns has been examined at the portfolio level (both univariate and bivariate). The portfolio-level analysis is non-parametric since no functional form on the relation between the ID and the future returns is imposed. In addition, it is possible that a large amount of information is lost via aggregation and it is difficult to control for multiple variables simultaneously via portfolio analysis. Moreover, the Gibbons et al. (1989) tests seldom come close to rejecting the hypothesis that the three-factor, four-factor, or five-factor model explains average returns.

Hence, I now examine the cross-sectional relation between ID and expected returns at the stock level using Fama and MacBeth (1973) regressions. The incremental predictive power of ID can be examined relative to other control variables known to explain the cross-section of returns.

Table 9 reports the time-series averages of the slope coefficients from the regressions of one-month-ahead stock returns on ID with and without control variables. The average slopes provide standard Fama and MacBeth (1973) tests for determining which explanatory variables on average have nonzero premiums. Specifically, I run the following monthly cross-sectional regressions at a monthly frequency from January 1983 to December 2019:

$$R_{i,m+1} = \alpha_m + \beta_m ID_{i,m} + \lambda_m X_{i,m} + \epsilon_{i,m+1}, \tag{21}$$

where $R_{i,m+1}$ is the realized excess return on stock i in month $m+1$, ID is the investor disagreement of stock i at the end of month m, and $X_{i,m}$ is the same set of stock-specific control variables at time m for stock i, including firm size (SIZE), book-to-market (BM) ratio, momentum (MOM), short-term reversal (REV), turnover ratio (TURN), idiosyncratic volatility (IVOL), illiquidity (ILILQ), demand for lottery stocks with extreme positive returns (MAX), institutional ownership ratio (IOR), the stock beta (BETA), co-skewness (COSKEW), and anaylst forecast dispersion (DISP).

[Insert Table 9 about here]

Table 9 reports the time-series averages of the slope coefficients with corresponding Newey and West (1987) t-statistics in parentheses. In the first column, the average slope coefficient from regressing realized returns on ID alone is 0.780 and highly significant (t-statistic = 3.85), indicating a strongly positive relation between ID and expected stock returns.

Column 2 of Table 9 controls for firm size (SIZE), book-to-market (BM) ratio, and momentum (MOM), and the coefficient on ID remains economically and statistically significant. Column 3 further controls for the short-term reversal (REV) and turnover ratio (TURN). Still, the average slope on ID is positive and highly significant. Column 4 of Table 9 shows that after including idiosyncratic volatility (IVOL), illiquidity (ILLIQ), demand for lottery sock with extreme positive returns (MAX), and institutional ownership ratio, the average slope on ID becomes 0.367 with a highly significant Newey and West (1987) t-statistic of 3.73. Column 5 further includes market beta (BETA) and co-skewness (COSKEW), and the coefficient on ID is still significantly positive. Finally, Column 6 incorporates analyst forecast dispersion and the coefficient on ID shrinks to 0.251 with a Newey and West (1987) t-statistic of 2.86.

The coefficients on most control variables are consistent with evidence in the literature. Stocks exhibit strong intermediate-horizon momentum and short-term reversals. The average slopes are significantly negative for idiosyncratic volatility, institutional ownership ratio, and analyst forecast dispersion, which is consistent with the evidence in Ang et al. (2006), Asquith et al. (2005), and Diether et al. (2002).

Overall, the multivariate Fama-MacBeth regression results in Table 9 indicate that when simultaneously controlling for various stock characteristics and risk factors, the average slopes on ID remain positive and highly significant, indicating a strongly positive relation between ID and the cross-section of expected stock returns.

4.7 Robustness checks

In this section, I provide a variety of robustness checks to test whether the positive cross-sectional relation between investor disagreement (ID) and future stocks returns is nonlinear and thus changes over time. I also examine the persistence of ID and the long-short ID strategy.

4.7.1 Business cycles, investor sentiment, and economic uncertainty

I first examine whether the long-short ID strategy is sensitive to business cycles and investor sentiment in Table 10. In the second and the third column, the five-factor alphas and corresponding Newey and West (1987) t-statistics of each ID decile and the long-short ID strategy are reported under economic expansions and recessions. The expansions and recessions months are issued by the National Bureau of Economic Research's (NBER) Business Cycle Dating Committee.[15] Specifically, a recession is the period between a peak of economic activity and its subsequent trough. Between trough and peak, the economy is in an expansion. There are 410 expansions and 34 recessions from January 1983 to December 2019.

[Insert Table 10 about here]

The equal-weighted five-factor alpha increases from −0.49% to 0.22% and from −0.55% to 0.69% per month for expansions and recessions, respectively. In particular, the difference in alphas is 0.71% (t-statistic=5.38) for expansions and 1.23% (t-statistic=2.04) for recessions. The results provide strong evidence that the significantly positive relation between ID and future stock returns is robust to different business cycles.

In addition, it is possible that the positive relation between ID and future stock returns is concentrated in certain investor sentiment periods. To mitigate this concern, I first classify each month as following either a high-sentiment month or a low-sentiment month. A high-sentiment (low-sentiment) month is one in which the value of the BW (Baker and Wurgler (2006)) sentiment index in the previous month is above (below) the median value for the sample period.[16] The fourth and the fifth column show that long-short ID strategy generates a five-factor alpha of 0.65% (t-statistic=5.25) and 0.92% (t-statistic=4.53) per month for low sentiment and high sentiment periods, respectively. The results indicate that the significantly positive relation between ID and expected stock returns is robust to investor sentiment.

Another robustness check is to examine whether macroeconomic uncertainty affects the positive relation between ID and expected stock returns. I use four economic uncertainty

[15] https://www.nber.org/research/business-cycle-dating

[16] The latest investor sentiment data is available till year 2018 and can be obtained from Professor Jeffrey Wurgler's website.

measures (macro, real, financial, and policy-related economic uncertainty) in the literature to classify each month as either a high-uncertainty month or a low-sentiment month. A high-sentiment month is one in which the value of the economic uncertainty index is above the median value for the sample period, and the low-sentiment months are those with below-median values.

Jurado et al. (2015) and Ludvigson et al. (2015) introduce time series measures of macroeconomic, real, and financial uncertainty.[17] In the two papers, real activity shocks are originated from technology, monetary policy, preferences, or government expenditure innovations, financial uncertainty arises because of expected volatility in financial markets, and macro uncertainty arises because of expected volatility in the macro economy, such as an expectation of greater difficulty in predicting future productivity, future monetary policy or future fiscal policy. Baker et al. (2016) constructs policy-related economic uncertainty index[18] by combining newspaper coverage of policy-related economic uncertainty, the number of federal tax code provisions set to expire in future years, and disagreement among economic forecasters.

[Insert Table 11 about here]

Table 11 reports the five-factor alphas and corresponding Newey and West (1987) t-statistics of each ID decile portfolio and the long-short ID strategy. In all columns, the five-factor alphas increase when moving from the lowest ID to the highest ID decile. In addition, the five-factor alphas of the long-short ID strategy are in the range of 0.72% to 0.92% per month, with t-statistics between 3.95 and 6.68. The results indicate that the long-short ID strategy prevails in either high- or low- macro, financial, real, and policy-related economic uncertainty periods.

4.7.2 Persistence of ID and the long-short ID strategy performance

First, I examine whether investor disagreement (ID) is persistent. To address this question, I examine the persistence of ID by running firm-level cross-sectional regressions of ID on lagged ID and 12 lagged cross-sectional predictors including firm size (SIZE), book-to-market (BM) ratio, momentum (MOM), short-term reversal (REV), turnover ratio (TURN), idiosyncratic volatility (IVOL), illiquidity (ILILQ), demand for lottery stocks with extreme positive returns (MAX), institutional ownership ratio (IOR), the stock beta (BETA), co-skewness (COSKEW), and anaylst forecast dispersion (DISP).

[17]The data is obtained from Professor Ludvigson's website.
[18]The data is obtained from https://www.policyuncertainty.com/index.html.

Panel A in Table 11 reports the average cross-sectional coefficients on ID from the univariate and multivariate cross-sectional regressions. The coefficients on ID are 0.552 and 0.468 for univariate and multivariate cross-sectional regressions, respectively, and are both extremely significant. The adjusted R-squared in both regressions are above 30%, indicating substantial cross-sectional explanatory power. The regression results suggest that stocks with high ID in one month on average tend to be of high ID in the subsequent month.

[Insert Table 11 about here]

Another way to examine the persistence of ID is to compute the average month-to-month decile portfolio transition matrix. Panel B in Table 11 reports the results, where column (i, j) is the average probability that a stock in ID decile i in month will be in ID decile j in the following month. If ID is completely random, then all the diagonal probabilities should be approximately 10%. First, all the diagonal elements of the transition matrix exceeds 10%, indicating that ID is indeed persistent. In particular, the persistence is especially strong within the extreme deciles. Stocks in decile 10 (high ID) have a 38.06% chance of remaining in the same decile in the subsequent month, and stocks in decile 1 (low ID) have a 42.87% chance of appearing in the same decile in the following month.

In addition, I vary the number of months in the formation of ID and examine the significance and magnitude and the corresponding long-short ID strategy. In particular, ID at the end of a given month is computed as the contemporaneous correlation coefficient of daily trading volume and absolute price change over the past T months, multiplied by -1. For different formation periods ranging from 3 to 12 months, Table 12 reports the next-month equal-weighted excess returns, CAPM alpha, three-factor alpha, four-factor alpha, and five-factor alpha between the highest and the lowest ID decile.

[Insert Table 12 about here]

The excess return of the long-ID strategy ranges from 0.46% to 0.58% per month, with Newey and West (1987) t-statistics between 2.20 and 3.44. The corresponding risk-adjusted returns are all positive and highly significant, indicating that the positive relation between ID and expected stock returns is robust to different formation months of ID.

Next, I examine the long-short ID strategy under different holding periods to ensure that the high returns generated by the long-short ID strategy are not caused by a statistical fluke. In particular, I vary the number of months one holds each ID portfolio after it has been formed following Jegadeesh and Titman (1993). For example, when the holding period equals to 3 months, the portfolio return in month t is the average return of the decile portfolios formed in $t-1$, $t-2$, and $t-3$. Hence, each decile portfolio changes one-third of its composition each month.

[Insert Table 13 about here]

Table 13 reports the equal-weighted excess returns, CAPM alpha, three-factor alpha, four-factor alpha, and five-factor alpha between the highest and the lowest ID decile for different holding months. Both excess returns and risk-adjusted returns remain significantly positive under all holding periods up to 12 months. In addition, the five-factor alpha decreases from 0.68% (t-statistic=6.57) to 0.37% (t-statistic=3.68) per month as the number of holding month increases. The results suggest that the positive relation between ID and future stock returns is most significant for short to intermediate horizons.

5 Investor disagreement and earnings announcements

So far I've only examined the significance of investor disagreement (ID) in the cross-sectional monthly pricing of stocks. Some investors, however, tend to trade stocks around earnings announcements (Kaniel et al. (2012) and Yang et al. (2020)). If the prediction of the model is correct, then it should also be the case that stocks with high ID prior to the earnings announcement significantly outperform those with low ID around the earnings announcement.

5.1 Data and variable definitions

To test this hypothesis, I first identify earnings announcement dates of firms with common stocks traded on NYSE, NASDAQ, and AMEX from Compustat, which according to WRDS are more reliable compared to announcement dates from IBES.[19] Next, I define reference and earnings announcement period as the 44-day window $[-45, -2]$ and 3-day window $[-1, 1]$, respectively, where $t = 0$ is the earnings announcement date. As a robustness check, I also use four other variations of reference and earnings announcement period in all my following tests.[20]

ID is defined as the contemporaneous correlation coefficient of daily trading volume and absolute price change in the reference period, multiplied by -1. Again, a stock trading day t is eligible if the price per share on $t-31$ is at least 5 dollars and has non-missing return and volume. Stocks are required to have at least 30 eligible trading days in the reference period

[19] https://wrds-www.wharton.upenn.edu/pages/support/support-articles/ibes/

[20] REF period $[-48, -5]$ with EAR period $[-4, 4]$, REF period $[-47, -4]$ with EAR period $[-3, 3]$, REF period $[-46, -3]$ with EAR period $[-2, 2]$, and REF period $[-45, -2]$ with EAR period $[-1, 1]$.

to compute ID. Figure 4 plots the number of eligible stocks issuing earnings announcement in each calendar quarter from the first quarter of 1983 to the fourth quarter of 2019.

[Insert Figure 4 about here]

Following most literature studying earnings announcements, stock performance around an earnings announcement is defined as the stock's cumulative abnormal return (CAR), which is the difference between the compounded stock return and value-weighted market return (in percent) over the earnings announcement period.

Other control variables are defined similarly as in Appendix I. SIZE is the log of market capitalization in millions of dollars and BM is book-to-market ratio. RET is the return (in percent) compounded over the reference period. TURN and IVOL are the average turnover ratio and idiosyncratic volatility in the reference period. IOR is the ratio of shares owned by institutions as reported in 13F filings in the last quarter.[21] NUMEST is the number of unique analysts that have eligible fiscal year one earnings estimates on IBES in the reference period.[22]

5.2 Portfolio analysis

I start my analysis by examining the relation between investor disagreement (ID) in the reference period and cumulative abnormal returns (CAR) around earnings announcements. First, every calendar quarters are classified into deciles based on their ID in the reference period. Then, I compute the cross-sectional mean CAR around earnings announcements for each ID quintile. Then, I compute the time-series (weighted) averages of these cross-sectional means across all quarters. The weights are based on the number of observations in each ID decile each quarter .

Table 14 presents time-series average of quarterly mean values of CAR around earnings announcement period within ID deciles. Looking at the second column, the average $\text{CAR}_{-1,1}$ increases from 0.12% to 0.76% when moving from the lowest to the highest ID decile. The difference in CARs is 0.65% with a significant Newey and West (1987) t-statistic of 4.77. As a robustness check, in the third to sixth column, I also examine other variations of reference and earnings announcement periods, and the results are similar. For example, in the last column the average $\text{CAR}_{-5,5}$ increases from -0.51% to 0.22% when moving from the lowest to the highest ID decile, and the return differential is 0.73% with a Newey and West (1987) t-statistic of 7.10.

[21]Nagel (2005) emphasizes the relation between short-sales constraints and divergence of opinion when examining stock returns.

[22]See Israelsen (2016), Lee and So (2017), and Ali and Hirshleifer (2020) for evidence of the relation between analyst coverage and stock returns.

[Insert Table 14 about here]

Overall, the results in Table 14 suggest that stocks with high ID prior to the earnings announcement experience significantly higher cumulative abnormal returns in the earnings announcement period.

