Liquidity and Mispricing: Decomposing Disagreement

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Abstract

This paper investigates how disagreement, asset returns and liquidity are affected by three types of heterogeneity in information environment: asymmetric information (AI), idiosyncratic noises (IN), and different opinion (DO). Using a market microstructure model, we incorporate analyst forecasts into endogenous informed trading. This framework allows us to empirically decompose analyst disagreement into these three components. Our model shows that AI increases both illiquidity and pricing error; IN reduces illiquidity but increases pricing error; DO reduces both illiquidity and pricing error. Empirical results support these predictions. Specifically, we find that stocks with high AI or high IN tend to be overpriced, and stocks with low DO tend to be underpriced.

JEL classification: G11, G12, G14

Keywords: disagreement, liquidity, pricing error, analyst forecasts

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In the last decades, many advances have been made in studying the nature of trades, including psychological bias and heterogeneous beliefs. One of the major preoccupations has been investigating the nature of information environment. For example, a trade could be initiated by agents' discrepancy in their information, noises, or opinions.[1] Knowing the composition of disagreement helps researchers to draw conclusions from the relation between disagreement and stock returns or liquidity. For example, a high level disagreement could imply high level asymmetric information (AI), idiosyncratic noises (IN), or different opinion (DO) among agents, if it was dominated by either its information, noise, or opinion component, respectively.[2]

The heterogeneous posterior beliefs among rational Bayesians could be constructed by all three components rather than a single one, e.g., Varian (1989), Barron, Kim, Lim, and Stevens (1998), and Hong and Stein (2007). It means that the disagreement's effect is its components' aggregated effect, i.e., either offset or enhance with each other. Therefore, making causal inference from level of proxies of disagreement (e.g., trading volume, stock turnover, and analyst disagreement) to variable of interest could be mislead unless we know the composition of disagreement. In view of the role of AI, IN, and DO much of the finance and accounting literature, it is surprising that a device has been developed for decomposing disagreement into its components empirically. Such results have, unfortunately, been out of reach because there are no clear measures of information, noise, and opinion components.

This paper studies how these basic components in the information environment generate disagreement among analysts and investors respectively, and then affect stock returns and liquidity in different ways. Specifically, we develop a theoretical model to show how pricing error and liquidity are affected by AI, IN, and DO among investors in a unified framework. Based on this model, we provide an empirical device to decompose analyst disagreement into three basic components. This device allows us to interpret the levels of information, noise, and opinion components as the level of AI, IN, and DO among traders, respectively.[3]

[1] Disagreement and heterogeneous beliefs are used interchangeably in this paper.

[2] See Diether, Malloy, and Scherbina (2002); Zhang (2006b); Sadka and Scherbina (2007); Berkman, Dimitrov, Jain, Koch, and Tice (2009); Garfinkel (2009); Cen, Wei, and Yang (2016).

[3] As an example of how these three components generate disagreement and initiate trades, investors i and j become aware of a piece of unpredicted good news about firm XYZ that indicates its financial outlook is positive. If these two investors have identical information, noise, and opinion, both of them want to buy firm XYZ's stock and they push the price upward to reflect its fundamental value. Both investor i and j will agree with that price and trade no more. Next, we relax the assumption of homogeneity in the following three cases and show that investor i would likely to short sell or sell his portion to j at the current price or, perhaps, a lower price according to their disagreement. This simple example shows the difficulty that drawing causality from trading activity to investors' heterogeneity in their information environment. First, if investor i is more pessimistic than j, it implies there is DO between them. Although there is no news, DO could still exist because the distribution of the current stock price is also common knowledge, as well as public information, to disagree. Second, if i is the only investor observing a noise and believing it is a bad

Different types of heterogeneity in information environment influences stock prices and liquidity in different ways. First, opinion component (i.e., a prior probability distribution) is related to DO in the sense that agents possess subjective prior distribution. DO could increase liquidity but have no impact on prices, as the two could offset each other (Varian, 1989; Kandel and Pearson, 1995). Second, noise component (i.e., different values of the likelihood function unrelated to asset value) is related to IN in the sense that agents observe value irrelevant signal based on noise as if it were information (Black, 1986) or their private interests, such as heterogeneous investment opportunities (Wang, 1994) and heterogeneous liquidity preferences (Mendelson and Tunca, 2004). IN could increase both liquidity and pricing errors since the noise trades prevent prices from converging to their fundamental value (Kyle, 1985; Wang, 1994). Third, information component (i.e., different values of the likelihood function related to asset value) is related to AI in the sense that one party has more or better information regarding common interests than the other (Kyle, 1985; Hong and Stein, 1999). AI could reduce liquidity but increase pricing errors since an illiquid stock could be too expensive to arbitrage (Kyle, 1985).

We speak to an important string of literature about investors' information environment which studies the relationship between analyst forecasts and stock returns or liquidity.[4] These studies assume that investors and analysts share some common components, such as information, noise, and opinion components, in their information environment. Therefore, analyst forecast dispersion (i.e., the cross-sectional standard deviation of analyst forecasts) is used to be a common empirical proxy of investors' disagreement.[5] However, without a unified framework to link analysts and investors' information environment, which should include information ,noise, and opinion components, the level of analyst disagreement could be interpreted as either DO (Diether et al., 2002; Berkman et al., 2009; Garfinkel, 2009; Cen et al., 2016), IN (Zhang, 2006b), or AI (Sadka and Scherbina, 2007).

Additionally, this article complements the literature on the impacts of AI, IN, and DO on stock returns and liquidity by addressing disagreement among agents. A high level of

news about XYZ, it implies there is IN among them. Third, if investor i can access an insider of XYZ and learns some negative news being withheld by the firm's manager, it implies there is AI among them.

[4]There is a considerable body of literature on sell-side analysts' role as information intermediaries of investors. For example, empirical evidence suggests that information about a firm's future earnings prospects is important to investors. Griffin (1976), Givoly and Lakonishok (1979, 1980), and Imhoff Jr and Lobo (1984) report on statistically significant abnormal stock returns before, during, and after the announcement of analysts' revised earnings forecasts. Moreover, analysts work harder and investors rely more heavily on analysts' forecasts during market downturns (Loh and Stulz, 2018). Jegadeesh, Kim, Krische, and Lee (2004) show that quarterly change in sell-side analysts' consensus recommendations is a robust return predictor. Kelly and Ljungqvist (2012) find stock prices and uninformed demand fall as asymmetry increases after the exogenous reduction of analyst coverage (brokerage closure).

[5]See Diether et al. (2002); Zhang (2006b); Sadka and Scherbina (2007); Berkman et al. (2009); Garfinkel (2009); Cen et al. (2016).

disagreement could reflect the heterogeneity of information, noise, and opinion component simultaneously. First, a high level of disagreement dominated by a large information component implies gradual information (Hong and Stein, 1999), which generates AI, reduces liquidity (Kyle, 1985), and introduces error into prices (Sadka and Scherbina, 2007). Second, a high level of disagreement dominated by a large noise component (Zhang, 2006a,b), which generates IN, trading volume, and pricing errors when informed traders and market makers are risk-neutral (Kyle, 1985; Chordia, Huh, and Subrahmanyam, 2009). Pricing errors generated by the noise-component can also be related to the noise traders' risk, which prevents the price from converging to its fundamental value when informed traders are risk-averse (De Long, Shleifer, and Summers, 1990a; De Long, Shleifer, Summers, and Waldmann, 1990b). Third, a high level of disagreement dominated by a large opinion component generates DO and trading volume but without moving the price and indicates unbiased market prices (Diamond and Verrecchia, 1987; Varian, 1989; Kandel and Pearson, 1995). Additionally, the DO on both the prior mean and variance can lead an agent to be overconfident and updates more information than opinion (Van den Steen, 2011) on his or her belief, which implies that the stock price could be more efficient since the traders' beliefs are based on more informative evidence.

We speak to a long-standing challenge of models of heterogeneous investors, which is to identify the nature of the information environment among investors empirically. In empirical side, one could either construct measures of AI, IN, and DO respectively or decompose disagreement into components. The former might only concern one characteristic each time, but the latter concerns three characteristics simultaneously. Therefore, the latter could mitigate the potential correlation between these components. This empirical issue is stated by Miller (1977); it is implausible that although the future is very uncertain (high level of AI), and forecasts are very difficult to make (high level of IN), all investors possess identical opinion of the return and risk (low level of DO) of every security. By incorporating information, noise, and opinion components into a unified framework, we provides an important empirical device to analyzing the nature of information environment. This devise not only decompose analyst disagreement into three components but also measures the level of AI, IN, and DO among investors empirically.

First, we show that how to differentiate information, noise, and opinion components from each other simultaneously and then decompose analyst disagreement empirically. More detail about decomposing analyst disagreement is discussed in Section II. Our results suggest that it is important to decompose disagreement when examine the relationship between disagreement and stock returns or liquidity in a real economy. It is because the effects of these three components could enhance or offset with each other differently.[6] Second, we interpret AI, IN, and DO from the components of analyst disagreement. We accomplish this goal by proposing a hybrid model of analyst disagreement and informed trading (ADIT), which modifies Kyle's (1985) framework. By applying this decomposing device, we find that consistent empirical impacts from AI, IN, and DO to stock returns and liquidity. This decomposing device generates monthly measures of AI, IN, and DO among traders by using commonly used databases, such as CRSP, Compustat, and I/B/E/S. Therefore, our analyses do not need to analyze intraday data or restrict the analysis to public announcements.[7]

The ADIT model shows that the transaction price and liquidity of an asset will reflect the information, noise, and opinion components of analyst disagreement, when a trade is initiated based on AI, IN, and DO among traders and if an informed trader accesses information advantage from analysts. In this model, an informed trader fails to maximize his or her profits and the equilibrium cannot exist if either DO or IN is unbounded. It is because that the informed trader recognizes his or her information source provides little information. Specifically, in equilibrium, we find that an increase in the information component increases AI between traders, which dries up liquidity and then prevents the price from converging toward its fundamental value. An increase in the noise component increases IN between traders, brings more liquidity, and introduces error into stock prices. Finally, an increase in the opinion component increases DO between traders and liquidity. Also, analysts and traders with higher opinion component put more weight on evidence than opinion. Therefore, an increase in the opinion component mitigates error in stock prices. We discuss ADIT model in depth in Section I.

We bridge the gap between Miller's (1977) price optimism model and empirical find-

[6]For example, when both information and opinion components are high, their impacts on pricing error (or liquidity) offset with each other. When both information an noise components are high, their impacts on pricing error enhance with each other but their impacts on liquidity offset with each other.

[7]Easley, Hvidkjaer, and O'Hara (2002) propose an empirical measure of the probability of informed trading (PIN), which is related to AI, given the assumption of risk neutrality and a common prior among traders. Back, Crotty, and Li (2018) propose a hybrid model of PIN and the Kyle's (1985) framework and demonstrate the theoretical and empirical relationship between PIN and Kyle's lambda. Moreover, by relaxing the assumption of risk neutrality of market makers, they could widen the bid-ask spread according to the inventory risk (related to IN), even without AI. Huang and Stoll (1997) provide a method for identifying three components of the spread: order processing, AI, and inventory holding cost (related to IN). Madhavan, Richardson, and Roomans (1997) estimate four parameters governing the behavior of transaction prices and quotes: AI, the cost of supplying liquidity (related to IN), the probability a transaction will take place inside the spread, and the autocorrelation of the order flow. Sadka (2006) decomposes firm-level liquidity into permanent and transitory price effects, which are related to AI and IN, respectively. Kandel and Pearson (1995) demonstrate that economically and statistically significant positive abnormal volumes are associated with quarterly earnings announcements, even when prices do not change in response to announcements. They argue that this finding is due to DO instead of AI or other alternative explanations. Berkman et al. (2009); Bamber, Barron, and Stober (1997) identify the dynamics of DO around earnings announcement days. Garfinkel (2009) proposes an empirical DO measure by using intraday transaction data.

ings. Miller suggests that when the level of risk, AI, IN, and DO go together, disagreement generates upward bias in prices because short-sale costs prevent pessimists from trading as aggressively as optimists. Specifically, our results help to explain two interesting but unexplained results reported by previous studies. First, under Miller's idea, Sadka and Scherbina (2007) suggest that AI can generate overpricing by increasing disagreement, drying up liquidity and raising the transaction cost. However, they also point out there is a J-shaped relationship between analyst disagreement and price impact.[8] We suggest that the puzzling combination of a slightly higher price impact and a low level of analyst disagreement (Sadka and Scherbina, 2007) could be driven by the low level of the noise and opinion components. Second, under Miller's model, a stock with low disagreement should not be underpriced since the short-sale constraint would not stop arbitrage from buying the undervalued stocks. However, there are puzzling underpricing phenomena of low-disagreement stocks, which are noted by Diether et al. (2002), Sadka and Scherbina (2007), and Berkman et al. (2009). Atmaz and Basak (2018) show that belief dispersion decreases the mean return for optimistic views. Our result suggests that this underpricing is related to the low opinion component rather than other components.[9]

Finally, we add to the literature focused on the use of analyst forecasts to infer characteristics of traders' information environments (Barry and Jennings, 1992; Abarbanell, Lanen, and Verrecchia, 1995; Barron et al., 1998). In their model, Barron et al. (1998) demonstrate how uncertainty and consensus result in forecast errors and analyst disagreement.[10] In contrast to Barron et al. (1998), we focus on how AI, IN, and DO among traders result in components of analyst disagreement.

The remainder of this article is organized as follows. In section I, we outline our model and describe how analyst disagreement, pricing errors, and liquidity are affected by AI, IN, and DO as their corresponding components. Section II describes the methodology for decomposing analyst disagreement into three components: information, opinion, and noise components. In section III, we show how AI, IN, and DO can be inferred among traders from these disagreement components by examining the influences of disagreement components on stock returns and liquidity. Section IV presents the robustness check methodology and results, and Section V presents the concluding remarks.

[8] There is a declining and rising pattern of a net increment of price impact when analyst disagreement increases.

[9] Our model only answers the question indirectly by showing that a low opinion component increases pricing errors without specifying a downward or upward price direction.

[10] In Barron et al. (1998)) definition, the term uncertainty refers to the expected squared error in individual forecasts aggregated (or averaged) across analysts and consensus refers to the degree to which analysts share a common belief.

I. The ADIT Model

The ADIT model is a hybrid of the analyst disagreement and informed trading model. There are two dates, 0 and 1. The asset is traded with asymmetric information, idiosyncratic noise, and different priors at date 0, and asset value $\tilde{\nu}$ is realized at date 1. There are N analysts and three types of traders: an informed trader, liquidity traders, and market makers. Additionally, there are two types of bias in the agents' beliefs, the noisy subjective prior they possess and the noisy signal they observe, which generate DO and IN among agents, respectively. This model extends Kyle's (1985) framework, incorporates the DO of the sort studied by Varian (1989) and Wang (1998), and incorporates the DI of the sort studied by Kim and Verrecchia (1991) and Chordia et al. (2009).

The different prior or opinion (i.e., DO) is defined as follows. Market makers possess the correct prior mean, $\bar{\nu}$, and variance, σ_ν^2, but analysts and informed trader possess noisy subjective priors. Specifically, the nth analyst possesses a noisy prior mean and variance with his or her subjective opinion, where $E_n[\tilde{\nu}] = \bar{\nu}_n, n = 1, 2, ..., N$ and $Var_n[\tilde{\nu}] = \eta_A \sigma_\nu^2$. Similarly, there are $E_I[\tilde{\nu}] = \bar{\nu}_I$ and $Var_I[\tilde{\nu}] = \eta_I \sigma_\nu^2$ for the informed trader. Finally, to simplify the computation, we assume the informed trader and analysts construct their prior by possessing the same source but with different biases on the mean, which means $\eta = \eta_A = \eta_I$.[11] In this model, we denote η as the level of DO among traders and the opinion component of analyst disagreement. [12]

Asymmetric information (AI) and idiosyncratic noise (IN) are defined as follows. There are noisy signals observed differently by various agents. The nth analyst observes the asset value $\tilde{\nu}$ with idiosyncratic noise $\tilde{\epsilon}_n \sim N(0, \sigma_\epsilon^2)$. Based on the Bayesian rule, the nth analysts generate their best forecast $\tilde{s}_n$ about $\tilde{\nu}$ based on their subjective opinion and available information. Before trade date 0, only a risk-neutral informed trader can access all $\tilde{s}_n$, and we assume he or she takes the average of all forecasts of analysts, $\tilde{S} \overset{def}{=} \frac{1}{N}\sum_{n=1}^{N} \tilde{s}_n$, as his or her private signal about $\tilde{\nu}$. After observing $\tilde{S}$, the informed trader submits a market order $\tilde{x}$. There are also liquidity trades, who are represented by a random variable $\tilde{z}$ that is normally distributed, $\tilde{z} \sim N(0, \sigma_z^2)$. All the $\tilde{\nu}$, $\tilde{\epsilon_n}$ and $\tilde{z}$ are assumed to be mutually independent. In this model, we denote σ_ν^2 as the level of AI among traders and the information component of analyst disagreement and σ_ϵ^2 as the level of IN among traders and the noise component of analyst disagreement.

[11] This assumption is based on the reasoning that the DO on mean and variance among agents share similar characteristics. The variance of the sample mean of a random variable is an increasing function of the variance of the random variable. For more details on the similarity of characteristics between different opinions on mean and variance, see Van den Steen (2011).

[12] We assume that η is larger than 1 to represent an agent possessing a noisier prior distribution than the market makers.

Market makers observe $\tilde{y} \stackrel{def}{=} \tilde{x} + \tilde{z}$. This is the aggregate order, and all trades take place at the same price, which is the price set by market makers after observing $\tilde{y}$. Using a risk-free asset as numeraire and assuming market makers are risk-neutral and compete in a Bertrand fashion to fill the aggregate order, we denote the equilibrium price by $p(\tilde{y})$.

A. *Equilibrium*

An equilibrium of this model is an informed order $\tilde{x}$ depending on $\tilde{S}$ and a price function p satisfying

$$p(\tilde{y}) = E[\tilde{\nu}|\tilde{y}], \tag{1}$$

$$\tilde{x} \in argmax_x \; E_I[x(\tilde{\nu} - p(x + \tilde{z}))|\tilde{S}]. \tag{2}$$

The first condition states that the price equals the expected asset value conditional on the information in the aggregate order. The second condition states that the informed trader maximizes his or her conditional expected gain from trade, understanding that the order affects the price.

An equilibrium is said to be linear if there are constants δ, λ, α and β such that $p(y) = \delta + \lambda y$ and $\tilde{x} = \alpha + \beta\tilde{S}$. There is a unique equilibrium given by

$$\delta = \bar{\nu}(2 - \rho_I^2) + \bar{\nu}_I(1 - \rho_I^2), \tag{3}$$

$$\lambda = \frac{1}{2}\frac{\sigma_\nu}{\sigma_z}\sqrt{\rho_I^2\Big(1 - \frac{(\eta_I - 1)\sigma_\epsilon^2}{N\eta_I\sigma_\nu^2 + \sigma_\epsilon^2}\Big)}, \tag{4}$$

$$\alpha = \frac{-1}{2\lambda}\Big[\delta + \frac{\sum_{n=1}^N \bar{\nu}_n}{N}\frac{\rho_I^2(1 - \rho_A^2)}{\rho_A^2} - 2\bar{\nu}_I(1 - \rho_I^2)\Big], \tag{5}$$

$$\beta = \frac{1}{2\lambda}\frac{\rho_I^2}{\rho_A^2}, \tag{6}$$

where

$$\rho_I^2 = \frac{N\eta_I\sigma_\nu^2}{N\eta_I\sigma_\nu^2 + \sigma_\epsilon^2} \quad \text{and} \quad \rho_A^2 = \frac{\eta_A\sigma_\nu^2}{\eta_A\sigma_\nu^2 + \sigma_\epsilon^2}. \tag{7}$$

We verify that this is the unique linear equilibrium at the Appendix A.

B. *Analysis*

According to our assumption that informed trader and analysts possess the same subjective prior variance, we may drop the agent subscripts of η for the following analysis.

THEOREM 1: *There is an equilibrium if both the IN (σ_ϵ^2) and DO (η) among traders are not very high simultaneously, in the sense that*

$$\Big(\frac{\eta-2}{\eta}\Big)\frac{\sigma_\epsilon^2}{N} < \sigma_\nu^2. \tag{8}$$

The intuition of Theorem 1 is that these two parameters, η and σ_ϵ^2, provide a camouflage effect as liquidity trades that absorb the information advantage of informed trader. Therefore, in the extreme case, when an informed trader possesses a very noisy prior and observes a very noisy signal, he or she could fail to make profits and trade like a liquidity or noise trader.

Analyst credibility, C_A, is defined as the ratio of the subjective prior variance to the idiosyncratic noise variance and can be thought of as a measure of credibility, where

$$C_A = \frac{\eta\sigma_\nu^2}{\sigma_\epsilon^2}. \tag{9}$$

Credible analysts give greater weight to the evidence than their own opinion; therefore, the ratio C_A should be larger than 1.

In defining analyst disagreement, we follow Barron et al. (1998) and define observed dispersion in forecasts, denoted by d, as the sample variance of the $\tilde{s}_n$:

$$d = \frac{1}{N-1}\sum_{n=1}^{N}(\tilde{s}_n - \tilde{S})^2. \tag{10}$$

The sample variance, d, is a random variable prior to the observation of forecasts. Analyst disagreement is defined as a non-random dispersion measure denoted by D, which is simply the unconditional expectation of d added to the sample variance of the analyst's opinion:

$$D = \frac{1}{N-1}\sum_{n=1}^{N} Var(\tilde{s}_n - \tilde{S}) = \rho_A^4\sigma_\epsilon^2 = \Big(\frac{\eta\sigma_\nu^2}{\eta\sigma_\nu^2+\sigma_\epsilon^2}\Big)^2\sigma_\epsilon^2. \tag{11}$$

We provide further details about the definition of D in Appendix B.

LEMMA 1: *(a) Analyst disagreement increases with the information and opinion component as AI (σ_ν^2) and DO (η) among traders, where*

$$\frac{\partial D}{\partial \sigma_\nu^2} > 0, \frac{\partial D}{\partial \eta} > 0. \tag{12}$$

(b) Analyst disagreement increases with the noise component as IN (σ_ϵ^2) among traders if

and only if the analysts are credible; otherwise, the relationship is the opposite, where

$$\frac{\partial D}{\partial \sigma_\epsilon^2}\begin{cases} > 0, & \textit{if } C_A > 1 \\ < 0, & \textit{otherwise} \end{cases}. \tag{13}$$

The intuition is that analysts disagree more when they possess a noisier subjective prior or the asset value is more volatile. Moreover, credible analysts disagree more when they observe a noisier signal; however, in contrast, non-credible analysts disagree more when they observe a less noisy signal. Specifically, the idiosyncratic noise that analysts observe has two opposite effects on D. One effect increases disagreement through its variance, and another decreases disagreement by mitigating the positive effect of subjective opinion on a prior. Surprisingly, analyst disagreement, D, and analyst credibility increase together in two cases: when there is a noisier subjective prior or when there are less noisy signals and analysts are non-credible.

The pricing error of an asset is defined as an inverse measure of price efficiency and is the variance $\tilde{\nu}$ conditional on $\tilde{y}$.

$$Var(\tilde{\nu}|y) = (1 - \frac{\rho_I^2}{2})\sigma_\nu^2 = \Big(\frac{N\eta\sigma_\nu^2 + 2\sigma_\epsilon^2}{N\eta\sigma_\nu^2 + \sigma_\epsilon^2}\Big)\sigma_\nu^2. \tag{14}$$

The variance of $\tilde{\nu}$ measures the ex-ante informational advantage of the informed trader. For example, if σ_ν^2 is large, then informed trader would frequently has an important informational advantage in the sense that their estimate $\tilde{\nu}$ of the asset value is quite far from the value $\tilde{\nu}$ perceived ex-ante by market makers. Moreover, a more credible informed trader, who possesses larger η or observes smaller σ_ϵ^2, reveal more information to his or her order. Thus, the level of pricing errors depends positively on σ_ν^2 and σ_ϵ^2 but negatively on η.

THEOREM 2: *(a) The price impact increases with AI (σ_ν^2) as the information component but decreases with IN (σ_ϵ^2) and DO (η) as the noise and opinion components, where*

$$\frac{\partial \lambda}{\partial \sigma_\nu^2} > 0,\ \frac{\partial \lambda}{\partial \sigma_\epsilon^2} < 0,\ \frac{\partial \lambda}{\partial \eta} < 0. \tag{15}$$

(b) Pricing errors increase with AI (σ_ν^2) and IN (σ_ϵ^2) as the information and noise components but decreases with DO (η) as the opinion component, where

$$\frac{\partial\ var(\tilde{\nu}|y)}{\partial \sigma_\nu^2} > 0,\ \frac{\partial\ var(\tilde{\nu}|y)}{\partial \sigma_\epsilon^2} > 0,\ \frac{\partial\ var(\tilde{\nu}|y)}{\partial \eta} < 0. \tag{16}$$

The intuition is that when an asset's value is more volatile, the AI among traders and the information component of analyst disagreement are higher. The informed trader trades less aggressively since the high level of AI decreases liquidity and increases trading costs. Therefore, the market makers quote a less efficient price with a higher price impact when AI is high. Next, when analysts and informed traders observe noisier signals, the IN among traders and the noise component of analyst disagreement are higher. A higher IN level reduces the price impact since it offers a camouflage effect that absorbs the informed trader's information advantage. Different from AI and DO, both the informed trader and analysts give less weight on their signals; the market makers quote a less efficient price but with a lower price impact when IN is high. Finally, when analysts and informed traders possess a noisier subjective prior, the DO among traders and the opinion component of analyst disagreement are higher. A higher level of DO reduces the impact on price since it offers a camouflage effect that hides the informed trader's information advantage. Different from AI and IN, both the informed trader and analysts give less weight to their opinions; the market makers quote prices with a lower price impact and smaller errors when DO is high.

The characteristics of stocks with high analyst disagreement can be summarized as follows: (1) when the information component is high, AI among traders tends to be higher, and the stock tends to be highly illiquid and mispriced; (2) when the noise component is high, DI among traders tends to be higher, and the stock tends to be highly liquid and mispriced; (3) when the opinion component is high, DO among traders tends to be higher, and the stock tends to be highly liquid but less mispriced. Thus, the aggregated influence of analyst disagreement on both the unsigned pricing errors and the price impact could be nonlinear. Moreover, these nonlinear relationships are closely related to two interesting empirical findings. First, there is a J-shape relationship between price impact and analyst disagreement (Sadka and Scherbina, 2007) because a high price impact coincides with either a low noise or opinion component or a high information component. Second, there are mispricing phenomena when analyst disagreement is either low or high (Diether et al., 2002; Sadka and Scherbina, 2007; Berkman et al., 2009) because the stock has either a high information, high noise, or low opinion component. Atmaz and Basak (2018) suggest a negative dispersion-mean return relation when investors are relatively optimistic and a positive relation otherwise.

C. Empirical Research Questions

Our empirical research question is mainly concerned with how AI, IN, and DO among traders can be inferred from the information component (σ_ν^2), noise component (σ_ϵ^2), and opinion component (η) of analyst disagreement. Our theoretical predictions are summarized as follows. First, if disagreement is driven by AI, we should observe a high price impact and strong mispricing. It is because the information component increases disagreement and decreases liquidity; considering the price impact as a limit to arbitrage, the informed trader trades less aggressively and mispricing is generated. Second, if disagreement is driven by IN, we should observe a low price impact and strong mispricing. The noise component increases disagreement (i.e., when analysts are credible) and increases liquidity. Unlike with the information component, the less informative informed trader fails to drive a price to its fundamental value even though the price impact is low. Third, if disagreement is driven by DO, we should observe a low price impact and little mispricing; we also expect to observe a high price impact and strong mispricing when disagreement is low. The opinion component increases disagreement and liquidity. A more divergent opinion makes informed trader updates more private information on his or her belief to eliminate pricing errors. However, less divergent opinions forces informed trader to update and reveal little private information related to the stock price.

To answer our empirical research question, we show consistent empirical relationships between stock returns (or liquidity) and disagreement components, as suggested by Theorem 2. First, we find a significant and positive liquidity differential between high and low information component portfolios and a significant and negative liquidity differential between high and low opinion and noise component portfolios. Second, larger pricing errors coincide with either high information, high noise, or the low opinion component.[13] Table 1 shows the theoretical (Panel A) and empirical (Panel B) predictions of analyst disagreement, price impact, and pricing errors from the disagreement components. In Appendix C, we show the empirical distribution given high or low levels of disagreement components. The overview of the sample distribution confirms the general disagreement component's effects on analyst disagreement and price impact in Table 1 .

[Place Table 1 about here]

II. Decomposing Analyst Disagreement

In this section, we provide a theory-based device for decomposing analyst disagreement empirically. At beginning, we explain how analyst disagreement can be decomposed according to the ADIT model. Next, we describe the data and the empirical relationships between our variables of interest. In particular, we show the time-series average periodic cross-sectional correlation between analyst disagreement, the candidate disagreement com-

[13]Our theorem suggests only the size of the pricing error rather than suggesting the direction of mispricing should be underpricing or overpricing.

ponents, and liquidity measures. This procedure helps us to mitigate some collinearity issues between different types of disagreement components. Finally, we test the determinants of analyst disagreement empirically. Specifically, we regress analyst disagreement on the variables related to disagreement components and decompose it into σ_ν^2, η and σ_ϵ^2.

