

# Disagreement about Fundamentals: Measurements and Consequences\*

Paul Fischer<sup>1</sup>, Chongho Kim<sup>2</sup>, and Frank Zhou<sup>†3</sup>

<sup>1,2,3</sup>The Wharton School, University of Pennsylvania

Very preliminary draft

Please do not circulate without permission.

## Abstract

This study constructs a measure of disagreement (i.e., divergence of opinions) based on analyst earnings forecasts and examines its determinants and consequences. Our measure relies the notion that when analysts agree, the law of iterated expectation applies and a regression of an analyst's forecast on the previous forecast issued by another analyst should produce a slope coefficient of one. We document a positive association between disagreement and expected returns and a negative association between disagreement and the issuance of management forecasts.

---

\*We thank participants in the Thirteenth Annual Bauer Accounting Research Symposium and workshop participants at Pennsylvania State University for helpful comments. All errors are our own.

<sup>†</sup>Mailing address: 3620 Locust Walk, Philadelphia, PA, 19103, USA. E-mail address: szho@wharton.upenn.edu. Telephone number: +1 (215)-746-8558.

# 1 Introduction

Models of financial markets have generally attributed divergent beliefs, which motivate trade, to one of two sources, information asymmetries and disagreement (i.e., differences of opinion). Information asymmetries arise because traders are assumed to have access to different information, and those asymmetries are sustained in equilibrium because of some source of noise trade. Disagreements, or differences of opinion, arise because traders simply agree to disagree, perhaps because they have different models (i.e., prior beliefs) for processing information, or perhaps because of some psychological biases. In some contexts, both perspectives offer similar implications. For example, increased information asymmetry and greater disagreement would both be predicted to be associated with increased trading volume. In other contexts, the implications may differ. For example, increases in disagreement may reasonably have different implications than information asymmetry for market liquidity or the impact of public disclosures on market behavior. Given that possibility, distinguishing disagreement from information asymmetry, and assessing the implications of each construct, is warranted. We seek to contribute to that endeavor by suggesting an approach for measuring the extent of disagreement in the marketplace, and then applying the measure to test a predicted association between disagreement and expected returns. In order to provide some insight into factors that may influence the extent of disagreement, we also provide some descriptive associations between the issuance of management forecasts and disagreement.

A challenge in distinguishing disagreement from information asymmetry empirically is that some obvious proxies, particularly the dispersion of earnings forecasts, are influenced by both information asymmetry and disagreement (e.g., [Banerjee, 2011](#)). We confront the empirical challenge by employing a proxy for disagreement that is motivated by the law of iterated expectations. Specifically, if forecasts represent statistical expectations and forecasters behave in a statistically consistent manner, an individual's forecast of some outcome offered at date  $t$  will equal their expectation of their date  $t + 1$  forecast of that outcome, which will be updated based on any new information between  $t$  and  $t + 1$ . It follows that, if two forecasters,  $i$  and  $j$ , are in agreement regarding how to update beliefs given any information set, forecaster  $i$ 's forecast at date  $t$  will be the expectation of  $j$ 's forecast at date  $t + 1$ . A deviation from the law of iterated expectations reflects disagreement because it suggests that the forecasters would have different beliefs given the same information.

Such deviations can stem from differences in either their prior beliefs about the outcome itself, or their prior beliefs about the relation between the outcome and available information (i.e., how information should be interpreted).

We apply the law of iterated expectations within the context of a linear regression framework by regressing an individual analyst's quarterly EPS forecast on the prior forecast of another analyst for the same quarterly earnings. When analysts agree, the law of iterated expectation implies a slope coefficient of one. The extent of disagreement is then reflected by the deviation of the slope coefficient from one. Our results suggest that about 75% of firms exhibit analyst disagreement, that is, for these firms the coefficient estimates are significantly different from one. These coefficient estimates, in turn, are consistent with analysts relying more on their own information and analysis than that of others. Within our framework, this is attributed to analysts perceiving that others are not updating their beliefs correctly.

To provide some validation that our measure captures the theoretical disagreement construct, we relate it to three existing measures reflecting beliefs divergence trading volume, forecast dispersion, and bid-ask spreads all of which can be influenced by disagreement as well as information asymmetry. Because disagreement causes divergent beliefs, and divergent beliefs motivate trade, we expect a positive relation between our disagreement measure and trading volume. We show that this relation holds empirically, which provides some assurance that our measure reflects divergent beliefs. Furthermore, we show that it holds after controlling for forecast dispersion and spreads, suggesting that our measure is capturing a construct that is not reflected in dispersion and spreads. With respect to bid-ask spreads, we conjecture that disagreement should not contribute to them and, if anything, should have a negative relation with them because disagreement is likely to reduce market makers' inventory holding costs. In particular, when there is more disagreement, trades are more likely to cross within shorter horizons, which should manifest in lower inventory holding costs and, consequently, lower bid-ask spreads. The conjectured negative relation between disagreement and spreads stands in contrast to the predicted positive relation between information asymmetry and spreads. Consistent with our prediction, we find a negative relation between our measure and bid-ask spreads, suggesting that our measure reflects a disagreement construct as opposed to an information asymmetry construct. Finally, we also find a negative relation between our measure and forecast dispersion. As forecast dispersion and bid-ask spread are positively correlated, our

finding suggests that forecast dispersion reflects information asymmetry more than disagreement.

To understand the nature of the disagreement measure and its implications, we next examine the relation between disagreement and expected returns. Our evidence suggests that firms with higher levels of disagreement have higher *contemporaneous* returns on average after controlling for other known predictors of returns, namely the Fama-French three factors and the momentum factor, as well as analyst forecast dispersion and bid-ask spread, which also reflect information asymmetry. We also test the relation between disagreement and expected returns at the portfolio level. We sort firms into three portfolios each month and compute the average contemporaneous portfolio returns and find consistent evidence that higher disagreement is associated with higher contemporaneous average returns.

The positive relation between disagreement and equity returns sheds light on the nature of disagreement. Based on the framework of [Bloomfield and Fischer \(2011\)](#), if investors believe that other investors overreact to some future information releases (errors of *commission*), they will anticipate more volatile future prices and alter their demands accordingly, which will induce a higher expected return. This type of disagreement in the marketplace is positively associated with expected returns. We also demonstrate this relation using our framework in an overlapping generations model.

Our paper contributes to the substantial literature regarding subjective beliefs (i.e., investors agreeing to disagree). Much of that work has primarily involved theoretical analyses that link disagreement with observed patterns in trading activity, trading volume, and/or returns (see, for example, [Harrison and Kreps, 1978](#); [Harris and Raviv, 1993](#); [Kandel and Pearson, 1995](#); [Cao and Ou-Yang, 2008](#); [Banerjee et al., 2009](#); [Banerjee and Kremer, 2010](#); [Banerjee, 2011](#); [Kondor, 2012](#)). [Banerjee \(2011\)](#) is closest in nature to ours in the sense that he endeavors to distinguish information asymmetry from disagreement. In particular, he employs a model that incorporates both constructs and shows that pure forms of the two constructs offer starkly different predictions for the relation between belief dispersion and expected returns, volatility, beta, and return autocorrelation. Empirical analysis suggests that, consistent with the information asymmetry construct, investors update beliefs based upon prices. In lieu of running a horserace between information asymmetry and disagreement, which are not mutually exclusive, we endeavor to identify an empirical metric that hones in on the extent of disagreement. Furthermore, consistent with the observation that the

two constructs are not mutually exclusive, our measure of disagreement is essentially a function of the extent to which individuals update on the information and, hence, beliefs of others, which is analogous to the extent to which investors update on price.

Within the context of our model, we focus on disagreement attributable to investors believing that others are committing information processing errors, which could be attributed to overconfidence in oneself or beliefs about the overconfidence of others. Overconfidence is a widely studied construct in the behavioral finance literature, which suggests that overconfidence can explain predictable patterns in returns and individual trading behaviors that cannot be easily explained by classical models with rational Bayesian investors (see [Daniel and Hirshleifer \(2015\)](#) for an overview or, for example, [Daniel et al. \(1998\)](#), [Odean \(1999\)](#), [Barber and Odean \(2001\)](#), [Gervais and Odean \(2001\)](#), [Scheinkman and Xiong \(2003\)](#), or [Grinblatt and Keloharju \(2009\)](#)). Within this literature, overconfidence leads to systematic errors in beliefs, which leads to predictable returns patterns that are not fully exploited in equilibrium because of frictions that limit arbitrage. We have used the more generic term disagreement in our analysis because, consistent with the subjective beliefs literature, we are agnostic as to which set of beliefs, if any, is correct.

## 2 Analytical Framework

Our analysis of disagreement hinges on identifying an empirical measure of disagreement that can serve as a plausible proxy for distinguishing firms experiencing higher levels of disagreement from those experiencing lower levels of disagreement. With such a measure, we can conduct some exploratory analyses regarding the consequences of disagreement as well as the determinants of disagreement. The measure we propose relies on the statistical relation between forecasts issued in sequence. The intuition underlying our approach stems from the idea that, when there is more disagreement, individuals will be less inclined to update their beliefs upon learning the forecasts of others. We couch that intuition within the context of a simple statistical argument.

### 2.1 A Generic Test for Agreement

In the empirical domain, forecasts are generally not observed at the same time, which means they are based upon different information. Furthermore, even if forecasts are made at the same time, one

could argue that they might still be based upon different information because the forecasters generally do not get observe the simultaneous forecasts of others, which might convey new information. Hence, it is difficult to use dispersion in forecasts to reflect disagreement because that statistic is also influenced by differences in information. If we consider a sequence of public forecasts, however, we can tease out a test of agreement that is, in theory, contaminated by differences in information. This test is then employed to partially motivate our measure of disagreement.

Our test of agreement is based upon first defining agreement in a statistical sense. Given that definition we show that, if two analysts are in agreement, one analyst's forecast equals the expectation of the other analyst's subsequent forecast if the latter analyst is aware for the former analyst's forecast. This observation, in turn, suggests that "regressing" one analyst's forecast on the prior forecast of another analyst should yield a "regression" coefficient of one if the two analysts are in agreement. Given this observation, we run regression of analyst forecasts on prior analyst forecasts and use the coefficient as a measure of disagreement, where the magnitude of the difference between one and the coefficient value is our measure.

