Return Anomalies, Disagreement and Trading Volume *

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Abstract

I propose a new measure of investor disagreement based on thirty-nine factors from the return-predicting anomaly literature. Consistent with theoretical work on volume, I show that a one standard deviation change in anomaly-based disagreement is associated with a 16.7% higher turnover in the next period. Disagreement effects on volume are stronger for firms with more complex information releases and weaken after the exogenous introduction of the SEC EDGAR filing system. Anomaly-based disagreement also explains analyst behavior where it relates positively to their forecast dispersion and absolute forecast errors in earnings and target prices.

Keywords: Disagreement, Return Anomalies, Trading Volume
JEL Classification: G11, G12, G14

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1 Introduction

While the prediction of firm stock returns has occupied the attention of financial economists for several decades, very few studies have attempted to predict firm volume (Lo and Wang (2010)). Perhaps the view that volume primarily relates to liquidity and portfolio rebalancing has dissuaded researchers from investigating its predictability. The economic importance of dollar volume and its meteoric growth in the last few decades (French (2008)) suggest that it is an important phenomenon to be modeled and predicted. Hong and Stein (2007) discuss another important reason to study volume — its role as an indicator of sentiment and a causative factor for speculative bubbles.

Volume has also been theoretically linked to differences in opinions and beliefs among traders (Varian (1989)). This literature predicts that trading volume will be increasing in disagreement among traders. If two traders hold opposing views regarding the future value of an asset relative to its current price, then the direction of their trades will differ, leading to volume (Harris and Raviv (1993); Kandel and Pearson (1995)). Disagreement can also arise if investors use different signals to predict the future value of an asset. Further, it could arise when investors interpret the same signal differently when predicting future returns.

In this study, I propose a new measure of disagreement related to stock market anomalies and show that it is a significant predictor of subsequent volume. To measure disagreement, I propose that dispersion in fundamental and price-related return predictors (anomaly factors, hereafter AF) can cause disagreement and lead to subsequent trading volume. The intuition for my measure of disagreement is as follows. I assume that different investors believe that different AFs predict future returns. An investor will initiate a buy (sell) trade if the AF predicts higher (lower) returns in the future. Because AFs differ in the sign of their relationship with future returns, dispersion in these signs captures disagreement.

To measure disagreement, I consider 39 AFs from the anomaly literature (Linnainmaa and Roberts (2018) and McLean and Pontiff (2016)). For each AF, at the end of each month, I sort stocks based on that AF's cross-sectional distribution. Specifically, I divide stocks into three AF-based groups: the top 30% of stocks are assigned a buy signal, the bottom 30% of stocks a sell signal, and the rest are classified as holds. This process is repeated for the 39 AFs yielding 39 buy/sell/hold signals for each stock in each month. For every firm-month, I measure disagreement as the standard deviation of these signals. I then estimate cross-sectional predictive regressions of monthly trading volume on lagged disagreement.

Using a large panel of US stocks from 1976–2019, I find that my AF-based disagreement measure is strongly related to subsequent monthly trading volume. This effect obtains after controlling for several factors identified in the prior literature on the determinants of the trading volume. A one standard deviation change in disagreement is associated with a 16.7% increase in next month's trading volume. The relationship is robust to different regression specifications, different volume measures, and the use of alternative sorts to define the buy/hold/sell signals. The exclusion of momentum AFs reduces the level of disagreement. However, excluding these anomalies do not materially impact the overall results.

Interestingly, the effect of analyst forecast dispersion (the most popular measure of disagreement from prior literature) on trading volume weakens or loses statistical significance when included in my AF-based measure of disagreement. Lagged AF-based disagreement is also a reliable predictor of volume in the first day and first week of the following month. Further, firms in pharmaceuticals, oil and gas, computers, and information technology industries — industries characterized by higher uncertainty in future cash flows, real options, and regulatory risks tend to have the highest disagreement levels.

Investors' reliance on AFs is likely to depend on the amount and complexity of other firm-specific information available to them. When there is less public information about a firm, investors are likely to rely more on AFs as simple and convenient heuristics to value and trade in those firms. Thus, I predict that the relation between disagreement and subsequent volume will be stronger for firms with less public information. Consistent with this prediction, I document that the monthly volume of small firms, young firms, and firms with lower analyst following — firms with less public information, is more positively related to lagged disagreement. I also document that information complexity influences the effect of disagreement on volume. When firm-specific information becomes more complex, investors are likely to depend less on this information and to rely more on simple AF-based heuristics for investment decisions. Measuring information disclosure complexity as the length of 10-K filings and the occurrence of informationally complex words in 10-Ks, I find that the volume-disagreement relation is stronger for informationally complex firms.

To provide more direct causal evidence on how the availability of information affects the volume-disagreement relationship, I exploit the unique EDGAR implementation studied by Chang, Hsiao, Ljungqvist, and Tseng (2020). The online access to corporate reports triggered by the EDGAR implementation presents investors with an additional source of value-relevant information to anomalies. I predict a substitution effect between anomalies and the shock to information caused by EDGAR. Specifically, the easy availability of these reports would cause investors to reduce their weights on anomalies when making trading decisions. Consistent with this prediction, I find that using a difference-in-difference design, firms that adopted EDGAR in January 1994 experience 25% less disagreement-induced trading compared to firms that adopted EDGAR later.

A critical assumption underlying my disagreement measure is that investors rely on AFs in their trading decisions. To provide direct evidence on this assumption, I examine how AF-based disagreement influences security analysts, an influential participant in financial markets. If analysts use AFs in making their forecasts and different analysts use different sets of AFs, then higher AF-based disagreement should lead to more dispersed analysts' forecasts and larger absolute forecast errors. I examine both earnings forecasts and target price forecasts. Consistent with my expectation, forecast dispersion and absolute forecast errors increase in lagged disagreement, with stronger effects for target price-related dispersion and forecast errors. These findings suggest that analyst forecasts are a channel through which investor disagreement affects the investment decisions of traders and validate the use of AF-based disagreement to predict volume.

In my final piece of analysis, I examine the trading volume associated with each of the thirty-nine individual AFs. For all AFs, I find that mean turnover in the month following AF portfolio formation is higher for the extreme AF portfolios (first and tenth deciles) than that of the remaining portfolios (second to ninth deciles). Thus, trading is clustered in stocks with extreme values of AFs. I define the difference in extreme and intermediate AF portfolios' mean volume as excess volume. I then estimate simple OLS regressions of turnover on disagreement and decompose turnover into its (predictable) disagreement-related and residual components. I find that for twenty-seven of the thirty-nine AFs, excess volume is primarily driven by disagreement-turnover. This evidence further strengthens my conclusion that disagreement related to AFs is an influential predictor of subsequent anomaly-related volume.

My study makes three broad contributions. First, my work contributes to the literature on the cross-sectional determinants of trading volume (Chordia, Huh, and Subrahmanyam

(2006); Carlin, Longstaff, and Matoba (2014); Jacobs and Hillert (2015)). I propose a new measure of investor disagreement that is a robust and significant predictor of volume after controlling for prior predictors of volume. I find that the extent to which investors rely on anomalies depends on the availability, amount, and complexity of firm-specific information. Disagreement effects on volume are stronger for firms with more complex information releases and weaken after the exogenous introduction of the SEC EDGAR filing system.

Second, my measure of disagreement is an alternative to and complements analyst forecast dispersion, the most popular measure of disagreement in prior research. I find that AF-based disagreement is a stronger predictor of volume than forecast dispersion. Further, unlike analyst forecast data available only for a subset of the stocks that analysts follow, my anomaly-based disagreement measure can be computed for a much larger sample. Specifically, AF-based disagreement can be computed for small and young stocks typically not followed by analysts.

Third, while the ability of AFs to predict returns has been widely studied, less is known about whether investors exploit these anomalies. By linking AF-based disagreement to the volume related to specific anomalies, I show that investors trade on these anomalies because they disagree about them. This important simple, intermediate link that precedes return prediction has escaped the attention of prior work. My paper complements McLean and Pontiff (2016), who, through return prediction tests, show that investors appear to have used published academic research in their trading strategies.

2 Prior Literature

2.1 Theoretical work

Varian (1989) examines how differences in opinions about the value of a risky asset affect its trading volume.[1] He shows that a trader's demand is determined solely by the deviation of his or her opinion from the average opinion. That is, volume is increasing in the dispersion of opinion, as measured by the sum of the absolute deviations of the priors. Varian (1989) also shows that even when a public signal arrives about the asset, trading volume depends only on differences in prior opinions and not on the information in the

[1]When discussing these opinion differences, Varian (1989) is agnostic about their nature — they are exogenous and could be rational or irrational.

signal. Prices, as expected, respond to the information contained in the public signal.

Harris and Raviv (1993) propose a model of a series of public signals about a risky asset. Payoffs to the asset are dependent on the cumulative value of these signals. They assume that two groups of traders disagree on the extent to which each signal (in the series) impacts future payoffs. A cumulative positive (negative) signal makes one (the other) group more optimistic (pessimistic). Trading volume occurs when the sign of the cumulative signal switches, causing groups to switch from optimism to pessimism. Thus, disagreement in the interpretation of public information causes volume.

Kandel and Pearson (1995), hereafter KP, model volume around the public announcement of a signal related to a risky asset. The asset's payoff is defined as the sum of the value of the signal and an error term; the error term is what allows traders to disagree in how they interpret the signal. KP assume that two groups of traders differ in their assessment of the mean of the error term and its variance. The two groups observe the same signal but interpret it differently — one group can be more or less optimistic (assess a higher or lower mean) about the asset than the other. KP shows that the volume around the announcement is positively related to the extent to which the two groups differ in the interpretation of the signal, measured as the difference in the means of the error assessed by the two groups.[2] Consistent with the differential interpretation of common information, KP find that the frequencies of analyst forecast revisions that diverge around earnings announcements are fairly high.

Hong and Stein (2007) discuss different ways in which volume could arise. In addition to heterogeneous beliefs and priors, they discuss two settings where investor differences in rationality can lead to volume. First, information could reach one group of smarter investors before the remaining investors. Volume arises when the less smart group reacts to public news already anticipated or known by the smarter group. Second, some investors pay attention only to a subset of publicly available information because of limited attention. Volume occurs when these investors trade with investors that are not handicapped by limited attention.

2.2 Empirical work

Most empirical tests of the effect of disagreement on volume have correlated monthly trading volume with dispersion in analysts' earnings forecasts, the most common proxy

[2]Volume also depends on the change in price induced by the announcement, the precision of the prior beliefs of the traders, and the precision of the signal.

for disagreement. Ajinkya, Atiase, and Gift (1991) document a positive relation between monthly trading volume and dispersion in analysts' forecasts in earnings per share for a sample of 420 firms for the years 1978–1981. Barron (1995) finds that monthly trading volume is positively related to prior dispersion in analysts' earnings forecasts and revisions in forecasts and negatively related to the degree of correlation between current and previous forecasts; his sample consists of 166 firms for the years 1984–1990. Chordia et al. (2006), hereafter CHS, examine the cross-sectional determinants of monthly turnover over the years 1963–2002. They predict monthly turnover to be a function of investor disagreement and past returns, stock visibility, the number of informed agents, and estimation uncertainty. They employ two proxies for investor disagreement — monthly dispersion in analysts' earnings forecasts and leverage and find that an increase in forecast dispersion increases monthly turnover in both NYSE/AMEX and NASDAQ samples. Leverage has a positive effect on turnover in the NYSE/AMEX sample but negatively affects the NASDAQ sample.[3]

Jacobs and Hillert (2015) extend CHS and propose that firms whose names are higher in the alphabetical listing have higher volume than the firms appearing at the end of the alphabetical ordering. In addition, they propose several other variables that might influence volume, including advertising expense, 52-week high/low events, idiosyncratic volatility, market model alpha, media coverage, S&P 500, and DJIA membership. They find that forecast dispersion and leverage, proxies for disagreement, are positively related to volume, consistent with CHS.

Carlin et al. (2014) examine how disagreement affects trading volume, volatility, and asset returns in the Mortgage-Backed Securities (MBS) market. They measure disagreement as the cross-sectional dispersion in prepayment speed forecasts among dealers in the market.[4] Using a vector-autoregression model of disagreement, volatility,

[3]While my focus is on the relation between disagreement and volume, which I believe is the first step to understanding the effects of disagreement, others have studied the relation between disagreement and returns. Diether, Malloy, and Scherbina (2002) show that higher analyst forecast dispersion stocks earn lower returns than other stocks. They interpret this result as consistent with pessimistic traders being kept out of the market, leading to stock overvaluation and lower returns. Banerjee (2011) develops a framework to differentiate between differences-in-opinion and rational expectation approaches to the disagreement-return relationship. He shows that disagreement will lead to higher (lower) returns under rational expectations (differences of opinion).}

[4]The timing of prepayments associated with mortgage-backed securities is uncertain, leading to dispersion in forecast among dealers.

and volume, they find that disagreement is positively related to MBS volume. Volume also increases with volatility, but only when disagreement is high. Investors learn from their trades — higher disagreement leads to higher volume, and subsequently, disagreement falls, resulting in a mean-reverting time series for disagreement.

Prior research has also correlated trading volume during earnings announcements with disagreement.[5] Ziebart (1990) reports that the abnormal change in trading volume during an earnings announcement is positively related to the change in dispersion in analyst forecasts around the announcement for a small sample of ninety firms for the years 1978–1983. Atiase and Bamber (1994) find that earnings announcement trading volume is positively related to pre-announcement forecast dispersion for a sample of about 5,300 earnings announcements from 1980–1989. Bamber, Barron, and Stober (1997) examine a sample of about 2,000 earnings announcements from 1984–1994. They find that dispersion in analyst forecasts, changes in forecast dispersion around earnings announcements, and one minus the correlation between pre-and post-announcement forecasts (which they refer to as belief jumbling) explain earnings announcement volume.

That disagreement can cause volume is now well-accepted. What is less understood is what causes investors to disagree. In this paper, I examine how dispersion in buy/sell signals related to various anomalies can create disagreement and thus cause subsequent volume. I then show that the relation between disagreement and volume varies as a function of the amount and complexity of new information releases and the firm's information environment. I also assess how signal dispersion influences the forecast properties of one important participant in equity markets — security analysts.

3 Disagreement and Trading Volume

Much of the theoretical literature focuses on how disagreement around an information event influences event-period volume. However, trading volume in non-information periods is significant. For example, Ball and Shivakumar (2008) document that abnormal earnings announcement volume is only 1.8% of the total annual trading volume. I propose that investors disagree without a specific information event occurring — disagreement can

[5] Much of this work is related to Kim and Verrecchia (1991), who show that volume during an earnings announcement is related to pre-announcement differences in the private information of different traders. Traders with more (less) precise private information revise their beliefs less (more) in response to the information in an earnings announcement. Differential belief revision causes volume.

arise because each investor uses different sets of signals when making investment decisions. These differences, in turn, cause volume.