5.3 Regression analysis

In this section, I perform a cross-sectional regression analysis that controls for various stock characteristics that may potentially affect the relation between investor disagreement (ID) in the reference period and cumulative abnormal returns (CAR) in the earnings announcement period. I implement Fama and MacBeth (1973) regressions in which the dependent variable is CAR in the earnings announcement period. In particular, I run the following cross-sectional regression every quarter:

$$CAR_{i,q} = \alpha_q + \beta_q ID_{i,q} + \lambda_q X_{i,q} + \epsilon_{i,q}, \tag{22}$$

where i refers to the stock, q refers to the calendar quarter, $\mathrm{ID}_{i,q}$ is investor disagreement in the reference period with respect to quarter q for stock i, and $X_{i,q}$ is the set of stock-specific control variables for stock i in quarter q, and $\mathrm{CAR}_{i,q}$ is cumulative abnormal return in the earnings announcement period for firm i in quarter q. Then, I average (weighted) the cross-sectional coefficients across all quarters, where the weights correspond to the number of observations in each quarterly cross-sectional regression. The choice of quarterly frequency is consistent with other papers in the earnings announcement literature (e.g., Garfinkel and Sokobin (2006), Johnson and So (2012), and Akbas (2016)). The coefficient of interest is ID in the reference period. If there indeed exists a positive relation between ID in the reference period and earnings announcement premium, β_q should be significantly positive.

Table 15 presents the results. The coefficients on ID are positive and highly significant across five different reference and earnings announcement periods. For example, looking at the second column, when the reference period is $[-45, -2]$ and the earnings announcement period is $[-1, 1]$, the coefficient on ID is 0.337 with a Newey and West (1987) t-statistic of 3.96. In other words, stocks with high ID prior to earnings announcements on average experience significantly higher cumulative abnormal returns around earnings announcements.

[Insert Table 15 about here]

The coefficients on control variables are mostly consistent with the literature. The coefficients on RET are significantly negative, which is consistent with the well-known reversal effect. The coefficients on BM are significantly positive, which implies that value stocks in the reference periods tend to perform better around earnings announcements periods (Porta et al. (1997)). The coefficients on IVOL are significantly negative, which is consistent with Ang et al. (2006). The coefficients of SIZE, however, are positive, while Chari et al. (1988) and Ball and Kothari (1991) suggest that earnings announcement returns are larger for smaller firms.

5.4 Investor disagreement: earnings announcements, news stories, and FOMC meetings

In this section, I examine investor disagreement before and after earnings announcements, firm-specific news stories, and FOMC meetings, respectively.

5.4.1 Evolution of ID: earnings announcements

I first compute investor disagreement (ID) before and after the earnings announcement. ID before the earnings announcement date (day 0) is defined as the correlation coefficient between daily trading volume and absolute price change over the 44-day window $[-45, -2]$, multiplied by -1. ID after the earnings announcement is defined similarly over the 44-day window $[2, 45]$. Then, ΔID is defined as $\Delta ID = ID_{\text{after}} - ID_{\text{before}}$.

Figure 5 plots the time-series average of mean values of ID before and after the earnings announcement. First, ID after earnings announcements seems to be slightly higher than ID before earnings announcements, although the difference in magnitude is small. This is consistent with findings in Table 11 that ID is highly persistent.

[Insert Figure 5 about here]

In particular, the mean ΔID is 0.0084 with a significant Newey and West (1987) t-statistic of 4.39. I also compute the mean ΔID for the sample period before and after the implementation of Regulation Fair Disclosure (Reg FD), which prevents firms from doing selective disclosure. Specifically, the pre-Reg-FD and post-Reg-FD mean ΔID are 0.0089 (t-statistic=5.67) and 0.0062 (t-statistic=2.16), respectively. The decrease from before to after implementation of Reg FD could be a result of more transparent and valid firm disclosures. Figure 6 suggests that on average, ID increases after earnings announcements.

5.4.2 Evolution of ID: firm-specific public news stories

I next examine whether ID also increases following firm-specific public news stories. In particular, I first obtain public news data from RavenPack News Analytics on WRDS. I select news events with a relevance score equal to 100, which are considered significantly relevant according to RavenPack.[23]

I further classify news events into six categories; Financial, Legal, M&A, Operational, Ratings, and Others. The news date is defined as the date when the first news story reporting an event about one or more entities is announced. To avoid double counting issue, subsequent news stories reporting the the same news events are not included. ID before and after news events are computed in the same fashion treating the news date as day 0.

[Insert Figure 6 about here]

Figure 6 plots the time-series average of mean values of ID before and after six types of news stories. Again, ID before and after behave very similarly, reassuring the persistence of ID. Specifically, the mean ΔID is 0.0177 (t-statistic=5.66) for financial news, 0.0058 (t-statistic=1.78) for legal news, 0.0089 (t-statistic=2.66) for M&A news, 0.0066 (t-statistic=2.09) for operational news, 0.0074 (t-statistic=2.21) for ratings news, and 0.0156 (t-statistic=2.66) for other news. The results indicate that other than earnings announcements, ID also increases after different types of firm-specific public news events.

5.4.3 Evolution of ID: FOMC meetings

Next, since investor disagreement proxies for security-level behavioral bias (Harvey et al. (2016)), it should not respond to macroeconomic events. If ID significantly increases after macroeconomic events, then it is possible that our disagreement measure simply captures economic uncertainty instead of investor disagreement.

To mitigate this concern, I examine ID before and after Federal Open Market Committee (FOMC) meetings. There are eight regularly scheduled FOMC meetings each year and meeting minutes are made public following the meetings. Prior work (e.g., Cieslak et al. (2019), Lucca and Moench (2015), and Bernanke and Kuttner (2005)) study stock market's reaction in the form of realized stock returns to FOMC announcements. In our context, however, the hypothesis is that mean ΔID should be insignificantly different from 0.

I obtain FOMC scheduled meetings from 1994 to 2019, as in the first meeting (February 3-4, 1994) a reasonable portion of the discussion centered on the need to make the committee's intentions clear to the public. I then examine ID before and after FOMC meetings following the same approach.

[Insert Figure 7 about here]

[23]According to the RavenPack, a value of 100 indicates that the entity identified plays a key role in the news story and is considered highly relevant.

Figure 7 plots the time-series average of mean values of ID before and after FOMC meetings. ID before and after behave virtually the same. In particular, the mean ΔID is 0.0007 with a significant Newey and West (1987) insignificant t-statistic of 0.33, which is consistent with the conjecture that ID proxies for firm-specific investor disagreement.

Together, Figure 5, Figure 6, and Figure 7 show that ID is sensitive to firm-specific information disclosure events but indifferent to macroeconomic news. When firm-specific news bring in a sudden influx of information, investors on average tend to slightly disagree more.

5.5 Investor disagreement: good and bad earnings news

Next, I examine whether the "sentiment" of earnings announcement affects the evolution of investor disagreement. Rogers et al. (2009), for example, find that short-term increase in uncertainty is attributable to forecasts that convey bad news. In a similar fashion, I test if the evolution of investor disagreement (ID) from before to after earnings announcements is asymmetric to good and bad earnings news.

I first use three-day cumulative abnormal returns centered at the earnings announcement date, $CAR_{-1,1}$, to determine whether an earnings announcement convey good news or bad news. In particular, $CAR_{-1,1}$ reveals investors' expectations regarding the firm's future cash flow prospects. $CAR_{-1,1}$ is defined as the compounded return over the $[-1, 1]$ window around the earnings announcement date ($t = 0$) in excess of the compounded value-weighted market return.

Table 16 presents the results. The mean ΔID for good earnings news ($CAR_{-1,1} > 0$) is 0.0032 with a Newey and West (1987) t-statistic of 2.08, while the mean ΔID for bad earnings news ($CAR_{-1,1} \leq 0$) is 0.0107 with a Newey and West (1987) t-statistic of 6.59. In particular, the difference in mean ΔID between bad news and good news is 0.0075 (t-statistic=7.42). The results suggest that ID increases more following bad earnings news than good earnings news.

[Insert Table 16 about here]

In addition, I examine the difference in mean ΔID between bad news and good news when controlling for firm size (SIZE). In each calendar quarter, I first sort stocks with earnings announcements into quintiles based on SIZE. Next, within each SIZE quintile, I examine the difference in mean ΔID between bad earnings news ($CAR_{-1,1} \leq 0$) and good earnings news ($CAR_{-1,1} > 0$). In particular, the mean ΔID differences are significantly positive in three out of the five SIZE quintiles, providing further support that the increase in ID is larger following bad earnings news than good earnings news. The SUE and SUEAF sample are smaller and largely comprise bigger firms.

As a robustness check, I use two other measures, standardized unexpected earnings (SUE) and standardized unexpected earnings using analysts' forecasts (SUEAF), to capture earnings surprises at earnings announcements. Following Livnat and Mendenhall (2006), Garfinkel and Sokobin (2006), Johnson and So (2012), and Akbas (2016), SUE is defined as the difference in EPS before extraordinary items in quarters q and $q-4$ divided by quarter $q-4$ end price. SUEAF is defined as the difference between the median analyst forecast over the 90-day period before the announcement and actual earnings divided by quarter $q-4$ end price.

Panel A of Table 17 presents ID before and after earnings announcements for good earnings news (SUE > 0) and bad earnings news (SUE ≤ 0) in each SIZE quintile. The differences in mean ΔID between bad news and good news are in the range of 0.0101 and 0.0171, with t-statistics between 4.47 and 8.83. Similarly, Panel B of Table 17 presents ID before and after earnings announcements for good earnings news for good earnings news (SUEAF > 0) and bad earnings news (SUEAF ≤ 0) across SIZE quintiles. The differences in mean ΔID are positively significant in all but the largest SIZE quintile. Together, Table 16 and Table 17 provide strong evidence that investor disagreement increases more following bad earnings news than good earnings news.

In addition, I run stock-level cross-sectional regression of ΔID on bad news indicator variables ($1_{CAR_{-1,1}\leq 0}$, $1_{SUE\leq 0}$, and $1_{SUEAF\leq 0}$) in Table 18 to control for multiple variables simultaneously. The coefficients on the bad news indicator variables are all positively significant, which indicates that compared to good earnings news, bad earnings news triggers a larger increase in investor disagreement.

6 Conclusion

This paper studies the role of investor disagreement (ID) in the cross-section of expected stock returns. In particular, I set up a disagreement model in which two types of traders differ in how to interpret a public signal. Traders don't know how to correctly interpret the contradicting interpretation at first glance and believe that its information quality can range from being less precise to more precise compared to their own interpretation. Hence, traders treat the contradicting interpretation as ambiguous.

The model along with traders being ambiguity-averse predicts that there exists a positive relation between investor disagreement and expected stock returns. The model also implies that when investor disagreement is higher, the relation between trading volume and absolute price change is weaker in equilibrium. Hence, I compute investor disagreement at the end of a given month as the contemporaneous correlation coefficient of daily trading volume and absolute price change over the past two months, multiplied by -1.

I find that stocks in the highest investor disagreement decile significantly outperform stocks in the lowest investor disagreement decile by an annualized risk-adjusted return of 9.24%. Bivariate portfolio-level analyses and stock-level cross-sectional regressions that control for many well-known return-predicting variables, including firm size, book-to-market ratio, momentum, short-term reversal, turnover ratio, illiquidity, market beta, co-skewness, demand for lottery stocks with extreme positive returns, and idiosyncratic volatility generate similar results, which provides further evidence of a significantly positive relation between investor disagreement and future stock returns in the cross section. I further perform a wide variety of robustness checks and show that the positive investor disagreement relation persists in high and low sentiment periods, recessions and expansions, high and low economic uncertainty periods, and different holding and formation periods.

Besides using monthly returns to examine the asset pricing implications of ID, I also examine the relation between ID and expected stock returns in the earnings announcement setting using portfolio analyses and stock-level cross-sectional regressions. In particular, stocks with high ID prior to earnings announcements earn significantly higher cumulative abnormal returns around earnings announcements compared to stocks with low ID. In addition, ID increases after earnings announcements and this effect is most pronounced in earnings announcements that convey bad news. Moreover, ID increases after firm-specific news stories but remains virtually the same following FOMC scheduled announcements.

References

Akbas, F. (2016). The calm before the storm. *The Journal of Finance 71*(1), 225–266.

Ali, U. and D. Hirshleifer (2020). Shared analyst coverage: Unifying momentum spillover effects. *Journal of Financial Economics 136*(3), 649–675.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets 5*(1), 31–56.

Andersen, T. G. (1996). Return volatility and trading volume: An information flow interpretation of stochastic volatility. *The Journal of Finance 51*(1), 169–204.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006). The cross-section of volatility and expected returns. *The Journal of Finance 61*(1), 259–299.

Asquith, P., P. A. Pathak, and J. R. Ritter (2005). Short interest, institutional ownership, and stock returns. *Journal of Financial Economics 78*(2), 243–276.

Back, K., K. Crotty, and T. Li (2018). Identifying information asymmetry in securities markets. *The Review of Financial Studies 31*(6), 2277–2325.

Bailey, W., H. Li, C. X. Mao, and R. Zhong (2003). Regulation fair disclosure and earnings information: Market, analyst, and corporate responses. *The Journal of Finance 58*(6), 2487–2514.

Baker, M. and J. Wurgler (2006). Investor sentiment and the cross-section of stock returns. *The journal of Finance 61*(4), 1645–1680.

Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring economic policy uncertainty. *The quarterly journal of economics 131*(4), 1593–1636.

Bali, T. G., S. J. Brown, and Y. Tang (2017). Is economic uncertainty priced in the cross-section of stock returns? *Journal of Financial Economics 126*(3), 471–489.

Bali, T. G., N. Cakici, and R. F. Whitelaw (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics 99*(2), 427–446.

Ball, R. and P. Brown (1968). An empirical evaluation of accounting income numbers. *Journal of accounting research*, 159–178.

Ball, R. and S. P. Kothari (1991). Security returns around earnings announcements. *Accounting Review*, 718–738.

Banerjee, S. and I. Kremer (2010). Disagreement and learning: Dynamic patterns of trade. *The Journal of Finance 65*(4), 1269–1302.

Barinov, A. (2013). Analyst disagreement and aggregate volatility risk. *Journal of Financial and Quantitative Analysis*, 1877–1900.

Bernanke, B. S. and K. N. Kuttner (2005). What explains the stock market's reaction to federal reserve policy? *The Journal of finance 60*(3), 1221–1257.

Bossaerts, P., P. Ghirardato, S. Guarnaschelli, and W. R. Zame (2010). Ambiguity in asset markets: Theory and experiment. *The Review of Financial Studies 23*(4), 1325–1359.

Cao, H. H. and H. Ou-Yang (2008). Differences of opinion of public information and speculative trading in stocks and options. *The Review of Financial Studies 22*(1), 299–335.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance 52*(1), 57–82.

Chang, Y.-C., P.-J. Hsiao, A. Ljungqvist, and K. Tseng (2020). Testing disagreement models. *Swedish House of Finance Research Paper* (20-5).

Chari, V. V., R. Jagannathan, and A. R. Ofer (1988). Seasonalities in security returns: The case of earnings announcements. *Journal of Financial Economics 21*(1), 101–121.

Cieslak, A., A. Morse, and A. Vissing-Jorgensen (2019). Stock returns over the fomc cycle. *The Journal of Finance 74*(5), 2201–2248.

Clark, P. K. (1973). A subordinated stochastic process model with finite variance for speculative prices. *Econometrica: journal of the Econometric Society*, 135–155.

Corwin, S. A. and J. F. Coughenour (2008). Limited attention and the allocation of effort in securities trading. *The Journal of Finance 63*(6), 3031–3067.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers (1997). Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of finance 52*(3), 1035–1058.

Daniel, K. and S. Titman (2006). Market reactions to tangible and intangible information. *The Journal of Finance 61*(4), 1605–1643.

David, A. (2008). Heterogeneous beliefs, speculation, and the equity premium. *The Journal of Finance 63*(1), 41–83.