Consider a setting in with two forecasters,  $A$  and  $B$ , who each forecast a firm's earnings for period  $t$ ,  $\tilde{e}_t$ . Furthermore, assume the forecasts offered by each forecaster equal that forecaster's expectation of terminal earnings. Formally, denote  $I$ 's,  $I \in \{A, B\}$ , forecast of  $\tilde{e}_t$  given  $I$ 's information  $\omega$  as

$$f_{It} = E[\tilde{e}_t | \omega; I] \tag{1}$$

where  $E[\tilde{e}_t | \omega; I]$  is  $I$ 's conditional expectation of  $\tilde{e}_t$ . Within this context,  $A$  and  $B$  are defined to agree if they have identical priors for all earnings realizations,  $\tilde{e}_t$ , and information events,  $\tilde{\omega}$ . More formally,  $A$  and  $B$  are defined to agree if and only if  $g(e_t, \omega; A) = g(e_t, \omega; B) = g(e_t, \omega)$  for all  $\{e_t, \omega\}$ , where  $g(e_t, \omega)$  is the joint density for  $\{e_t, \omega\}$  that reflects the common beliefs of  $A$  and  $B$ . The definition of agreement naturally implies that, given the same information  $\omega$ ,  $A$  and  $B$  would have the same forecast

$$E[\tilde{e}_t | \omega; A] = E[\tilde{e}_t | \omega; B] = E[\tilde{e}_t | \omega],$$

where  $E[\tilde{e}_t | \omega]$  represents the common expectation operator.

With agreement defined, assume now that  $A$  and  $B$  forecast in sequence, with  $A$  forecasting first and  $B$ , after observing  $A$ 's forecast, forecasting second. If the two analysts are in agreement,

the law of iterated expectations is easily exploited to show that the common expectation for the  $B$ 's forecast conditional upon a  $A$ 's forecast is simply  $A$ 's forecast. In particular, let  $\omega_A$  denote  $A$ 's information at the time  $A$  forecasts, and  $\{f_{At}, \omega_B\}$  denote  $B$ 's information at the time  $B$  forecasts. By the law of iterated expectations, we know that

$$E[\tilde{f}_{Bt}|f_{At}] = E[E[\tilde{e}_t|f_{At}, \omega_B]|f_{At}] = E[\tilde{e}_t|f_{At}]$$

The observation that  $E[\tilde{f}_{Bt}|f_{At}] = f_{At}$  is completed by noting trivially that

$$E[\tilde{e}_t|f_{At}] = E[\tilde{e}_t|E[\tilde{e}_t|\omega_A]] = E[\tilde{e}_t|\omega_A] = f_{At}.$$

Hence, if the two analysts agree, they believe  $E[\tilde{f}_{Bt}|f_{At}] = f_{At}$ . Empirically, we employ the insight that  $E[\tilde{f}_{Bt}|f_{At}] = f_{At}$  if the analysts are in agreement, and use deviations in a regression coefficient from 1 to identify instances of in which there is some disagreement. In particular, we employ a sequence of analyst's forecasts and run a regression of the form

$$f_{it} = \lambda f_{jt} + \varepsilon_t,$$

where a significant deviation of  $\lambda$  from 1 rejects the null that the analysts are in agreement.

## 2.2 A Disagreement Measure

Simply identifying a test that might allow us to reject agreement in the marketplace, however, is insufficient for pursuing our research questions, which rely on distinguishing settings with more disagreement from those with less disagreement. Within the context of a simple structured model of the underlying analyst information, however, we can extend the general logic underlying the test of agreement above to establish a rationale for linking the magnitude of the coefficient's deviation from 1 to the extent of disagreement.

Prior to forecasting  $\tilde{e}_t$ , assume analyst  $A$  privately observes the realization for  $\{\tilde{a}_t, \tilde{\alpha}_t\}, \{a_t, \alpha_t\}$ . Furthermore, assume analyst  $B$  observes  $A$ 's forecast, as well as privately observing the realization for  $\{\tilde{b}_t, \tilde{\beta}_t\}, \{b_t, \beta_t\}$ , prior to issuing a subsequent forecast. Both analysts believe  $\{a_t, \alpha_t, b_t, \beta_t\}$  are mutually independent mean 0 normally distributed random variables. Disagreement is introduced

by assuming that the analysts have different beliefs about the relation between  $\tilde{e}_t$  and  $\{\tilde{a}_t, \tilde{\alpha}_t, \tilde{b}_t, \tilde{\beta}_t\}$ , as well as their variances. Analyst  $A$  believes

$$\tilde{e}_t = \tilde{a}_t + \tilde{\alpha}_t + \tilde{b}_t + \tilde{\varepsilon}_t, \quad (2)$$

where  $\tilde{\varepsilon}_t$  is a mean 0 normally distributed random variable with variance  $\sigma$ , and that  $\tilde{\varepsilon}_t$  is independent of all other random variables. Furthermore  $A$  believes the variance of  $\tilde{a}_t$  is  $s - c$ , the variance of  $\tilde{\alpha}_t$  is  $c$ , the variance of  $\tilde{b}_t$  is  $s$  and the variance of  $\tilde{\beta}_t$  is  $c$ , where  $s > c$ . In contrast,  $B$  believes

$$\tilde{e}_t = \tilde{a}_t + \tilde{b}_t + \tilde{\beta}_t + \tilde{\varepsilon}_t, \quad (3)$$

where  $\tilde{\varepsilon}_t$  is a mean 0 normally distributed random variable with variance  $\sigma$ ,  $\tilde{\varepsilon}_t$  is independent of all other random variables, the variance of  $\tilde{a}_t$  is  $s$ , the variance of  $\tilde{\alpha}_t$  is  $c$ , the variance of  $\tilde{b}_t$  is  $s - c$  and the variance of  $\tilde{\beta}_t$  is  $c$ . Hence, given both sets of information,  $A$  believes that  $B$ 's beliefs reflect errors of omission because they fail to fully respond to the relevant information in  $\tilde{\alpha}_t$ , and they reflect errors of commission because they respond to the noise in  $\tilde{\beta}_t$ .  $B$  has mirror image perceptions of  $A$ 's beliefs conditional upon both sets of information. Disagreement within this simple environment is fully captured by the parameter  $c$ , which we have introduced in a way such that alterations in  $c$  do not change the analyst prior uncertainty regarding earnings,  $2s + \sigma$ , nor their uncertainty about earnings conditional upon all of the information,  $\{\tilde{a}_t, \tilde{\alpha}_t, \tilde{b}_t, \tilde{\beta}_t\}$ ,  $\sigma$ , which is useful when we consider the relation between disagreement and expected returns.

Within the context of the modelled information structure,  $A$ 's forecast of  $\tilde{e}_t$  is

$$f_{At} = a_t + \alpha_t.$$

$B$ 's subsequent forecast is conditioned not only on  $B$ 's private information,  $\{b_t, \beta_t\}$ , but also the surprise in  $A$ 's previous forecast, which is just  $A$ 's forecast in this setting. From  $B$ 's perspective,  $A$ 's previous forecast conveys information about  $\tilde{a}_t$  with the noise introduced by  $\tilde{\alpha}_t$ . It follows that  $B$ 's forecast is

$$f_{Bt} = \frac{s}{s+c} f_{At} + b_t + \beta_t.$$



If  $B$  perceives no perceived errors of commission by  $a$ ,  $c = 0$ , the predicted regression coefficient is 1. Once  $B$  perceives errors of commission in  $A$ 's forecast, the predicted regression coefficient would be less than 1. Hence, the way disagreement is characterized in our simple model suggests a simple monotonic relation between the extent of disagreement and the predicted regression coefficient, where a smaller coefficient implies greater disagreement attributable to perceived errors of commission.

In our hypothetical world, is it possible that the analysts could be in complete agreement and yet have the predicted regression coefficient deviate from 1? One reason that the answer to this question could be yes is if analysts are in agreement but have a particular type of common error in their beliefs. For example, assume that analyst  $A$  and  $B$  agree that  $\tilde{e} = \tilde{z}_A + \tilde{z}_B + \tilde{z}_n$ , where  $\tilde{z}_A$ ,  $\tilde{z}_B$ , and  $\tilde{z}_n$  are independent normally distributed randomly distributed random variables, analyst  $A$  observes  $z_A$  prior to forecasting, and analyst  $B$  observes analyst  $A$ 's forecast and  $z_B$  prior to forecasting. In this simple example,  $f_A = z_A$  and  $f_B = f_A + z_B$ . Assume that the two analysts are wrong regarding the independence of  $\tilde{z}_A$  and  $\tilde{z}_B$ , and that  $\tilde{z}_B = m\tilde{z}_A + \tilde{\gamma}$  where  $\tilde{\gamma}$  is a mean 0 normally distributed random variable that is independent of all other random variables. In a true "regression" of the forecast of  $A$  on  $B$ , it would be the case that the coefficient in the regression would be  $1 + m$  instead of 1. Hence, our empirical approach for rejecting agreement not only relies on our definition of agreement, but also relies on the analysts having common priors that do not cause  $E[\varepsilon_t|f_{jt}] \neq 0$  when  $\beta$  is constrained to its true value of 1 in the regression.

### 2.3 Disagreement and Expected Returns

In order to motivate why disagreement may be plausibly be associated with expected returns, we impose our simple information structure into an  $n$ -period overlapping generations model, which is a parsimonious way to model behaviors driven by higher order beliefs. Within our model, each generation, which is represented by a continuum of investors of measure one, engages in the market for two periods, a period where they enter and acquire asset claims and a period where they exit and settle those claims. The investors trade claims to a risky asset, as well as holding or shorting cash (i.e., risk-free bonds paying a net return normalized to 0). There is one unit of the risky asset per investor generation and the supply of risky bonds is unbounded. The risky asset yields a

terminal cash flow per share at the end of the  $n$  periods of

$$\tilde{E}_T = \sum_{t=1}^n \tilde{e}_t, \quad (4)$$

where all actors agree that the components of terminal cash flow (i.e.,  $\tilde{e}_1, \tilde{e}_2, \dots$ ), earnings, are iid normally distributed random variables with means normalized to 0 and variances  $2s + \sigma$ . Finally, at the beginning of period  $t$ , the realization of earnings  $\tilde{e}_{t-1}$  is publicly released.

Prior to trade in each period, but after the public release of the prior period's earnings, the investors entering the market are informed by two analysts,  $A$  and  $B$ , who provide sequential forecasts of the period's earnings, with  $A$  forecasting first. The information available to the analysts each period, as well as their beliefs about the relation between that information and earnings, is as specified above. In particular, analyst  $A$  privately observes  $\{a_t, \alpha_t\}$  prior to forecasting and analyst  $B$  observes  $A$ 's forecast, as well as privately observing  $\{b_t, \beta_t\}$  prior to issuing a subsequent forecast.

