Disclosure, Mispricing and Price Efficiency

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Abstract

The prevailing view is that high-quality public disclosure enhances market efficiency. However, this study challenges that notion by showing that lower-quality 10-K filings lead to more effective mispricing corrections. We find that such filings are associated with higher abnormal returns on filing days, particularly in environments with intense private information acquisition. This suggests that lower-quality disclosures may incentivize greater private information gathering, ultimately facilitating more effective correction of mispricing. Our findings question conventional assumptions about disclosure quality and offer new insights into the complex relationship between public disclosure and market efficiency, with implications for both regulatory policy and investor behavior.

1. Introduction

The influence of disclosure quality on market efficiency is a central topic in the accounting literature. Traditionally, researchers have argued that high-quality public disclosure unequivocally enhances price efficiency in financial markets (Verrecchia, 1980; Brown & Hillegeist, 2007; Bushee & Leuz, 2005; Gelb & Zarowin, 2002). However, this belief in the uniformly beneficial effects of transparency is not universally accepted. Recent theoretical developments challenge this conventional view. For example, Goldstein and Yang (2017) contend that high-quality disclosure may crowd out valuable private information acquisition. They argue that when public disclosure quality is high, investors are more likely to rely on public signals and expect others to do the same, thereby diminishing the incentive to process or trade on private information. As a result, private information is less likely to be incorporated into prices, potentially reducing price efficiency. Banerjee, Davis, and Gondhi (2018) further extend this line of reasoning by suggesting that although higher disclosure quality may discourage the acquisition of fundamental information, it may simultaneously promote the acquisition of price information—behavior that can also impair price efficiency.

Despite these theoretical predictions, empirical evidence on the potential adverse effects of high-quality disclosure remains limited. Motivated by this gap between theory and evidence, we re-examine the causal relationship between disclosure quality and price efficiency. Our study contributes to the literature in two key ways. First, while prior research often relies on noisy proxies that capture only certain aspects of price efficiency, we draw on methodologies from the asset pricing literature to directly measure it through the mispricing of individual stocks. Second, rather than evaluating the overall price efficiency of firms with varying disclosure quality, we focus on specific public disclosure events, enabling a more precise identification of the causal impact of disclosure on price efficiency.

In particular, we concentrate on 10-K filing events for several reasons. First, unlike the extensively studied earnings announcements, 10-K filings are more heavily regulated and closely monitored, offering unique implications for regulatory policy. Second, 10-Ks provide comprehensive information about firms; their complexity increases the importance of disclosure quality, whereas earnings announcements typically leave little room for interpretation. Third, the richness of both textual and numerical content in 10-Ks allows for more precise measurement of disclosure quality. Finally, empirical studies focusing on 10-K filings remain relatively sparse compared to those examining earnings announcements.

To capture mispricing, we follow the methodologies of Engelberg et al. (2018) and Stambaugh, Yu, and Yuan (2015), constructing a stock-month mispricing measure known as *NET*. This variable synthesizes information from 11 anomalies identified by Stambaugh, Yu, and Yuan (2015), which are widely recognized for explaining cross-sectional variation in stock returns and are interpreted as indicators of mispricing rather than risk. To proxy for the quality of 10-K disclosures, we primarily use a widely accepted measure—accruals quality (*AQ*)—which captures the opaqueness of filings based on the extent of discretionary accruals.

Using *NET* to capture the predictive power of mispricing anomalies, we first examine how mispricing behaves on 10-K filing days, following the methodology of

Engelberg et al. (2018). We find that anomaly returns on 10-K filing days are exceptionally high, comparable to those on earnings announcement days, and nearly ten times higher than on non-disclosure days. According to previous literature, anomaly returns reflect the correction of mispricing, with higher returns indicating a stronger correction. Thus, our results suggest that 10-K filings provide valuable information that helps correct mispricing.

After establishing that 10-K filings help correct mispricing, we examine how the impact of these filings on mispricing varies with disclosure quality. We categorize the 10-K filing days into groups based on different levels of disclosure quality and estimate anomaly returns for each group. The results show that anomaly returns are higher on 10-K filing days with lower disclosure quality. For stocks with a *NET* value of 0.03, daily returns on 10-K filing days are as high as 14.02 basis points for low-quality 10-Ks, compared to only 5.76 basis points for high-quality 10-Ks.