Anecdotally, there is considerable evidence that different investors use different signals when forming portfolios. For example, in the mutual fund industry, growth funds and value funds form portfolios based on different signals. Growth funds focus on stocks that are expected to grow faster than others and pick stocks with high price multiples relative to sales and profits. On the other hand, value funds select stocks that are likely undervalued and have low multiples. Thus, growth and value funds disagree on which stocks are likely to perform well and are likely to trade against each other. Another pair of investor types that use different signals are fundamental investors and technical traders. Fundamental investors use financial statement information and price multiples to pick stocks; in contrast, technical traders focus primarily on historical price movements and patterns in these movements. Thus, when price movements and financial statement numbers diverge in terms of expected performance, disagreement occurs and is followed by trade. Another evidence suggesting that different traders would use different signals is the differences in stock screens available on screening websites. For example, whereas the screener offered by `www.marketwatch.com` suggests ten screens based on price, volume, fundamentals, technical, exchange/industry, `www.finviz.com` offers screens based on sixty-three characteristics that span descriptive, fundamental, and technical characteristics. To the extent different traders use different screeners to pick stocks, disagreement is likely and will stimulate trade.[6]

Besides the public and anecdotal evidence that investors follow divergent trading strategies, behavioral theories also provide reasons for disagreement and hence volume. In a rational world, every signal with explanatory power for future returns should be considered by all investors. Then, how does one explain the fact that some investors rely only on a subset of signals? One explanation relates to investor differences in attention and information processing ability. Because attention requires effort and the number of signals available is vast, some investors are likely to be selective in which signals they use to pick stocks (Kahneman (1973)). Because investors differ in their attention and information processing abilities, they could pick different subsets; consequently, disagreement and volume ensue. A second explanation relates to salience. Odean (1999) and Barber and Odean (2008) argue that retail investors limit their searches to stocks that have recently

[6] `www.stocktwits.com`, a stock microblogging website, provides a broader classification of strategies that classifies users' investment approaches into technical, fundamental, global macro, momentum, growth, and value.

caught their attention — stocks in the news, with significant price movements. In contrast, institutional traders that are less prone to the salience bias are likely to consider a larger universe when picking stocks.

The two necessary conditions for disagreement are that (a) investors use a subset of all possible available signals to add/sell stocks to/from their portfolios, and (b) different investors use different sets of signals. Additionally, for disagreement to lead to volume, the signals themselves should differ in return predictions. As signals become more dispersed in terms of the expected performance associated with them, disagreement will increase. Therefore, I hypothesize that:

H1: *Trading volume is positively related to the lagged dispersion in signals that predict future returns.*

The assumption underlying the first hypothesis is that different investors use different sets of signals in their trading decisions. The choice of information sets is static and does not change over time. However, in a world where new information (outside of the signals) arrives, rational investors, as Bayesians, would weigh both the signals and the new information in making their trading decisions. These weights are likely to depend on the nature of the new information. If the new information is very noisy or complex, investors will use only their respective signal sets and ignore the new information. In this case, the relation between disagreement and volume is unlikely to be affected by the new information.

On the other hand, if the new information is informative and easy to comprehend, investors are likely to weigh their signal sets less and the new information more. Because all investors weigh the new information more, the role of the signals becomes less important. Hence, the relation between disagreement and subsequent volume weakens as the quality/precision of new information increases. Therefore, I predict:

H2a: *The relation between trading volume and lagged signal dispersion is stronger when new information is imprecise or complex.*

To measure the precision/complexity of new information, I focus on 10-K filings and their textual characteristics. A growing literature in Accounting and Finance documents that textual characteristics, such as readability and file size, have consequences for investor behavior (Li (2008), Loughran and McDonald (2011), Lawrence (2013)). I posit that the effect of disagreement on volume will be higher for firms with more complex 10-Ks. In addition to 10-K textual variables, I also examine the effect of three attributes of a firm's information environment — firm size, firm age, and the number of analysts following a stock. Small and younger firms tend to release fewer discretionary disclosures in markets (Frankel, McNichols, and Wilson (1995)). Hence, investors are more likely to rely on fundamental and price signals in their investment decisions for these firms. Similarly, for firms followed by fewer analysts, fundamental and price signals become the dominant source of information for trading decisions. I, therefore, predict that the disagreement-volume relationship will decrease in firm size, firm age, and analyst following.

Easy access to corporate disclosures (like 10-Q and 10-K reports) via EDGAR can reduce investor disagreement by limiting heterogeneous interpretation of fundamentals (Kandel and Pearson (1995)). Further, this access can also reduce overconfidence through better availability of hard, verifiable information (Scheinkman and Xiong (2003)). Together with the increased dissemination of disclosures via the internet, the EDGAR system has increased the price informativeness of individual investor trades (Gao and Huang (2020)). As prices better reflect fundamentals, disagreement arising from these fundamentals is likely to be lower. That is, 10-K and 10-Q reports serve as additional sources of value-relevant information to investors (Griffin (2003)). Therefore, I predict that the availability of EDGAR reports would cause investors to reduce their weights on anomalies in making trading decisions and cause the relation between anomaly-based disagreement and volume to decrease.

H2b: *The relation between trading volume and lagged signal dispersion is weaker if firm-specific information is available online.*

Studying the effect of signal-related disagreement on volume allows one to identify a market-level effect. To examine if a specific group of individuals is affected by signal-related disagreement, I examine analyst forecasts. If dispersion in return-predicting anomalies causes analysts to disagree more, dispersion in analyst forecasts should increase. Barron, Kim, Lim, and Stevens (1998) show that forecast dispersion reflects the private information of the analysts. In contrast, the mean forecast error of analysts reflects both common public and private information.[7] Because signal-related disagreement can affect both types of information, I also expect it to be positively related to forecast accuracy. Therefore, my third hypothesis is:

H3: *Dispersion in analyst forecasts and the absolute value of mean analyst forecast errors increase with lagged signal dispersion.*

In my empirical work, I study both earnings per share and target price forecasts.

[7]Signal-related disagreement can be caused by either differential interpretation of public information by analysts or differences in analysts' private information.

4 Variable Measurement

To test my first hypothesis, I estimate a panel regression of volume in month t on signal-related disagreement and control variables measured in month $t-1$. For my second hypothesis, I estimate this regression for subsamples partitioned on EDGAR availability, information complexity, and environment measures. The third hypothesis is tested through regressions of analyst forecast dispersion and accuracy on signal-related disagreement. This section defines my dependent variables, the main independent variable — disagreement, and regression control variables. I include year dummies to account for time trends in volume and Fama-French 48 industry dummies for cross-industry variation in turnover in all regressions.

4.1 Measuring Volume

I measure volume as share turnover, defined as the ratio of monthly shares traded to shares outstanding at the beginning of the month (TURN). Unlike alternate volume metrics such as undeflated dollar volume and shares traded, turnover does not depend on a firm's size or share price. Further, Lo and Wang (2010) show that turnover is the most natural measure for studying the relation between trading volume and equilibrium market models such as CAPM if the two-fund separation holds.

As an alternative to TURN and its logarithm L_TURN, CHS create an adjusted turnover measure based on Gallant, Rossi, and Tauchen (1992). They propose this measure because the two turnover measures are potentially non-stationary. Briefly, CHS compute adjusted turnover (TURN_GRT) in three stages. In the first stage, for each firm, they estimate a time-series regression of monthly TURN observations on eleven monthly dummies and linear and quadratic time trends (t, t^2):

$$TURN = x'\phi + \xi \tag{1}$$

where x is the matrix of eleven monthly dummies and linear and quadratic time trends, and ξ is the vector of residuals. Next, in the second stage, the natural logarithm of the estimated squared residuals from the first stage regression $(\hat{\xi})$ are regressed on the same set of explanatory variables:

$$\log(\hat{\xi}^2) = x'\theta + u \tag{2}$$

In the third stage, TURN_GRT is defined by choosing parameters α and λ in Eq. (3)

below such that the sample means and variances of TURN_GRT are the same as those of TURN, for each firm.

$$TURN\_GRT = \alpha + \lambda \left(\frac{\hat{\xi}}{\exp(x'\theta/2)} \right) \tag{3}$$

To be consistent with CHS, I evaluate the relation between TURN_GRT and disagreement as a robustness check.

4.2 Measuring Disagreement

To measure disagreement, I need to define a set of signals that investors are likely to use in their buy/sell decisions. My maintained hypothesis is that investors differ in the subset (drawn from this set) of signals they use to make their trading decisions. In theory, hundreds of firm characteristics could be used to define this set. Nevertheless, to enhance the power of my tests, I choose signals drawn from the anomaly literature. Anomaly factors (AFs) have been documented to predict subsequent returns making them good candidates for signals that investors use. Additionally, McLean and Pontiff (2016) show that investors appear to have used published academic research in their trading strategies.

Several recent studies examine the zoo of anomaly factors, and hence the question of which set of anomalies to use arises. Table 1 shows that the number of anomalies ranges from eleven in Stambaugh, Yu, and Yuan (2012) to 452 in Hou, Xue, and Zhang (2020). Choosing a larger number of anomalies could lead to the inclusion of several highly correlated factors that do not contribute to disagreement and reduce the power of my disagreement measure. On the other hand, choosing too few factors could lead to my measure not having sufficient variation and not capturing actual disagreement in markets. In light of this tradeoff, I choose an intermediate number of anomalies — thirty-four, from the Linnainmaa and Roberts (2018) study.

[Insert Table 1 here]

A potentially important source of disagreement is between fundamentals-based traders and technical-based traders who trade on fundamentals and pure price-based factors, respectively. Because Linnainmaa and Roberts (2018) do not consider any pure price-based factors, I augment their thirty-four AFs with five momentum-based AFs from McLean and Pontiff (2016).[8] Table IA.1 in the Internet Appendix contains the complete list of thirty-nine AFs. I measure disagreement based on the thirty-nine AFs at the end of each calendar month and predict trading volume in the next month.[9]

The thirty-nine AFs span seven categories: Profitability (6), Earnings Quality (3), Valuation (5), Momentum (5), Investment (10), Financing (6), and Distress (3).[10] In general, the sign of the relationship between AFs and future returns is predicted to be similar for AFs within each category; variation in signs is predicted only for AFs within the Momentum category. Because the signs of the AF-future return relationships vary across AFs, I multiply the signal values for AFs expected to bear a negative relation with future returns by -1. In this way, all thirty-nine AFs are expected to be positively related to future returns. Appendix A.1 explains how each AF is constructed; I carefully follow the definitions provided in the original study that identified these AFs.

The procedure to construct my measure of disagreement is as follows. For each of the thirty-nine AFs and each calendar month, I form three portfolios based on the AF's cross-sectional distribution. The cut-offs to form the portfolios are — top 30%, middle 40%, and bottom 30%. Then, each stock is assigned to one of the three portfolios for a particular AF and month. Depending on the predictions from the first paper that documented the AF, these assignments generate one of three signals — buy, hold, or sell. Buy signals are set to equal 1, hold signals are set to 0, and sell signals are set to -1. For example, a stock with a high accruals value is expected to earn lower-than-average returns (Sloan (1996)). If a stock's accrual value places it in the top 30% of the accruals cross-sectional distribution at the end of December 2005, it would be assigned a sell signal of -1 for the Accruals AF in that month. This process is repeated for all thirty-nine AFs giving a vector of thirty-nine buy/sell/hold signals for each stock-month. For each stock-month, I measure disagreement as the standard deviation of the thirty-nine signals

[8] I leave out three composite anomalies from Linnainmaa and Roberts (2018) — Piotroski's F-score, Market-to-book and accruals, and Quality-minus-Junk. I do so since they include AFs that have already been considered in my list of thirty-four AFs. For instance, the market-to-book and accrual combination anomaly assign stocks in the highest market-to-book quintile and lowest accrual quintile a buy signal and the stocks in the lowest market-to-book quintile and highest accrual quintile a sell signal. The variation in this AF is captured by the market-to-book ratio and accruals that are in my list of thirty-nine AFs.

[9] I also examine the effect of disagreement at the end of the month on volume on the first day and first week of the following month and find similar results.

[10] One AF, industry concentration, cannot be categorized in any of the above groups and is labeled 'Miscellaneous.'

that take on one of three values -1, 0, or $+1$ (STD_DEV). As robustness checks, I also compute disagreement based on (i) the absolute deviation of the thirty-nine signals and (ii) the standard deviation based on buy/hold/sell signals using portfolio cut-offs of 20% (top), 60 (middle), and 20% (low) of the AFs' cross-sectional distributions.

In constructing STD_DEV, I ignore cross-signal variation in the magnitude of predictable returns. For example, suppose prior research has documented that the hedge portfolio return for factor A is one percent and that for B is only 0.1 percent. Despite this difference, I assign a value of $+1$ for both factors. Computing disagreement that weighs factors based on their past return prediction magnitudes is a subject for future research.

4.3 Information Quality and Environment

My second hypothesis is that the relationship between turnover and disagreement is stronger for firms that release complex new information. Consistent with Loughran and McDonald (2014), my first two complexity measures are the size of a firm's 10-K in megabytes and the number of words in the 10-K.[11] As a third measure, I employ a simple and more direct measure of complexity proposed by Loughran and McDonald (2020). This measure is based on a list of 374 words most commonly attributed to a firm's business or information complexity. Firm complexity is defined as the frequency with which complex words occur in a firm's 10-K filing.

I also examine the volume-disagreement regressions for sub-samples based on a firm's information environment. My measures of information environment are firm size, age, and analyst following. Firm size is measured as market capitalization at the end of the month before the month in which turnover is measured. Firm age is the natural log of months since the firm first appeared on the CRSP monthly database. Analyst following is the number of analysts following a firm each month.

4.4 Control Variables

I closely follow CHS in my choice of control variables for the turnover regression. CHS posit that volume is likely to be associated with past returns, visibility, the mass of informed agents, estimation uncertainty, and dispersion of opinion. Past return movements are likely to cause firms' performance ranks to change and induce portfolio rebalancing. Because of

[11] Loughran and McDonald (2014) argue that the most popular measure of readability — Fog Index — is poorly specified for financial disclosures.

short-selling constraints and the disposition effect, past positive and negative returns could differentially influence volume; hence, I include two variables for past returns — RET^+ and RET^-. RET^+ (RET^-) is the one-month lagged return if it is positive (negative) and zero otherwise. CHS predict that volume is increasing in the visibility of stock. Since firms with low book-to-market ratios (BTM) tend to be more visible growth stocks, they predict a negative relation between BTM and volume. BTM is defined as the most recent fiscal year-end book value of equity plus deferred taxes, divided by the market value measured at the end of the month before the month in which volume is measured (hereafter, the previous month). In addition, CHS include three additional proxies for visibility — the log of firm share price (L_PRC), the log of firm market capitalization (L_ME), and the log of one plus firm age in months since its first date of trading (L_FAGE). All three variables are measured at the end of the previous month. To capture volume related to informed trades, I measure the number of informed agents as the number of analysts following a stock (NUMEST) in the previous month.