After observing the two forecasts, trade ensues between the entering and exiting investors, whose preferences are characterized by the negative exponential utility function,  $-\exp(-W)$ , where  $W$  is the terminal wealth of the investor when they exit the market, which is a function of their portfolio of risky assets and cash held after the last period of trade. To introduce disagreement among investors that is reflected by the disagreement among the analysts, we assume half of the investors of each generation have beliefs identical to Analyst  $A$  and the other half have beliefs identical to  $B$ , which we refer to as  $A$  and  $B$  investors respectively.

As shown in the appendix, there exists a unique sequence of equilibrium prices, where the price at any date  $t$  is

$$P_t = \sum_{j=1}^{t-1} e_j + \frac{1}{2} \frac{2s+c}{s+c} (a_t + b_t + \alpha_t + \beta_t) - \left( \frac{sc}{s+c} + \sigma \right) - (n-t) \left( \frac{sc}{s+c} + \sigma + \frac{1}{2} \frac{(2s+c)^3}{(s+c)^2} \right). \quad (5)$$

The price in period  $t$  equals the sequence of earnings realized up until period  $t$ ,  $\sum_{j=1}^{t-1} e_j$ , plus the average expectation of period  $t$  earnings,  $\frac{1}{2} \frac{2s+c}{s+c} (a_t + b_t + \alpha_t + \beta_t)$ , less a discount for the uncertainty regarding the exit price,  $\left( \frac{sc}{s+c} + \sigma \right) + (n-t) \left( \frac{sc}{s+c} + \sigma + \frac{1}{2} \frac{(2s+c)^3}{(s+c)^2} \right)$ . The uncertainty regarding the exit price perceived by a generation of entering investors in period  $t < n$  is  $\frac{sc}{s+c} + \sigma + \frac{1}{4} \frac{(2s+c)^3}{(s+c)^2}$ . The first component,  $\frac{sc}{s+c} + \sigma$ , represents the uncertainty each investor perceives about current earnings,

$\tilde{e}_t$ , and the second component,  $\frac{1}{4} \frac{(2s+c)^3}{(s+c)^2}$ , represents the uncertainty each investor attributes to the arrival of new information regarding subsequent period earnings,  $\{a_{t+1}, \alpha_{t+1}, b_{t+1}, \beta_{t+1}\}$ . The uncertainty about  $\tilde{e}_t$  is increasing in disagreement,  $c$ , because investors believe that one of the analyst forecasts becomes a noisier source of relevant information. The latter source of uncertainty, uncertainty attributable to information arrival, is captured by the variance of  $\tilde{a}_t + \tilde{b}_t + \tilde{\alpha}_t + \tilde{\beta}_t$  (i.e.,  $2s+c$ ), and the price response to that information, which is captured by the pricing coefficient  $\frac{1}{2} \frac{2s+c}{s+c}$ . The impact of disagreement,  $c$ , on this source of uncertainty is ambiguous because increases in  $c$  increase the uncertainty regarding the information impacting price, but decrease the price response to that information. When perceived errors of commission are low, the latter effect dominates and when perceived errors of commission are high the former effect dominates. If we consider the overall uncertainty regarding the exit price,  $\frac{sc}{s+c} + \sigma + \frac{1}{4} \frac{(2s+c)^3}{(s+c)^2}$ , it simplifies to  $2s + \sigma + \frac{c^2(2s+c)}{4(s+c)^2}$ , which is increasing in disagreement.

Our returns prediction stems from considering the expected change in price, using the common expectation of all investors. The predicted change in price from any  $t < n$  to  $t + 1$  is simply

$$2s + \sigma + \frac{c^2(2s+c)}{4(s+c)^2}.$$

The expected change in price provides the compensation that entering investors in  $t$  require to absorb the risks they associate with holding the risky asset claims to  $t + 1$ . In addition to the risk associated with uncertainty regarding the fundamentals,  $2s + \sigma$ , this risk is driven by each investor's perceived uncertainty attributable to errors made by half of the other investors, which is not surprisingly increasing in disagreement,  $c$ .<sup>1</sup>

## 2.4 Two Caveats

While our analytical framework provides a rationale for our proxy for disagreement and for there to be a positive relation between disagreement and expected returns, some caveats are warranted, two of which can be motivated directly from the analytical framework itself. The first focuses

---

<sup>1</sup>We have link disagreement to the expected change in price, as opposed to the expected return. The exact same analytical result holds if we consider expected returns conditioned on current period price. If we considered unconditional expected returns, that expected return do not exist because the moments of the ratio of two normally distributed random variables do not exist.

on assessing whether the regression coefficient our proxy relies upon could deviate from 1 when there is agreement. The second alters the information structure within the model to highlight that the relationship between disagreement and expected returns need not be positive, and to highlight that interpreting the regression coefficient might be somewhat more challenging than our previous analysis might suggest.

With respect to the first caveat, it is possible to envision a predicted coefficient that deviates from 1 even though there is general agreement. For example, assume that analyst  $A$  and  $B$  agree that  $\tilde{e} = \tilde{z}_A + \tilde{z}_B + \tilde{z}_n$ , where  $\tilde{z}_A$ ,  $\tilde{z}_B$ , and  $\tilde{z}_n$  are independent normally distributed random variables, analyst  $A$  observes  $z_A$  prior to forecasting, and analyst  $B$  observes analyst  $A$ 's forecast and  $z_B$  prior to forecasting. In this simple example,  $f_A = z_A$  and  $f_B = f_A + z_B$ . Assume that the two analysts are wrong regarding the independence of  $\tilde{z}_A$  and  $\tilde{z}_B$ , and that  $\tilde{z}_B = m\tilde{z}_A + \tilde{\gamma}$  where  $\tilde{\gamma}$  is a mean 0 normally distributed random variable that is independent of all other random variables. In a true "regression" of the forecast of  $A$  on  $B$ , it would be the case that the coefficient in the regression would be  $1 + m$  instead of 1. Hence, our empirical approach for rejecting agreement not only relies on our definition of agreement, but also relies on the analysts having common priors that do not cause  $E[\varepsilon_t | f_{jt}] \neq 0$  when  $\beta$  is constrained to its true value of 1 in the regression.

With respect to the second caveat, we expand and alter the information structure to show that disagreement need not always be positively associated with expected returns. In addition, while the regression coefficient will still reflect disagreement, interpreting the regression coefficient becomes a bit more challenging. Consider our existing model with two alterations. First, we have assumed that the disagreement is reflected by a single parameter  $c$ , which reflects perceptions for both errors of omission (i.e., failure to respond to relevant information) and errors of commission (i.e., responding to noise). To introduce errors of commission and errors of omission as separate constructs, assume that  $A$  believes  $\tilde{a}_t$  has variance  $s - o$ ,  $\tilde{\alpha}_t$  has variance  $s - o$ ,  $\tilde{b}_t$  has variance  $s$ , and  $\tilde{\beta}_t$  has variance  $c$ , whereas  $B$  believes  $\tilde{a}_t$  has variance  $s$ ,  $\tilde{\alpha}_t$  has variance  $c$ ,  $\tilde{b}_t$  has variance  $s - o$ , and  $\tilde{\beta}_t$  has variance  $o$ . In this expanded setting  $c$  represents beliefs about errors of commission and  $o$  represents beliefs about errors of omission. In our primary setting in which only analyst forecasts are observed, the explicit introduction of different parameters to reflect different constructs has no implications for measuring disagreement or security pricing because pure reliance on forecasts to

communicate information washes out the impacts of errors of omission. When considered in the context of the second alteration, however, the introduction of two different constructs matters. In particular, in the primary model we assume that the only information conveyed by analysts are the analyst forecasts, which limits the ability of other analysts or investors to effectively extract the detailed information or analysis underlying the forecast. For example, analyst  $B$  cannot tease out just  $a_t$  from analyst  $A$ 's forecast. Instead  $B$  observes  $a_t$  with the perceived noise,  $\alpha_t$ , added by  $A$  to the forecast. Analyst forecasts, however, are often revealed in conjunction with a broader analyst report. Such a report might allow other analysts or investors to observed the detailed information or analysis underlying the forecast, which they can employ as they see fit. Hence, our second alteration allows the analysts and investors to perfectly extract the information underlying the forecasts.

In this alternative setting, the equilibrium prices are characterized by

$$P_t = \sum_{j=1}^{t-1} e_j + \left( a_t + b_t + \frac{1}{2}\alpha_t + \frac{1}{2}\beta_t \right) - \sigma - (n-t)(2s + \sigma + \frac{1}{4}c - \frac{3}{4}o), \quad (6)$$

and the expected change in prices for any  $t < n$  is

$$2s + \sigma + \frac{1}{4}c - \frac{3}{4}o.$$

Like our primary model, the incremental risk discount associated with any period  $t < n$ , and the associated price change, is again increasing in disagreement attributable to  $c$  but is decreasing in perceived errors of omission. This counterbalance arises for two reasons. First, when investors can observe the primitives underlying the forecasts, the errors of comission committed by one analyst do not thwart an investors ability to extract just the relevant information about earnings that are aggregated into the forecast. Second, perceived errors of omission reduce the uncertainty associated with the price response to the arrival of new information. As a consequence of these alterations, the relation between disagreement and expected returns is driven by the nature of the disagreement. If perceived errors of comission dominate,  $c > 3o$ , then the positive relation is still predicted. If not,  $c < 3o$ , then a negative relation is predicted.

