When Day Meets Night: Measuring Investor Disagreement and Its Impact on Future Stock Returns

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Abstract

We propose a novel empirical measure of disagreement based on the sum of the absolute values of overnight (close-to-open) and intraday (open-to-close) returns, scaled by realized variance and show it can be a proxy of disagreement by developing a four-period model. Our empirical analysis shows a strong positive relationship between disagreement and future stock returns. We further empirically explore the underlying mechanism and find evidence supporting an information uncertainty-based explanation, rather than a mispricing hypothesis. Our findings highlight the critical role of investor disagreement in shaping stock market dynamics.

Keywords: Heterogeneous investors; Overnight return; Intraday return; Investor disagreement; Information uncertainty; Stock returns.

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1 Introduction

Disagreement has long been regarded as a central factor driving trading activity in financial markets. So understanding the impact of disagreement on security prices is a fundamental issue in finance. On one hand, much of the existing theoretical work suggests a positive risk premium should be associated with divergence in beliefs or opinions in the market. For instance, Papers by Varian (1985), and Abel (1989) posit that an investor who takes a position based on subjective beliefs should be compensated for bearing trading risk, or adverse selection risk. More recently, Banerjee (2011) develops a dynamic model and shows that, under rational expectations, investor disagreement positively correlates with expected returns. On the other hand, a prominent exception in this theoretical literature is Miller (1977), who argues that in the presence of short-sale constraints, differences of opinion in the market can result in higher stock prices and lower expected returns.

Despite extensive theoretical research on the impact of heterogeneous beliefs, empirical studies remain relatively limited due to the challenges in measuring investor beliefs. Many studies rely on the standard deviation of analyst forecasts as a proxy for disagreement (Diether et al., 2002; Anderson et al., 2009; Yu, 2011). However, this approach restricts the sample to analyst-covered stocks and is subject to biases, such as overoptimism (La Porta, 1996; Hong and Stein, 2003), herding, and anti-herding behaviours (Hong et al., 2000). Additionally, analysts' forecasts may be stale and influenced by compounding uncertainties faced during the prediction process (Doukas et al., 2006; van Binsbergen et al., 2023). Other studies use trading variables, such as trading volume, open interest, and turnover, to proxy for disagreement (Bessembinder et al., 1996; Boehme et al., 2006; Garfinkel and Sokobin, 2006). However, this method poses challenges for researchers attempting to investigate the often-weak relationship between investor beliefs and trading activity (Giglio et al., 2021; Charles et al., 2024).

In this paper, we introduce a novel empirical measure of belief dispersion for a given stock by summing the absolute values of overnight ((close-to-open) and intraday (open-to-close) returns over a monthly period, scaled by realized variance to account for volatility effects. Recent finance literature indicates the existence of systematic return patterns throughout the daily trading cycle. Specifically, both individual stocks and long-short portfolios sorted by stock characteristics show returns of similar size overnight and intraday, but the returns move in opposite directions (Branch and Ma, 2012; Berkman et al., 2012). Lou et al.(2019) provide a general explanation, attributing these return patterns to the opposing trading demands of distinct investor clienteles during overnight and intraday periods. Building on this, we explore heterogeneity in beliefs among different investor clienteles between the night and day trading sessions. Our key insight is as follows: information availability for a stock varies with factors such as firm age, size, and the level of investor attention. This variation in data provision and transparency, combined with differences in the financial sophistication of overnight and daytime investors, results in differential information processing and, consequently, heterogeneous beliefs about the same public information. Institutional investors, with superior computational power and analytical resources, can process and interpret information more comprehensively than individual investors, who often face constraints in knowledge and time. This disparity further widens the informational gap between retail and institutional investors. Consequently, the divergence between overnight and intraday returns reflects the dispersion in beliefs or preferences between these investor groups. When investors hold differing views or interpret information inconsistently, greater belief dispersion arises, leading to higher variability between overnight and intraday returns. Thus, the divergence not only influences asset prices but also serves as a proxy for disagreement, offering valuable insights into future stock performance.

A main concern is whether our measurement effectively captures disagreement. To better resolve the controversy, we propose a four-period theoretical model aligned with a close-open-close market cycle. The model features two types of investors, each with constant absolute risk aversion (CARA) utility, who trade a risky asset and a risk-free asset during the first three periods and optimize their expected terminal-period utilities. At the market open, new public signals about the final stock payoff are introduced. In line with Harris and Raviv (1993), Kandel and Pearson (1995), Cao and Ou-Yang (2009) and Banerjee and Kremer (2010), we assume that investors interpret these public signals using different likelihood functions, leading to disagreement on the mean. This disagreement reflects varying degrees of conditional optimism or pessimism about the asset's value. As a result, these differences in the interpretation of common information drive equilibrium price formation, affecting both overnight and intraday returns. The model's key implication is to show that greater belief dispersion regarding public information positively correlates with the absolute magnitude of close-to-open (overnight) and open-to-close (intraday) price changes.

We then conduct our main analysis to examine how differences of opinion among investors influence stock returns. Using data on U.S. equities from August 1992 to December 2022, we find a positive cross-sectional relationship between disagreement and future returns, supporting the results proposed by Varian (1985), Abel (1989), David (2008) and Banerjee (2011). Specifically, stocks with the highest level of disagreement generate approximately 1.177% higher monthly returns compared to stocks with the lowest disagreement. This positive return spread remains robust across various methods for risk adjustment and when controlling for other stock characteristics. These findings also hold when we exclude months with earnings announcements and account for short-sale constraints. Moreover, we further investigate whether our measure simply captures the dispersion of analyst forecasts, which has traditionally been used as a proxy for disagreement (Diether et al., 2002; Park, 2005; Avramov et al.,2009; Yu, 2011). The results suggest that while higher dispersion between overnight and intraday returns correlates with greater analyst disagreement, the effect of return dispersion cannot be fully explained by analyst forecast dispersion. This aligns with the idea that analyst dispersion may only reflect the views of professional analysts, who may not actively participate in trading, whereas our measure of dispersion reflects the heterogeneous beliefs and interactions between two distinct investor clientele.

Given our finding of a positive relationship between dispersion and future stock returns, we explore the potential economic mechanisms driving this pattern. Building on the theoretical framework and empirical evidence presented in this paper, we propose an information uncertainty hypothesis to explain our results. In rational expectations models, disagreement is linked to information uncertainty, which is expected to result in higher future stock returns (Klein and Bawa,1976; Barry and Brown,1985; Coles and Loewenstein, 1988; Wang 1994; He and Wang 1995). Specifically, the availability of information for a given stock depends on factors such as firm age, size, and investor attention. A lack of information and reduced transparency heighten information uncertainty, limiting investors' ability to analyse the stock. High levels of information uncertainty about a firm's fundamental values can lead to greater dispersion in the interpretation of a given public signal, which, in turn, amplifies differences in beliefs among investors. In our case, disagreement between daytime and nighttime investors is heightened when public signals relate to firms with limited information availability. This heightened disagreement manifests as greater divergence between overnight and intraday returns. Hence, if our disagreement indeed captures information uncertainty, greater disagreement should be associated with a higher required rate of return as compensation for bearing this uncertainty.

The results from multiple tests provide strong support for this hypothesis. First, under the information uncertainty hypothesis, an increase in disagreement (reflecting high uncertainty) is expected to result in a decline in contemporaneous stock returns. Consistent with this expectation, we find that the average cross-sectional correlation between disagreement and contemporaneous stock returns is -0.098%, which is statistically significant. Second, we expect the predictive power of our measure to be more pronounced among stocks with higher levels of information uncertainty. To test this, we examine the performance of our measure across stocks with varying levels of information uncertainty. Following Zhang (2006), we use firm size (Size), stock volatility (Volatility) and analyst coverage from I/B/E/S as proxies for information uncertainty. Implementing a double-sorting approach, we find that the returns and Fama-French 4-factor alphas for portfolios sorted by disagreement are significantly higher for stocks with high information uncertainty (smaller size, high volatility and less analyst coverage).

Third, if our measure of disagreement captures information uncertainty, the return predictability we observe should weaken during periods of increased news flow, which reduces information uncertainty. As noted by Jeon et al. (2022), the majority of firm-specific news articles are concentrated in the post-2000 period, with a distribution heavily skewed towards large firms. Consistent with this view, our results show a decline in return predictability after 2000. Furthermore, the difference in predictive returns between the pre-2000 and post-2000 periods is more pronounced for value-weighted portfolios, which place greater weights on large firms.

Fourth, we examine the relationship between our measure of disagreement and subsequent earnings announcement returns. If our measure captures information uncertainty, we would expect a positive correlation, as earnings announcements reduce uncertainty by revealing fundamental information to the public. Consistent with this expectation, the results show that stocks with higher pre-announcement disagreement earn higher cumulative abnormal returns following the earnings announcement. This positive relationship supports the notion that greater belief dispersion prior to earnings announcements reflects higher information uncertainty, which subsequently resolves when fundamental information is disclosed.

Fifth, to make our analysis more comprehensive, we examine whether our results are driven by mispricing or sentiment. We first estimate alphas using the mispricing factors of Stambaugh and Yu (2017) and the behavioural factors of Daniel al. (2020) and find that alphas remain significant, suggesting they cannot be explained by either mispricing or behavioural biases. Additionally, we investigate the time-varying predictive power of disagreement during periods of high and low market sentiment. If our risk-based explanation holds, the predictive power of our measure should remain consistent regardless of market sentiment. In support of this view, the coefficients on the sentiment index are small and statistically insignificant. These findings confirm that neither mispricing nor sentiment accounts for the observed relationship, reinforcing the validity of our risk-based explanation.

Our paper contributes to the literature in three distinct areas. First, we introduce a novel measure of disagreement derived from overnight and intraday returns. While existing research often relies on the standard deviation of analyst forecasts to proxy for disagreement (Diether et al., 2002; Park, 2005; Avramov et al.,2009; Yu, 2011), this method is limited to stocks covered by analysts and is prone to biases, such as overoptimism, herding, and anti-herding behaviours (La Porta, 1996; Hong and Stein, 2003; Hong et al., 2000). Additionally, trading-based proxies, such as volume, open interest, and turnover (Bessembinder et al., 1996; Boehme et al., 2006; Garfinkel and Sokobin, 2006), pose challenges for researchers attempting to investigate the often-weak relationship between investor beliefs and trading activity (Giglio et al., 2021; Charles et al., 2024). In contrast, our measure relies solely on open and close prices, which are widely available across all stocks. This approach effectively captures belief dispersion between retail and institutional investors, providing a more comprehensive perspective on disagreement, rather than reflecting solely divergence among professional analysts who might not actively trade.

Second, our paper contributes to the literature on how dispersion in beliefs influences asset prices. Following many theoretical studies, we provide empirical evidence that a positive risk premium should be associated with divergence in beliefs or opinions in the market to compensate for bearing information uncertainty risk. Previous literature typically models information uncertainty as either the information asymmetry component of the cost of capital (Easley and O'Hara, 2004; Verrecchia, 2001; Lambert et al., 2012; Ertugrul et al., 2017) or as estimation risk (Klein and Bawa, 1976; Chen and Moore, 1982; Coles and Loewenstein, 1988), both of which are associated with higher expected stock returns. Our fundings provide empirical evidence that supports this relationship through the disagreement channel. Specifically, we show that disagreement about public information can serve as a proxy for information uncertainty. When information is limited or transparency is reduced, uncertainty rises, leading to greater variation in how investors interpret public signals. This heightened dispersion in beliefs necessitates a higher required rate of return to compensate for the increased uncertainty. By connecting belief dispersion to information uncertainty, we provide a clearer understanding of the mechanisms driving expected stock returns.

Third, our paper contributes to the growing body of research examining the differences in average returns across overnight and intraday periods. Lou et al. (2019) attribute these return patterns to a recurring "tug of war" between two distinct groups of investors trading at different periods. Other research highlights the impact of heterogeneity in margin requirements and lending fees (Bogousslavsky, 2021), behavioural biases (Branch and Ma, 2012; Akbas et al., 2022), and liquidity provision (Lu et al., 2023). We provide a novel explanation by linking the divergence in overnight and intraday returns to differences in investor beliefs. Our model illustrates how varying interpretations of public signals during the close-open-close cycle lead to belief dispersion, and theoretically demonstrate that the magnitude of overnight and intraday returns reflect the extent of disagreement among investors.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 considers the economic model. Section 4 describes the data and methodology. Section 5 presents the empirical results. Section 6 presents a series of robustness checks. Section 7 presents our potential economic explanation. Section 8 concludes.