CHS predict that estimation uncertainty can induce volume either because of portfolio rebalancing or learning caused by earnings shocks. Estimation uncertainty is measured with three variables — the absolute surprise in a firm's quarterly earnings (ESURP), earnings volatility (EVOL), and a stock's beta (CAPM_BETA). ESURP is the absolute value of the most recent quarterly earnings per share (EPS) minus the earnings per share from four quarters ago, scaled by the share price at the end of the fiscal quarter in which EPS is measured. EVOL is the standard deviation of earnings of the most recent eight quarterly earnings per share, scaled by the quarter-end share price. CAPM_BETA is the beta coefficient from firm-level rolling sixty-month CAPM regressions ending with the previous month, with a minimum of 48 months required to estimate the regressions.

CHS propose two alternate measures of disagreement — forecast dispersion and leverage. FDISP is the standard deviation of earnings per share (EPS) forecasts in the previous month, computed using a minimum of two analysts. Because leverage is an indicator of risk, CHS argue that differences of opinion could increase with leverage. Leverage (LEV) is the debt-to-asset ratio from the most recent fiscal year. Finally, to account for differences in trading structure between NYSE/AMEX and NASDAQ exchanges and any double-counting issues identified by Atkins and Dyl (1997), I also include a dummy for NASDAQ stocks in all regressions. A complete description of variable definitions for the dependent variables, the main independent variable, and control variables is provided in A.2.

I estimate the regression in Eq. (4) below:

$$L\_TURN_{i,t} = \sum_k \alpha_k \cdot Controls_{k,i,t-1} + \beta \cdot STD\_DEV_{i,t-1} + \sum_d \gamma_d \cdot Dummies_{i,t-1} + \epsilon_{i,t} \quad (4)$$

4.5 Analyst Forecast Dispersion and Accuracy

My third hypothesis predicts that analyst forecast dispersion and absolute forecast errors are increasing in lagged signal-related disagreement. I define month $t-1$ as the month in which disagreement is measured. I compute forecast dispersion for both annual earnings per share forecasts (EPS) and target price forecasts in month t. For EPS, dispersion is the standard deviation of forecasts of annual earnings per share. I measure target price forecast dispersion as the standard deviation of twelve-month-ahead target price forecasts. Both standard deviations are scaled by the absolute value of respective mean forecasts in month t. Earning forecast error is defined as the difference between actual and mean forecast (month t) EPS, scaled by the absolute value of mean forecast EPS (month t). Similarly, target price error is the difference between twelve-month ahead actual price and mean target price forecast (month t), scaled by the mean target price forecast (month t). To reduce the impact of outliers, I transform the forecast dispersion and accuracy variables into ranks.

In regressions of earnings forecast dispersion and forecast errors on lagged disagreement, I follow Liu and Natarajan (2012) and include the following control variables: firm size, book-to-market ratio, CAPM beta, idiosyncratic volatility measured as the standard deviation of residuals from firm-specific CAPM regressions, momentum measured over month $t-12$ to $t-2$, earnings volatility and surprise measured for previous eight quarters, an indicator for firms reporting negative earnings, number of analyst following the firm, the logarithm of turnover, leverage, sales to assets ratio from the most recent fiscal year, mean earnings forecast, and the logarithm of stock price. Except for momentum, all variables are measured at time $t-1$. I use the same controls for target price forecast dispersion and forecast errors with one change: I replace earnings surprise and volatility with the standard deviation of daily returns measured in month $t-1$.

5 Data Sources and Sample

I obtain monthly stock returns, prices, shares outstanding, and volume data from the Centre for Research in Security Prices (CRSP) database, financial statement data from the COMPUSTAT annual and quarterly files, and consensus analyst earnings forecasts data from the Institutional Brokers' Estimate System (IBES) database. I construct my dependent variables - turnover, forecast accuracy and dispersion, disagreement measure, and control variables from these three data sources. To measure industry effects, I use Fama-French 48 Industries from Professor Ken French's website.[12]

For the variables related to information complexity, I use the parsed EDGAR filings from 1993–2018 provided by Bill McDonald at the Software Repository for Accounting and Finance website of the University of Notre Dame. I also use the summary file available on that website. The summary file is used to obtain the size of the 10K filing and the number of words in the 10K. Additionally, I use the occurrence frequency of the 374 complex words identified by Loughran and McDonald (2020) in parsed 10-K EDGAR files.[13]

My sample period is 1976–2019. I begin in 1976 because analysts' forecast data is available only from January 1976. Requiring non-missing data for all the regression variables needed to estimate Eq. (4) yields a sample of about 872,000 firm-months. Except for dummy variables and variables expressed as ranks, all variables are winsorized at the 0.5% levels. For the regressions related to information complexity and environment, which require data from 10-K filings, my sample begins in 1994 and consists of about 544,000 firm-months.[14]

6 Results

6.1 Descriptive Statistics

Figure 1 plots turnover (TURN) and the natural logarithm of turnover (L_TURN) over the sample period — 1963–2019. Each observation in the plot is a cross-sectional monthly average. Both series show a clear linear time trend; turnover has grown exponentially over the sample period from 2.4% to 22.5%. In all tabulated results, I use L_TURN as

[12] The list of industry codes is available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html

[13] The parsed EDGAR files are present at https://sraf.nd.edu/, and the summary file is located at https://sraf.nd.edu/textual-analysis/resources/#LM_10X_Summaries. The list of complex words is available at https://sraf.nd.edu/data/complexity/.

[14] Loughran and McDonald (2020) create a list of complex words from 10-K filings for the period 2001–2018. Hence the sample with LM complex word counts is smaller with roughly 386,000 firm-months.

the dependent variable and include year dummies to control for time trends. Results for TURN are discussed but not tabulated.

[Insert Figure 1 here]

My measure of disagreement, STD_DEV, is computed as the firm-specific standard deviation in thirty-nine AFs. Disagreement is likely to be higher in markets when there is variation in the correlations between AF pairs. Figure 2 presents a correlation heat map for the thirty-nine AFs $(-1, 0, +1)$ for the years 1976–2019. A heat map helps visualize the correlation between signals better than a correlation matrix. In the figure, blue circles represent positive correlations, and red circles indicate negative correlations. The size of each circle is proportional to the magnitude of the correlation. The lower triangle contains the Pearson correlations, and the upper triangle the Spearman rank correlations.

[Insert Figure 2 here]

The correlations indicate that, except for Momentum and Financing, all AFs tend to be positively correlated with each other within each category. Profitability (Signals #1-6) AFs are mostly negatively correlated with investment AFs (Signals #20-29) and Earnings Quality AFs (Signals #7-9) and positively correlated with Distress AFs (Signals #36-38). Earnings Quality (Signals #7-9) signals are positively correlated with investment signals (Signals #20-29). Overall, there is considerable variation in inter-signal correlations, one of the necessary conditions for my measure of disagreement to be valid.

Figure 3 reports the time series of the cross-sectional means for disagreement and the associated 95% confidence intervals. The mean disagreement over the sample period is 0.75, and its standard deviation is 0.10. Unlike turnover, mean disagreement does not display a trend (see Figure 1) and appears stationary. This finding suggests that, at the economy level, the volume-disagreement relationship is not driven by a common trend. Mean disagreement has three distinct peaks in 1979, 1990, and 2011 and three troughs in 1985, 2001, and 2017.[15]

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[15]In unreported results, I find that the time-series of cross-sectional means of monthly STD_DEV is strongly correlated with time-series of economy-wide belief dispersion computed from the University of Michigan's consumer sentiment data (consumer sentiment and consumer expectations). This finding strengthens the face validity of my AF-based measure as an indicator of investor disagreement. The establishment of causal links between these two series is a subject for future research.

[Insert Figure 3 here]

To see how different anomaly categories affect disagreement, I compute the mean disagreement, dropping one AF category at a time. My AF categories are Profitability, Earnings Quality, Valuation, Momentum, Investment, Financing, and Distress. If a category contributes to disagreement, then its removal would cause the mean disagreement to fall. Figure 4 indicates that the Momentum category impacts mean disagreement significantly.[16] In contrast, the figure indicates that the mean disagreement does not change much when any of the other categories are removed. Given the unique impact of Momentum category AFs on disagreement, I measure disagreement with and without the Momentum category AFs as a robustness check in my empirical analysis.

[Insert Figure 4 here]

A natural question is whether disagreement varies by industry. Table 2 shows mean disagreement for the forty-eight Fama-French industries with the top ten and bottom ten mean disagreement ranks. Pharmaceuticals, Precious Metals, and Medical Equipment have the highest mean disagreement, while Business Supplies, Shipping Containers, and Utilities have the lowest mean disagreement. Firms in technology industries such as IT services, Computers, Pharmaceuticals, and Chips face higher levels of fundamental uncertainty and have more growth and real options. On the other hand, established industries such as Food, Chemicals, Business Supplies, and Utilities have lower uncertainty and fewer growth options. Table 2 indicates that these differences in uncertainty and options are reflected in my measure of disagreement. In my regression tests, I include industry fixed effects to account for cross-industry variation in disagreement.[17]

[Insert Table 2 here]

Panel A of Table 3 presents summary statistics for L_TURN, STD_DEV, and the control variables in my main regression, Eq. (4). L_TURN has a close to a normal

[16]In untabulated findings, excluding the Momentum category causes mean disagreement to drop from 0.75 to 0.73.

[17]Firms in the oil and drug industry derive their real options from exploration activities. Firms in the oil industry have an option to explore a potential oil field, whether to develop the site, and finally when to start drilling and extraction of petroleum products. Besides, the oil industry is also heavily dependent on global crude prices, which adds an extra degree of uncertainty. The drug development process is also full of real options at various stages of drug development, clinical trials, regulatory approvals, and patents.

distribution with a mean of -2.73. STD_DEV also shows a minimal departure from normality; its mean is 0.75. Turning to the control variables, the two lagged monthly return variables (RET^{+} and RET^{-}), BTM, ESURP, and EVOL are considerably non-normal, as indicated by their skewness and kurtosis. On average, about seven analysts follow a sample firm (NUMEST), and forecast dispersion (FDISP) is about 21%. The mean BTM is 0.76, the mean LEV is 55%, and the mean CAPM_BETA is 1.27.

[Insert Table 3 here]

Panel B of Table 3 reports correlations among the turnover regression right-hand-side variables. Pearson (Spearman) correlations are in the lower (upper) triangle. Focusing on the Pearson correlations, STD_DEV is positively correlated with ESURP and EVOL. Because these two variables measure fundamental uncertainty, the results suggest that disagreement increases with uncertainty. Disagreement is negatively related to the three measures of visibility — L_PRC, L_ME, and L_FAGE. As visibility increases disagreement falls. Lastly, STD_DEV bears a positive and modest correlation with FDISP, a primary measure of disagreement. This suggests that the two measures capture different aspects of disagreement. Among the control variables, L_ME is highly correlated with some of the other control variables, L_PRC (0.74), NUMEST (0.68), ESURP (-0.37), and EVOL (-0.45). The other significant correlation is between ESURP and EVOL (0.67).

6.2 Regressions

Table 4 reports the regressions of the log of monthly turnover (L_TURN) on lagged monthly disagreement (STD_DEV). All regressions include industry and year fixed effects; standard errors are clustered by firm and month (Petersen (2009)). Column (1) of the table contains the base specification from CHS. The sign and relative importance of coefficients are similar to those reported in CHS. The only difference relates to earnings volatility, a proxy for fundamental uncertainty, which is expected to be positively related to volume. While CHS find that the coefficient on EVOL is insignificant for their full sample, I find that it has a positive and significant coefficient (t-statistic = 3.059).

[Insert Table 4 here]

In column (2) of Table 4, I include STD_DEV as an additional explanatory variable. As predicted, monthly turnover is positively and significantly related to disagreement (t-statistic = 24.067). The coefficient on STD_DEV is 1.545, and its standard deviation is

0.10, implying that a one-standard-deviation increase in STD_DEV causes next month's log turnover to increase by 0.155 (1.545*0.10), which is equivalent to a 16.7% increase in turnover. The other two measures of disagreement, FDISP, and LEV, are also positively related to volume; but their coefficients drop in size when STD_DEV is included. The coefficient on EVOL also becomes insignificant.

In column (3), I substitute dispersion of earnings forecasts, FDISP, with the dispersion of target price forecasts, PRC_DISP. The latter substantially affects turnover in comparison to the former. A one-standard-deviation increase in PRC_DISP associates with 11.6% higher turnover in the next month. Since PRC_DISP is only available since 1999, the sample in column (3) is substantially smaller, making comparisons with other specifications difficult.

The specification in column (2) does not include the log of market capitalization (L_ME) because it is highly correlated with many control variables. In column (4), I report regression results with L_ME included. STD_DEV remains positively and significantly related to L_TURN. Because the inclusion of L_ME could cause multicollinearity, I do not include it in all subsequent analyses.

For the results in columns (2)–(4), disagreement is computed as the standard deviation of buy/hold/sell signals defined using cut-offs of top 30%, middle 40%, and bottom 30% for each anomaly factor. In column (5), I report results using a 20%-60%-20% design instead. The coefficient of FDISP loses significance with this choice of disagreement. The impact of disagreement is larger with this alternative measure of disagreement and implies that a one standard deviation increases in STD_DEV increase monthly volume by 20.5%. As robustness against momentum anomalies driving my results (see Figure 4), I exclude five momentum anomalies and compute disagreement from the remaining 34 anomalies. I report the results using the modified disagreement in column (6). Although diminishing the impact of disagreement on volume, the exclusion of momentum anomalies does not change the overall tenor of results. A one standard deviation increase disagreement increases next month's volume by roughly 12%.

To reduce the impact of outliers and allow for a more intuitive interpretation, I also perform rank regressions where the rank of L_TURN is regressed on the ranks of STD_DEV and control variables. Ranks are defined for each variable based on the monthly cross-sectional distribution of that variable. The details of how ranks are calculated are present in Appendix A.2. Column (7) of Table 4 contains the rank regression results. The coefficient of the rank of STD_DEV is 0.139 (t-value = 19.56). Moving from the 25th to the 75th disagreement percentile causes the rank of L_TURN to be higher by 7 percentiles $(0.139 \times (0.75 - 0.25))$.

In columns (8) and (9) of Table 4, instead of next-month turnover, I report regressions where the dependent variable is the log of turnover on the first day and first five days of the next month, respectively. Disagreement is a significant predictor of turnover for those horizons as well. A one-standard-deviation increase in in STD_DEV increases next day (week) turnover by 16.2% (16.6%).