Turning to the measure of disagreement, note first that  $A$ 's forecast of  $\tilde{e}_t$  is again

$$f_{At} = a_t + \alpha_t.$$

$B$ 's subsequent forecast is conditioned not only on  $B$ 's private information,  $\{b_t, \beta_t\}$ , but also  $A$ 's information,  $\{a_t, \alpha_t\}$ . It follows that  $B$ 's forecast is

$$f_{Bt} = a_t + b_t + \beta_t.$$

The expectation of  $B$ 's forecast conditioned solely on  $A$ 's forecast is

$$E[\tilde{f}_{Bt}|f_{At}] = \frac{\text{var}[\tilde{a}_t]}{\text{var}[\tilde{a}_t] + \text{var}[\tilde{\alpha}_t]} f_{At},$$

where we have used variances instead of parameters, because the coefficient is not longer determined by  $B$ 's beliefs but by some underlying truth. If  $B$ 's beliefs are correct, the coefficient is the same as in the primary model,

$$\frac{\text{var}[\tilde{a}_t]}{\text{var}[\tilde{a}_t] + \text{var}[\tilde{\alpha}_t]} = \frac{s}{s + c},$$

and the coefficient picks up the extent of disagreement due to perceived errors of commission. In this case, a lower value for the coefficient would suggest higher expected changes in price. If  $A$ 's beliefs are correct, however, the coefficient is

$$\frac{\text{var}[\tilde{a}_t]}{\text{var}[\tilde{a}_t] + \text{var}[\tilde{\alpha}_t]} = \frac{s - o}{s},$$

which implies that the coefficient picks up perceived errors of omission. In this case, a lower value of the coefficient would suggest lower expected changes in price. Hence, if one finds this alternative information representation more plausible, the coefficient picks up disagreement, but not the nature of the disagreement. Nonetheless, the model would still suggest a potential relation between expected returns and disagreement, although that relation would depend upon which set of beliefs are correct.

### 3 Sample and Variable Measurements

The empirical analysis combines several data sources. We collect analyst earnings forecasts (EPS) issued between 01/01/2002 and 12/31/2017 from I/B/E/S unadjusted detailed history file. We obtain stock price, bid-ask spreads, returns, trading volume, and the number of shares outstanding from CRSP daily and monthly files. Accounting data is from Compustat. Monthly Fama-French three factors and the momentum factors are from WRDS Fama French & Liquidity Factors. We collect management forecasts from I/B/E/S Guidance.

To construct our disagreement measure, we first process the I/B/E/S data to obtain a sample of quarterly EPS forecasts. For each firm quarter, we keep all quarterly EPS forecasts issued for that quarter, and require that the forecasts be announced within six months prior to the fiscal quarter end date and that a firm quarter have at least two analysts and a minimum of four forecasts. We then adjust all forecasts for stock splits and scale them by the stock price one month prior to the first forecast of a firm quarter.

We then run regressions at the firm-quarter level to produce a quarterly measure of disagreement. Specifically, we regress an analyst forecast on the most recent forecast issued by a different analyst. We require that the two analyst forecasts be issued by at least one week apart to allow for sufficient time for the second analyst to process information from the first analyst’s forecast. When the most recent forecasts are multiple forecasts issued by different analysts, we use the mean of these forecasts. Each regression needs to have at least four observations. The regression model is

$$f_{it,m} = \gamma_{0,it} + \gamma_{1,it}g_{it,m} + \epsilon_{it,m}, \quad (7)$$

where  $f_{it,m}$  denotes the  $m^{th}$  quarterly EPS forecast issued for firm  $i$  in quarter  $t$  and  $g_{it,m}$  denotes the most recent forecast issued by a different analyst.

Recall from Section 2 that the coefficient  $\alpha_1$  should equal one when there is no disagreement, and should be less than one otherwise. We obtain our disagreement measure by computing the extent that the coefficient *statistically* differs from one:

$$Disagree_{it}^c = \frac{1 - \alpha_{1,it}}{se(\alpha_{1,it})}, \quad (8)$$

where  $se(\alpha_{1,it})$  denotes the robust standard error from the regression model (7). We adjust for the standard error because a small  $\alpha_1$  does not necessarily imply large disagreement when it is estimated imprecisely. Imprecision can be problematic for our measure because the firm-quarter regressions often have a small number of observations (the median is 12, and the mean is 15). Scaling by the standard error facilitates cross-sectional comparisons by standardizing the noise in the data. To reduce the chance of misclassifying disagreement, we create a second measure of disagreement that is discrete based on whether the coefficient  $\alpha_1$  statistically differs from one at the 5% level in a two-tailed test:

$$Disagree_{it}^d = \begin{cases} 1 & \text{if } \frac{1-\alpha_{1,it}}{se(\alpha_{1,it})} \geq 1.96 \\ 0 & \text{if } -1.96 < \frac{1-\alpha_{1,it}}{se(\alpha_{1,it})} < 1.96. \end{cases} \quad (9)$$

The interpretation of this measure is straightforward. For example, as we cannot conclude that  $\alpha_1$  statistically differs from one when the statistic in (9) falls between -1.96 and 1.96, we classify the firm quarter as having no disagreement. Across both measures, a higher value denotes more disagreement.<sup>2</sup>

We also employ several measures of belief divergence used by various prior studies: trading volume (Garfinkel and Sokobin, 2006), analyst forecast dispersion (Diether et al., 2002), and bid-ask spread (Garfinkel, 2009). All variables are expressed in percentage points. The details of the variable construction are discussed below:

1. Trading volume (*Volume*): the average daily trading volume divided by the total number of shares outstanding.

$$Volume = avg \left( \frac{Share\ volume_{it}}{Share\ outstanding_{it}} \right).$$

2. Bid-ask spread (*Spread*): the average daily bid-ask spread.

$$Spread = avg \left( \frac{Ask - Bid}{\frac{Ask + Bid}{2}} \right).$$

3. Forecast dispersion (*Dispersion*): the standard deviation of analyst forecast divided by stock

---

<sup>2</sup>We remove the rare cases of  $\frac{1-\alpha_{1,it}}{se(\alpha_{1,it})} \leq -1.96$ , as these cases are not theoretically defined.



price one month prior to the first forecast.

$$Dispersion = \frac{\sigma(Forecast_{it,m})}{Price_{it-1}}.$$

We assess the relation between these measures of belief divergence and our disagreement measure to assess whether the relations are consistent with our measure reflecting disagreement. First, disagreement, like any driver of belief differentials (e.g., information asymmetry), should motivate trade and, as a consequence, should be positively associated with trading volume. Second, bid-ask spread is anticipated to be increasing in information asymmetry (i.e., adverse selection) as well as inventory holding costs, such as the uncertainty faced during a market maker’s holding period. Disagreement might be expected to lower inventory holding costs due to a greater likelihood of orders crossing within a shorter time frame. Hence, the relation between the disagreement measure and the bid-ask spread is expected to be negative. Finally, dispersion in analyst forecasts would reflect differences in information (e.g., information asymmetry) as well as overall uncertainty (Barron et al., 1998). Forecast dispersion is also expected to reflect disagreement, implying that the relation between forecast dispersion and disagreement should be positive.

## 4 Results

### 4.1 Measure validation

Table 1 Panel A presents the distribution of our disagreement measures, defined in equations (8) and (9), trading volume, analyst forecast dispersion, and bid-ask spread. The average disagreement, using the continuous measure  $Disagree^c$ , is 4.22, suggesting that the average regression coefficient of an analyst’s forecast on the forecast of the predecessor analyst is significantly smaller than one. A regression coefficient of one corresponds to the case without disagreement. The mean of the discrete measure,  $Disagree^d$  is, 0.75. Since the measure only takes the value 0 and 1, the result implies that the regression coefficients,  $\alpha_1$ , are significantly different from one for 75% of firm quarters. Disagreement has a large variation over the cross section, as can be seen from the standard deviation and Figure 1, which presents the kernel density of  $Disagree^c$ . Trading volume, analyst forecast dispersion, and bid-ask spread, which prior studies use to capture disagreement,

similarly have large cross-sectional variation.

[Insert Table 1.]

[Insert Figure 1.]

Table 1 Panel B describes the average disagreement over calendar years. Across both measures, disagreement stays relatively stable and slightly increases over time. The amount of increase per year, however, is quite small compared to the standard deviation, suggesting that the aggregate disagreement does not change much and that the variation of disagreement our measures capture is mainly cross-sectional.

Table 2 examines the relation between our measure of disagreement and the measures of disagreement from prior studies. Panel A presents univariate results. We sort *Disagree<sup>c</sup>* into terciles and compute the averages of our disagreement measures, trading volume, analyst forecast dispersion, and bid-ask spread for each tercile. Doing so would allow us to capture any nonlinearity in the relations among these variables. The results show that as *Disagree<sup>c</sup>* (our first measure) increases, trading volume increases, as predicted. There is a negative relation between disagreement and bid-ask spread, also as predicted. This relation is consistent with the intuition that asymmetric information, captured by bid-ask spread, creates trading frictions and lowers trading volume, whereas disagreement increases incentives to trade. The relation between analyst forecast dispersion and disagreement is negative, suggesting that analyst forecast dispersion likely captures information asymmetry (i.e., bid-ask spread) more than it reflects our measure of disagreement.

Panel B presents the correlation table across all the measures. The correlation results are consistent with Panel A. The disagreement measures we construct are positively correlated with each other and with trading volume. On the other hand, analyst forecast dispersion and bid-ask spread are positively correlated with each other but are negatively correlated with our measures of disagreement, again suggesting that analyst forecast dispersion reflects information asymmetry. However, forecast dispersion is also positively associated with trading volume, consistent with it capturing disagreement.

[Insert Table 2.]

Table 3 further investigates the relation between trading volume and our measures of disagreement in regressions. Specifically, if disagreement reflects a construct that is distinct from information asymmetry, we would expect it to continue to explain trading volume after controlling for forecast dispersion and bid-ask spread, as these latter constructs plausibly pick up both disagreement and information asymmetry. To assess whether these observations hold, we run regressions of the form:

$$Volume_{it} = \alpha_0 + \alpha_1 Disagree_{it} + \Gamma' Controls_{it} + \epsilon_{it},$$

where  $Volume_{it}$  is the average daily volume of firm  $i$  in quarter  $t$ . The coefficient of interest is  $\alpha_1$ , which is predicted to be positive according to our model. Standard errors are clustered at the firm level. Calendar year fixed effects are included in all specifications.

[Insert Table 3.]

The results from Table 3 are consistent with our prediction that disagreement generates trading volume. According to column (1), where we do not include any control variables, the coefficient on  $Disagree^c$  is positive and significant. A one-standard deviation increase in disagreement is associated with an increase in trading volume of 0.04 percentage points of the total shares outstanding ( $0.011 \times 3.28$ ). Column (2) includes analyst forecast dispersion and bid-ask spread as controls. We find that forecast dispersion is positively associated with trading volume and that bid-ask spread is negatively associated with trading volume, consistent with results from prior studies and our predictions. The coefficient on  $Disagree^c$  is little affected, consistent with  $Disagree^c$  capturing distinct constructs from forecast dispersion and bid-ask spread. Column (3) uses the discrete disagreement measure. When analysts disagree, the trading volume increases by 0.06 percentage points relative to when they agree.