In addition to using accruals quality as a direct measure of 10-K disclosure quality, we also examine whether market outputs—specifically, the noisiness of the information environment surrounding public disclosures—influence mispricing correction on disclosure event days. Prior literature suggests that such market outputs reflect the quality of public disclosure, allowing us to use them as indirect proxies for disclosure quality. In our study, we focus on abnormal bid-ask spreads and abnormal intraday volatility. Our findings indicate that, on 10-K filing days, wider bid-ask spreads and higher intraday volatility—both indicative of lower disclosure quality—are associated with larger anomaly-based returns. These results are consistent with our hypothesis that lower-quality disclosures trigger greater private information acquisition and thus more effective mispricing correction.

To address endogeneity concerns, we exploit the implementation of SFAS No. 131 as a natural experiment. This new accounting standard requires multi-sector firms to report earnings separately, which increases the level of information disaggregation in their 10-K filings. Prior research shows that this exogenous change improves the disclosure quality of affected firms. We use firms unaffected by the rule, including single-sector firms and others, as a control group and apply a Difference-in-Differences approach to analyze the causal relationship between disclosure quality and anomaly returns on 10-K filing days. Our results show that before the implementation of SFAS No. 131, affected and unaffected firms exhibited similar anomaly returns on 10-K filing days, suggesting that both groups provided a similar level of information to correct mispricing. However, after the implementation, as the disclosure quality of affected firms increased, their anomaly returns on 10-K filing days were significantly lower than those of unaffected firms, with a difference of 7.47 basis points for a *NET* value of 0.03.

Our results are consistent with recent theories, such as Goldstein and Yang (2017), but we go a step further by empirically examining the underlying mechanism. We propose that high-quality public disclosures may crowd out private information acquisition. When disclosures are highly transparent, they offer clear public signals, reducing investors' incentives to seek out and process private information. Consequently, market participants may rely predominantly on these public signals, limiting the role of private information in correcting mispricing. In contrast, less transparent disclosures create a noisier information environment, increasing the value of private information and encouraging its acquisition—thereby enhancing the correction of mispricing.

To test this mechanism, we construct a novel measure of private information acquisition based on non-current EDGAR search volume, which captures investor efforts to obtain firm-specific information beyond recent filings. We find that, for low-quality 10-K filings, mispricing corrections are primarily driven by firms with higher non-current EDGAR search volume. This evidence supports our hypothesis that lower-quality disclosures stimulate private information gathering, which in turn facilitates more effective mispricing correction.

To ensure the robustness of our findings, we re-examine our results using alternative measures of both mispricing and disclosure quality. For mispricing, we construct *NET97*, following Engelberg et al. (2018), which incorporates the full set of 97 anomalies identified by McLean and Pontiff (2016). Our results remain consistent with this broader measure, reinforcing the validity of our main findings. For disclosure quality, we incorporate additional direct measures from the literature, including Disaggregation Quality, which reflects the extent of information disaggregation based on the value-weighted ratio of non-missing items in 10-K filings, and Readability, which captures the linguistic complexity of the filings. These measures reflect different dimensions of disclosure quality—both numerical and textual. We also examine Timeliness, defined as the number of days between the fiscal period end and the 10-K filing date, as an indirect proxy for disclosure quality, with longer delays potentially indicating higher auditing costs or reporting frictions.

The implications of our research extend beyond 10-K filings to public disclosures more broadly. To generalize our findings, we apply our regression framework to earnings announcement events, using measures of disclosure quality that are also applicable in this context—specifically, bid-ask spreads, intraday volatility, and the timeliness of earnings announcements. Consistent with our findings for 10-K filings, we observe that only low-quality earnings announcements are associated with significant mispricing correction. Importantly, these results are not driven by the content of the earnings announcements themselves, as we control for earnings surprises in our analysis.

We also conduct a dynamic analysis by comparing anomaly returns on 10-K filing days between high- and low-disclosure quality firms over 5-year rolling windows. Our results remain robust across different time periods, confirming the stability of our main findings. Additionally, we observe a declining trend in anomaly returns on 10-K filing days over time, consistent with the patterns documented by McLean and Pontiff (2016) and Bowles et al. (2024).