Davis, J. L., E. F. Fama, and K. R. French (2000). Characteristics, covariances, and average returns: 1929 to 1997. *The Journal of Finance 55*(1), 389–406.

DellaVigna, S. and J. M. Pollet (2009). Investor inattention and friday earnings announcements. *The Journal of Finance 64*(2), 709–749.

Diamond, D. W. and R. E. Verrecchia (1987). Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics 18*(2), 277–311.

Diamond, D. W. and R. E. Verrecchia (1991). Disclosure, liquidity, and the cost of capital. *The journal of Finance 46*(4), 1325–1359.

Diether, K. B., C. J. Malloy, and A. Scherbina (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance 57*(5), 2113–2141.

Doukas, J. A., C. F. Kim, and C. Pantzalis (2006). Divergence of opinion and equity returns. *Journal of Financial and Quantitative Analysis 41*(3), 573–606.

Easley, D. and M. O'HARA (2010). Microstructure and ambiguity. *The Journal of Finance 65*(5), 1817–1846.

Ellsberg, D. (1961). Risk, ambiguity, and the savage axioms. *The quarterly journal of economics*, 643–669.

Epstein, L. G. and M. Schneider (2007). Learning under ambiguity. *The Review of Economic Studies 74*(4), 1275–1303.

Epstein, L. G. and M. Schneider (2008). Ambiguity, information quality, and asset pricing. *The Journal of Finance 63*(1), 197–228.

Fama, E. F. and K. R. French (1992). The cross-section of expected stock returns. *the Journal of Finance 47*(2), 427–465.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of*.

Fama, E. F. and K. R. French (1996). Multifactor explanations of asset pricing anomalies. *The journal of finance 51*(1), 55–84.

Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *Journal of political economy 81*(3), 607–636.

Gallant, A. R., P. E. Rossi, and G. Tauchen (1992). Stock prices and volume. *The Review of Financial Studies 5*(2), 199–242.

Gao, G. P., X. Lu, Z. Song, and H. Yan (2019). Disagreement beta. *Journal of Monetary Economics 107*, 96–113.

Garfinkel, J. A. and J. Sokobin (2006). Volume, opinion divergence, and returns: A study of post–earnings announcement drift. *Journal of Accounting Research 44*(1), 85–112.

Gervais, S., R. Kaniel, and D. H. Mingelgrin (2001). The high-volume return premium. *The Journal of Finance 56*(3), 877–919.

Gibbons, M. R., S. A. Ross, and J. Shanken (1989). A test of the efficiency of a given portfolio. *Econometrica: Journal of the Econometric Society*, 1121–1152.

Gilboa, I. and D. Schmeidler (1989). Maxmin expected utility with non-unique prior. *Journal of mathematical economics 18*(2), 141–153.

Gizatulina, A. and Z. Hellman (2019). No trade and yes trade theorems for heterogeneous priors. *Journal of Economic Theory 182*, 161–184.

Goetzmann, W. N. and M. Massa (2005). Dispersion of opinion and stock returns. *Journal of Financial Markets 8*(3), 324–349.

Hansen, L. P. and T. J. Sargent (2007). Recursive robust estimation and control without commitment. *Journal of Economic Theory 136*(1), 1–27.

Harris, M. and A. Raviv (1993). Differences of opinion make a horse race. *The Review of Financial Studies 6*(3), 473–506.

Harrison, J. M. and D. M. Kreps (1978). Speculative investor behavior in a stock market with heterogeneous expectations. *The Quarterly Journal of Economics 92*(2), 323–336.

Harvey, C. R., Y. Liu, and H. Zhu (2016). and the cross-section of expected returns. *The Review of Financial Studies 29*(1), 5–68.

Harvey, C. R. and A. Siddique (2000). Conditional skewness in asset pricing tests. *The Journal of Finance 55*(3), 1263–1295.

Hirshleifer, D. and S. H. Teoh (2003). Limited attention, information disclosure, and financial reporting. *Journal of accounting and economics 36*(1-3), 337–386.

Illeditsch, P. K. (2011). Ambiguous information, portfolio inertia, and excess volatility. *The Journal of Finance 66*(6), 2213–2247.

Israelsen, R. D. (2016). Does common analyst coverage explain excess comovement? *Journal of Financial and Quantitative Analysis 51*(4), 1193–1229.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of finance 45*(3), 881–898.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance 48*(1), 65–91.

Johnson, T. L. and E. C. So (2012). The option to stock volume ratio and future returns. *Journal of Financial Economics 106*(2), 262–286.

Jurado, K., S. C. Ludvigson, and S. Ng (2015). Measuring uncertainty. *American Economic Review 105*(3), 1177–1216.

Kandel, E. and N. D. Pearson (1995). Differential interpretation of public signals and trade in speculative markets. *Journal of Political Economy 103*(4), 831–872.

Kaniel, R., S. Liu, G. Saar, and S. Titman (2012). Individual investor trading and return patterns around earnings announcements. *The Journal of Finance 67*(2), 639–680.

Karpoff, J. M. (1987). The relation between price changes and trading volume: A survey. *Journal of Financial and quantitative Analysis 22*(1), 109–126.

Kim, O. and R. E. Verrecchia (1991). Trading volume and price reactions to public announcements. *Journal of accounting research 29*(2), 302–321.

Klibanoff, P., M. Marinacci, and S. Mukerji (2005). A smooth model of decision making under ambiguity. *Econometrica 73*(6), 1849–1892.

Krinsky, I. and J. Lee (1996). Earnings announcements and the components of the bid-ask spread. *The Journal of Finance 51*(4), 1523–1535.

Lee, C. M. and E. C. So (2017). Uncovering expected returns: Information in analyst coverage proxies. *Journal of Financial Economics 124*(2), 331–348.

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *The Quarterly Journal of Economics 105*(1), 1–28.

Lewellen, J. and J. Shanken (2002). Learning, asset-pricing tests, and market efficiency. *The Journal of finance 57*(3), 1113–1145.

Livnat, J. and R. R. Mendenhall (2006). Comparing the post–earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of accounting research 44*(1), 177–205.

Lucca, D. O. and E. Moench (2015). The pre-fomc announcement drift. *The Journal of finance 70*(1), 329–371.

Ludvigson, S. C., S. Ma, and S. Ng (2015). Uncertainty and business cycles: exogenous impulse or endogenous response? Technical report, National Bureau of Economic Research.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The Journal of Finance 42*(3), 483–510.

Milgrom, P. and N. Stokey (1982). Information, trade and common knowledge. *Journal of economic theory 26*(1), 17–27.

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *The Journal of finance 32*(4), 1151–1168.

Nagel, S. (2005). Short sales, institutional investors and the cross-section of stock returns. *Journal of financial economics 78*(2), 277–309.

Newey, W. K. and K. D. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation. *Econometrica 55*(3), 703–708.

Pástor, L. and V. Pietro (2003). Stock valuation and learning about profitability. *The Journal of Finance 58*(5), 1749–1789.

Pástor, L. and R. F. Stambaugh (2003). Liquidity risk and expected stock returns. *Journal of Political economy 111*(3), 642–685.

Peng, L. and W. Xiong (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics 80*(3), 563–602.

Pevzner, M., F. Xie, and X. Xin (2015). When firms talk, do investors listen? the role of trust in stock market reactions to corporate earnings announcements. *Journal of Financial Economics 117*(1), 190–223.

Porta, R. L., J. Lakonishok, A. Shleifer, and R. Vishny (1997). Good news for value stocks: Further evidence on market efficiency. *The Journal of Finance 52*(2), 859–874.

Rogers, J. L., D. J. Skinner, and A. Van Buskirk (2009). Earnings guidance and market uncertainty. *Journal of Accounting and Economics 48*(1), 90–109.

Sadka, R. and A. Scherbina (2007). Analyst disagreement, mispricing, and liquidity. *The Journal of Finance 62*(5), 2367–2403.

Scheinkman, J. A. and W. Xiong (2003). Overconfidence and speculative bubbles. *Journal of political Economy 111*(6), 1183–1220.

Tauchen, G. E. and M. Pitts (1983). The price variability-volume relationship on speculative markets. *Econometrica: Journal of the Econometric Society*, 485–505.

Varian, H. R. (1985). Divergence of opinion in complete markets: A note. *The Journal of Finance 40*(1), 309–317.

Verrecchia, R. E. (1983). Discretionary disclosure. *Journal of accounting and economics 5*, 179–194.

Wermers, R. (2003). Is money really'smart'? new evidence on the relation between mutual fund flows, manager behavior, and performance persistence. *New Evidence on the Relation Between Mutual Fund Flows, Manager Behavior, and Performance Persistence (May 2003)*.

Yang, Y. C., B. Zhang, and C. Zhang (2020). Is information risk priced? evidence from abnormal idiosyncratic volatility. *Journal of Financial Economics 135*(2), 528–554.

Appendix I: Variable definitions

In this section, I define various variables used in the paper.

Following Fama and French (1992), Fama and French (1993), and Davis et al. (2000), firm size (SIZE) for July of year t to June of t+1 is defined as the natural logarithm of market value of equity at the end of December of year $t-1$, and the book-to-market (BM) ratio from July of year t through June of year $t+1$, is computed as the shareholders' book value of equity plus deferred taxes and investment tax credit (if available) minus the book value of preferred stock at the end of the last fiscal year, $t-1$, divided by the market value of equity at the end of December of year $t-1$. Depending on availability, the redemption, liquidation, or par value is used to estimate the book value of preferred stock. Following Daniel and Titman (2006), the minimum 6-month lag is to ensure the firm's annual report is publicly available information.

Following Jegadeesh and Titman (1993), momentum (MOM) is computed as the cumulative return of a stock of 11 months ending one month prior to the given month. Following Jegadeesh (1990), short-term reversal (REV) is defined as the stock return over the portfolio formation month. Turnover ratio (TURN) is computed as the percentage of trading volume divided by the total number of shares outstanding shares over the portfolio formation month. A minimum of 15 daily observations in the given month is required to calculate TURN.

Following Amihud (2002), stock illiquidity for each stock in month m as the ratio of the absolute monthly stock return to its dollar trading volume, multiplied by 10^6:

$$ILLIQ_{i,m} = 10^6 \times Avg\left[\frac{|R_{i,d}|}{DTV_{i,d}}\right], \tag{23}$$

where $R_{i,d}$ and $DTV_{i,d}$ are the daily return and dollar trading volume for stock i on day d, respectively. A minimum of 15 daily observations in the given month is required to calculate ILLIQ.

Stock beta (BETA), is computed by regressing the stock's monthly excess return on monthly market excess return and lagged market excess return to accommodate non-synchronous trading effects:

$$R_{i,m} = \alpha_i + \beta_{i,1}R_{M,m} + \beta_{i,2}R_{M,m-1} + \epsilon_{i,m}, \tag{24}$$

where $R_{i,m}$ and $R_{M,m}$ are the monthly excess returns on stock i and the CRSP value-weighted market index, respectively. Following Fama and French (1992), I run the regression each month over a moving window covering the most recent 60 months, requiring at least 36 months of non-missing data. The stock's monthly beta is defined as $\widehat{\beta_{i,1}} + \widehat{\beta_{i,2}}$.

Following Bali et al. (2011) and Bali et al. (2017), demand for lottery-like stocks (MAX) is defined as the average of the five highest daily daily returns of the stock during the portfolio formation month. A minimum of 15 daily observations in the given month is required to calculate MAX.

Following Harvey and Siddique (2000), the co-skewness (COSKEW) of stock i in month m is defined as the estimated slope $\widehat{\gamma_{i,m}}$ in the following regression:

$$R_{i,m} = \alpha_i + \beta_i R_{M,m} + \gamma_i R^2_{M,m} + \epsilon_{i,m}. \tag{25}$$

Similar to stock beta, regression are performed over a moving window covering the most recent 60 months, requiring at least 36 months of non-missing data.

Following Ang et al. (2006), the monthly idiosyncratic volatility of stock i (IVOL) is computed as the standard deviation of the daily residuals estimated from the following regression:

$$R_{i,d} = \alpha_i + \beta_i MKT_{M,d} + \gamma_i SMB_d + \phi_i HML_d + \gamma_i UMD_d \epsilon_{i,d}, \tag{26}$$

where $R_{i,d}$ and $MKT_{M,d}$ are the daily excess returns on stock i and the CRSP value-weighted market index, respectively. SMB_d and HML_d are the daily size and book-to-market factors of Fama and French (1996), respectively. UMD_d is the momentum factor.

Following Diether et al. (2002), Analyst forecast dispersion (DISP) is defined as the standard deviation of fiscal year one earnings forecasts scaled by the absolute value of the mean earnings forecast in a given month. To compute analyst forecast dispersion, each stock must be covered by two or more analysts during that month.

Appendix II: Proof

The posterior beliefs of type i traders on X at $t = 1'$ are represented by

$$\begin{cases} X \sim N(\frac{Z_i X_i + (\frac{1-\beta_1}{2-\beta_1}\sigma^2+\sigma_\eta^2)^{-1}(S-\frac{(1-\beta_1)\mu_i+\mu_{-i}}{2-\beta_1})}{Z_i+(\frac{1-\beta_1}{2-\beta_1}\sigma^2+\sigma_\eta^2)^{-1}}, (Z_i + (\frac{1-\beta_1}{2-\beta_1}\sigma^2 + \sigma_\eta^2)^{-1})^{-1}) & \text{if } \mu_{-i} - \mu_i > 0 \\ X \sim N(\frac{Z_i X_i + (\frac{1+\beta_2}{2+\beta_2}\sigma^2+\sigma_\eta^2)^{-1}(S-\frac{(1+\beta_2)\mu_i+\mu_{-i}}{2+\beta_2})}{Z_i+(\frac{1+\beta_2}{2+\beta_2}\sigma^2+\sigma_\eta^2)^{-1}}, (Z_i + (\frac{1+\beta_2}{2+\beta_2}\sigma^2 + \sigma_\eta^2)^{-1})^{-1}) & \text{if } \mu_{-i} - \mu_i < 0 \end{cases} \tag{27}$$

Since, using $\frac{1+\beta_2}{2+\beta_2}\sigma^2 << \sigma_\eta^2$, we have $(\frac{1+\beta_2}{2+\beta_2}\sigma^2 + \sigma_\eta^2) \approx \sigma_\eta^2$ and $(\frac{1-\beta_1}{2-\beta_1}\sigma^2 + \sigma_\eta^2) \approx \sigma_\eta^2$. Using the above properties, (27) is given by

$$\begin{cases} X \sim N(\frac{Z_i X_i + \sigma_\eta^{-2}(S-\frac{(1-\beta_1)\mu_i+\mu_{-i}}{2-\beta_1})}{Z_i+\sigma_\eta^{-2}}, (Z_i + \sigma_\eta^{-2})^{-1}) & \text{if } \mu_{-i} - \mu_i > 0 \\ X \sim N(\frac{Z_i X_i + \sigma_\eta^{-2}(S-\frac{(1+\beta_2)\mu_i+\mu_{-i}}{2+\beta_2})}{Z_i+\sigma_\eta^{-2}}, (Z_i + \sigma_\eta^{-2})^{-1}) & \text{if } \mu_{-i} - \mu_i < 0 \end{cases} \tag{28}$$

Using the market-clearing condition ($\frac{1}{2}m_{1,1'} + \frac{1}{2}m_{2,1'} = 0$), the equilibrium price at time $1'$, $P_{1'}^*$, is given by

$$\begin{cases} \frac{Z_1X_1+Z_2X_2+\sigma_\eta^{-2}[(S-\mu_1)+(S-\mu_2)-\frac{\beta_1+\beta_2}{(2-\beta_1)(2+\beta_2)}(\mu_2-\mu_1)]}{Z_1+Z_2+2\sigma_\eta^{-2}} & \text{if } \mu_2 - \mu_1 > 0 \\ \frac{Z_1X_1+Z_2X_2+\sigma_\eta^{-2}[(S-\mu_1)+(S-\mu_2)-\frac{\beta_1+\beta_2}{(2-\beta_1)(2+\beta_2)}(\mu_1-\mu_2)]}{Z_1+Z_2+2\sigma_\eta^{-2}} & \text{if } \mu_2 - \mu_1 < 0, \end{cases} \tag{29}$$

which can be simplified to (15). Similarly, P_2^* can be computed accordingly as in (16). The return $R = P_2^* - P_{1'}^*$ is thus given by

$$\frac{\frac{(\alpha_1+\alpha_2)(\beta_1+\beta_2)}{(2-\beta_1)(2+\beta_2)}|\mu_1 - \mu_2|}{Z_1 + Z_2 + 2\sigma_\eta^{-2}}. \tag{30}$$

Since $0 < \beta_1 < 1$, $(2 - \beta_1) > 0$. Hence, R is increasing in investor disagreement, $|\mu_1 - \mu_2|$.