In summary, the results from the univariate and regression analysis are consistent with our measure of disagreement reflecting disagreement. Furthermore, they also suggest that our measure reflects a distinct source of belief dispersion in the sense that it is empirically distinct from other measures of beliefs dispersion that also reflect differences in analysts' or investors' information sets.

## 4.2 Disagreement and Expected Returns

We apply our disagreement measure to test for a predicted relation between disagreement and expected returns. We do so by matching monthly stock returns to firms' fiscal quarters, defined as the period within three months prior to the fiscal quarter end date. We express returns in percentage points.

Table 4 Panel A presents the results for our univariate analysis. We first sort the continuous disagreement measure,  $Disagree^c$ , into terciles and compute the average monthly stock return for each tercile. This analysis allows us to examine whether the relation between disagreement and average monthly stock returns is monotonic. Likewise, we compute the average monthly return for each value of the discrete disagreement measure,  $Disagree^d$ . For both disagreement measures, higher disagreement is associated with larger expected returns. The average stock return of the highest  $Disagree^c$  tercile is 1.38%, compared to 0.46% for the lowest  $Disagree^c$  tercile. The difference is statistically and economically significant. Likewise, the average return of firm quarters with disagreement ( $Disagree^d = 1$ ) amounts to 1.22%, which is significantly higher than 0.24%, the average return of firm quarters with no statistically significant disagreement ( $Disagree^d = 0$ ).

[Insert Table 4]

Table 4 Panels B to D further examine whether the results documented in Panel A purely reflects well-known cross-sectional determinants of expected returns, such as firm size, book-to-market, and past returns. We perform the analysis by first sorting each conditioning variable into terciles and then computing the average monthly stock return for all combinations of the terciles of each conditioning variable and the  $Disagree^c$  tercile.

Table 4 Panel B presents the results using size as the conditioning variable, where size is the market value of equity three months prior to the fiscal quarter end date. Across all size terciles, the relation between disagreement and average stock returns is positive. The differences in the average return between the highest and the lowest disagreement terciles vary between 0.77% to 1.22%. Next, Table 4 Panel C presents the results using book-to-market ratio as the conditioning variable, where the book value of equity divided by the market value of equity three months prior to the fiscal quarter end date. Across all book-to-market terciles, the relation between disagreement and average returns is positive. The differences in the average return between the highest and

the lowest disagreement terciles vary between 0.60% to 1.26%, which are again statistically and economically significant. Finally, Table 4 Panel D presents the results using prior year return as the conditioning variable, where prior year return is one quarter before the fiscal quarter end date minus the value-weighted market return. Across all prior year return terciles, the relation between disagreement and average return is positive. The differences in the average return between the highest and the lowest disagreement quintiles vary between 0.33% to 1.57%, which resembles the results from the previous two panels.

Table 4 Panels B to D suggest that the effects of disagreement do not merely reflect the effects of firm size, book-to-market, or momentum. We further examine this by regressing monthly stock return on the contemporaneous disagreement, Fama-French three factors (market, size, and book-to-market) and the momentum factor. The regression model is:

$$R_{it}^m - R_{f_t} = \alpha + \beta Disagree_{it} + \beta_1 MktRf_{it} + \beta_2 SMB_{it} + \beta_3 HML_{it} + \beta_4 UMD_{it} + \eta_{it}, \quad (10)$$

where  $MktRf_{it}$ ,  $SMB_{it}$ ,  $HML_{it}$ ,  $UMD_{it}$  are respectively the Fama-French three factors (market, size, and book-to-market) and the momentum factor, all at the monthly level.

Table 5 reports our findings using regression model (10). Across all the columns, we find a significant and positive relation between our disagreement measure and the monthly returns. Column (1) only uses the Fama-French factors and the momentum factor. Column (2) includes the pricing factors and the continuous disagreement measure. A one-standard deviation in disagreement is associated with average monthly returns that are 0.28 percentage points higher. The results are little changed when adding analyst forecast dispersion and bid-ask spread as controls. We find similar results when using the discrete disagreement measure. Average monthly return is 0.75 percentage points higher when analysts disagree than when they do not. The results are again little changed when we control for analyst forecast dispersion and bid-ask spread.

[Insert Table 5.]

Table 5 concentrates on firm-level monthly stock returns. We next take a portfolio approach. We sort stocks into portfolios based on disagreement terciles in each month and examine the hedge portfolio returns where we long stocks from the top disagreement tercile and short stocks from

the bottom disagreement tercile. We form both equal- and value-weighted portfolios and regress the portfolio returns on the returns of the contemporaneous Fama-French three factors and the momentum factor. Note that we aim to examine the effect of disagreement on contemporaneous expected returns rather than demonstrate an anomaly. Therefore, the disagreement measure is concurrent to the monthly returns.

Table 6 presents the results of the 182 monthly hedge portfolio returns. The findings continue to support our claim that more disagreement is associated with larger expected returns. The monthly alpha between the highest and lowest disagreement terciles amounts to 0.79% (0.14%) for the equal- (value-) weighted portfolios.

[Insert Table 6.]

Overall, we document a positive association between disagreement and expected returns at the firm level and the portfolio level, which is consistent with disagreement being associated with perceptions of investor uncertainty about future prices. Furthermore, if the conceptual story underlying our theoretical framing of the relation between disagreement and investor uncertainty is relevant, the empirical association between disagreement and expected returns suggests that disagreement is driven to a larger extent by perceived errors of commission as opposed to perceived errors of omission.

#### 4.2.1 Robustness checks

This section performs robustness checks regarding the main findings in Table 5. First, one may concern that the noise in the small sample size drives our results. We restrict firm quarters with at least 30 EPS forecasts to mitigate the concern of small sample size. The result, reported in Table 7 Column (1), indicates little change in the economic effect of disagreement. We also control for the standard error in the coefficient estimate  $\alpha_{1,it}$ . The coefficient estimate on *Disagree*<sup>c</sup>, reported in Column (2), in fact increases from the baseline of 0.130 to 0.158.

[Insert Table 7.]

Our main results use quarterly EPS forecasts. As an alternative, we use annual EPS forecasts to construct disagreement. In addition to demonstrating robustness, using annual forecasts alleviates

the concern that quarterly forecasts might be guided down by management.

To construct the measure, for each firm year, we keep all annual EPS forecasts issued for that fiscal year, and require that the forecasts be announced within twelve months prior to the fiscal year end date and that a firm year have at least two analysts and a minimum of four forecasts. We then adjust all forecasts for stock splits and scale them by the stock price one month prior to the first forecast of a firm year. For each firm year, we regress an analyst forecast on the most recent forecast issued by a different analyst. We require that the two analyst forecasts be issued by at least one week apart to allow for sufficient time for the second analyst to process information from the first analyst’s forecast. Each regression needs to have at least four observations. The regression model is

$$f_{it,m} = \alpha_{0,it} + \alpha_{1,it}g_{it,m} + \epsilon_{it,m},$$

where  $f_{it,m}$  denotes the  $m^{th}$  annual EPS forecast issued for firm  $i$  in year  $t$  and  $g_{it,m}$  denotes the most recent forecast issued by a different analyst. We then use equations (8) and (9) to construct the annual disagreement measures.

Table 8 presents the results. Consistent with Table 5, higher disagreement is positively associated with average monthly returns. From Column (1), the coefficient estimate on  $Disagree^c$  is about 30% of that in Column (2) of Table 5 but remains statistically significant. The smaller coefficient likely reflects the higher noise in the annual disagreement measure relative to the quarterly measure. Consistent with this, the coefficient estimate on the discrete measure,  $Disagree^d$ , which is less prone to measurement error, is 0.625. The magnitude is only slightly smaller than 0.750 documented in Column (3) of Table 5 using the quarterly measure of  $Disagree^d$ .

[Insert Table 8.]

## 5 Conclusion

We construct a measure of disagreement (i.e., divergence of opinions) based on analyst earnings forecasts. We first examine properties of analyst forecast under disagreement and analytically demonstrate that when analysts agree, the law of iterated expectation applies and a regression of an analyst’s forecast on the previous forecast issued by another analyst should produce a slope

coefficient of one. Therefore, any deviation from one would suggest disagreement.

We apply this idea in the context of analyst forecasts of quarterly earnings and find that for about 75% of firm-years, analysts disagree with each other's forecast. We validate the measure by showing that it is positively associated with trading volume. The measure is also distinct from existing measures of opinion divergence, as it continues to explain trading volume even after controlling for analyst forecast dispersion and bid-ask spread.

We then extend the analysis to examine the relation between disagreement and expected returns. Higher disagreement is positively associated with monthly stock returns, after accounting for the Fama-French three factors and momentum factor. The result also holds at the portfolio level, where we sort stocks into five disagreement terciles each month and construct both equal- and value-weighted portfolios.



## References

- Banerjee, S. (2011). Learning from prices and the dispersion in beliefs. *The Review of Financial Studies* 24(9), 3025–3068.
- Banerjee, S., R. Kaniel, and I. Kremer (2009). Price drift as an outcome of differences in higher-order beliefs. *The Review of Financial Studies* 22(9), 3707–3734.
- Banerjee, S. and I. Kremer (2010). Disagreement and learning: Dynamic patterns of trade. *The Journal of Finance* 65(4), 1269–1302.
- Barber, B. M. and T. Odean (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics* 116(1), 261–292.
- Barron, O. E., O. Kim, S. C. Lim, and D. E. Stevens (1998). Using analysts' forecasts to measure properties of analysts' information environment. *The Accounting Review* 73(4), 421–433.
- Bloomfield, R. and P. E. Fischer (2011). Disagreement and the cost of capital. *Journal of Accounting Research* 49(1), 41–68.
- Cao, H. H. and H. Ou-Yang (2008). Differences of opinion of public information and speculative trading in stocks and options. *The Review of Financial Studies* 22(1), 299–335.
- Daniel, K. and D. Hirshleifer (2015). Overconfident investors, predictable returns, and excessive trading. *Journal of Economic Perspectives* 29(4), 61–88.
- Daniel, K., D. Hirshleifer, and A. Subrahmanyam (1998). Investor psychology and security market under- and overreactions. *the Journal of Finance* 53(6), 1839–1885.
- Diether, K. B., C. J. Malloy, and A. Scherbina (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance* 57(5), 2113–2141.
- Garfinkel, J. A. (2009). Measuring investors' opinion divergence. *Journal of Accounting Research* 47(5), 1317–1348.
- Garfinkel, J. A. and J. Sokobin (2006). Volume, opinion divergence, and returns: A study of post-earnings announcement drift. *Journal of Accounting Research* 44(1), 85–112.
- Gervais, S. and T. Odean (2001). Learning to be overconfident. *The Review of Financial Studies* 14(1), 1–27.