2 Related Literature

2.1 Disagreement

Disagreement can arise at any time due to differing priors, asymmetric information or varying interpretation of the same information (for example, Harris and Raviv, 1993; Kandel and Pearson,1995; He and Wang, 1995; Cao and Ouyang, 2009; Banerjee and Kremer, 2010; Banerjee and Green, 2015; Huang et al.,2024). For example, He and Wang (1995) develop a multi-period expectations model in which investors with differential information trade competitively, demonstrating that trading volume reflects the flow of information and reveals investors' private signals through market-clearing prices. Banerjee and Kremer (2010) develops a dynamic model with investor disagreement about public information, deriving conditions for positive autocorrelation in volume, and positive correlation between volume and volatility. Moreover, Research by Kandel and Pearson (1995), Cao and Ouyang (2009) and Huang et al. (2024) examine investor disagreement on both the mean and precision of public signals around announcements. For example, Kandel and Pearson (1995) propose that differential interpretations of information lead to the dynamic of trading volume and stock returns around public announcements. Then this model is further extended to option trading by Cao and Ouyang (2009). Huang et al. (2024) further propose that Investor disagreement about the precision of public signals explains market dynamics around earnings announcements, leading to lower price efficiency and trading volume before the news, and higher efficiency and trading volume after.

Understanding how disagreement impacts security prices and expected returns is a critical issue in finance. A substantial portion of existing studies suggest that a positive risk premium is likely correlated with disagreement among investors. For instance, in an Arrow-Debreu framework where agents hold differing subjective probabilities, Varian (1985) shows that greater differences in subjective probabilities lead to lower asset prices and higher risk premiums under typical levels of risk aversion. Banerjee (2011) develops a dynamic model showing that, under rational expectations, investor disagreement leads to higher expected returns if investors condition their beliefs on prices. Some empirical studies provide evidence of this positive relationship (Doukas et al., 2006; Avramov et al., 2009).

However, Miller (1977) argues that in the presence of short-sale constraints, differences of opinion can result in higher stock prices and lower expected returns. This hypothesis is supported by various empirical studies. For example, Chen et al. (2002), for example, demonstrate that greater divergence of opinion reduces the breadth of stock market ownership, driving stock prices higher and lowering expected returns. Additionally, studies using the dispersion of analysts' earnings forecasts as a proxy for disagreement, such as Diether et al. (2002), indicate that stocks with higher forecast dispersion tend to have significantly lower future returns than comparable stocks. Supporting this, Yu (2011) identifies a negative relationship between bottom-up analyst disagreement from the Institutional Brokers' Estimate System (I/B/E/S) and subsequent market returns, further suggesting that increased disagreement correlates with lower expected returns.

In those empirical studies, the proxy for disagreement is mixed. Some research predominantly employs analyst forecast dispersion as proxies for disagreement (Kandel and Pearson,1995; Diether et al.,2002; Anderson et al., 2009; Doukas et al., 2006; Sadka and Scherbina, 2007; Berkman et al., 2009; Yu, 2011; Carlin et al., 2014). However, this approach restricts the sample to analyst-covered stocks and introduces biases such as overoptimism (La Porta, 1996;

Hong and Stein, 2003; Brown, 1997), herding, and cognitive biases (Werner and Thaler, 1990; Trueman, 1994; Hong et al., 2000; Chen and Jiang, 2006). Furthermore, analysts' forecasts may become stale and influenced by compounding uncertainties during the prediction process (Doukas et al., 2006; van Binsbergen et al., 2023). Other studies use trading-related variables, such as trading volume, open interest, breadth of institutional ownership, and turnover, to proxy for disagreement (Jones et al., 1994; Bessembinder et al., 1996; Chen et al., 2002; Boehme et al., 2006; Garfinkel and Sokobin, 2006). However, this approach poses challenges for researchers attempting to investigate the often-weak relationship between investor beliefs and trading activity (Harris and Raviv, 1993; Giglio et al., 2021; Charles et al., 2024; Huang et al.,2024). More recently, social media data has been extensively used to measure disagreement (Antweiler and Frank, 2004; Cookson and Niessner, 2020,2023). Although this method shows promise, it is limited by the short length of the available sample periods.

2.2 Disagreement and uncertainty

The dispersion of professional forecasters is also widely recognized as a reliable measure of uncertainty and is extensively employed in finance research. For example, Anderson et al. (2009) measure economic uncertainty using disagreement among professional forecasters, and find a significant correlation with market excess returns, highlighting a positive cross-sectional price of uncertainty. Similarly, research by Andrei and Hasler (2015) uses analyst forecast dispersion to investigate how investor attention and learning uncertainty influence asset prices. Additionally, disagreement among professional forecasters is also applied to examine ambiguity aversion and stock market participation (Antoniou et al.,2015).

In macroeconomic contexts, the dispersion of forecasts for GDP growth and inflation is a common proxy for ambiguity. Research by Drechsler (2013), Ulrich (2013), David and Veronesi (2013), and Kostopoulos et al.(2022) highlight the role of forecast dispersion in capturing uncertainty about economic fundamentals. In the meantime, forecast dispersion also plays a significant role in business cycle models. For example, Ilut and Schneider (2014) analyse a New Keynesian business cycle model with agents who are averse to ambiguity by incorporating the dispersion of survey forecasts about growth as a measure of ambiguity. Expanding on this, Ilut and Saijo (2021) develop a heterogeneous-firm business cycle model where GDP forecast dispersion reflects Knightian uncertainty about firm profitability. In the corporate setting, Senga (2018) shows that firms with higher forecast dispersion experience lower sales and employment levels, reflecting the impact of uncertainty on firm performance.

2.3 Tug of war

Recent finance literature indicates the existence of systematic return patterns throughout the daily trading cycle. Specifically, both individual stocks and long-short portfolios sorted by stock characteristics show returns of similar size overnight and intraday, but the returns move in opposite directions (Cooper et al., 2008; Branch and Ma, 2012; Berkman et al., 2012; Hendershott et al., 2020).

Lou et al.(2019) provide a general explanation, attributing these return patterns to the opposing trading demands of distinct investor clienteles during overnight and intraday periods. Additional studies propose other explanations: attention-driven retail buying at the market open (Berkman et al., 2012) and market-maker behaviour leading to a negative correlation between overnight and intraday returns (Branch and Ma, 2012). Cooper et al. (2008) show that the U.S. equity premium over the past decade is entirely driven by overnight returns, which consistently exceed intraday returns across various time intervals. This pattern is partly due to negative reversals during the day. Hendershott et al. (2020) link the positive relationship between beta and overnight returns to a risk-return tradeoff, while the negative beta-intraday return relationship stems from speculative trading at the open. Moreover, the intensity of daily return reversals predicts higher future returns, suggesting that daytime arbitrageurs tend to overcorrect (Akbas et al., 2022). Capital-constrained arbitrageurs reduce their positions by day's end to mitigate overnight risks like illiquidity and large price movements, leading to predictable intraday return patterns, particularly for mispricing anomalies (Bogousslavsky, 2021). Recently, Lu et al. (2023) provide a complementary explanation focusing on heterogeneity in liquidity provision.

While previous research has investigated disagreement using proxies like analyst forecast dispersion and trading volume, these measures are often limited by sample constraints, biases, and indirect connections to actual trading behaviour. At the same time, studies on daily return patterns have highlighted the roles of different investor clienteles, liquidity constraints, and market-maker behaviour but have not directly linked these patterns to investor disagreement. Our paper bridges these gaps by introducing a novel measure of disagreement derived from the divergence between overnight and intraday returns. This approach captures the heterogeneity of beliefs between different investor clienteles who dominate trading at different times of the day. By developing a four-period model and conducting empirical analysis, we demonstrate a strong positive relationship between disagreement and future stock returns, providing evidence that supports an information uncertainty-based explanation over mispricing. This work advances our understanding of how investor disagreement influences stock market dynamics, providing new evidence on the relationship between belief dispersion and asset pricing.

3 A disagreement model

In this section, we outline the theoretical motivation for our measure of disagreement. Disagreement among investors can arise at any time due to factors such as differing prior beliefs, asymmetric information, and varying interpretations of the same information (for example, Harris and Raviv, 1993; Kandel and Pearson,1995; He and Wang, 1995; Cao and Ouyang, 2009; Banerjee and Kremer, 2010; Banerjee and Green, 2015; Huang et al.,2024). In our model, we focus on investors who hold heterogeneous beliefs about the same public information and develop a tractable model to explore the relationship between these differing opinions and overnight and intraday return patterns.

Timing: We develop a four-period model ($t = 1{,}2{,}3\ and\ T\ (terminal)$), corresponding to a close-open-close market cycle. In this model, we define $t = 1$ as yesterday's close, $t = 2$ as today's open, $t = 3$ as today's close and terminal time T. Accordingly, the time interval between $t = 1$ and $t = 2$ represents the overnight period, while the interval between $t = 2$ and $t = 3$ corresponds to the intraday period.

Agents: There are two types of investors indexed by $i = 1{,}2$: informed investors ($i = 1$) and uninformed investors ($i = 2$). The mass of investors is 1, and the proportion of informed investors is α.

Securities: There are only two assets traded in the market: a risk-free asset with a zero rate of return and a risky asset with zero net supply with a final payoff D at the terminal period T.

Information and belief: There are four time periods indexed by $t = 1, 2, 3,$ and $terminal\ time\ T$: at *t=1* (yesterday's close), before any signals are observed, investors have different prior beliefs about the final payoff D of the risky asset. The structure of D and priors are given by

$$D_i = X_i + d_i, \tag{1}$$

where $X_i \sim \mathcal{N}(\mu_i, \tau_x^{-1})$ represents the component of fundamentals that investors can learn. while $d_i \sim \mathcal{N}(h_i, \tau_d^{-1})$ is residual uncertainty. The mean μ_i represents the different prior beliefs of the ith investor. Furthermore, since investors receive no information about d, we assume that informed investors are rational, holding the belief that the residual uncertainty follows $d_1 \sim \mathcal{N}(0, \tau_d^{-1})$. In contrast, uninformed investors disagree on the residual uncertainty, assuming $d_2 \sim \mathcal{N}(h, \tau_d^{-1})$.

At $t = 2$ (today's open), all investors obtain the same public signal L but may interpret it differently. The signal L is given by

$$L = X + \varepsilon_i, \tag{2}$$

where $\varepsilon \sim \mathcal{N}(e_i, \tau_\varepsilon^{-1})$ is normally distributed, and e_i and τ_ε^{-1} denote the mean and precision of the ith investor, respectively. For simplicity, we assume that investor i's interpretation of the public signal is as follows:

$$e_1 = \delta, e_2 = -\delta, \tag{3}$$

where $\delta > 0$ proxies for the magnitude of disagreement. As a result, there is uncertainty regarding how future signals L will be interpreted, and the δ reflects the disagreement on the meaning of public information of investors for the same public signal. Moreover, to highlight the impact of different interpretations of the public signal, we assume that investors share a common belief about the precision of the public signal.

Then at $t = 3$ (today's close), the public news is realized and incorporated into the common prior for future periods.

Preference: At $t < T$, investors exhibit mean-variance preferences and seek to maximize their constant absolute risk aversion (CARA) utility of terminal wealth $W_{i,,T}$, given their information set $\mathcal{F}_{i,t}$ at time t. Specifically, the optimal risky asset position held by each type of investor, $q_{i,t}$, is given by:

$$q_{i,t} = arg \max_{q_{i,t}} \mathbb{E}_i\left[-e^{-\gamma W_{i,T}} \middle| \mathcal{F}_{i,t}\right], \qquad i = 1,2, \tag{4}$$

where γ is the degree of risk aversion and we set it to one for simplicity. The supply of the risky asset is assumed to be zero, so that in equilibrium $\alpha q_{1,t} + (1 - \alpha) q_{2,t} = 0$ under market clearing conditions. Given these preferences, the optimal risky asset demand is given by:

$$q_{i,t} = \frac{\mathbb{E}_t[D] - P_t}{\gamma Var_t[D]}. \quad (5)$$

Equilibrium characterization: The results outlined below characterize the equilibrium of this model.

Proposition 1: At each time $t \in \{1,2,3\}$, A unique equilibrium exists, and the equilibrium price is given by

$$P_1 = \alpha\mu_1 + (1-\alpha)(\mu_2 + h), \quad (6)$$

$$P_2 = \rho[\alpha\mu_1 + (1-\alpha)(\mu_2 + h)] + (1-\rho)[\alpha(L - e_1) + (1-\alpha)(L - e_2)], \quad (7)$$

$$P_3 = X + (1-\alpha)h, \quad (8)$$

where $\rho = \frac{\tau_X + \tau_d}{\tau_X + \tau_d + \tau_\varepsilon}$ represents the relative weight that investors assign to their prior beliefs compared to the new information contained in the public signal L.