The coefficients on STD_DEV in columns (8) and (9) for daily and weekly turnover are very similar to those from the monthly turnover regressions (column (2)) because I use logarithmized dependent variables. When I use raw turnover levels instead of the log-transformed turnover as the dependent variable, the coefficients on STD_DEV in columns (2), (8), and (9) are 0.269, 0.012, and 0.064, respectively. This finding suggests that disagreement predicts volume at all three frequencies, and this effect lasts for a month and is not confined to just the first day or week of the following month.

In Table 5, I assess the robustness of the results to the choice of the dependent variable. I replace L_TURN with four alternative measures of turnover — monthly change in L_TURN ($L\_TURN_t - L\_TURN_{t-1}$), the adjusted turnover measure proposed by CHS, and the residuals obtained from estimating firm-specific time-series regressions of L_TURN on value-weighted and equally-weighted log market turnover, respectively. Column (1) reports the results with L_TURN, the baseline specification, and columns (2) to (5) contain the results for the four alternate dependent variables. The coefficient on STD_DEV is positive and significant at conventional levels for all four alternative dependent variables. In contrast, the sign of forecast dispersion (FDISP) turns negative when the dependent variable is the change in turnover or the two market-adjusted turnover measures. Thus, STD_DEV appears to better capture disagreement than does FDISP.[18]

[Insert Table 5 here]

I also evaluate the robustness of my results by using the absolute deviation of the buy/hold/sell signals instead of the standard deviation. In untabulated results, I find that my conclusions are unchanged with this alternate metric. Additionally, I estimate the model for three different sample splits based on NYSE versus NASDAQ membership,

[18]Results of the regression where the change in L_TURN is the dependent variable indicates that the coefficients on RET^+ and RET^- are reversed, which is in stark contrast to all other regressions. Coefficients on other variables are also severely attenuated. One reason for these findings could be that L_TURN is highly persistent, and differencing it reduces its variation considerably.

S&P 500 firms versus other firms, and financial versus non-financial firms. In untabulated results, STD_DEV is positively and significantly related to subsequent turnover for all sub-samples. The effect of STD_DEV is higher for NASDAQ and non-S&P 500 firms than that for NYSE and S&P 500 firms. The effects of disagreement on turnover are qualitatively similar for financial and non-financial firms.

Overall, my results indicate that disagreement arising from the variance in buy/hold/sell signals based on anomaly factors is a significant predictor of subsequent turnover. The result is robust to changes in specifications and how turnover and disagreement are measured.

7 Information Environment

In my second hypothesis, I predict that the complexity of new information releases and the firm's information environment can affect the disagreement-volume relationship. Specifically, I expect that more (less) complex/noisy information can cause the disagreement-volume relationship to become more (less) positive.[19] Consistent with the textual analysis literature, I measure the precision/complexity of new information from 10K filings. My measures are the size of the 10-K filing, the number of words in the 10K, and the frequency of complex words in the 10-K. In addition, I expect that this relationship is stronger for smaller and younger firms and firms with fewer analysts.

Panel A of Table 6 provides descriptive statistics on the information complexity and environment variables. The mean document size is about 5.8 MB; the mean number of words is about 47,300, and each document contains about 82 of the 374 complex words defined by Loughran and McDonald (2020). In terms of environment variables, the means for the log of market capitalization, log of age, and the number of analysts are 19.06, 4.40, and 6.83, respectively. Panel B reports correlation among the information variables. The 10K variables are positively correlated with each other, as are the information environment variables. Table 7 reports turnover-disagreement regressions for various sub-samples formed based on the information complexity and environment variables. I divide the sample into terciles based on the document size, the number of words (length), and percent

[19] In unreported results, I find that disagreement coefficient, capturing the weight investors place on AFs, reduces by 11.4% for firms that adopt EDGAR system of information disbursal in the period 1993–1996. The findings are consistent with Bird, Karolyi, Ruchti, and Truong (2021) who find that sensitivity of investment to Tobin's q fall with publicizing of internal information on the EDGAR system.

complex words. Firm size sub-samples are based on 30%-40%-30% NYSE breakpoints for market capitalization. Analyst following subsamples are formed using the following cut-offs: 2-3 analysts; 4-10 analysts, and > 10 analysts. In column (2), I report a baseline specification without disagreement to evaluate the impact of disagreement; column (3) reports regressions with STD_DEV included. I report only the FDISP (forecast dispersion) and STD_DEV (disagreement) coefficients to conserve space.

[Insert Table 6 here]

[Insert Table 7 here]

I first discuss the information complexity variables. In the baseline specification, the results indicate that the effect of FDISP on subsequent turnover is positive and significant for the small and large document size and length sub-samples. Contrary to expectation, the effect is not monotonic. With document complexity, FDISP is insignificant.

In column (2), the inclusion of STD_DEV leads to the coefficient on FDISP turning insignificant for all sub-samples, except for the large document size subsample. In contrast, the coefficient of STD_DEV is positive and significant for all the textual-variable sub-samples. As predicted, when document size and length increase, the effect of STD_DEV on subsequent turnover is increasing. This result suggests that as information becomes more (less) complex, investors focus more (less) on signals in their trading decisions, and the resultant disagreement causes volume. However, the effect of text complexity on the disagreement-volume relationship is not monotonic.

Table 7 also reports the effects of disagreement on volume for information environment variables. Disagreement is significant both economically and statistically across the three size groups. Across the three size groups, a one SD change in disagreement predicts next month's turnover to be higher by 14.4%, 18.6%, and 10.5% for small, medium, and large stocks, respectively. Thus, contrary to expectation, the effect of size on the disagreement-volume relationship is not monotonically decreasing. In contrast, the results for firm age and analysts indicate that as these two variables increase, the coefficient on STD_DEV decreases. As age and analyst following increases, the effect of disagreement on volume decreases because of the availability of alternative sources of information.

7.1 EDGAR Implementation

EDGAR was implemented in ten waves between April 26, 1993, and May 6, 1996.[20] However, online access to firm reports only began on January 17, 1994, when firms' historical and current filings from the first four batches of EDGAR and other voluntary filers went online through NYU online access.[21] The remaining filers went online after a year in January 1995. This staggered implementation of EDGAR provided me with a novel setting, where I can classify firms (in phases 1 to 4) that went online all at once in January 1994 as treatment firms and the remaining firms that went online a year later as control firms.

For my tests, I consider firm months spanning twenty months — March 1993 to December 1993 and March 1994 to December 1994. I exclude the months of January and February of 1994 from the sample for clean identification. I keep the firms in phases 1 to 4 in the treatment group as they all adopted EDGAR on January 17, 1994. The rest of the firms, i.e., phases 5 to 10, make the control group.[22] I estimate a difference-in-difference model where firm-months from 1994 are labeled "POST" and firm-months from 1993 are labeled "TREAT."

The assignment of firms to different EDGAR waves was random conditional only on firm size (Chang, Hsiao, et al. (2020)). Since my primary interest is to see how disagreement-induced trading changes with online EDGAR dissemination, I choose control firm months based on nearest-neighbor propensity match controlling for firm size and anomaly disagreement. This design ensures that the level of disagreement is constant across treatment and control groups of firm months. My final sample has 8,428 treatment firm-months and an equal number of control firm-months. All control firms (phases 5-10) eventually enter EDGAR in the future (May 1995 to May 1996).

I estimate the base specification (column (2) from Table 4) and add additional

[20]Appendix A in Chang, Ljungqvist, and Tseng (2020) contains a summary of the original, revised, and online access dates for the ten EDGAR waves. The first four batches went online on January 17, 1994. EDGAR implementation had provisions for a mid-implementation review of six months beginning after phase-4. However, due to the delay in review the next two phases (5 and 6) were suspended and could resume only on January 30, 1995.

[21]I thank Yen-Cheng Chang (National Taiwan University) for sharing the EDGAR phase-in data.

[22]Phase 5 and 6 were scheduled for inclusion in 1994 but were delayed. Choosing control firms from phases 7 to 10, i.e., by skipping phases 5 and 6 so as to avoid any anticipatory effects by investors, does not change the overall tenor of results.

interactions of STD_DEV with POST, TREAT and, POST × TREAT in Table 8. I transform all variables to respective ranks in the regression and include industry fixed effects and cluster errors at the firm level.[23] The coefficient on STD_DEV × POST is close to zero, suggesting that the disagreement volume relationship is not significantly different in the period around the online inclusion of firms in the first four EDGAR waves. In specification (3), however, the interaction of STD_DEV and TREAT is negative, implying that disagreement-induced trading activity is smaller for TREAT firms, i.e., firms adopting internet dissemination of corporate filings. From specification (4), the inclusion of STD_DEV × POST × TREAT reduces the disagreement coefficient by roughly 25% (0.043/0.177). The results suggest that the impact of anomaly disagreement on trading volume is lower after EDGAR. Overall, my results suggest that the exogenous increase in alternative information (EDGAR) caused the relation between disagreement and volume to decrease.

[Insert Table 8 here]

8 Disagreement and Analyst Forecasts

The evidence thus far suggests that signal-related disagreement increases trading volume. To provide more direct evidence of the effect of disagreement, I examine one class of market participants — security analysts. If analysts, like investors, use AFs in making their forecasts and different analysts use different sets of AFs, then higher anomaly disagreement should lead to more dispersed analysts' forecasts and larger absolute forecast errors (Hypothesis 3).[24] I examine earnings forecasts and target price forecasts; both variables are measured as cross-sectional ranks where ranks are constructed every month.

In Panel A of Table 9, I examine the effect of disagreement on earnings forecast properties. The regression includes control variables from Liu and Natarajan (2012) and industry effects, but these are not reported to conserve space. Column (1) contains the results where forecast dispersion is the dependent variable. The results indicate that when

[23]Dummies (POST, TREAT and, POST × TREAT) are highly correlated with their STD_DEV interaction counterparts. For instance, TREAT and STD_DEV × TREAT has a correlation of 0.75. For this reason, I exclude standalone dummy variables from all regressions.

[24]In unreported results, I compute average portfolio returns with respect to FDISP and STD_DEV and find that both disagreement measures have a negative association with future returns in my sample.

disagreement increases from the 25th to 75th percentile, forecast dispersion increases by 3.3 percentiles. The effect is statistically significant at the 1% level. In column (2), I report results for mean absolute forecast errors. Again, disagreement is significantly and positively related to forecast errors. When disagreement increases by 50 percentile, absolute forecast errors increase by 2.3 percentiles. Thus, disagreement increases forecast dispersion and reduces forecast accuracy.

Because anomaly factors are traded on to predict future prices, examining the effect of disagreement on analysts' target price forecast dispersion, and accuracy provides a more powerful test. In Panel B of Table 9, I examine target price dispersion in column (1) and absolute target price forecast errors in column (2). The results indicate that signal-disagreement positively and significantly increases the dispersion and the absolute value of target price forecast errors. An increase of disagreement rank by one increases target price dispersion by 10.1 percentiles and absolute target price forecast errors by 9.8 percentiles. Thus, the effects of disagreement on target price forecast dispersion and accuracy are about twice the effects for earnings forecast dispersion and accuracy.

[Insert Table 9 here]

9 Disagreement and Anomaly-related Turnover

Thus far, my study examines whether signal-related disagreement predicts subsequent turnover in stock, regardless of which anomaly generated the turnover. In this section, I link disagreement to turnover associated with each of the thirty-nine AFs. If investors trade to take advantage of an AF, then turnover should be higher for stocks with extreme values of the AF (long and short portfolios). I define the difference between volume for the extreme portfolios and intermediate portfolios as 'excess volume.' By correlating excess volume for each AF with disagreement, I attempt to provide more direct evidence that disagreement causes anomaly-related volume.

To set the stage, I begin by documenting hedge portfolio returns for each of the thirty-nine anomalies. For each AF, stocks are divided into ten portfolios at the end of each month, and equally-weighted average returns are computed for next month's top and bottom deciles (D1 and D10). The hedge portfolio return is defined as mean (D10 - D1) returns. Column (2) of Table 10 and Panel A of Figure 5 contain the results.

[Insert Table 10 here]

[Insert Figure 5 here]

Table 10 indicates that of the thirty-nine AFs, twenty-six generate positive mean hedge portfolio returns in July. The average returns range from 0.15% for the Industry Concentration AF to 1.94% for the Short-term Reversal AF. Interestingly, thirteen AFs have negative mean hedge portfolio returns. These range from -0.17% for the (Growth in Sales – Growth in Inventory) Anomaly to -2.15% for the Distress Risk Anomaly. Panel A of Figure 5 provides a visual representation of the return evidence. The red (black) circles are the mean returns to the D1 (D10) portfolios for each AF. When an AF generates positive (negative) hedge portfolio returns, the two circles are connected by a green (purple) line. The preponderance of green lines suggests that most AFs generate positive hedge portfolio returns.

To measure turnover associated with each AF, I compute the average turnover for the D1 and D10 portfolios. Because log turnover is difficult to interpret, I convert it into cross-sectional ranks that range from 0 to 1 and multiply the same by 100. I then compare the mean turnover ranks of the D1 and D10 portfolios with those of the intermediate D2 to D9 portfolios for each AF. I label this difference as excess anomaly-related turnover. Columns (2) and (3) of Table 10 report the mean turnover ranks for the D1 and D10 portfolios and the D2 to D9 portfolios, respectively. Column (4) reports the mean excess turnover ranks. The results indicate that for thirty-four of the thirty-nine AFs, extreme portfolio turnover ranks are larger than intermediate portfolios. Panel B of Figure 5 provides the same information pictorially. Black (red) circles represent mean turnover ranks for extreme (intermediate) AF portfolios, and green (purple) lines indicate AFs for which extreme AF portfolios are associated with higher turnover than intermediate portfolios. A large number of green lines support the idea that AFs based on month-end sorts generate excess turnover in the next month.[25]

To assess whether disagreement drives the excess turnover, I decompose turnover into two components — disagreement-related and 'other.' Specifically, I estimate cross-sectional regressions of turnover ranks on lagged disagreement ranks in each month. The predicted turnover from these regressions is labeled as disagreement- turnover, and the residual is labeled as other- turnover. Excess-disagreement (other) turnover is then computed as

[25]In unreported results, I find that most anomalies exhibit a U-shaped (or V-shaped) pattern with respect to turnover. Turnover is higher for the first and tenth anomaly deciles than that of all other deciles. This finding supports the evidence of positive excess turnover in column (4) of Table 10.

the difference between average extreme decile disagreement (other) turnover and average intermediate decile disagreement (other) turnover.

Columns (5) and (6) of Table 10 present the mean excess-disagreement and excess-other turnover ranks. For all the thirty-nine AFs, excess-disagreement turnover ranks are positive. Additionally, for twenty-seven AFs, the mean ranks of excess-disagreement turnover are larger than those of excess-other turnover. Panels C and D of Figure 5 provide a similar picture. The preponderance of green lines in Panel C indicates that disagreement-turnover is positive for most AFs. In contrast, most other turnover lines are purple, suggesting that they are negative and shorter in length than those of the disagreement-turnover lines. A notable exception is other turnover ranks corresponding to momentum anomalies (#15-19). For these anomalies, excess-other turnover is mostly positive and larger than excess-disagreement turnover. Excess turnover columns in Table 10 (columns 4-6) directly correspond to the height of lines in Figure 5 (panels B-D).