- Grinblatt, M. and M. Keloharju (2009). Sensation seeking, overconfidence, and trading activity. *The Journal of Finance* 64(2), 549–578.
- Harris, M. and A. Raviv (1993). Differences of opinion make a horse race. *The Review of Financial Studies* 6(3), 473–506.
- Harrison, J. M. and D. M. Kreps (1978). Speculative investor behavior in a stock market with heterogeneous expectations. *The Quarterly Journal of Economics* 92(2), 323–336.
- Kandel, E. and N. D. Pearson (1995). Differential interpretation of public signals and trade in speculative markets. *Journal of Political Economy* 103(4), 831–872.
- Kondor, P. (2012). The more we know about the fundamental, the less we agree on the price. *The Review of Economic Studies* 79(3), 1175–1207.
- Odean, T. (1999). Do investors trade too much? *American Economic Review* 89(5), 1279–1298.
- Scheinkman, J. A. and W. Xiong (2003). Overconfidence and speculative bubbles. *Journal of Political Economy* 111(6), 1183–1220.

## Appendix

The proof of the equilibrium price characterization in the primary model relies on the following two remarks.

Remark A1. The equilibrium price in the period  $n$  round of trade must satisfy

$$P_n = E_{n-1} + \frac{1}{2} \frac{2s+c}{s+c} (a_n + b_n + \alpha_n + \beta_n) - \frac{sc}{s+c} - \sigma. \quad (11)$$

Proof. Note first that the forecasts satisfy

$$f_{An} = a_n + \alpha_n$$

and

$$f_{Bn} = \frac{s}{s+c} f_{An} + b_n + \beta_n.$$

This implies that the beliefs about  $\tilde{e}_n$  for a type  $A$  investor prior to trade are that  $\tilde{e}_n$  is normally distributed with mean

$$E[\tilde{e}_n | f_{An}, f_{Bn}; A] = f_{An} + \frac{s}{s+c} \left( f_{Bn} - \frac{s}{s+c} f_{An} \right) = a_n + \alpha_n + \frac{s}{s+c} (b_n + \beta_n)$$

and variance

$$\text{Var}[\tilde{e}_n | f_{An}, f_{Bn}; A] = \frac{s}{s+c} c + \sigma.$$

Similarly, the beliefs about  $\tilde{e}_n$  for a type  $B$  investor prior to trade are that  $\tilde{e}_n$  is normally distributed with mean

$$E[\tilde{e}_n | f_{An}, f_{Bn}; A] = f_{Bn} = \frac{s}{s+c} (a_n + \alpha_n) + b_n + \beta_n$$

and variance

$$\text{Var}[\tilde{e}_n | f_{An}, f_{Bn}; A] = \frac{s}{s+c} c + \sigma.$$

Because of the linear pricing function and the negative exponential utility function, the expected utility of a period  $n$  entering investor of type  $I$  can be written as

$$- \exp \left( - \left( q_n (E_{n-1} + E[\tilde{e}_n | f_{An}, f_{Bn}; I] - P_n) - \frac{1}{2} q_n^2 \text{Var}[\tilde{e}_n | f_{An}, f_{Bn}; I] \right) \right), \quad (12)$$

where  $E_{n-1} = \sum_{j=1}^{n-1} e_j$ . The value for  $q_n$  that maximizes the expected utility is

$$q_{nI} = \frac{E_{n-1} + E[\tilde{e}_n | f_{An}, f_{Bn}; I] - P_n}{\text{Var}[\tilde{e}_n | f_{An}, f_{Bn}; I]}. \quad (13)$$

The market clearing condition,

$$\frac{1}{2}q_{nA} + \frac{1}{2}q_{nB} = 1, \quad (14)$$

implies that the period  $n$  price must be

$$P_n = E_{n-1} + \frac{1 + \frac{s}{s+c}}{2} (a_n + \alpha_n) + \frac{1 + \frac{s}{s+c}}{2} (b_n + \beta_n) - \frac{s}{s+c} c - \sigma = E_{n-1} + \frac{1}{2} \frac{2s+c}{s+c} (a_n + b_n + \alpha_n + \beta_n) - \frac{sc}{s+c} - \sigma. \quad (15)$$

Remark A2. Assume  $P_{t+1} = E_t + \frac{1}{2} \frac{2s+c}{s+c} (a_{t+1} + b_{t+1} + \alpha_{t+1} + \beta_{t+1}) - V_{t+1}$ , where  $V_{t+1}$  is a constant that is contingent upon  $t$ . The equilibrium price at date  $t$  must satisfy

$$P_t = E_{t-1} + \frac{1}{2} \frac{2s+c}{s+c} (a_t + b_t + \alpha_t + \beta_t) - V_t, \quad (16)$$

where  $V_t = V_{t+1} + \frac{sc}{s+c} + \sigma + \frac{1}{2} \frac{(2s+c)^3}{(s+c)^2}$ .

Proof. Because of the linear pricing function and the negative exponential utility function, the expected utility of an entering investor of type  $I$  can be written as

$$- \exp \left( - \left( q_t (E_{t-1} + E[\tilde{e}_t | f_{At}, f_{Bt}; I] - V_{t+1} - P_t) - \frac{1}{2} q_t^2 \left( \sigma + s + \frac{1}{2} (c - o) \right) \right) \right), \quad (17)$$

where  $E_t = \sum_{j=1}^t e_t$ . The  $q_t$  that maximizes the expected utility is

$$q_{tI} = \frac{E_{t-1} + E[\tilde{e}_t | f_{At}, f_{Bt}; I] - V_{t+1} - P_t}{\frac{sc}{s+c} + \sigma + \frac{1}{2} \frac{(2s+c)^3}{(s+c)^2}}. \quad (18)$$

The market clearing condition,

$$\frac{1}{2}q_{tA} + \frac{1}{2}q_{tB} = 1, \quad (19)$$

implies that the equilibrium  $P_t$  satisfies

$$\begin{aligned} P_t &= E_{t-1} + \frac{1}{2} \frac{2s+c}{s+c} (a_t + b_t + \alpha_t + \beta_t) - V_{t+1} - \frac{sc}{s+c} - \sigma - \frac{1}{2} \frac{(2s+c)^3}{(s+c)^2} \\ &= E_{t-1} + \frac{1}{2} \frac{2s+c}{s+c} (a_t + b_t + \alpha_t + \beta_t) - V_t. \end{aligned} \quad (20)$$

The proof of the equilibrium price characterization is completed by taking the period  $n$  price from Remark A1 and using Remark A2 to develop the sequence of prior prices.

The proof of the equilibrium price characterization in the altered model relies on the following two remarks.

Remark A3. The equilibrium price in the period  $n$  round of trade must satisfy

$$P_n = E_{n-1} + a_n + b_n + \frac{1}{2}\alpha_n + \frac{1}{2}\beta_n - \sigma. \quad (21)$$

Proof. The beliefs about  $\tilde{e}_n$  for a type  $A$  investor prior to trade are that  $\tilde{e}_n$  is normally distributed with mean

$$E[\tilde{e}_n | \{a_t, b_t, \alpha_t, \beta_t\}; A] = a_n + \alpha_n + b_n$$

and variance

$$\text{Var}[\tilde{e}_n | \{a_t, b_t, \alpha_t, \beta_t\}; A] = \sigma.$$

Similarly, the beliefs about  $\tilde{e}_n$  for a type  $B$  investor prior to trade are that  $\tilde{e}_n$  is normally distributed with mean

$$E[\tilde{e}_n | \{a_t, b_t, \alpha_t, \beta_t\}; B] = a_n + b_n + \beta_n$$

and variance

$$\text{Var}[\tilde{e}_n | \{a_t, b_t, \alpha_t, \beta_t\}; B] = \sigma.$$

Because of the linear pricing function and the negative exponential utility function, the expected utility of a period  $n$  entering investor of type  $I$  can be written as

$$-\exp\left(-\left(q_n(E_{n-1} + E[\tilde{e}_n | \{a_t, b_t, \alpha_t, \beta_t\}; I] - P_n) - \frac{1}{2}q_n^2 \text{Var}[\tilde{e}_n | \{a_t, b_t, \alpha_t, \beta_t\}; I]\right)\right), \quad (22)$$

where  $E_{n-1} = \sum_{j=1}^{n-1} e_j$ . The value for  $q_n$  that maximizes the expected utility is

$$q_{nI} = \frac{E_{n-1} + E[\tilde{e}_n | \{a_t, b_t, \alpha_t, \beta_t\}; I] - P_n}{\text{Var}[\tilde{e}_n | \{a_t, b_t, \alpha_t, \beta_t\}; I]}. \quad (23)$$

The market clearing condition,

$$\frac{1}{2}q_{nA} + \frac{1}{2}q_{nB} = 1, \quad (24)$$

implies that the period  $n$  price must be

$$P_n = E_{n-1} + a_n + b_n + \frac{1}{2}\alpha_n + \frac{1}{2}\beta_n - \sigma. \quad (25)$$

Remark A4. Assume  $P_{t+1} = E_t + a_{t+1} + b_{t+1} + \frac{1}{2}\alpha_{t+1} + \frac{1}{2}\beta_{t+1} - V_{t+1}$ , where  $V_{t+1}$  is a constant that is

contingent upon  $t$ . The equilibrium price at date  $t$  must satisfy

$$P_t = E_{t-1} + a_t + b_t + \frac{1}{2}\alpha_t + \frac{1}{2}\beta_t - V_t, \quad (26)$$

where  $V_t = V_{t+1} + 2s + \sigma + \frac{1}{4}c - \frac{3}{4}o$ .