A. *How to Decompose Analyst Disagreement?*

The major difficulty in decomposing analyst disagreement is that its components are unobservable. Additionally, as pointed out in Lemma 1, the influence of disagreement components on analyst disagreement depends on the credibility of analysts. Equation (11) in below suggests that analyst disagreement, D, is an increasing function of ρ_A^2 and σ_ϵ^2. However, both of them are unobservable. Fortunately, our model suggests that ρ_A^2 equals the covariance of asset value, $\tilde{\nu}$, and average analyst forecast, $\tilde{S}$, scaled by the variance of asset value, σ_ν^2, where

$$\rho_A^2 = \frac{cov(\tilde{\nu}, \tilde{S})}{\sigma_\nu^2}. \tag{17}$$

Equivalently, the analyst-disagreement, D, is

$$D = (|cov(\tilde{\nu}, \tilde{S})|)^2 \Big(\frac{\sigma_\epsilon^2}{\sigma_\nu^4}\Big). \tag{18}$$

When compared to Equation (11), Equation (18) has two advantages for decomposing analyst disagreement using $|cov(\tilde{\nu}, \tilde{S})|$, which is denoted as $|EAC|$. First, it can be related to the covariance of earnings and average analyst forecast, which are observable. Second, the relationship between $|EAC|$ and disagreement components is simpler than the relationship between analyst disagreement and its components since the latter one is conditioned on unobservable analyst credibility. Specifically, $|EAC|$ increases with η and σ_ν^2 and decreases with σ_ϵ^2.

The natural log of analyst disagreement, D, is a linear combination of $ln(|EAC|)$, while $ln(\sigma_\epsilon^2)$ is the variance of idiosyncratic noise, IN, or the noise component, and $ln(\sigma_\nu^4)$ is the AI or information component, where

$$ln(D) = b_1 * ln(|cov(\tilde{\nu}, \tilde{S})|) + b_2 * ln(\sigma_\epsilon^2) + b_3 * ln(\sigma_\nu^2). \tag{19}$$

Therefore, the decomposition of analyst disagreement can be performed by regressing the $|EAC|$, information, and noise components. Moreover, the decomposition can be done with $|EAC|$ and only one of the information or noise components if $|EAC|$ is as good a proxy for η as the opinion component. This is because the residual will capture the remainder of regression.

The major variables we use are described as follows. The proxy for the degree of analyst disagreement is the standard deviation of analyst forecasts divided by the mean forecast (Diether et al., 2002) and is denoted D. The information component is related to $EVOL$, as earnings volatility. However, the information component could be related to the characteristic of risk and affect our conclusions. For example, the size effect suggests that small firms generate higher returns and are more illiquid than large firms. Therefore, we further control several common proxies for risk when decomposing analyst disagreement. Intuitively, there are four common variables: β_{CAPM} as the β of CAPM asset pricing model; MV as the market capitalization of stocks, which captures risk related to market capitalization; BM as the book-to-market ratio, which captures risk related to the fundamentals of the firm; and $SIGMA$ as the stock return volatility.

The opinion component is related to $|EAC|$, as the absolute value of covariance between unexpected earnings and the unexpected mean analyst forecast, to its drift-adjusted version (denoted $|EAC_D|$), and to its orthogonalized portion with $EVOL$ (denoted EAC_R).[14] The $|EAC|$ implies the informativeness of evidence observed by analysts since it is the absolute value of co-movement between earnings and forecasts.[15] To examine whether $|EAC|$ is a result of the opinion component rather than the other components, we apply two analyses. First, we use correlation and portfolio analysis to show that high $|EAC|$ stocks tend to be more liquid (i.e., a lower price impact), which clearly rejects the possibility of $|EAC|$ being a measure of either the information component or an inverse of the noise component. Second, we isolate the information component from $|EAC|$ by regressing it on earnings volatility and find its negative effect on price impact becomes stronger.

The noise component could be related to the remaining portion of D (denoted as D_{R1} or D_{R2}) and the orthogonalized portion of COV with MV and BM (denoted COV_R), according to Diether et al. (2002).[16] COV is the number of analyst coverage in I/B/E/S. Finally, we choose Amihud's (2002) illiquidity measure, denoted λ as a proxy for the price impact.

[14] $|EAC|$ may be positively correlated with the information and opinion components but negatively correlated with the noise component. Empirically, we do find a strong correlation between the proxy of $|EAC|$ and that of the information component but find minimal correlation between $|EAC|$ and the noise component. Therefore, for robustness, we further orthogonalize the two components to each other and construct a cleaner measure of the disagreement component for use in inferring AI, IN, and DO among traders. Further details of this orthogonalization are described in Section II.

[15] According to the Bayesian rule, the portions of evidence and opinion are independent of the direction of the signal. This means that even if the pieces of evidence observed by two analysts point in different directions, their updates contain beliefs with the same portions of opinion and evidence.

[16] Diether et al. (2002) suggest that residual analyst coverage is positively correlated with dispersion in analysts' forecasts, indicating that there is a higher demand for expert opinions when existing information is difficult to interpret.

Another variable is stock turnover (denoted $TURN$), which is an alternative measure of disagreement among investors. Appendix D describes these variable definitions.

B. Sample Selection

Analysts' earnings forecasts are taken from the Institutional Brokers Estimate System (I/B/E/S) U.S. Summary History datasets. Data on stock returns, prices, and shares outstanding are retrieved from the monthly stock files of the Center for Research in Security Prices (CRSP). The accounting data are obtained from the Compustat database. We use stocks priced at no less than \$5 per share to minimize the problem of bid-ask bounce. Because we are interested in analyst disagreement (dispersion in analysts' earnings-per-share forecasts), we consider only stocks in the I/B/E/S database that are followed by at least two analysts. On average, the number of stocks in this intersection priced above \$5 and followed by at least two analysts is $2,553$ per month for the period of January 1987 to December 2016. Finally, for the purpose of decomposing disagreement, we further exclude from the sample stocks without valid observations of both $EVOL$ and $|EAC|$. This lowers the average number of stocks per month to $1,698$.

Table 2 presents the average cross-sectional descriptive statistics for the variables of interest. All variables, except RET, are winsorized at the top and bottom 1%. The sample in Panel A is the intersection of I/B/E/S, CRSP, and Compustat databases, and the sample in Panel B only includes the data points available to decompose disagreement. For the stocks, which can be decomposed, the mean monthly return is 1.02% and the median is 0.70%, indicating a slight right skewness in the distribution. Although I/B/E/S tends to cover large firms, there is a large variation in MV in our sample. The market value ranges from \$60 million to \$88 billion. Stock returns are volatile, as suggested by a mean $SIGMA$ of 4.80% per week and a median of 4.32% per week.

The mean stock illiquidity is 7.65 and the median is about a 0.73% price change per million-dollar volume, indicating a serious right skew, as Amihud (2002) suggests. The mean stock turnover is 0.72%, and the median is 0.55%. Obviously, since we focus on the firm with analyst-disagreement, the coverage of a firm is from 2 to 33 analysts. The mean analyst disagreement is 0.12, and the median is 0.04. $EVOL$ is the mean standard deviation of EPS divided by its mean, which is 0.97 and the median is 0.34, indicating a right skew. EAC, as the covariance of unexpected earnings and unexpected mean forecasts, ranges from 0.66 to 24.17. Its mean and median are 1.02 and 0.12, respectively, indicating a serious right skew.

[Place Table 2 about here]

C. The Correlations Analysis

Table 3 shows the correlation matrix. Analyst disagreement is positively correlated with both price impact (Pearson = 0.24; Spearman = 0.24) and stock turnover (Pearson = 0.18; Spearman = 0.19), suggesting that the different disagreement components affect stock liquidity. Analyst disagreement is also negatively correlated with firm size and analyst coverage but positively correlated with market beta, BM, return volatility, and all measures of disagreement components. Price impact is positively correlated with measures of the information component and negatively correlated with measures of the opinion and noise components. One exception is the correlation between price impact and residual disagreement, which is only a slight correlation (Pearson = -0.01 and Spearman = -0.01 for D_{R1}).

The Pearson and Spearman correlations between analyst disagreement and $EVOL$ are 0.50 and 0.49, respectively, and between price impact and $EVOL$, they are 0.22 and 0.21, respectively. These confirm the information component's effects on disagreement and liquidity. $|EAC|$ is positively correlated with analyst disagreement (Pearson = 0.29; Spearman = 0.30) but negatively correlated with price impact (Pearson = -0.12; Spearman = -0.12), which confirms the opinion component's effects on disagreement and liquidity. This result is related to the puzzling J-shape relationship between price impact and analyst disagreement suggested by Sadka and Scherbina (2007).[17] $EVOL$ and $|EAC|$ are highly correlated (Pearson = 0.44; Spearman = 0.46), which implies they share similar information.[18]

Analyst coverage is highly correlated with firm size (Pearson = 0.76; Spearman = 0.77), and it is negatively correlated with analyst disagreement (Pearson = -0.16; Spearman = -0.17) and, even more strongly, price impact (Pearson = -0.80; Spearman = -0.81). After controlling for size and BM, the residual coverage is positively correlated with analyst disagreement (Pearson = 0.07; Spearman = 0.08), and the correlation between residual coverage and price impact becomes moderate (Pearson = -0.18; Spearman = -0.20), which suggests that the residual coverage tends to capture the noise component's effect. Residual disagreement is highly correlated with analyst disagreement (e.g., Pearson = 0.79 and Spearman = 0.75 for D_{R1}) but not correlated with price impact or stock turnover. This indicates that, for the most part, analyst disagreement does not necessarily decrease liquidity, which is incon-

[17] Sadka and Scherbina (2007) find that the stocks in the lowest analyst disagreement portfolio also appear to be relatively illiquid and suggest it might be explained by analysts tending to herd in highly uncertain environments.

[18] After controlling the collinearity portion of $EVOL$ and $|EAC|$, untabulated result shows their orthogonalized portions have weaker correlations with analyst disagreement (i.e., Pearson = 0.45 for $EVOL_R$; Pearson = 0.11 for EAC_R) but stronger correlations with price impact (i.e., Pearson = 0.28 for $EVOL_R$; Pearson = -0.23 for EAC_R), which confirms that the effects of information and opinion components on liquidity can offset each other.

sistent with Sadka and Scherbina's (2007) findings. However, the correlation analysis does not capture the noise component's nonlinear and negative effects on price impact. We find a reversed J-shape relationship between price impact and the noise component in Section III.

[Place Table 3 about here]

D. *Testing the Determinants of Analyst Disagreement*

In this subsection, we test the determinants of analyst disagreement as well as regress analyst disagreement on the variables related to the disagreement components and other control variables. The intuition is based on the linear relationship between analyst disagreement and its component, reflected in Equation (19). This analysis shows, using real data, precisely how the dispersion in analysts' forecasts is affected by variables that are candidates for its information, noise, and opinion components.

We run a series of Fama and MacBeth (1973) cross-sectional regressions to illustrate the relationship between analyst disagreement at month t and multiple control variables at month t. In particular, we run the regressions monthly to obtain a monthly measure of disagreement components. The standard error is adjusted by autocorrelation and heteroskedasticity. All variables are winsorized at the top and bottom 1%. Following our theoretical framework and previous analysis, we control all the candidates for disagreement components as our baseline regression of decomposition, which is specification (10) in Table 4 , as follows:

$$ln(D) = \underbrace{\beta_{CAPM} + ln(MV) + ln(BM) + SIGMA + ln(K) + COV_R}_{\text{Controll Variables}} + \tag{20}$$

$$\underbrace{ln(EVOL)}_{\text{Information-Component } (\sigma_\nu^2)} + \underbrace{ln(|EAC|)}_{\text{Opinion-Component } (\eta)} + \underbrace{D_{R1}}_{\text{Noise-Component } (\sigma_\epsilon^2)} . \tag{21}$$

Variable K is included in the regression as the sequence number of the mean analyst forecast for the same stocks. This variable helps control potential issues of different fiscal-year ends in the cross-section analysis. For example, for a stock that announced annual earnings in February with a fiscal year-end in December, at its mean earnings forecast right before announcement date, $K = 12$. Moreover, K also makes it possible for us to capture the effect of earnings announcements on stock returns and liquidity. However, K is related to disagreement components in two ways. First, the closer the earnings announcement date (larger K), the smaller the noise components because there is less uncertainty or noise about the true earnings figures, and the forecasts should be the most accurate. Second, immediately after the earnings announcement (small K), the opinion component is smaller. It is related to the dynamic of DO around earnings announcements and the dynamic of DI. The intuition is that analysts underreact to the persistence of their forecast errors (Zhang, 2006a). Also, given the existence of DO, the public announcement helps to moderate the DO level (Garfinkel, 2009). As a result, we use K only as a control variable for earnings announcements rather than including it in a disagreement component.

The results, reported in Table 4 , cast doubt on the interpretation of analyst disagreement as a single proxy for either AI, IN, or DO among investors. To gain a better understanding of the empirical determinants of analyst disagreement, we start from the simple regression of each explanatory variable. Analyst disagreement is strongly and positively related to β_{CAPM}, the book-to-market ratio (BM), and the standard deviation of past returns ($SIGMA$) and is negatively related to firm size (MV). These variables are commonly used as measures of risk. In specification (9), controlling for all four variables related to risk, the adjusted R-squared is 0.264. Controlling for risk and K, analyst disagreement is still positively correlated with the measures of information and opinion components. Also, these disagreement components provide additional explanation for analyst disagreement. The adjusted R^2 increases to 0.392 for specifications (10).

Finally, considering the moderate R^2 of specifications (7), we find that the residual coverage is a weak determinant of disagreement as well as a weak proxy for the noise component, and the residual portion of analyst disagreement for specifications (10) may be a better proxy for the noise component. In Sections III and IV, we find consistent evidence to support the idea that D_{R1} (or D_{R2}) is the major candidate variable of the noise component.

[Place Table 4 about here]

III. Disagreement Components, Liquidity and Mispricing

In this section, through a series of portfolio analyses, we examine the relationship between stock returns (or price impact) and analyst disagreement as aggregations of either offsetting or enhancing effects by various disagreement components. Specifically, stocks are sorted into portfolios for each month based on analyst disagreement or disagreement components as of the previous month. We hold stocks for 3 months and calculate monthly portfolio returns according to Jegadeesh and Titman's (1993) methodology.[19] The corresponding portfolio

[19]To illustrate that a stock is currently mispriced, it is important to follow the stock's performance for some time into the future to allow for the concurrent price adjustment. In the un-tabulated results, we find even stronger mispricing results if we hold the portfolio for only one month. Also, holding the portfolio for

analyst disagreement and Amihud (2002) illiquidity are also calculated. We report the alpha of CAPM, Fama–French three-factor (FF3), and Fama-French three-factor plus momentum (FF4). We report the alpha and factor sensitivity of the two mispricing factors (MGMT and PERF) in Stambaugh and Yuan's (2016) mispricing factor model (M4). Also, we run Fama-MacBeth regression to examine both the linear and nonlinear effects from disagreement components on stocks' future returns. Standard errors are adjusted for autocorrelation and heteroskedasticity.

A. *Liquidity and Disagreement Components*

We begin by documenting the portfolios' average analyst disagreement and price impact. In Table 5 , we sort portfolios by analyst disagreement (D), the information component σ_ν^2 ($EVOL$), the noise component σ_ϵ^2 (D_{R1}), and the opinion component η ($|EAC|$). Each column shows equally weighted average analyst disagreement and price impact for 25 disagreement-sorted portfolios. Note that each portfolio contains an average of 67 stocks.

The results indicate that the major driving forces behind disagreement and liquidity are contributed by different disagreement components. The pattern of aλ in portfolios is dominated by the information component. However, the level of analyst disagreement is dominated by the noise component. Specifically, we find that the largest difference in analyst disagreement between high and low portfolios is from the noise component at 1.05, while those from information and opinion components are 0.33 and 0.19, respectively. The largest difference in price impact between high and low portfolios is from the information component at 9.99, with those from noise and opinion components at -3.69 and -7.07, respectively.

All patterns across the portfolio are monotonically or nearly monotonically (the exception is the relationship between price impact and the noise component) increasing or decreasing. There is a reversed J-shaped relationship between price impact and the noise component, which traces a declining and rising pattern in average price impact for a net reduction in price impact. The second-highest price impact in the highest noise component portfolio could be driven by the coincidence of a high information component.[20] All differences are significant at the 1% level. These results confirm our theoretical predictions of price impact, which is that stocks with a high information component or low noise or opinion components tend to be more illiquid.

[Place Table 5 about here]

three months can mitigate the issue of return reversal.

[20]See Table C.1 at Appendix C.

B. Mispricing and Disagreement Components

Next, in Table 6 , we report average returns in alphas measured relative to the CAPM, FF3, FF4, and M4 models. We also report the factor sensitivity of MGMT and PERF in the M4 model. In Panels A, B, C, and D, 25 portfolios are sorted by analyst disagreement (D), the information component σ_ν^2 ($EVOL$), the noise component σ_ϵ^2 (D_{R1}), and the opinion component η ($|EAC|$). Each portfolio contains an average of 67 stocks. We interpret the abnormal returns as mispricing when the alphas, MGMT, or PERF of M4 is significant, given that the alpha of CAPM, FF3, or FF4 is significant. The intuition is quite simple. In our analysis, the abnormal return of CAPM, FF3, or FF4 could be related to some premium related to high risk, high uncertainty, or poor liquidity. Therefore, we apply the M4 model to determine whether the significant alpha from CAPM, FF3, or FF4 is related to the mispricing factors.[21]

We show that the strong negative relationship between analyst disagreement and future returns is driven by (1) underperforming stocks with high information components σ_ν^2 ($EVOL$) or high noise components σ_ϵ^2 (D_{R1}) and (2) outperforming stocks with low opinion components η ($|EAC|$). In Panel A, we find strong mispricing in the portfolios with both the lowest (i.e., three of four alphas are significant) and highest (i.e., four of four alphas are significant) levels of disagreement. Stocks with low disagreement tend to be underpriced, which is related to management (MGMT)-type anomalies, while stocks with high disagreement tend to be overpriced, which is related to both the performance (PERF)- and management (MGMT)-type anomalies. Furthermore, the alpha differentials are all significantly negative across all models.

In Panels B, C, and D, we analyze the disagreement components. Panel B shows strong overpricing in high portfolios (i.e., four of four alphas are significant), which is related to both the MGMT and PERF mispricing factors. Panel C shows strong overpricing in high portfolios (i.e., three of four alphas are significant), which is related to the PERF mispricing factor. Panel D shows strong underpricing in low portfolios (i.e., three of four alphas are significant), which is related to both the MGMT and PERF mispricing factors. These results confirm our prediction of mispricing, which is that mispricing is more pronounced for stocks with high information or noise components or with low opinion components.

We find in Panel B, however, that there is underpricing in the lowest $EVOL$ portfolio (i.e., two of four alphas are significant); in panel D, we find moderate overpricing in the highest portfolio (i.e., one of four alphas is significant). These inconsistent results are driven by the

[21] Stambaugh and Yuan (2016) suggest that their four-factor model's ability to accommodate a wide range of anomalies exceeds that of both the four-factor model of Hou, Xue, and Zhang (2015) and the five-factor model of Fama and French (2015).

correlation between $EVOL$ and $|EAC|$. In Section IV, we find that after orthogonalizing their collinear portions, the mispricing of low $EVOL_R$ and high EAC_R portfolios weakens.

[Place Table 6 about here]

C. Linear and Non-Linear Effects of Disagreement Components

In this section, we run Fama-MacBeth cross-sectional regressions for each month on all securities in the intersection of CRSP, Compustat, and I/B/E/S datasets from February 1987 to December 2016. Specifically, we regress the cross-section of individual stock returns at time t on a constant, the one-month lag of $ln(D)$ (the log of analyst disagreement), the one-month lag of information component σ_ν^2 ($EVOL$), the one-month lag of opinion component η ($|EAC|$), the one-month lag of noise component σ_ϵ^2 (D_{R1}), the dummy variable of the top 20% of the one-month lag of σ_ν^2 the bottom 20% of the one-month lag of η, the top 20% of the one-month lag of σ_ϵ^2, market β, $ln(MV)$ (i.e., the log of market capitalization at t -1), $ln(BM)$, a stock's past-year return (ret -12 : -2, the one-month past return (ret -1 : -1), a stock's long-run past return (ret -36 : -13), and $ln(TURN)$ (i.e., the log of turnover). Standard errors are adjusted for autocorrelation and heteroskedasticity.

We use the top 20% σ_ν^2, top 20% σ_ϵ^2, and bottom 20% η dummies to capture the nonlinear effects of disagreement components. The one-month past return variable is included to control for liquidity and microstructure effects documented by Jegadeesh (1990) that cause a short-term reversal in individual stock returns. The long-run past return variable is simply the return from t - 36 to t - 13 and is included to capture the 3–5-year reversal effect documented by De Bondt and Thaler (1985). Since one can argue that turnover is another measure of differences of opinion (Harris and Raviv, 1993; Lee and Swaminathan, 2000), and since turnover has been shown to predict returns (Lee and Swaminathan, 2000), we include this variable in our regressions to test whether turnover subsumes dispersion.

Table 7 shows the results of the Fama-MacBeth cross-sectional regressions. In Panel A, we examine the linear effects of disagreement components on future returns. The coefficient of the analyst disagreement variable is strongly negative in the first and second specifications, in line with the patterns observed in Table 5 . By using the three disagreement components' true values, from the third to eighth specifications, we find that all components have negative effects on returns. In specifications (9) and (10), we control all components simultaneously. We find that the disagreement effect is mainly driven by the information component; the effect of the noise component seems to pick up the momentum effect, and the effect of the opinion component seems to pick up the effect of the information component.

In panel B, we further control the potential nonlinear effects of disagreement components.

In specification (1), the high information component has a strong negative effect on future returns (-0.50% with a -4.53 t-value); in specification (3), the high noise component has a moderate negative effect on future returns (-0.17% with a -2.23 t-value); in specification (5), the low opinion component has a moderately positive effect on future returns (0.15% with a 2.35 t-value). The information component's and opinion component's effects are quite persistent, but the noise component's effect disappears after controlling the turnover and past return variables.

[Place Table 7 about here]

D. Discussion

Four of these findings are worth summarizing: first, we infer the level of different opinions among traders from the opinion component of analyst disagreement. Stocks with a low opinion component tend to be illiquid and underpriced, and this underpricing are potentially explained by two streams of literature. In the first one, the market could be underreacting to corporate events (Ross, 1977; Hirshleifer, 2001). Also, analysts could underreact by lowering their estimates gradually after receiving bad news or increasing them gradually after receiving good news from firms as the forecast horizon decreases and more information becomes available (Zhang, 2006a). According to the second stream, underpricing could be explained by the behavior of firm managers, who tend to disclose good news fully but, to some degree, withhold bad news (Zhang, 2006a). Considering that analysts and informed traders can construct their prior based on evidence provided by the firm manager, less error in the prior decreases the divergence of opinions and implies the future of the firm is likely to be positive.

Stocks with a high opinion component tend to be liquid and less mispriced than stocks with a high information component or a high noise component. Our model suggests that more divergent opinions among traders imply they will update their beliefs based more on information and less on their own opinions. However, an investor will be considered overconfident from the perspective of other investors when they possess divergent opinions (Van den Steen, 2011). As a result, when the prior of an informed trader is more divergent from market makers, he or she will submit a more informative order, which should increase price impact and reduce liquidity. Market makers, however, will believe their counterpart is overconfident about the signals, which will reduce price impact and increase liquidity. The empirical results support this explanation.

Second, we infer the level of asymmetric information among traders from the information component of analyst disagreement. Stocks with a high information component tend to be illiquid and overpriced because stocks with high illiquidity, as a limit to arbitrage and high analyst disagreement, are more difficult for arbitragers to short-sell, which is supported by Miller (1977) price-optimism hypothesis. Stocks with a low information component tend to be liquid and underpriced. We find that this underpricing is due to the coincidence of a low opinion component rather than being due to the information component itself.

Third, we infer the level of idiosyncratic noise observed by traders from the noise component of analyst disagreement. Stocks with a high noise component tend to be liquid and overpriced. However, there is a reverse J-shaped relationship between the noise component and illiquidity because the high noise component is coincident with a high information component, and illiquidity is more sensitive to the information component. Moreover, we find that the overpricing of high noise component stocks is related to but weaker than that of high information component stocks. Therefore, we suggest that this overpricing is also related to Miller (1977) hypothesis but weakened by the increasing liquidity, which reduces the limit to arbitrage.

Finally, in addition to explaining the puzzling mispricing of low analyst disagreement stocks (Diether et al., 2002; Sadka and Scherbina, 2007; Berkman et al., 2009) and the unexplained J-shaped relationship between analyst disagreement and price impact (Sadka and Scherbina, 2007), we provide an easier and inexpensive way to construct measures of asymmetric information, different information, and different opinions among traders. Specifically, instead of using intraday transaction data or restricting the analysis to public announcements, our empirical decomposing device for analyst disagreement only uses common databases, such as CRSP, Compustat, and I/B/E/S.

IV. Robustness Checks

To ascertain that the persistent relations between returns (or liquidity) and disagreement components we have documented thus far are consistent with our prediction and not caused by a statistical fluke, we employ additional portfolio strategies and regression tests to demonstrate robustness in Appendix E. Overall, we find similar results.

The first robustness check is size neutral portfolio analysis. We double-sort on firm size (MV) and analyst disagreement or disagreement components to test whether we are merely picking up a size effect in returns. The results confirm our mispricing predictions are not simply picking up the size effect. The second robustness check is using alternative disagreement components to do portfolio analysis and Fama-MacBeth regression. These results confirm that the inconsistent mispricing in main result (i.e., moderate underpricing at low information component portfolios) is driven by the correlation between $EVOL$ and $|EAC|$. The third robustness check analyzes portfolio in several subperiods: 1987–1996, 1997–2006, 2007–2016, a high sentiment period, and a low sentiment period. The mispricing phenomena in high information and low opinion components portfolios exist in all subperiods (except for the high information component portfolio at 1987-1996). The mispricing phenomena of high noise component portfolio, somehow, only exist in low sentiment and 2007-2016 periods. It could be explained by the limitation of our noise component of analyst disagreement since it only captures part of the noise observed by traders (i.e., the portion related to analyst forecast).

V. Conclusions

This study proposes a hybrid model of analyst disagreement and informed trading (ADIT). In equilibrium, analysts' and traders' decisions are endogenously determined by the basic components of information environment. In other words, analyst disagreement, stock price, and liquidity reflect the heterogeneity between information, noises, and opinions. We find consistent results to support the ADIT model. Specifically, the information component increases AI (i.e., asymmetric information) among traders, decreases liquidity, and increases pricing errors; the noise component increases the amount of IN (i.e., idiosyncratic noise) observed by informed trader and analysts, liquidity, and pricing errors; and the opinion component increases the level of DO (i.e., differing opinions) among analysts and traders, respectively, increases liquidity, and reduces pricing errors.

Besides, we empirical decompose analyst disagreement into information, noise, and opinion components and find (1) low opinion component portfolios predict underpricing and (2) high information or noise component portfolios predict overpricing. The latter is in line with Miller's (1977) price optimism model, but, surprisingly, the former is not. This surprising result could be explained in twofold. First, the ADIT model suggests low opinion component is related to large pricing error, but the model do not suggest its sign. Next, a partial explanation for this result may lie in the fact that analysts could underreact by increasing their estimates gradually after receiving good news from firms as the forecast horizon decreases and more information becomes available (Ross, 1977; Hirshleifer, 2001; Zhang, 2006a).

These empirical findings are in line with previous studies, which examine the effects of analyst disagreement to the stock returns and liquidity (Diether et al., 2002; Zhang, 2006b; Sadka and Scherbina, 2007; Berkman et al., 2009; Garfinkel, 2009; Cen et al., 2016), although no previous studies has asked this question in detail. Instead of treating the interpretations of analyst disagreement as competing hypotheses (i.e., AI, IN, or DO), we decompose analyst disagreement into three components: information, noise, and opinion. By disentangling the components, we provide evidence that elucidates the meaning of analyst disagreement, which had become confused. We contribute to the debate on how to interpret levels of analyst disagreement. Previous studies present competing hypotheses that interpret analyst disagreement as the level of either asymmetric information (Sadka and Scherbina, 2007), noises (Zhang, 2006b), or different opinions (Diether et al., 2002; Berkman et al., 2009; Garfinkel, 2009; Cen et al., 2016). Our findings suggest that these three interpretations of analyst disagreement are not necessarily mutually exclusive.

This study has taken a step in the direction of analyzing the effects of basic components in information environment systemically. Having acknowledged the limitations of using analyst disagreement components (i.e., it may not fully reflect the disagreement among investors), we can nevertheless confirm that the information environments of investors and analysts are connected tightly. Several implications can be drawn from this study. First, the disagreement-return (or liquidity) relation may be non-linear since an increase in the level of disagreement could increase or decrease pricing error (or liquidity), which depends on which component dominates the disagreement. Second, we suggest that aggregate variables (e.g., analyst disagreement, trading volume, return volatility, and stock turnover) should be viewed through an aggregation of AI, IN, and DO. Third, the $|EAC|$ (i.e., absolute value of covariance of unexpected earnings and unexpected average analyst forecast) is a good proxy for DO since it is dominated by opinion component instead of other components in the information environment. Fourth, we provide low frequency measures for the level of AI, IN, and DO. These empirical measures could be usefully applied to the market microstructure.