An alternative explanation for our results is that firms filing high-quality 10-Ks may possess better information prior to the filing, allowing mispricing to be corrected on non-disclosure days. Consequently, no additional mispricing correction would be observed on 10-K filing days. To address this possibility, we conduct regressions on a non-disclosure day subsample and find that firms with high-quality 10-K filings do not experience higher anomaly returns on these non-disclosure days. This evidence suggests that mispricing correction on non-disclosure days does not differ significantly between firms with high and low disclosure quality.

Finally, we conduct separate analyses on stocks classified as overpriced and underpriced. We find that our main results vanish in the underpriced subsample but become even stronger for the overpriced subsample. These findings suggest that both the predictive power of mispricing and the association between low disclosure quality and mispricing correction are primarily driven by overpricing rather than underpricing.

This research makes two key contributions to the literature. First, it advances the corporate disclosure literature by highlighting the nuanced effects of transparency on market efficiency. Second, within the broader market efficiency and mispricing literature in asset pricing, it deepens our understanding of the conditions under which mispricing is corrected. Overall, this work enriches the ongoing discourse on market efficiency by illustrating how private information acquisition interacts with public disclosure to influence price dynamics. By bridging these areas, our findings offer valuable implications for regulators and policymakers, who must carefully balance the benefits of transparency with its potential unintended consequences on market efficiency.

T The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data and sample, including the construction of disclosure quality measures and mispricing proxies. Section 4 presents the empirical results, encompassing our main findings, causality and mechanism tests, robustness checks, and additional analyses. Finally, Section 5 concludes with a summary of the findings and discusses implications for future research and policy.

2. Literature Review

This study is grounded in two distinct strands of literature: the impacts of corporate disclosure on market dynamics and mispricing in financial markets.

2.1 Corporate Disclosure and Market Dynamics

Early finance and accounting literature emphasized the crucial role of information processing costs in market efficiency (Grossman & Stiglitz, 1980; Verrecchia, 1982; Kyle, 1989). Disclosure quality—often framed as disclosure transparency or accounting quality—reflects the cost of processing information, making it central to the study of disclosure effects. The intuitive notion emerged that higher disclosure quality reduces information processing costs, enabling stock prices to adjust more efficiently to new information and thereby improving market efficiency (Verrecchia, 1980). Empirical research supports these beneficial effects. For example, Gelb and Zarowin (2002) find that better disclosure quality helps stock prices better reflect future earnings. Hutton, Marcus, and Tehranian (2009) provide evidence that improved disclosure is associated with less price synchronicity and reduced crash risk. Callen, Kahn, and Hu (2013) also show that enhanced disclosure correlates with lower stock price delay.

However, the multi-dimensional and complex nature of information efficiency continues to fuel debate regarding the relationship between disclosure quality and market efficiency. Recent theoretical work suggests potential negative effects of high transparency. For example, Goldstein and Yang (2017) argue that information acquisition costs and integration costs interact in ways that can reverse the expected positive link between disclosure transparency and information efficiency. Specifically, when public disclosure quality is high, integration costs are low, which reduces incentives for direct information acquisition and may crowd out valuable private information as its marginal value diminishes. Building on this, Banerjee, Davis, and Gondhi (2018) distinguish between fundamental and price information acquisition, proposing that these are complementary. While higher disclosure quality initially lowers the cost of acquiring fundamental information, its marginal benefits decline at high levels of disclosure. Further improvements may encourage investors to rely more on price information, potentially reducing price informativeness—especially in markets with a large proportion of unsophisticated investors. Despite these theoretical advances, empirical evidence documenting a negative impact of disclosure transparency on market efficiency remains scarce.

Among the various studies on public disclosure, research on 10-K filings is particularly relevant to our work. Li and Ramesh (2009) find that the market reacts to 10-K filings primarily when they coincide with the first public earnings announcements. In contrast, Huddard, Ke, and Shi (2007) show that insiders engage in the most trading around 10-K and 10-Q filings. While such studies are limited, our research makes a significant contribution to this area.