Overall, the evidence indicates that firms with extreme values for AFs have higher subsequent turnover than firms with intermediate levels of AFs. Further, much of the anomaly-related turnover is driven by trader disagreement.

10 Conclusion

I construct a new measure of investor disagreement that links the return anomaly literature to the differences of opinion literature. The former links abnormal return prediction to firm characteristics (anomalies), while the latter links proxies for differences of opinion (disagreement) to trading activity. I measure disagreement as the dispersion in buy/sell trading signals generated by these anomalies. Using thirty-nine return anomaly factors, I construct a firm-level measure of investor disagreement and find that a one standard deviation change in disagreement predicts 16.7% additional trading volume in the next month after controlling for previously established determinants of volume, including analyst forecast dispersion.

As more direct evidence on how disagreement affects actual market participants, I examine security analysts' forecasts of earnings and target prices. Consistent with my expectation, I find that analysts' forecast dispersion and absolute forecast errors are increasing in lagged disagreement, with stronger effects obtaining for dispersion and forecast errors related to target prices. These findings suggest that analyst forecasts are a channel through which investor disagreement affects the investment decisions of traders and validate the use of AF-based disagreement to predict volume.

I document that the monthly volume of small firms, young firms, and firms with lower analyst following — firms with less public information, is more positively related to lagged disagreement. Measuring information disclosure complexity as the length of 10-K filings and the occurrence of informationally complex words in 10-Ks, I find that the volume-disagreement relation is stronger for informationally complex firms. Thus, the information environment of a firm shapes how disagreement affects subsequent volume.

I also link anomaly-factor disagreement to the volume associated with individual anomalies. I find that volume in extreme anomaly portfolios is driven largely by disagreement-turnover for twenty-seven of the thirty-nine anomalies. This evidence further strengthens my conclusion that disagreement related to anomalies is an influential predictor of subsequent anomaly-related volume.

References

Ajinkya, B. B., Atiase, R. K., & Gift, M. J. (1991). Volume of trading and the dispersion in financial analysts' earnings forecasts. *The Accounting Review*, 389–401.

Atiase, R. K., & Bamber, L. S. (1994). Trading volume reactions to annual accounting earnings announcements: The incremental role of predisclosure information asymmetry. *Journal of Accounting and Economics*, *17*(3), 309–329.

Atkins, A. B., & Dyl, E. A. (1997). Market structure and reported trading volume: Nasdaq versus the nyse. *Journal of Financial Research*, *20*(3), 291–304.

Ball, R., & Shivakumar, L. (2008). How much new information is there in earnings? *Journal of Accounting Research*, *46*(5), 975–1016.

Bamber, L. S., Barron, O. E., & Stober, T. L. (1997). Trading volume and different aspects of disagreement coincident with earnings announcements. *The Accounting Review*, 575–597.

Banerjee, S. (2011). Learning from prices and the dispersion in beliefs. *The Review of Financial Studies*, *24*(9), 3025–3068.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The review of financial studies*, *21*(2), 785–818.

Barron, O. E. (1995). Trading volume and belief revisions that differ among individual analysts. *The Accounting Review*, 581–597.

Barron, O. E., Kim, O., Lim, S. C., & Stevens, D. E. (1998). Using analysts' forecasts to measure properties of analysts' information environment. *The Accounting Review*, 421–433.

Bird, A., Karolyi, S. A., Ruchti, T. G., & Truong, P. (2021). More is less: Publicizing information and market feedback. *Review of Finance*, *25*(3), 745–775.

Carlin, B. I., Longstaff, F. A., & Matoba, K. (2014). Disagreement and asset prices. *Journal of Financial Economics*, *114*(2), 226–238.

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

Chang, Y.-C., Ljungqvist, A., & Tseng, K. (2020). Do corporate disclosures constrain strategic analyst behavior? *Swedish House of Finance Research Paper*(20-12).

Chordia, T., Goyal, A., & Saretto, A. (2020). Anomalies and false rejections. *The Review of Financial Studies*, *33*(5), 2134–2179.

Chordia, T., Huh, S.-W., & Subrahmanyam, A. (2006). The cross-section of expected trading activity. *The Review of Financial Studies*, *20*(3), 709–740.

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

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

Fama, E. F., & French, K. R. (1997). Industry costs of equity. *Journal of Financial Economics*, *43*(2), 153–193.

Feng, G., Giglio, S., & Xiu, D. (2020). Taming the factor zoo: A test of new factors. *The Journal of Finance*, *75*(3), 1327–1370.

Frankel, R., McNichols, M., & Wilson, G. P. (1995). Discretionary disclosure and external financing. *Accounting Review*, 135–150.

French, K. R. (2008). Presidential address: The cost of active investing. *The Journal of Finance*, *63*(4), 1537–1573.

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

Gao, M., & Huang, J. (2020). Informing the market: The effect of modern information technologies on information production. *The Review of Financial Studies*, *33*(4), 1367–1411.

Green, J., Hand, J. R., & Zhang, X. F. (2017). The characteristics that provide independent information about average us monthly stock returns. *The Review of Financial Studies*, *30*(12), 4389–4436.

Griffin, P. A. (2003). Got information? investor response to form 10-k and form 10-q edgar filings. *Review of Accounting Studies*, *8*(4), 433–460.

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

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

Hong, H., & Stein, J. C. (2007). Disagreement and the stock market. *Journal of Economic Perspectives*, *21*(2), 109–128.

Hou, K., Xue, C., & Zhang, L. (2020). Replicating anomalies. *The Review of Financial Studies*, *33*(5), 2019–2133.

Jacobs, H., & Hillert, A. (2015). Alphabetic bias, investor recognition, and trading behavior. *Review of Finance*, *20*(2), 693–723.

Kahneman, D. (1973). *Attention and effort.* Englewood Cliffs, N.J. Prentice-Hall.

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

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

Lawrence, A. (2013). Individual investors and financial disclosure. *Journal of Accounting and Economics*, *56*(1), 130–147.

Li, F. (2008). Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and economics*, *45*(2-3), 221–247.

Linnainmaa, J. T., & Roberts, M. R. (2018). The history of the cross-section of stock returns. *The Review of Financial Studies*, *31*(7), 2606–2649.

Liu, X. G., & Natarajan, R. (2012). The effect of financial analysts' strategic behavior on analysts' forecast dispersion. *The Accounting Review*, *87*(6), 2123–2149.

Lo, A. W., & Wang, J. (2010). Stock market trading volume. In *Handbook of financial econometrics: Applications* (pp. 241–342). Elsevier.

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? textual analysis, dictionaries, and 10-ks. *The Journal of finance*, *66*(1), 35–65.

Loughran, T., & McDonald, B. (2014). Measuring readability in financial disclosures. *The Journal of Finance*, *69*(4), 1643–1671.

Loughran, T., & McDonald, B. (2020). Measuring firm complexity. *Available at SSRN 3645372*.

McLean, R. D., & Pontiff, J. (2016). Does academic research destroy stock return predictability? *The Journal of Finance*, *71*(1), 5–32.

Odean, T. (1999). Do investors trade too much? *American economic review*, *89*(5), 1279–1298.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, *22*(1), 435–480.

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

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, 289–315.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, *104*(2), 288–302.

Varian, H. R. (1989). Differences of opinion in financial markets. In *Financial risk: Theory, evidence and implications* (pp. 3–37). Springer.

Ziebart, D. A. (1990). The association between consensus of beliefs and trading activity surrounding earnings announcements. *The Accounting Review*, 477–488.

Appendix

A.1 Construction of Anomalies

All anomalies[26] are constructed using monthly CRSP files and annual fundamentals from COMPUSTAT. Anomalies are computed for each firm for every period (year-month). Anomalies constructed using only the annual fundamental data are repeated 11 times, i.e., they remain the same over a period of 12 months. If the predicted relationship of an anomaly is negative, i.e., a higher value of anomaly predicts lower future returns, then I multiply the anomaly by -1 so that the relationship becomes positive. Subscript t represents the current time period. $\Delta x_t \equiv x_t - x_{t-1}$ and $\overline{x_t} \equiv \frac{x_t + x_{t-1}}{2}$. For momentum anomalies, $ret.\{b\}t\{a\} \equiv \prod_{t=-a}^{t=-b}(1 + ret_t) - 1$, where $a \leq b$ and ret_t is the return in month t. The book value of a firm's equity is defined as stockholder's equity plus deferred taxes minus preferred shares (Fama and French (1992)). $BE_t = seq_t + txditc_t - pstkrv_t$. If seq is not present, then $(ceq + pstk)$ is used. If either ceq or $pstk$ is not present, then $(at - lt)$ is used. The market value of equity is the product of shares outstanding and share price: $ME_t = (prc_t / cfacpr_t) * (shrout_t * cfacshr_t)$. If a security's return is not available, its delisting return is used from the CRSP monthly stock events file. Only firms traded on NYSE, AMEX, or NASDAQ ($exchd \in 1, 2, 3$) having a share code ($shrcd$) of 10 or 11 are considered. Missing return and volume data in an otherwise continuous series are filled with zeros. Accounting data for a firm performing its operations in a year y is matched with trading data of June of year $y + 1$ and carried forward 11 months, i.e., the same annual fundamental data is used from June of year $y + 1$ to May of year $y + 2$ (Fama and French (1992)).

A.2 Variable Definitions

The number of analysts following a firm ($NUMEST$) and dispersion in analyst forecast ($FDISP$) uses the I/B/E/S data available from Thomson Reuters. I use the EPS summary file for the US companies and restrict the sample to annual forecasts (having $fpi == 1$). To account for missing data due to analysts unfollowing a firm, both $NUMEST$ and $FDISP$ are repeated until forecast data is available. Earnings surprise ($ESURP$) and earnings volatility ($EVOL$) are constructed using quarterly fundamentals from COMPUSTAT. Since earnings are reported once in three months, $ESURP$ and $EVOL$ are repeated for

[26] Definition of all anomalies appears in the Internet Appendix.

two months to get a monthly measure.

The number of words, unique words, complex words, and document size is computed using EDGAR 10-K files. Bill McDonald has provided parsed EDGAR filings for the period 1994-2018. He has also compiled a summary file that directly gives the number of total words, unique words, and document size for each filing. For finding the number of unique occurrences of complex words, I search 374 complex words in the parsed 10-K files. I only consider 10-K, 10-K405, 10-KSB, and 10-KSB40 form types. The list of complex words is taken from Loughran and McDonald (2020). Variables derived from parsing 10-K files are merged with Compustat using CIK firm identifier and fiscal yearnends. Like annual fundamentals, EDGAR-related variables from parsing 10-K of fiscal year y are merged with CRSP data from June of year $y+1$ to May of year $y+2$. Since 10-K are typically available only once in a calendar year, the variables are carried forward until a new filing is available.

Table 11 gives the definitions of variables used in the regressions.

[Insert Table 11 here]

Plots and Tables

Figure 1: Turnover Trend

Time-series of share turnover ($TURN$) and the natural logarithm of turnover (L_TURN) over 1976–2019. Turnover is defined as the ratio of monthly shares traded to shares outstanding at the beginning of the month. For each month, the cross-sectional average of turnover across all NYSE, AMEX, and NASDAQ stocks is plotted.

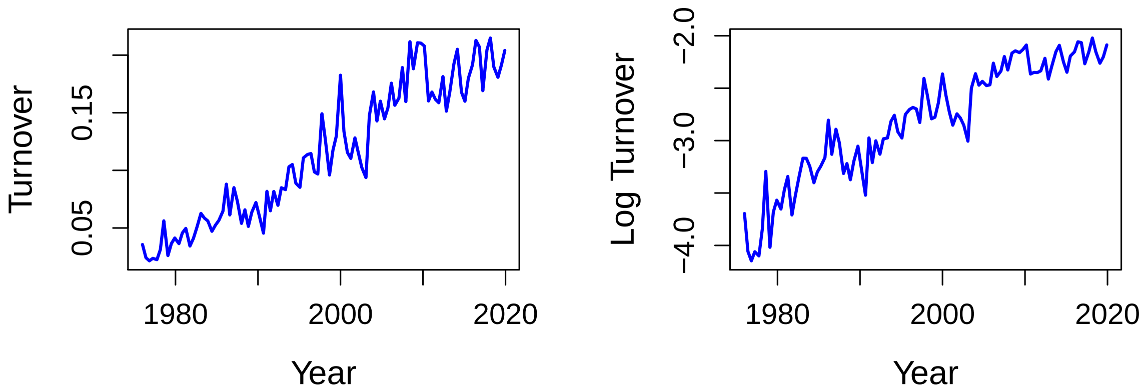

Figure 2: Heatmap of Anomaly Correlations

A matrix heat map of pairwise correlations among the 39 anomaly signals. Blue circles represent positive correlations, while red circles are negative correlations. A bigger circle represents a higher magnitude of correlations. The lower half represents signals correlations, while the upper half represents signal rank correlations. Anomaly signals and their ranks are computed cross-section every month.