The security market is considered a vehicle for amalgamating unorganized knowledge (Maloney and Mulherin, 2003). Therefore, features of the information environment play a vital role in decision making of market participants since these features are important forces in driving stock prices and liquidity. Besides, the changes of market mechanisms, the sentiment of investors, and the psychological bias are also important and related to our findings. However, discussion of these elements is beyond the scope of this paper. Among the many topics to be explored in future research, some important ones can be listed as follows. How does the composition of information environment changes right after the changes of market mechanisms? What's the difference of AI, IN, and DO in affecting stock returns and liquidity between high investor sentiment and low investor sentiment?

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Table 1
Model Predictions of Disagreement Components

This table reports the model predictions of disagreement components on analyst disagreement (D) and price impact (λ) in Panel A, which summarizes the results of Lemma 1 and Theorem 2. In Panel B, we report the predicted relationships between analyst disagreement, stock illiquidity, mispricing, and disagreement components.

Panel A. Theoretical Predictions of Y from X ($\frac{\partial Y}{\partial X}$)

	X		
Y	σ_ν^2 Information Component	σ_ϵ^2 Noise Component	η Opinion Component
Analyst Disagreement: D			
(If Analysts Are Credible)	+	+	+
(If Analysts Are Noncredible)	+	-	+
Price Impact: λ	+	-	-
Price Error: $var(\nu\|p)$	+	+	-

Panel B. Predicted Empirical Relationships between Y and X

	Corresponding Level of X		
Level of Y	σ_ν^2 Information Component	σ_ϵ^2 Noise Component	η Opinion Component
Large Dispersion of Analyst Forecasts			
(If Analysts Are Credible)	High	High	High
(If Analysts Are Non-Credible)	High	Low	High
High Illiquidity	High	Low	Low
Strong (Unsigned) Mispricing	High	High	Low

Table 2
Average Cross-Sectional Summary Statistics

This table reports descriptive statistics for NYSE/AMEX/Nasdaq stocks during the period from January 1987 to December 2016. RET is the monthly stock return. MV is the market capitalization at month t. BM is the book value of equity divided by its market value at month t. β_{CAPM} is the sensitivity of the excess return of the market portfolio to the excess individual stock return. SIGMA is the standard deviation of weekly market excess returns over the year ending at month t. λ is Amihud's (2002) illiquidity measure, which is the average ratio of the daily absolute return to the (dollar) trading volume on that day in the previous 12 months, multiplied by 100,000,000. TURN is the annual average of the number of shares traded daily, divided by the number of outstanding shares. COV is the number of analysts following the firm in the previous year. D is the standard deviation of analyst forecasts scaled by the mean forecast at month t. EVOL is the time-series standard deviation of earnings divided by its time-series mean. EAC is the time-series covariance of unexpected earnings and the unexpected mean analyst forecast. $|EAC|$ is the absolute value of EAC. A stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than \$5.

	N	Mean	Std.	Min.	5%	25%	Med.	75%	95%	Max.
RET(%)	1,698	1.02	10.39	-51.80	-14.66	-4.62	0.70	6.24	17.73	70.71
MV(Million)	1,698	4,912	12,454	60	119	387	1,068	3,395	21,863	88,590
BM	1,698	0.58	0.39	0.05	0.12	0.29	0.50	0.76	1.33	2.15
β_{CAPM}	1,698	1.13	0.61	0.06	0.29	0.70	1.04	1.46	2.32	3.04
SIGMA(%)	1,698	4.80	2.07	1.96	2.33	3.22	4.32	5.92	8.91	11.68
λ	1,689	7.65	21.57	0.01	0.03	0.16	0.73	4.05	40.88	145.65
TURN(%)	1,689	0.72	0.57	0.08	0.16	0.35	0.55	0.89	1.90	3.21
COV	1,698	10.44	7.53	2.00	2.01	4.52	8.27	14.72	25.72	33.57
Analyst disagreement, information, and opinion components										
D	1,698	0.12	0.27	0.01	0.01	0.02	0.04	0.09	0.44	2.00
EVOL	1,698	0.97	2.32	0.05	0.09	0.20	0.34	0.68	3.52	17.51
EAC	1,698	0.96	3.18	-0.66	-0.07	0.02	0.10	0.48	4.50	24.17
$\|EAC\|$	1,698	1.02	3.26	0.00	0.00	0.03	0.12	0.52	4.62	24.89

Table 3
Correlation Coefficient

Pearson correlations are shown above the diagonal, with Spearman below. The sample period is from January 1987 to December 2016. D is the standard deviation of analyst forecasts scaled by the mean forecast at month t. λ is the Amihud (2002) illiquidity measure, which is the average ratio of the daily absolute return to the (dollar) trading volume on that day in the previous 12 months, multiplied by 100,000,000. TURN is the annual average of daily number of shares traded divided by the number of shares outstanding. β_{CAPM} is the sensitivity of excess return of market portfolio to the excess individual stock return. MV is the market capitalization at month t. BM is the book value of equity divided by its market value at month t. SIGMA is the standard deviation of weekly market excess returns over the year ending at month t. EVOL is the time-series standard deviation of earnings divided by its time-series mean. EAC is the time-series covariance of unexpected earnings and unexpected mean analyst forecast. $|EAC|$ is the absolute value of EAC. COV is the number of analysts following the firm in the previous year. COV_R is the residual part of regressing $\ln(COV)$ on $\ln(MV)$ and $\ln(BM)$. D_{R1} is the residual part of the regression of equation (II.D). A stock is "eligible" to be included in our analysis if it has a 1- (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than $5.

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
V1=ln(D)	.	0.24	0.19	0.22	-0.30	0.26	0.42	0.49	0.30	-0.17	0.08	0.75
V2=$ln(\lambda)$	0.24	.	-0.31	0.02	-0.94	0.23	0.39	0.21	-0.12	-0.81	-0.20	-0.02
V3=ln(TURN)	0.18	-0.34	.	0.43	0.08	-0.19	0.51	0.35	0.19	0.27	0.38	-0.03
V4=β_{CAPM}	0.22	0.02	0.43	.	-0.10	-0.12	0.47	0.36	0.16	0.01	0.14	-0.01
V5=ln(MV)	-0.30	-0.93	0.07	-0.11	.	-0.26	-0.50	-0.29	0.08	0.77	0.08	0.02
V6=ln(BM)	0.22	0.22	-0.20	-0.13	-0.26	.	-0.08	0.02	0.19	-0.18	-0.04	0.08
V7=SIGMA	0.42	0.35	0.51	0.48	-0.46	-0.10	.	0.55	0.11	-0.28	0.16	0.00
V8=ln(EVOL)	0.50	0.22	0.30	0.34	-0.29	0.02	0.49	.	0.46	-0.17	0.08	0.00
V9=ln($\|EAC\|$)	0.29	-0.12	0.18	0.15	0.08	0.18	0.11	0.44	.	0.07	0.00	0.05
V10=ln(COV)	-0.16	-0.80	0.29	0.00	0.76	-0.17	-0.26	-0.17	0.07	.	0.65	0.02
V11=COV_R	0.07	-0.18	0.38	0.14	0.05	-0.04	0.15	0.07	-0.01	0.67	.	0.01
V12=D_{R1}	0.79	-0.01	-0.02	0.00	0.02	0.04	0.01	0.00	0.05	0.02	0.00	.

Table 4
Determinants of Analyst Disagreement

Fama and MacBeth's (1973) cross-sectional regressions are run every month from January 1987 to December 2016. Dispersion in analysts' forecasts (i.e., the standard deviation of analyst forecasts scaled by the mean forecast at month t) is regressed on β_{CAPM} (estimated using the past 36 to 60 months of data), MV (market capitalization at month t), BM (book value of equity divided by its current market value at the month t), SIGMA (standard deviation of weekly market excess returns over the year ending at month t), EVOL (the time-series standard deviation of earnings divided by its time-series mean), $|EAC|$ (the absolute value of EAC, which is the time-series covariance of unexpected earnings and the unexpected mean analyst forecast), COV (the number of analysts following the firm in the previous year), COV_R (the residual part of regressing ln[COV] on ln[MV] and ln[BM]), or K (the sequence of the mean analyst forecast at month t). An NYSE/AMEX/Nasdaq stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than \$5. All variables are winsorized at the top and bottom 1%. The standard errors are adjusted for autocorrelation and heteroskedasticity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β_{CAPM}	0.44^{***}								0.15^{***}	0.03^{**}
	(30.15)								(11.50)	(2.33)
$ln(MV)$		-0.23^{***}							-0.04^{***}	-0.04^{***}
		(-54.68)							(-7.04)	(-9.16)
$ln(BM)$			0.37^{***}						0.43^{***}	0.35^{***}
			(22.52)						(27.47)	(25.69)
$SIGMA$				0.26^{***}					0.24^{***}	0.14^{***}
				(37.21)					(31.47)	(24.67)
$ln(EVOL)$					0.56^{***}					0.34^{***}
					(84.26)					(66.11)
$ln(\lvert EAC\rvert)$						0.16^{***}				0.06^{***}
						(45.90)				(18.33)
COV_R							0.19^{***}			0.06^{***}
							(14.57)			(5.61)
$ln(K)$								-0.35^{***}		-0.33^{***}
								(-16.85)		(-19.05)
Adj. R^2	0.058	0.090	0.058	0.177	0.255	0.087	0.007	0.023	0.264	0.392

Table 5
Characteristics Analysis of Portfolios

This table reports average D (i.e., analyst disagreement) and λ (i.e., Amihud's [2002] illiquidity measure). The stocks are sorted into 25 portfolios for each month based on D, the proxy of information component σ_ν^2 (EVOL), the proxy of noise component σ_ϵ^2 (D_{R1}), and the proxy of opinion component η ($|EAC|$) for the previous month. We hold stocks for 3 months and calculate the average of monthly portfolio D and λ. D is the standard deviation of analyst forecasts scaled by the mean forecast at month t. λ is Amihud's (2002) illiquidity measure, which is the average ratio of the daily absolute return to the (dollar) trading volume on that day in the previous 12 months, multiplied by 100,000,000. EVOL is the time-series standard deviation of earnings divided by its time-series mean. EAC is the time-series covariance of unexpected earnings and the unexpected mean analyst forecast. $|EAC|$ is the absolute value of EAC. D_{R1} is the residual part of the regression of Equation (II.D). The results are reported from January 1986 to December 2016. An NYSE/AMEX/Nasdaq stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than \$5. Standard errors are adjusted for autocorrelation and heteroskedasticity. On average, there are 67 stocks in each portfolio. $*$, $**$, and $***$ indicate the significance level at 0.1, 0.05, and 0.01, respectively.

Table 5 –*Continued*

	Analyst Disagreement X=D		Information Component X=$EVOL$		Noise Component X=D_{R1}		Opinion Component X=$\|EAC\|$	
X	D	λ	D	λ	D	λ	D	λ
1(L)	0.01	4.57	0.03	2.81	0.02	14.79	0.05	9.82
	0.01	5.25	0.03	4.36	0.02	9.59	0.06	9.68
	0.01	5.13	0.03	5.02	0.02	8.51	0.06	9.56
	0.01	4.71	0.04	5.53	0.02	7.84	0.06	9.79
5	0.02	5.43	0.04	6.18	0.03	7.57	0.07	10.12
	0.02	5.23	0.04	6.26	0.03	7.11	0.07	10.03
	0.02	5.14	0.04	6.43	0.03	7.21	0.07	8.99
	0.02	5.28	0.04	6.98	0.04	6.80	0.08	8.66
	0.02	5.45	0.04	6.57	0.04	6.56	0.08	8.91
10	0.03	5.96	0.05	6.74	0.04	6.67	0.09	8.30
	0.03	6.34	0.05	7.24	0.04	6.16	0.10	8.16
	0.03	6.43	0.05	7.57	0.05	6.35	0.10	8.33
	0.04	7.03	0.06	6.68	0.05	6.44	0.10	8.53
	0.04	6.95	0.07	6.20	0.06	6.19	0.11	7.93
15	0.05	7.58	0.07	6.81	0.06	6.60	0.12	7.54
	0.06	7.71	0.08	7.53	0.07	6.34	0.12	7.30
	0.06	8.12	0.10	6.91	0.08	6.25	0.13	7.24
	0.07	8.96	0.12	7.88	0.09	6.39	0.14	6.75
	0.09	9.44	0.15	7.51	0.09	6.88	0.14	6.24
20	0.10	10.03	0.20	9.69	0.11	7.33	0.16	5.96
	0.13	10.48	0.25	11.90	0.13	7.35	0.17	5.77
	0.17	11.39	0.30	11.47	0.16	7.90	0.18	5.83
	0.23	12.21	0.34	11.98	0.21	8.26	0.19	4.96
	0.39	13.36	0.34	12.58	0.35	9.54	0.21	4.42
25(H)	1.25	13.44	0.36	12.80	1.07	11.09	0.24	2.75
25-1	1.25***	8.87***	0.33***	9.99***	1.05***	−3.69***	0.19***	−7.07***
	(24.07)	(6.99)	(19.67)	(6.49)	(23.11)	(-4.67)	(14.80)	(-6.74)

Table 6

Portfolios Mispricing Analysis: Analyst Disagreement and Components

This table reports average risk-adjusted returns and factor sensitivity for portfolios sorted by the variables related to analyst disagreement or disagreement components. We hold stocks for 3 months and calculate returns using Jegadeesh and Titman's (1993) methodology. We report the alpha of CAPM, Fama-French three-factor (FF3), Fama-French three-factor plus momentum (FF4), and Stambaugh and Yuan's (2016) mispricing factor models. Factor sensitivity is reported as the two mispricing factors (MGMT and PERF) as described by Stambaugh and Yuan (2016). Twenty-five portfolios are sorted by D, the proxy of information component σ_ν^2 (EVOL), the proxy of noise component σ_ϵ^2 (D_{R1}), and the proxy of opinion component η ($|EAC|$) for the previous month. D is the standard deviation of analyst forecasts scaled by the mean forecast at month t. EVOL is the time-series standard deviation of earnings divided by its time-series mean. EAC is the time-series covariance of unexpected earnings and the unexpected mean analyst forecast. $|EAC|$ is the absolute value of EAC. D_{R1} is the residual part of the regression of Equation (II.D). The results are reported from January 1987 to December 2016. An NYSE/AMEX/Nasdaq stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than $5. The standard errors are adjusted for autocorrelation and heteroscedasticity. On average, there are 67 stocks in each portfolio. $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

Table 6 –*Continued*

Panel A. Sorted by Analyst-Disagreement (D)												
	Alpha								Factor Sensitivity			
D	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.37**	(2.48)	0.28**	(2.36)	0.25**	(2.33)	0.06	(0.59)	0.27***	(3.38)	0.07	(1.56)
	0.39**	(2.54)	0.29**	(2.49)	0.27**	(2.48)	0.06	(0.64)	0.26***	(3.74)	0.06	(1.47)
	0.35**	(2.46)	0.26**	(2.45)	0.26***	(2.64)	0.06	(0.68)	0.24***	(3.54)	0.04	(1.14)
	0.32**	(2.50)	0.23**	(2.43)	0.25***	(2.70)	0.11	(1.15)	0.20***	(3.48)	−0.01	(−0.30)
5	0.20	(1.63)	0.11	(1.21)	0.14	(1.55)	0.00	(−0.03)	0.20***	(3.77)	−0.02	(−0.81)
	0.25*	(1.83)	0.13	(1.39)	0.16*	(1.86)	0.02	(0.19)	0.24***	(3.90)	−0.03	(−1.04)
	0.28**	(2.10)	0.19**	(2.05)	0.22**	(2.46)	0.10	(1.13)	0.13**	(2.17)	−0.01	(−0.25)
	0.23*	(1.71)	0.13	(1.35)	0.18*	(1.95)	0.06	(0.66)	0.16***	(2.96)	−0.06**	(−2.32)
	0.22*	(1.77)	0.12	(1.42)	0.18**	(2.14)	0.07	(0.75)	0.14**	(2.41)	−0.05**	(−2.30)
10	0.14	(1.03)	0.04	(0.41)	0.09	(1.04)	−0.01	(−0.07)	0.12**	(2.24)	−0.07**	(−2.36)
	0.10	(0.83)	0.01	(0.13)	0.07	(0.95)	−0.02	(−0.29)	0.10*	(1.94)	−0.07***	(−2.81)
	0.10	(0.75)	−0.01	(−0.06)	0.07	(0.81)	0.00	(−0.05)	0.11*	(1.77)	−0.10***	(−3.06)
	0.14	(1.11)	0.04	(0.55)	0.11	(1.58)	0.04	(0.50)	0.09	(1.53)	−0.10***	(−3.91)
	0.06	(0.47)	−0.05	(−0.57)	0.04	(0.53)	−0.02	(−0.18)	0.07	(1.47)	−0.12***	(−4.55)
15	0.13	(0.98)	0.01	(0.16)	0.10	(1.34)	0.03	(0.42)	0.11	(1.39)	−0.12***	(−3.78)
	0.16	(1.19)	0.05	(0.68)	0.11*	(1.68)	0.04	(0.49)	0.09	(1.48)	−0.10***	(−3.22)
	0.04	(0.24)	−0.08	(−0.93)	0.01	(0.15)	−0.07	(−0.76)	0.07	(1.02)	−0.13***	(−4.18)
	0.02	(0.16)	−0.10	(−1.23)	−0.02	(−0.25)	−0.10	(−1.13)	0.11	(1.36)	−0.14***	(−4.27)
	0.07	(0.44)	−0.06	(−0.68)	0.04	(0.49)	−0.02	(−0.17)	0.09	(1.23)	−0.16***	(−4.70)
20	−0.07	(−0.43)	−0.18**	(−1.97)	−0.06	(−0.77)	−0.09	(−0.94)	0.02	(0.27)	−0.17***	(−5.27)
	−0.08	(−0.49)	−0.17*	(−1.80)	−0.07	(−0.81)	−0.06	(−0.61)	−0.08	(−0.76)	−0.16***	(−3.68)
	−0.09	(−0.46)	−0.21*	(−1.91)	−0.09	(−0.85)	−0.05	(−0.39)	−0.07	(−0.86)	−0.23***	(−6.82)
	−0.24	(−1.17)	−0.39***	(−3.25)	−0.25**	(−2.18)	−0.23*	(−1.73)	0.01	(0.10)	−0.28***	(−5.98)
	−0.29	(−1.35)	−0.43***	(−3.46)	−0.24**	(−2.15)	−0.19	(−1.63)	−0.02	(−0.27)	−0.34***	(−9.30)
25(H)	−0.46**	(−2.10)	−0.59***	(−4.34)	−0.37***	(−2.94)	−0.29**	(−2.28)	−0.08	(−1.35)	−0.38***	(−11.63)
25-1	−0.83***	(−3.49)	−0.87***	(−4.37)	−0.63***	(−3.27)	−0.34*	(−1.92)	−0.35***	(−4.21)	−0.45***	(−8.02)

(continued)

Table 6 –*Continued*

Panel B. Sorted by Information Component (EVOL)												
	Alpha								Factor Sensitivity			
EVOL	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.33**	(2.33)	0.17	(1.62)	0.20**	(1.99)	−0.01	(−0.13)	0.49***	(8.57)	−0.08**	(−1.97)
	0.21	(1.46)	0.05	(0.53)	0.09	(1.06)	−0.12	(−1.27)	0.47***	(6.43)	−0.08**	(−2.02)
	0.22	(1.60)	0.08	(0.91)	0.11	(1.26)	−0.09	(−1.12)	0.38***	(5.90)	−0.04	(−1.23)
	0.15	(1.05)	0.01	(0.05)	0.06	(0.69)	−0.11	(−1.32)	0.36***	(6.28)	−0.09***	(−3.20)
5	0.21	(1.44)	0.07	(0.68)	0.11	(1.12)	−0.08	(−0.82)	0.36***	(5.26)	−0.06**	(−2.01)
	0.25	(1.48)	0.11	(0.94)	0.16	(1.59)	−0.06	(−0.70)	0.35***	(4.38)	−0.03	(−0.72)
	0.27*	(1.84)	0.13	(1.30)	0.18*	(1.92)	−0.02	(−0.15)	0.32***	(3.90)	−0.05	(−1.13)
	0.31*	(1.93)	0.15	(1.48)	0.20**	(2.06)	−0.01	(−0.14)	0.36***	(3.93)	−0.04	(−0.88)
	0.20	(1.25)	0.06	(0.61)	0.13	(1.29)	−0.05	(−0.49)	0.27***	(3.63)	−0.07	(−1.63)
10	0.21	(1.40)	0.08	(0.84)	0.13	(1.49)	0.00	(−0.02)	0.20***	(2.92)	−0.06	(−1.53)
	0.17	(1.13)	0.05	(0.49)	0.10	(1.02)	−0.03	(−0.32)	0.18***	(2.64)	−0.05	(−1.17)
	0.25*	(1.65)	0.17*	(1.79)	0.21**	(2.21)	0.09	(1.12)	0.08	(0.90)	−0.03	(−0.75)
	0.30**	(2.22)	0.19**	(2.19)	0.24***	(2.90)	0.14*	(1.66)	0.13*	(1.90)	−0.06*	(−1.74)
	0.23*	(1.70)	0.14*	(1.65)	0.19**	(2.49)	0.16*	(1.92)	0.02	(0.34)	−0.08**	(−2.18)
15	0.31**	(2.24)	0.22***	(2.68)	0.27***	(3.53)	0.22***	(2.96)	0.00	(−0.06)	−0.07**	(−2.13)
	0.30**	(2.02)	0.21**	(2.06)	0.30***	(3.06)	0.22**	(2.31)	0.04	(0.58)	−0.11***	(−4.16)
	0.21	(1.24)	0.12	(1.20)	0.23**	(2.13)	0.20*	(1.84)	−0.09	(−1.21)	−0.11***	(−3.11)
	0.17	(1.12)	0.11	(1.08)	0.18*	(1.73)	0.18	(1.60)	−0.15**	(−2.33)	−0.08***	(−2.78)
	0.09	(0.64)	0.03	(0.30)	0.14	(1.57)	0.21**	(2.26)	−0.21***	(−3.30)	−0.15***	(−5.09)
20	0.01	(0.07)	−0.04	(−0.38)	0.08	(0.70)	0.17	(1.34)	−0.24***	(−4.57)	−0.16***	(−6.79)
	−0.03	(−0.14)	−0.11	(−0.88)	−0.01	(−0.09)	0.03	(0.31)	−0.15**	(−2.03)	−0.16***	(−5.85)
	−0.20	(−1.24)	−0.29***	(−2.75)	−0.16	(−1.60)	−0.09	(−0.75)	−0.13	(−1.61)	−0.23***	(−5.97)
	−0.38*	(−1.92)	−0.47***	(−3.60)	−0.33**	(−2.53)	−0.21	(−1.53)	−0.19***	(−2.91)	−0.27***	(−6.25)
	−0.72***	(−3.42)	−0.82***	(−5.70)	−0.70***	(−4.79)	−0.64***	(−3.94)	−0.13**	(−2.19)	−0.25***	(−5.45)
25(H)	−0.71***	(−3.17)	−0.80***	(−5.67)	−0.67***	(−4.69)	−0.62***	(−3.89)	−0.15**	(−2.50)	−0.27***	(−6.12)
25-1	−1.04***	(−4.20)	−0.97***	(−5.13)	−0.87***	(−4.47)	−0.60***	(−2.93)	−0.64***	(−8.29)	−0.20***	(−3.10)

(continued)

Table 6 −*Continued*

Panel C. Sorted by Noise Component (D_{R1})												
	Alpha								Factor Sensitivity			
EVOL	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.07	(0.38)	−0.04	(−0.29)	0.05	(0.44)	0.03	(0.26)	−0.03	(−0.43)	−0.15***	(−3.57)
	0.18	(1.07)	0.09	(0.76)	0.17	(1.59)	0.08	(0.75)	0.04	(0.65)	−0.08**	(−2.33)
	0.18	(1.13)	0.08	(0.81)	0.11	(1.13)	−0.02	(−0.22)	0.08	(1.31)	−0.02	(−0.86)
	0.15	(1.03)	0.08	(0.79)	0.12	(1.32)	0.00	(0.05)	0.04	(0.58)	−0.03	(−0.79)
5	0.15	(1.11)	0.06	(0.76)	0.10	(1.24)	0.00	(−0.03)	0.08	(1.51)	−0.04*	(−1.77)
	0.10	(0.69)	0.00	(0.05)	0.05	(0.63)	−0.05	(−0.58)	0.10	(1.54)	−0.06**	(−2.00)
	0.25*	(1.88)	0.16*	(1.81)	0.22***	(2.59)	0.14	(1.60)	0.07	(1.34)	−0.05*	(−1.68)
	0.13	(1.07)	0.04	(0.49)	0.09	(1.25)	0.01	(0.08)	0.09*	(1.80)	−0.07**	(−2.56)
	0.10	(0.83)	−0.01	(−0.15)	0.07	(1.00)	−0.03	(−0.42)	0.14**	(2.55)	−0.10***	(−3.45)
10	0.19	(1.42)	0.07	(0.94)	0.14**	(2.06)	0.03	(0.38)	0.16**	(2.43)	−0.08***	(−2.84)
	0.18	(1.38)	0.08	(0.96)	0.14*	(1.80)	0.05	(0.52)	0.13*	(1.74)	−0.08**	(−2.35)
	0.14	(1.09)	0.01	(0.21)	0.09	(1.33)	0.00	(−0.02)	0.16**	(2.44)	−0.10***	(−3.00)
	0.07	(0.51)	−0.04	(−0.61)	0.04	(0.54)	−0.02	(−0.26)	0.12**	(2.05)	−0.12***	(−5.45)
	0.11	(0.92)	0.00	(−0.03)	0.07	(1.04)	−0.04	(−0.51)	0.17***	(3.17)	−0.10***	(−4.30)
15	0.05	(0.38)	−0.08	(−1.10)	0.02	(0.23)	−0.08	(−1.04)	0.17**	(2.52)	−0.13***	(−3.91)
	0.06	(0.44)	−0.06	(−0.73)	0.00	(0.06)	−0.11	(−1.38)	0.19***	(3.52)	−0.10***	(−3.66)
	0.13	(0.96)	0.01	(0.13)	0.08	(1.02)	−0.01	(−0.14)	0.16**	(2.08)	−0.10***	(−3.08)
	0.16	(1.19)	0.06	(0.78)	0.11	(1.50)	0.02	(0.24)	0.10*	(1.84)	−0.09***	(−3.81)
	0.12	(0.88)	−0.01	(−0.14)	0.07	(0.97)	0.01	(0.10)	0.15**	(2.38)	−0.13***	(−4.83)
20	0.12	(0.87)	0.00	(−0.01)	0.07	(0.95)	0.01	(0.12)	0.12**	(1.98)	−0.13***	(−4.48)
	0.02	(0.11)	−0.11	(−1.33)	−0.03	(−0.44)	−0.08	(−1.01)	0.12	(1.64)	−0.15***	(−4.16)
	0.07	(0.49)	−0.05	(−0.67)	0.03	(0.41)	−0.05	(−0.65)	0.12	(1.61)	−0.13***	(−4.00)
	−0.06	(−0.38)	−0.20**	(−2.32)	−0.10	(−1.16)	−0.13	(−1.44)	0.08	(0.99)	−0.17***	(−5.04)
	−0.02	(−0.11)	−0.15	(−1.51)	−0.03	(−0.35)	−0.05	(−0.46)	0.04	(0.47)	−0.19***	(−5.02)
25(H)	−0.27	(−1.58)	−0.39***	(−3.52)	−0.24**	(−2.24)	−0.20**	(−2.00)	−0.03	(−0.60)	−0.26***	(−10.16)
25-1	−0.34**	(−2.37)	−0.35**	(−2.30)	−0.29*	(−1.92)	−0.24	(−1.52)	−0.01	(−0.12)	−0.11**	(−2.11)

(continued)