2.2 Mispricing in Financial Markets.

To investigate the impact of disclosure transparency on market efficiency, we draw on the asset pricing literature. The concept of market efficiency was formalized by Fama (1970), yet researchers have consistently documented that certain stock characteristics predict cross-sectional stock returns (Jegadeesh & Titman, 1993; Lakonishok, Shleifer, & Vishny, 1994; Hou, Xue, & Zhang, 2015; Stambaugh & Yuan, 2017), despite the Efficient Market Hypothesis (EMH) suggesting that returns should only vary due to risk. These stock characteristics, commonly referred to as “anomalies,” sparked debate about whether they reflect risk or mispricing. Over time, it has become widely accepted that anomalies primarily result from mispricing. For instance, Baker and Wurgler (2006) link anomaly predictability to investor sentiment, underscoring the behavioral origins of these patterns. Mclean and Pontiff (2016) find that anomaly return predictability diminishes after anomalies are publicly documented, indicating that markets arbitrage away mispricing.

Among this literature, Engelberg, Mclean, and Pontiff (2018) provide the most relevant framework for our study. They examine 97 anomalies and construct a stock-month measure of mispricing, finding that anomaly returns are especially pronounced on public disclosure days. They interpret this as evidence that public disclosures deliver valuable information facilitating mispricing correction. Elevated anomaly returns on these days reflect investors updating their beliefs, resulting in concentrated mispricing correction aligned with disclosure events. Their work bridges the literature on mispricing and disclosure, highlighting how public disclosure enhances market efficiency by correcting mispricing. Our study extends this framework by investigating how variations in disclosure quality modulate this relationship.

In summary, this research integrates insights from these two key strands of literature to explore the complex relationship between corporate disclosure quality and market efficiency. By addressing empirical gaps and extending theoretical frameworks, it aims to deepen understanding of how disclosure dynamics shape financial markets.

3. Data

In this section we describe the data sample and variable constructions.

3.1 Sample

Our dataset combines market and firm-specific data from multiple sources. Market data, including stock returns and trading volumes, are sourced from CRSP, while firm-level disclosure data are obtained from the WRDS SEC Analytics Suite and COMPUSTAT. The sample spans from 1996 to 2019, a period after the implementation of EDGAR, ensuring the reliability of 10-K filing dates.

We apply standard filters to construct the sample. Firms from the financial (SIC codes 6000-6999) and utility (SIC codes 4900-4999) sectors are excluded due to their unique regulatory environments. Additionally, we exclude firms with an annual average stock price below $5 to ensure data reliability. The final sample consists primarily of firms listed on the NYSE, AMEX, and NASDAQ.

3.2 Measure of mispricing

We use 11 anomalies proposed by Stambaugh, Yu, and Yuan (2015) to measure stock-month level mispricing. Specifically, we follow the methodology outlined by Engelberg et al. (2018): For each anomaly, we rank stocks into deciles based on the anomaly characteristics at the beginning of each month. For each stock-month, we then sum the number of long extreme portfolios (*Long*) and short extreme portfolios (*Short*) that the stock belongs to — that is, the 1st or 10th decile based on the anomaly ranking. Our measure of mispricing, denoted as *NET*, is the difference between *Long* and *Short*, divided by 100. Thus, a higher *NET* value for a stock in a given month indicates that more anomalies predict that the stock will have an abnormally high (or low) return.

We use 11 anomalies instead of the 97 anomalies proposed by Engelberg et al. (2018) for two main reasons. First, these 11 anomalies effectively capture cross-sectional return differences, so adding more anomalies does not increase the predictive power of the mispricing measure. Second, Engelberg, Mclean, and Pontiff (2018) note that many of the 97 anomalies in their study may be due to risk factors rather than mispricing. In contrast, the 11 anomalies from Stambaugh, Yu, and Yuan (2015) are widely regarded as indicators of mispricing. Thus, for a more accurate measurement of mispricing, these 11 anomalies are preferred. For robustness, we also calculate *NET97* using the same methodology with the full set of 97 anomalies.

3.3 Measure of disclosure quality

Earnings are often regarded as the primary indicator of firm performance. Accordingly, our study uses the opaqueness of earnings as the primary measure of disclosure quality. Accruals Quality (AQ), a widely accepted metric in accounting literature, is commonly used to capture this opaqueness, and we adopt it as our main measure of disclosure quality. Specifically, AQ reflects the extent to which a firm's reported accruals deviate from the expected "normal" accruals based on industry norms.