Next, using the equilibrium price at each point in time, we compute overnight and intraday returns and analyse their relationship with belief dispersion.

Proposition 2: When equilibrium, the overnight and intraday returns is given by

Overnight return:

$$r_{overnight} = P_2 - P_1 = (1-\rho)[\alpha(L - e_1 - \mu_1) + (1-\alpha)(L - e_2 - \mu_2 - h)], \quad (9)$$

Intraday return:

$$r_{intraday} = P_3 - P_2 = X + (1-\rho)[\alpha(e_1 - L) + (1-\alpha)(h - L - e_2)] - \rho[\alpha\mu_1 + (1-\alpha)\mu_2]. \quad (10)$$

Since we assume $e_1 = \delta, e_2 = -\delta$, the absolute value of overnight return, $r_{overnight}$, and the absolute value of intraday return, $r_{intraday}$, are given by,

$$|r_{overnight}| = \left|(1-\rho)\left[L + (1-2\alpha)\delta - \left(\alpha\mu_1 + (1-\alpha)(\mu_2 + h)\right)\right]\right|, \quad (11)$$

$$|r_{intraday}| = |X + (1-\rho)[(2\alpha - 1)\delta - L + (1-\alpha)h] - \rho[\alpha\mu_1 + (1-\alpha)\mu_2]|. \quad (12)$$

When investors hold opposing views on the public signal, the relationship between the absolute value of overnight (intraday) returns and disagreement depends on the proportion of different types of investors. More specifically, during the overnight period, when $\alpha < \frac{1}{2}$ and the level of disagreement (δ) is sufficiently large, greater disagreement is positively correlated with the absolute value of the price change (overnight return). Conversely, during the intraday period, when $\alpha > \frac{1}{2}$ and the level of disagreement (δ) is sufficiently large, increased disagreement is also positively correlated with the absolute value of the price change (intraday return).

Overall, as long as two distinct types of investors dominate the market in different time intervals —consistent with Lou et al. (2019), who propose that two distinct clienteles dominate the overnight and daytime trading sessions—our model suggests that larger price changes occur with greater disagreement.

4 Data and Methodology

4.1 Data

We collect monthly and daily stock data, including daily prices, monthly returns and shares outstanding from the Center for Research in Security Prices (CRSP). Our dataset includes ordinary common shares (CRSP share codes 10 and 11) listed on the NYSE, AMEX, and NASDAQ. Where applicable, we adjust individual stock returns for delisting returns. To ensure the data fully reflects investor disagreement, we exclude stocks with any missing trading days within a month. To avoid microstructure issues, we omit "penny stocks" with prices below $1. We obtain the risk-free rate and Fama-French (1993) factors from Kenneth French's website.[1] Analyst forecasts and dispersion come from the Thomson Reuters Institutional Brokers' Estimate System (I/B/E/S). Institutional ownership data is sourced from the Thomson Reuters 13F database. The sample period spans from August 1992 to December 2022, for which the open prices for the NASDAQ SmallCap Market were first reported in June 1992.

4.2 Disagreement Measurement

Return decomposition

Building upon earlier studies by Lou et al. (2019), we decompose close-to-close returns into overnight and intraday components. Specifically, for stock s on the same trading day d, we define the intraday return as the price change between the market open and the market close on the same day. The overnight return is then estimated by this intraday return and the daily close-to-close return.

[1] See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

$$r^s_{intraday,d} = \frac{p^s_{close,d}}{p^s_{open,d}} - 1, \tag{13}$$

$$r^s_{overnight,d} = \frac{1 + r^s_{close-to-close,d}}{1 + r^s_{intraday,d}} - 1, \tag{14}$$

where $p^s_{close,d}$ and $p^s_{open,d}$ are the close and open price for stock s at day d, $r^s_{intraday,d}$ is the intraday return for stock s at day d, and $r^s_{overnight,d}$ is the overnight return for stock s at day d.

<u>Disagreement measurement</u>

We next calculate the daily divergence between overnight and intraday returns to capture variation in beliefs between different investor clienteles,

$$dis^s_d = \left|r^s_{intraday,d}\right| + \left|r^s_{overnight,d}\right|, \tag{15}$$

where $\left|r^s_{intraday,d}\right|$ captures the extent to which investors trading intraday disagree with those trading overnight, and $\left|r^s_{overnight,d}\right|$ reflects the disagreement between investors trading overnight and those trading intraday. Consequently, the dispersion in beliefs (Dis) for stock s in month t is defined as:

$$Dis^s_t = \frac{\sum^{1}_{d=\frac{1}{N}} dis^s_d}{Std_{s,t}\left(r^s_{close-to-close,d}\right)}, \tag{16}$$

where N is the number of daily dispersion observations (dis^s_d) for stock s in month t. The term $Std_{s,t}\left(r^s_{close-to-close,d}\right)$ represents the standard deviation of close-to-close returns for stock s in that month. To account for differences in the magnitude of return changes across stocks, we adjust the dispersion by normalizing it with the realized standard deviation of returns for that month.

4.3 Data Description

In this section, we provide summary statistics for our measure of disagreement and other related stock characteristics[2]. Panel A of Table 1 shows the time-series average of the cross-sectional means and standard deviations for each stock characteristic, while Panel B reports their monthly cross-sectional correlations. In the interest of conciseness, definitions of all stock characteristics are provided in the Appendix. As expected, disagreement is negatively correlated with firm size (ME) and positively correlated with volatility (VOL), both of which are linked to information uncertainty.

[Insert Table 1 here]

Beyond the correlation between Dis and individual stock characteristics, we compute the portfolio characteristics for decile portfolios sorted by past monthly Dis. Each decile portfolio is equal-weighted. For these portfolios, we calculate the cross-sectional average of each stock characteristic and then derive its time-series average over the entire sample. The summary statistics, reported in Table 2 confirm that Stocks with high Dis tend to be smaller in size, with this difference primarily driven by the top decile. Additionally, the high-minus-low Dis portfolio exhibits a lower beta (BETA), higher idiosyncratic volatility (IVOL), greater past-month maximum returns (MAX), and a return distribution that is more positively skewed (SK) and leptokurtic (KT). Such findings align with expectations, as such characteristics are typically associated with opaque information environments. In this environment, investors face challenges in interpreting information, leading to divergent opinions and greater belief dispersion.

[Insert Table 2 here]

5 Empirical results

5.1 Univariate portfolio sorts

We begin our empirical analysis with univariate portfolio sorts. At the end of each month (t), we rank stocks into deciles according to their estimated Dis and compute both equal-weighted and value-weighted portfolio returns for the following month ($t + 1$). Stocks with the lowest Dis are placed in Decile 1, while those with the highest Dis are allocated to Decile 10. We also construct a long-short strategy that takes a long position in the top decile (highest disagreement)

[2] The definition of each stock characteristic is in the Appendix A1.

and a short position in the bottom decile (lowest disagreement). Table 3 presents the results for these decile portfolios, including average raw returns for the next month, CAPM alphas (Sharpe, 1964, Lintner, 1965), Fama-French 3-factor alphas based on the Fama and French (1993) model, and four-factor alphas derived from the Carhart (1997) model.

Panel A of Table 3 reports the results for equal-weighted decile portfolios sorted by the level of disagreement (Dis). The first row shows a near-monotonic increase in average monthly raw returns, rising from 1.240% in decile 1 (low disagreement) to 2.417% in decile 10 (high disagreement). The return spread between the highest and lowest disagreement portfolios is 1.177%, which is both economically significant and statistically robust, with a t-statistic of 7.46. Furthermore, this return difference cannot be explained by market, size, value, and momentum factors, with a four-factor alpha of 1.394% (t-statistic=7.41).

This return difference between the high- and low-Dis deciles remains significant even for value-weighted portfolios. The average value-weighted return difference between the top and bottom deciles is 0.355% per month, which a t-statistic of 2.10. Consistent with our expectations, these results are less pronounced compared to the equal-weighted portfolios, since larger firms tend to be more transparent, making it easier for investors to converge on common expectations regarding their future performance.

To gain deeper insight, we further decompose future one-month returns into intraday and overnight components. Panel C of Table 3 shows the corresponding results. The results demonstrate that the positive predictive relationship between disagreement and future returns is primarily driven by the intraday returns. Specifically, the high-minus-low disagreement portfolio shows an average intraday return of 3.214% for the following month, with a t-statistic of 16.70. In contrast, the overnight return component is negative and comparatively smaller, at -0.194% (t-statistic=-1.49).

[Insert Table 3 here]

Overall, these findings establish that the difference in returns between high- and low-Dis deciles is both statistically significant and economically large, and it can not be explained by common risk factors. Nevertheless, one potential issue is that Dis might be associated with various firm characteristics that also influence return patterns. Therefore, in the following analysis, we further explore whether this positive relationship between disagreement and future returns persists when controlling for these firm characteristics.

5.2 Bivariate portfolio sorts and Fama-MacBeth regressions

In this section, we implement double sorts and Fama-MacBeth (1973) regressions to account for the influence of other firm characteristics. At the end of each month, we first classify stocks into tercile portfolios based on a specific stock characteristic that may influence the dispersion effect. Within each tercile, we further divide stocks into ten sub-decile portfolios based on their Dis levels. We then compute the equal-weighted returns for these 30 portfolios (3×10) for the following month. By averaging the returns of Dis sub-deciles across the initial tercile sorts, we create portfolios that differentiated by Dis while holding stock characteristics comparable.

The results, presented in Table 4, show that the return spread between high- and low-Dis portfolios remains economically substantial and statistically significant even after controlling for 12 firm characteristics. Specifically, the monthly return difference between the top and bottom Dis deciles ranges from 0.493% to 1.390% per month and is significant at the 1% level. Similarly, the four-factor alphas for the high-minus-low Dis portfolios vary between 0.599% and 1.573% per month, all of which are statistically significant.

Comparing these double-sort results to the single-sort findings in Table 3, we find that firm characteristics have a limited impact on the return spread between high-and low-Dis portfolios. This aligns with the U-shaped relationship between Dis and many firm characteristics, as shown in Table 2. For example, both high- and low- Dis decile portfolios display higher kurtosis (KT). We also note that both average return and alpha spreads decrease significantly when controlling for market capitalization. This finding is in line with the single-sort results, where value-weighted high-minus-low portfolios generate smaller returns compared to equal-weighted portfolios. Hence, although many stock characteristics show significant variation across Dis-sorted portfolios, the findings in Table 4 suggest that the predictive ability of Dis is distinct from other known cross-sectional return predictors.

[Insert Table 4 here]

However, the double-sort portfolio analysis described above only allows us to consider limited characteristics simultaneously. To address this, we apply Fama-MacBeth (1973) cross-sectional regressions, which enable us to control for several firm characteristics concurrently. Each month, we estimate the following regression model:

$$r_{t+1}^{s} - r_{f,t+1} = \alpha + \sum_{j=1}^{K} \beta_{j,t} z_{j,t}^{s} + \epsilon_{t+1}^{s}, \tag{17}$$

where r_{t+1}^s is the return for stock s in month $t+1$, $r_{f,t+1}$ is the risk-free rate, and $z_{j,t}^s$ represents stock-specific characteristic j for stock s measured at the end of month t. We then compute the time series averages of the estimated coefficients $\beta_{j,t}$, along with their standard errors.

Panel A of Table 5 reports the results of regressions with a single explanatory variable. Consistent with our prior findings, the coefficient on Dis is positive and significant, confirming a positive relationship between Dis and future returns. In Panel B, we extend the analysis by including multiple explanatory variables simultaneously. The coefficient on Dis remains positive sign and statistically significant across all specifications, even when controlling for all stock characteristics. These results from Tables 4 and 5 reinforce that disagreement plays a distinct role in explaining cross-sectional return variations, independent of previously identified firm characteristics.

[Insert Table 5 here]

6 Robustness checks

6.1 Dispersion and firm-specific news

In this subsection, we investigate whether our findings are driven by firm-specific news announcements, which are typically disclosed during post-market periods. To address this, we collect earnings announcement dates from Compustat and re-run the Fama-Macbeth regressions, excluding firms with earnings announcements in month t or t+1.

The results are provided in Table 6. In all specifications tested, the magnitude and statistical significance of the coefficient on Dis remains unchanged after excluding announcement months. In particular, when firms with earnings announcements in the subsequent month are excluded, the coefficient on Dis remains at 0.003 or 0.002, significant at the 1% level, which is almost identical to the results with earnings announcement month in Table 5. This evidence indicates that the predictive power of Disagreement (Dis) is not driven by firm-specific news announcements.