Proof. Because of the linear pricing function and the negative exponential utility function, the expected utility of an entering investor of type  $I$  can be written as

$$- \exp \left( - \left( q_t (E_{t-1} + E[\tilde{e}_t | \{a_t, b_t, \alpha_t, \beta_t\}; I] - V_{t+1} - P_t) - \frac{1}{2}q_t^2 \left( 2s + \sigma + \frac{1}{4}c - \frac{3}{4}o \right) \right) \right), \quad (27)$$

where  $E_t = \sum_{j=1}^t e_t$ . The  $q_t$  that maximizes the expected utility is

$$q_{tI} = \frac{E_{t-1} + E[\tilde{e}_t | \{a_t, b_t, \alpha_t, \beta_t\}; I] - V_{t+1} - P_t}{2s + \sigma + \frac{1}{4}c - \frac{3}{4}o}. \quad (28)$$

The market clearing condition,

$$\frac{1}{2}q_{tA} + \frac{1}{2}q_{tB} = 1, \quad (29)$$

implies that the equilibrium  $P_t$  satisfies

$$P_t = P_t = E_{t-1} + a_t + b_t + \frac{1}{2}\alpha_t + \frac{1}{2}\beta_t - V_{t+1} - 2s - \sigma - \frac{1}{4}c - \frac{3}{4}o. \quad (30)$$

The proof of the equilibrium price characterization is completed by taking the period  $n$  price from Remark A3 and using Remark A4 to develop the sequence of prior prices.

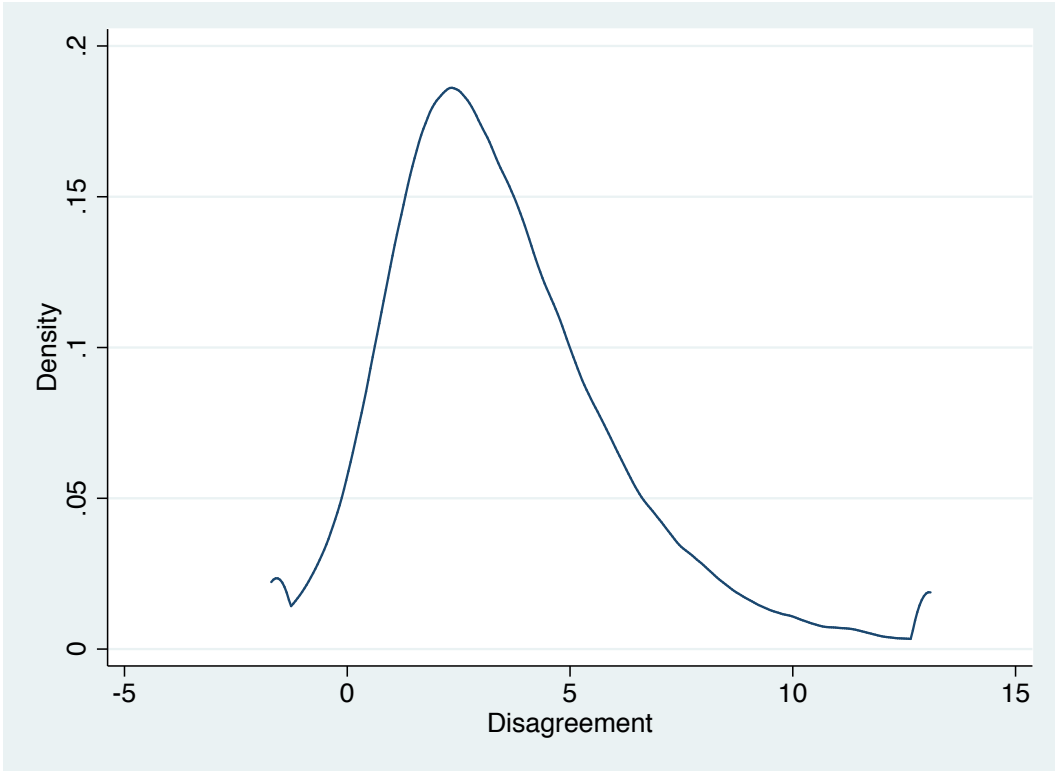


Figure 1: The Density of Disagreement

This figure plots the density of our disagree measure. To measure disagreement, we collect analyst quarterly EPS forecasts within six months before the fiscal quarter end date and regress an analyst forecast on the most recent forecast issued by a different analyst. The two analyst forecasts need to be issued by at least one week apart to allow for sufficient time for the second analyst to process information from the first analyst's forecast. Each regression needs to have at least four observations. The regression model is  $f_{it,m} = \alpha_{0,it} + \alpha_{1,it}g_{it,m} + \epsilon_{it,m}$ , where  $f_{it,m}$  denotes the  $m^{\text{th}}$  quarterly EPS forecast issued for firm  $i$  in year  $t$  and  $g_{it,m}$  denotes the most recent forecast issued by a different analyst. Disagreement in this figure is defined as  $\frac{1-\alpha_{1,it}}{se(\alpha_{1,it})}$ , as shown in equation (8).

Table 1: Summary Statistics

This table presents summary statistics. To measure disagreement, we collect analyst quarterly EPS forecasts within six months before the fiscal quarter end date and regress an analyst forecast on the most recent forecast issued by a different analyst for the same firm quarter. The two analyst forecasts need to be issued by at least one week apart to allow for sufficient time for the second analyst to process information from the first analyst's forecast. The regression is performed at the firm quarter level. Each regression needs to have at least four observations. The regression model is  $f_{it,m} = \alpha_{0,it} + \alpha_{1,it}g_{it,m} + \epsilon_{it,m}$ , where  $f_{it,m}$  denotes the  $m^{th}$  quarterly EPS forecast issued for firm  $i$  in quarter  $t$  and  $g_{it,m}$  denotes the most recent forecast issued by a different analyst. Disagreement measures are based on  $\alpha_{1,it}$  and are defined in equations (8) and (9).

Panel A: Summary statistics

VARIABLES	n	Mean	Std	5%	25%	50%	75%	95%
<i>Disagree<sup>c</sup></i>	148,840	4.216	3.281	-0.072	2.055	3.679	5.749	10.304
<i>Disagree<sup>d</sup></i>	148,840	0.754	0.454	0.000	1.000	1.000	1.000	1.000
<i>Volume</i>	148,995	0.732	0.729	0.000	0.254	0.567	0.980	2.140
<i>Dispersion</i>	148,995	0.353	0.650	0.024	0.063	0.140	0.341	1.386
<i>Spread</i>	124,316	0.185	0.271	0.019	0.051	0.101	0.195	0.652

Panel B: Disagreement by year

year	<i>Disagree<sup>c</sup></i>	<i>Disagree<sup>d</sup></i>
2003	3.992	0.730
2004	3.954	0.722
2005	3.945	0.718
2006	4.017	0.740
2007	3.984	0.728
2008	3.709	0.704
2009	4.101	0.742
2010	4.395	0.780
2011	4.268	0.763
2012	4.400	0.769
2013	4.558	0.780
2014	4.428	0.780
2015	4.420	0.774
2016	4.474	0.783
2017	4.464	0.776



Table 2: Correlation of Disagreement Measures

This table examines the relation among the disagreement measures. To measure disagreement, we collect analyst quarterly EPS forecasts within six months before the fiscal quarter end date and regress an analyst forecast on the most recent forecast issued by a different analyst for the same firm quarter. The two analyst forecasts need to be issued by at least one week apart to allow for sufficient time for the second analyst to process information from the first analyst’s forecast. The regression is performed at the firm quarter level. Each regression needs to have at least four observations. The regression model is  $f_{it,m} = \alpha_{0,it} + \alpha_{1,it}g_{it,m} + \epsilon_{it,m}$ , where  $f_{it,m}$  denotes the  $m^{th}$  quarterly EPS forecast issued for firm  $i$  in quarter  $t$  and  $g_{it,m}$  denotes the most recent forecast issued by a different analyst. Disagreement measures are based on  $\alpha_{1,it}$  and are defined in equations (8) and (9). Panel A presents univariate relation between disagreement and the other measures reflecting beliefs dispersion. We sort  $Disagree^c$  into terciles and compute the average trading volume, analyst forecast dispersion, and bid-ask spread for each tercile. Panel B presents the correlation between these variables.

Panel A: Disagreement quintiles

Disagree <sup>c</sup> Tercile	Disagree <sup>c</sup>	Disagree <sup>d</sup>	Volume	Dispersion	Spread
1	1.152	0.261	0.699	0.400	0.223
2	3.710	1.000	0.719	0.338	0.182
3	7.785	1.000	0.779	0.323	0.149
(3) -(1)	6.632***	0.739***	0.080***	-0.077***	-0.074***

Panel B: Correlation

	Disagree <sup>c</sup>	Disagree <sup>d</sup>	Volume	Dispersion	Spread
Disagree <sup>c</sup>	1.000				
Disagree <sup>d</sup>	0.602	1.000			
Volume	0.044	0.022	1.000		
Dispersion	-0.046	-0.056	0.116	1.000	
Spread	-0.100	-0.090	-0.159	0.348	1.000

Table 3: Disagreement and trading volume

This table examines the relation among the disagreement measures. To measure disagreement, we collect analyst quarterly EPS forecasts within six months before the fiscal quarter end date and regress an analyst forecast on the most recent forecast issued by a different analyst for the same firm quarter. The two analyst forecasts need to be issued by at least one week apart to allow for sufficient time for the second analyst to process information from the first analyst's forecast. The regression is performed at the firm quarter level. Each regression needs to have at least four observations. The regression model is  $f_{it,m} = \alpha_{0,it} + \alpha_{1,it}g_{it,m} + \epsilon_{it,m}$ , where  $f_{it,m}$  denotes the  $m^{th}$  quarterly EPS forecast issued for firm  $i$  in quarter  $t$  and  $g_{it,m}$  denotes the most recent forecast issued by a different analyst. Disagreement measures are based on  $\alpha_{1,it}$  and are defined in equations (8) and (9). The table reports results of the regression model form:

$$Volume_{it} = \alpha_0 + \alpha_1 Disagree_{it} + \Gamma' Controls_{it} + \epsilon_{it},$$

where  $Volume_{it}$  is the average daily volume of firm  $i$  in quarter  $t$ . The standard error is clustered at the firm level.