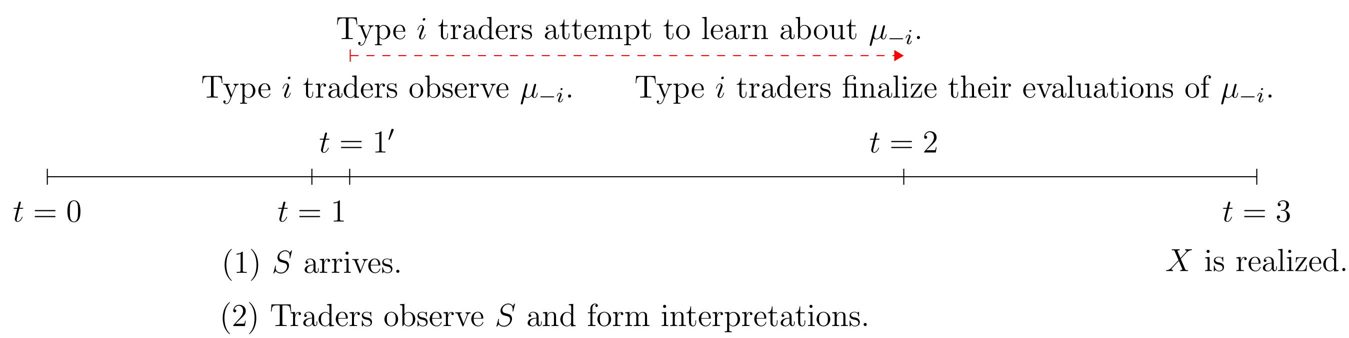


Figure 1: Model Timeline. S is the public signal and μ_{-i} is the other type's interpretation of S from type i traders' perspective, $i \in \{1, 2\}$.

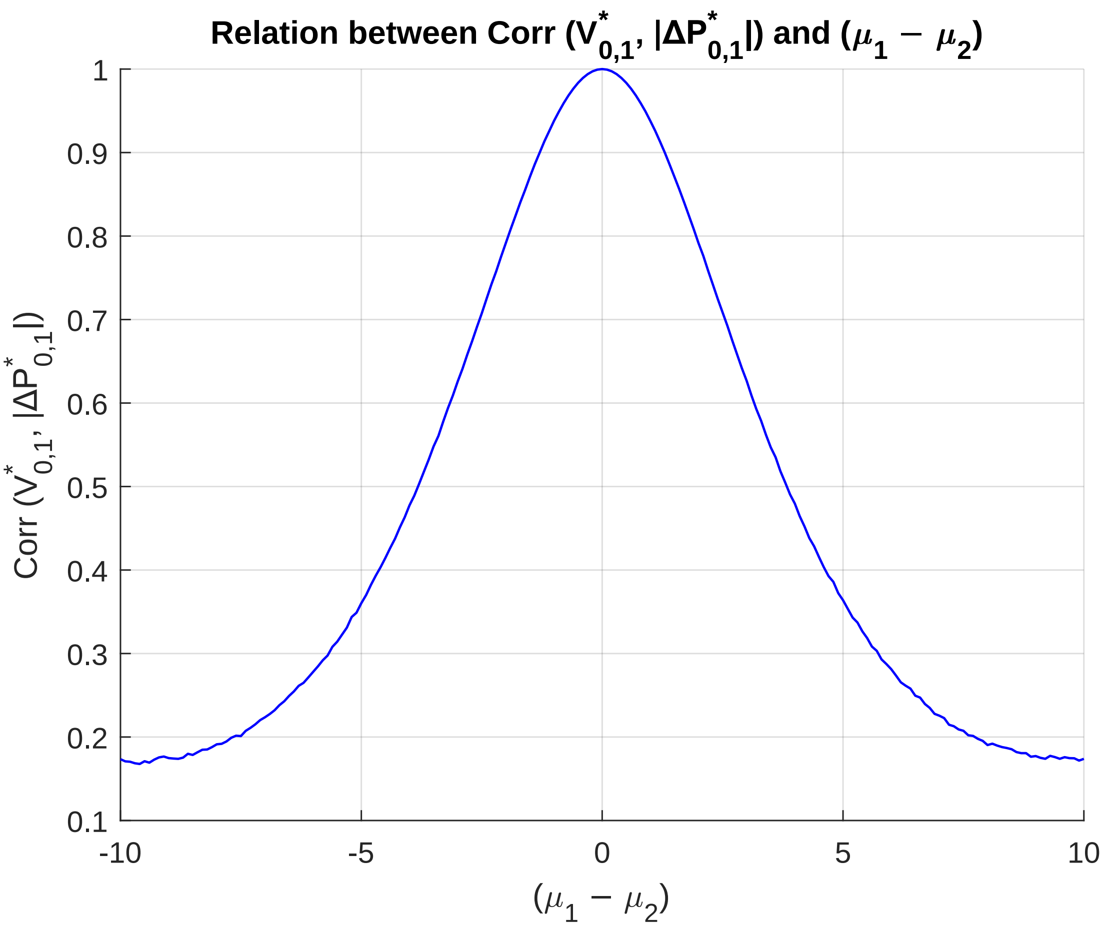


Figure 2: Relation between $Corr(V^*_{0,1}, |\Delta P^*_{0,1}|)$ and $(\mu_1 - \mu_2)$. The figure plots the correlation coefficient between equilibrium trading volume and absolute price change as a function of $(\mu_1 - \mu_2)$. Without loss of generality, μ_1 is fixed to 0, so $(\mu_1 - \mu_2)$ varies under different values of μ_2. For a given value of $(\mu_1 - \mu_2)$, I draw 100,000 observations from the distribution of $\eta \sim N(\mu_\eta = 0, \sigma^2_\eta = 2,000)$ and thus acquire 100,000 observations of S since $S = X + \eta$. The equilibrium trading volume, absolute price change, and the correlation between the two can be computed accordingly. Other model parameters are as follows: $X = 50$, $X_1 = 49$, $X_2 = 51$, $Z_1 = 1.05$, $Z_2 = 0.95$, $\lambda = 0.5$, and $\sigma^2 = 0.01$.

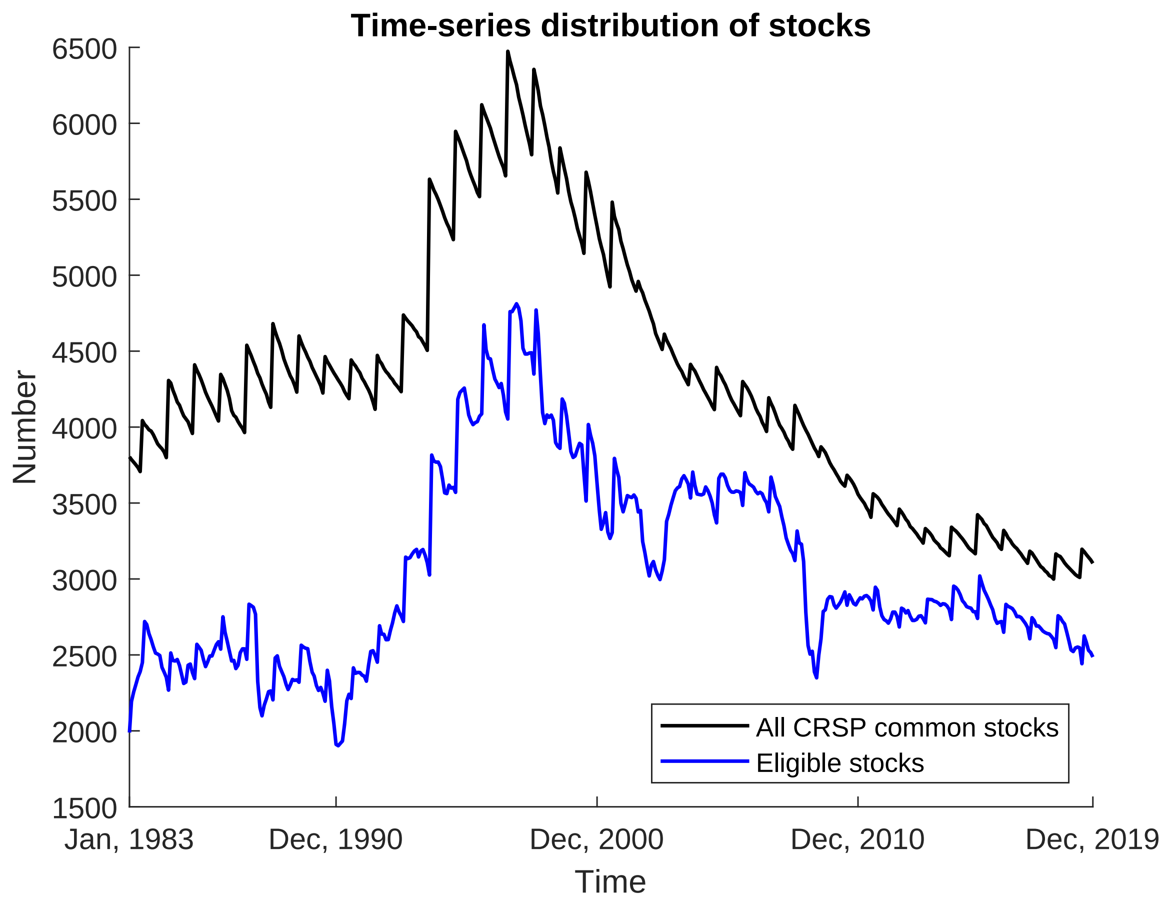


Figure 3: Time-series distribution of stocks. The figure plots the time-series distribution of all CRSP common stocks, eligible stocks, and eligible stocks with non-missing analyst forecast dispersion (DISP). Eligible stocks are stocks with non-missing investor disagreement (ID) at the end of each month. ID and DISP are defined in Section 4.2 and 4.3. The sample period is from January 1983 to December 2019 (444 months).

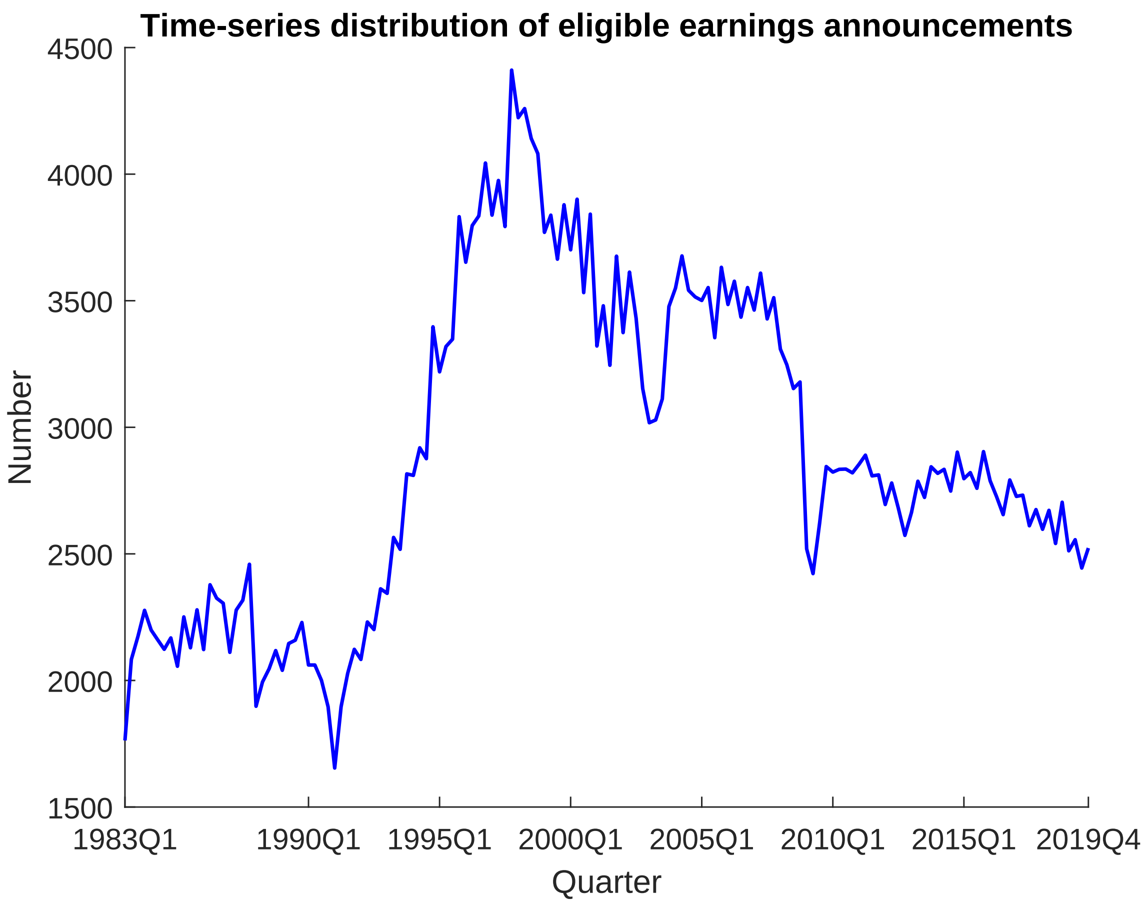


Figure 4: Time-series distribution of eligible earnings announcements. This figure plots the total number of eligible quarterly earnings announcements over time. It covers all NYSE, NASDAQ, and Amex firms available from the Compustat quarterly file with nonmissing earnings. In addition, investor disagreement before the earnings announcement (ID_{before}) is required to be non-missing. ID_{before} is defined as the contemporaneous correlation coefficient of daily trading volume and absolute price change over the window $[-45, -2]$, multiplied by -1, where $t = 0$ is the earnings announcement date. The sample period is from the first quarter of 1983 to the fourth quarter of 2019 (148 quarters).