Following the methodologies of McNichols (2002) and Baxter and Cotter (2009), we calculate *AQ* with the following steps: First, for each firm in each two-digit SIC industry, we estimate the following regression for each year:

$$TCA_{i,y} = \alpha_0 + \alpha_1 CFO_{i,y-1} + \alpha_2 CFO_{i,y} + \alpha_3 CFO_{i,y+1} + \alpha_4 \varDelta REV_{i,y} + \alpha_5 \varDelta PPE_{i,y} + \mu_{i,y} \quad (1)$$

Where $TCA_{i,y}$ denotes total current accruals, which is the difference between the income before extraordinary item and the cash flow from operations (or *CFO* in following references) for firm i in year y. The above mentioned $CFO_{i,y}$ represents cash flow from operations, calculated as net income before extraordinary items, adjusted for changes in working capital, depreciation, and amortization expenses. Additionally, $\varDelta REV_{i,y}$ represents the change in revenue and $\varDelta PPE_{i,y}$ refers to change in gross property, plant, and equipment for firm i in year y. All variables are deflated by average total assets of firm i in year y.

Next, *AQ* is calculated using the parameter estimates from the regression in equation (1) as follows:

$$AQ_{i,y} = -|TCA_{i,y} - (\widehat{\alpha_0} + \alpha_1 CFO_{i,y-1} + \widehat{\alpha_2} CFO_{i,y} + \widehat{\alpha_3} CFO_{i,y+1} + \widehat{\alpha_4} \varDelta REV_{i,y} + \widehat{\alpha_5} \varDelta PPE_{i,y})| \quad (2)$$

Where hats over the coefficients ($\hat{\alpha}$) denote estimated values from regression Eq. (1). Thus, our measure of disclosure quality, $AQ_{i,y}$, captures the absolute value of accruals that cannot be explained by industry norms for firm i in year y. A negative sign is applied to ensure that higher AQ values indicate better disclosure quality, as they reflect less discretion in the accruals process.

3.4 Control Variables

In our analyses, we follow the framework established by Engelberg et al. (2018), where the dependent variable is the daily return. As discussed earlier, firm-specific characteristics that may predict returns are already captured by the mispricing measure *NET*, meaning no additional firm characteristics need to be controlled for in our regressions. However, daily returns can be influenced by microstructure issues, which we account for by including control variables typically used in similar studies.

To address these potential microstructure effects, we adopt the same control variables as Engelberg et al. (2018), specifically the 10-day lag of daily returns, the square of the daily return, and daily trading volume. These controls help mitigate any biases related to market frictions that may affect the observed return patterns.

3.5 Descriptive Statistics and Correlation

Table I shows the descriptive statistics and the correlation of variables. Panel A reports the firm-day level variables, including daily return (*RET*), daily turnover (*Volume*), and the previously introduced mispricing measure *NET*. For the disclosure quality measure *AQ*, which is matched to a specific 10-K filing, its descriptive statistics are reported in Panel B.

[Insert Table I]

In Table I, daily return (*RET*) is shown in percentage terms. In our sample, the average daily return is around 0.067%, while the median is close to 0, and the standard deviation is 4.724%. *Volume* refers to the turnover rate (daily share volume divided by shares outstanding), presented as a percentage. The average daily *Volume* is 0.915%, with a median of 0.46% and a standard deviation of 47.3%, indicating a highly right-skewed distribution. Our measure for mispricing, *NET*, ranges between -0.11 and 0.11 by design. Both the mean and median are close to 0, with a standard deviation of approximately 0.029. As shown in Panel B, *AQ*, our primary disclosure quality measure, has an average of -0.561, a median of -0.128, and a standard deviation of 2.433.

[Insert Table II]

In Table II, we report the correlations among variables, all matched at the firm-day level on a calendar basis. While most correlations are quite weak (below 0.1), a few are noteworthy. The correlation between daily return (*RET*) and the mispricing measure (*NET*), although small, is positive (0.003), reflecting the return-predictive power of *NET*. Our measure of accrual quality (AQ) shows a slight negative correlation with *RET* (-0.007) and trading volume (-0.014), and a small positive correlation with *NET* (0.015). Overall, these correlations remain very low, indicating limited linear association among these variables at the daily level.

4. Empirical Analysis

This section contains the results of our studies, including the results of main tests, causality tests, mechanism tests, robustness tests and additional tests.

4.1 Baseline

In this section, we first test whether 10-K filings provide additional information for correcting mispricing, given that existing literature mainly focuses on earnings announcements rather than 10-K filings as the primary public disclosure.