Table 6 –*Continued*

Panel D. Sorted by Opinion Component ($\|EAC\|$)												
	Alpha								Factor Sensitivity			
$\|EAC\|$	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.44***	(2.84)	0.37***	(3.35)	0.35***	(3.18)	0.13	(1.36)	0.16**	(2.46)	0.06**	(2.34)
	0.25*	(1.72)	0.17	(1.64)	0.16*	(1.69)	−0.04	(−0.40)	0.17***	(3.02)	0.03	(1.14)
	0.25*	(1.80)	0.17*	(1.73)	0.19**	(1.99)	0.02	(0.25)	0.14**	(2.34)	0.00	(0.10)
	0.18	(1.26)	0.08	(0.84)	0.12	(1.32)	−0.07	(−0.85)	0.19***	(2.65)	−0.02	(−0.52)
5	0.15	(1.11)	0.06	(0.67)	0.11	(1.17)	−0.01	(−0.14)	0.11**	(2.05)	−0.05	(−1.59)
	0.18	(1.32)	0.09	(1.05)	0.14*	(1.65)	0.00	(−0.01)	0.12***	(2.65)	−0.05**	(−2.19)
	0.12	(0.96)	0.02	(0.28)	0.09	(1.02)	−0.07	(−0.82)	0.16***	(2.84)	−0.06**	(−2.35)
	0.12	(0.85)	0.03	(0.42)	0.08	(0.98)	−0.05	(−0.65)	0.11**	(1.98)	−0.05**	(−2.54)
	0.08	(0.62)	−0.02	(−0.22)	0.03	(0.39)	−0.08	(−1.06)	0.12**	(2.39)	−0.06**	(−2.27)
10	0.14	(1.07)	0.05	(0.57)	0.11	(1.41)	0.02	(0.22)	0.09	(1.57)	−0.08***	(−3.03)
	0.10	(0.74)	0.01	(0.13)	0.06	(0.71)	−0.03	(−0.38)	0.09*	(1.69)	−0.08***	(−3.08)
	0.14	(1.02)	0.04	(0.45)	0.13	(1.62)	0.04	(0.52)	0.08	(1.19)	−0.11***	(−4.07)
	0.06	(0.48)	−0.02	(−0.31)	0.05	(0.63)	−0.03	(−0.45)	0.07	(1.31)	−0.10***	(−4.98)
	0.07	(0.54)	−0.02	(−0.27)	0.06	(0.75)	−0.01	(−0.11)	0.08	(1.44)	−0.12***	(−4.57)
15	0.02	(0.14)	−0.10	(−1.09)	−0.02	(−0.29)	−0.10	(−1.28)	0.11*	(1.70)	−0.12***	(−3.61)
	0.13	(0.88)	0.01	(0.12)	0.11	(1.36)	0.01	(0.17)	0.10*	(1.66)	−0.11***	(−4.28)
	0.03	(0.20)	−0.10	(−1.18)	0.01	(0.14)	−0.05	(−0.55)	0.12*	(1.92)	−0.17***	(−6.09)
	0.07	(0.49)	−0.05	(−0.53)	0.06	(0.76)	0.05	(0.58)	0.04	(0.59)	−0.17***	(−4.68)
	0.09	(0.61)	−0.02	(−0.17)	0.07	(0.83)	0.05	(0.50)	0.03	(0.36)	−0.13***	(−3.87)
20	−0.01	(−0.08)	−0.13	(−1.43)	−0.04	(−0.39)	−0.05	(−0.52)	0.07	(0.98)	−0.16***	(−4.64)
	−0.14	(−0.85)	−0.29***	(−2.97)	−0.17*	(−1.88)	−0.22**	(−2.08)	0.14*	(1.75)	−0.20***	(−4.92)
	−0.12	(−0.69)	−0.25**	(−2.25)	−0.09	(−0.92)	−0.05	(−0.43)	0.01	(0.07)	−0.26***	(−6.81)
	0.00	(0.01)	−0.11	(−0.96)	−0.03	(−0.25)	0.03	(0.30)	−0.02	(−0.21)	−0.17***	(−4.78)
	0.00	(0.02)	−0.16	(−1.46)	−0.05	(−0.47)	0.01	(0.07)	0.09	(0.93)	−0.22***	(−5.03)
25(H)	−0.03	(−0.16)	−0.24**	(−2.00)	−0.10	(−0.89)	−0.04	(−0.30)	0.22**	(2.02)	−0.29***	(−5.25)
25-1	−0.47***	(−2.63)	−0.60***	(−3.72)	−0.45***	(−2.81)	−0.17	(−1.08)	0.05	(0.58)	−0.35***	(−6.09)

Table 7
Fama-MacBeth Regressions: Cross-Sectional Individual Stock Returns

Fama and MacBeth (1973) cross-sectional regressions are run every month from January 1987 to December 2016. The cross-section of expected returns at time t is regressed on a constant; D (the analyst disagreement at time t-1); the proxy of information component σ^2_ν (EVOL), which is the time-series standard deviation of earnings divided by its time-series mean at time t -1; the proxy of noise component σ^2_ϵ (D_{R1}), which is the residual part of the regression of Equation (II.D) at time t-1; the proxy of opinion component η ($|EAC|$, which is the absolute value of EAC (the time-series covariance of unexpected earnings and the unexpected mean analyst forecast); H σ^2_ν as the dummy variable of the top 20% of the one-month lag of EVOL; H σ_{ϵ^2} as the dummy variable of the top 20% of the one-month lag of D_{R1}; L η as the dummy variable of the bottom 20% of the one-month lag of $|EAC|$; β_{CAPM}, estimated using the past 24–60 months of data; MV (market capitalization at t - 1); BM (book value of equity divided by its current market value at month t - 1); ret - 12 : -2 (a stock's past-year return); ret - 36 : -13 (stock's long-run past return); ret - 1 : -1 (the one-month past return); and TURN (annual average of the daily number of shares traded divided by the number of shares outstanding at time t -1). An NYSE/MEX/Nasdaq stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than $5. All variables are winsorized at the top and bottom 1%. The standard errors are adjusted for autocorrelation and heteroskedasticity. $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

Panel A. Linear Effects of Disagreement Component										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.79*	0.72	0.97**	0.87**	1.03***	0.85*	0.90**	0.71	0.99**	0.86*
	(1.88)	(1.53)	(2.52)	(1.97)	(2.71)	(1.91)	(2.18)	(1.52)	(2.51)	(1.92)
ln(D)	−0.12***	−0.09**								
	(−2.92)	(−2.32)								
σ^2_ν: ln(EVOL)			−0.16***	−0.17***					−0.17***	−0.17***
			(−3.27)	(−3.83)					(−3.78)	(−4.11)
σ^2_ϵ: D_{R1}					−0.08**	−0.04			−0.07**	−0.03
					(−2.09)	(−1.12)			(−2.07)	(−1.01)
η: ln($\lvert EAC\rvert$)							−0.03*	−0.04**	0.01	0.00
							(−1.75)	(−2.35)	(0.53)	(−0.15)
β_{CAPM}	0.14	0.16	0.17	0.19	0.09	0.14	0.11	0.15	0.17	0.20
	(0.73)	(1.02)	(0.91)	(1.25)	(0.44)	(0.90)	(0.56)	(0.98)	(0.93)	(1.28)
ln(MV)	−0.04	−0.03	−0.04	−0.04	−0.01	−0.01	−0.01	0.00	−0.04	−0.04
	(−0.96)	(−0.82)	(−1.02)	(−1.05)	(−0.32)	(−0.35)	(−0.14)	(−0.11)	(−1.10)	(−1.07)
ln(BM)	0.04	0.08	0.01	0.08	0.01	0.06	0.03	0.09	0.01	0.08
	(0.43)	(0.99)	(0.12)	(1.05)	(0.12)	(0.71)	(0.28)	(1.20)	(0.06)	(1.00)
ln(TURN)		−0.09		−0.06		−0.11		−0.09		−0.06
		(−1.05)		(−0.70)		(−1.31)		(−1.08)		(−0.67)
ret_{-1}		−0.03***		−0.03***		−0.03***		−0.03***		−0.03***
		(−6.07)		(−5.94)		(−6.09)		(−6.00)		(−6.09)
$ret_{-12,-2}$		0.00***		0.01***		0.00***		0.01***		0.01***
		(2.67)		(2.99)		(2.74)		(2.83)		(2.85)
$ret_{-36,-13}$		0.00		0.00		0.00		0.00		0.00
		(−0.64)		(−0.36)		(−0.48)		(−0.46)		(−0.31)

(continued)

Table 7 –*Continued*

Panel B. Nonlinear Effects of Disagreement Component: 20% and 80% Threshold								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	1.24***	1.12***	1.08***	0.88**	0.98**	0.80*	1.24***	1.10***
	(3.44)	(2.66)	(2.86)	(2.00)	(2.53)	(1.78)	(3.39)	(2.60)
H σ_{ν}^2: ln(EVOL)	−0.50***	−0.48***					−0.47***	−0.46***
	(−4.53)	(−4.95)					(−4.65)	(−5.03)
H σ_{ϵ}^2: D_{R1}			−0.17**	−0.11			−0.11	−0.05
			(−2.23)	(−1.52)			(−1.58)	(−0.72)
L η: $\ln(\|EAC\|)$					0.15**	0.16***	0.06	0.09*
					(2.35)	(2.99)	(1.24)	(1.89)
β_{CAPM}	0.15	0.18	0.09	0.14	0.10	0.15	0.15	0.18
	(0.79)	(1.13)	(0.43)	(0.88)	(0.49)	(0.92)	(0.81)	(1.14)
ln(MV)	−0.04	−0.04	−0.02	−0.02	−0.01	−0.01	−0.04	−0.04
	(−0.97)	(−0.95)	(−0.40)	(−0.39)	(−0.25)	(−0.24)	(−0.95)	(−0.92)
ln(BM)	0.03	0.09	0.01	0.06	0.02	0.08	0.03	0.10
	(0.28)	(1.13)	(0.10)	(0.72)	(0.20)	(0.99)	(0.32)	(1.20)
ln(TURN)		−0.07		−0.11		−0.10		−0.07
		(−0.87)		(−1.31)		(−1.20)		(−0.81)
ret_{-1}		−0.03***		−0.03***		−0.03***		−0.03***
		(−5.94)		(−6.10)		(−5.98)		(−6.09)
$ret_{-12,-2}$		0.01***		0.01***		0.01***		0.01***
		(2.92)		(2.76)		(2.88)		(2.88)
$ret_{-36,-13}$		0.00		0.00		0.00		0.00
		(−0.61)		(−0.55)		(−0.50)		(−0.57)

Online Appendix for "Mispricing and Liquidity: Decomposing Disagreement"

by

Hongyi Chen, Zhanhui Chen, Roman Weiru Hua, and Weiyu Kuo

Appendix A. Proof of Equilibrium

An equilibrium of this model is an informed order $\tilde{x}$ depending on her prior and average analyst forecast $\tilde{S}$, and a price function p satisfying

$$p(\tilde{y}) = E[\tilde{\nu}|\tilde{y}], \tag{A.1}$$

$$\tilde{x} \in \arg\max_{x} \quad E_I[x(\tilde{\nu} - p(x + \tilde{x}))|\tilde{S}]. \tag{A.2}$$

The n-th analyst's best estimate about the asset value ν given their signals and opinions is

$$\tilde{s}_n = E_n[\tilde{\nu}|\tilde{\nu} + \tilde{\epsilon}_n] \tag{A.3}$$

$$= (1 - \rho_A^2)\bar{\nu}_n + \rho_A^2(\tilde{\nu} + \tilde{\epsilon}_n) \tag{A.4}$$

$$= \Big(\frac{\sigma_\epsilon^2}{\eta_A\sigma_\nu^2 + \sigma_\epsilon^2}\Big)\bar{\nu}_n + \Big(\frac{\eta_A\sigma_\nu^2}{\eta_A\sigma_\nu^2 + \sigma_\epsilon^2}\Big)(\tilde{\nu} + \tilde{\epsilon}_n). \tag{A.5}$$

Assume informed trader can accesses the average analyst forecasts as her private information, which is

$$\tilde{S} = \frac{\sum_{n=1}^{N}\tilde{s}_n}{N} \tag{A.6}$$

$$= (1 - \rho_A^2)\frac{\sum_{n=1}^{N}\bar{\nu}_n}{N} + \rho_A^2(\tilde{\nu} + \frac{\sum_{n=1}^{N}\tilde{\epsilon}_n}{N}) \tag{A.7}$$

$$= \Big(\frac{\sigma_\epsilon^2}{\eta_A\sigma_\nu^2 + \sigma_\epsilon^2}\Big)\frac{\sum_{n=1}^{N}\bar{\nu}_n}{N} + \Big(\frac{\eta_A\sigma_\nu^2}{\eta_A\sigma_\nu^2 + \sigma_\epsilon^2}\Big)(\tilde{\nu} + \frac{\sum_{n=1}^{N}\tilde{\epsilon}_n}{N}). \tag{A.8}$$

We want to establish that Equation (1) is the unique linear equilibrium, and we want to verify the statements made above about information revelation. Suppose the informed trade is $\tilde{x} = \alpha + \beta\tilde{S}$ for some α and β. Then,

$$p(\tilde{y}) = E[\tilde{\nu}|\tilde{x}+\tilde{z}] \tag{A.9}$$

$$= \bar{\nu} + \frac{cov(\tilde{\nu}, \tilde{x}+\tilde{z})}{var(\tilde{x}+\tilde{z})}(\tilde{x}+\tilde{z}-E[\tilde{x}+\tilde{z}]) \tag{A.10}$$

$$= \bar{\nu} - \frac{cov(\tilde{\nu}, \tilde{x})}{var(\tilde{x}+\tilde{z})}(\alpha+\beta E[\tilde{S}]) + \frac{cov(\tilde{\nu}, \tilde{x})}{var(\tilde{x}+\tilde{z})}(\tilde{x}+\tilde{z}). \tag{A.11}$$

Thus, in a linear equilibrium, we must have

$$\lambda = \frac{cov(\tilde{\nu}, \tilde{x})}{var(\tilde{x}+\tilde{z})} \tag{A.12}$$

$$= \frac{\beta\rho_A^2\sigma_\nu^2}{\beta^2\rho_A^4(\sigma_\nu+\sigma_\epsilon^2/N)+\sigma_z^2}. \tag{A.13}$$

$$\delta = \bar{\nu} - \lambda(\alpha+\beta E[\tilde{S}]). \tag{A.14}$$

On the other hand, if $p(y) = \delta + \lambda\tilde{y}$ for any δ and λ, then the informed trader's optimization problem is to maximize

$$E_I[(\tilde{\nu}-p(y))\tilde{x}|\tilde{S}] = \tilde{x}E_I[\tilde{\nu}-\delta-\lambda(\tilde{x}+\tilde{z})|\tilde{S}] \tag{A.15}$$

$$= -\lambda\tilde{x}^2 + \tilde{x}E_I[\tilde{\nu}-\delta|\tilde{S}] \tag{A.16}$$

$$= -\lambda\tilde{x}^2 + \tilde{x}E_I[\tilde{\nu}-\delta] + \tilde{x}\frac{\rho_I^2}{\rho_A^2}(\tilde{S}-E_I[\tilde{S}]). \tag{A.17}$$

The first-order condition of Equation (A.15) gives

$$-2\lambda\tilde{x} + E_I[\tilde{\nu}-\delta] + \frac{\rho_I^2}{\rho_A^2}(\tilde{S}-E_I[\tilde{S}]) = 0. \tag{A.18}$$

There is a solution to this problem only if λ ¿ 0, and, in that case, the solution is

$$\tilde{x} = \frac{1}{2\lambda}\Big(-\delta+\bar{\nu}_I(1-\rho_I^2) - \frac{\rho_I^2(1-\rho_A^2)}{\rho_A^2}\frac{\sum_{n=1}^N \bar{\nu}_n}{N}\Big) + \frac{1}{2\lambda}\Big(\frac{\rho_I^2}{\rho_A^2}\tilde{S}\Big). \tag{A.19}$$

Thus, in a linear equilibrium, we must have

$$\lambda = \frac{1}{2}\frac{\sigma_\nu}{\sigma_z}\sqrt{\rho_I^2\Big(1 - \frac{(\eta_I - 1)\sigma_\epsilon^2}{N\eta_I\sigma_\nu^2 + \sigma_\epsilon^2}\Big)}, \tag{A.20}$$

$$\delta = \bar{\nu}(2 - \rho_I^2) + \bar{\nu}_I(1 - \rho_I^2\rho_A^2), \tag{A.21}$$

$$\beta = \frac{1}{2\lambda}\frac{\rho_I^2}{\rho_A^2}, \tag{A.22}$$

$$\alpha = \frac{-1}{2\lambda}\Big[\delta + \rho_I^2(1 - \rho_A^2)\frac{\sum_{n=1}^N \bar{\nu}_n}{N} - (1 - \rho_I^2)\bar{\nu}_I\Big]. \tag{A.23}$$

Appendix B. Theoretical Definition of Analyst Disagreement

We define analyst disagreement D as

$$\begin{aligned} D &= \frac{1}{N-1}\sum_{n=1}^N \Big(Var[(\tilde{s}_n - \tilde{S})]\Big) && \text{(B.1)}\\ &= \frac{1}{N-1}\sum_{n=1}^N \Big(Var\Big[\rho_A^2\frac{(N-1)\tilde{\epsilon}_n - \sum_{j\neq n}^{N-1}\tilde{\epsilon}_j}{N}\Big]\Big) && \text{(B.2)}\\ &= \rho_A^4\sigma_\epsilon^2 && \text{(B.3)}\\ &= \Big(\frac{\eta\sigma_\nu^2}{\eta\sigma_\nu^2 + \sigma_\epsilon^2}\Big)^2\sigma_\epsilon^2. && \text{(B.4)}\end{aligned}$$

It is different from Barron et al. (1998), which defines analyst disagreement as E[d]. In their model, analysts possess homogeneous prior, therefore the E[d] simply equals

$$\frac{1}{N-1}\sum_{n=1}^N \Big(Var[(\tilde{s}_n - \tilde{S})]\Big). \tag{B.5}$$

In our model, the unconditioned sample variance of analyst forecast, E[d], is

$$
\begin{aligned}
E[d] &= E\Big[\frac{1}{N-1}\sum_{n=1}^{N}(\tilde{s}_n - \tilde{S})^2\Big] && \text{(B.6)}\\
&= \frac{1}{N-1}\sum_{n=1}^{N}\Big(E[(\tilde{s}_n - \tilde{S})^2]\Big) && \text{(B.7)}\\
&= \frac{1}{N-1}\sum_{n=1}^{N}\Big(Var[(\tilde{s}_n - \tilde{S})] + E[\tilde{s}_n - \tilde{S}]^2\Big) && \text{(B.8)}\\
&= \frac{1}{N-1}\sum_{n=1}^{N}Var[(\tilde{s}_n - \tilde{S})] + \frac{1}{N-1}\sum_{n=1}^{N}E[\tilde{s}_n - \tilde{S}]^2 && \text{(B.9)}\\
&= D + \frac{1}{N-1}\sum_{n=1}^{N}\Big(\bar{\nu}_n - \frac{\sum_{n=1}^{N}\bar{\nu}_n}{N}\Big)^2. && \text{(B.10)}
\end{aligned}
$$

One factor of E[d] is sample variance of analysts' prior mean, $\frac{1}{N-1}\sum_{n=1}^{N}\Big(\bar{\nu}_n - \frac{\sum_{n=1}^{N}\bar{\nu}_n}{N}\Big)^2$, and denotes S_A. According to the usual argument that sample variance $\eta\sigma_\nu^2$ can be used to estimate the variance of the sample mean S_A, we assume that $S_A = \eta * C$ and C is a constant. Another factor of E[d] is D, which is also positively related to the parameter η. Therefore, the prediction of Lemma 1 remains the same, if we replace the definition of analyst disagreement to E[d].

Appendix C. Sample Distribution of Disagreement Components

Table C.1 shows the distribution given high or low levels of disagreement components. In this table, there are eight groups. A high or low level refers to the value of the disagreement component above or below its median, respectively. The range of the average cross-sectional distribution of each group is 8.04-17.28%, which shows a slight concentration in certain groups. Among these groups, about one-third are in the group with all high levels of disagreement components (HHH) or all low levels (LLL), while about one-third are in the group with one low and two high levels of disagreement components (HLH, LHH, and HHL), and about one-third are in the group with only one disagreement component at a high level (HLL, LHL, and LLH).

Conditioned on the level of disagreement component, we find the probability that analyst disagreement is above the median tends to be highest if all components are high (97.08%), and it tends to be lowest if all components are low (4.43%). Following our theoretical prediction regarding analyst disagreement, this result suggests that analysts tend to be credible. Also, conditioned on the level of disagreement component, we find the probability that price impact is above its median tends to be second-highest if the information component level is high and other component levels are low (62.13%), and it tends to be the lowest if the component levels are reversed (29.71%). The sample's distribution confirms the general disagreement component's effects on analyst disagreement and price impact.

Table C.1
Empirical Distribution of Disagreement Components

This table reports the average cross-sectional distribution of eight combinations of disagreement components and the conditional probability of high D or high λ. The information, noise, and opinion components are proxied by EVOL, D_{R1}, and $|EAC|$, respectively. Each disagreement component is divided into H and L groups. When the value of the disagreement component is above its median, it is denoted H; otherwise, it is denoted L. P(σ_ν^2, σ_ϵ^2, η) is group size, which represents the average cross-section percent of the population. High D (or λ) represents the case in which the value of D (or λ) is higher than its cross-section median. P(High D — σ_ν^2, σ_ϵ^2, η) is the probability of high analyst disagreement conditioned on the level of disagreement components, while P(High —) is the probability of high price impact conditioned on the level of disagreement components. D is the standard deviation of analyst forecasts scaled by the mean forecast at month t. λ is Amihud's (2002) illiquidity measure, which is the average ratio of the daily absolute return to the (dollar) trading volume on that day in the previous 12 months, multiplied by 100,000,000. EVOL is the time-series standard deviation of earnings divided by its time-series mean. EAC is the time-series covariance of unexpected earnings and the unexpected mean analyst forecast. $|EAC|$ is the absolute value of EAC. D_{R1} is the residual part of the regression of Equation (II.D). The results are reported from January 1987 to December 2016. An NYSE/AMEX/Nasdaq stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than $5.

Group Type (The Combinations of Level of Disagreement Component)			Distribution and Conditional Probability		
σ_ν^2 (EVOL)	σ_ϵ^2 (D_{R1})	η ($\|EAC\|$	P(σ_ν^2, σ_ϵ^2 , η): Group Size (% of Population)	P(high D — σ_ν^2, σ_ϵ^2 , η): % of High D in Group	P(high λ — σ_ν^2, σ_ϵ^2 , η): % of High λ in Group
L	L	L	16.93	4.43	47.94
L	L	H	8.36	6.90	33.11
H	L	L	16.41	29.41	62.13
L	H	L	8.28	54.39	48.55
H	L	H	8.60	45.51	55.47
L	H	H	16.09	69.91	29.71
H	H	L	8.04	91.63	69.16
H	H	H	17.28	97.08	51.52

Appendix D. Definitions of Variables

Table D.1 Table of Variables

Variables	Abbreviation	Definition
Panel A. Control Variables		
Market beta	β_{CAPM}	We calculate the market beta (β_{CAPM}) of stock i in month t as the slope coefficient from a regression of the excess returns of the stock on the excess returns of the market portfolio using monthly stock return data from all month within previous five years. We require a minimum of 24 worth of valid monthly return data to calculate β_{CAPM}. Values of β_{CAPM} for which this criterion is not met are considered missing. The excess return of stock i in month t is calculated as the return of stock i in month t minus the return of the risk-free security in month t.
Market value	MV	We define the market value (MV) for stock i in month t as the number of shares outstanding times the price of the stock at the portfolio formation date divided by one million. Thus, is measured in millions of dollars.
Book-to-market ratio	BM	The book-to-market ratio (BM) of a stock is calculated as the book value of the firm's book equity (BE) divided by the market value of the firm's equity (MV). The BE/MV ratio is updated each month. We match the yearly book equity figure for all fiscal years ending in calendar year - 1. We followed (Daniel and Titman, 1997), and define book equity (BE) to be stockholder's equity plus any deferred taxes and any investment tax credit, minus the value of any preferred stock. Specifically, $$BE = SEQ + TXDB + ITCB - PSTKRV, \qquad (D.1)$$ where SEQ is stockholders' equity, TXDB is deferred taxes, ITCB is investment tax credit, PSTKRV is preferred stock minus redemption value. If SEQ is missing, we use CEQ (total common equity) plus PSTK (preferred stock par value). If PSTKRV is missing, we use PSTKL (preferred stock minus liquidating value) or PSTK (proffered stock minus caring value, stock capital minus total). All variables used to calculate BE is from Compustat.
Return volatility	$SIGMA$	Return volatility is the standard deviation of weekly market excess returns over the year ending at the portfolio formation date. A 1-year estimation period is chosen to provide a reasonable number of observations.

Stock turnover	$TURN$	Stock turnover is the share turnover measured by the annual average of daily number of shares traded divided by the number of shares outstanding.
Analyst coverage	COV	Analyst coverage is the number of analysts following the firm in the previous year. This variable is from I/B/E/S Summary History. According to the I/B/E/S DETAIL HISTORY USER GUIDE, estimates are updated by a contributing analyst sending a confirmation, revision or drop in coverage. If an estimate has not been updated for 105 days, the estimate is filtered, footnoted and excluded from the mean. When Q4 is the current reporting period, Q4 and FY1 estimates are an exception to this rule: Q4 and FY1 estimates will be filtered when they have not been updated for 120 days. This allows extra time for companies to report year-end results.
Residual coverage	COV_R	The residual of analyst coverage is constructed as Diether et al. (2002) suggested. $$ln(COV) = a_1 * ln(MV) + a_2 * ln(BM) + COV_R. \quad (D.2)$$
Panel B. Parametor Estimation		
Price impact λ	λ	We estimate price impact λ by using Amihud's (2002) illiquidity measure, which is the average ratio of the daily absolute return to the (dollar) trading volume on that day in the previous 12 months. For presentation, we multiply the numbers by 100,000,000.
Analyst disagreement D	D	In the prior literature, analyst disagreement (forecast dispersion) is widely used as a proxy for uncertainty about future earnings or the degree of consensus among analysts or market participants (e.g., Barron et al. (1998); Barron and Stuerke (1998); Diether et al. (2002); Imhoff Jr and Lobo (1992); Lang and Lundholm (1996)). We measure analyst disagreement as the standard deviation of analyst forecasts scaled by the mean forecast. This variable is from I/B/E/S Summary History.
Information		

component σ_ν^2	$EVOL$	We define information component as the earning volatility is the standard deviation of annual earnings from the past 5 years (at least 3 years) divided by their mean. $$EVOL_{i,t} = \frac{stdev(e_{i,y})}{mean(e_{i,y})}, \quad (D.3)$$ where $e_{i,y}$ is annual earnings per share for the most recent 5 years announced as of month t for stock i, with y denoting the fiscal year of the earnings numbers. The $e_{i,y}$ is from I/B/E/S Summary History. We adjust $e_{i,y}$ by stock splits.
Orthogonalized information component	$EVOL_R$	The orthogonalized information component is the residual of earnings volatility which is regressed on opinion component. $$ln(EVOL) = b_1 * ln(\|EAC\|) + EVOL_R. \quad (D.4)$$
Unexpected earnings	UE	The unexpected earning for stock i in month t is defined as, $$UE_{i,t} = e_{i,y} - e_{i,y-1}, \quad (D.5)$$ where $e_{i,y}$ is annual earnings per share most recently announced as of month t for stock i, y denotes the fiscal year of earnings numbers, and $e_{i,y-1}$ is earnings per share 1 year ago.
Unexpected average forecasts	UA	The unexpected mean analyst forecast for stock i in month t is thus defined as $$UA_{i,t} = \bar{A}_{i,k,y} - e_{i,y-1}, \quad (D.6)$$ where $\bar{A}_{i,k,y}$ is the average forecast of annual earnings per share in the I/B/E/S summary database as of month t for stock i, and y denotes the fiscal year of earnings numbers. We give each monthly average forecast a sequence number, K, to represent the first (1) $\bar{A}_{i,k,y}$ to the last (12) $\bar{A}_{i,k,y}$ average forecast of annual earnings per share. If there are more than 12 monthly average forecasts for annual earnings, we only keep the first to the 11th and the last forecasts, and then we force the last forecast as K = 12.
Opinion		

component η	$\lvert EAC \rvert$	We define opinion component as the absolute value of covariance of UE and UA for the stock i in month t, is calculated with data from at least 3 of the previous 5 years. For example, the fiscal year end of stock XYZ is December. For January 1990, if there is a first average forecast in that fiscal year, then the K = 1. We compute the EAC by using the average forecast with the same K from 1986 to 1990 and their corresponding true earnings number.
Orthogonalized opinion component	EAC_R	Orthogonalized opinion component is the residual of the opinion component which is regressed on information component. $$ln(\lvert EAC \rvert) = c_1 * ln(EVOL) + EAC_R. \quad \text{(D.7)}$$
Unexpected earnings (drift adjusted)	UE_D	The unexpected earning (drift adjusted) for stock i in month t is defined as, $$UE_{D,i,t} = e_{i,y} - e_{i,y-1} - \frac{\sum_{j=1}^{2}(e_{i,y-j} - e_{i,y-j-1})}{2}, \quad \text{(D.8)}$$ where $\frac{\sum_{j=1}^{2}(e_{i,y-j} - e_{i,y-j-1})}{2}$ is the expected drift term of annual earnings per share followed the idea of Jegadeesh and Livnat (2006).
Unexpected average forecasts (drift adjusted)	UA_D	The unexpected mean analyst forecast for stock i in month t is thus defined as $$UA_{D,i,t} = \bar{A}_{i,k,y} - e_{i,y-1} - \frac{\sum_{j=1}^{2}(e_{i,y-j} - e_{i,y-j-1})}{2}. \quad \text{(D.9)}$$
Opinion component (drift adjusted)	$\lvert EAC_D \rvert$	We define opinion component (drift adjusted) as the absolute value of covariance of UE_D and UA_D for the stock i in month t, is calculated with data from at least 3 of the previous 5 years.
Noise		

component σ_ϵ^2	D_{R1}	We define this noise component as the residual of decomposing regression (II.D) in Chapter II.
Alternative noise component	D_{R2}	We define this noise component as the residual of decomposing regression, which is $$\begin{aligned} ln(D) &= \beta_{CAPM} + ln(MV) + ln(BM) + SIGMA + ln(K) \\ &+ COV_R + EVOL_R + EAC_R. \qquad \text{(D.10)} \end{aligned}$$

Appendix E. Robustness Checks

]

This appendix contains the robustness results discussed in Section IV: (1) size neutral portfolio analysis, (2) using alternative disagreement components, (3) subperiods analysis.