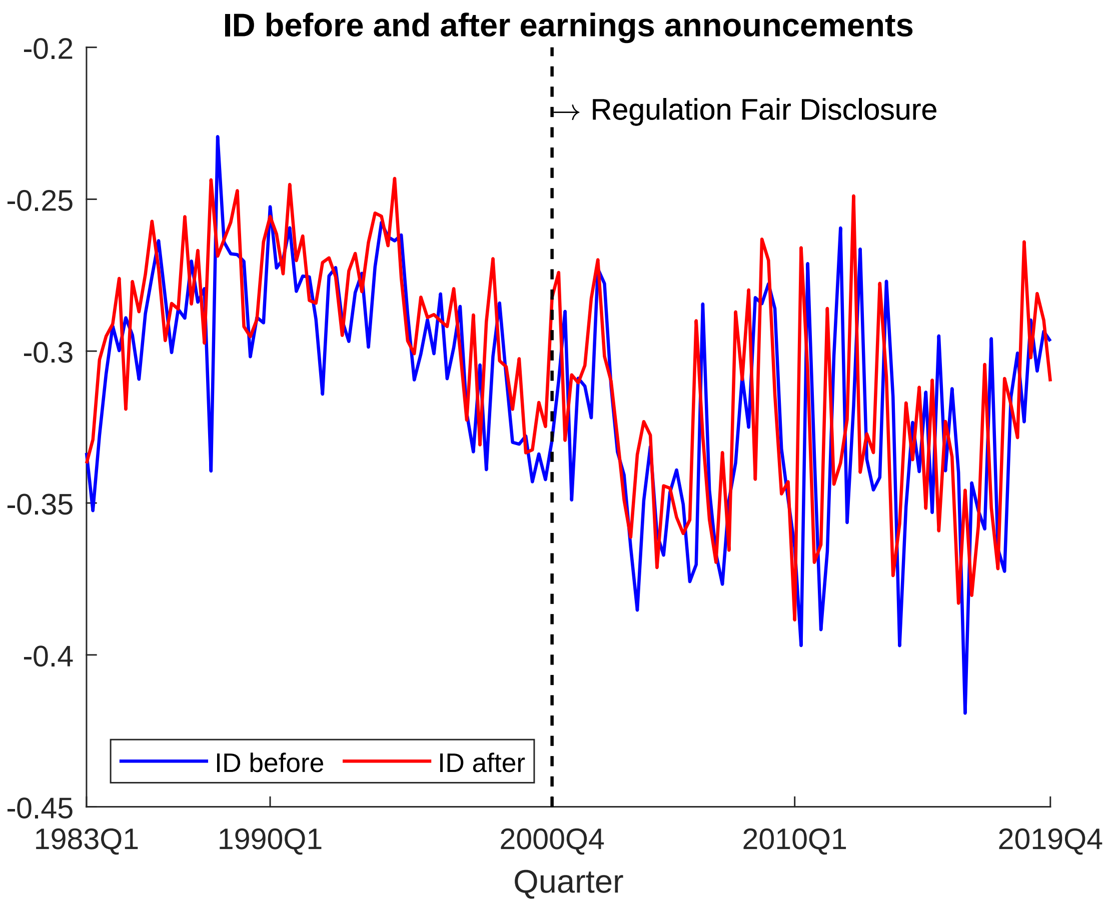
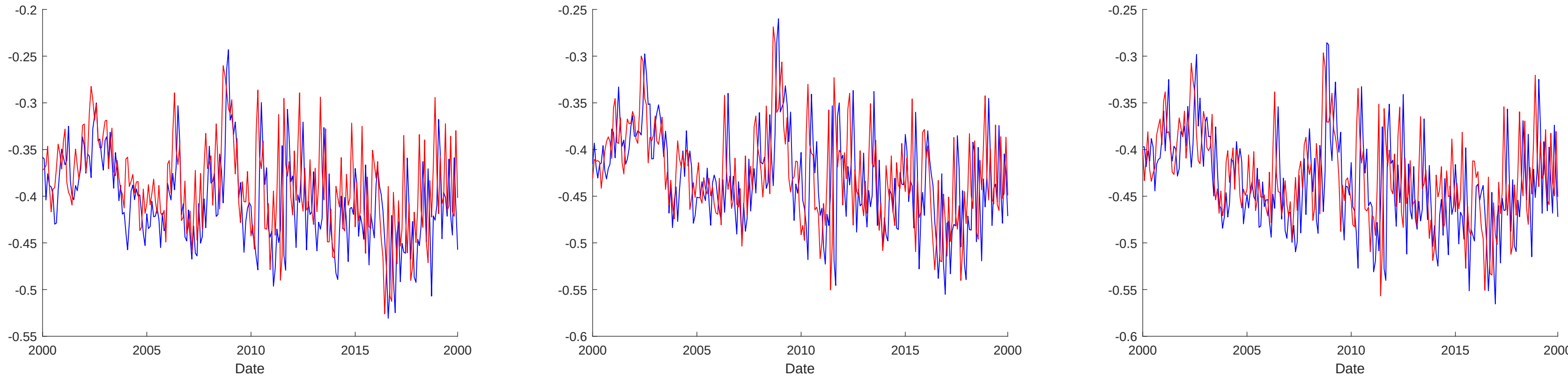
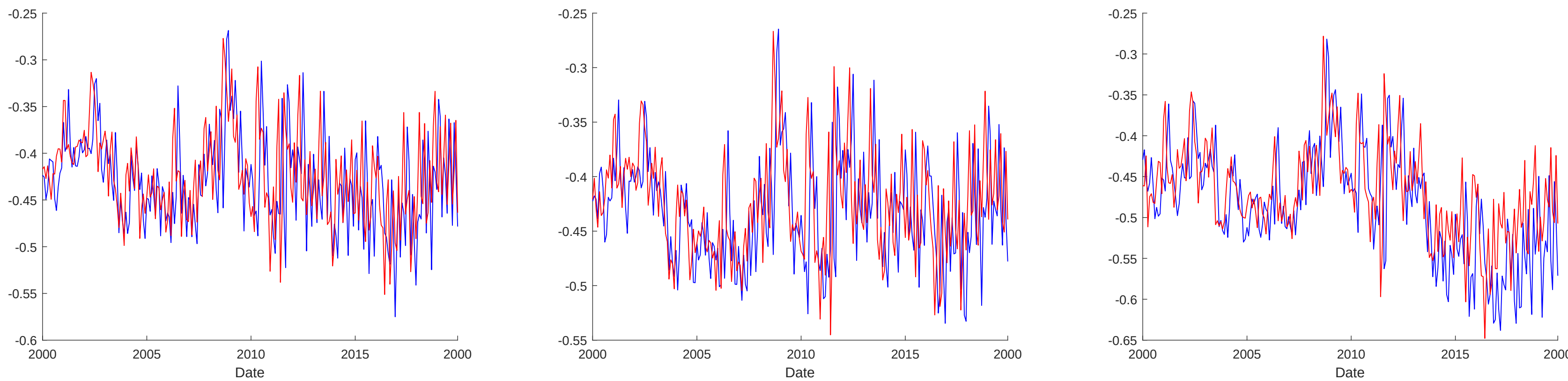


Figure 5: Investor disagreement (ID) before and after earnings announcement. The figure presents time series of cross-sectional average investor disagreement (ID) before and after the earnings announcement. ID_{before} and ID_{after} are defined as the contemporaneous correlation coefficient of daily trading volume and absolute price change over the window $[-45,-2]$ and $[2,45]$, multiplied by -1, where $t=0$ is the earnings announcement date. The sample period is from the first quarter of 1983 to the fourth quarter of 2019 (148 quarters). There are 413,454 observations.



(a) ID before and after financial news (b) ID before and after legal news (c) ID before and after M&A news



(d) ID before and after operational news (e) ID before and after ratings news (f) ID before and after other news

Figure 6: Investor disagreement (ID) before and after news stories. The figure presents time series of cross-sectional average investor disagreement (ID) before (blue) and after (red) 6 types (financial, legal, M&A, operational, ratings, and others) of news stories. ID before the news (day 0) is defined as the correlation coefficient between daily trading volume and absolute price change over the 44-day window $[-45, -2]$, multiplied by -1. ID after the earnings announcement is defined similarly over the 44-day window $[2, 45]$. News data is obtained from RavenPack News Analytics on WRDS. The sample period is from January 2000 to December 2019.

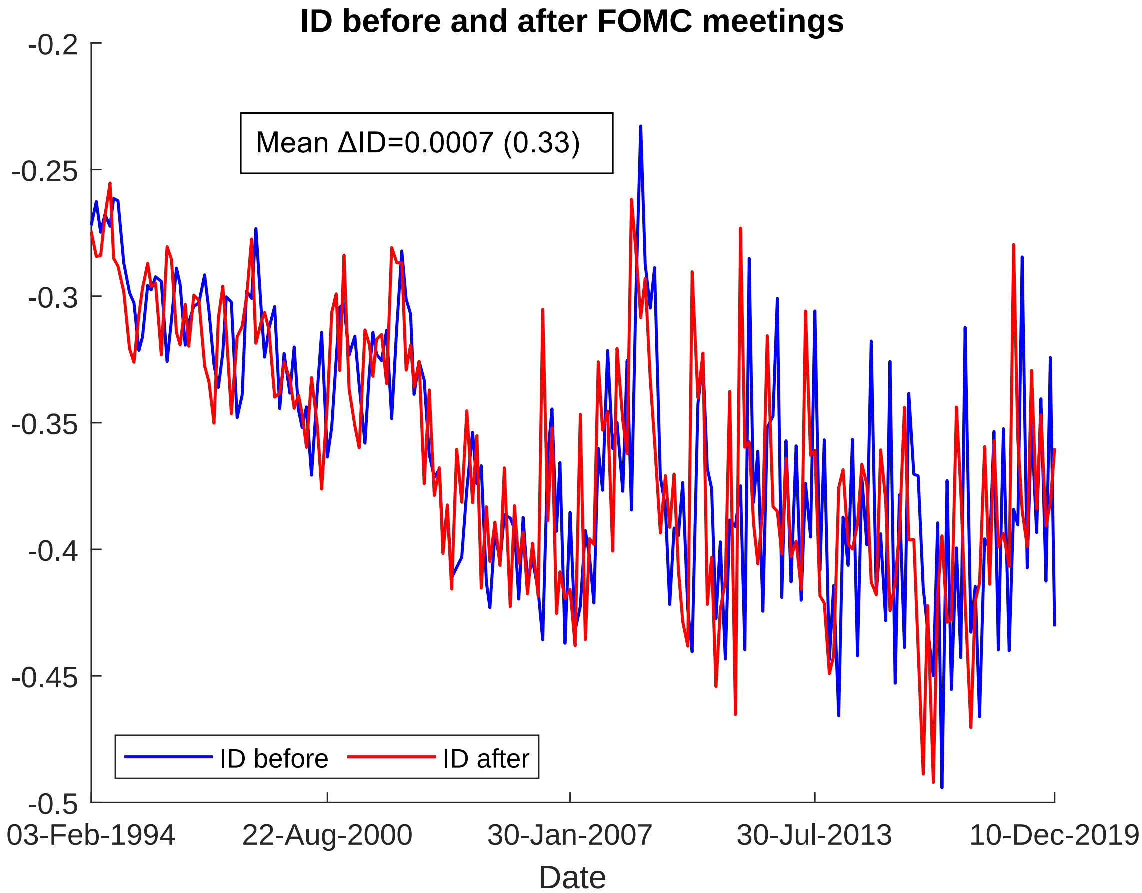


Figure 7: Investor disagreement before and after FOMC meetings. The figure presents time series of cross-sectional average investor disagreement before (ID_{before}) and after (ID_{after}) the earnings announcement. ID_{before} and ID_{after} are defined as the contemporaneous correlation coefficient of daily trading volume and absolute price change over the window $[-45, -2]$ and $[2, 45]$, multiplied by -1, where $t = 0$ is the FOMC date. The sample period is from 1994 to 2019 (208 FOMC announcements). There are 665,013 observations.

Table 1: Returns of equal-weighted portfolios sorted on investor disagreement. For each month, decile portfolios are formed by sorting individual stocks based on their investor disagreement (ID) at the end of previous month. Portfolio 1 (10) is the portfolio of stocks with the lowest (highest) ID at the end of last month. Stocks are held for one month and portfolio returns are equal-weighted. ID at the end of a given month is defined as the correlation coefficient of daily trading volume and absolute price change in the past 2 months, multiplied by -1. The second column reports the time series average of monthly excess returns. The third to fifth column report corresponding alphas with respect to the CAPM, Fama-French three-factor model, and Fama-French-Carhart four-factor model. The sixth column reports the alpha of the five-factor model that in addition includes the liquidity factor of Pástor and Stambaugh (2003). The row labeled "$10-1$" presents the the differences in monthly excess returns and alphas between decile 10 (High ID) and decile 1 (Low ID). Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 1983 to December 2019.

ID deciles	Excess return	CAPM alpha	3-factor alpha	4-factor alpha	5-factor alpha
1 (Low)	0.18	-0.63	-0.57	-0.50	-0.51
	(0.60)	(-4.07)	(-6.93)	(-6.23)	(-6.43)
2	0.32	-0.49	-0.44	-0.39	-0.40
	(1.13)	(-3.7)	(-7.06)	(-6.47)	(-6.79)
3	0.39	-0.40	-0.39	-0.31	-0.31
	(1.43)	(-3.69)	(-7.26)	(-5.73)	(-5.91)
4	0.46	-0.33	-0.34	-0.25	-0.25
	(1.67)	(-2.88)	(-5.69)	(-4.78)	(-4.80)
5	0.56	-0.19	-0.21	-0.14	-0.14
	(2.20)	(-1.76)	(-4.10)	(-2.62)	(-2.66)
6	0.57	-0.17	-0.21	-0.10	-0.10
	(2.24)	(-1.49)	(-3.48)	(-1.51)	(-1.55)
7	0.69	-0.01	-0.07	0.04	0.05
	(2.79)	(-0.11)	(-1.07)	(0.56)	(0.67)
8	0.73	0.04	-0.02	0.10	0.10
	(3.04)	(0.36)	(-0.27)	(1.22)	(1.37)
9	0.65	0.00	-0.08	0.03	0.03
	(2.72)	(0.02)	(-0.89)	(0.31)	(0.37)
10 (High)	0.82	0.23	0.14	0.25	0.26
	(3.63)	(1.61)	(1.42)	(2.46)	(2.69)
$10-1$	0.65	0.87	0.71	0.75	0.77
	(3.91)	(5.64)	(5.47)	(5.94)	(6.28)
MKT BETA		-0.31	-0.20	-0.21	-0.21
		(-8.25)	(-5.66)	(-6.05)	(-5.80)
SMB BETA			-0.37	-0.37	-0.37
			(-3.04)	(-3.19)	(-3.18)
HML BETA			0.38	0.36	0.36
			(6.17)	(6.81)	(6.73)
UMD BETA				-0.06	-0.06
				(-1.02)	(-1.00)
LIQ BETA					-0.06
					(-1.69)
Adj. R^2		18.82%	48.30%	48.78%	49.08%

Table 2: Returns of value-weighted portfolios sorted on investor disagreement. For each month, decile portfolios are formed by sorting individual stocks based on their investor disagreement (ID) at the end of previous month. Portfolio 1 (10) is the portfolio of stocks with the lowest (highest) ID at the end of last month. Stocks are held for one month and portfolio returns are value-weighted. ID at the end of a given month is defined as the correlation coefficient of daily trading volume and absolute price change in the past 2 months, multiplied by -1. The second column reports the time series average of monthly excess returns. The third to fifth column report corresponding alphas with respect to the CAPM, Fama-French three-factor model, and Fama-French-Carhart four-factor model. The sixth column reports the alpha of the five-factor model that in addition includes the liquidity factor of Pástor and Stambaugh (2003). The row labeled "$10-1$" presents the the differences in monthly excess returns and alphas between decile 10 (High ID) and decile 1 (Low ID). Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 1983 to December 2019.