[Insert Table 6 here]

6.2 Short-sale constraints

Bogousslavsky (2021) shows that different types of investors prefer to trade or hold stocks at different times due to market liquidity or short-sale constraints. To examine whether the impact of dispersion merely captures the effect of short-sale constraints, we use institutional ownership as a proxy, given that institutional investors are predominantly responsible for share lending. Stocks with low institutional ownership are typically more difficult and costly to short-sell (Nagel, 2005; Chen et al., 2002). We repeat the double-sorting process. Specifically, each month, stocks are first sorted into tercile portfolios based on institutional ownership. Within each institutional ownership group, we further sort stocks into decile portfolios based on disagreement (Dis). We then examine the 1-month-ahead returns of these portfolios.

Panel A of Table 7 presents the average returns and FF 4-factor alphas for the resulting decile portfolios. We can find that the effect of short-sale constraints is limited to the magnitude of the return of the high-minus-low portfolio. In particular, the return difference between the high- and low-Dis deciles remains significant, with an average return of 0.929% per month and a four-factor alpha of 1.082% per month, both statistically significant at the 1% level. Furthermore, we analyse the corresponding results for the 30 short-sale constraints/Dis portfolios and the high-low portfolios. The return of the high-minus-low Dis portfolios increases monotonically with short-sales constraints, raising from 0.235% to 1.849%. These results suggest that while the impact of disagreement is more pronounced among stocks with high short-sale constraints, the effect of dispersion remains economically and statistically significant even after controlling for short-sale constraints.

[Insert Table 7 here]

6.3 Analyst Dispersion

Professional forecasters are always considered a reliable measure of disagreement in many previous studies (Diether et al., 2002; Park, 2005; Anderson et al., 2009; Yu, 2011; Andrei and Hasler, 2015). To address the concern that our findings might be driven by analyst forecast dispersion, we collect analysts' earnings forecast data from I/B/E/S. Then we first calculate the cross-sectional average of analyst forecast dispersion (A_disp) for each decile portfolio and then implement double sort to examine the impact of the analyst forecast dispersion.

The results are presented in Table 8. Panel A shows that the analyst forecast dispersion in each decile portfolio. As expected, stocks with higher Dis tend to have higher analyst forecast dispersion, suggesting that greater dispersion between overnight and intraday returns is associated with greater disagreement among analysts. The results in Panel B show the returns and FF-4 alphas for double-sorting portfolios and indicate that the effect of our disagreement measure cannot be explained by analyst forecast dispersion. For example, the return difference between the high- and low-Dis deciles is 0.678% per month when controlling for analyst forecast dispersion and remains significant at the 1% level. The corresponding four-factor alpha is 0.838% per month and is also statistically significant. When compared with the single-sorting results in Table 3, the magnitude of the high-minus-low portfolio return decreases, indicating that our measure contains some information embedded in analyst forecast dispersion. When the dispersion in analysts' earnings forecasts is high, the divergence of overnight and intraday returns tends to be high to reflect the divergence of investor beliefs. Therefore we hypothesize that the predictive relationship should be stronger in portfolios with higher analyst forecast dispersion. Panel C supports our hypothesis, showing that the high-minus-low returns are highest in the tercile portfolios with the highest analyst forecasts dispersion.

Hence, these findings confirm that our measure of disagreement reflects investor belief divergence and cannot be fully explained by analyst forecast dispersion. This conclusion aligns with recent work suggesting that analyst forecasts often exhibit biases, and these biases challenge the use of analyst forecast dispersion as a reliable proxy for investor disagreement. Moreover, analyst forecast dispersion may only capture the opinions of professional analysts who may not actively participate in trading, whereas our measure of disagreement reflects the diverse beliefs and interactions of distinct investor clienteles directly engaged in trading activities.

[Insert Table 8 here]

6.4 Trading Volume

Earlier studies documents disagreement is positively related to trading volume (Harris and Raviv, 1993; Shalen, 1993; Kandel and Pearson,1995). To investigate the effect of Dispersion on subsequent month's trading activity or changes in trading activity, we use the natural log of stock trading volume as a proxy for trading activity. Given the strong persistence in trading volume, we include a lagged depend variable in regressors. Additionally, we also include other significant factors known to influence trading activity, including beta (BETA), firm size (ME), momentum (MOM), short-term reversal (REV), idiosyncratic volatility (IVOL), illiquidity (ILLQ) and a dummy variable of earnings announcements (Earn_Ann). We then run Fama-MacBeth regressions, regressing the natural log of trading volume or changes in the natural log of trading volume on Dis and the control variables. Based on the theoretical framework, we expect a positive coefficient for Dis, indicating that higher dispersion leads to increased trading activity.

Table 9 reports the results from the Fama-MacBeth regression analysis, demonstrating a positive relationship between Dispersion (Dis) and subsequent trading activity, as well as changes in trading activity. In particular, the coefficients of Dis across all regressions are positive and highly significant. This indicates that stocks with higher disagreement are followed by both higher trading volume and greater increases in trading volume. This effect can be seen as supporting the findings of Harris and Raviv (1993).

[Insert Table 9 here]

7 Potential economic explanations/mechanism

Given our finding of a positive cross-sectional association between dispersion and future stock returns, we explore the potential economic mechanisms underlying this relationship. Drawing from the theoretical framework and empirical evidence presented in this paper, we propose an information uncertainty hypothesis to explain these findings.

Rational expectations models suggest that disagreement captures information uncertainty, which, in turn, is expected to drive a contemporaneous decline in stock prices and higher future stock returns (Wang, 1994; He and Wang, 1995; Easley and O' Hara, 2004). Specifically, for a given stock, the availability of information varies based on factors such as firm age, size, and investor attention. Limited information and reduced transparency increase information uncertainty, constraining investors' ability to analyse the stock effectively. A great level of information uncertainty regarding a firm's fundamental values can amplify the dispersion in how public signals are interpreted, leading to greater divergence in beliefs and differences of opinions among investors.

If disagreement indeed reflects information uncertainty, an increase in disagreement should correspond to a higher required rate of return, resulting in a cotemporaneous decline in stock prices as compensation for the higher level of uncertainty. Consistent with this hypothesis, our results in Table 1 show a statistically significant average cross-sectional correlation of -0.098% between our disagreement measure and contemporaneous stock returns.

7.1 Interaction with information uncertainty

Earlier literature highlights that stocks characterized by small size, high volatility and low analyst coverage exhibit high levels of information uncertainty (Zhang, 2006). If our measure is associated with information uncertainty, the returns associated with this measurement should be more pronounced for stocks characterized by higher levels of information uncertainty. To examine it, we follow Zhang (2006) to use firm size (Size), stock volatility (Volatility) and analyst coverage from I/B/E/S as proxies for information uncertainty. At the end of each month, we first sort all of the stocks into tercile portfolios based on proxies of information uncertainty (Size/Volatility/Analyst coverage). Each tercile portfolio is further divided into ten additional Dis sub-decile portfolios and computes the equal-weighted returns over the subsequent month for the resulting 30 (3×10) portfolios. We then take the average of each of the Dis portfolios across the ten deciles that were formed from the first sort. The results are shown in Table 10.

Consistent with the information uncertainty hypothesis, we find that there is an increasing relation between the return forecasting power of our measure of disagreement and the degree of information uncertainty. Table 10 shows that the returns and F-F 4-factor alphas for Dis-sorted portfolios are both positive and larger in magnitude for stocks characterized by high information uncertainty (smaller size, high volatility and less analyst coverage). In contrast, the raw returns and HML Fama-French 4-factor alphas for Dis-sorted portfolios are comparatively smaller for stocks with low information uncertainty (e.g., larger size, lower volatility, and higher analyst coverage). For example, the return and alpha spread between stocks with low and high stock volatility yield a highly significant difference in the Dis premium. The alpha spread difference is 2.086%, with a t-statistic of 6.48. Moreover, using analyst coverage as a proxy of information uncertainty, the high-minus-low returns are most pronounced in tercile portfolios with the lowest analyst coverage. These findings provide robust support for the information uncertainty hypothesis.

[Insert Table 10 here]

7.2 Intensity of news releasement

Asset pricing theory has long established a connection between the quantity and quality of information flows and fluctuations in asset prices. For instance, information that resolves uncertainty about a firm's future prospects can lead to adjustments in its current stock price. According to Jeon et al. (2022), the increased price informativeness of news is attributed to enhanced data provision, greater transparency, and advancements in technology and accounting practices. They document that the majority of firm-specific news articles are concentrated in the post-2000 period, with the distribution of news articles across firms heavily skewed towards large firms. Motivated by this perspective, if the predictive power of Dis is driven by information uncertainty, it should be less pronounced after 2000 due to the greater volume of news (i.e., lower information uncertainty). Furthermore, this effect should be more evident in value-weighted portfolios, which place more weight on large firms.

We divide our sample into two subsamples---pre-2000 and post-2000---and repeat the analysis from Table 3. The results, presented in Table 11, support our hypothesis. Panel A reports that in equal-weighted decile portfolios, both average monthly raw returns and alphas decline in the post-2000 period; the return spread between the high-and low-Dis deciles decreases from 1.336% to 1.127%. This decline is more pronounced in value-weighted portfolios (Panel B), where the pre-2000 return spread of 0.638% (t-statistic of 7.46) falls to 0.264% and becomes statistically insignificant in the post-2000 period. These findings provide further support for our information uncertainty hypothesis, indicating that the predictive power of Dis diminishes as information uncertainty resolves, particularly for large firms that dominate value-weighted portfolios.

[Insert Table 11 here]

7.3 Earnings announcements

If our measure of disagreement indeed reflects information uncertainty, we expect to observe a positive correlation between disagreement and subsequent earnings announcement returns. This correlation arises because the release of fundamental information during earnings announcements reduces information uncertainty. In particular, we hypothesis that stocks with higher disagreement exhibit stronger performance following earnings announcements. To examine this hypothesis, we calculate the five-day and twenty-day cumulative abnormal returns (CAR) following an earnings announcement as the difference between a stock’s realized cumulative return and its expected cumulative return. The expected return is derived using the capital asset pricing model (CAPM) with the value-weighted CRSP market index as a proxy for the market portfolio. We test our conjecture by estimating the following panel regression:

$$CAR_{s,t} = \alpha + \beta_{dis} Dis_{s,t-1} + \sum_{j=1}^{K} \beta_{j,t} z_{s,t}^{j} + \varepsilon_{s,t}, \tag{18}$$

where $CAR_{s,t}$ is either the five-day cumulative abnormal return (CAR[1,5]) or twenty-day cumulative abnormal return (CAR[1,20]) after the earnings announcement day. $Dis_{s,t-1}$ is the pre-disagreement calculated by using data from one month prior to the announcement day. $z_{j,t}^{s}$

is the stock-specific variable j for stock s measured at the end of month $t-1$. All panel regressions include quarterly fixed effects, with standard errors clustered by both firm and time.

Table 12 presents the regression results. Columns (1) and (3) report the results for the baseline panel regression, which includes only Dis as the explanatory variable. Columns (2) and (4) introduce additional control variables to account for relevant stock characteristics. The results consistently show that stocks with higher disagreement earn higher cumulative abnormal returns following the earnings announcement. In particular, the coefficient on Dis is positive and statistically significant in both baseline regression and when we control for the stock characteristics. This finding supports the hypothesis of a positive relationship between pre-disagreement and subsequent earnings announcement returns.

[Insert Table 12 here]

7.4 Mispricing and sentiment effect

Recent studies highlight that sentiment significantly impacts investors' behaviour and contributes to market mispricing (Aboody et al., 2018; Baker and Wurgler, 2006; Yu and Yuan, 2011; Stambaugh et al., 2012; Daniel et al., 2020). Miller (1977) argues that, under short-sale constraints, disagreement can lead to stock overpricing, as pessimistic investors are sidelined from the market. In our results so far, we examine the role of short-sale constraints and propose a risk-based economic explanation for the observed patterns. To ensure the robustness of our findings, we now examine whether the results are driven by mispricing and sentiment. We begin by estimating alphas using the mispricing factors of Stambaugh and Yu (2017) and the behavioural factors of Daniel al. (2020). Next, we analyse the time-varying predictive power of disagreement across periods of high and low market sentiment. Specifically, we regress the high-minus-low (HML) portfolio return sorted by Dis on sentiment. The following time-series regression model is employed:

$$HML_t = \alpha + \sum_{j=1}^{K} \beta_t^j f_t^j + \gamma Sentiment_{t-1} + \varepsilon_t, \tag{19}$$

where HML is the returns of the high-minus-low portfolio. We regress HML portfolio returns on the risk factors from the F-F 3-factor or 4-factor model (f_t^j), along with the lagged monthly sentiment measure from Baker and Wurgler (2006) ($Sentiment_{t-1}$). In addition to the continuous sentiment measure, we incorporate a high sentiment dummy variable. Following Barroso and Detzel (2021), this dummy classifies each month as having "high" or "low" sentiment based on whether the Baker and Wurgler (2006) index (monthly) is above or below its sample median at the end of the prior year, calculated using annual data. We conjecture that our results can not be explained by mispricing-related factors or sentiment effects.