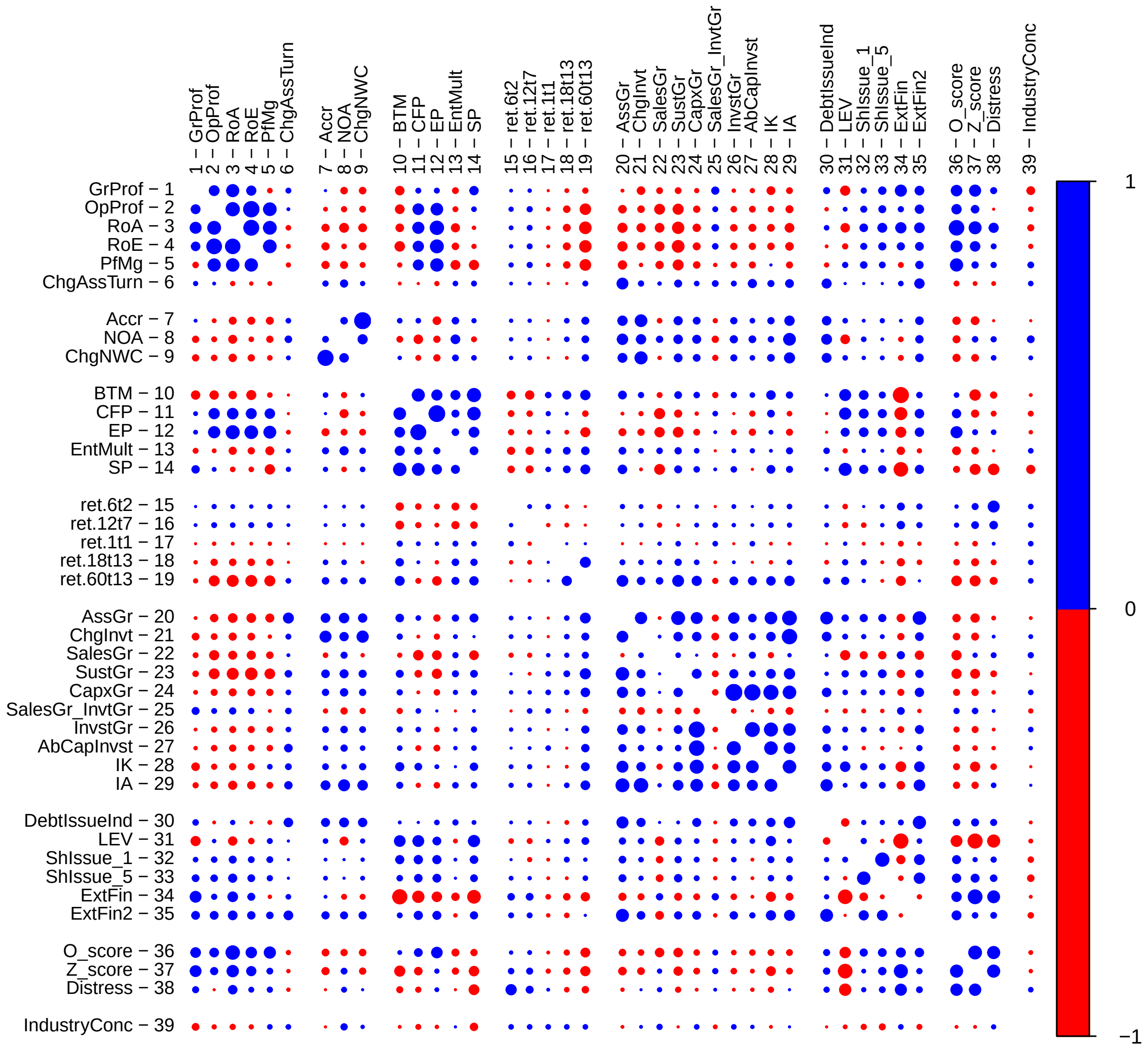

Figure 3: Disagreement Trend

Monthly cross-sectional mean and standard error of the disagreement measure (STD_DEV) over 1976–2019. The confidence interval is set to two standard errors.

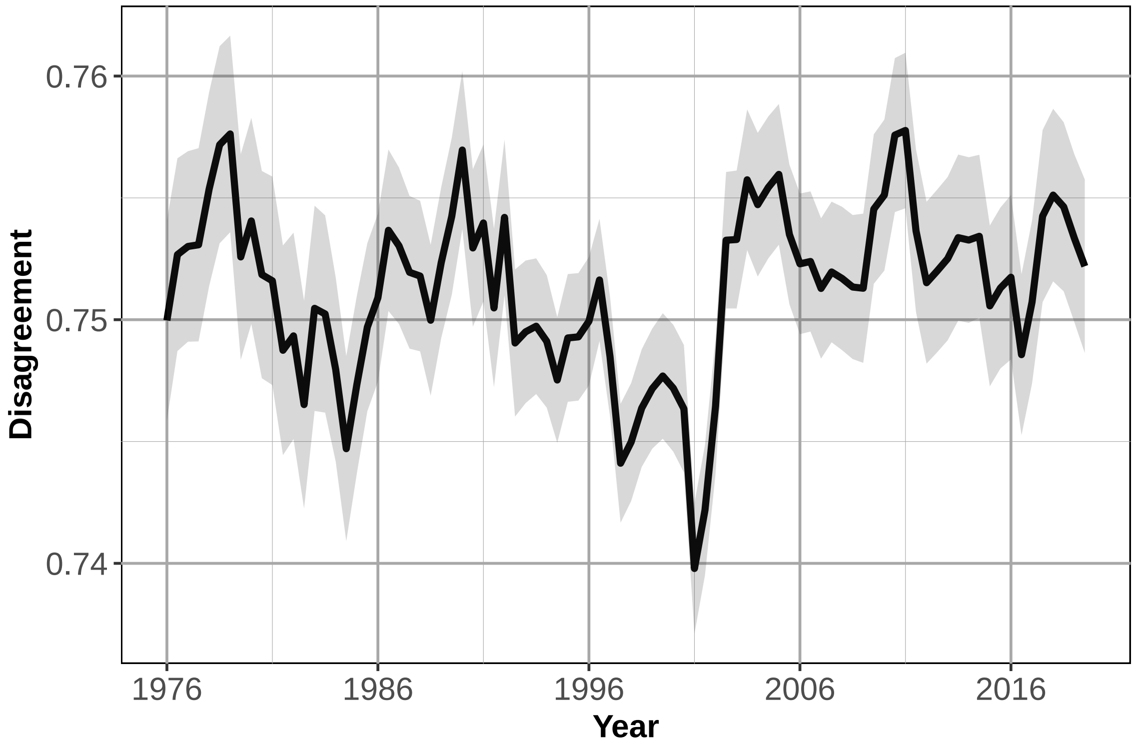

Figure 4: Disagreement and Anomaly Groups

Average monthly Disagreement, over the period 1976–2019, using all but one group of anomalies over time. The number in paranthesis represents the number of AFs skipped in constructing disagreement.

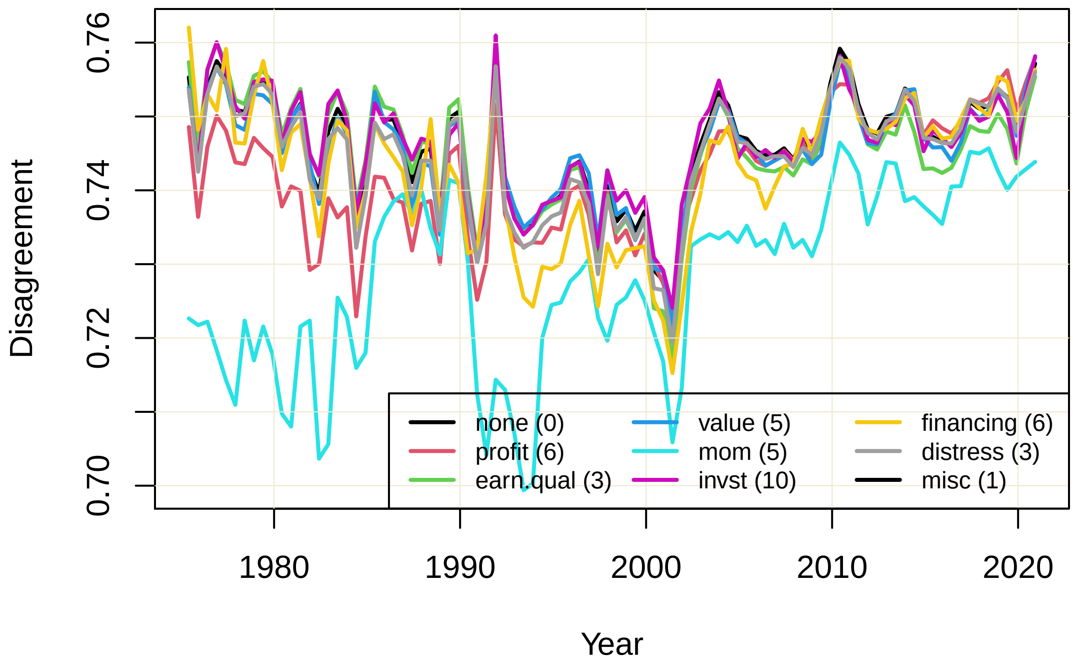

Figure 5: Anomalies and Turnover

Extreme decile (D1 and D10) and middle decile (D2 to D9) percentage returns, turnover ranks, disagreement-turnover ranks, and other-turnover ranks with respect to anomalies. Decile portfolios based on anomalies are constructed each month-end, and all variables are computed at the end of next month. Returns are monthly percentages, while turnover is in cross-sectional percentiles (100 × Ranks). Extreme decile turnover is $0.5 \times (TURN^{D1} + TURN^{D10})$ and intermediate decile turnover is $0.125 \times (TURN^{D2} + \cdots + TURN^{D9})$. Disagreement- and excess-turnover is computed similarly.

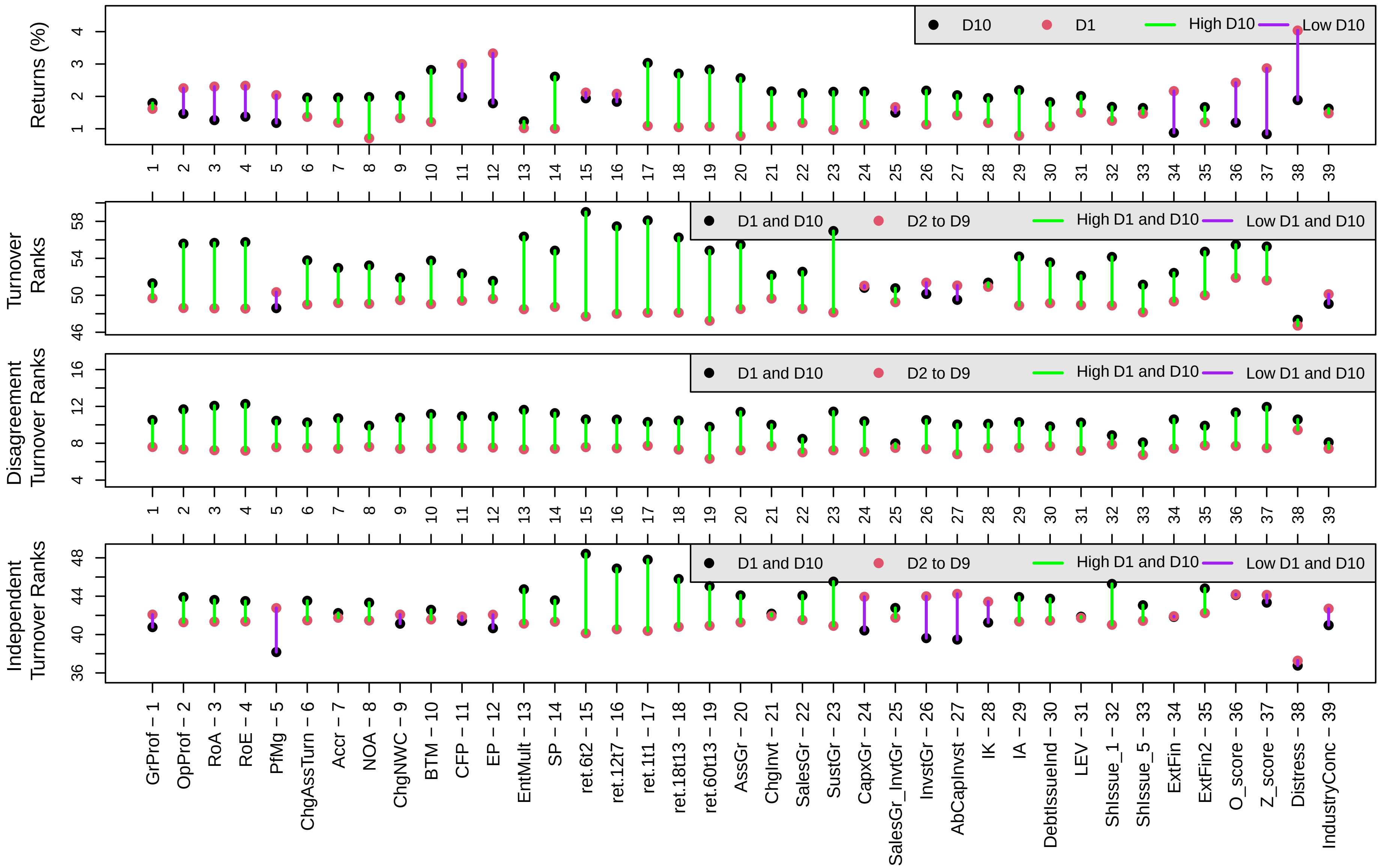

Table 1: Anomaly Papers

A brief list of anomaly papers and the number of anomalies used in the study.

S.No.	Source	Number of Anomalies
1	Stambaugh, Yu, and Yuan (2012)	11
2	Linnainmaa and Roberts (2018)	34
3	Green, Hand, and Zhang (2017)	94
4	McLean and Pontiff (2016)	97
5	Feng, Giglio, and Xiu (2020)	150
6	Chordia, Goyal, and Saretto (2020)	185
7	Harvey, Liu, and Zhu (2016)	316
8	Hou, Xue, and Zhang (2020)	452

Table 2: Disagreement by Industry

Average disagreement ranks (×100) and its standard deviation across 48 FF industry classifications (Fama and French (1997)). Only the top ten and bottom ten industries having the highest and lowest levels of average disagreement are shown. The second column shows the percentage of firm-months in the respective industry.