VARIABLES	(1) Volume	(2) Volume	(3) Volume
Disagree <sup>c</sup>	0.011*** [0.001]	0.012*** [0.001]	
Disagree <sup>d</sup>			0.059*** [0.006]
Dispersion		0.325*** [0.015]	0.326*** [0.015]
Spread		-0.766*** [0.020]	-0.770*** [0.020]
Observations	148,840	124,169	124,169
R-squared	0.018	0.128	0.127
Year FE	Yes	Yes	Yes

Table 4: Disagreement and the Cross-Section of Monthly Returns

This table examines the relation between disagreement and monthly returns. To measure disagreement, we collect analyst quarterly EPS forecasts within six months before the fiscal quarter end date and regress an analyst forecast on the most recent forecast issued by a different analyst for the same firm quarter. The two analyst forecasts need to be issued by at least one week apart to allow for sufficient time for the second analyst to process information from the first analyst's forecast. The regression is performed at the firm quarter level. Each regression needs to have at least four observations. The regression model is  $f_{it,m} = \alpha_{0,it} + \alpha_{1,it}g_{it,m} + \epsilon_{it,m}$ , where  $f_{it,m}$  denotes the  $m^{th}$  quarterly EPS forecast issued for firm  $i$  in quarter  $t$  and  $g_{it,m}$  denotes the most recent forecast issued by a different analyst. Disagreement measures are based on  $\alpha_{1,it}$  and are defined in equations (8) and (9). Panel A sorts the continuous disagreement measure,  $Disagree^c$  into terciles and compute the average monthly stock return for each tercile. Panel A also presents the average monthly return conditional on the value of the discrete disagreement measure,  $Disagree^d$ . Panels B to D double-sort the disagreement measure and three conditioning variables: size, book-to-market, and past return. Size and book-to-market are measured three months prior to the fiscal quarter end date, and the past return is the cumulative monthly stock return from six to three months prior to the fiscal year end date. All returns are expressed in percentage.

Panel A: Average return based on disagreement terciles

Disagree <sup>c</sup> Tercile	Monthly Return	Disagree <sup>d</sup>	Monthly Return
1	0.461	0	0.236
2	1.138	1	1.219
3	1.384		
(3)-(1)	0.923***	(1)-(0)	0.984***

Panel B: Average return based on size terciles and disagreement terciles

Size tercile	Disagreement tercile			(3)-(1)
	1	2	3	
1	0.394	1.252	1.611	1.217***
2	0.313	1.073	1.278	0.965***
3	0.363	0.799	1.130	0.767***

Panel C: Average return based on book-to-market terciles and disagreement terciles

BTM tercile	Disagreement tercile			(3)-(1)
	1	2	3	
1	0.443	0.796	1.041	0.598***
2	0.293	0.998	1.255	0.962***
3	0.325	1.334	1.600	1.275***

Panel D: Average return based on past return terciles and disagreement terciles

Past return tercile	Disagreement terciles			(3)-(1)
	1	2	3	
1	-0.018	1.204	1.555	1.574***
2	0.317	0.997	1.235	0.918***
3	0.795	0.925	1.120	0.325***

Table 5: Disagreement and the Cross-Section of Monthly Returns

This table regresses monthly stock returns on the contemporaneous disagreement, Fama-French three factors (market, size, and book-to-market) and the momentum factor. The regression model is:

$$R_{it}^m - Rf_t = \alpha + \beta \text{Disagree}_{it} + \beta_1 \text{MktRf}_{it} + \beta_2 \text{SMB}_{it} + \beta_3 \text{HML}_{it} + \beta_4 \text{UMD}_{it} + \eta_{it},$$

where  $\text{MktRf}_{it}$ ,  $\text{SMB}_{it}$ ,  $\text{HML}_{it}$ ,  $\text{UMD}_{it}$  are respectively the Fama-French three factors (market, size, and book-to-market) and the momentum factor, all at the monthly level. Columns (2) and (4) use the continuous measure of disagreement,  $\text{Disagree}^c$ , and columns (3) and (5) use the discrete measure of disagreement,  $\text{Disagree}^d$ . Columns (4)-(5) use the same specification as columns (1)-(3) except that we add analyst forecast dispersion and bid-ask spread as additional control variables. The standard error is clustered at the calendar time level.

VARIABLES	(1) $R^m - Rf$	(2) $R^m - Rf$	(3) $R^m - Rf$	(4) $R^m - Rf$	(5) $R^m - Rf$
Disagree <sup>c</sup>		0.088*** [0.010]		0.087*** [0.010]	
Disagree <sup>d</sup>			0.751*** [0.090]		0.757*** [0.087]
Mkt -Rf	1.106*** [0.017]	1.104*** [0.017]	1.104*** [0.017]	1.091*** [0.014]	1.091*** [0.014]
SMB	0.689*** [0.032]	0.690*** [0.032]	0.692*** [0.032]	0.772*** [0.027]	0.771*** [0.027]
HML	0.023 [0.031]	0.023 [0.031]	0.023 [0.031]	0.062*** [0.022]	0.062*** [0.022]
UMD	-0.199*** [0.025]	-0.200*** [0.025]	-0.200*** [0.025]	-0.185*** [0.025]	-0.185*** [0.025]
Dispersion				0.079 [0.251]	0.085 [0.251]
Spread				-0.813*** [0.157]	-0.812*** [0.157]
Constant	-0.079 [0.059]	-0.455*** [0.069]	-0.657*** [0.088]	-0.283*** [0.101]	-0.497*** [0.110]
Observations	442,189	441,724	441,724	368,190	368,190
R-squared	0.175	0.175	0.175	0.178	0.178

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 6: Disagreement and the Cross-Section of Monthly Returns  
Portfolio Level

This table regresses monthly portfolio returns on the contemporaneous disagreement, Fama-French three factors (market, size, and book-to-market) and the momentum factor. The regression model is:

$$R_{it}^m - R_{f_t} = \alpha + \beta_1 MktR_{f_{it}} + \beta_2 SMB_{it} + \beta_3 HML_{it} + \beta_4 UMD_{it} + \eta_{it},$$

where  $MktR_{f_{it}}$ ,  $SMB_{it}$ ,  $HML_{it}$ ,  $UMD_{it}$  are respectively the Fama-French three factors (market, size, and book-to-market) and the momentum factor, all at the monthly level. Each month, we sort stocks based on disagreement,  $Disagree^c$ , into terciles, and construct equal-weighted (column (1)) and value-weighted (column (2)) portfolios that long stocks in the highest disagreement tercile and short stocks in the lowest disagreement tercile. The monthly portfolio returns are used as the dependent variables. Robust standard errors are reported in parentheses.

VARIABLES	Equal-weighted	Value-weighted
Mkt -Rf	-0.052* [0.030]	-0.116* [0.060]
SMB	-0.140*** [0.039]	-0.126* [0.069]
HML	-0.155*** [0.056]	-0.165* [0.096]
UMD	-0.049** [0.024]	-0.062 [0.083]
Constant	0.785*** [0.087]	0.638*** [0.156]
Observations	182	182
R-squared	0.241	0.139

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 7: Disagreement and the Cross-Section of Monthly Returns  
Robustness

This table regresses monthly stock returns on the contemporaneous disagreement, Fama-French three factors (market, size, and book-to-market) and the momentum factor. The regression model is:

$$R_{it}^m - R_{ft} = \alpha + \beta \text{Disagree}_{it} + \beta_1 \text{MktRf}_{it} + \beta_2 \text{SMB}_{it} + \beta_3 \text{HML}_{it} + \beta_4 \text{UMD}_{it} + \eta_{it},$$

where  $\text{MktRf}_{it}$ ,  $\text{SMB}_{it}$ ,  $\text{HML}_{it}$ ,  $\text{UMD}_{it}$  are respectively the Fama-French three factors (market, size, and book-to-market) and the momentum factor, all at the monthly level. Column (1) requires at least 30 observations to estimate disagreement using model (7). Column (2) controls for the standard error of the coefficient estimate  $\alpha_1$  in model (7). The standard error is clustered at the calendar time level.

VARIABLES	(1) $R^m - R_f$	(2) $R^m - R_f$
Disagree <sup>c</sup>	0.098*** [0.016]	0.105*** [0.012]
Disagree <sup>raw</sup>		
Mkt -Rf	1.120*** [0.028]	1.104*** [0.017]
SMB	0.451*** [0.055]	0.691*** [0.032]
HML	0.009 [0.048]	0.022 [0.031]
UMD	-0.249*** [0.024]	-0.201*** [0.025]
SE( $\alpha_1$ )		0.331*** [0.103]
Constant	-0.751*** [0.116]	-0.645*** [0.099]
Observations	105,109	441,724
R-squared	0.208	0.175

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 8: Disagreement and the Cross-Section of Monthly Returns  
Alternative Measures

This table regresses monthly stock returns on the contemporaneous disagreement, Fama-French three factors (market, size, and book-to-market) and the momentum factor. The regression model is:

$$R_{it}^m - Rf_t = \alpha + \beta \text{Disagree}_{it} + \beta_1 \text{MktRf}_{it} + \beta_2 \text{SMB}_{it} + \beta_3 \text{HML}_{it} + \beta_4 \text{UMD}_{it} + \eta_{it},$$

where  $\text{MktRf}_{it}$ ,  $\text{SMB}_{it}$ ,  $\text{HML}_{it}$ ,  $\text{UMD}_{it}$  are respectively the Fama-French three factors (market, size, and book-to-market) and the momentum factor, all at the monthly level. To measure disagreement, we collect analyst annual EPS forecasts within 12 months before the fiscal quarter end date and regress an analyst forecast on the most recent forecast issued by a different analyst for the same firm year. The two analyst forecasts need to be issued by at least one week apart to allow for sufficient time for the second analyst to process information from the first analyst's forecast. The regression is performed at the firm year level. Each regression needs to have at least four observations. The regression model is  $f_{it,m} = \alpha_{0,it} + \alpha_{1,it}g_{it,m} + \epsilon_{it,m}$ , where  $f_{it,m}$  denotes the  $m^{\text{th}}$  annual EPS forecast issued for firm  $i$  in year  $t$  and  $g_{it,m}$  denotes the most recent forecast issued by a different analyst. Disagreement measures are based on  $\alpha_{1,it}$  and are defined in equations (8) and (9). The standard error is clustered at the calendar time level.

VARIABLES	(1) $R^m - Rf$	(2) $R^m - Rf$
Disagree <sup>c</sup>	0.029*** [0.009]	
Disagree <sup>d</sup>		0.609*** [0.098]
Mkt -Rf	1.105*** [0.018]	1.105*** [0.017]
SMB	0.693*** [0.034]	0.693*** [0.034]
HML	0.021 [0.031]	0.021 [0.031]
UMD	-0.199*** [0.027]	-0.198*** [0.027]
Constant	-0.245*** [0.075]	-0.603*** [0.096]
Observations	402,128	402,128
R-squared	0.187	0.187

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1