We follow the methodology of Engelberg et al. (2018) with the following equation:

$$R_{i,t} = \beta_1 * NET_{i,t} + \beta_2 * NET_{i,t} * EDays_{i,t} + \beta_3 * EDays_{i,t} + \beta_4 * NET_{i,t} * 10\mathrm{K}FilingDays_{i,t} + \beta_5 * 10\mathrm{K}FilingDays_{i,t} + Controls + \mu_t + \varepsilon_{i,t} \quad (3)$$

In the equation, $EDays_{i,t}$ and $10KFilingDays_{i,t}$ are indicator variables that denote whether day t is within the three-day window of an earnings announcement and a 10-K filing for firm i, respectively. $NET_{i,t}$ is calculated at the beginning of the month. Notice that day fixed effects are added because our mispricing measures focus on the cross-sectional level.

Although we aim to examine the specific effect of 10-K filing days, earnings announcements are often bundled with 10-K filings, so we control for earnings announcement days. In this regression, we focus on the estimation of β_2 and β_4, which capture the predictability of *NET* for daily returns on earnings announcement days and 10-K filing days.

[Insert Table III]

Table III shows the results. In Column (1), the results with controls of 10-day lags of daily returns, the square of the daily return, and daily trading volume is reported. The coefficient of *NET* (or β_1) indicates the average anomaly return on trading days that are neither earnings announcement days nor 10-K filing days, and the coefficient is 0.391 with 1% significance. Economically, a stock with a *Net* value of 0.03 (about 1 standard deviation) has expected returns of 1.173 basis points. This suggests our mispricing measure, *NET*, is valid for predicting returns.

Consistent with Engelberg et al. (2018), β_2, the coefficient of interaction term of *NET* and *Edays*, which captures anomaly returns on earnings announcement days, is 3.657 with a t-statistic larger than 10, Economically, for a *NET* value of 0.03, expected returns are 12.14 basis points, which is nearly ten times larger than on non-earnings announcement days.

The coefficient of the interaction term of *NET* and *10KFilingDays* (β_4) is 3.459. While the statistical significance is less than β_2 (but still significant on 1% level), the economic magnitude is comparable. For a stock with a *NET* value of 0.03, expected returns are 11.55 basis points on 10-K filing days.

In Column (2), the regression excludes the control variables of 10-day lags of daily returns, the square of the daily return, and daily trading volume. The coefficient of *NET* (or β_1) is 0.246 with 10% significance, slightly less significant than in Column (1). The coefficients of interaction terms of *NET* * *EDays,* and NET * 10KFilingDays are very similar to in Column (1), respectively 3.740 and 3.202, both with 1% significance of 1%. Overall Column (2) suggests the results are very similar with or without control variables.

According to Engelberg et al. (2018), anomaly returns are higher on earnings announcement days because earnings announcements provide information that can correct mispricing. With more significant correction of mispricing on earnings announcement days, the anomaly returns are higher. Our results show that 10-K filings also provide mispricing-correcting information. These results hold even after controlling for interaction with earnings announcement days, suggesting that 10-K filings provide additional information.

Once we establish that 10-K filings help correct mispricing, we explore the heterogeneous effects of 10-K filings with varying levels of quality. The estimation equation is as follows:

$$R_{i,t} = \beta_1 * NET_{i,t} + \beta_2 * NET_{i,t} * EDays_{i,t} + \beta_3 * EDays_{i,t} + \beta_4 * NET_{i,t} * LowQuality10K_{i,t} + \beta_5 * LowQuality10K_{i,t} + \beta_6 * NET_{i,t} * MedianQuality10K_{i,t} + \beta_7 * MedianQuality10K_{i,t} + \beta_8 * NET_{i,t} * HighQuality10K_{i,t} + \beta_9 * HighQuality10K_{i,t} + Controls + \mu_t + \varepsilon_{i,t} \quad (4)$$

In this equation, we further divide 10-K filing days into three groups (*LowQuality10K/MedianQuality10K/HighQuality10K*) based on their disclosure quality, using the 30/70 percentile cutoffs for each calendar year. For instance, $HighQuality10K_{i,t}$ equals 1 if day t is a 10-K filing day and its value of accruals quality (*AQ*) is in the highest 30% across firms in that year.