E.1. Size Neutral Portfolio Analysis

In this section, we double-sort on firm size (MV) and analyst disagreement or disagreement components to test whether we are merely picking up a size effect in returns. Stocks are first sorted into five categories based on the level of market capitalization at the end of the previous month. Within each size category, the stocks are sorted into five groups based on analyst disagreement or disagreement component groups within each resulting group. Table E.1 presents the returns of the resulting 25 bivariate portfolios. Each portfolio contains an average of 67 stocks.

Consistent with our main results, we show that the strong negative relationship between analyst disagreement and future returns is driven by two factors: (1) the underperforming stocks with a high information component σ_ν^2 ($EVOL$) or high noise component σ_ϵ^2 (D_{R1}) and (2) the outperforming stocks with low opinion component η ($|EAC|$), after controlling for the size effect. However, we do find that firm size impacts the effects of disagreement components.

In Panel A, across all size categories, we find strong mispricing in portfolios with both the lowest (i.e., fifteen of twenty alphas are significant) and highest (i.e., nine of twenty alphas are significant) levels of disagreement. The size effect seems to be more pronounced on the overpricing of high disagreement stocks than on the underpricing of low disagreement stocks. Stocks with low disagreement tend to be underpriced, which is related to the management-type anomalies (MGMT), while stocks with high disagreement tend to be overpriced, which is related to both the performance (PERF)- and management (MGMT)-type anomalies. The alpha differential shows that the high disagreement stocks persistently underperform (i.e., seventeen of twenty are significant) the low disagreement stocks across all sizes.

In Panels B, C, and D, we analyze the disagreement components in the given size groups. Panel B shows strong overpricing in the high $EVOL$ portfolio (i.e., twelve of twenty alphas are significant), which is stronger in small firms but weaker in large firms. Panel C shows strong overpricing of high D_{R1} portfolios (i.e., four of twenty alphas are significant), which is concentrated in small firms only. Panel D shows strong underpricing of low $|EAC|$ portfolios (i.e., nine of twenty alphas are significant), which is stronger in small firms but weaker in large firms across firm sizes. These results confirm our mispricing predictions are not simply picking up the size effect.

[Place Table E.1 about here]

E.2. Portfolio Analysis for the Alternative Disagreement Components

In Table E.2 , the results are quite similar to our main results. The information component effect dominates the portfolio's liquidity, and the noise component (D_{R2}) effect dominates the portfolio's analyst disagreement. After orthogonalization, $EVOL_R$ and EAC_R have weaker effects on analyst disagreement but stronger effects on price impact. This result confirms our prediction that the information and opinion components are correlated but have opposite effects on liquidity. Considering that our measure of UE and UA might not capture the idea of "unexpected" earnings and forecasts, we use $|EAC_D|$ as an additional alternative opinion component. This measure is the absolute value of covariance between UE_D and UA_D, which are drift-adjusted unexpected earnings measures and similar to Jegadeesh and Livnat's (2006) work. The result of D_{R2} is quite similar to that of D_{R1}, and the weak result of residual coverage suggests that it is not a good proxy for the noise component. We focus on $EVOL_R$, D_{R2}, EAC_R, and $|EAC_D|$ in the following analyses.

We find that the largest difference in analyst disagreement between high and low portfolios is for the noise component (D_{R2}) at 1.05 (the original is 1.05), and those of the information and two opinion components are 0.33, 0.06, and 0.17 (the original values are 0.33 and 0.19), respectively. The largest difference in price impact between high and low portfolios is for the information component at 12.40 (the original value is 8.87), and those of the noise component (D_{R2}) and two opinion components are -3.52, -10.05, and -6.82 (the original values are -3.69 and -7.07), respectively. All patterns across the portfolios are monotonically or nearly monotonically increasing or decreasing, except for the relationship between price impact and the noise component. Similar to the main result, there is a reversed J-shaped relationship between price impact and the noise component, which is a declining and rising pattern in the average price impact for a net reduction in price impact. The second-highest price impact with the highest noise component portfolio could be driven by the coincidence of a high information component, as we show in Table C.1 . All differences are significant at the 1% level.

[Place Table E.2 about here]

In Table E.3 , we find persistent evidence that supports our main results. We show that the strong negative relationship between analyst disagreement and future returns is driven by two factors: (1) underperforming stocks with a high alternative information component σ_ν^2 ($EVOL_R$) or high alternative noise component σ_ϵ^2 (D_{R2}) and (2) outperforming stocks with a low alternative opinion component η (EAC_R and $|EAC_D|$).

Panel A shows strong overpricing of high $EVOL_R$ portfolios (i.e., four of four alphas are significant), which is related to both the MGMT and PERF mispricing factors. Panel B shows strong overpricing of high D_{R2} portfolios (i.e., four of four alphas are significant), which is related to the PERF mispricing factor. Panel C shows no overpricing of high COV_R portfolios. Panel D shows strong underpricing of low EAC_R portfolios (three of four alphas are significant), which is related to the PERF mispricing factor (the original is related to both the MGMT and PERF mispricing factors). Panel E shows strong underpricing of low $|EAC_D|$ portfolios (i.e., four of four alphas are significant), which is related to the MGMT mispricing factor (the original is related to both the MGMT and PERF mispricing factors). These results confirm our mispricing prediction, which is that mispricing is more pronounced for stocks with high information or noise components or a low opinion component.

Moreover, we find that in Panel A, the significant underpricing at the lowest $EVOL_R$ portfolio is for only one of four alphas, which is less than that for (i.e., two of four alphas are significant); in panel D, we find no overpricing for the highest EAC_R portfolio, which is less than that for the original opinion component (i.e., one of four alphas is significant). These results confirm that the inconsistent mispricing in our main result is driven by the correlation between $EVOL$ and $|EAC|$.

[Place Table E.3 about here]

E.3. Fama-MacBeth Regressions: Using Alternative Disagreement Components

We run Fama and MacBeth's (1973) cross-sectional regressions for each month on all securities in the intersection of CRSP, Compustat, and I/B/E/S datasets from February 1987 to December 2016. We run the regressions again and replace the disagreement components ($EVOL$, D_{R1}, and $|EAC|$) with their alternative measures ($EVOL_R$, D_{R2}, EAC_R, and $|EAC_D|$). Specifically, we regress the cross-section of individual stock returns at time t on a constant, the one-month lag of alternative information component σ_ν^2 ($EVOL_R$), the one-month lag of alternative opinion component η (EAC_R or $|EAC_D|$), the one-month lag of alternative noise component σ_ϵ^2 (D_{R2}), the dummy variable of the top 20% of the one month lag of σ_ν^2, the bottom 20% of the one-month lag of η, the top 20% of the one-month lag of σ_ϵ^2, market β, $ln(MV)$ (log of market capitalization at t-1), $ln(BM)$, a stock's past-year return ret-12 : -2), the one-month past return (ret-1 : -1), a stock's long-run past return (ret-36 : -13), and $ln(TURN)$ (log of turnover). Standard errors are adjusted for autocorrelation and heteroskedasticity.

Table E.4 shows the results of applying Fama and MacBeth's (1973) cross-sectional regressions. The findings are similar to our main results. In Panel A, we examine the linear effects of disagreement components on future returns. By using the true value of three disagreement components, from the specification (1) to (8), we find that all components have negative effects on returns. However, the alternative opinion component, EAC_R, only has insignificant negative effects on stock returns. In specifications (9) and (10), we control all components simultaneously. We find that the disagreement effect is mainly driven by the alternative information component; the of the alternative noise component's effect seems to pick up the momentum effect, and interestingly, the alternative opinion component's effect becomes significant after controlling the turnover and past return variables.

In panel B, we further control the potential nonlinear effects of alternative disagreement components. In specification (1), the high alternative information component has a strong negative effect on future returns (-0.38% with a -4.05 t-value); in specification (3), the high alternative noise component has a moderate negative effect on future returns (-0.18% with a -2.43 t-value); in specification (5), the low alternative opinion component (EAC_R) has an insignificant positive effect on future returns (0.04% with a 0.74 t-value); in specification (7), the low alternative opinion component ($|EAC_D|$) has a significant positive effect on future returns (0.14% with a 2.44 t-value). The alternative information and noise components' effects are quite persistent, but the alternative opinion component's (EAC_R) effect becomes significant only after controlling the turnover and past return variables.

These results suggest that the of the alternative information and noise components' effects are quite similar to the effects of their original variables. However, the effect of the alternative opinion component, which orthogonalizes its collinear portion with the information component, becomes weaker and sensitive to the stock turnover and past return variables.

[Place Table E.4 about here]

E.4. Portfolio Analysis for the Subperiods

In this subsection, we analyze portfolio strategies in different subperiods: 1987–1996, 1997–2006, 2007–2016, a high sentiment period, and a low sentiment period. In the high sentiment period, the liquidity and mispricing phenomena could be different from the low sentiment period. Also, the market structure changes over time, and it could have different impacts on our results. Therefore, we apply a subperiod portfolio analysis as a robustness check. In general, we find similar results, which confirms that changes in market structure and the level of investor sentiment do not drive our results. The sentiment period is identified by Baker and Wurgler's (2006) orthogonalized sentiment index.[22]

Also, several important market structure changes took place in the 1997–2006 time period, and they are thought to impact market liquidity. For example, in early 1997, the Securities and Exchange Commission (SEC) introduced rules that exposed Nasdaq market makers to competition from the general public. On the NYSE, the tick size was $1/8 for stocks with prices over one dollar until June 1997, when, under regulatory pressure, it was reduced to $1/16 and finally, in 2000, to $0.01. Decimalization was also imposed on Nasdaq and AMEX. In 2002, the NYSE started releasing information on limit orders.

In Table E.5 , the results are quite similar to our main results. In all subperiods, the information component's ($EVOL$) effect dominates the portfolio's liquidity, and the noise component's (D_{R1}) effect dominates the portfolio's analyst disagreement. Portfolio average analyst disagreement and price impact do not seem to differ significantly between high and low sentiment periods. The average analyst disagreement decreases dramatically during 1997-2006 and then increases after 2007. The average price impact decreases over time, and it may reflect changes in market structure.

[Place Table E.5 about here]

In Table E.6 , we show that the overpricing/underpricing phenomena of high/low analyst disagreement is strong when sentiment is low, in the 1987–1996 and 2007–2016 periods. During the high sentiment and 1997–2006 periods, the mispricing of low and high analyst disagreement become weaker. In Table E.7 , we show that the overpricing phenomenon of the high information component exists in all subperiods. It is strong during the high sentiment, 1997–2006, and 2007–2016 periods but moderate during the low sentiment and 1987–1996 periods. In Table E.8 , we show that the overpricing phenomenon of the high noise component exists during the low sentiment and 2007–2016 subperiods. It disappears during the high sentiment, 1987–1996, and 1997–2006 periods. In Table E.9 , we show that the overpricing phenomenon of the low opinion component exists in all subperiods. It is strong during the high sentiment and 1987–1996 periods but moderate during the low sentiment, 1997–2006, and 2007–2016 subperiods.

[Place Table E.6 about here]
[Place Table E.7 about here]

[22] Baker and Wurgler (2006) propose two indexes: investor sentiment and orthogonalized sentiment; we choose the second one because it conducts the business cycle component, which could mislead sentiment. For instance, the number of IPOs varies with the business cycle, in part, for entirely rational reasons. Orthogonalized sentiment is the annual frequency from 1960 to 2010. Specifically, this index identifies 1987, 1988, 1992, 1996, 1997, 1999, 2000, 2001, 2004, 2006, and 2007 as high investor sentiment periods between 1987 and 2010.

[Place Table E.8 about here]
[Place Table E.9 about here]

Table E.1
Portfolios Mispricing Analysis: Size Effect

This table reports average risk-adjusted returns and factor sensitivity for 5X5 portfolios. We hold stocks for 3 months and calculate returns according to Jegadeesh and Titman's (1993) methodology. We report the alpha of CAPM, Fama-French three-factor (FF3), Fama-French three-factor plus momentum (FF4), and Stambaugh and Yuan's (2016) mispricing factor models. Factor sensitivities are reported for the two mispricing factors (MGMT and PERF) in Stambaugh and Yuan (2016). In Panel A, portfolios are sequentially sorted by firm size (MV) and then sorted by D (analyst disagreement); in Panel B, portfolios are sequentially sorted by MV and then by the information component σ_ν^2 (EVOL); in Panel C, portfolios are sequentially sorted by MV and then by the noise component σ_ϵ^2 (D_{R1}); in Panel D, portfolios are sequentially sorted by MV and then by the opinion component η ($|EAC|$). D is the standard deviation of analyst forecasts scaled by the mean forecast at month t. EVOL is the time-series standard deviation of earnings divided by its time-series mean. D_{R1} is the residual part of the regression of Equation (II.D). EAC is the time-series covariance of unexpected earnings and unexpected mean analyst forecasts. $|EAC|$ is the absolute value of EAC. The results are reported from January 1987 to December 2016. An NYSE/AMEX/Nasdaq stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than \$5. On average, there are 67 stocks in each portfolio. $*$, $**$, and $***$ indicate the significance level at 0.1, 0.05, and 0.01, respectively.

Panel A. Double Sorting: Firm Size (MV) X Analyst-Disagreement (X=D)									
MV	X	CAPM		FF3		FF4		M4	
1(L)	1(L)	0.46**	(2.08)	0.29**	(2.04)	0.36***	(2.66)	0.20	(1.48)
		0.36*	(1.70)	0.20	(1.51)	0.30**	(2.55)	0.12	(1.04)
		0.00	(0.02)	-0.14	(-1.15)	-0.01	(-0.06)	-0.12	(-0.95)
		-0.14	(-0.59)	−0.30**	(-2.42)	-0.15	(-1.21)	-0.22	(-1.60)
	5(H)	−0.46*	(-1.92)	−0.62***	(-5.08)	−0.44***	(-3.37)	−0.42***	(-3.10)
2	1	0.37**	(2.01)	0.21*	(1.79)	0.24**	(2.11)	0.01	(0.07)
		0.29*	(1.71)	0.17	(1.50)	0.26**	(2.42)	0.08	(0.77)
		0.20	(1.20)	0.07	(0.67)	0.14	(1.46)	0.01	(0.14)
		0.09	(0.52)	-0.01	(-0.14)	0.11	(1.04)	0.04	(0.34)
	5	-0.30	(-1.31)	−0.45***	(-3.74)	−0.28**	(-2.45)	−0.31**	(-2.33)
3	1	0.34**	(2.16)	0.22**	(2.03)	0.25**	(2.37)	0.05	(0.44)
		0.21	(1.39)	0.09	(0.89)	0.14	(1.40)	0.01	(0.06)
		0.09	(0.59)	-0.02	(-0.17)	0.04	(0.44)	-0.10	(-0.93)
		0.06	(0.37)	-0.06	(-0.66)	0.01	(0.08)	-0.09	(-0.84)
	5	-0.10	(-0.51)	-0.21	(-1.57)	-0.10	(-0.83)	-0.07	(-0.48)
4	1	0.33**	(2.24)	0.24**	(2.05)	0.23**	(2.01)	0.06	(0.51)
		0.23*	(1.74)	0.15	(1.43)	0.17*	(1.71)	0.04	(0.35)
		0.06	(0.50)	-0.03	(-0.36)	0.03	(0.33)	0.01	(0.13)
		0.08	(0.56)	-0.02	(-0.15)	0.05	(0.48)	0.03	(0.26)
	5	-0.12	(-0.78)	−0.21*	(-1.76)	-0.09	(-0.87)	0.00	(-0.02)
5(H)	1	0.29**	(2.45)	0.25***	(2.63)	0.21**	(2.14)	0.05	(0.51)
		0.12	(1.39)	0.07	(1.00)	0.07	(0.95)	0.00	(-0.03)
		0.03	(0.43)	-0.01	(-0.12)	0.03	(0.45)	0.01	(0.09)
		-0.01	(-0.12)	-0.05	(-0.80)	0.00	(-0.07)	0.03	(0.46)
	5	-0.13	(-0.90)	−0.21*	(-1.70)	-0.10	(-0.88)	0.05	(0.44)

(continued)

Table E.1 –*Continued*

1	5-1	−0.92***	(-4.64)	−0.92***	(-4.74)	−0.79***	(-4.31)	−0.62***	(-3.58)
2	5-1	−0.67***	(-3.42)	−0.66***	(-3.78)	−0.52***	(-3.13)	−0.31*	(-1.79)
3	5-1	−0.44**	(-2.34)	−0.43**	(-2.38)	−0.35**	(-2.03)	-0.11	(-0.61)
4	5-1	−0.46***	(-2.78)	−0.46***	(-2.89)	−0.33**	(-2.18)	-0.06	(-0.39)
5	5-1	−0.42**	(-2.26)	−0.46***	(-2.62)	−0.32*	(-1.80)	0.00	(0.03)
5-1	1	-0.17	(-0.82)	-0.04	(-0.33)	-0.15	(-1.24)	-0.15	(-1.14)
5-1	5	0.33	(1.52)	0.42***	(3.17)	0.33**	(2.41)	0.47***	(2.96)
Panel B. Double Sorting: Firm Size (MV) X Information Component (X=EVOL)									
MV	X	CAPM		FF3		FF4		M4	
1(L)	1(L)	0.31	(1.49)	0.14	(1.02)	0.25*	(1.88)	0.05	(0.40)
		0.43**	(1.97)	0.24**	(1.97)	0.33***	(2.77)	0.15	(1.19)
		0.28	(1.16)	0.10	(0.75)	0.24*	(1.79)	0.13	(0.93)
		-0.15	(-0.72)	−0.30**	(-2.31)	-0.14	(-1.11)	-0.20	(-1.48)
	5(H)	−0.63**	(-2.52)	−0.77***	(-5.34)	−0.61***	(-3.86)	−0.55***	(-3.28)
2	1	0.26	(1.60)	0.09	(0.91)	0.14	(1.38)	-0.14	(-1.50)
		0.34*	(1.74)	0.18	(1.59)	0.25**	(2.41)	0.02	(0.15)
		0.36**	(2.08)	0.24**	(2.46)	0.30***	(2.98)	0.20**	(2.12)
		0.14	(0.76)	0.03	(0.30)	0.18*	(1.67)	0.16	(1.29)
	5	−0.47**	(-2.25)	−0.57***	(-4.45)	−0.42***	(-3.27)	−0.42***	(-2.72)
3	1	0.27*	(1.85)	0.11	(1.10)	0.14	(1.48)	-0.07	(-0.75)
		0.20	(1.12)	0.05	(0.47)	0.12	(1.22)	-0.05	(-0.52)
		0.30*	(1.84)	0.18*	(1.84)	0.22**	(2.28)	0.06	(0.60)
		0.13	(0.83)	0.06	(0.54)	0.14	(1.20)	0.11	(0.84)
	5	-0.31	(-1.53)	−0.37***	(-2.74)	−0.29**	(-2.16)	-0.24	(-1.54)
4	1	0.24	(1.57)	0.09	(0.85)	0.12	(1.25)	-0.08	(-0.73)
		0.23	(1.45)	0.09	(0.73)	0.14	(1.29)	-0.03	(-0.26)
		0.19	(1.49)	0.10	(0.99)	0.13	(1.26)	0.05	(0.47)
		0.16	(1.15)	0.11	(1.04)	0.17	(1.61)	0.19*	(1.83)
	5	-0.26	(-1.46)	−0.27*	(-1.87)	-0.18	(-1.33)	-0.01	(-0.08)
5(H)	1	0.16	(1.22)	0.04	(0.42)	0.06	(0.71)	-0.11	(-1.23)
		0.09	(0.79)	-0.01	(-0.08)	0.01	(0.14)	-0.15	(-1.53)
		0.16	(1.55)	0.09	(1.19)	0.10	(1.34)	0.00	(-0.01)
		0.06	(0.72)	0.05	(0.66)	0.10	(1.22)	0.19**	(2.31)
	5	-0.17	(-1.22)	-0.12	(-0.92)	-0.08	(-0.59)	0.19*	(1.65)
1	5-1	−0.94***	(-4.15)	−0.91***	(-4.38)	−0.86***	(-3.99)	−0.61***	(-2.91)
2	5-1	−0.73***	(-4.27)	−0.66***	(-4.28)	−0.55***	(-3.53)	-0.28	(-1.61)
3	5-1	−0.58***	(-2.89)	−0.48***	(-2.84)	−0.42***	(-2.65)	-0.17	(-1.00)
4	5-1	−0.49**	(-2.27)	−0.35**	(-1.97)	−0.30*	(-1.77)	0.07	(0.41)
5	5-1	-0.32	(-1.48)	-0.16	(-0.84)	-0.14	(-0.75)	0.31*	(1.78)
5-1	1	-0.16	(-0.82)	-0.11	(-0.81)	-0.19	(-1.41)	-0.17	(-1.22)
5-1	5	0.46*	(1.82)	0.65***	(3.97)	0.53***	(3.02)	0.75***	(3.97)

(continued)

Table E.1 −*Continued*

Panel C. Double Sorting: Firm Size (MV) X Noise Component (X=D_{R1})									
MV	X	CAPM		FF3		FF4		M4	
1(L)	1(L)	0.20	(0.86)	0.04	(0.30)	0.15	(1.03)	0.06	(0.40)
		0.06	(0.29)	-0.11	(-0.97)	0.01	(0.10)	-0.13	(-1.15)
		0.07	(0.31)	-0.10	(-0.86)	0.05	(0.52)	-0.06	(-0.49)
		0.10	(0.50)	-0.05	(-0.51)	0.08	(0.76)	-0.01	(-0.09)
	5(H)	-0.20	(-0.88)	-0.37^{***}	(-3.12)	-0.22^{*}	(-1.72)	-0.29^{**}	(-2.30)
2	1	0.19	(1.05)	0.08	(0.67)	0.17	(1.49)	0.02	(0.17)
		0.16	(1.02)	0.04	(0.40)	0.11	(1.22)	-0.01	(-0.09)
		0.20	(1.17)	0.05	(0.54)	0.16^{*}	(1.70)	-0.01	(-0.13)
		0.11	(0.60)	-0.04	(-0.43)	0.05	(0.54)	-0.05	(-0.55)
	5	-0.03	(-0.17)	-0.16	(-1.56)	-0.03	(-0.34)	-0.11	(-1.11)
3	1	0.06	(0.35)	-0.02	(-0.13)	0.04	(0.36)	-0.04	(-0.28)
		0.18	(1.21)	0.07	(0.79)	0.13	(1.60)	0.00	(0.03)
		0.20	(1.33)	0.07	(0.81)	0.13	(1.45)	0.04	(0.37)
		0.10	(0.66)	-0.04	(-0.50)	0.01	(0.14)	-0.16^{*}	(-1.70)
	5	0.05	(0.31)	-0.07	(-0.65)	0.00	(0.02)	-0.05	(-0.44)
4	1	0.22	(1.52)	0.16	(1.43)	0.18^{*}	(1.67)	0.12	(1.12)
		0.13	(1.09)	0.05	(0.55)	0.12	(1.27)	0.07	(0.68)
		0.08	(0.66)	-0.01	(-0.15)	0.02	(0.24)	-0.05	(-0.51)
		0.15	(1.11)	0.03	(0.34)	0.07	(0.83)	0.00	(-0.03)
	5	0.00	(-0.03)	-0.10	(-0.99)	-0.02	(-0.17)	-0.01	(-0.12)
5(H)	1	0.14	(1.50)	0.11	(1.36)	0.10	(1.25)	0.05	(0.68)
		0.18^{**}	(2.00)	0.14^{*}	(1.94)	0.16^{**}	(2.13)	0.10	(1.48)
		0.01	(0.21)	-0.03	(-0.47)	0.00	(0.04)	-0.01	(-0.15)
		0.07	(0.97)	0.02	(0.32)	0.05	(0.80)	0.01	(0.20)
	5	-0.09	(-0.80)	-0.19^{**}	(-2.12)	-0.11	(-1.32)	-0.03	(-0.29)
1	5-1	-0.40^{***}	(-2.88)	-0.41^{***}	(-2.91)	-0.37^{***}	(-2.77)	-0.35^{***}	(-2.76)
2	5-1	-0.23^{*}	(-1.72)	-0.24^{*}	(-1.77)	-0.20	(-1.55)	-0.13	(-1.02)
3	5-1	-0.01	(-0.04)	-0.05	(-0.36)	-0.04	(-0.27)	-0.01	(-0.08)
4	5-1	-0.22^{**}	(-2.11)	-0.26^{**}	(-2.42)	-0.20^{*}	(-1.77)	-0.14	(-1.04)
5	5-1	-0.23^{*}	(-1.92)	-0.29^{***}	(-2.60)	-0.21^{*}	(-1.79)	-0.08	(-0.70)
5-1	5	0.10	(0.50)	0.18	(1.37)	0.11	(0.79)	0.27^{*}	(1.76)
5-1	1	-0.06	(-0.28)	0.07	(0.52)	-0.05	(-0.34)	-0.01	(-0.04)

(continued)

Table E.1 –*Continued*

Panel D. Double Sorting: Firm Size (MV) X Opinion Component (X=$\lvert EAC \rvert$)									
MV	X	CAPM		FF3		FF4		M4	
1(L)	1(L)	0.33	(1.59)	0.22*	(1.72)	0.26**	(2.04)	0.04	(0.34)
		0.09	(0.42)	-0.08	(-0.62)	0.03	(0.27)	-0.07	(-0.56)
		-0.01	(-0.04)	-0.16	(-1.40)	-0.02	(-0.18)	-0.12	(-1.10)
		0.06	(0.30)	-0.10	(-0.92)	0.07	(0.63)	-0.01	(-0.06)
	5(H)	-0.25	(-1.02)	−0.46***	(-3.50)	−0.27**	(-2.14)	−0.26*	(-1.89)
2	1	0.27	(1.52)	0.16	(1.57)	0.18*	(1.70)	-0.06	(-0.64)
		0.10	(0.58)	-0.02	(-0.25)	0.03	(0.30)	-0.16	(-1.62)
		0.12	(0.76)	0.01	(0.13)	0.11	(1.09)	0.00	(-0.03)
		0.13	(0.74)	-0.01	(-0.08)	0.11	(1.18)	0.02	(0.17)
	5	0.01	(0.03)	-0.16	(-1.34)	0.04	(0.35)	0.04	(0.28)
3	1	0.20	(1.27)	0.10	(0.88)	0.12	(1.09)	-0.08	(-0.81)
		0.16	(1.22)	0.07	(0.81)	0.11	(1.20)	-0.07	(-0.77)
		0.12	(0.82)	0.02	(0.24)	0.09	(1.05)	-0.01	(-0.14)
		0.06	(0.37)	-0.08	(-0.79)	0.01	(0.10)	-0.02	(-0.18)
	5	0.04	(0.22)	-0.10	(-0.83)	0.00	(0.00)	-0.01	(-0.07)
4	1	0.25*	(1.94)	0.19*	(1.77)	0.20*	(1.90)	0.04	(0.39)
		0.19	(1.63)	0.12	(1.35)	0.16*	(1.87)	0.07	(0.80)
		0.13	(1.07)	0.05	(0.50)	0.08	(0.95)	0.04	(0.40)
		0.02	(0.15)	-0.09	(-0.90)	-0.01	(-0.13)	-0.01	(-0.14)
	5	-0.02	(-0.11)	-0.14	(-1.07)	-0.05	(-0.40)	-0.01	(-0.07)
5(H)	1	0.17**	(2.15)	0.16**	(2.09)	0.16**	(2.07)	0.09	(1.15)
		0.10	(1.40)	0.07	(1.14)	0.11	(1.59)	0.05	(0.71)
		0.02	(0.26)	-0.01	(-0.16)	0.01	(0.20)	-0.05	(-0.75)
		0.09	(0.99)	0.04	(0.52)	0.07	(1.05)	0.08	(1.23)
	5	-0.08	(-0.54)	−0.20*	(-1.90)	-0.15	(-1.48)	-0.04	(-0.32)
1	5-1	−0.58***	(-3.32)	−0.68***	(-4.29)	−0.53***	(-3.44)	−0.30**	(-1.99)
2	5-1	−0.27**	(-2.03)	−0.33**	(-2.55)	-0.14	(-1.12)	0.10	(0.73)
3	5-1	-0.16	(-1.01)	-0.20	(-1.26)	-0.12	(-0.79)	0.08	(0.50)
4	5-1	−0.27*	(-1.80)	−0.34**	(-2.39)	−0.25*	(-1.79)	-0.05	(-0.37)
5	5-1	-0.25	(-1.60)	−0.35***	(-2.60)	−0.31**	(-2.26)	-0.12	(-0.87)
5-1	1	-0.16	(-0.78)	-0.07	(-0.54)	-0.10	(-0.84)	0.04	(0.38)
5-1	5	0.17	(0.81)	0.26**	(1.98)	0.12	(0.90)	0.22	(1.28)

Table E.2
Portfolio Characteristics: Alternative Disagreement Components

This table reports average D (i.e., analyst disagreement) and λ (i.e., Amihud's [2002] illiquidity measure). The stocks are sorted into 25 portfolios for each month based on the proxy of alternative information component σ_ν^2 ($EVOL_R$), the proxy of alternative noise component σ_ϵ^2 (D_{R2}), and the proxy of alternative opinion component η (EAC_R) for the previous month. We hold stocks for 3 months and calculate the average of monthly portfolio D and λ. D is the standard deviation of analyst forecasts scaled by the mean forecast at month t. λ is Amihud's (2002) illiquidity measure, which is the average ratio of the daily absolute return to the (dollar) trading volume on that day in the previous 12 months, multiplied by 100,000,000. EVOL is the time-series standard deviation of earnings divided by its time-series mean. $EVOL_R$ is residual part of regressing $\ln(EVOL)$ on $\ln(|EAC|)$. EAC is the time-series covariance of unexpected earnings and the unexpected mean analyst forecast. $|EAC|$ is the absolute value of EAC. EAC_R is the residual part of regressing $\ln(|EAC|)$ on $\ln(EVOL)$. $|EAC_D|$ is absolute value of covariance of UE_D and UA_D, where UE_D and UA_D are the drift adjusted version unexpected earnings and average analyst forecast. D_{R2} is the residual part of the regression of Equation (D.10). The results are reported from January 1986 to December 2016. An NYSE/AMEX/Nasdaq stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than $5. Standard errors are adjusted for autocorrelation and heteroskedasticity. On average, there are 67 stocks in each portfolio (except the portfolio sorted by $|EAC_D|$ contains average 63 stocks). $*$, $**$, and $***$ indicate the significance level at 0.1, 0.05, and 0.01, respectively.