ID deciles	Excess return	CAPM alpha	3-factor alpha	4-factor alpha	5-factor alpha
1 (Low)	0.50	-0.23	-0.21	-0.07	-0.07
	(2.06)	(-2.55)	(-2.30)	(-0.71)	(-0.74)
2	0.62	-0.08	-0.08	-0.01	-0.00
	(2.91)	(-1.05)	(-1.11)	(-0.08)	(-0.01)
3	0.54	-0.17	-0.19	-0.10	-0.10
	(2.38)	(-2.37)	(-2.76)	(-1.36)	(-1.41)
4	0.67	-0.04	-0.07	0.00	0.01
	(3.03)	(-0.59)	(-1.02)	(0.07)	(0.14)
5	0.67	-0.05	-0.06	0.03	0.04
	(2.92)	(-0.62)	(-0.98)	(0.50)	(0.54)
6	0.61	-0.09	-0.12	-0.04	-0.05
	(2.88)	(-1.31)	(-1.70)	(-0.56)	(-0.67)
7	0.67	-0.04	-0.09	-0.01	-0.01
	(3)	(-0.56)	(-1.27)	(-0.09)	(-0.08)
8	0.76	0.09	0.04	0.10	0.10
	(3.45)	(1.03)	(0.51)	(1.25)	(1.20)
9	0.71	0.05	-0.03	0.09	0.06
	(3.28)	(0.53)	(-0.29)	(0.88)	(0.70)
10 (High)	0.91	0.29	0.18	0.29	0.29
	(4.51)	(2.31)	(1.72)	(2.65)	(2.71)
$10-1$	0.41	0.52	0.40	0.37	0.36
	(2.78)	(3.56)	(3.12)	(2.67)	(2.68)
MKT BETA		-0.15	-0.09	-0.08	-0.08
		(-4.02)	(-2.76)	(-2.26)	(-2.26)
SMB BETA			-0.02	-0.02	-0.02
			(-0.36)	(-0.36)	(-0.36)
HML BETA			0.36	0.37	0.37
			(6.59)	(6.57)	(6.54)
UMD BETA				0.04	0.04
				(0.83)	(0.83)
LIQ BETA					0.01
					(0.23)
Adj. R^2		5.33%	18.45%	18.59%	18.41%

Table 3: Investor disagreement decile: average stock characteristics. Stocks are sorted into decile portfolios based on investor disagreement (ID) at the end of each month. Decile 1 (10) is the portfolio of stocks with the lowest (highest) investor disagreement at the end of each month. Investor disagreement (ID) at the end of a given month is defined as the correlation coefficient of daily trading volume and absolute price change in the past 2 months, multiplied by -1. The table presents for each ID decile, the time-series average of mean values of stock characteristics, including firm size (SIZE), book-to-market (BM) ratio, the cumulative return (in percent) over the 11 months prior to the portfolio formation month (MOM), the return (in percent) in the portfolio formation month (REV), average turnover ratio (TURN), idiosyncratic volatility (IVOL) as defined in Ang et al. (2006), Amihud (2002) illiquidity ratio (ILLIQ), lottery demand (MAX) as defined in Bali et al. (2011), institutional owernship ratio (IOR) defined the ratio of shares owned by institutions as reported in 13F filings in the last quarter, the stock beta (BETA), and co-skewness (COSKEW) as defined in Harvey and Siddique (2000). The weights are based on the number of observations in each portfolio in each month, and the variables are defined in detail in Section 4.2 and 4.3. Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 1983 to December 2019 and there is an average of 306 stocks per decile portfolio.

	Investor disagreement (ID) decile portfolio									
	1 (Low)	2	3	4	5	6	7	8	9	10 (High)
ID	-0.77	-0.61	-0.52	-0.44	-0.37	-0.3	-0.23	-0.16	-0.07	0.07
ID (next month)	-0.58	-0.49	-0.44	-0.39	-0.35	-0.32	-0.28	-0.24	-0.19	-0.12
SIZE	5.90	6.10	6.16	6.16	6.11	6.04	5.94	5.82	5.66	5.37
BM	0.62	0.63	0.64	0.65	0.67	0.68	0.70	0.72	0.74	0.77
MOM	24.91	26.48	24.7	22.65	20.46	18.83	17.21	15.93	14.62	12.82
REV	2.57	1.75	1.23	0.89	0.69	0.45	0.26	0.15	0.03	-0.19
TURN	1.00	0.70	0.60	0.53	0.47	0.43	0.39	0.35	0.31	0.26
IVOL	3.30	2.56	2.33	2.18	2.09	2.03	1.98	1.95	1.93	1.96
ILLIQ	0.08	0.12	0.16	0.20	0.27	0.24	0.09	0.35	0.43	0.30
MAX	9.99	7.45	6.65	6.12	5.82	5.56	5.38	5.21	5.09	4.99
IOR	0.49	0.48	0.48	0.47	0.47	0.46	0.45	0.44	0.42	0.39
BETA	1.47	1.42	1.37	1.32	1.27	1.22	1.18	1.13	1.09	1.01
COSKEW	0.10	0.14	0.15	0.07	0.02	-0.05	-0.16	-0.20	-0.37	-0.59

Table 4: Mean portfolio returns by firm size (SIZE) and investor disagreement (ID). Each month, individual stocks are first sorted into quintiles based on firm size (SIZE) in the previous month. Next, within each SIZE decile, stocks are further sorted into deciles based on investor disagreement (ID) in the previous month. Stocks are held for one month, and portfolio returns are equal-weighted. The table reports time series averages of monthly excess returns. SIZE is the log of market capitalization in millions of dollars. Investor disagreement (ID) at the end of a given month is defined as the correlation coefficient of daily trading volume and absolute price change in the past 2 months, multiplied by -1. "$10-1$", "CAPM alpha" , "3-factor alpha", "4-factor alpha", and "5-factor alpha" report the difference in excess returns, CAPM alpha, three-factor alpha (MKT, SMB, and HML), four-factor alpha (MKT, SMB, HML, and UMD), and five-factor alpha (MKT, SMB, HML, UMD, and LIQ) between high ID and low ID decile in each SIZE quintile, respectively. The corresponding Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 1983 to December 2019.

	Size quintiles				
ID deciles	Small caps	2	3	4	Large caps
1 (Low)	-0.39	0.16	0.07	0.37	0.56
2	-0.14	0.16	0.40	0.42	0.68
3	0.06	0.30	0.33	0.56	0.71
4	0.16	0.33	0.57	0.71	0.6
5	0.25	0.49	0.55	0.75	0.80
6	0.37	0.53	0.73	0.63	0.77
7	0.47	0.34	0.67	0.77	0.64
8	0.49	0.56	0.88	0.85	0.77
9	0.63	0.67	0.76	0.69	0.81
High	0.68	0.77	0.83	0.89	0.84
$10-1$	1.07	0.62	0.77	0.52	0.28
	(3.75)	(2.86)	(3.80)	(2.94)	(2.14)
CAPM alpha	1.32	0.81	0.96	0.69	0.41
	(4.68)	(3.92)	(4.81)	(3.97)	(3.37)
3-factor alpha	1.17	0.65	0.77	0.53	0.30
	(4.19)	(3.18)	(4.55)	(3.81)	(2.67)
4-factor alpha	1.27	0.75	0.79	0.50	0.30
	(4.33)	(3.63)	(4.73)	(3.33)	(2.26)
5-factor alpha	1.32	0.78	0.80	0.49	0.29
	(4.57)	(3.82)	(4.82)	(3.28)	(2.29)

Table 5: Mean portfolio returns by book-to-market (BM) ratio and investor disagreement (ID). Each month, individual stocks are first sorted into quintiles based on book-to-market (BM) ratio in the previous month. Next, within each BM decile, stocks are further sorted into deciles based on investor disagreement (ID) in the previous month. Stocks are held for one month, and portfolio returns are equal-weighted. The table reports time series averages of monthly excess returns. Investor disagreement (ID) at the end of a given month is defined as the correlation coefficient of daily trading volume and absolute price change in the past 2 months, multiplied by -1. "$10-1$", "CAPM alpha" , "3-factor alpha", "4-factor alpha", and "5-factor alpha" report the difference in excess returns, CAPM alpha, three-factor alpha (MKT, SMB, and HML), four-factor alpha (MKT, SMB, HML, and UMD), and five-factor alpha (MKT, SMB, HML, UMD, and LIQ) between high ID and low ID decile in each BM quintile, respectively. The corresponding Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 1983 to December 2019.

	Book-to-market quintiles				
ID deciles	Low BM	2	3	4	High BM
Low	-0.40	0.31	0.37	0.37	0.38
2	-0.28	0.49	0.50	0.53	0.59
3	-0.11	0.42	0.57	0.61	0.61
4	0.01	0.32	0.67	0.73	0.65
5	0.02	0.61	0.69	0.69	0.80
6	0.17	0.45	0.69	0.84	0.78
7	0.20	0.58	0.69	0.84	0.84
8	0.30	0.58	0.85	0.82	0.82
9	0.38	0.51	0.81	0.79	0.81
High	0.56	0.72	0.76	0.89	0.99
$10-1$	0.97	0.41	0.39	0.52	0.61
	(5.33)	(2.07)	(2.47)	(3.08)	(3.26)
CAPM alpha	1.07	0.56	0.56	0.72	0.82
	(5.85)	(2.91)	(3.78)	(4.68)	(4.66)
3-factor alpha	0.95	0.43	0.44	0.63	0.76
	(5.41)	(2.23)	(3.24)	(4.20)	(4.26)
4-factor alpha	1.01	0.53	0.47	0.66	0.81
	(5.13)	(2.92)	(3.33)	(4.57)	(4.79)
5-factor alpha	1.00	0.56	0.51	0.66	0.84
	(5.17)	(3.15)	(3.65)	(4.71)	(5.01)

Table 6: Mean portfolio returns by momentum (MOM) and investor disagreement (ID). Each month, individual stocks are first sorted into quintiles based on momentum (MOM) in the previous month. Next, within each MOM decile, stocks are further sorted into deciles based on investor disagreement (ID) in the previous month. Stocks are held for one month, and portfolio returns are equal-weighted. The table reports time series averages of monthly excess returns. MOM is computed as the cumulative return of a stock of 11 months ending one month prior to the portfolio formation month. Investor disagreement (ID) at the end of a given month is defined as the correlation coefficient of daily trading volume and absolute price change in the past 2 months, multiplied by -1. "$10-1$", "CAPM alpha" , "3-factor alpha", "4-factor alpha", and "5-factor alpha" report the difference in excess returns, CAPM alpha, three-factor alpha (MKT, SMB, and HML), four-factor alpha (MKT, SMB, HML, and UMD), and five-factor alpha (MKT, SMB, HML, UMD, and LIQ) between high ID and low ID decile in each MOM quintile, respectively. The corresponding Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 1983 to December 2019.

	Momentum quintiles				
ID deciles	Losers	2	3	4	Winners
Low	-0.69	0.35	0.55	0.50	0.44
2	-0.66	0.40	0.68	0.78	0.56
3	-0.49	0.52	0.70	0.65	0.68
4	-0.40	0.39	0.58	0.82	0.68
5	-0.29	0.53	0.69	0.81	0.83
6	-0.40	0.63	0.76	0.84	0.91
7	0.12	0.75	0.75	0.86	0.77
8	0.25	0.66	0.87	0.83	0.86
9	0.12	0.77	0.78	0.91	0.73
High	0.68	0.74	0.86	0.83	0.94
$10-1$	1.37	0.39	0.32	0.35	0.50
	(5.74)	(2.69)	(1.89)	(2.22)	(3.00)
CAPM alpha	1.54	0.53	0.48	0.54	0.64
	(6.58)	(3.73)	(3.14)	(3.68)	(3.68)
3-factor alpha	1.40	0.44	0.36	0.40	0.48
	(6.44)	(3.44)	(2.54)	(2.68)	(3.33)
4-factor alpha	1.50	0.46	0.36	0.40	0.48
	(6.37)	(3.68)	(2.73)	(2.78)	(3.02)
5-factor alpha	1.54	0.49	0.38	0.42	0.47
	(6.57)	(3.87)	(2.95)	(2.93)	(2.98)

Table 7: Bivariate portfolio sorts on investor disagreement and control variables. Double-sorted, equally-weighted decile portfolios are formed every month based on investor disagreement (ID) after controlling for market capitalization (SIZE), book-to-market ratio (BM), momentum (MOM), short-term reversals (REV), turnover (TURN), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), demand for lottery stocks (MAX), institutional ownership ratio (IOR), stock market beta (BETA), co-skewness (COSKEW), and analyst forecast dispersion (DISP). ID at the end of a given month is computed as the contemporaneous correlation coefficient of daily trading volume and absolute price change over the past 2 months, multiplied by -1. The other control variables are defined in Section 3.2 and 3.3. In each case, I first sort stocks into deciles using the control variable, then within each decile I sort stocks into decile portfolios based on ID. The ten ID portfolios are then averaged over each of the ten control deciles to compute excess returns. "$10-1$" and "5-factor alpha" report the differences in average monthly excess returns and alphas with respect to the five-factor model (MKT, SMB, HML, UMD, and LIQ) between the High ID and Low ID decile portfolios, respectively. The sample period is from January 1983 to December 2019. Newey and West (1987) t-statistics are reported in parentheses.