[Insert Table IV]

Table IV reports the results for direct measures of 10-K quality. In Column (1), 10-K filing days are grouped by the value of *AQ*. The coefficient of the interaction term of *NET* and *LowQuality10K* (β_4) captures the anomaly return on 10-K filing days when the 10-K filing has the lowest *AQ*. The coefficient is 4.283, with 1% level significance. Economically, these firms with a NET value of 0.03 have expected returns of 14.02 basis points. The coefficient of the interaction term of *NET* and *MedianQuality10K* (β_6) is 1.969 with 10% level significance (expected returns are 7.08 basis points with a *NET* value of 0.03). This coefficient is more than 50% less than the one interacting with *LowQuality10K*, and its significance level is also lower. The coefficient of the interaction term of *NET* and *HighQuality10K* (β_8) is 1.530 (expected returns are 5.76 basis points with *NET* value of 0.03), and is not statistically significant. Economically, this means that if firms file a high-quality 10-K, there would be no significantly higher anomaly returns on the filing days. There is a clear decreasing pattern of the coefficients of the three interaction terms (β_4, β_6 andβ_8,), both in economic magnitude and statistical significance. The difference in expected return between 10-K filing days for high-quality and low-quality firms is as large as 8.26 basis points (about 20.8% annualized) assuming both firms have a NET value of 0.03, while the result of Wald test between β_4 and β_8 gives a p-value of 0.044, indicating that the difference is also statistically significant. In Column (2), the regression is conducted without control variables (10-day lag of daily returns, the square of the daily return, and daily trading volume). Except for the coefficient of *NET* alone, which is slightly less significant, all the other coefficients have the similar results compared to Column (1), both in magnitude and significance. Column (3) and (4) replicate the regressions without the control of earnings announcement days, and the results also hold. Past literature attributes anomaly returns to the correction of mispricing. In our tests, higher anomaly returns on 10-K filing days represent a stronger correction of mispricing, indicating that 10-K filings with lower (higher) disclosure quality correct more (less) mispricing.

4.2 Market Outcome Variables

In addition to using Accruals Quality (AQ)—which directly measures disclosure quality based on the content of 10-K filings—we also utilize market-based variables to infer disclosure quality. Previous studies (Welker, 1995; Brown and Hillegeist, 2007, among others) suggest that higher transparency influences market outcomes by reducing noise in the information environment. Therefore, by examining various market outputs surrounding public disclosures, we can indirectly assess the quality of those disclosures.

The first market-based measure we use to capture the outcome of disclosure quality is the quoted bid-ask spread (*QSPD*), a common proxy for information asymmetry in finance and accounting research (Kyle, 1985; Venkatesh and Chiang, 1986; Ranaldo and Somogyi, 2021, among others). A higher bid-ask spread indicates greater information asymmetry and thus a noisier information environment. We calculate the quoted bid-ask spread as the time-weighted average of the percentage bid-ask spread over a three-day window surrounding the 10-K filing date. Rather than using the raw spread measure during the event window (*QSPD*[-1,1]), we follow prior studies (Lee and Watts, 2021, etc.) by constructing an abnormal quoted spread (*abnQSPD*), defined as the difference between the event window spread *QSPD*[-1,1] and the spread during a non-event one-month window *QSPD*[-22,-2].

The second measure we use is intraday volatility (*IVOL*), which captures the level of disagreement among investors and serves as a proxy for noise in the information environment, as documented in prior research (Sadka and Scherbina, 2007; Chang et al., 2008; Bollerslev, Li, and Xue, 2018, among others). *IVOL* is calculated as the standard deviation of second-by-second mid-price returns, where the mid-price is defined as the average of the bid and ask prices ((bid + ask)/2). Higher IVOL indicates a noisier information environment. Similar to the bid-ask spread, we construct abnormal intraday volatility (*abnIVOL*) by taking the difference between IVOL during the event window and IVOL during a non-event window. This abnormal measure serves as an additional proxy for the quality of public disclosure.

For the market outcome measures of 10-K quality, we use regression models similar to Equation (4). However, instead of employing direct disclosure quality measures, we classify 10-K filing days based on whether their abnormal quoted bid-ask spread (*abnQSPD*) or abnormal intraday volatility (*abnIVOL*) falls above or below the 30/70 percentiles.