Table E.2 −*Continued*

	Alternative Information Component		Alternative Noise Component				Alternative Opinion Component			
	X=$EVOL_R$		X=D_{R2}		X=COV_R		X=EAC_R		X=$\lvert EAC_D \rvert$	
X	D	λ	D	λ	D	λ	D	λ	D	λ
1(L)	0.03	2.14	0.02	14.59	0.12	5.80	0.10	11.50	0.07	9.40
	0.04	2.99	0.02	9.68	0.12	9.23	0.10	11.73	0.06	8.50
	0.04	3.31	0.02	8.60	0.12	11.33	0.11	12.25	0.07	8.93
	0.04	4.07	0.03	7.72	0.12	12.47	0.11	11.58	0.07	9.31
5	0.04	4.52	0.03	7.59	0.11	12.30	0.11	11.14	0.08	9.11
	0.04	4.79	0.03	7.30	0.11	11.74	0.11	11.40	0.10	7.94
	0.05	4.82	0.03	7.02	0.10	10.74	0.11	11.36	0.16	7.86
	0.05	5.53	0.03	6.83	0.10	9.83	0.11	10.42	0.08	7.58
	0.05	6.00	0.04	6.52	0.10	9.57	0.11	9.75	0.08	7.39
10	0.05	6.14	0.04	6.63	0.10	8.78	0.11	9.02	0.08	6.69
	0.06	6.62	0.04	6.24	0.10	8.07	0.11	8.89	0.09	6.89
	0.07	6.74	0.05	6.03	0.10	7.24	0.11	8.13	0.09	8.16
	0.07	7.51	0.05	6.35	0.10	6.46	0.11	8.13	0.09	7.32
	0.08	7.78	0.06	6.65	0.10	5.79	0.11	8.05	0.10	6.88
15	0.09	7.51	0.06	6.30	0.09	6.06	0.12	6.78	0.10	6.56
	0.10	8.43	0.07	6.39	0.11	5.99	0.11	6.78	0.11	6.18
	0.11	9.02	0.08	6.38	0.10	5.97	0.12	5.83	0.13	6.22
	0.12	9.32	0.08	6.23	0.11	6.30	0.12	5.31	0.13	5.72
	0.15	9.66	0.10	6.93	0.11	5.28	0.12	4.68	0.14	6.03
20	0.18	10.14	0.11	7.20	0.12	5.57	0.12	4.21	0.15	5.52
	0.21	11.83	0.13	7.47	0.13	5.57	0.12	3.95	0.16	5.26
	0.25	11.44	0.16	7.88	0.14	5.17	0.12	3.38	0.17	4.80
	0.29	13.38	0.21	8.35	0.14	5.42	0.14	3.37	0.19	4.57
	0.34	13.39	0.35	9.76	0.17	5.24	0.15	2.52	0.21	4.27
25(H)	0.36	14.54	1.07	11.08	0.20	5.70	0.15	1.45	0.23	2.58
25-1	0.33***	12.40***	1.05***	−3.52***	0.07***	-0.10	0.06***	−10.05***	0.17***	−6.82***
	(20.60)	(6.78)	(23.06)	(-4.65)	(9.59)	(-0.31)	(7.41)	(-7.33)	(14.00)	(-5.94)

Table E.3
Portfolios Mispricing Analysis: Alternative Disagreement Components

This table reports average risk-adjusted returns and factor sensitivity for portfolios sorted by the variables related to alternative disagreement components. We hold stocks for 3 months and calculate returns using Jegadeesh and Titman's (1993) methodology. We report the alpha of CAPM, Fama-French three-factor (FF3), Fama-French three-factor plus momentum (FF4), and Stambaugh and Yuan's (2016) mispricing factor models. Factor sensitivity is reported as the two mispricing factors (MGMT and PERF) as described by Stambaugh and Yuan (2016). Twenty-five portfolios are sorted by D, the proxy of alternative information component σ_ν^2 ($EVOL_R$), the proxy of alternative noise component σ_ϵ^2 (D_{R2}), and the proxy of alternative opinion component η (EAC_R or $|EAC_D|$) for the previous month. EVOL is the time-series standard deviation of earnings divided by its time-series mean. $EVOL_R$ is residual part of regressing $\ln(EVOL)$ on $\ln(|EAC|)$. EAC is the time-series covariance of unexpected earnings and the unexpected mean analyst forecast. $|EAC|$ is the absolute value of EAC. EAC_R is the residual part of regressing $\ln(|EAC|)$ on $\ln(EVOL)$. $|EAC_D|$ is absolute value of covariance of UE_D and UA_D, where UE_D and UA_D are the drift adjusted version unexpected earnings and average analyst forecast. D_{R2} is the residual part of the regression of Equation (D.10). The results are reported from January 1987 to December 2016. An NYSE/AMEX/Nasdaq stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than \$5. The standard errors are adjusted for autocorrelation and heteroscedasticity. On average, there are 67 stocks in each portfolio (except the portfolio sorted by $|EAC_D|$ contains average 63 stocks). $*$, $**$, and $***$ indicate the significance level at 0.1, 0.05, and 0.01, respectively.

Table E.3 –*Continued*

Panel A. Sorted by Alternative Information Component σ^2_ν ($EVOL_R$)												
	Alpha								Factor Sensitivity			
$EVOL_R$	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.26*	(1.85)	0.09	(1.01)	0.14	(1.56)	-0.04	(-0.37)	0.49***	(6.93)	-0.11**	(-2.52)
	0.23*	(1.65)	0.07	(0.73)	0.12	(1.53)	-0.09	(-0.91)	0.46***	(7.21)	-0.08**	(-2.29)
	0.20	(1.29)	0.02	(0.23)	0.09	(1.07)	-0.09	(-1.00)	0.45***	(5.25)	-0.11**	(-2.54)
	0.26*	(1.72)	0.10	(1.01)	0.14	(1.48)	-0.04	(-0.40)	0.39***	(4.58)	-0.07	(-1.52)
5	0.16	(1.14)	0.01	(0.09)	0.07	(0.99)	-0.08	(-0.95)	0.35***	(4.83)	-0.10***	(-3.20)
	0.22	(1.45)	0.07	(0.72)	0.11	(1.30)	-0.05	(-0.59)	0.33***	(4.63)	-0.07*	(-1.78)
	0.12	(0.90)	0.00	(0.00)	0.07	(0.74)	-0.04	(-0.46)	0.22***	(3.65)	-0.08**	(-2.26)
	0.23	(1.54)	0.09	(0.88)	0.15*	(1.69)	-0.01	(-0.13)	0.30***	(4.01)	-0.08**	(-2.10)
	0.30*	(1.94)	0.15*	(1.69)	0.21**	(2.49)	0.04	(0.52)	0.29***	(3.40)	-0.07	(-1.58)
10	0.32**	(2.20)	0.18**	(2.15)	0.24***	(3.02)	0.12	(1.28)	0.22***	(2.96)	-0.08*	(-1.86)
	0.18	(1.22)	0.07	(0.70)	0.16*	(1.72)	0.04	(0.44)	0.16**	(2.30)	-0.10**	(-2.30)
	0.15	(1.03)	0.04	(0.40)	0.09	(0.99)	-0.03	(-0.29)	0.15	(1.63)	-0.06	(-1.37)
	0.23	(1.57)	0.11	(1.36)	0.14*	(1.74)	0.03	(0.40)	0.15**	(2.15)	-0.06	(-1.62)
	0.26*	(1.88)	0.16*	(1.88)	0.22***	(2.70)	0.15*	(1.77)	0.06	(1.04)	-0.07**	(-2.44)
15	0.18	(1.23)	0.08	(0.87)	0.17*	(1.88)	0.10	(1.05)	0.03	(0.45)	-0.10***	(-3.21)
	0.19	(1.30)	0.09	(1.07)	0.18**	(2.07)	0.16*	(1.76)	-0.03	(-0.44)	-0.12***	(-4.73)
	0.26*	(1.81)	0.21**	(2.27)	0.28***	(3.21)	0.21**	(2.57)	-0.09	(-1.35)	-0.06**	(-2.01)
	0.17	(1.12)	0.11	(1.19)	0.19**	(2.12)	0.14	(1.52)	-0.11	(-1.43)	-0.06**	(-2.12)
	0.04	(0.28)	-0.04	(-0.44)	0.03	(0.31)	0.03	(0.25)	-0.10	(-1.19)	-0.10***	(-2.64)
20	0.16	(0.97)	0.11	(1.07)	0.20**	(1.97)	0.21*	(1.87)	-0.15***	(-2.71)	-0.13***	(-6.04)
	0.19	(1.15)	0.14	(1.25)	0.21*	(1.88)	0.20	(1.61)	-0.16***	(-2.71)	-0.09***	(-3.36)
	-0.08	(-0.48)	-0.13	(-1.10)	-0.03	(-0.20)	0.08	(0.57)	-0.27***	(-5.48)	-0.19***	(-4.46)
	-0.45**	(-2.40)	-0.52***	(-4.36)	-0.40***	(-3.25)	-0.36**	(-2.52)	-0.17**	(-2.10)	-0.21***	(-4.64)
	-0.65***	(-3.30)	-0.73***	(-5.78)	-0.61***	(-4.77)	-0.53***	(-3.74)	-0.21***	(-3.81)	-0.24***	(-5.20)
25(H)	-0.80***	(-3.67)	-0.87***	(-6.48)	-0.75***	(-5.37)	-0.70***	(-4.52)	-0.19***	(-3.46)	-0.24***	(-5.11)
25-1	-1.06***	(-4.40)	-0.97***	(-5.57)	-0.88***	(-4.89)	-0.66***	(-3.39)	-0.68***	(-7.76)	-0.14*	(-1.87)

(continued)

Table E.3 –*Continued*

Panel B. Sorted by Alternative Noise Component σ^2_ϵ (D_{R2})												
	Alpha								Factor Sensitivity			
D_{R2}	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.09	(0.46)	-0.02	(-0.18)	0.06	(0.51)	0.04	(0.32)	-0.02	(-0.28)	-0.15***	(-3.41)
	0.12	(0.72)	0.03	(0.24)	0.12	(1.11)	0.04	(0.39)	0.03	(0.42)	-0.09**	(-2.49)
	0.23	(1.46)	0.14	(1.27)	0.17*	(1.66)	0.04	(0.36)	0.08	(1.51)	-0.03	(-1.16)
	0.17	(1.12)	0.09	(0.92)	0.13	(1.38)	0.00	(0.04)	0.05	(0.84)	-0.03	(-0.92)
5	0.15	(1.09)	0.06	(0.66)	0.10	(1.27)	-0.01	(-0.17)	0.10*	(1.82)	-0.05*	(-1.78)
	0.13	(0.92)	0.03	(0.36)	0.08	(0.95)	-0.02	(-0.21)	0.11	(1.59)	-0.06**	(-2.21)
	0.21	(1.56)	0.13	(1.42)	0.18**	(2.21)	0.10	(1.19)	0.05	(0.81)	-0.04	(-1.24)
	0.15	(1.24)	0.06	(0.81)	0.11	(1.52)	0.01	(0.15)	0.10*	(1.88)	-0.05**	(-2.32)
	0.09	(0.79)	-0.02	(-0.21)	0.06	(0.88)	-0.04	(-0.48)	0.15**	(2.56)	-0.10***	(-3.27)
10	0.18	(1.36)	0.07	(0.88)	0.13**	(1.97)	0.05	(0.59)	0.13*	(1.90)	-0.09***	(-2.59)
	0.22	(1.59)	0.10	(1.22)	0.16**	(1.96)	0.05	(0.61)	0.16***	(2.76)	-0.09***	(-2.97)
	0.07	(0.62)	-0.04	(-0.51)	0.04	(0.55)	-0.04	(-0.47)	0.14*	(1.83)	-0.10**	(-2.57)
	0.07	(0.55)	-0.05	(-0.65)	0.04	(0.58)	-0.02	(-0.28)	0.13**	(2.33)	-0.13***	(-6.00)
	0.09	(0.74)	-0.02	(-0.31)	0.06	(0.91)	-0.04	(-0.56)	0.15***	(2.61)	-0.11***	(-4.36)
15	0.09	(0.66)	-0.04	(-0.58)	0.04	(0.64)	-0.07	(-0.94)	0.20***	(3.40)	-0.13***	(-3.98)
	0.11	(0.83)	0.00	(-0.02)	0.06	(0.78)	-0.05	(-0.66)	0.17***	(2.75)	-0.08***	(-3.19)
	0.10	(0.76)	-0.01	(-0.12)	0.06	(0.87)	-0.02	(-0.25)	0.13*	(1.89)	-0.11***	(-3.93)
	0.12	(0.92)	0.01	(0.11)	0.07	(0.96)	-0.01	(-0.18)	0.12**	(1.99)	-0.10***	(-4.21)
	0.13	(0.91)	-0.01	(-0.08)	0.08	(1.03)	0.01	(0.12)	0.14**	(2.24)	-0.13***	(-4.28)
20	0.15	(1.12)	0.04	(0.49)	0.09	(1.35)	0.03	(0.37)	0.13**	(2.05)	-0.11***	(-4.45)
	0.04	(0.27)	-0.09	(-1.04)	-0.02	(-0.31)	-0.08	(-1.01)	0.13*	(1.80)	-0.13***	(-3.54)
	0.03	(0.20)	-0.08	(-1.12)	0.00	(0.01)	-0.07	(-0.84)	0.09	(1.23)	-0.13***	(-4.26)
	-0.04	(-0.22)	-0.17**	(-2.06)	-0.07	(-0.81)	-0.11	(-1.22)	0.09	(1.17)	-0.18***	(-5.39)
	-0.03	(-0.17)	-0.15	(-1.59)	-0.05	(-0.50)	-0.05	(-0.51)	0.02	(0.30)	-0.19***	(-5.07)
25(H)	-0.31*	(-1.76)	-0.42***	(-3.86)	-0.27**	(-2.57)	-0.24**	(-2.41)	-0.03	(-0.53)	-0.26***	(-10.37)
25-1	-0.39***	(-2.63)	-0.40**	(-2.54)	-0.34**	(-2.18)	-0.29*	(-1.84)	-0.01	(-0.21)	-0.11**	(-2.07)

(continued)

Table E.3 –*Continued*

Panel C. Sorted by Alternative Noise Component σ_ϵ^2 (COV_R)												
	Alpha								Factor Sensitivity			
D_{R2}	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.02	(0.13)	-0.10	(-1.25)	-0.12	(-1.54)	-0.21**	(-2.21)	0.16***	(3.68)	-0.05*	(-1.74)
	0.18	(1.19)	0.04	(0.59)	0.04	(0.56)	-0.03	(-0.27)	0.15***	(4.28)	-0.10***	(-4.80)
	0.16	(1.06)	0.04	(0.44)	0.06	(0.73)	-0.01	(-0.11)	0.11***	(3.10)	-0.09***	(-2.74)
	0.12	(0.86)	0.01	(0.10)	0.03	(0.40)	-0.03	(-0.29)	0.11***	(3.23)	-0.11***	(-4.18)
5	0.12	(0.84)	0.01	(0.12)	0.01	(0.16)	-0.07	(-0.76)	0.13***	(3.92)	-0.07***	(-2.78)
	0.09	(0.74)	-0.01	(-0.11)	0.03	(0.38)	-0.05	(-0.64)	0.12***	(3.25)	-0.10***	(-3.94)
	0.06	(0.43)	-0.06	(-0.79)	-0.02	(-0.23)	-0.10	(-1.20)	0.13***	(2.71)	-0.08***	(-3.68)
	0.19	(1.45)	0.08	(1.14)	0.12*	(1.93)	0.01	(0.21)	0.13***	(2.60)	-0.06**	(-2.34)
	0.06	(0.52)	-0.04	(-0.57)	0.00	(0.04)	-0.06	(-0.79)	0.11**	(2.31)	-0.09***	(-3.64)
10	0.12	(0.88)	0.01	(0.15)	0.06	(0.79)	-0.03	(-0.35)	0.14**	(2.53)	-0.09***	(-3.22)
	0.03	(0.25)	-0.09	(-1.13)	-0.06	(-0.74)	-0.13*	(-1.77)	0.17***	(3.26)	-0.08***	(-3.47)
	0.11	(0.84)	0.00	(-0.06)	0.05	(0.71)	-0.04	(-0.50)	0.17***	(2.72)	-0.10***	(-3.44)
	0.14	(1.08)	0.01	(0.07)	0.07	(1.02)	0.00	(0.00)	0.18***	(2.64)	-0.12***	(-3.37)
	0.15	(1.25)	0.05	(0.68)	0.09	(1.35)	0.01	(0.19)	0.14***	(2.98)	-0.09***	(-3.68)
15	0.11	(0.95)	0.01	(0.08)	0.07	(0.97)	-0.01	(-0.17)	0.15***	(2.76)	-0.10***	(-3.87)
	0.16	(1.28)	0.06	(0.76)	0.13*	(1.80)	0.04	(0.56)	0.13**	(2.48)	-0.11***	(-3.78)
	0.09	(0.71)	0.00	(0.03)	0.07	(0.89)	-0.02	(-0.22)	0.08	(1.17)	-0.07**	(-2.57)
	0.09	(0.70)	0.00	(-0.03)	0.06	(0.81)	-0.05	(-0.61)	0.12	(1.57)	-0.08***	(-2.77)
	0.00	(0.01)	-0.11	(-1.26)	-0.02	(-0.18)	-0.10	(-1.04)	0.12	(1.59)	-0.13***	(-4.36)
20	0.10	(0.63)	-0.02	(-0.16)	0.09	(0.92)	-0.01	(-0.13)	0.14	(1.61)	-0.13***	(-3.42)
	0.07	(0.42)	-0.03	(-0.35)	0.09	(0.97)	0.02	(0.18)	0.05	(0.52)	-0.14***	(-3.30)
	0.11	(0.65)	-0.02	(-0.21)	0.14	(1.42)	0.03	(0.30)	0.11	(1.03)	-0.16***	(-3.35)
	0.06	(0.35)	-0.05	(-0.36)	0.11	(0.99)	0.06	(0.47)	0.01	(0.05)	-0.16***	(-3.18)
	0.09	(0.42)	0.00	(0.02)	0.20	(1.33)	0.11	(0.67)	-0.09	(-0.68)	-0.13**	(-2.45)
25(H)	-0.10	(-0.43)	-0.18	(-0.93)	0.11	(0.63)	0.11	(0.52)	-0.22	(-1.52)	-0.25***	(-4.04)
25-1	-0.12	(-0.54)	-0.08	(-0.36)	0.23	(1.16)	0.31	(1.28)	-0.37***	(-2.84)	-0.20***	(-3.00)

(continued)

Table E.3 –*Continued*

Panel D. Sorted by Alternative Opinion Component η (EAC_R)												
	Alpha								Factor Sensitivity			
EAC_R	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.30*	(1.89)	0.25**	(2.37)	0.25**	(2.24)	0.09	(0.91)	0.00	(0.01)	0.05**	(2.00)
	0.06	(0.44)	0.01	(0.10)	0.00	(0.00)	-0.14	(-1.62)	0.02	(0.32)	0.04	(1.01)
	0.09	(0.59)	0.01	(0.12)	0.04	(0.41)	-0.12	(-1.37)	0.06	(0.94)	0.00	(-0.06)
	0.15	(1.10)	0.08	(0.95)	0.14	(1.54)	0.01	(0.10)	0.04	(0.66)	-0.04	(-1.42)
5	0.00	(0.01)	-0.10	(-1.25)	-0.05	(-0.59)	-0.15	(-1.64)	0.10**	(1.98)	-0.08**	(-2.43)
	0.07	(0.50)	-0.02	(-0.22)	0.05	(0.61)	-0.08	(-0.96)	0.08	(1.40)	-0.06**	(-2.50)
	0.05	(0.43)	-0.02	(-0.23)	0.04	(0.61)	-0.06	(-0.86)	0.03	(0.51)	-0.05*	(-1.85)
	0.07	(0.56)	-0.01	(-0.07)	0.08	(0.89)	0.01	(0.13)	0.03	(0.55)	-0.12***	(-3.97)
	0.11	(0.85)	0.03	(0.36)	0.10	(1.36)	0.01	(0.12)	0.05	(1.00)	-0.09***	(-4.16)
10	0.10	(0.76)	0.01	(0.15)	0.08	(1.09)	-0.02	(-0.21)	0.07*	(1.87)	-0.10***	(-3.69)
	0.02	(0.15)	-0.08	(-1.02)	-0.03	(-0.36)	-0.15*	(-1.95)	0.11**	(2.40)	-0.08***	(-3.88)
	0.06	(0.40)	-0.04	(-0.54)	0.02	(0.31)	-0.08	(-0.99)	0.12*	(1.95)	-0.10***	(-4.31)
	-0.05	(-0.40)	-0.16*	(-1.95)	-0.09	(-1.11)	-0.14	(-1.58)	0.07	(1.25)	-0.11***	(-4.49)
	0.08	(0.54)	-0.02	(-0.18)	0.08	(0.92)	0.00	(0.03)	0.05	(0.82)	-0.11***	(-3.51)
15	0.04	(0.28)	-0.06	(-0.64)	0.02	(0.29)	-0.06	(-0.63)	0.08	(1.05)	-0.10***	(-2.82)
	0.05	(0.39)	-0.07	(-0.88)	0.00	(0.06)	-0.05	(-0.59)	0.13**	(2.47)	-0.15***	(-6.04)
	0.09	(0.67)	-0.03	(-0.39)	0.07	(0.92)	0.05	(0.57)	0.09	(1.46)	-0.17***	(-5.12)
	0.14	(0.87)	0.00	(0.04)	0.12	(1.38)	0.04	(0.44)	0.15*	(1.80)	-0.16***	(-3.80)
	0.15	(1.07)	0.04	(0.45)	0.13*	(1.69)	0.07	(0.81)	0.10*	(1.85)	-0.14***	(-5.61)
20	0.11	(0.73)	-0.03	(-0.33)	0.06	(0.73)	0.00	(0.00)	0.17**	(2.30)	-0.15***	(-3.30)
	0.13	(0.81)	-0.03	(-0.32)	0.08	(0.98)	0.04	(0.40)	0.19***	(2.59)	-0.20***	(-5.34)
	0.13	(0.81)	-0.02	(-0.22)	0.10	(1.08)	0.07	(0.69)	0.19**	(2.24)	-0.21***	(-5.37)
	0.16	(0.96)	0.00	(-0.02)	0.09	(0.94)	0.06	(0.58)	0.18**	(1.96)	-0.16***	(-3.78)
	0.19	(1.19)	0.00	(0.05)	0.10	(1.11)	0.07	(0.61)	0.26**	(2.27)	-0.20***	(-3.25)
25(H)	0.05	(0.27)	-0.15	(-1.33)	-0.04	(-0.39)	0.01	(0.04)	0.23*	(1.90)	-0.20***	(-3.43)
25-1	-0.25	(-1.39)	-0.40***	(-2.60)	-0.29*	(-1.83)	-0.09	(-0.51)	0.22**	(2.06)	-0.26***	(-3.59)

(continued)

Table E.3 –*Continued*

Panel E. Sorted by Alternative Opinion Component ($\lvert EAC_D \rvert$)												
	Alpha								Factor Sensitivity			
EAC_R	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.47***	(2.94)	0.40***	(3.25)	0.42***	(3.29)	0.23**	(2.04)	0.13**	(2.02)	0.02	(0.63)
	0.36**	(2.31)	0.29**	(2.36)	0.32**	(2.54)	0.08	(0.77)	0.16**	(2.44)	0.03	(0.65)
	0.27*	(1.82)	0.19*	(1.76)	0.22**	(2.22)	0.02	(0.18)	0.16**	(2.56)	0.00	(0.03)
	0.31**	(2.29)	0.23**	(2.49)	0.26***	(2.67)	0.09	(1.04)	0.12**	(2.16)	0.00	(0.01)
5	0.26*	(1.87)	0.17*	(1.88)	0.20**	(2.18)	0.03	(0.40)	0.15***	(3.02)	-0.02	(-0.72)
	0.27*	(1.67)	0.17	(1.39)	0.21*	(1.82)	0.03	(0.29)	0.17***	(3.16)	-0.02	(-0.65)
	0.14	(0.93)	0.03	(0.28)	0.09	(0.88)	-0.05	(-0.50)	0.16**	(2.39)	-0.05	(-1.43)
	0.15	(1.07)	0.06	(0.65)	0.09	(0.92)	-0.06	(-0.58)	0.12*	(1.94)	-0.02	(-0.58)
	0.16	(1.13)	0.06	(0.57)	0.11	(1.01)	-0.04	(-0.36)	0.14**	(2.51)	-0.04	(-0.95)
10	0.18	(1.25)	0.08	(0.72)	0.13	(1.20)	0.01	(0.11)	0.16***	(2.72)	-0.07**	(-2.31)
	0.13	(0.94)	0.02	(0.26)	0.08	(0.88)	-0.07	(-0.7)	0.18***	(3.00)	-0.07**	(-2.36)
	0.11	(0.76)	-0.01	(-0.09)	0.08	(0.93)	-0.04	(-0.43)	0.16**	(2.46)	-0.10***	(-2.62)
	0.19	(1.22)	0.08	(0.75)	0.14	(1.43)	0.00	(0.00)	0.15**	(2.13)	-0.06*	(-1.73)
	0.10	(0.71)	-0.01	(-0.10)	0.05	(0.65)	0.00	(0.02)	0.09	(1.44)	-0.11***	(-3.49)
15	0.19	(1.25)	0.08	(0.88)	0.15	(1.53)	0.01	(0.09)	0.14**	(2.43)	-0.08**	(-2.57)
	0.22	(1.52)	0.12	(1.43)	0.18**	(2.14)	0.06	(0.76)	0.11**	(2.29)	-0.08***	(-3.50)
	0.10	(0.66)	-0.01	(-0.06)	0.09	(0.83)	-0.02	(-0.15)	0.10**	(2.10)	-0.12***	(-4.31)
	-0.03	(-0.20)	-0.17	(-1.61)	-0.07	(-0.71)	-0.14	(-1.41)	0.15**	(2.25)	-0.16***	(-5.12)
	0.05	(0.33)	-0.09	(-0.86)	0.03	(0.30)	-0.02	(-0.20)	0.12*	(1.95)	-0.18***	(-5.72)
20	-0.008	(-0.50)	-0.20*	(-1.87)	-0.09	(-0.81)	-0.10	(-0.85)	0.07	(1.03)	-0.19***	(-6.01)
	-0.06	(-0.34)	-0.19*	(-1.83)	-0.09	(-0.82)	-0.11	(-1.05)	0.12*	(1.80)	-0.19***	(-5.40)
	-0.02	(-0.11)	-0.15	(-1.27)	-0.04	(-0.35)	-0.05	(-0.37)	0.07	(0.96)	-0.21***	(-5.30)
	0.08	(0.49)	-0.03	(-0.31)	0.08	(0.71)	0.11	(0.95)	0.00	(0.04)	-0.19***	(-5.88)
	0.09	(0.55)	-0.07	(-0.65)	0.02	(0.21)	0.05	(0.36)	0.14	(1.30)	-0.20***	(-4.17)
25(H)	-0.03	(-0.16)	-0.25**	(-1.97)	-0.11	(-0.94)	-0.10	(-0.76)	0.28**	(2.49)	-0.29***	(-5.07)
25-1	-0.51***	(-2.71)	-0.66***	(-4.04)	-0.53***	(-3.33)	-0.33**	(-2.00)	0.14	(1.62)	-0.31***	(-5.15)

Table E.4
Fama-MacBeth Regressions: Using Alternative Disagreement Components

Fama and MacBeth (1973) cross-sectional regressions are run every month from January 1987 to December 2016. The cross-section of expected returns at time t is regressed on a constant; the proxy of alternative information component σ_ν^2 ($EVOL_R$), which is residual part of regressing ln($EVOL$) on ln($|EAC|$) at time t-1; the proxy of alternative noise component σ_ϵ^2 (D_{R2}), which is the residual part of the regression of Equation (D.10) at time t-1; the first proxy of alternative opinion component η (EAC_R), which is the residual part of regressing ln($|EAC|$) on ln($EVOL$); the second proxy of alternative opinion component $|EAC_D|$, which is absolute value of covariance of UE_D and UA_D, where UE_D and UA_D are the drift adjusted version unexpected earnings and average analyst forecast; H σ_ν^2 as the dummy variable of the top 20% of the one-month lag of $EVOL_R$; H σ_{ϵ^2} as the dummy variable of the top 20% of the one-month lag of D_{R2}; L η as the dummy variable of the bottom 20% of the one-month lag of EAC_R or $|EAC_D|$; β_{CAPM}, estimated using the past 24–60 months of data; MV (market capitalization at t - 1); BM (book value of equity divided by its current market value at month t - 1); ret - 12 : -2 (a stock's past-year return); ret - 36 : -13 (stock's long-run past return); ret - 1 : -1 (the one-month past return); and TURN (annual average of the daily number of shares traded divided by the number of shares outstanding at time t -1). An NYSE/AMEX/Nasdaq stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than $5. All variables are winsorized at the top and bottom 1%. The standard errors are adjusted for autocorrelation and heteroskedasticity. $*$, $**$, and $***$ indicate the significance level at 0.1, 0.05, and 0.01, respectively.