The results are presented in Table 13. Columns (1) and (2) report regression results that control for the mispricing factors of Stambaugh and Yu (2017) and the behavioural factors of Daniel al. (2020), respectively. In both cases, the return difference between the high- and low-Dis Portfolios remains economically large and statistically significant. Columns (3) to (8) report six different specifications of Eq. (19). The coefficients on the sentiment measures in these regressions are all statistically insignificant, suggesting that the Dis pattern is not driven by sentiment. These findings support our risk-based explanation, reinforcing that the predictive power of Dis is indeed associated with information uncertainty rather than mispricing or sentiment effects.

[Insert Table 13 here]

8 Conclusion:

Disagreement has long been recognized as a key factor driving trading activity in financial markets, making its impact on security prices a fundamental issue in finance. However, empirical research is relatively limited, primarily due to the challenges of accurately measuring investor beliefs. In this paper, we introduce a four-period model aligned with the close-open-close trading cycle to analyse the relationship between overnight and intraday returns and belief dispersion. Based on this framework, we construct a novel empirical measure of belief dispersion by summing the absolute values of overnight (close-to-open) and intraday (open-to-close) returns over a month, scaled by realized variance to adjust for volatility effects. We then examine the relationship between disagreement and future returns and find a positive cross-sectional relationship. This predictive power remains robust across a series of checks, including the exclusion of months with earnings announcements and consideration of short-sale constraints. Moreover, this measure is not subsumed by analyst forecast dispersion, which is commonly used as a proxy for disagreement.

To explain these findings, we propose an information uncertainty hypothesis and conduct a comprehensive analysis. We find that the predictive power of our disagreement measure (Dis) is more pronounced for stocks with higher information uncertainty and during periods of heightened uncertainty, such as the pre-2000 era. Furthermore, our results indicate a positive correlation between disagreement and subsequent earnings announcement returns, consistent with the notion that new fundamental information reduces uncertainty. Finally, we examine whether our results are driven by mispricing or sentiment. The findings show that alphas remain significant even after controlling for the mispricing factors, and the predictive power of our measure does not vary between periods of high and low market sentiment. These results collectively support the robustness of our proposed measure and its association with information uncertainty.

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Table 1 Descriptive Statistics of Stock Characteristics. This table shows the descriptive statistics for stock characteristics. Panel A reports the time-series average of cross-sectional mean and standard deviations. Panel B shows the monthly cross-sectional correlations. The definition of each stock characteristic is given in the appendix. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from August 1992 to December 2022.

	DIS	RET	NIGHT	INTRAD	BETA	ME	MOM	REV	IVOL	MAX	MIN	VOL	SK	KT	ILLIQ	TO
Panel A Cross-Sectional Summary Statistics																
Mean	4.931	0.009	0.008	0.003	1.006	4.762	0.213	0.017	0.014	0.041	-0.038	0.021	0.081	3.949	0.216	0.148
Std.	0.243	0.044	0.026	0.035	0.017	3.015	0.202	0.044	0.005	0.017	0.016	0.007	0.185	0.520	1.001	0.052
Panel B Cross-Sectional Correlations																
DIS	1	-0.098***	-0.055***	0.015***	-0.191***	-0.026***	-0.049***	-0.002	-0.217***	-0.261***	0.217***	0.022***	-0.112***	-0.406***	0.148***	-0.145***
RET		1	0.331***	0.687***	-0.023***	0.005**	0.246***	-0.017***	0.203***	0.404***	0.253***	0.054***	0.377***	0.083***	-0.009***	0.131***
NIGHT			1	-0.363***	0.023***	-0.011***	0.068***	-0.034***	0.281***	0.359***	-0.007	0.178***	0.238***	0.087***	-0.025***	0.185***
INTRAD				1	-0.046***	0.003	0.165***	-0.001	0.054***	0.176***	0.205***	-0.022***	0.205***	0.023***	0.05***	-0.007
BETA					1	0.003	0.017**	-0.019***	0.06***	0.11***	-0.162***	0.101***	0.009**	-0.027***	-0.113***	0.129***
ME						1	0.018***	0.005***	-0.134***	-0.095***	0.117***	-0.165***	-0.022***	-0.038***	-0.054***	-0.025***
MOM							1	0.243***	-0.017**	0.036***	0.097***	0.043***	0.064***	0	-0.044***	0.124***
REV								1	-0.035***	-0.044***	0.011	0.04***	-0.029***	-0.011***	-0.019***	0.048***
IVOL									1.0***	0.888***	-0.706***	0.659***	0.201***	0.393***	0.155***	0.385***
MAX										1	-0.422***	0.544***	0.478***	0.462***	0.097***	0.362***
MIN											1	-0.519***	0.315***	-0.345***	-0.103***	-0.295***
VOL												1	0.129***	0.122***	0.139***	0.271***
SK													1	0.236***	0.018***	0.056***
KT														1	-0.015***	0.15***
ILLIQ															1	-0.112***
TO																1

Table 2 Portfolio Characteristics Sorted by Dispersion. The table shows the portfolio characteristics sorted by Dis. Stocks are sorted by their past monthly Dis. Stocks are sorted by their past monthly Dis and used to form ten equal-weighted portfolios We then compute equal-weighted averages of the various stock characteristics within each decile portfolio and then calculate the time-series averages over the entire sample period covered from August 1992 to December 2022. HML is the high-minus-low portfolio. Heteroskedasticity-robust t-statistics are reported in parentheses. '*', '**' and '***' indicate significance at the 10%, 5% and 1% levels, respectively.

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**HML**	**t (High-Low)**
DIS	4.830	4.797	4.832	4.887	4.938	5.005	5.089	5.196	5.362	5.771	0.941***	(46.23)
NIGHT	0.021	0.017	0.016	0.017	0.017	0.018	0.018	0.019	0.021	0.019	-0.002	(-1.49)
INTRAD	-0.002	0.000	0.001	0.003	0.003	0.004	0.006	0.008	0.013	0.030	0.032***	(16.70)
BETA	1.010	1.080	1.092	1.089	1.076	1.047	1.009	0.949	0.860	0.650	-0.360***	(-31.87)
ME (in billions)	3.017	4.194	4.892	5.272	5.578	5.699	5.786	5.486	5.022	2.681	-0.336**	(-2.46)
MOM	0.219	0.219	0.211	0.207	0.203	0.194	0.182	0.168	0.143	0.099	-0.119***	(-15.11)
REV	0.054	0.025	0.020	0.017	0.015	0.012	0.009	0.007	-0.001	-0.010	-0.064***	(-21.75)
IVOL	0.026	0.025	0.024	0.024	0.025	0.025	0.025	0.026	0.027	0.030	0.004***	(10.62)
MAX	0.075	0.072	0.070	0.070	0.071	0.072	0.073	0.075	0.078	0.084	0.008***	(8.91)
MIN	-0.061	-0.060	-0.060	-0.059	-0.060	-0.060	-0.060	-0.061	-0.062	-0.064	-0.002***	(-3.10)
VOL	0.038	0.034	0.033	0.033	0.033	0.034	0.034	0.035	0.036	0.037	-0.001	(-1.36)
SK	0.211	0.185	0.175	0.174	0.177	0.179	0.182	0.194	0.208	0.256	0.045***	(8.40)
KT	4.493	4.433	4.409	4.388	4.393	4.399	4.405	4.398	4.416	4.531	0.038**	(2.21)
ILLIQ	0.872	0.738	0.745	0.778	0.841	0.961	1.149	1.436	1.841	2.789	1.916***	(34.92)
TO	0.271	0.209	0.205	0.203	0.228	0.201	0.198	0.186	0.181	0.153	-0.119	(-14.95)

Table 3 Returns on Portfolios Sorted by Dispersion. The table reports the average monthly returns and CAPM alphas, Fama-French 3-factor alphas and 4-factor alphas on each decile portfolio sorted by Dis over the sample period covered from August 1992 to December 2022. Each month, we initially rank all stocks in ascending order based on estimated dispersion (Dis) and then assign the stocks to decile portfolios. The decile 1 (Low) portfolio comprises stocks with the lowest estimated dispersion (Dis), while the decile 10 (High) portfolio includes stocks with the highest estimated dispersion (Dis). Heteroskedasticity-robust t-statistics are reported in parentheses. '*', '**' and '***' indicate significance at the 10%, 5% and 1% levels, respectively.

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**HML**
Panel A Equal-Weighted Returns											
Raw return	1.240***	1.201***	1.163***	1.280***	1.357***	1.432***	1.501***	1.653***	1.911***	2.417***	1.177***
	(3.74)	(3.66)	(3.62)	(3.84)	(4.01)	(4.26)	(4.44)	(4.84)	(5.42)	(7.16)	(7.46)
CAPM alpha	0.220	0.147	0.112	0.195	0.262*	0.356**	0.434***	0.594***	0.875***	1.461***	1.241***
	(1.22)	(0.94)	(0.77)	(1.30)	(1.74)	(2.25)	(2.59)	(3.35)	(4.24)	(6.81)	(7.99)
3F alpha	0.175*	0.0983	0.0677	0.145*	0.218***	0.323***	0.411***	0.567***	0.846***	1.442***	1.267***
	(1.68)	(1.21)	(0.95)	(1.90)	(2.80)	(3.76)	(4.31)	(4.74)	(5.45)	(8.43)	(8.04)
4F alpha	0.310***	0.204**	0.171**	0.251***	0.362***	0.473***	0.556***	0.748***	1.095***	1.704***	1.394***
	(3.07)	(2.53)	(2.50)	(3.32)	(4.26)	(5.47)	(5.57)	(5.28)	(5.55)	(8.88)	(7.41)
Panel B Value-Weighted Returns											
Raw return	0.910***	1.000***	1.017***	0.805***	0.807***	0.821***	0.868***	0.849***	1.068***	1.265***	0.355**
	(3.62)	(4.00)	(4.03)	(3.21)	(3.24)	(3.35)	(3.57)	(3.34)	(4.09)	(5.32)	(2.10)
CAPM alpha	0.0298	0.115	0.112	-0.102	-0.0992	-0.0700	-0.0109	-0.0598	0.174	0.473***	0.443**
	(0.28)	(1.22)	(1.33)	(-1.35)	(-1.42)	(-0.95)	(-0.14)	(-0.68)	(1.49)	(3.52)	(2.48)
3F alpha	0.0248	0.107	0.109	-0.109	-0.110	-0.0788	-0.0135	-0.0473	0.181	0.454***	0.429**
	(0.23)	(1.15)	(1.26)	(-1.44)	(-1.60)	(-1.08)	(-0.17)	(-0.55)	(1.52)	(3.53)	(2.44)
4F alpha	0.0242	0.112	0.113	-0.0922	-0.115	-0.0368	-0.0332	-0.0533	0.166	0.438***	0.413**
	(0.22)	(1.18)	(1.22)	(-1.14)	(-1.62)	(-0.45)	(-0.41)	(-0.61)	(1.37)	(3.41)	(2.25)
Panel C Decomposing future monthly returns into overnight and daytime components （Equal weighted）											
Intraday Returns											
Raw return	-0.208	0.0262	0.0650	0.252	0.284	0.405	0.582**	0.834***	1.338***	3.006***	3.214***
	(-0.78)	(0.10)	(0.24)	(0.93)	(1.04)	(1.49)	(2.11)	(3.03)	(4.66)	(10.10)	(16.70)
CAPM alpha	-0.954***	-0.764***	-0.714***	-0.519***	-0.523***	-0.378**	-0.199	0.0659	0.587***	2.342***	3.297***
	(-5.07)	(-4.31)	(-4.02)	(-2.64)	(-2.91)	(-2.07)	(-1.02)	(0.34)	(2.73)	(9.52)	(17.45)
3F alpha	-0.993***	-0.800***	-0.747***	-0.548***	-0.550***	-0.402***	-0.213	0.0358	0.560***	2.307***	3.300***
	(-6.65)	(-5.56)	(-4.99)	(-3.24)	(-3.75)	(-2.62)	(-1.30)	(0.22)	(3.00)	(10.34)	(16.97)
4F alpha	-0.841***	-0.665***	-0.609***	-0.408**	-0.403***	-0.246	-0.0654	0.176	0.715***	2.474***	3.316***
	(-5.27)	(-4.27)	(-3.82)	(-2.31)	(-2.60)	(-1.56)	(-0.38)	(1.04)	(3.74)	(10.55)	(14.68)
Overnight Returns											
Raw return	2.089***	1.686***	1.644***	1.683***	1.741***	1.774***	1.848***	1.905***	2.082***	1.896***	-0.194
	(12.95)	(11.01)	(10.67)	(10.75)	(10.85)	(10.62)	(10.73)	(10.71)	(10.99)	(9.44)	(-1.49)
CAPM alpha	1.651***	1.248***	1.207***	1.231***	1.284***	1.311***	1.389***	1.442***	1.635***	1.451***	-0.200
	(11.71)	(9.42)	(9.12)	(9.29)	(9.36)	(9.18)	(9.13)	(9.45)	(9.79)	(8.02)	(-1.51)
3F alpha	1.646***	1.234***	1.193***	1.212***	1.265***	1.295***	1.371***	1.438***	1.629***	1.469***	-0.177
	(11.54)	(9.13)	(8.84)	(8.93)	(9.00)	(8.85)	(8.85)	(9.16)	(9.57)	(8.12)	(-1.35)
4F alpha	1.645***	1.216***	1.166***	1.191***	1.275***	1.302***	1.389***	1.479***	1.710***	1.586***	-0.0582
	(10.94)	(8.40)	(7.99)	(8.02)	(8.39)	(8.25)	(8.27)	(8.35)	(8.81)	(8.46)	(-0.43)