Industry	% Sample	Avg. Disagreement (Ranks)	SD Disagreement (Ranks)
Top 10			
Pharmaceuticals	5.52	69.6	22.3
Precious-Metals	0.28	59.9	23.9
Medical-Equipment	2.88	58.1	25.8
Computers	3.43	56.2	24.9
Real-Estate	0.75	56.0	24.6
IT Services	9.87	54.3	24.9
Construction	1.27	53.4	24.3
Coal	0.19	53.2	24.4
Trading	2.30	52.9	23.5
Electronic Chips	5.23	52.3	25.2
Bottom 10			
Automobiles	1.48	40.9	24.7
Food-Products	1.68	39.6	24.0
Publishing	0.73	39.5	24.3
Beer-&-Liquor	0.32	39.0	23.3
Insurance	3.28	37.5	22.3
Aircraft	0.57	37.5	24.7
Chemicals	1.83	37.2	25.9
Business-Supplies	1.27	36.3	23.7
Shipping-Containers	0.33	32.4	23.0
Utilities	3.52	29.7	18.7

Table 3: Descriptive Statistics and Correlations

Panel A: Descriptive Statistics

Panel A presents pooled cross-section descriptive statistics of turnover and explanatory variables. Variable definitions are present in Appendix A.2

	Mean	SD	Min	p25	Median	p75	Max	Skew	Kurt
L_TURN	−2.73	1.20	−7.22	−3.53	−2.68	−1.88	1.56	−0.17	2.86
STD_DEV	0.75	0.10	0.43	0.68	0.75	0.83	0.99	−0.20	2.55
$FDISP$	0.21	0.63	0.00	0.02	0.05	0.14	13.00	7.44	75.67
$NASDAQ$	0.55	0.50	0.00	0.00	1.00	1.00	1.00	−0.19	1.04
RET^{+}	0.05	0.11	0.00	0.00	0.00	0.07	2.56	4.52	41.00
RET^{-}	−0.04	0.08	−0.70	−0.06	0.00	0.00	0.00	−2.63	11.46
LEV	0.55	1.35	0.00	0.01	0.15	0.52	27.19	6.60	65.02
$CAPM\_\beta$	1.27	0.54	0.08	0.92	1.26	1.53	2.88	0.35	2.72
BTM	0.76	0.92	−2.56	0.27	0.55	0.96	18.95	4.21	36.50
L_PRC	2.54	1.05	0.00	1.83	2.67	3.31	6.34	−0.27	2.64
L_FAGE	4.40	1.24	0.00	3.69	4.63	5.33	6.54	−0.90	3.66
L_ME	19.06	2.06	13.67	17.54	18.90	20.44	26.27	0.38	2.82
$ESURP$	0.04	0.13	0.00	0.00	0.01	0.02	4.28	10.81	176.54
$EVOL$	0.04	0.14	0.00	0.00	0.01	0.03	4.27	10.88	178.90
$NUMEST$	6.83	7.02	1.00	2.00	4.00	9.00	56.00	1.74	6.15

Panel B: Correlations

Panel B reports pooled cross-section correlation coefficients. The lower triangle represents variable correlation, while the upper triangle consists of rank correlations. Variable definitions are present in Appendix A.2

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	L_TURN		0.16	0.05	0.03	0.16	−0.05	−0.08	0.01	−0.22	0.17	−0.04	0.30	0.02	−0.03	0.29
(2)	STD_DEV	0.14		0.14	0.20	0.12	−0.18	0.10	0.02	−0.01	−0.39	−0.27	−0.28	0.19	0.21	−0.15
(3)	$FDISP$	0.00	0.27		0.04	0.04	−0.06	0.08	−0.02	0.10	−0.23	−0.10	−0.34	0.10	0.10	−0.11
(4)	$NASDAQ$	0.12	0.20	0.10		0.00	−0.05	−0.27	0.10	−0.08	−0.24	−0.52	−0.34	0.05	0.03	−0.32
(5)	RET^{+}	0.18	0.07	0.03	0.05		0.53	−0.05	0.00	−0.11	0.06	−0.01	0.06	0.05	0.03	−0.01
(6)	RET^{-}	−0.10	−0.18	−0.12	−0.08	0.27		0.02	−0.01	−0.03	0.18	0.08	0.10	−0.08	−0.09	0.06
(7)	LEV	−0.04	−0.16	0.05	−0.13	−0.01	−0.07		−0.02	0.38	−0.03	0.19	0.04	0.15	0.24	0.05
(8)	$CAPM\_\beta$	0.19	−0.01	0.00	0.09	−0.06	0.03	−0.04		0.00	0.07	−0.08	0.00	−0.01	−0.01	−0.01
(9)	BTM	−0.13	−0.21	0.16	−0.12	−0.05	−0.08	0.45	−0.09		−0.21	0.15	−0.25	0.23	0.33	−0.12
(10)	L_PRC	0.18	−0.36	−0.39	−0.25	−0.04	0.23	−0.16	0.10	−0.24		0.30	0.73	−0.42	−0.51	0.51
(11)	L_FAGE	0.00	−0.28	−0.03	−0.36	−0.05	0.09	0.05	0.15	0.10	0.23		0.32	−0.03	−0.04	0.28
(12)	L_ME	0.37	−0.31	−0.17	−0.27	−0.02	0.10	−0.12	0.20	−0.26	0.74	0.33		−0.16	−0.17	0.73
(13)	$ESURP$	0.04	0.29	0.39	0.03	0.08	−0.07	0.24	−0.02	0.21	−0.26	−0.08	−0.37		0.68	−0.21
(14)	$EVOL$	0.03	0.31	0.45	0.03	0.09	−0.06	0.27	−0.02	0.20	−0.28	−0.05	−0.45	0.67		−0.25
(15)	$NUMEST$	0.27	−0.16	−0.18	−0.31	−0.06	0.07	−0.04	0.05	−0.08	0.49	0.34	0.68	−0.09	−0.10	

Table 4: Cross-sectional regression: different specifications

Log turnover regressed on lagged disagreement and controls. $L\_TURN_{i,t} = \beta \cdot STD\_DEV_{i,t-1} + \alpha \cdot CONTROLS_{i,t-1} + \gamma \cdot DUMMIES_{i,t-1} + \epsilon_{i,t}$. Specification (5) uses 80/20 stock splits to compute disagreement, while others use 70/30 split. In specification (6), I compute disagreement by excluding all momentum signals viz. $ret.6t2$, $ret.12t7$, $ret.1t1$, $ret.18t13$, and $ret.60t13$. In specification (7), all dependent variables except $NASDAQ$ dummy and $NUMEST$ are converted to their respective cross-sectional ranks. Specification (8) and (9) has log turnover computed on the following day and week (5 days), respectively. Specification (3) has 256,507 firm-months of observations while all other specifications have 872,061 firm-months. All independent variables are one-month lagged variables. Definitions of all the variables appear in Appendix A.2. All regression specifications have industry and year fixed effects. t-statistics are present in paranthesis based on standard errors double clustered by firm and year-month. Statistical significance of 10%, 5% and 1% are indicated by *, ** and *** respectively.

	Monthly L_TURN						$TURN$ Rank	Next-day L_TURN	Next-week L_TURN
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
STD_DEV		1.545***	1.272***	1.557***	1.460***	1.092***	0.139***	1.499***	1.536***
		(24.067)	(15.226)	(24.419)	(28.262)	(18.766)	(19.566)	(21.862)	(23.198)
$FDISP$	0.030***	0.011*		0.013**	0.009	0.016**	0.034***	0.007	0.008
	(4.498)	(1.743)		(1.997)	(1.384)	(2.493)	(5.508)	(0.999)	(1.172)
PRC_DISP			1.009***						
			(14.318)						
L_ME				0.107***					
				(9.970)					
$NASDAQ$	0.141***	0.122***	0.009	0.165***	0.118***	0.127***	0.040***	0.069***	0.098***
	(6.175)	(5.430)	(0.322)	(7.538)	(5.309)	(5.641)	(6.482)	(3.050)	(4.301)
RET^{+}	1.701***	1.522***	1.094***	1.521***	1.457***	1.625***	0.126***	2.385***	2.028***
	(25.922)	(25.529)	(17.233)	(25.201)	(25.269)	(25.874)	(46.224)	(26.646)	(28.155)
RET^{-}	−2.438***	−2.210***	−2.014***	−2.214***	−2.116***	−2.342***	−0.154***	−3.238***	−2.779***

Table 4: Cross-sectional regression: different specifications *(continued)*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	(−29.884)	(−29.507)	(−22.778)	(−29.303)	(−29.057)	(−29.891)	(−47.884)	(−36.001)	(−36.772)
LEV	0.076***	0.062***	0.025**	0.059***	0.053***	0.065***	0.087***	0.063***	0.062***
	(9.601)	(8.189)	(2.272)	(7.825)	(7.180)	(8.540)	(11.398)	(7.730)	(7.844)
$CAPM\_\beta$	0.081**	0.085***	0.119***	0.080***	0.087***	0.085***	0.008	0.116**	0.092***
	(2.524)	(2.813)	(3.269)	(2.619)	(2.940)	(2.733)	(1.263)	(2.362)	(2.816)
BTM	0.002	0.024*	−0.019	0.048***	0.028**	0.018	−0.061***	0.006	0.018
	(0.128)	(1.871)	(−1.089)	(3.764)	(2.186)	(1.351)	(−6.726)	(0.410)	(1.314)
L_PRC	0.192***	0.229***	0.176***	0.148***	0.242***	0.218***	0.221***	0.304***	0.264***
	(16.253)	(19.148)	(11.145)	(10.638)	(20.212)	(18.217)	(18.994)	(23.458)	(21.468)
L_FAGE	−0.160***	−0.134***	−0.108***	−0.156***	−0.124***	−0.143***	−0.098***	−0.099***	−0.128***
	(−12.253)	(−10.547)	(−6.119)	(−11.895)	(−9.809)	(−11.135)	(−9.845)	(−7.302)	(−9.751)
$ESURP$	0.277***	0.232***	0.174***	0.220***	0.218***	0.248***	0.069***	0.222***	0.255***
	(7.631)	(7.005)	(3.716)	(6.420)	(6.807)	(7.273)	(22.049)	(5.607)	(6.979)
$EVOL$	0.148***	0.021	0.197**	0.021	−0.029	0.055	0.048***	−0.053	−0.038
	(3.059)	(0.443)	(2.391)	(0.441)	(−0.603)	(1.161)	(6.307)	(−1.002)	(−0.756)
$NUMEST$	0.035***	0.033***	0.024***	0.020***	0.034***	0.033***	0.010***	0.038***	0.035***
	(23.284)	(22.717)	(13.175)	(12.029)	(23.029)	(22.716)	(24.610)	(24.894)	(23.541)
Adj.R^2	0.392	0.407	0.360	0.413	0.413	0.401	0.289	0.374	0.391

Table 5: Cross-sectional regression: different measures of turnover

Different measures of turnover regressed on lagged disagreement and controls. $TURNOVER_{i,t} = \beta \cdot STD\_DEV_{i,t-1} + \alpha \cdot CONTROLS_{i,t-1} + \gamma \cdot DUMMIES_{i,t-1} + \epsilon_{i,t}$. ΔL_TURN_t is $L\_TURN_{i,t} - L\_TURN_{i,t-1}$, GRT adj. L_TURN is adjusted log turnover proposed by CHS and, VW L_TURN (EW L_TURN) is the residual from regressing L_TURN on value-weighted (equal-weighted) market turnover. All specifications have 947,909 firm-month observations. All independent variables are one-month lagged variables. Definitions of all the variables appear in Appendix A.2. All regression specifications have industry and year fixed effects. t-statistics are present in paranthesis based on standard errors double clustered by firm and year-month. Statistical significance of 10%, 5% and 1% are indicated by *, ** and *** respectively.

	L_TURN	ΔL_TURN	GRT adj. L_TURN	VW L_TURN	EW L_TURN
	(1)	(2)	(3)	(4)	(5)
STD_DEV	1.575***	0.022**	0.941***	0.504***	0.512***
	(25.522)	(2.533)	(16.520)	(17.909)	(18.282)
$FDISP$	0.010	−0.003***	0.013**	−0.006*	−0.008**
	(1.638)	(−3.106)	(2.212)	(−1.797)	(−2.311)
$NASDAQ$	0.128***	0.001	0.110***	0.069***	0.057***
	(5.828)	(0.721)	(5.880)	(8.174)	(6.326)
RET^+	1.497***	−0.744***	0.753***	0.992***	0.969***
	(24.849)	(−18.660)	(18.823)	(20.202)	(21.558)
RET^-	−2.144***	0.710***	−0.899***	−1.381***	−1.531***
	(−28.905)	(11.784)	(−14.538)	(−25.452)	(−33.715)
LEV	0.062***	0.002***	0.045***	0.014***	0.015***
	(9.116)	(4.064)	(7.405)	(5.091)	(5.157)
$CAPM\_\beta$	0.086***	0.038	0.011	0.056**	0.016
	(2.902)	(1.002)	(0.374)	(2.320)	(0.774)
BTM	0.024**	0.002	0.050***	−0.010**	−0.010**
	(2.048)	(1.354)	(4.664)	(−2.005)	(−2.159)
L_PRC	0.229***	−0.015***	0.095***	0.124***	0.135***
	(19.331)	(−5.469)	(9.779)	(19.714)	(19.561)
L_FAGE	−0.130***	−0.005***	−0.421***	0.002	0.007
	(−10.652)	(−3.534)	(−30.552)	(0.469)	(1.644)
$ESURP$	0.245***	0.025**	0.077***	0.116***	0.144***
	(7.764)	(2.181)	(2.889)	(5.967)	(7.860)
$EVOL$	0.000	0.014	0.177***	−0.083***	−0.101***
	(0.007)	(1.049)	(4.661)	(−2.819)	(−3.194)
$NUMEST$	0.033***	0.000	0.031***	−0.001***	0.000
	(23.747)	(0.280)	(23.327)	(−2.631)	(0.873)
Adj. R^2	0.404	0.018	0.243	0.083	0.088

Table 6: Descriptive Statistics and Correlations

Panel A: Descriptive Statistics

Pooled cross-section descriptive statistics of information quality variables. *DOC_SIZE* is the size of raw 10-K filing in megabytes, *LENGTH* (in 1000s) is the number of words in a 10-K document and, *CMP_WORDS* is the number of unique occurrences of 374 complex words identified in Loughran and McDonald (2020). Variable definitions are present in Appendix A.2.

	Mean	**SD**	**Min**	**p25**	**Median**	**p75**	**Max**	**Skew**	**Kurt**
DOC_SIZE	5.85	10.81	0.00	0.38	1.32	6.83	434.66	6.50	139.54
LENGTH	47.33	36.46	0.01	25.89	39.16	57.46	1530.66	4.87	78.57
CMP_WORDS	81.45	21.07	16.00	66.00	80.00	95.00	177.00	0.32	3.15
L_ME	19.06	2.06	13.67	17.54	18.90	20.44	26.27	0.38	2.82
L_FAGE	4.40	1.24	0.00	3.69	4.63	5.33	6.54	−0.90	3.66
NUMEST	6.83	7.02	1.00	2.00	4.00	9.00	56.00	1.74	6.15

Panel B: Correlations

Pooled cross-section correlation coefficients. The lower triangle represents variable correlation, while the upper triangle consists of rank correlations. Variable definitions are present in Appendix A.2

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	*DOC_SIZE*		0.65	0.42	0.37	0.20	0.21
(2)	*LENGTH*	0.33		0.81	0.33	0.04	0.22
(3)	*CMP_WORDS*	0.31	0.73		0.34	−0.05	0.28
(4)	*L_ME*	0.32	0.31	0.38		0.33	0.73
(5)	*L_FAGE*	0.12	−0.01	−0.03	0.32		0.28
(6)	*NUMEST*	0.27	0.25	0.26	0.68	0.34	

Table 7: Information Environment: Summary of Regression Splits

The table summarizes turnover regressions across portfolios made using several variables related to the firm's information environment. Two sets of regressions corresponding to specifications 1 and 2 of Table 4 are estimated for each portfolio. Forecast dispersion is included in both regressions. Other explanatory variables (Table 4), standard errors, and R^2 statistics are skipped for brevity. Definitions of all the variables appear in Appendix A.2. All regression specifications have industry and year fixed effects. Standard errors are double clustered by firm and year-month. Statistical significance of 10%, 5% and 1% are indicated by *, ** and *** respectively.