Panel A. Linear Effects of Disagreement Component

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	1.15***	1.02**	1.03***	0.85*	1.02***	0.82*	1.01**	0.83*	1.10***	0.98**
	(3.15)	(2.42)	(2.71)	(1.91)	(2.63)	(1.82)	(2.45)	(1.77)	(2.95)	(2.29)
σ_ν^2: $EVOL_R$	-0.17***	-0.17***							-0.18***	-0.19***
	(-3.50)	(-3.92)							(-3.33)	(-3.78)
σ_ϵ^2 : D_{R2}			-0.08**	-0.04					-0.08**	-0.04
			(-2.22)	(-1.21)					(-2.17)	(-1.09)
η: EAC_R					0.00	-0.01			-0.02	-0.03*
					(-0.27)	(-0.86)			(-1.20)	(-1.81)
η: $\|EAC_D\|$							-0.03	-0.04**		
							(-1.64)	(-2.41)		
β_{CAPM}	0.16	0.19	0.09	0.14	0.09	0.14	0.14	0.17	0.17	0.20
	(0.82)	(1.19)	(0.43)	(0.90)	(0.44)	(0.89)	(0.69)	(1.06)	(0.92)	(1.27)
ln(MV)	-0.05	-0.05	-0.01	-0.01	-0.01	-0.01	-0.03	-0.02	-0.04	-0.04
	(-1.25)	(-1.20)	(-0.32)	(-0.35)	(-0.31)	(-0.24)	(-0.61)	(-0.49)	(-1.08)	(-1.05)
ln(BM)	-0.01	0.06	0.01	0.06	0.01	0.07	0.02	0.11	0.01	0.08
	(-0.07)	(0.75)	(0.11)	(0.71)	(0.08)	(0.88)	(0.23)	(1.44)	(0.06)	(0.98)
ln(TURN)		-0.07		-0.12		-0.11		-0.08		-0.06
		(-0.88)		(-1.31)		(-1.26)		(-0.89)		(-0.69)
ret_{-1}		-0.03***		-0.03***		-0.03***		-0.03***		-0.03***
		(-5.93)		(-6.09)		(-5.98)		(-5.87)		(-6.09)
$ret_{-12,-2}$		0.01***		0.00***		0.01***		0.01***		0.01***
		(2.98)		(2.73)		(2.80)		(2.98)		(2.82)
$ret_{-36,-13}$		0.00		0.00		0.00		0.00		0.00
		(-0.44)		(-0.49)		(-0.54)		(-0.14)		(-0.33)

(continued)

Table E.4 –*Continued*

Panel B. Nonlinear Effects of Disagreement Component: 20% and 80% Threshold										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	1.22***	1.05**	1.09***	0.89**	1.02***	0.82*	1.05***	0.87*	1.23***	1.05**
	(3.36)	(2.49)	(2.87)	(2.01)	(2.65)	(1.84)	(2.64)	(1.89)	(3.36)	(2.48)
H σ_ν^2: $EVOL_R$	-0.38***	-0.36***							-0.39***	-0.38***
	(-4.05)	(-4.29)							(-4.10)	(-4.41)
H σ_ϵ^2: D_{R2}			-0.18**	-0.12*					-0.14**	-0.08
			(-2.43)	(-1.70)					(-2.04)	(-1.20)
L η: EAC_R					0.04	0.07			0.08	0.11**
					(0.74)	(1.45)			(1.43)	(2.09)
L η: $\|EAC_D\|$							0.14**	0.18***		
							(2.44)	(3.29)		
β_{CAPM}	0.13	0.17	0.09	0.14	0.09	0.14	0.13	0.17	0.14	0.17
	(0.68)	(1.07)	(0.43)	(0.88)	(0.43)	(0.87)	(0.64)	(1.03)	(0.71)	(1.08)
ln(MV)	-0.04	-0.03	-0.02	-0.02	-0.01	-0.01	-0.03	-0.02	-0.04	-0.03
	(-0.94)	(-0.89)	(-0.41)	(-0.39)	(-0.31)	(-0.27)	(-0.67)	(-0.58)	(-0.93)	(-0.87)
ln(BM)	0.01	0.07	0.01	0.06	0.01	0.07	0.02	0.10	0.01	0.08
	(0.07)	(0.87)	(0.10)	(0.72)	(0.11)	(0.87)	(0.17)	(1.22)	(0.14)	(0.99)
ln(TURN)		-0.09		-0.11		-0.11		-0.09		-0.09
		(-1.10)		(-1.31)		(-1.27)		(-1.01)		(-1.01)
ret_{-1}		-0.03***		-0.03***		-0.03***		-0.03***		-0.03***
		(-5.95)		(-6.09)		(-5.93)		(-5.85)		(-6.06)
$ret_{-12,-2}$		0.01***		0.01***		0.01***		0.01***		0.01***
		(2.92)		(2.76)		(2.87)		(3.00)		(2.85)
$ret_{-36,-13}$		0.00		0.00		0.00		0.00		0.00
		(-0.44)		(-0.56)		(-0.55)		(-0.20)		(-0.43)

Table E.5
Characteristics Analysis of Portfolios: Subperiods

This table reports average D (i.e., analyst disagreement) and λ (i.e., Amihud's [2002] illiquidity measure). The stocks are sorted into 25 portfolios for each month based on D, the proxy of information component σ_{ν}^2 (EVOL), the proxy of noise component σ_{ϵ}^2 (D_{R1}), and the proxy of opinion component η ($|EAC|$) for the previous month. We hold stocks for 3 months and calculate the average of monthly portfolio D and λ. D is the standard deviation of analyst forecasts scaled by the mean forecast at month t. λ is Amihud's (2002) illiquidity measure, which is the average ratio of the daily absolute return to the (dollar) trading volume on that day in the previous 12 months, multiplied by 100,000,000. EVOL is the time-series standard deviation of earnings divided by its time-series mean. EAC is the time-series covariance of unexpected earnings and the unexpected mean analyst forecast. $|EAC|$ is the absolute value of EAC. D_{R1} is the residual part of the regression of Equation (II.D). The results are reported from January 1986 to December 2016. An NYSE/AMEX/Nasdaq stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than $5. Standard errors are adjusted for autocorrelation and heteroskedasticity. We analyse portfolio during high sentiment, low sentiment, 1987-1996, 1997-2006, and 2007-2016 periods. High or low sentiment period follows the definition of Baker and Wurgler (2006). $*$, $**$, and $***$ indicate the significance level at 0.1, 0.05, and 0.01, respectively.

Table E.5 –*Continued*

Panel A. Sorted by Analyst Disagreement (D)

	Average D					Average λ				
	Sentiment Period		Time Period			Sentiment Period		Time Period		
D	Low	High	1987-1996	1997-2006	2007-2016	Low	High	1987-1996	1997-2006	2007-2016
1(L)	0.01	0.01	0.01	0.00	0.00	3.95	4.02	8.74	3.11	0.40
2	0.01	0.01	0.01	0.01	0.01	4.16	5.51	9.30	4.29	0.55
3	0.01	0.01	0.02	0.01	0.01	4.33	5.18	9.32	4.25	0.46
4	0.01	0.01	0.02	0.01	0.01	4.44	4.23	8.36	3.97	0.62
5	0.01	0.02	0.02	0.01	0.01	4.79	5.24	10.47	3.87	0.60
21	0.12	0.12	0.15	0.11	0.12	9.62	9.56	20.31	6.50	2.05
22	0.16	0.16	0.18	0.14	0.16	9.93	9.79	20.37	6.73	2.35
23	0.23	0.22	0.25	0.20	0.23	10.99	10.54	22.31	7.66	2.53
24	0.38	0.35	0.39	0.33	0.40	11.87	10.85	23.00	7.95	2.83
25(H)	1.27	1.30	1.51	1.05	1.34	12.15	11.66	25.42	7.92	2.62
H-L	1.27***	1.29***	1.50***	1.05***	1.34***	8.20***	7.64***	16.68***	4.81***	2.21***
	(19.97)	(6.37)	(5.87)	(18.32)	(12.96)	(5.28)	(5.11)	(6.70)	(6.82)	(6.30)

Panel B. Sorted by Information Component ($EVOL$)

	Average D					Average λ				
	Sentiment Period		Time Period			Sentiment Period		Time Period		
$EVOL$	Low	High	1987-1996	1997-2006	2007-2016	Low	High	1987-1996	1997-2006	2007-2016
1(L)	0.03	0.03	0.04	0.03	0.03	2.09	2.59	3.01	2.93	0.97
2	0.03	0.04	0.05	0.03	0.03	3.47	4.31	6.55	4.17	0.72
3	0.03	0.04	0.05	0.03	0.03	4.14	4.97	7.99	4.31	1.01
4	0.03	0.04	0.05	0.03	0.03	4.20	5.77	8.61	4.96	0.63
5	0.03	0.04	0.05	0.03	0.03	4.52	5.55	9.10	5.11	0.51
21	0.26	0.25	0.30	0.19	0.28	11.52	8.44	22.97	5.58	2.11
22	0.30	0.36	0.42	0.24	0.33	11.01	9.50	22.87	5.83	2.74
23	0.34	0.30	0.37	0.28	0.34	10.77	9.36	19.99	7.44	3.03
24	0.33	0.31	0.35	0.29	0.33	10.41	13.58	23.58	8.27	3.05
25(H)	0.35	0.32	0.36	0.31	0.36	11.88	12.39	25.53	7.71	3.18
H-L	0.32***	0.29***	0.32***	0.29***	0.34***	9.78***	9.80***	22.52***	4.78***	2.21***
	(18.89)	(19.53)	(17.36)	(14.84)	(13.52)	(5.48)	(5.04)	(9.34)	(6.09)	(5.39)

Table E.5 –*Continued*

Panel C. Sorted by Noise Component (D_{R2})										
	Average D					Average λ				
	Sentiment Period		Time Period			Sentiment Period		Time Period		
D_{R2}	Low	High	1987-1996	1997-2006	2007-2016	Low	High	1987-1996	1997-2006	2007-2016
1(L)	0.02	0.02	0.02	0.01	0.01	13.77	12.86	30.06	8.05	2.42
2	0.02	0.02	0.03	0.01	0.02	8.58	9.66	18.97	6.42	1.57
3	0.02	0.02	0.03	0.02	0.02	7.09	8.38	15.48	5.90	1.20
4	0.02	0.03	0.04	0.02	0.02	6.80	7.34	14.02	5.83	1.17
5	0.03	0.03	0.04	0.02	0.02	7.01	7.75	15.73	5.11	1.07
21	0.13	0.12	0.14	0.11	0.13	6.36	6.67	12.57	5.34	1.35
22	0.16	0.15	0.17	0.14	0.16	6.47	7.21	12.96	5.75	1.52
23	0.20	0.20	0.22	0.19	0.21	7.58	7.20	14.35	5.96	1.73
24	0.35	0.31	0.34	0.30	0.36	8.68	8.20	17.33	6.43	1.86
25(H)	1.10	1.13	1.33	0.89	1.17	9.94	9.30	20.07	7.14	1.97
H-L	1.08***	1.11***	1.31***	0.87***	1.15***	-3.83***	-3.56***	-9.99***	-0.91	-0.45***
	(18.96)	(5.45)	(5.07)	(17.53)	(12.40)	(-3.80)	(-3.37)	(-6.54)	(-1.40)	(-2.98)

Panel D. Sorted by Opinion Component ($\lvert EAC \rvert$)										
	Average D					Average λ				
	Sentiment Period		Time Period			Sentiment Period		Time Period		
$\lvert EAC \rvert$	Low	High	1987-1996	1997-2006	2007-2016	Low	High	1987-1996	1997-2006	2007-2016
1(L)	0.05	0.05	0.06	0.04	0.05	8.12	9.67	17.59	7.04	1.30
2	0.05	0.18	0.23	0.04	0.06	7.78	8.78	16.69	6.66	1.05
3	0.06	0.06	0.06	0.05	0.06	8.72	8.51	17.67	6.85	1.30
4	0.06	0.06	0.07	0.05	0.06	9.04	9.11	19.58	6.15	1.35
5	0.07	0.06	0.08	0.05	0.07	9.78	8.06	19.68	5.93	1.33
21	0.17	0.15	0.16	0.16	0.18	4.90	4.98	9.89	3.78	1.10
22	0.19	0.16	0.18	0.16	0.19	4.37	4.76	9.04	3.78	1.00
23	0.19	0.17	0.20	0.17	0.19	4.25	4.10	8.21	3.44	0.91
24	0.22	0.18	0.23	0.18	0.22	3.69	5.06	9.18	2.62	0.96
25(H)	0.23	0.22	0.22	0.20	0.28	2.11	3.25	4.33	2.45	1.02
H-L	0.18***	0.18***	0.17***	0.16***	0.23***	-6.01***	-6.41***	-13.26***	-4.59***	-0.28**
	(12.39)	(13.60)	(14.04)	(12.83)	(9.27)	(-5.57)	(-6.03)	(-10.83)	(-6.55)	(-2.31)

Table E.6
Portfolios Mispricing Analysis: Analyst Disagreement (D) in Subperiods

This table reports average risk-adjusted returns and factor sensitivity for portfolios sorted by the analyst disagreement D for the previous month. We hold stocks for 3 months and calculate returns using Jegadeesh and Titman's (1993) methodology. We report the alpha of CAPM, Fama-French three-factor (FF3), Fama-French three-factor plus momentum (FF4), and Stambaugh and Yuan's (2016) mispricing factor models. Factor sensitivity is reported as the two mispricing factors (MGMT and PERF) as described by Stambaugh and Yuan (2016). Twenty-five portfolios are sorted by D for the previous month. D is the standard deviation of analyst forecasts scaled by the mean forecast at month t. We analyse portfolio during high sentiment, low sentiment, 1987-1996, 1997-2006, and 2007-2016 periods. High or low sentiment period follows the definition of Baker and Wurgler (2006). An NYSE/AMEX/Nasdaq stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than \$5. The standard errors are adjusted for autocorrelation and heteroscedasticity. $*$, $**$, and $***$ indicate the significance level at 0.1, 0.05, and 0.01, respectively.

Panel A. High Sentiment Period												
	Alpha								Factor Sensitivity			
D	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.44	(1.52)	0.30	(1.33)	0.28	(1.20)	-0.06	(-0.31)	0.41***	(5.06)	0.09**	(2.16)
2	0.53*	(1.81)	0.41*	(1.79)	0.38	(1.57)	-0.01	(-0.03)	0.39***	(5.35)	0.12**	(2.06)
3	0.58**	(2.12)	0.47**	(2.08)	0.46**	(2.00)	0.11	(0.50)	0.38***	(5.31)	0.08*	(1.66)
4	0.44*	(1.71)	0.32	(1.56)	0.36*	(1.65)	0.09	(0.41)	0.33***	(4.40)	0.02	(0.40)
5	0.22	(0.90)	0.12	(0.67)	0.17	(0.90)	-0.08	(-0.40)	0.28***	(4.31)	0.00	(-0.06)
21	0.09	(0.28)	0.01	(0.05)	0.14	(0.61)	0.00	(0.00)	0.02	(0.22)	-0.12**	(-2.42)
22	-0.10	(-0.28)	-0.17	(-0.71)	-0.02	(-0.10)	-0.13	(-0.54)	-0.03	(-0.28)	-0.16***	(-3.04)
23	0.11	(0.33)	0.03	(0.14)	0.24	(1.18)	0.15	(0.63)	-0.01	(-0.10)	-0.24***	(-3.71)
24	0.06	(0.16)	-0.03	(-0.12)	0.26	(1.44)	0.19	(0.89)	0.03	(0.35)	-0.34***	(-7.23)
25(H)	-0.23	(-0.63)	-0.30	(-1.19)	0.00	(0.02)	0.03	(0.13)	-0.03	(-0.35)	-0.40***	(-9.60)
H-L	-0.66*	(-1.89)	-0.60*	(-1.76)	-0.27	(-0.81)	0.10	(0.29)	-0.44***	(-3.96)	-0.50***	(-7.68)

(continued)

Table E.6 –*Continued*

Panel B. Low Sentiment Period												
	Alpha								Factor Sensitivity			
D	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.21*	(1.78)	0.20	(1.63)	0.22**	(2.06)	0.19*	(1.80)	0.03	(0.52)	0.00	(0.06)
2	0.19*	(1.92)	0.17	(1.57)	0.19*	(1.95)	0.16	(1.57)	0.03	(0.56)	-0.01	(-0.14)
3	0.16	(1.52)	0.13	(1.19)	0.16	(1.54)	0.10	(0.94)	0.07	(1.09)	-0.01	(-0.12)
4	0.22**	(2.29)	0.20**	(1.96)	0.22***	(2.63)	0.19**	(2.15)	0.04	(0.69)	-0.02	(-0.48)
5	0.13	(1.44)	0.10	(1.06)	0.14	(1.58)	0.09	(0.92)	0.09	(1.57)	-0.05	(-1.07)
21	-0.11	(-0.67)	-0.16*	(-1.71)	-0.08	(-0.83)	-0.02	(-0.20)	-0.04	(-0.55)	-0.23***	(-7.82)
22	-0.11	(-0.59)	-0.17	(-1.53)	-0.08	(-0.68)	0.01	(0.07)	-0.09	(-1.35)	-0.28***	(-6.90)
23	-0.41*	(-1.77)	-0.49***	(-3.64)	-0.40***	(-2.96)	-0.32**	(-2.32)	-0.01	(-0.16)	-0.33***	(-7.70)
24	-0.46*	(-1.81)	-0.54***	(-3.43)	-0.42***	(-2.94)	-0.29*	(-1.91)	-0.09	(-1.11)	-0.37***	(-7.36)
25(H)	-0.54**	(-2.08)	-0.61***	(-3.67)	-0.45***	(-2.97)	-0.28*	(-1.73)	-0.20**	(-2.43)	-0.42***	(-7.92)
H-L	-0.75**	(-2.31)	-0.82***	(-3.52)	-0.68***	(-3.16)	-0.47**	(-2.14)	-0.24**	(-2.24)	-0.42***	(-4.43)

Panel C. Time Period 1987-1996												
	Alpha								Factor Sensitivity			
D	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.40**	(2.09)	0.57***	(2.95)	0.49**	(2.34)	0.30**	(1.99)	-0.08	(-1.03)	0.23***	(3.96)
2	0.24	(1.26)	0.35*	(1.93)	0.25	(1.27)	0.04	(0.22)	0.06	(0.76)	0.22***	(4.26)
3	0.27	(1.30)	0.39**	(1.99)	0.33	(1.51)	0.13	(0.68)	0.01	(0.11)	0.17***	(2.76)
4	0.22	(1.19)	0.30*	(1.66)	0.26	(1.27)	0.18	(1.14)	-0.04	(-0.50)	0.09	(1.32)
5	0.13	(0.88)	0.23	(1.55)	0.20	(1.16)	0.16	(0.94)	-0.09	(-1.11)	0.04	(0.74)
21	0.04	(0.13)	0.13	(0.48)	0.23	(0.77)	-0.02	(-0.06)	0.05	(0.39)	-0.14	(-1.62)
22	-0.21	(-0.78)	-0.06	(-0.30)	-0.04	(-0.17)	-0.29*	(-1.68)	0.02	(0.16)	-0.04	(-0.28)
23	-0.25	(-0.86)	-0.17	(-0.96)	-0.08	(-0.52)	-0.31**	(-2.20)	0.08	(0.80)	-0.21***	(-2.77)
24	-0.29	(-0.96)	-0.24	(-1.01)	-0.11	(-0.49)	-0.33	(-1.42)	0.08	(0.51)	-0.26**	(-2.50)
25(H)	-0.44	(-1.21)	-0.36	(-1.32)	-0.14	(-0.57)	-0.08	(-0.34)	-0.27	(-1.56)	-0.43***	(-4.93)
H-L	-0.84**	(-2.11)	-0.93***	(-2.86)	-0.63**	(-1.96)	-0.39	(-1.23)	-0.20	(-1.15)	-0.66***	(-7.13)

(continued)

Table E.6 –*Continued*

Panel D. Time Period 1997-2006												
	Alpha								Factor Sensitivity			
D	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.54	(1.52)	0.00	(-0.01)	-0.01	(-0.05)	-0.10	(-0.38)	0.54***	(3.90)	-0.05	(-0.91)
2	0.60	(1.64)	0.07	(0.30)	0.11	(0.52)	-0.02	(-0.07)	0.51***	(4.69)	-0.08	(-1.28)
3	0.66**	(1.97)	0.14	(0.73)	0.19	(1.05)	0.09	(0.37)	0.47***	(4.36)	-0.09	(-1.57)
4	0.57*	(1.90)	0.09	(0.48)	0.17	(0.97)	0.10	(0.40)	0.41***	(4.16)	-0.12**	(-2.36)
5	0.37	(1.19)	-0.09	(-0.44)	0.01	(0.04)	-0.07	(-0.30)	0.37***	(4.06)	-0.14**	(-2.50)
21	0.22	(0.63)	-0.33*	(-1.72)	-0.15	(-0.95)	-0.10	(-0.46)	0.14	(1.21)	-0.24***	(-4.63)
22	0.35	(0.79)	-0.24	(-0.89)	-0.02	(-0.09)	0.04	(0.13)	0.13	(1.03)	-0.31***	(-5.35)
23	0.27	(0.62)	-0.34	(-1.24)	-0.11	(-0.39)	-0.11	(-0.35)	0.17	(0.93)	-0.31***	(-4.25)
24	0.23	(0.49)	-0.36	(-1.48)	-0.07	(-0.31)	-0.08	(-0.30)	0.14	(1.08)	-0.38***	(-5.98)
25(H)	0.06	(0.14)	-0.37*	(-1.78)	-0.13	(-0.64)	-0.19	(-0.78)	0.05	(0.45)	-0.32***	(-7.83)
H-L	-0.48	(-1.12)	-0.37	(-1.44)	-0.12	(-0.45)	-0.09	(-0.22)	-0.49**	(-2.39)	-0.27***	(-3.26)

Panel E. Time Period 2007-2016												
	Alpha								Factor Sensitivity			
D	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.29***	(2.80)	0.29***	(2.92)	0.29***	(2.87)	0.19*	(1.77)	0.12**	(2.38)	0.03	(0.84)
2	0.26***	(2.70)	0.25***	(3.23)	0.25***	(3.21)	0.17*	(1.66)	0.10**	(2.09)	0.02	(0.48)
3	0.23**	(2.45)	0.24***	(3.14)	0.23***	(3.16)	0.09	(1.01)	0.18***	(4.48)	0.04	(1.42)
4	0.21**	(2.28)	0.22***	(2.79)	0.22***	(2.78)	0.12	(1.35)	0.15***	(3.55)	0.01	(0.41)
5	0.18	(1.52)	0.20**	(2.44)	0.20**	(2.38)	0.09	(1.00)	0.17***	(4.16)	0.00	(-0.11)
21	-0.30	(-1.57)	-0.27***	(-2.66)	-0.26***	(-2.79)	-0.16	(-1.42)	-0.19***	(-2.72)	-0.17***	(-5.47)
22	-0.37*	(-1.68)	-0.31***	(-2.84)	-0.30***	(-3.09)	-0.17	(-1.37)	-0.17*	(-1.87)	-0.25***	(-6.69)
23	-0.56**	(-2.13)	-0.49***	(-3.46)	-0.47***	(-3.60)	-0.30**	(-1.98)	-0.14**	(-2.44)	-0.31***	(-6.53)
24	-0.66**	(-2.03)	-0.55**	(-2.47)	-0.52***	(-2.74)	-0.29	(-1.62)	-0.08	(-1.16)	-0.42***	(-7.31)
25(H)	-0.78**	(-2.39)	-0.66***	(-2.75)	-0.62***	(-3.16)	-0.32	(-1.54)	-0.08	(-0.99)	-0.50***	(-7.39)
H-L	-1.07***	(-3.27)	-0.94***	(-3.37)	-0.90***	(-4.15)	-0.51**	(-2.21)	-0.20**	(-2.40)	-0.53***	(-6.49)

Table E.7
Portfolios Mispricing Analysis: Information component ($EVOL$) in Subperiods

This table reports average risk-adjusted returns and factor sensitivity for portfolios sorted by the information components σ_ν^2 (EVOL) for the previous month. We hold stocks for 3 months and calculate returns using Jegadeesh and Titman's (1993) methodology. We report the alpha of CAPM, Fama-French three-factor (FF3), Fama-French three-factor plus momentum (FF4), and Stambaugh and Yuan's (2016) mispricing factor models. Factor sensitivity is reported as the two mispricing factors (MGMT and PERF) as described by Stambaugh and Yuan (2016). Twenty-five portfolios are sorted by D for the previous month. EVOL is the time-series standard deviation of earnings divided by its time-series mean. We analyse portfolio during high sentiment, low sentiment, 1987-1996, 1997-2006, and 2007-2016 periods. High or low sentiment period follows the definition of Baker and Wurgler (2006). An NYSE/AMEX/Nasdaq stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than $5. The standard errors are adjusted for autocorrelation and heteroscedasticity. $*$, $**$, and $***$ indicate the significance level at 0.1, 0.05, and 0.01, respectively.