Table 4 Returns on Portfolios Sorted by Stock Characteristics and Dispersion. The Table reports the average monthly returns and 4-factor alphas on each decile portfolio sorted by stock characteristics and Dis over the sample period covered from August 1992 to December 2022. Each month, we first sort all of the stocks into tercile portfolios based on stock characteristics that could relate to the Dis effect. Each tercile portfolio is further divided into ten additional Dis sub-decile portfolios and computes the equal-weighted returns over the subsequent month for the resulting 30 (3×10) portfolios. We then take the average of each of the Dis portfolios across the ten deciles that were formed from the first sort. Heteroskedasticity-robust t-statistics are reported in parentheses. '*', '**' and '***' indicate significance at the 10%, 5% and 1% levels, respectively.

	Low	2	3	4	5	6	7	8	9	High	HML	HML (4F Alpha)
BETA	1.246***	1.270***	1.148***	1.246***	1.352***	1.527***	1.552***	1.645***	1.906***	2.371***	1.125***	1.263***
	(3.91)	(3.96)	(3.67)	(3.85)	(4.10)	(4.56)	(4.47)	(4.65)	(5.17)	(6.12)	(6.44)	(6.17)
ME	1.124***	1.111***	1.161***	1.117***	1.261***	1.277***	1.318***	1.381***	1.422***	1.617***	0.493***	0.599***
	(3.85)	(3.69)	(3.87)	(3.64)	(4.06)	(4.09)	(4.29)	(4.55)	(4.82)	(5.85)	(4.33)	(4.77)
MOM	1.224***	1.212***	1.195***	1.284***	1.399***	1.463***	1.581***	1.697***	1.951***	2.424***	1.200***	1.373***
	(3.74)	(3.56)	(3.59)	(3.74)	(4.02)	(4.25)	(4.53)	(4.89)	(5.62)	(7.25)	(8.45)	(8.31)
REV	1.236***	1.220***	1.154***	1.237***	1.407***	1.413***	1.549***	1.605***	1.966***	2.406***	1.170***	1.381***
	(3.71)	(3.63)	(3.51)	(3.64)	(4.10)	(4.11)	(4.50)	(4.64)	(5.51)	(6.96)	(7.72)	(7.63)
IVOL	1.191***	1.232***	1.141***	1.202***	1.296***	1.506***	1.550***	1.693***	1.970***	2.538***	1.347***	1.509***
	(4.30)	(3.92)	(3.52)	(3.56)	(3.81)	(4.32)	(4.43)	(4.70)	(5.48)	(7.19)	(7.62)	(7.80)
MAX	1.201***	1.230***	1.140***	1.196***	1.277***	1.436***	1.557***	1.660***	1.990***	2.583***	1.382***	1.573***
	(4.27)	(4.13)	(3.61)	(3.67)	(3.85)	(4.14)	(4.42)	(4.63)	(5.27)	(6.88)	(7.02)	(7.13)
MIN	1.188***	1.207***	1.148***	1.208***	1.280***	1.418***	1.552***	1.728***	1.967***	2.578***	1.390***	1.562***
	(4.09)	(3.93)	(3.61)	(3.68)	(3.84)	(4.16)	(4.41)	(4.86)	(5.33)	(7.05)	(8.08)	(8.48)
VOL	1.220***	1.236***	1.177***	1.240***	1.439***	1.520***	1.612***	1.687***	1.913***	2.324***	1.104***	1.300***
	(3.85)	(3.69)	(3.50)	(3.66)	(4.12)	(4.46)	(4.67)	(4.93)	(5.72)	(7.27)	(8.15)	(8.09)
SK	1.148***	1.208***	1.200***	1.217***	1.400***	1.500***	1.479***	1.733***	1.888***	2.401***	1.253***	1.452***
	(3.60)	(3.72)	(3.64)	(3.67)	(4.20)	(4.42)	(4.31)	(4.99)	(5.34)	(7.02)	(7.68)	(7.37)
KT	1.156***	1.133***	1.215***	1.246***	1.335***	1.447***	1.522***	1.713***	1.934***	2.443***	1.288***	1.562***
	(3.67)	(3.45)	(3.67)	(3.77)	(3.94)	(4.32)	(4.42)	(4.89)	(5.51)	(7.19)	(7.13)	(7.14)
ILLIQ	1.340***	1.219***	1.249***	1.394***	1.504***	1.471***	1.604***	1.692***	1.725***	2.123***	0.784***	0.927***
	(4.11)	(3.74)	(3.94)	(4.21)	(4.49)	(4.38)	(4.85)	(4.91)	(5.22)	(6.27)	(5.22)	(5.11)
TO	1.252***	1.208***	1.202***	1.278***	1.405***	1.430***	1.564***	1.624***	1.893***	2.294***	1.042***	1.161***
	(4.02)	(3.72)	(3.70)	(3.90)	(4.19)	(4.24)	(4.57)	(4.68)	(5.29)	(6.23)	(6.41)	(5.80)

Table 5 Fama-MacBeth Cross-Sectional Regressions. The table reports the regression coefficients obtained from Fama-MacBeth cross-sectional regressions for monthly stock excess returns over the sample period covered from August 1992 to December 2022. We run the following cross-sectional regression every month, $r^s_{t+1} - r_{f,t+1} = \alpha + \sum_{j=1}^{K} \beta_{j,t} z^s_{j,t} + \epsilon^s_{t+1}$, where$r^s_{t+1}$ denotes the return for stock i over month t+1, $r_{f,t+1}$ is the risk-free rate in month t+1, and $z^s_{j,t}$ is stock-specific variables measured at the end of month t. The coefficient $\beta_{j,t}$ in each month can be estimated by running this regression. After that, we calculate the time-series averages of the coefficient estimates to evaluate the predictive ability of the different controls on future returns. Heteroskedasticity-robust t-statistics are reported in parentheses. '*', '**' and '***' indicate significance at the 10%, 5% and 1% levels, respectively.

	DIS	NIGHT	INTRAD	BETA	ME	MOM	REV	IVOL	MAX	MIN	VOL	SK	KT	ILLQ	TO
Panel A Single Regressions															
	0.003***	0.010**	-0.017***	-0.002*	0.000***	-0.002	-0.004	0.156***	0.022*	-0.076***	0.221***	0.001	0.000	0.001***	-0.007*
	(7.13)	(2.30)	(-4.03)	(-1.74)	(-3.02)	(-1.03)	(-0.95)	(2.79)	(1.78)	(-3.10)	(2.98)	(1.16)	(1.38)	(8.80)	(-1.73)
Panel B Multiple Regressions															
I	0.003***	0.012***													
	(7.22)	(2.79)													
II	0.003***	0.003	-0.016***												
	(7.20)	(0.75)	(-3.45)												
III	0.003***	0.002	-0.019***	-0.002**	<0.000***	<0.000	-0.003								
	(7.15)	(0.57)	(-4.67)	(-2.35)	(-2.78)	(-0.06)	(-1.02)								
IV	0.004***	-0.012***	-0.028***	-0.002***	<0.001	0.001	-0.005**	0.259***	-0.048***	-0.026	0.146**	0.003***	<0.001		
	(8.54)	(-2.76)	(-6.78)	(-2.63)	(0.04)	(1.14)	(-1.98)	(3.25)	(-2.90)	(-1.25)	(2.54)	(5.77)	(0.99)		
V	0.003***	-0.008*	-0.028***	-0.002**	<0.001	0.002	-0.003	0.203***	-0.028*	-0.039*	0.149***	0.003***	<0.001	0.001***	-0.012***
	(7.60)	(-1.74)	(-6.89)	(-2.19)	(0.32)	(1.58)	(-1.37)	(2.58)	(-1.68)	(-1.91)	(2.60)	(5.18)	(0.75)	(5.86)	(-5.08)

Table 6 Dis and future return: excluding firms with earnings announcements in the same month (t) or the next month (t+1). This table reports the regression coefficients obtained from Fama-MacBeth cross-sectional regressions for monthly stock excess returns over the sample period covered from August 1992 to December 2022 while excluding firms with earnings announcements either in month t+1 (Panel A), or in month t (Panel B). we run the following cross-sectional regression every month, $r_{t+1}^{s} - r_{f,t+1} = \alpha + \sum_{j=1}^{K} \beta_{j,t} z_{j,t}^{s} + \epsilon_{t+1}^{s}$, where$r_{t+1}^{s}$ denotes the return for stock i over month t+1, $r_{f,t+1}$ is the risk-free rate in month t+1, and $z_{j,t}^{s}$ is stock-specific variables measured at the end of month t. The coefficient $\beta_{j,t}$ in each month can be estimated by running this regression. After that, we calculate the time-series averages of the coefficient estimates to evaluate the predictive ability of the different controls on future returns. Heteroskedasticity-robust t-statistics are reported in parentheses. '*', '**' and '***' indicate significance at the 10%, 5% and 1% levels, respectively.

	DIS	NIGHT	INTRAD	BETA	ME	MOM	REV	IVOL	MAX	MIN	VOL	SK	KT	ILLQ	TO
Panel A Excluding Firms with Earnings Announcements in Month t+1															
I	0.003***	0.010**													
	(6.52)	(2.28)													
II	0.003***	0.003	-0.015***												
	(6.52)	(0.63)	(-2.90)												
III	0.003***	0.003	-0.017***	-0.002*	<0.000***	-0.001	-0.006*								
	(6.46)	(0.60)	(-3.92)	(-1.81)	(-2.79)	(-0.35)	(-1.89)								
IV	0.003***	-0.013***	-0.027***	-0.002*	<0.000	0.001	-0.008***	0.267***	-0.045**	-0.025	0.139**	0.004***	<0.000		
	(7.82)	(-2.56)	(-6.12)	(-1.97)	(-0.31)	(0.92)	(-2.72)	(2.89)	(-2.30)	(-0.99)	(2.27)	(5.59)	(-0.35)		
V	0.003***	-0.008	-0.027***	-0.001	<0.001	0.002	-0.007**	0.219*	-0.026	-0.038	0.145**	0.003***	<0.000	0.001***	-0.013***
	(6.86)	(-1.57)	(-6.09)	(-1.58)	(0.09)	(1.34)	(-2.19)	(2.39)	(-1.31)	(-1.52)	(2.37)	(4.96)	(-0.40)	(5.00)	(-5.17)
Panel B Excluding Firms with Earnings Announcements in Month t															
I	0.003***	0.018***													
	(7.01)	(4.17)													
II	0.003***	0.010**	-0.015***												
	(7.00)	(2.21)	(-3.23)												
III	0.003***	0.009**	-0.017***	-0.002**	<0.000***	<0.000	-0.001								
	(6.89)	(2.10)	(-4.28)	(-2.10)	(-2.65)	(-0.02)	(-0.39)								
IV	0.003***	-0.007	-0.027***	-0.002**	<0.001	0.001	-0.003	0.250***	-0.051***	0.003	0.200***	0.003***	<0.001**		
	(7.65)	(-1.42)	(-6.54)	(-2.01)	(1.00)	(0.97)	(-1.15)	(2.74)	(-2.67)	(0.13)	(3.05)	(5.01)	(2.19)		
V	0.003***	-0.003	-0.027***	-0.001*	<0.001	0.002	-0.002	0.214**	-0.036*	-0.011	0.207***	0.003***	<0.001*	0.001***	-0.013***
	(6.94)	(0.64)	(-6.59)	(-1.69)	(1.18)	(1.40)	(-0.55)	(2.38)	(-1.86)	(-0.48)	(3.17)	(4.63)	(1.99)	(4.31)	(-5.36)

Table 7 The effect of short-sale constraints. This table reports the average monthly returns and 4-factor alphas on each decile portfolio sorted by institutional ownership and Dis over the sample period covered from August 1992 to December 2022. At the end of each month, we first sort all of the stocks into tercile portfolios based on institutional ownership and then each tercile portfolio is further divided into ten additional Dis sub-decile portfolios and compute the equal-weighted returns over the subsequent month for the resulting 30 (3×10) portfolios. We then take the average of each of the Dis portfolios across the ten deciles that were formed from the first sort. Heteroskedasticity-robust t-statistics are reported in parentheses. '*', '**' and '***' indicate significance at the 10%, 5% and 1% levels, respectively.