Portfolio Criterion	w/o STD_DEV	with STD_DEV	
	$FDISP_{t-1}$	$FDISP_{t-1}$	STD_DEV_{t-1}
10-K Document Size			
$DOC\_SIZE - 1$	0.034***	0.019*	1.482***
$DOC\_SIZE - 2$	0.014	−0.000	1.433***
$DOC\_SIZE - 3$	0.026**	0.010	1.651***
10-K Report Length			
$LENGTH - 1$	0.032**	0.016	1.353***
$LENGTH - 2$	0.010	−0.002	1.398***
$LENGTH - 3$	0.019**	0.002	1.670***
10-K Complex Words			
$CMP\_WORDS - 1$	0.025	0.009	1.371***
$CMP\_WORDS - 2$	0.010	−0.002	1.223***
$CMP\_WORDS - 3$	0.024	0.012	1.440***
Firm Size			
$FIRM\_SIZE - 1$	0.026***	0.014**	1.630***
$FIRM\_SIZE - 2$	0.036***	0.009	1.932***
$FIRM\_SIZE - 3$	0.085***	0.066***	1.135***
Firm Age			
$FIRM\_AGE - 1$	0.022***	0.007	1.754***
$FIRM\_AGE - 2$	0.030***	0.014	1.359***
$FIRM\_AGE - 3$	0.024	0.007	1.000***
Number of Analysts			
$NUMEST \in \{2, 3\}$	0.021***	0.005	1.865***
$NUMEST \in \{4 \ldots 10\}$	0.032***	0.014**	1.738***
$NUMEST \geq 11$	0.062***	0.043***	1.282***

Table 8: Difference-in-Difference regression: EDGAR Implementation

Log turnover is regressed on controls, lagged disagreement and its interaction with TREAT and POST. TREAT equals one for firm-months where the firm is amongst the firms adopting EDGAR and going online on January 17, 1994. POST is one for dates February 1994 to January 1995. Following controls are not shown: $NASDAQ$, RET^{+}, RET^{-}, LEV, $CAPM\_BETA$, BTM, L_PRC, L_FAGE, $ESURP$, $EVOL$, $NUMEST$, $FDISP$, L_ME. Variables are transformed to their cross-sectional ranks. Independent variables are lagged by one-month. All specifications have 20,140 firm-month observations. Definitions of all the variables appear in Appendix A.2. All regression specifications have industry fixed effects. t-statistics are present in paranthesis based on standard errors clustered by firm. Statistical significance of 10%, 5% and 1% are indicated by *, ** and *** respectively.

	L_TURN			
	(1)	(2)	(3)	(4)
STD_DEV	0.160***	0.169***	0.189***	0.171***
	(7.961)	(7.916)	(7.977)	(8.335)
$STD\_DEV \times POST$		−0.017		
		(−1.148)		
$STD\_DEV \times TREAT$			−0.056**	
			(−2.284)	
$STD\_DEV \times POST \times TREAT$				−0.045***
				(−2.677)
Adj. R^2	0.338	0.338	0.339	0.339

Table 9: Analyst Forecasts and Disagreement

Panel A: EPS Forecasts

Several measures of earnings forecast accuracy are regressed on a set of controls (including log turnover, L_TURN_t) and lagged disagreement (STD_DEV_{t-1}). Following controls (not shown) were used: L_ME_t, BTM_t, $CAPM\_BETA_t$, $ret.12t2_t$, $EVOL_t$, $EARN\_CHANGE_t$, $LOSS\_FIRM_t$, $CAPM\_IVOL_t$, $NUMEST_t$, LEV_t, $SALES\_TO\_ASSETS_t$, $EPS\_MEAN\_EST_t$ and, L_PRC_t. All variables are transformed to cross-sectional ranks.

	EPS_DISP_t		EPS_AFE_t		EPS_RANGE_t	
	(1)	(2)	(3)	(4)	(5)	(6)
L_TURN_t	0.097***	0.086***	0.093***	0.086***	0.231***	0.223***
	(11.973)	(10.724)	(15.198)	(14.125)	(26.123)	(25.298)
STD_DEV_{t-1}		0.066***		0.045***		0.049***
		(9.241)		(7.491)		(6.340)
Adj. R^2	0.380	0.382	0.322	0.323	0.312	0.312
Observations	491,907	491,907	491,907	491,907	491,907	491,907

Panel B: Target Price Forecasts

Several measures of target price forecast accuracy are regressed on a set of controls (including log turnover, L_TURN_t) and lagged disagreement (STD_DEV_{t-1}). Following controls (not shown) were used: L_ME_t, BTM_t, $CAPM\_BETA_t$, $ret.12t2_t$, RET_VOL_t, $LOSS\_FIRM_t$, $CAPM\_IVOL_t$, PRC_NUMEST_t, LEV_t, $SALES\_TO\_ASSETS_t$, $PRC\_MEAN\_EST_t$ and, L_PRC_t. All variables are transformed to cross-sectional ranks.

	PRC_DISP_t		PRC_AFE_t		PRC_RANGE_t	
	(1)	(2)	(3)	(4)	(5)	(6)
L_TURN_t	0.210***	0.192***	0.168***	0.151***	0.246***	0.231***
	(19.802)	(17.950)	(16.294)	(15.153)	(23.741)	(22.036)
STD_DEV_{t-1}		0.101***		0.098***		0.085***
		(11.885)		(12.015)		(10.187)
Adj. R^2	0.301	0.305	0.138	0.142	0.410	0.413
Observations	251,377	251,377	251,377	251,377	251,377	251,377

Note: Definitions of all the variables appear in Appendix A.2. All regression specifications have industry and year fixed effects. t-statistics are present in paranthesis based on standard errors double clustered by firm and year-month. Statistical significance of 10%, 5% and 1% are indicated by *, ** and *** respectively.

Table 10: Excess Turnover by Anomaly

Portfolio deciles (D1 to D10) are constructed each month with respect to each anomaly. The second column gives the average long-short return (in %). The third column gives the average turnover rank (x 100) for extreme deciles (D1 and D10). The fourth column is the average turnover rank (x 100) in the intermediate deciles (D2 to D9). Excess turnover (fifth column) is the difference between extreme decile turnover (third column) and intermediate decile turnover (fourth column). I partition turnover into two components — disagreement turnover and residual turnover — by running monthly regressions of turnover ranks on lagged disagreement ranks. The sixth and seventh column gives excess turnover for the two turnover components: disagreement and residual.

Anomaly	**Return (D10 - D1)**	**Turnover (D1 & D10)**	**Turnover (D2 to D9)**	**Excess Turnover**	**Excess Turnover (Disagreement)**	**Excess Turnover (residual)**
Gross Profitability	0.18	51.30	49.68	1.62	2.92	−1.31
Operating Profitability	−0.79	55.59	48.63	6.96	4.34	2.62
Return on Assets	−1.04	55.67	48.58	7.08	4.82	2.26
Return on Equity	−0.95	55.75	48.56	7.19	5.07	2.12
Profit Margin	−0.86	48.61	50.33	−1.72	2.86	−4.59
Change in Asset Turnover	0.59	53.78	48.99	4.78	2.74	2.04
Accruals	0.77	52.95	49.17	3.78	3.29	0.49
Net Operating Assets	1.27	53.23	49.08	4.15	2.28	1.86
Changes in Net Working Capital	0.68	51.89	49.48	2.41	3.36	−0.95
Book to market	1.61	53.75	49.05	4.70	3.70	1.00
Cash flow to price	−1.02	52.35	49.41	2.94	3.39	−0.45
Earnings to Price	−1.54	51.55	49.61	1.95	3.35	−1.41
Enterprise Multiple	0.21	56.34	48.50	7.85	4.28	3.57
Sales to price	1.61	54.83	48.74	6.08	3.86	2.22
Short term momentum	−0.18	59.01	47.71	11.29	3.01	8.29
Lagged Momentum	−0.25	57.46	48.01	9.45	3.12	6.34
Short-term reversal	1.94	58.10	48.12	9.99	2.57	7.41
Medium-term reversal	1.65	56.25	48.12	8.13	3.14	4.98

Table 10: Excess Turnover by Anomaly *(continued)*

Anomaly	Return (D10 - D1)	Turnover (D1 & D10)	Turnover (D2 to D9)	Excess Turnover	Excess Turnover (Disagreement)	Excess Turnover (residual)
Long-term reversal	1.76	54.83	47.24	7.59	3.46	4.13
Asset Growth	1.78	55.49	48.52	6.97	4.16	2.81
Inventory Growth	1.07	52.18	49.65	2.53	2.29	0.24
Sales Growth	0.91	52.54	48.53	4.01	1.46	2.55
Sustainable Growth	1.17	56.95	48.15	8.80	4.20	4.61
CAPX Growth	1.00	50.81	51.03	−0.22	3.29	−3.52
Growth in Sales minus growth in Inventory	−0.17	50.76	49.26	1.50	0.48	1.02
Investment Growth	1.05	50.14	51.36	−1.22	3.13	−4.36
Abnormal CAPX	0.62	49.51	51.06	−1.55	3.22	−4.77
Investment to Capital Ratio	0.76	51.36	50.92	0.44	2.62	−2.17
Investment to Asset Ratio	1.41	54.19	48.89	5.30	2.76	2.54
Increase in Debt Issuance	0.74	53.56	49.15	4.41	2.13	2.28
Leverage	0.51	52.11	48.93	3.18	3.05	0.13
One year Share Issuance	0.43	54.15	48.90	5.25	1.00	4.25
Five year Share Issuance	0.17	51.14	48.16	2.99	1.36	1.63
External Financing - I	−1.29	52.42	49.34	3.08	3.16	−0.07
External Financing - II	0.47	54.71	50.00	4.71	2.15	2.57
O-Score	−1.23	55.47	51.90	3.57	3.63	−0.07
Z-Score	−2.03	55.28	51.61	3.67	4.47	−0.80
Distress Risk	−2.15	47.34	46.72	0.62	1.13	−0.51
Industry Concentration	0.15	49.08	50.12	−1.04	0.68	−1.72

Table 11: Variable Definitions

Variable	Definition
$NASDAQ$	Dummy set to 1 if the stock is traded at NASDAQ ($exchcd = 3$)
RET^{+} and RET^{-}	Monthly return is decomposed into two variables based on its sign. $RET^{+} = \max(ret, 0)$ and $RET^{-} = \min(ret, 0)$. ret is adjusted for delisting of firms.
BE, ME and BTM	The book value of equity, the market value of equity, and the ratio of book value to the market value of equity. Construction of book equity is described in Appendix A.1.
LEV	Ratio of long-term debt to book value of equity.
$CAPM\_BETA$	The slope coefficient from regressing a firm's excess returns on market excess returns. Regression parameters are obtained in a rolling fashion using the past 60 months of returns data (from t to $t-59$). Additionally, at least 24 non-missing return observations are required to estimate the regression.
PRC	Stock price adjusted for splits, rights issues, and other corporate events that affect the face value of a share.
L_FAGE	Firm age is the natural log of months since the firm first appeared on the CRSP monthly database.
$ESURP$	Absolute earning surprise is the absolute difference between the most recent quarterly earnings per share (EPS_q) and EPS 4 quarters ago (EPS_{q-4}) scaled by quarter-end stock price (P_q). EPS and stock price is adjusted for splits. $ESURP = \frac{\lvert EPS_q - EPS_{q-4} \rvert}{P_q}$ for quarter q.
$EVOL$	Volatility of earnings is the standard deviation of eight recent quarterly earnings per share scaled by the quarter-end stock price. $EVOL = \frac{1}{7 \cdot P_q} \cdot \sum_{i=0}^{7} (EPS_{q-i} - \overline{EPS_q})^2$, where $\overline{EPS_q}$ is the mean EPS over the same period.
$NUMEST$	Number of analysts following a firm in a given month

Table 11: Variable Definitions ***(continued)***

Variable	Definition
$FDISP$	Standard deviation of analyst forecasts following a firm scaled by the absolute value of mean forecast estimate. I require that at least two analysts are following the firm ($NUMEST \geq 2$)
STD_DEV	Standard deviation of all signals for a firm in a month. I require that at least ten signals are present to estimate standard deviation reliably.
$TURN$	Monthly share turnover calculated as monthly share volume divided by adjusted shares outstanding.
$TURN\_GRT$	Turnover adjusted as per Gallant et al. (1992). Non-stationarity and calendar effects are removed from both the mean and variance of turnover time-series.[a]
VW_L_TURN and EW_L_TURN	Residuals from regressing L_TURN on an intercept and log of value (equal) weighted market turnover[b].
EPS_DISP, EPS_AFE, EPS_RANGE and EPS_MEAN_EST	The standard deviation of analysts' earnings estimates, the absolute difference of actual earnings and mean estimate, and the difference between highest and lowest estimates, respectively. All are scaled by mean eps forecast estimate, EPS_MEAN_EST, fetched directly from IBES eps summary file. EPS_DISP is same as $FDISP$
PRC_DISP, PRC_AFE, PRC_RANGE, PRC_NUMEST and PRC_MEAN_EST	The standard deviation of 12-month ahead target price estimates, the absolute difference of target price estimate and twelve months ahead stock price, and the difference between highest and lowest price target estimates. All are scaled by mean price target estimate, PRC_MEAN_EST, which, along with the number of analysts following a stock, PRC_NUMEST, are fetched directly from the IBES price target summary file.
$EARN\_CHANGE$	Difference between current earnings and previous year earnings scaled by previous year earnings $\left(\frac{ib_t - ib_{t-1}}{ib_{t-1}}\right)$.

Table 11: **Variable Definitions** ***(continued)***

Variable	Definition
$LOSS\_FIRM$	Dummy variable taking value one if a firm reports zero or negative actual earnings in the IBES eps summary file.
$SALES\_TO\_ASSETS$	Ratio of revenues to assets $\left(\frac{revt}{at}\right)$.
RET_VOL	Monthly return volatility computed as the standard deviation of daily stocks returns.
$LENGTH$ and DOC_SIZE	The total number of words and the file size of EDGAR 10-K filing in megabytes. Both the variables are borrowed from the LM summary file compiled by Bill McDonald at https://sraf.nd.edu/
CMP_WORDS	Number of unique occurrences of 374 complex words in firm's 10-K filing. The list of complex words is from Loughran and McDonald (2020).

[a] GRT adjustment is carried out in two steps. In the first step, the variable to be adjusted, X is regressed on linear and quadratic time trends as well as calendar month dummies: $X_t \sim \beta_0 + \beta_1 \cdot t + \beta_2 \cdot t^2 + \gamma \cdot D_{1...11} + \epsilon_t$. Here $D_{1...11}$ represents 11 monthly dummies. In the next step squared residuals are regressed on the same set of variables: $\log(\epsilon_t^2) \sim \beta_0 + \beta_1 \cdot t + \beta_2 \cdot t^2 + \gamma \cdot D_{1...11} + u_t$. Then the GRT adjusted series is defined as $X\_GRT_t = \exp(u_t/2)$. Finally, X_GRT is linearly transformed so that its mean and variance matches that of X

[b] Value weighted market turnover is $\sum_{i=1}^{D_t} \frac{ME_{i,t}}{\widehat{ME_t}} \cdot TURN_{i,t}$, and equal-weighted market turnover is $\frac{1}{D_t} \cdot \sum_{i=1}^{D_t} TURN_{i,t}$, where $\widehat{ME_t} = \sum_{i=1}^{D_t} ME_{i,t}$ and D_t is the number of firms at time t.