Panel A. High Sentiment Period

	Alpha								Factor Sensitivity			
$EVOL$	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.41	(1.40)	0.23	(0.91)	0.23	(0.87)	-0.18	(-0.75)	0.63***	(10.45)	0.03	(0.46)
2	0.34	(1.12)	0.15	(0.65)	0.17	(0.70)	-0.24	(-1.00)	0.59***	(7.03)	0.04	(0.57)
3	0.19	(0.68)	0.04	(0.17)	0.06	(0.25)	-0.30	(-1.34)	0.51***	(7.86)	0.03	(0.51)
4	0.22	(0.73)	0.05	(0.24)	0.13	(0.57)	-0.19	(-0.82)	0.48***	(6.42)	-0.04	(-0.79)
5	0.38	(1.34)	0.21	(0.96)	0.29	(1.33)	-0.07	(-0.33)	0.51***	(6.67)	-0.03	(-0.66)
21	0.23	(0.67)	0.20	(0.73)	0.37	(1.48)	0.41	(1.63)	-0.20*	(-1.95)	-0.20***	(-4.29)
22	0.26	(0.82)	0.21	(0.91)	0.44**	(2.11)	0.49**	(2.13)	-0.13	(-1.24)	-0.27***	(-5.28)
23	-0.42	(-1.14)	-0.45*	(-1.66)	-0.23	(-0.92)	-0.23	(-0.84)	-0.20**	(-2.18)	-0.24***	(-4.10)
24	-0.84**	(-2.43)	-0.90***	(-3.98)	-0.64***	(-3.36)	-0.62***	(-2.95)	-0.07	(-0.92)	-0.35***	(-8.45)
25(H)	-0.81**	(-2.03)	-0.85***	(-3.21)	-0.58***	(-2.59)	-0.63**	(-2.43)	-0.10	(-1.19)	-0.34***	(-6.29)
H-L	-1.22***	(-3.26)	-1.08***	(-3.42)	-0.81**	(-2.49)	-0.46	(-1.44)	-0.73***	(-7.33)	-0.36***	(-5.05)

(continued)

Table E.7 –*Continued*

Panel B. Low Sentiment Period												
	Alpha								Factor Sensitivity			
EVOL	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.23**	(2.13)	0.17*	(1.66)	0.21**	(2.19)	0.08	(0.80)	0.33***	(5.64)	-0.09	(-1.48)
2	0.09	(0.78)	0.03	(0.32)	0.08	(0.89)	-0.01	(-0.10)	0.29***	(5.15)	-0.13**	(-2.21)
3	0.08	(0.70)	0.02	(0.25)	0.06	(0.64)	-0.02	(-0.19)	0.25***	(4.58)	-0.11**	(-2.08)
4	0.01	(0.08)	-0.05	(-0.49)	0.01	(0.09)	-0.07	(-0.89)	0.24***	(4.73)	-0.13***	(-2.83)
5	0.14	(1.28)	0.09	(0.97)	0.14*	(1.68)	0.08	(0.87)	0.18***	(3.27)	-0.10**	(-2.19)
21	-0.12	(-0.63)	-0.15	(-1.29)	-0.11	(-0.93)	-0.06	(-0.51)	-0.15**	(-2.07)	-0.12***	(-4.17)
22	-0.20	(-1.01)	-0.25*	(-1.78)	-0.17	(-1.22)	-0.10	(-0.62)	-0.09	(-1.01)	-0.23***	(-5.07)
23	-0.42*	(-1.79)	-0.47***	(-3.16)	-0.41***	(-2.67)	-0.27	(-1.50)	-0.20***	(-2.88)	-0.24***	(-4.00)
24	-0.55**	(-2.21)	-0.61***	(-4.37)	-0.59***	(-4.01)	-0.56***	(-3.11)	-0.02	(-0.19)	-0.15***	(-2.67)
25(H)	-0.53**	(-1.96)	-0.58***	(-3.63)	-0.52***	(-3.17)	-0.47**	(-2.57)	-0.11	(-1.39)	-0.22***	(-3.81)
H-L	-0.76**	(-2.35)	-0.76***	(-3.68)	-0.73***	(-3.69)	-0.56**	(-2.54)	-0.44***	(-4.68)	-0.13	(-1.46)

Panel C. Time Period 1987-1996												
	Alpha								Factor Sensitivity			
EVOL	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.17	(0.74)	0.12	(0.49)	-0.01	(-0.02)	-0.26	(-1.02)	0.39***	(2.92)	0.20**	(2.39)
2	-0.08	(-0.34)	-0.10	(-0.40)	-0.11	(-0.41)	-0.39*	(-1.82)	0.31***	(2.97)	0.08	(1.17)
3	-0.06	(-0.27)	-0.08	(-0.36)	-0.03	(-0.12)	-0.18	(-0.93)	0.16	(1.50)	-0.05	(-0.64)
4	-0.09	(-0.41)	-0.08	(-0.33)	-0.07	(-0.25)	-0.36*	(-1.75)	0.25**	(2.48)	0.04	(0.61)
5	0.32**	(1.98)	0.35**	(2.21)	0.36**	(2.15)	0.12	(0.90)	0.16	(1.53)	0.07	(1.06)
21	0.26	(0.81)	0.43	(1.44)	0.45	(1.49)	0.44	(1.56)	-0.27*	(-1.94)	-0.08	(-0.87)
22	0.11	(0.36)	0.29	(1.04)	0.31	(1.10)	0.18	(0.70)	-0.17	(-1.10)	-0.05	(-0.41)
23	-0.81**	(-2.42)	-0.70***	(-3.00)	-0.63**	(-2.51)	-0.62**	(-2.33)	-0.19**	(-2.02)	-0.25***	(-3.26)
24	-0.72**	(-2.07)	-0.62***	(-3.31)	-0.53***	(-2.77)	-0.65**	(-2.45)	-0.07	(-0.47)	-0.24***	(-2.60)
25(H)	-0.50	(-1.58)	-0.31	(-1.30)	-0.14	(-0.57)	-0.33	(-1.41)	-0.21*	(-1.94)	-0.21**	(-2.40)
H-L	-0.67*	(-1.78)	-0.43	(-1.43)	-0.13	(-0.44)	-0.07	(-0.20)	-0.60***	(-3.31)	-0.41***	(-3.50)

(continued)

Table E.7 –*Continued*

Panel D. Time Period 1997-2006												
	Alpha								Factor Sensitivity			
EVOL	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.57*	(1.86)	-0.02	(-0.13)	0.06	(0.33)	-0.13	(-0.61)	0.66***	(7.18)	-0.17***	(-2.75)
2	0.57*	(1.67)	-0.07	(-0.46)	0.03	(0.18)	-0.14	(-0.61)	0.70***	(6.30)	-0.21***	(-3.51)
3	0.49	(1.58)	-0.09	(-0.56)	-0.03	(-0.16)	-0.24	(-1.19)	0.65***	(8.09)	-0.15***	(-3.04)
4	0.52	(1.55)	-0.12	(-0.64)	0.00	(-0.02)	-0.15	(-0.75)	0.64***	(7.25)	-0.23***	(-5.65)
5	0.41	(1.23)	-0.21	(-1.20)	-0.11	(-0.65)	-0.29	(-1.19)	0.65***	(6.75)	-0.20***	(-4.94)
21	0.18	(0.45)	-0.25	(-1.11)	-0.06	(-0.29)	0.02	(0.07)	-0.02	(-0.14)	-0.24***	(-3.99)
22	0.33	(0.90)	-0.14	(-0.59)	0.09	(0.43)	0.19	(0.71)	0.06	(0.46)	-0.32***	(-6.21)
23	-0.03	(-0.07)	-0.48*	(-1.78)	-0.25	(-0.94)	-0.13	(-0.40)	-0.08	(-0.70)	-0.27***	(-4.35)
24	-0.49	(-1.13)	-0.99***	(-3.57)	-0.75***	(-2.78)	-0.75**	(-2.26)	0.07	(0.57)	-0.34***	(-5.72)
25(H)	-0.66	(-1.36)	-1.15***	(-5.33)	-0.91***	(-4.17)	-0.98***	(-3.63)	0.03	(0.24)	-0.32***	(-5.00)
H-L	-1.23**	(-2.53)	-1.12***	(-3.86)	-0.96***	(-3.34)	-0.85**	(-2.38)	-0.63***	(-3.76)	-0.14	(-1.58)

Panel E. Time Period 2007-2016												
	Alpha								Factor Sensitivity			
EVOL	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.37**	(2.34)	0.42***	(3.13)	0.43***	(3.18)	0.26**	(2.06)	0.48***	(8.91)	-0.04	(-1.13)
2	0.19	(1.20)	0.24**	(2.11)	0.25**	(2.14)	0.11	(1.08)	0.37***	(9.11)	-0.05*	(-1.93)
3	0.19	(1.32)	0.22**	(2.10)	0.23**	(2.07)	0.13	(1.37)	0.28***	(5.75)	-0.05*	(-1.67)
4	0.05	(0.33)	0.09	(0.79)	0.10	(0.85)	0.03	(0.35)	0.25***	(5.58)	-0.08**	(-2.07)
5	0.20	(1.19)	0.24**	(2.48)	0.24**	(2.56)	0.14*	(1.72)	0.27***	(4.81)	-0.06**	(-2.43)
21	-0.29	(-1.38)	-0.26**	(-1.99)	-0.25**	(-1.98)	-0.14	(-1.02)	-0.26***	(-3.17)	-0.17***	(-4.11)
22	-0.38*	(-1.70)	-0.33**	(-2.19)	-0.32**	(-2.25)	-0.19	(-1.35)	-0.11	(-1.13)	-0.25***	(-6.58)
23	-0.51**	(-1.98)	-0.45**	(-2.27)	-0.44**	(-2.23)	-0.33*	(-1.69)	-0.17*	(-1.75)	-0.23***	(-3.38)
24	-1.00***	(-4.46)	-0.93***	(-4.17)	-0.93***	(-4.17)	-0.90***	(-3.68)	0.05	(0.63)	-0.20***	(-3.23)
25(H)	-0.89***	(-2.97)	-0.79***	(-3.33)	-0.78***	(-3.26)	-0.67***	(-2.78)	0.12	(1.25)	-0.34***	(-5.20)
H-L	-1.26***	(-4.22)	-1.21***	(-4.12)	-1.20***	(-3.98)	-0.93***	(-2.99)	-0.36***	(-3.25)	-0.31***	(-3.62)

Table E.8
Portfolios Mispricing Analysis: Noise Component (D_{R1}) in Subperiods

This table reports average risk-adjusted returns and factor sensitivity for portfolios sorted by the noise component σ^2_ϵ (D_{R1}) for the previous month. We hold stocks for 3 months and calculate returns using Jegadeesh and Titman's (1993) methodology. We report the alpha of CAPM, Fama-French three-factor (FF3), Fama-French three-factor plus momentum (FF4), and Stambaugh and Yuan's (2016) mispricing factor models. Factor sensitivity is reported as the two mispricing factors (MGMT and PERF) as described by Stambaugh and Yuan (2016). Twenty-five portfolios are sorted by D for the previous month. D_{R1} is the residual part of the regression of equation (II.D). We analyse portfolio during high sentiment, low sentiment, 1987-1996, 1997-2006, and 2007-2016 periods. High or low sentiment period follows the definition of Baker and Wurgler (2006). An NYSE/AMEX/Nasdaq stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than \$5. The standard errors are adjusted for autocorrelation and heteroscedasticity. $*$, $**$, and $***$ indicate the significance level at 0.1, 0.05, and 0.01, respectively.

Panel A. High Sentiment Period

	Alpha								Factor Sensitivity			
D_{R2}	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.13	(0.34)	0.02	(0.07)	0.21	(0.90)	0.08	(0.32)	0.12*	(1.91)	-0.22***	(-4.20)
2	0.30	(0.85)	0.20	(0.76)	0.32	(1.22)	0.07	(0.24)	0.18**	(2.37)	-0.06	(-0.87)
3	0.46	(1.56)	0.37*	(1.86)	0.41**	(2.08)	0.16	(0.87)	0.16**	(2.39)	0.00	(-0.08)
4	0.42	(1.42)	0.31	(1.49)	0.39*	(1.86)	0.12	(0.59)	0.20***	(2.74)	-0.02	(-0.66)
5	0.15	(0.59)	0.05	(0.29)	0.14	(0.83)	-0.03	(-0.15)	0.19***	(2.87)	-0.08***	(-2.81)
21	0.24	(0.85)	0.13	(0.75)	0.22	(1.27)	0.00	(-0.03)	0.21**	(2.39)	-0.07	(-1.55)
22	0.36	(1.22)	0.27	(1.23)	0.37*	(1.81)	0.15	(0.77)	0.13	(1.38)	-0.05	(-0.82)
23	0.11	(0.36)	0.00	(0.00)	0.11	(0.59)	-0.09	(-0.45)	0.15	(1.41)	-0.08	(-1.51)
24	0.36	(1.15)	0.26	(1.13)	0.41*	(1.89)	0.26	(1.16)	0.10	(1.06)	-0.14***	(-3.08)
25(H)	0.07	(0.22)	0.01	(0.06)	0.21	(0.94)	0.17	(0.75)	-0.01	(-0.13)	-0.25***	(-7.37)
H-L	-0.06	(-0.21)	0.00	(-0.02)	0.00	(0.00)	0.08	(0.28)	-0.13**	(-1.98)	-0.03	(-0.48)

(continued)

Table E.8 –*Continued*

Panel B. Low Sentiment Period

D_{R2}	Alpha								Factor Sensitivity			
	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.02	(0.10)	-0.02	(-0.15)	0.05	(0.35)	0.09	(0.60)	-0.13	(-1.36)	-0.13*	(-1.66)
2	0.00	(0.02)	-0.03	(-0.22)	0.02	(0.17)	0.01	(0.07)	-0.04	(-0.51)	-0.07	(-1.33)
3	0.01	(0.10)	-0.01	(-0.13)	0.03	(0.31)	0.02	(0.21)	-0.07	(-1.22)	-0.05	(-1.30)
4	0.02	(0.19)	0.00	(-0.05)	0.05	(0.47)	0.05	(0.48)	-0.06	(-1.28)	-0.08*	(-1.89)
5	0.02	(0.16)	-0.01	(-0.05)	0.03	(0.30)	-0.02	(-0.23)	0.01	(0.13)	-0.04	(-1.32)
21	-0.10	(-0.80)	-0.15*	(-1.82)	-0.10	(-1.21)	-0.06	(-0.62)	0.02	(0.54)	-0.19***	(-4.86)
22	-0.08	(-0.71)	-0.13*	(-1.75)	-0.04	(-0.63)	-0.03	(-0.36)	-0.01	(-0.25)	-0.19***	(-7.65)
23	-0.10	(-0.67)	-0.15	(-1.52)	-0.08	(-0.83)	-0.02	(-0.29)	-0.02	(-0.49)	-0.21***	(-8.22)
24	-0.22	(-1.32)	-0.29***	(-2.69)	-0.18*	(-1.93)	-0.09	(-0.83)	-0.06	(-1.06)	-0.29***	(-10.08)
25(H)	-0.45**	(-2.18)	-0.52***	(-3.83)	-0.39***	(-3.06)	-0.27**	(-2.29)	-0.12	(-1.57)	-0.33***	(-10.23)
H-L	-0.47**	(-2.53)	-0.49***	(-2.65)	-0.44**	(-2.50)	-0.36**	(-1.96)	0.01	(0.09)	-0.21**	(-2.52)

Panel C. Time Period 1987-1996

D_{R2}	Alpha								Factor Sensitivity			
	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.24	(0.78)	0.43*	(1.90)	0.47*	(1.91)	0.44**	(2.05)	-0.29*	(-1.92)	-0.10	(-1.21)
2	0.02	(0.10)	0.19	(1.01)	0.16	(0.71)	0.03	(0.14)	-0.12	(-1.44)	0.04	(0.41)
3	0.28	(1.41)	0.47**	(2.41)	0.47**	(2.36)	0.35**	(2.06)	-0.21***	(-3.05)	0.07	(1.12)
4	0.20	(0.97)	0.32*	(1.77)	0.40**	(2.16)	0.33**	(2.34)	-0.18***	(-2.69)	-0.08*	(-1.72)
5	0.00	(0.01)	0.09	(0.59)	0.13	(0.80)	0.13	(0.97)	-0.16**	(-2.27)	-0.09*	(-1.83)
21	0.03	(0.15)	0.09	(0.54)	0.11	(0.62)	-0.05	(-0.32)	0.05	(0.56)	-0.03	(-0.38)
22	-0.05	(-0.23)	0.05	(0.22)	0.14	(0.61)	-0.15	(-0.98)	0.03	(0.30)	0.02	(0.16)
23	-0.19	(-0.75)	-0.13	(-0.62)	-0.08	(-0.33)	-0.41**	(-2.13)	0.21*	(1.92)	-0.05	(-0.68)
24	-0.08	(-0.29)	-0.04	(-0.17)	0.10	(0.40)	-0.04	(-0.20)	0.01	(0.06)	-0.21**	(-2.55)
25(H)	-0.29	(-0.87)	-0.17	(-0.55)	-0.08	(-0.27)	-0.17	(-0.64)	-0.11	(-0.62)	-0.22**	(-2.24)
H-L	-0.53	(-1.60)	-0.60*	(-1.76)	-0.55	(-1.55)	-0.60	(-1.57)	0.18	(0.99)	-0.12	(-1.58)

(continued)

Table E.8 –*Continued*

Panel D. Time Period 1997-2006												
	Alpha								Factor Sensitivity			
D	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.31	(0.69)	-0.33	(-1.33)	-0.10	(-0.51)	-0.12	(-0.41)	0.34***	(3.55)	-0.35***	(-4.46)
2	0.40	(0.94)	-0.17	(-0.65)	0.00	(-0.02)	-0.03	(-0.11)	0.30***	(3.15)	-0.20***	(-3.31)
3	0.38	(1.03)	-0.15	(-0.64)	-0.09	(-0.43)	-0.10	(-0.38)	0.25***	(2.72)	-0.09**	(-2.25)
4	0.47	(1.33)	-0.08	(-0.50)	0.01	(0.04)	-0.03	(-0.11)	0.28***	(3.73)	-0.10**	(-2.39)
5	0.31	(0.96)	-0.18	(-1.08)	-0.10	(-0.61)	-0.13	(-0.59)	0.23**	(2.55)	-0.09**	(-2.05)
21	0.43	(1.27)	-0.18	(-0.99)	-0.03	(-0.18)	-0.07	(-0.32)	0.38***	(3.42)	-0.24***	(-4.48)
22	0.47	(1.43)	-0.11	(-0.73)	0.05	(0.32)	0.06	(0.28)	0.28**	(2.38)	-0.22***	(-4.15)
23	0.44	(1.30)	-0.06	(-0.33)	0.10	(0.55)	0.10	(0.48)	0.20*	(1.73)	-0.20***	(-4.43)
24	0.52	(1.50)	-0.05	(-0.27)	0.15	(0.79)	0.16	(0.72)	0.21*	(1.81)	-0.26***	(-5.20)
25(H)	0.20	(0.54)	-0.23	(-1.00)	-0.03	(-0.14)	-0.04	(-0.19)	0.09	(1.17)	-0.27***	(-7.97)
H-L	-0.12	(-0.43)	0.10	(0.42)	0.07	(0.32)	0.08	(0.28)	-0.25***	(-2.68)	0.08	(0.99)
Panel E. Time Period 2007-2016												
	Alpha								Factor Sensitivity			
D_{R2}	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	-0.08	(-0.49)	-0.05	(-0.35)	-0.05	(-0.32)	-0.10	(-0.58)	0.02	(0.32)	-0.08*	(-1.76)
2	0.04	(0.27)	0.05	(0.50)	0.05	(0.54)	0.03	(0.31)	-0.02	(-0.47)	-0.06	(-1.50)
3	0.14	(0.96)	0.15**	(1.96)	0.16*	(1.85)	0.10	(1.17)	0.04	(0.84)	-0.04	(-1.31)
4	0.10	(0.70)	0.12	(1.04)	0.13	(1.07)	0.11	(0.88)	0.02	(0.24)	-0.08**	(-2.25)
5	0.16	(1.15)	0.18**	(2.05)	0.19**	(2.04)	0.14	(1.49)	0.12**	(2.37)	-0.08***	(-2.99)
21	-0.26*	(-1.70)	-0.23***	(-3.24)	-0.22***	(-2.98)	-0.19**	(-2.07)	-0.02	(-0.47)	-0.13***	(-5.82)
22	-0.12	(-0.94)	-0.08	(-0.93)	-0.07	(-0.83)	-0.01	(-0.12)	-0.02	(-0.52)	-0.16***	(-5.06)
23	-0.29*	(-1.72)	-0.25**	(-2.45)	-0.24**	(-2.53)	-0.15	(-1.55)	-0.13*	(-1.66)	-0.17***	(-5.23)
24	-0.21	(-0.86)	-0.14	(-1.01)	-0.12	(-1.08)	-0.01	(-0.04)	-0.15*	(-1.87)	-0.23***	(-4.43)
25(H)	-0.48**	(-1.96)	-0.41***	(-2.61)	-0.38***	(-2.60)	-0.19	(-1.34)	-0.10	(-1.33)	-0.32***	(-6.95)
H-L	-0.40*	(-1.86)	-0.35	(-1.60)	-0.33*	(-1.65)	-0.09	(-0.40)	-0.12	(-1.21)	-0.25***	(-3.83)

Table E.9

Portfolios Mispricing Analysis: Opinion Component ($|EAC|$) in Subperiods

This table reports average risk-adjusted returns and factor sensitivity for portfolios sorted by the opinion component η ($|EAC|$) for the previous month. We hold stocks for 3 months and calculate returns using Jegadeesh and Titman's (1993) methodology. We report the alpha of CAPM, Fama-French three-factor (FF3), Fama-French three-factor plus momentum (FF4), and Stambaugh and Yuan's (2016) mispricing factor models. Factor sensitivity is reported as the two mispricing factors (MGMT and PERF) as described by Stambaugh and Yuan (2016). Twenty-five portfolios are sorted by D for the previous month. EAC is the time-series covariance of unexpected earnings and unexpected mean analyst forecast. $|EAC|$ is the absolute value of EAC. We analyse portfolio during high sentiment, low sentiment, 1987-1996, 1997-2006, and 2007-2016 periods. High or low sentiment period follows the definition of Baker and Wurgler (2006). An NYSE/AMEX/Nasdaq stock is 'eligible' to be included in our analysis if it has a one (fiscal) year I/B/E/S earnings estimate, is covered by two or more analysts, and has a price greater than $5. The standard errors are adjusted for autocorrelation and heteroscedasticity. $*$, $**$, and $***$ indicate the significance level at 0.1, 0.05, and 0.01, respectively.

Panel A. High Sentiment Period												
	Alpha								Factor Sensitivity			
$\lvert EAC\rvert$	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.71**	(2.46)	0.61**	(2.55)	0.59**	(2.47)	0.18	(0.83)	0.34***	(4.72)	0.10**	(2.12)
2	0.46*	(1.66)	0.34*	(1.68)	0.32	(1.55)	-0.06	(-0.30)	0.33***	(4.61)	0.10**	(2.11)
3	0.51*	(1.82)	0.42*	(1.90)	0.45**	(2.20)	0.13	(0.67)	0.24***	(3.47)	0.04	(0.84)
4	0.43	(1.58)	0.32*	(1.69)	0.40**	(2.20)	0.10	(0.49)	0.26***	(2.97)	0.00	(-0.08)
5	0.40	(1.45)	0.30	(1.44)	0.38**	(2.05)	0.11	(0.55)	0.20**	(2.51)	0.01	(0.17)
21	0.06	(0.19)	-0.06	(-0.27)	0.06	(0.33)	-0.10	(-0.56)	0.20**	(2.16)	-0.13***	(-2.64)
22	0.00	(0.01)	-0.10	(-0.41)	0.16	(0.76)	0.16	(0.66)	0.06	(0.58)	-0.30***	(-5.81)
23	0.10	(0.34)	-0.01	(-0.04)	0.11	(0.65)	0.04	(0.19)	0.11	(1.27)	-0.14***	(-3.70)
24	0.06	(0.22)	-0.04	(-0.22)	0.09	(0.51)	0.02	(0.12)	0.08	(0.88)	-0.14***	(-2.64)
25(H)	-0.07	(-0.21)	-0.24	(-1.04)	-0.04	(-0.22)	-0.19	(-0.76)	0.34***	(2.89)	-0.21***	(-3.01)
H-L	-0.78**	(-2.45)	-0.85***	(-2.86)	-0.64**	(-2.18)	-0.37	(-1.15)	-0.01	(-0.06)	-0.31***	(-3.68)

(continued)

Table E.9 –*Continued*

Panel B. Low Sentiment Period												
	Alpha								Factor Sensitivity			
$\|EAC\|$	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.25**	(2.22)	0.24**	(2.31)	0.29***	(2.66)	0.23**	(2.00)	-0.09	(-1.00)	0.01	(0.15)
2	0.11	(1.00)	0.10	(0.89)	0.13	(1.45)	0.05	(0.50)	0.02	(0.26)	0.00	(0.04)
3	0.03	(0.29)	0.00	(0.03)	0.05	(0.46)	-0.03	(-0.25)	0.05	(0.86)	-0.05	(-0.89)
4	0.05	(0.46)	0.04	(0.30)	0.09	(0.93)	0.06	(0.60)	-0.04	(-0.79)	-0.06	(-1.22)
5	0.07	(0.61)	0.04	(0.45)	0.07	(0.75)	0.05	(0.60)	-0.02	(-0.34)	-0.06	(-1.43)
21	-0.30**	(-2.10)	-0.37***	(-3.57)	-0.26**	(-2.47)	-0.17	(-1.59)	-0.03	(-0.51)	-0.27***	(-6.39)
22	-0.23	(-1.31)	-0.30**	(-2.18)	-0.19	(-1.38)	-0.09	(-0.74)	-0.04	(-0.60)	-0.30***	(-6.15)
23	-0.08	(-0.46)	-0.15	(-1.25)	-0.07	(-0.55)	0.09	(0.77)	-0.08	(-1.09)	-0.30***	(-8.55)
24	-0.09	(-0.56)	-0.17	(-1.39)	-0.10	(-0.79)	0.02	(0.20)	0.00	(-0.03)	-0.29***	(-7.63)
25(H)	-0.20	(-1.04)	-0.32**	(-2.57)	-0.21*	(-1.69)	-0.02	(-0.13)	0.06	(0.72)	-0.43***	(-9.75)
H-L	-0.45**	(-1.97)	-0.57***	(-3.29)	-0.50***	(-2.81)	-0.25	(-1.35)	0.14	(1.13)	-0.43***	(-6.15)

Panel C. Time Period 1987-1996												
	Alpha								Factor Sensitivity			
$\|EAC\|$	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.43*	(1.74)	0.65***	(3.14)	0.70***	(3.11)	0.51**	(2.11)	-0.21*	(-1.84)	0.06	(1.00)
2	0.10	(0.56)	0.26	(1.55)	0.23	(1.31)	0.04	(0.33)	-0.07	(-1.07)	0.11**	(2.24)
3	0.12	(0.60)	0.27	(1.41)	0.29	(1.52)	0.06	(0.33)	-0.08	(-1.03)	0.13**	(2.25)
4	0.06	(0.33)	0.22	(1.56)	0.26**	(2.04)	0.17	(1.38)	-0.22***	(-2.77)	0.01	(0.28)
5	0.07	(0.37)	0.20	(1.04)	0.18	(0.99)	0.04	(0.32)	-0.09	(-1.16)	0.07	(0.84)
21	-0.08	(-0.31)	-0.04	(-0.20)	0.03	(0.16)	-0.10	(-0.80)	0.02	(0.20)	-0.12	(-1.25)
22	-0.10	(-0.40)	-0.05	(-0.25)	0.05	(0.24)	-0.03	(-0.28)	-0.05	(-0.43)	-0.16**	(-2.51)
23	0.02	(0.12)	0.04	(0.27)	0.14	(0.88)	0.09	(0.59)	-0.03	(-0.21)	-0.19*	(-1.93)
24	-0.07	(-0.36)	-0.08	(-0.44)	-0.05	(-0.32)	-0.24	(-1.23)	0.18	(1.46)	-0.08	(-0.73)
25(H)	0.09	(0.34)	0.02	(0.11)	0.18	(1.14)	0.16	(1.22)	0.08	(0.89)	-0.36***	(-3.87)
H-L	-0.34	(-0.90)	-0.62**	(-2.44)	-0.52**	(-2.07)	-0.35	(-1.21)	0.30*	(1.84)	-0.41***	(-4.23)

(continued)

Table E.9 –*Continued*

Panel D. Time Period 1997-2006												
	Alpha								Factor Sensitivity			
$\|EAC\|$	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.79**	(2.52)	0.28	(1.59)	0.32*	(1.77)	0.15	(0.70)	0.40***	(4.80)	-0.04	(-1.06)
2	0.55	(1.59)	-0.03	(-0.15)	0.01	(0.08)	-0.12	(-0.48)	0.45***	(5.29)	-0.07	(-1.56)
3	0.48	(1.43)	-0.06	(-0.27)	0.02	(0.11)	-0.06	(-0.28)	0.39***	(4.69)	-0.15**	(-2.44)
4	0.52	(1.55)	-0.06	(-0.36)	0.05	(0.27)	-0.02	(-0.08)	0.41***	(3.91)	-0.16***	(-3.09)
5	0.46	(1.47)	-0.06	(-0.40)	0.06	(0.36)	0.02	(0.11)	0.31***	(3.65)	-0.15***	(-3.57)
21	0.27	(0.77)	-0.27	(-1.35)	-0.14	(-0.72)	-0.16	(-0.76)	0.27**	(2.43)	-0.19***	(-2.82)
22	0.24	(0.56)	-0.34	(-1.23)	-0.06	(-0.22)	0.00	(0.01)	0.27**	(2.30)	-0.42***	(-7.08)
23	0.30	(0.76)	-0.32	(-1.64)	-0.17	(-0.90)	-0.12	(-0.51)	0.31**	(2.55)	-0.25***	(-5.66)
24	0.28	(0.81)	-0.30	(-1.55)	-0.14	(-0.66)	-0.04	(-0.20)	0.27**	(2.20)	-0.27***	(-4.19)
25(H)	0.24	(0.67)	-0.44**	(-2.24)	-0.28	(-1.55)	-0.18	(-0.68)	0.36**	(2.22)	-0.19**	(-2.03)
H-L	-0.55*	(-1.79)	-0.72**	(-2.47)	-0.60**	(-2.12)	-0.34	(-1.19)	-0.04	(-0.29)	-0.14	(-1.30)
Panel E. Time Period 2007-2016												
	Alpha								Factor Sensitivity			
$\|EAC\|$	CAPM		FF3		FF4		M4		MGMT		PERF	
1(L)	0.23	(1.45)	0.23**	(2.13)	0.23**	(2.12)	0.09	(0.90)	0.22***	(5.52)	0.02	(1.03)
2	0.28**	(2.30)	0.28***	(3.00)	0.28***	(3.00)	0.17	(1.58)	0.15***	(2.75)	0.02	(0.52)
3	0.19	(1.30)	0.21**	(2.01)	0.21**	(2.01)	0.09	(0.94)	0.14**	(2.50)	0.00	(-0.13)
4	0.26*	(1.94)	0.28***	(3.31)	0.29***	(3.59)	0.20**	(2.41)	0.17***	(4.17)	-0.04	(-1.63)
5	0.25*	(1.75)	0.27***	(2.92)	0.27***	(2.94)	0.15	(1.41)	0.16***	(4.78)	-0.01	(-0.51)
21	-0.45***	(-2.61)	-0.38***	(-2.87)	-0.36***	(-3.06)	-0.22*	(-1.65)	-0.05	(-0.82)	-0.27***	(-7.05)
22	-0.44**	(-2.17)	-0.39***	(-2.68)	-0.37***	(-2.93)	-0.22*	(-1.85)	-0.16**	(-2.36)	-0.25***	(-6.23)
23	-0.15	(-0.69)	-0.09	(-0.63)	-0.08	(-0.51)	0.08	(0.63)	-0.19***	(-2.78)	-0.25***	(-5.84)
24	-0.16	(-0.74)	-0.11	(-0.58)	-0.09	(-0.52)	0.10	(0.64)	-0.31***	(-3.05)	-0.25***	(-6.38)
25(H)	-0.57**	(-2.12)	-0.47**	(-2.07)	-0.44**	(-2.16)	-0.20	(-1.00)	-0.09	(-0.91)	-0.40***	(-8.52)
H-L	-0.80***	(-3.32)	-0.70***	(-2.83)	-0.68***	(-2.91)	-0.29	(-1.33)	-0.31***	(-2.70)	-0.42***	(-8.02)