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**HML**	**HML FF4-alpha**
Panel A Double Sort												
Institutional Ownership	1.268***	1.112***	1.213***	1.331***	1.386***	1.609***	1.526***	1.673***	1.770***	2.148***	0.880***	1.049***
	(3.77)	(3.36)	(3.68)	(3.91)	(4.06)	(4.67)	(4.55)	(5.00)	(5.42)	(6.66)	(6.61)	(6.90)
Panel B. Decomposition of Double Sort												
Low short-sale constraints	1.255***	1.224***	1.228***	1.187***	1.303***	1.415***	1.242***	1.263***	1.264***	1.578***	0.323**	0.366**
	(3.83)	(3.82)	(3.89)	(3.70)	(4.02)	(4.32)	(3.91)	(3.98)	(4.04)	(5.15)	(2.15)	(2.16)
2	1.236***	1.139***	1.154***	1.166***	1.172***	1.370***	1.262***	1.375***	1.571***	1.853***	0.617***	0.746***
	(3.80)	(3.48)	(3.56)	(3.53)	(3.48)	(4.10)	(3.87)	(4.26)	(4.74)	(5.94)	(4.54)	(4.98)
High short-sale constraints	1.313***	0.972**	1.258***	1.639***	1.683***	2.041***	2.075***	2.382***	2.476***	3.013***	1.700***	2.033***
	(3.20)	(2.48)	(3.17)	(3.90)	(4.07)	(4.79)	(4.86)	(5.68)	(6.41)	(7.31)	(7.02)	(7.46)
High-low	0.0576	-0.252	0.0304	0.453*	0.380	0.625**	0.833***	1.119***	1.212***	1.435***	1.377***	1.667***
	(0.23)	(-1.07)	(0.13)	(1.73)	(1.48)	(2.35)	(2.84)	(4.17)	(5.01)	(5.04)	(5.32)	(5.78)

Table 8 The effect of dispersion of Analyst Forecast. This table reports the average monthly returns and 4-factor alphas on each decile portfolio sorted by analyst dispersion and Dis over the sample period covered from August 1992 to December 2022. At the end of each month, we first sort all of the stocks into tercile portfolios based on analyst dispersion and then each tercile portfolio is further divided into ten additional Dis sub-decile portfolios and compute the equal-weighted returns over the subsequent month for the resulting 30 (3×10) portfolios. We then take the average of each of the Dis portfolios across the ten deciles that were formed from the first sort. Heteroskedasticity-robust t-statistics are reported in parentheses. '*', '**' and '***' indicate significance at the 10%, 5% and 1% levels, respectively.

Panel A. Portfolio Characteristics

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**HML**	**t-statis**
Dispersion of Analysts Forecast	0.028	0.024	0.023	0.021	0.022	0.023	0.024	0.024	0.027	0.034	0.006	5.06

Panel B. Double Sort

	Dis Deciles											
	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**HML**	**HML FF4-alpha**
Dispersion of Analysts Forecast	1.207***	1.170***	1.092***	1.162***	1.336***	1.299***	1.342***	1.430***	1.522***	1.885***	0.678***	0.838***
	(3.71)	(3.54)	(3.38)	(3.50)	(3.97)	(3.86)	(4.01)	(4.25)	(4.45)	(5.70)	(4.84)	(5.23)

Panel C. Decomposition of Double Sort

Dispersion of Analysts Forecast												
Low	1.536***	1.486***	1.385***	1.542***	1.647***	1.633***	1.615***	1.740***	1.992***	2.117***	0.581***	0.860***
	(5.16)	(5.16)	(4.85)	(5.26)	(5.59)	(5.42)	(5.37)	(5.63)	(6.36)	(6.93)	(3.20)	(4.53)
2	1.039***	1.028***	1.094***	0.985***	1.052***	1.090***	1.151***	1.066***	1.173***	1.294***	0.255*	0.314**
	(3.51)	(3.47)	(3.67)	(3.26)	(3.45)	(3.61)	(3.85)	(3.67)	(4.01)	(4.76)	(1.89)	(2.19)
High	1.046**	0.995**	0.798*	0.958**	1.308***	1.173***	1.260***	1.485***	1.402***	2.244***	1.198***	1.338***
	(2.46)	(2.26)	(1.89)	(2.19)	(2.92)	(2.62)	(2.86)	(3.27)	(2.99)	(4.88)	(5.26)	(5.05)
High-Low	-0.490**	-0.492**	-0.586**	-0.584**	-0.338	-0.461*	-0.355	-0.255	-0.590**	0.708**	0.617***	0.478**
	(-2.07)	(-2.15)	(-2.58)	(-2.52)	(-1.36)	(-1.90)	(-1.59)	(-1.08)	(-2.43)	(2.34)	(2.78)	(2.08)

Table 9 Dispersion and Future Trading volume. This table shows the regression coefficients obtained from Fama-MacBeth cross-sectional regressions. We regress the natural log of stock volume or change of natural log of stock volume on Dis, a lagged dependent variable and other factors which can influence the trading activity. The sample period covered from August 1992 to December 2022. Heteroskedasticity-robust t-statistics are reported in parentheses. '*', '**' and '***' indicate significance at the 10%, 5% and 1% levels, respectively.

	VOLUME (t,t+1)		ΔVOLUME (t,t+1)	
Variables	**1**	**2**	**3**	**4**
Constant	0.266***	0.515***	-0.167***	0.010***
	(11.54)	(22.73)	(-19.44)	(0.94)
Dis	0.046***	0.021***	0.036	0.019***
	(35.81)	(16.75)	(27.47)	(13.50)
Dependent variable (t-1,t)	0.953***	0.953***	-0.320	-0.281***
	(508.11)	(498.55)	(-101.92)	(-86.28)
BETA		0.022***		0.005***
		(15.30)		(4.18)
ME		0.002***		0.000***
		(11.86)		(-2.41)
MOM		0.000		0.009***
		(-0.07)		(4.62)
REV		-0.079***		-0.155***
		(-11.52)		(-21.44)
IVOL		-5.409***		-3.315***
		(-36.25)		(-22.74)
ILLQ		0.012***		0.016***
		(21.54)		(27.71)
Earn_Ann		-0.129***		-0.083***
		(-37.52)		(-23.23)

Table 10 Returns by Disagreement and information uncertainty. This Table shows the average monthly returns and 4-factor alphas on each decile portfolio sorted by proxies of information uncertainty (Size/Volatility/Analyst coverage) and Dis over the sample period covered from August 1992 to December 2022. At the end of each month, we first sort all of the stocks into tercile portfolios based on proxies of information uncertainty (Size/Volatility/Analyst coverage). Each tercile portfolio is further divided into ten additional Dis sub-decile portfolios and computes the equal-weighted returns over the subsequent month for the resulting 30 (3×10) portfolios. We then take the average of each of the Dis portfolios across the ten deciles that were formed from the first sort. Heteroskedasticity-robust t-statistics are reported in parentheses. '*', '**' and '***' indicate significance at the 10%, 5% and 1% levels, respectively.

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**HML**	**HML FF4-alpha**
						Panel A. Size						
Size												
Low	1.450***	1.361***	1.475***	1.454***	1.809***	1.863***	2.000***	2.220***	2.395***	2.810***	1.360***	1.630***
	(3.81)	(3.56)	(3.82)	(3.72)	(4.50)	(4.64)	(4.96)	(5.58)	(6.22)	(7.57)	(7.22)	(7.87)
2	0.947***	0.912***	0.950***	0.936***	1.062***	1.046***	1.036***	1.006***	0.995***	1.069***	0.122	0.142
	(3.15)	(2.90)	(3.08)	(3.04)	(3.32)	(3.31)	(3.29)	(3.28)	(3.22)	(3.75)	(0.86)	(0.94)
High	0.976***	1.061***	1.059***	0.963***	0.913***	0.921***	0.917***	0.916***	0.875***	0.973***	-0.00270	0.0258
	(4.02)	(4.17)	(4.20)	(3.66)	(3.56)	(3.50)	(3.63)	(3.51)	(3.46)	(4.01)	(-0.02)	(0.17)
High-Low	-0.475*	-0.301	-0.416*	-0.491**	-0.896***	-0.942***	-1.083***	-1.305***	-1.521***	-0.477*	-1.362***	-1.604***
	(-1.90)	(-1.23)	(-1.68)	(-2.14)	(-3.50)	(-3.80)	(-4.19)	(-4.84)	(-5.62)	(-1.83)	(-6.58)	(-7.09)
						Panel B. Volatility						
Volatility												
Low	1.071***	1.167***	1.082***	1.032***	1.053***	1.118***	1.107***	1.113***	1.303***	1.413***	0.342***	0.413***
	(5.17)	(5.45)	(4.89)	(4.73)	(4.73)	(5.32)	(5.12)	(5.32)	(6.35)	(7.41)	(3.94)	(4.49)
2	1.096***	1.058***	1.185***	1.164***	1.191***	1.332***	1.430***	1.324***	1.574***	1.909***	0.814***	0.988***
	(3.54)	(3.18)	(3.62)	(3.51)	(3.44)	(4.00)	(4.26)	(4.07)	(4.73)	(6.12)	(5.80)	(6.45)
High	1.492***	1.482***	1.265**	1.525***	2.074***	2.112***	2.298***	2.625***	2.862***	3.649***	2.157***	2.499***
	(2.93)	(2.76)	(2.36)	(2.86)	(3.68)	(3.79)	(4.06)	(4.53)	(5.19)	(6.77)	(7.75)	(7.42)
High-Low	0.421	0.315	0.184	0.493	1.021**	0.994**	1.192**	1.512***	1.559***	2.578***	1.814***	2.086***
	(1.01)	(0.71)	(0.42)	(1.16)	(2.18)	(2.14)	(2.52)	(3.06)	(3.31)	(5.52)	(6.68)	(6.48)
						Panel C Analyst Coverage						
Analyst Coverage												
Low	1.540***	1.355***	1.726***	1.929***	1.923***	2.187***	2.394***	2.555***	2.716***	2.958***	1.417***	1.738***
	(4.08)	(3.73)	(4.60)	(4.91)	(4.93)	(5.63)	(6.08)	(6.37)	(7.21)	(8.21)	(6.64)	(7.66)
2	1.159***	1.132***	0.956***	1.046***	1.211***	1.260***	1.298***	1.277***	1.415***	1.854***	0.695***	0.824***
	(3.30)	(3.15)	(2.76)	(2.98)	(3.37)	(3.51)	(3.65)	(3.59)	(3.94)	(5.09)	(3.67)	(3.58)
High	1.148***	1.092***	1.015***	1.079***	1.053***	1.075***	1.044***	1.041***	1.028***	1.228***	0.0796	0.134
	(3.79)	(3.57)	(3.39)	(3.52)	(3.40)	(3.48)	(3.50)	(3.37)	(3.39)	(4.11)	(0.55)	(0.83)
High-low	-0.392	-0.263	-0.711***	-0.850***	-0.869***	-1.112***	-1.349***	-1.514***	-1.688***	-0.313	-1.338***	-1.603***
	(-1.62)	(-1.22)	(-3.27)	(-3.65)	(-3.70)	(-4.74)	(-5.46)	(-5.70)	(-6.79)	(-1.23)	(-5.82)	(-6.64)

Table 11 Returns on Portfolios Sorted by Dispersion in different subsample. The table reports the average monthly returns and CAPM alphas, Fama-French 3-factor alphas and 4-factor alphas on each decile portfolio sorted by Dis over different subsample. Each month, we initially rank all stocks in ascending order based on estimated dispersion (Dis) and then assign the stocks to each decile portfolio. The decile 1 (Low) portfolio comprises stocks with the lowest estimated dispersion (Dis), while the decile 10 (High) portfolio includes stocks with the highest estimated dispersion (Dis). Panel A reports the raw returns and alphas of equal-weighted portfolios in 1992-1999 and 2000-2022. Panel B reports the raw returns and alphas of value-weighted portfolios in 1992-1999 and 2000-2022. Heteroskedasticity-robust t-statistics are reported in parentheses. '*', '**' and '***' indicate significance at the 10%, 5% and 1% levels, respectively.