	Investor disagreement (ID) decile											
	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	$10-1$	5-factor alpha
SIZE	0.16	0.32	0.38	0.47	0.57	0.60	0.64	0.75	0.68	0.80	0.64	0.72
	(0.56)	(1.14)	(1.35)	(1.76)	(2.20)	(2.35)	(2.57)	(3.14)	(2.88)	(3.57)	(4.14)	(6.50)
BM	0.22	0.36	0.45	0.46	0.53	0.61	0.60	0.68	0.65	0.79	0.57	0.71
	(0.77)	(1.30)	(1.68)	(1.76)	(2.04)	(2.42)	(2.42)	(2.86)	(2.68)	(3.45)	(4.19)	(6.32)
MOM	0.26	0.34	0.42	0.41	0.55	0.58	0.69	0.66	0.65	0.81	0.55	0.62
	(0.94)	(1.24)	(1.55)	(1.55)	(2.18)	(2.26)	(2.75)	(2.71)	(2.66)	(3.50)	(4.21)	(6.05)
REV	0.22	0.37	0.48	0.53	0.57	0.58	0.60	0.68	0.62	0.73	0.52	0.60
	(0.78)	(1.40)	(1.77)	(2.00)	(2.16)	(2.25)	(2.38)	(2.79)	(2.54)	(3.16)	(4.51)	(6.57)
TURN	0.20	0.32	0.40	0.50	0.55	0.56	0.62	0.70	0.67	0.84	0.64	0.65
	(0.75)	(1.27)	(1.50)	(1.93)	(2.12)	(2.18)	(2.46)	(2.81)	(2.72)	(3.43)	(6.78)	(6.50)
IVOL	0.40	0.41	0.50	0.53	0.52	0.41	0.60	0.63	0.61	0.75	0.34	0.45
	(1.62)	(1.57)	(1.91)	(1.99)	(1.96)	(1.58)	(2.31)	(2.47)	(2.45)	(3.13)	(3.67)	(5.29)
ILLIQ	0.13	0.31	0.34	0.52	0.56	0.64	0.67	0.67	0.70	0.81	0.68	0.72
	(0.46)	(1.10)	(1.27)	(1.95)	(2.20)	(2.56)	(2.73)	(2.81)	(2.98)	(3.73)	(4.58)	(6.90)
MAX	0.38	0.43	0.49	0.51	0.55	0.51	0.62	0.60	0.57	0.72	0.34	0.45
	(1.45)	(1.62)	(1.89)	(1.96)	(2.12)	(1.98)	(2.38)	(2.45)	(2.27)	(2.96)	(3.41)	(4.65)
IOR	0.24	0.32	0.43	0.51	0.57	0.56	0.66	0.70	0.68	0.79	0.55	0.63
	(0.83)	(1.17)	(1.57)	(1.95)	(2.23)	(2.26)	(2.74)	(2.92)	(2.82)	(3.39)	(3.58)	(5.68)
BETA	0.20	0.30	0.42	0.50	0.52	0.58	0.64	0.72	0.66	0.81	0.61	0.66
	(0.74)	(1.13)	(1.59)	(1.91)	(1.99)	(2.32)	(2.54)	(2.95)	(2.67)	(3.40)	(5.41)	(7.09)
COSKEW	0.23	0.28	0.43	0.47	0.51	0.62	0.61	0.73	0.66	0.83	0.60	0.69
	(0.80)	(1.02)	(1.63)	(1.74)	(1.96)	(2.45)	(2.47)	(3.00)	(2.70)	(3.59)	(4.19)	(6.26)
DISP	0.27	0.34	0.43	0.46	0.59	0.58	0.57	0.62	0.63	0.73	0.45	0.50
	(0.97)	(1.22)	(1.61)	(1.69)	(2.29)	(2.29)	(2.30)	(2.48)	(2.59)	(3.10)	(3.42)	(5.03)

Table 8: Fama-Macbeth Cross-Sectional Regressions. The table reports the time-series averages of the slope coefficients obtained from regression monthly excess returns on investor disagreement (ID) in the previous month and a set of lagged predictive variables using the Fama-Macbeth (1973) approach. The control variables are the log market capitalization in millions of dollars (SIZE), book-to market (BM) ratio, momentum (MOM), short-term reversal (REV), turnover ratio (TURN), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), demand for lottery stocks (MAX), institutional ownership ratio (IOR), stock beta (BETA), co-skewness (COSKEW), and anlayst forecast dispersion (DISP). ID at the end of a given month is computed as the contemporaneous correlation coefficient of daily trading volume and absolute price change over the past 2 months, multiplied by -1. The other control variables are defined in Section 3.2 and 3.3. The sample period is from January 1983 to December 2019. Newey and West (1987) t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
ID	0.780	0.824	0.599	0.367	0.300	0.251
	(3.85)	(4.51)	(4.67)	(3.73)	(3.44)	(2.86)
SIZE		0.095	0.104	0.037	0.032	0.023
		(2.83)	(2.97)	(1.21)	(1.11)	(0.76)
BM		0.208	0.207	0.166	0.111	0.058
		(2.12)	(2.18)	(1.83)	(1.29)	(0.57)
MOM		0.003	0.004	0.003	0.003	0.005
		(1.93)	(2.26)	(2.00)	(2.61)	(3.45)
REV			-0.025	-0.031	-0.035	-0.038
			(-6.13)	(-7.03)	(-8.00)	(7.32)
TURN			-0.241	0.091	0.041	0.075
			(-1.91)	(0.91)	(0.47)	(0.77)
IVOL				-0.361	-0.350	-0.376
				(-6.81)	(-6.88)	(-6.72)
ILLIQ				0.017	0.012	-0.041
				(1.61)	(1.12)	(-0.29)
MAX				0.040	0.041	0.042
				(3.81)	(3.90)	(3.36)
IOR				-0.722	-0.808	-1.297
				(-4.54)	(-5.85)	(-8.79)
BETA					0.050	0.070
					(0.51)	(0.63)
COSKEW					-0.002	0.001
					(-0.44)	(0.16)
DISP						-0.058
						(-3.04)
Intercept	1.084	0.243	0.213	1.237	1.345	1.574
	(4.68)	(0.69)	(0.59)	(4.27)	(5.45)	(4.96)
Adj. R^2	0.33%	2.37%	3.73%	5.09%	6.09%	8.07%
observations	1,355,834	1,355,834	1,355,831	1,293,882	1,178,701	707,856

Table 9. Investor disagreement premium: business cycles and investor sentiment. Stocks are sorted into decile portfolios based on investor disagreement (ID) at the end of each month. Decile 1 (10) is the portfolio of stocks with the lowest (highest) investor disagreement at the end of each month. The table reports alphas with respect to the five-factor model (MKT, SMB, HML, UMD, and LIQ) in different sample periods. NBER expansion and recession periods are set by the NBER's Business Cycle Dating Committee. A high-sentiment month (low-sentiment) month is one in which the value of the BW (Baker and Wurgler (2006)) sentiment index in the previous month is above (below) the median value for the sample period. The row labeled "10 − 1" reports the five-factor alphas of the long-short ID strategy. The sample period for business cycles is January 1983 to December 2019, and the sampe period for investor sentiment is from January 1983 to December 2018. Newey and West (1987) t-statistics are reported in parentheses.

ID decile	NBER Expansions	NBER Recessions	Low Sentiment	High Sentiment
1 (Low)	-0.49	-0.55	-0.39	-0.65
	(-6.00)	(-1.52)	(-3.78)	(-5.38)
2	-0.39	-0.48	-0.33	-0.46
	(-6.27)	(-2.19)	(-4.27)	(-5.22)
3	-0.32	-0.17	-0.19	-0.42
	(-5.91)	(-0.60)	(-2.56)	(-5.23)
4	-0.24	-0.03	-0.10	-0.35
	(-4.54)	(-0.14)	(-1.58)	(-4.10)
5	-0.14	-0.12	-0.07	-0.18
	(-2.51)	(-0.77)	(-1.01)	(-2.15)
6	-0.09	-0.05	-0.05	-0.10
	(-1.45)	(-0.18)	(-0.17)	(-0.92)
7	0.05	0.14	0.02	0.17
	(0.67)	(0.53)	(0.22)	(1.56)
8	0.09	0.50	0.07	0.18
	(1.17)	(1.73)	(1.00)	(1.41)
9	0.06	0.04	-0.03	0.16
	(0.62)	(0.10)	(-0.39)	(1.08)
10 (High)	0.22	0.69	0.27	0.27
	(2.09)	(1.37)	(3.33)	(1.54)
10 − 1	0.71	1.23	0.65	0.92
	(5.38)	(2.04)	(5.25)	(4.53)
# of months	410	34	215	217

Table 10. Investor disagreement premium: economic uncertainty. Stocks are sorted into decile portfolios based on investor disagreement (ID) at the end of each month. Decile 1 (10) is the portfolio of stocks with the lowest (highest) investor disagreement at the end of each month. The table reports alphas with respect to the five-factor model (MKT, SMB, HML, UMD, and LIQ) over high and low economic uncertainty periods. The row labeled "10 − 1" reports the five-factor alphas of the long-short ID strategy. A high-sentiment month is one in which the value of the economic uncertainty index is above the median value for the sample period, and the low-sentiment months are those with below-median values. Macro, financial, real economic uncertainty measures are defined in Jurado et al. (2015) and Ludvigson et al. (2015). Policy-related economic uncertainty is defined in Baker et al. (2016). The sample period for macro, financial, and real economic uncertainty is from January 1983 to December 2019, and the sample period for policy-related economic uncertainty index is from January 1985 to December 2019. Newey and West (1987) t-statistics are reported in parentheses.

ID decile	Low Macro_UNC	High Macro_UNC	Low Fin_UNC	High Fin_UNC	Low Real_UNC	High Real_UNC	Low Policy_UNC	High Policy_UNC
1 (Low)	-0.58	-0.44	-0.59	-0.46	-0.50	-0.52	-0.59	-0.47
	(-5.64)	(-3.91)	(-6.71)	(-3.74)	(-4.71)	(-4.44)	(-4.80)	(-4.61)
2	-0.47	-0.34	-0.43	-0.36	-0.47	-0.33	-0.35	-0.40
	(-6.20)	(-4.28)	(-5.43)	(-4.16)	(-6.48)	(-4.05)	(-3.67)	(-5.28)
3	-0.34	-0.27	-0.37	-0.27	-0.38	-0.23	-0.34	-0.23
	(-4.48)	(-3.75)	(-5.35)	(-3.33)	(-5.18)	(-3.21)	(-4.2)	(-2.92)
4	-0.30	-0.15	-0.23	-0.22	-0.21	-0.21	-0.21	-0.18
	(-4.15)	(-1.96)	(-3.29)	(-2.84)	(-2.88)	(-2.95)	(-2.83)	(-2.39)
5	-0.14	-0.10	-0.15	-0.14	-0.19	-0.05	-0.07	-0.11
	(-2.36)	(-1.10)	(-2.07)	(-1.58)	(-2.81)	(-0.59)	(-0.96)	(-1.76)
6	-0.11	-0.07	-0.15	-0.08	-0.17	0.02	-0.08	-0.03
	(-1.66)	(-0.69)	(-2.19)	(-0.81)	(-2.76)	(0.20)	(-0.91)	(-0.42)
7	-0.02	0.09	0.05	0.04	0.05	0.08	0.12	0.05
	(-0.24)	(0.92)	(0.85)	(0.34)	(0.70)	(0.84)	(1.52)	(0.52)
8	0.13	0.06	0.03	0.12	0.14	0.09	0.16	0.11
	(-2.33)	(0.55)	(0.47)	(1.03)	(2.36)	(0.83)	(2.00)	(1.04)
9	0.07	0.02	0.06	0.06	0.02	0.10	0.15	0.04
	(1.08)	(0.11)	(0.87)	(0.42)	(0.22)	(0.82)	(1.73)	(0.32)
10 (High)	0.23	0.27	0.15	0.37	0.22	0.31	0.33	0.32
	(3.19)	(1.85)	(2.17)	(2.40)	(2.75)	(2.23)	(3.20)	(2.26)
10 − 1	0.81	0.72	0.74	0.83	0.72	0.83	0.92	0.79
	(6.65)	(3.95)	(6.68)	(4.21)	(5.53)	(4.84)	(5.30)	(5.43)
# of months	222	222	222	222	222	222	210	211

Table 11: Persistence of investor disagreement. The table examines the persistence of investor disagreement (ID). Panel A reports coefficients of regressing firm-level ID on lagged ID and lagged cross-sectional variables, including firm size (SIZE), book-to market (BM) ratio, momentum (MOM), short-term reversal (REV), turnover ratio (TURN), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), demand for lottery stocks (MAX), institutional ownership ratio (IOR), stock beta (BETA), and co-skewness (COSKEW). Panel B presents the average month-to-month investor disagreement (ID) decile transition matrix. Column (i, j) is the average probability (in percentage) that a stock in ID decile i in one month will be in decile j in the subsequent month. Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 1983 to December 2019.

Panel A: Predictive regression	
Univariate predictive regression	0.552
	(185.20)
Adj. R^2	30.58%
Controlling for lagged variables	0.468
	(104.08)
Adj. R^2	34.54%

Panel B: Transition matrix (in %)

	ID deciles in next month									
ID deciles	Low	2	3	4	5	6	7	8	9	High
Low	42.87	18.26	9.99	7.14	5.64	4.48	3.80	3.23	2.57	2.02
2	17.15	24.20	17.38	11.72	8.47	6.47	5.07	4.14	3.10	2.31
3	9.76	16.82	18.61	15.30	11.65	8.86	6.81	5.28	4.10	2.80
4	7.10	11.16	15.07	16.24	14.01	11.48	9.07	6.94	5.28	3.67
5	5.68	8.09	11.39	11.93	14.94	13.83	11.27	9.06	7.09	4.71
6	4.77	6.40	8.62	11.16	13.49	14.76	13.85	11.69	9.13	6.12
7	4.09	5.19	6.71	8.66	11.35	13.66	15.27	14.45	12.13	8.50
8	3.50	4.22	5.21	6.91	8.87	11.41	14.50	16.85	16.27	12.26
9	2.81	3.29	4.12	5.30	6.91	8.99	11.97	16.18	20.96	19.46
High	2.17	2.30	2.89	3.59	4.64	6.17	8.44	12.25	19.48	38.06

Table 12: Investor disagreement premium: formation periods. At the end of each month, stocks are sorted into deciles based on investor disagreement (ID) and assigned into portfolios. Stocks are then held in the portfolio for the subsequent month. ID at the end of a given month is computed as the contemporaneous correlation coefficient of daily trading volume and absolute price change over the past T months, multiplied by -1. Portfolio returns are equal-weighted. The table presents the difference in excess returns, CAPM alpha, three-factor alpha (MKT, SMB, and HML), four-factor alpha (MKT, SMB, HML, and UMD), and five-factor alpha (MKT, SMB, HML, UMD, and LIQ) between the highest and the lowest ID decile. The sample period is from January 1983 to December 2019. Newey and West (1987) t-statistics are reported in parentheses.

Formation period (in months)	Excess return	CAPM alpha	3-factor alpha	4-factor alpha	5-factor alpha
3	0.58	0.82	0.66	0.70	0.72
	(3.44)	(5.29)	(5.10)	(5.57)	(5.85)
4	0.50	0.77	0.59	0.59	0.61
	(2.91)	(4.67)	(4.45)	(4.81)	(5.01)
5	0.56	0.84	0.66	0.65	0.67
	(3.17)	(5.15)	(5.07)	(5.35)	(5.58)
6	0.50	0.80	0.61	0.58	0.60
	(2.73)	(4.60)	(4.42)	(4.52)	(4.73)
7	0.47	0.78	0.57	0.54	0.57
	(2.42)	(4.19)	(3.90)	(4.00)	(4.28)
8	0.50	0.82	0.61	0.58	0.61
	(2.56)	(4.41)	(4.30)	(4.37)	(4.70)
9	0.52	0.85	0.62	0.60	0.63
	(2.57)	(4.42)	(4.35)	(4.46)	(4.81)
10	0.50	0.83	0.60	0.54	0.57
	(2.50)	(4.41)	(4.26)	(3.81)	(4.21)
11	0.49	0.84	0.60	0.53	0.56
	(2.41)	(4.40)	(4.11)	(3.43)	(3.89)
12	0.46	0.81	0.57	0.48	0.52
	(2.20)	(4.21)	(3.86)	(3.19)	(3.59)

Table 13: Investor disagreement premium: holding periods. At the end of each month, stocks are sorted into deciles based on investor disagreement (ID) and assigned into portfolios. Stocks are then held in the portfolio for T months, with $\frac{1}{T}$ of each portfolio reinvested monthly. ID at the end of a given month is computed as the contemporaneous correlation coefficient of daily trading volume and absolute price change over the past 2 months, multiplied by -1. Portfolio returns are equal-weighted. The table presents the difference in excess returns, CAPM alpha, three-factor alpha (MKT, SMB, and HML), four-factor alpha (MKT, SMB, HML, and UMD), and five-factor alpha (MKT, SMB, HML, UMD, and LIQ) between the highest and the lowest ID decile. The sample period is from January 1983 to December 2019. Newey and West (1987) t-statistics are reported in parentheses.