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**HML**
						Panel A Equal-Weighted Returns					
						1992-1999					
Raw return	1.553***	1.588***	1.636***	1.665***	1.889***	2.194***	2.274***	2.380***	2.508***	2.888***	1.336***
	(2.87)	(3.01)	(3.11)	(3.02)	(3.41)	(3.70)	(3.88)	(3.96)	(4.19)	(4.85)	(5.02)
CAPM alpha	-0.327	-0.299	-0.235	-0.280	-0.0829	0.222	0.347	0.492	0.721	1.119**	1.446***
	(-1.04)	(-0.99)	(-0.76)	(-0.88)	(-0.26)	(0.61)	(0.89)	(1.17)	(1.60)	(2.55)	(5.86)
3F alpha	-0.135	-0.163	-0.0664	-0.114	0.0915	0.452***	0.617***	0.750***	0.988***	1.370***	1.505***
	(-1.09)	(-1.17)	(-0.52)	(-0.91)	(0.72)	(2.70)	(3.06)	(3.10)	(3.79)	(5.11)	(5.76)
4F alpha	-0.0232	0.0187	0.139	0.0933	0.296**	0.663***	0.845***	0.990***	1.253***	1.593***	1.616***
	(-0.19)	(0.13)	(1.08)	(0.74)	(2.33)	(4.02)	(4.26)	(4.06)	(5.05)	(5.78)	(6.14)
						2000-2022					
Raw return	1.140***	1.078***	1.012***	1.157***	1.188***	1.189***	1.255***	1.422***	1.720***	2.267***	1.127***
	(2.84)	(2.70)	(2.60)	(2.87)	(2.90)	(2.97)	(3.11)	(3.49)	(4.06)	(5.63)	(5.92)
CAPM alpha	0.409*	0.318*	0.255	0.375**	0.400**	0.420**	0.489**	0.659***	0.970***	1.583***	1.175***
	(1.89)	(1.72)	(1.52)	(2.19)	(2.27)	(2.36)	(2.58)	(3.33)	(4.08)	(6.30)	(6.27)
3F alpha	0.262**	0.179*	0.124	0.239***	0.266***	0.297***	0.372***	0.547***	0.855***	1.480***	1.217***
	(2.05)	(1.78)	(1.46)	(2.61)	(2.81)	(2.97)	(3.40)	(3.95)	(4.61)	(7.15)	(6.56)
4F alpha	0.357***	0.246**	0.188**	0.303***	0.361***	0.398***	0.467***	0.665***	1.020***	1.660***	1.303***
	(2.95)	(2.54)	(2.33)	(3.41)	(3.86)	(4.19)	(4.34)	(4.47)	(4.91)	(7.93)	(6.35)
						Panel B Value-Weighted Returns					
						1992-1999					
Raw return	1.414***	1.708***	1.721***	1.665***	1.688***	1.685***	1.726***	1.827***	2.412***	2.052***	0.638**
	(3.19)	(4.05)	(3.96)	(4.02)	(4.14)	(4.19)	(4.08)	(3.98)	(4.68)	(4.32)	(2.12)
CAPM alpha	-0.342**	0.0426	-0.0481	-0.0333	0.0311	0.0448	0.0188	0.0535	0.637**	0.452	0.794***
	(-2.11)	(0.28)	(-0.37)	(-0.30)	(0.18)	(0.35)	(0.14)	(0.32)	(2.21)	(1.52)	(2.84)
3F alpha	-0.312**	0.0486	-0.0662	0.000493	0.0110	0.0273	-0.00314	0.0990	0.744**	0.542*	0.854***
	(-2.19)	(0.27)	(-0.46)	(0.00)	(0.06)	(0.20)	(-0.02)	(0.53)	(2.23)	(1.98)	(2.73)
4F alpha	-0.310**	0.0310	0.0300	-0.0298	-0.108	0.137	-0.0892	0.0197	0.534*	0.682***	0.992***
	(-2.01)	(0.20)	(0.22)	(-0.26)	(-0.61)	(0.80)	(-0.66)	(0.10)	(1.85)	(2.75)	(3.42)
						2000-2022					
Raw return	0.749**	0.774**	0.793***	0.531*	0.526*	0.545*	0.594**	0.537*	0.640**	1.014***	0.264
	(2.50)	(2.58)	(2.63)	(1.76)	(1.75)	(1.85)	(2.05)	(1.79)	(2.14)	(3.71)	(1.31)
CAPM alpha	0.131	0.146	0.155	-0.113	-0.120	-0.0890	-0.0246	-0.102	0.0162	0.461***	0.331
	(1.02)	(1.31)	(1.51)	(-1.24)	(-1.52)	(-1.03)	(-0.26)	(-1.03)	(0.14)	(3.18)	(1.58)
3F alpha	0.116	0.127	0.158	-0.123	-0.137*	-0.103	-0.0293	-0.0866	0.0195	0.429***	0.313
	(0.92)	(1.17)	(1.51)	(-1.37)	(-1.75)	(-1.22)	(-0.31)	(-0.91)	(0.16)	(3.10)	(1.53)
4F alpha	0.113	0.130	0.155	-0.110	-0.134*	-0.0774	-0.0371	-0.0862	0.0224	0.407***	0.295
	(0.87)	(1.18)	(1.43)	(-1.17)	(-1.70)	(-0.86)	(-0.39)	(-0.89)	(0.18)	(2.92)	(1.39)

Table 12 Dispersion and Cumulative abnormal returns. This table reports the panel regression coefficients obtained from regressing cumulative abnormal returns on pre-disagreement and additional control variables. Disagreement is calculated using data from one month prior to the announcement date. The results include quarterly fixed effects, and standard errors are clustered both time and firm. The sample period covered from August 1992 to December 2022. The t-values in parentheses, *,**, and ***, indicate significance at the 10%, 5%, and 1% levels, respectively.

	Cumulative abnormal returns [1,5]		**Cumulative abnormal returns [1,20]**	
Variables	**1**	**2**	**3**	**4**
Dis	0.000568***	0.000482**	0.00273***	0.00248***
	(2.77)	(2.36)	(6.00)	(5.52)
ME		0.00000197		-0.0000252*
		(0.41)		(-1.77)
TO		-0.00122**		-0.00336***
		(-2.18)		(-2.71)
ILLQ		0.0000582		0.000185*
		(1.43)		(1.69)
Constant	-0.00586***	-0.00528***	-0.0169***	-0.0150***
	(-5.42)	(-4.88)	(-6.58)	(-6.00)
Fix effects	Quarter	Quarter	Quarter	Quarter
Clustered errors	Firm/time	Firm/time	Firm/time	Firm/time
Adj. R-squared	0.006	0.006	0.023	0.024
N	424,709	424,709	424,709	424,709

Table 13 The effect of Sentiment on Dispersion. This table reports the effect of sentiment. In columns (1) and (2), we estimate the alphas using the mispricing factors of Stambaugh and Yu (2017) and the behavioural factors of Daniel al. (2020). In column (3)-(8), we regress HML portfolio returns on the various risk factors in the F-F 3-factor or 4-factor model, along with the lagged value of the monthly sentiment measure from Baker and Wurgler (2006). In addition to this continuous monthly sentiment measure, we also analyze a high sentiment dummy variable that like Barroso and Detzel (2021), classifies each month as having "high" and "low" sentiment if the Baker and Wurgler (2006) index (monthly) is above or below its sample median at the end of the prior year calculated by using annual data. The sample size is from August 1992 to December 2016 in column (1) and August 1992 to December 2018 due to the availability of factors. For the remaining columns, the sample covers from August 1992 to August 2022 for the availability of sentiment index. Heteroskedasticity-robust t-statistics are reported in parentheses. '*', '**' and '***' indicate significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HML	**HML**	**HML**	**HML**	**HML**	**HML**	**HML**	**HML**
MKT	-0.238***	-0.190***		-0.0764*	-0.139***		-0.0836**	-0.145***
	(-3.33)	(-3.20)		(-1.85)	(-2.93)		(-2.05)	(-2.89)
SMB	-0.118			-0.0586	-0.0453		-0.0555	-0.0418
	(-1.30)			(-0.65)	(-0.55)		(-0.61)	(-0.50)
HML				-0.128*	-0.195**		-0.112	-0.173**
				(-1.70)	(-2.28)		(-1.55)	(-2.10)
MOM					-0.176*			-0.169*
					(-1.92)			(-1.80)
MGMT	-0.298***							
	(-2.76)							
PERF	-0.131							
	(-1.52)							
PEAD		-0.198						
		(-1.44)						
FIN		-0.144						
		(-1.51)						
Sentiment			0.455	0.504	0.643			
(**Continues**)			(1.07)	(1.13)	(1.53)			
Sentiment						0.201	0.213	0.335
(**Dummy**)						(0.63)	(0.66)	(1.01)
Alphas	1.607***	1.365***	1.079***	1.155***	1.261***	1.069***	1.151***	1.218***
	(6.46)	(5.98)	(7.33)	(7.96)	(8.02)	(5.57)	(6.16)	(6.32)

Appendix
A1 Definition of Stock Characteristics

- Beta: CAPM beta
- ME: The product of stock price and share outstanding (in millions)
- MOM: Compound gross return based on the past 12 months (Jegadeesh and Titman, 1993)
- REV: The lagged 1-month return (Jegadeesh, 1990)
- IVOL: Idiosyncratic volatility from Fama-French 3-factor model (Ang et al., 2006)
- MAX: The maximum daily raw returns over the previous month (Bali et al., 2011)
- MIN: The minimum daily raw returns over the previous month (Bali et al., 2011)
- VOL: Volatility (Zhang, 2006)
- SK: Skewness
- KT: Kurtosis
- ILLIQ: The natural log of the average ratio of the daily absolute return to the trading volume on that day over the previous month (Amihud,2002)
- TO: The average number of shares traded during the previous three months divided by the number
- A_Disp (Dispersion of Analyst Forecast): The standard deviation in analysts' next fiscal year’s IBES earnings forecasts, scaled by price.
- A_Covg (Analyst Coverage): The number of analysts following the firm.

B1 Proof of Propositions

At $t = 1$, the posterior mean and posterior variance are

$$\mathbb{E}_{i,1}[D] = \mu_i + h_i, \tag{B.1}$$

$$Var_{i,1}[D] = (\tau_{X,1} + \tau_d)^{-1}. \tag{B.2}$$

Therefore,

$$q_{i,1} = \frac{\mathbb{E}_1[D] - P_1}{\gamma Var_1[D]} = \frac{\mu_i + h_i - P_1}{(\tau_{X,1} + \tau_d)^{-1}} = (\mu_i + h_i - P_1)\big(\tau_{X,1} + \tau_d\big). \tag{B.3}$$

With the market clearing condition,

$$\alpha q_{1,1} + (1-\alpha) q_{2,1} = 0, \tag{B.4}$$

the price at t=1 (P_1) is given

$$P_1 = \alpha\mu_1 + (1-\alpha)(\mu_2 + h). \tag{B.5}$$

Similarly, for $t = 2$,

$$P_2 = \frac{\alpha(\tau_X + \tau_d + \tau_\varepsilon)\mathbb{E}_{1,2}[D] + (1-\alpha)(\tau_X + \tau_d + \tau_\varepsilon)\mathbb{E}_{2,2}[D]}{\alpha(\tau_X + \tau_d + \tau_\varepsilon) + (1-\alpha)(\tau_X + \tau_d + \tau_\varepsilon)}. \tag{B.6}$$

Together with $\mathbb{E}_{i,2}[D] = \frac{(\tau_X+\tau_d)(\mu_i+h_i)+\tau_\varepsilon(L-e_1)}{\tau_X+\tau_d+\tau_\varepsilon}$, and $Var_{i,2}[D] = (\tau_X + \tau_d + \tau_\varepsilon)^{-1}$, the price at $t = 2$ (P_2) is

$$P_2 = \rho[\alpha\mu_1 + (1-\alpha)(\mu_2 + h)] + (1-\rho)[\alpha(L - e_1) + (1-\alpha)(L - e_2)], \tag{B.7}$$

where $\rho = \frac{\tau_X+\tau_d}{\tau_X+\tau_d+\tau_\varepsilon}$ represents the relative weight that investors assign to their prior beliefs versus the new information contained in the public signal L.

And for t=3,

$$P_3 = X + (1-\alpha)h. \tag{B.8}$$