Holding period (in months)	Excess return	CAPM alpha	3-factor alpha	4-factor alpha	5-factor alpha
2	0.57	0.80	0.65	0.66	0.68
	(3.85)	(5.82)	(5.80)	(6.20)	(6.57)
3	0.48	0.71	0.57	0.55	0.58
	(3.42)	(5.49)	(5.64)	(5.62)	(6.05)
4	0.45	0.69	0.55	0.52	0.55
	(3.33)	(5.57)	(5.76)	(5.4)	(5.85)
5	0.44	0.68	0.54	0.51	0.53
	(3.27)	(5.57)	(5.69)	(5.13)	(5.57)
6	0.49	0.65	0.51	0.47	0.49
	(5.21)	(5.34)	(5.4)	(4.80)	(5.21)
7	0.38	0.63	0.48	0.44	0.46
	(2.83)	(5.07)	(5.11)	(4.51)	(4.91)
8	0.37	0.61	0.47	0.42	0.43
	(2.70)	(4.92)	(4.96)	(4.25)	(4.64)
9	0.34	0.59	0.44	0.38	0.40
	(2.50)	(4.66)	(4.65)	(3.80)	(4.18)
10	0.34	0.58	0.43	0.37	0.39
	(2.46)	(4.60)	(4.59)	(3.61)	(3.99)
11	0.33	0.58	0.44	0.36	0.38
	(2.42)	(4.57)	(4.55)	(3.47)	(3.84)
12	0.33	0.58	0.43	0.35	0.37
	(2.4)	(4.55)	(4.52)	(3.32)	(3.68)

Table 14: Average cumulative abnormal return (*CAR*) around earnings announcement by investor disagreement (*ID*). The table presents time-series average of quarterly mean values of cumulative market-adjusted returns (CAR) within investor disagreement (ID) deciles. The weights are based on the number of observations in each portfolio in each calendar quarter. CAR_{-t_1,t_1} is defined as the compounded return over the $[-t_1, t_1]$ window around the earnings announcement date ($t = 0$) in excess of the compounded value-weighted market return (in percent). The corresponding reference period is defined as the 44-day $[t_1 - 44, t_1 - 1]$ window prior to the earnings announcement date. In each calendar quarter, stocks are sorted into deciles by ID, which is defined as the contemporaneous correlation coefficient of volume and absolute price change in the reference period, multiplied by -1. The row labeled "$10 - 1$" reports the difference in CAR between decile 10 (High ID) and decile 1 (Low ID). The sample period is from the first quarter of 1983 to the fourth quarter of 2019 (444 quarters). Newey and West (1987) t-statistics are reported in parentheses.

ID deciles	$CAR_{-1,1}$ (1)	$CAR_{-2,2}$ (2)	$CAR_{-3,3}$ (3)	$CAR_{-4,4}$ (4)	$CAR_{-5,5}$ (5)
1 (Low)	0.12	-0.54	-0.57	-0.51	-0.51
	(0.45)	(-3.99)	(-8.02)	(-7.12)	(-7.07)
2	0.27	-0.39	-0.44	-0.39	-0.40
	(1.06)	(-3.36)	(-8.24)	(-7.49)	(-7.62)
3	0.37	-0.30	-0.37	-0.29	-0.29
	(1.43)	(-2.87)	(-7.59)	(-6.03)	(-6.13)
4	0.42	-0.23	-0.31	-0.23	-0.22
	(1.65)	(-2.16)	(-6.05)	(-4.87)	(-4.72)
5	0.53	-0.10	-0.19	-0.13	-0.12
	(2.22)	(-1.03)	(-4.06)	(-2.58)	(-2.46)
6	0.52	-0.10	-0.21	-0.11	-0.11
	(2.19)	(-1.01)	(-4.09)	(-2.07)	(-2.01)
7	0.66	0.06	-0.07	0.04	0.05
	(2.84)	(0.62)	(-1.20)	(0.66)	(0.78)
8	0.66	0.08	-0.06	0.07	0.07
	(2.95)	(0.82)	(-0.93)	(1.04)	(1.13)
9	0.69	0.13	-0.02	0.10	0.10
	(3.09)	(1.20)	(-0.25)	(1.29)	(1.41)
10 (High)	0.76	0.25	0.09	0.21	0.22
	(3.56)	(2.15)	(1.05)	(2.53)	(2.72)
$10 - 1$	0.65	0.79	0.65	0.72	0.73
	(4.77)	(6.18)	(5.90)	(6.88)	(7.10)

Table 15. Investor disagreement and earnings announcement returns. The table presents results of quarterly weighted Fama and MacBeth (1973) regressions using cumulative abnormal returns around the earnings announcement date, CAR_{-t_1,t_1}, as the dependent variable. The weights correspond to the number of observations used in each quarterly cross-sectional regression. CAR_{-t_1,t_1} is defined as the compounded return over the $[-t_1, t_1]$ window around the earnings announcement date ($t = 0$) in excess of the compounded value-weighted market return (in percent). The corresponding reference period defined as the 44-day $[t_1-44, t_1-1]$ window prior to the earnings announcement date. ID (investor disagreement) is defined as the contemporaneous correlation coefficient of volume and absolute price change in the reference period, multiplied by -1. SIZE is the log of market capitalization in millions of dollars and BM is book-to-market ratio. RET is the return (in percent) compounded over the reference period. TURN and IVOL are the average turnover ratio and idiosyncratic volatility in the reference period, respectively. IOR is the ratio of shares owned by institutions as reported in 13F filings in the last quarter. NUMEST is the number of unique analysts that have eligible fiscal year one earnings estimates on IBES in the reference period. The sample period is from the first quarter of 1983 to the fourth quarter of 2019. Newey and West (1987) t-statistics are reported in parentheses.

	$CAR_{-1,1}$ (1)	$CAR_{-2,2}$ (2)	$CAR_{-3,3}$ (3)	$CAR_{-4,4}$ (4)	$CAR_{-5,5}$ (5)
ID	0.337	0.379	0.431	0.493	0.539
	(3.96)	(4.33)	(4.18)	(4.35)	(4.58)
SIZE	0.031	0.04	0.058	0.061	0.064
	(1.52)	(1.83)	(2.35)	(2.28)	(2.18)
BM	0.189	0.198	0.220	0.198	0.189
	(4.46)	(3.78)	(3.78)	(2.80)	(2.13)
RET	-0.013	-0.015	-0.017	-0.019	-0.022
	(-7.84)	(-7.21)	(-6.68)	(-6.64)	(-6.66)
TURN	-9.405	-7.964	-6.324	-5.409	1.008
	(-1.75)	(-1.20)	(-0.78)	(-0.56)	(0.09)
IVOL	-0.121	-0.158	-0.175	-0.186	-0.212
	(-4.44)	(-5.16)	(-4.77)	(-4.43)	(-4.79)
IOR	-0.650	-0.710	-0.779	-0.827	-0.904
	(-6.57)	(-6.48)	(-5.99)	(-5.79)	(-5.84)
NUMEST	0.011	0.012	0.012	0.015	0.016
	(2.68)	(2.55)	(2.29)	(2.6)	(2.59)
Intercept	0.331	0.352	0.274	0.279	0.323
	(2.52)	(2.55)	(1.54)	(1.31)	(1.39)
Adj. R^2	0.87%	0.98%	1.34%	1.64%	1.93%
# of observations	428,194	428,003	427,892	427,764	427,648

Table 16. Investor disagreement: good and bad earnings. In each calendar quarter, stocks are first sorted into quintiles based on firm size (SIZE). Next, within each SIZE decile, stocks are further sorted into good earnings ($CAR_{-1,1} > 0$) and bad earnings ($CAR_{-1,1} \leq 0$) portfolios. The table presents the time-seires of quarterly mean values of ΔID in each portfolio. ΔID is defined as $\Delta ID = ID_{\text{after}} - ID_{\text{before}}$. ID_{after} and ID_{before} are defined as the contemporaneous correlation coefficient of daily trading volume and absolute price change over the window $[2, 45]$ and $[-45, -2]$, multiplied by -1, where $t = 0$ is the earnings announcement date. $CAR_{-1,1}$ is defined as the compounded return over the $[-1, 1]$ window around the earnings announcement date ($t = 0$) in excess of the compounded value-weighted market return (in percent).There are 413,454 stock-quarter observations. The sample period is from the first quarter of 1983 to the fourth quarter of 2019 (444 quarters). Newey and West (1987) t-statistics are reported in parentheses.

	Good news ($CAR > 0$)	Bad news ($CAR \leq 0$)	Bad-Good
Small	0.02	1.58	1.56
	(0.07)	(8.55)	(6.76)
2	0.18	1.53	1.35
	(0.82)	(6.44)	(6.03)
3	0.34	1.03	0.69
	(1.69)	(5.09)	(3.42)
4	0.51	0.78	0.27
	(2.36)	(3.27)	(1.17)
Large	0.57	0.30	-0.27
	(2.36)	(1.27)	(-1.46)
All	0.32	1.07	0.75
	(2.08)	(6.59)	(7.42)

Table 17. Investor disagreement: good and bad earnings announcement news. In each calendar quarter, stocks are first sorted into quintiles based on firm size (SIZE). Next, within each SIZE decile, stocks are further sorted into good earnings portfolio($SUE > 0$) and bad earnings portfolio ($SUE \leq 0$) in Panel A and into good earnings portfolio ($SUEAF > 0$) and bad earnings portfolio ($SUEAF \leq 0$) in Panel B. The table presents the time-series of quarterly mean values of ΔID in each portfolio. ID_{after} and ID_{before} are defined as the contemporaneous correlation coefficient of daily trading volume and absolute price change over the window $[2, 45]$ and $[-45, -2]$, multiplied by -1, where $t = 0$ is the earnings announcement date. SUE is standardized unexpected earnings defined as the difference in EPS before extraordinary items between quarters q and $q-4$ divided by the $q-4$ quarter-end price. $SUEAF$ is the difference between the median analyst forecast over the 90-day period before the announcement and actual earnings divided by the $q-4$ quarter-end price. There are 382,724 and 258,544 stock-quarter observations for SUE and $SUEAF$ sample, respectively. The sample period is from the first quarter of 1983 to the fourth quarter of 2019 (444 quarters). Newey and West (1987) t-statistics are reported in parentheses.

	Panel A: sorted on SIZE and SUE		
SIZE quintile	Good news ($SUE > 0$)	Bad news ($SUE \leq 0$)	Bad-Good
Small	0.34	1.35	1.01
	(1.52)	(6.41)	(4.49)
2	0.23	1.58	1.35
	(1.04)	(6.56)	(6.63)
3	-0.01	1.70	1.71
	(-0.05)	(7.85)	(8.83)
4	-0.05	1.61	1.66
	(-0.25)	(5.89)	(6.96)
Large	0.04	1.12	1.08
	(0.17)	(4.29)	(4.47)
All	0.10	1.47	1.38
	(0.61)	(8.54)	(11.30)

	Panel B: sorted on SIZE and $SUEAF$		
SIZE quintile	Good news ($SUEAF > 0$)	Bad news ($SUEAF \leq 0$)	Bad-Good
Small	-0.12	1.44	1.56
	(-0.21)	(4.07)	(3.02)
2	0.38	1.52	1.14
	(1.36)	(4.88)	(2.90)
3	0.64	1.57	0.93
	(2.26)	(7.04)	(3.16)
4	0.32	0.89	0.57
	(1.42)	(2.61)	(2.11)
Large	0.31	0.67	0.36
	(1.17)	(2.46)	(1.38)
All	0.41	1.12	0.71
	(2.27)	(5.47)	(4.74)

Table 18. Change in investor disagreement: bad earnings announcement. The table reports stock-level cross-sectional regression of of ΔID on 3 bad earnings announcement indicator variable ($1_{CAR_{-1,1}\leq 0}$, $1_{SUE\leq 0}$, and $1_{SUEAF\leq 0}$) with a variety of control variables. ΔID is defined as $\Delta ID = ID_{\text{after}} - ID_{\text{before}}$. ID_{after} (ID_{before}) is defined as the contemporaneous correlation coefficient of daily trading volume and absolute price change over the window $[2, 45]$ and $[-45, -2]$, multiplied by -1, where $t = 0$ is the earnings announcement date. $1_{CAR_{-1,1}\leq 0}$ is an indicator variable that equals to one if $CAR_{-1,1} \leq 0$. $1_{SUE\leq 0}$ is an indicator variable that equals to one if $SUE \leq 0$. $1_{SUEAF\leq 0}$ is an indicator variable that equals to one if $SUEAF \leq 0$. $CAR_{-1,1}$ is defined as the compounded return over the $[-1, 1]$ window around the earnings announcement date ($t = 0$) in excess of the compounded value-weighted market return (in percent). SUE is standardized unexpected earnings defined as the difference in EPS before extraordinary items between quarters q and $q - 4$ divided by the $q - 4$ quarter-end price. $SUEAF$ is the difference between the median analyst forecast over the 90-day period before the announcement and actual earnings divided by the $q - 4$ quarter-end price. SIZE is the log of market capitalization in millions of dollars and BM is book-to-market ratio. RET is the return (in percent) compounded over the period $[-45, -2]$. TURN and IVOL are the average turnover ratio and idiosyncratic volatility in the period $[-45, -2]$, respectively. IOR is the ratio of shares owned by institutions as reported in 13F filings in the last quarter. NUMEST is the number of unique analysts that have eligible fiscal year one earnings estimates on IBES in the period $[-45, -2]$. The sample period is from the first quarter of 1983 to the fourth quarter of 2019. Newey and West (1987) t-statistics are reported in parentheses.

	(1)	(2)	(3)
$1_{CAR_{-1,1}\leq 0}$	0.007		
	(6.51)		
$1_{SUE\leq 0}$		0.011	
		(9.28)	
$1_{SUEAF\leq 0}$			0.006
			(4.73)
SIZE	0.018	0.018	0.017
	(9.85)	(9.55)	(6.56)
BEME	-0.003	-0.003	-0.003
	(-1.94)	(-1.87)	(-1.49)
RET	0.001	0.001	0.0004
	(7.38)	(7.45)	(5.16)
TURN	-0.335	-0.465	-1.518
	(-2.10)	(-2.63)	(-6.36)
IVOL	0.047	0.05	0.073
	(20.84)	(19.99)	(20.29)
IOR	-0.011	-0.014	-0.008
	(-2.65)	(-3.31)	(-1.70)
NUMEST	0.001	0.001	0.001
	(3.11)	(2.85)	(3.88)
Intercept	-0.203	-0.214	-0.251
	(-15.65)	(-15.15)	(-12.10)
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adj. R^2	3.50%	3.69%	5.04%
# of observations	412,620	382,091	257,699