[Insert Table V]

In Table V, Panel A, we present the results for abnormal returns on 10-K filing days, segmented by levels of abnormal quoted bid-ask spreads (*abnQSPD*). The variable *LowQSPD10K* indicates whether a day falls within the three-day window around a 10-K filing and the average *abnQSPD* for that day is in the lowest 30th percentile across firms in that year. Similarly, *MedianQSPD10K* and *HighQSPD10K* correspond to the median 40th and highest 30th percentiles, respectively. In Column (1), the coefficient on the interaction term between *NET* and *LowQSPD10K* is -2.044 (t-statistic = -1.319). The interaction of *NET* and *MedianQSPD10K* has a coefficient of 0.330 (t-statistic = 0.365), while *NET* interacted with *HighQSPD10K* yields a coefficient of 4.145 (t-statistic = 3.551). These results demonstrate a clear upward trend in both the magnitude and significance of the coefficients as *abnQSPD* increases.

In Panel B, the results with the measure *abnIVOL* are presented. Similarly, *LowIVOL10K* (*MedianIVOL10K*/*HighIVOL10K*) indicates whether the days fall within the three-day window of 10-K filing days, and the average *abnIVOL* of those days is in the lowest 30th (Median 40th/Top 30th) percentile across firms' 10-K filing days. The pattern of the coefficients is similar: the coefficients of the interaction terms increase from -2.155 to 0.411, and then to 3.753, with t-statistics increasing from -1.338 to 0.453 and then to 2.655, as the *abnIVOL* increases from the bottom 30% to the top 30%.

These results indirectly strengthen the evidence that only low-quality 10-K filings correct mispricing, as high anomaly returns on filing days are observed exclusively in cases where the market outcomes indicate low disclosure quality.

4.3 Causality Test

In our previous tests, we show that 10-K filings with lower (higher) disclosure quality correct more (less) mispricing. However, endogeneity could be a concern. A natural question is how *NET* interacts with disclosure quality. For instance, the eleven anomalies used to compute *NET* include information on accruals, but our measure of disclosure quality also uses information on accruals. This overlap may compromise the validity of the results. While we partially address this issue by adopting a variety of disclosure quality measures, further identification is still needed.

To address the potential endogeneity problem, we use the natural experiment of the adoption of accounting rule SFAS No. 131 as our identification strategy. As described by Berger and Hann (2003), SFAS No. 131 was issued by the Financial Accounting Standards Board (FASB) and implemented for all firms for fiscal years commencing after December 15, 1997. Before SFAS No. 131, SFAS No. 14 was in effect, which did not require firms to report their earnings separately for different business segments, although firms could voluntarily do so. After the adoption of SFAS 131, firms with multiple business segments were required to disaggregate their earnings for different segments on newly issued 10-Ks. According to Berger and Hann (2003) and Jayaraman and Wu (2019), firms affected by SFAS No. 131 improved their disclosure disaggregation level and had better disclosure quality after adoption. This accounting rule change provides us with an opportunity to use a natural experiment to alleviate the endogeneity problem.

We conduct our testing model following Jayaraman and Wu (2019)'s method. First, we retrieve the 10-K reported segment data from the COMPUSTAT Segment database. Then, for each firm, we identify the last fiscal year it adopted SFAS No. 14 (i.e., the year before SFAS No. 131) and the first fiscal year it adopted SFAS No. 131. We compare the business segments from the two 10-K forms under the old and new standards. If the number of business segments increases, we classify the firm as affected; otherwise, we classify it as unaffected. In our sample, there are 4,423 firms, and 1,174 firms are affected by SFAS 131.

Finally, we perform a regression analysis as follows:

$$R_{i,t} = \beta_1 * NET_{i,t} + \beta_2 * NET_{i,t} * EDays_{i,t} + \beta_3 * EDays_{i,t} + \beta_4 * NET_{i,t} * Unaffected10K_{i,t} + \beta_5 * Unaffected10K_{i,t} + \beta_6 * NET_{i,t} * Affected10K_{i,t} + \beta_7 * Affected10K_{i,t} + Controls + \mu_t + \varepsilon_{i,t} \quad (5)$$

Where $Affected10K_{i,t}$ equals 1 if day t is within the three-day window of 10-K filings of firm i, and firm i is affected by SFAS No. 131, and vice versa for $Unaffected10K_{i,t}$. The regression is estimated separately for the three years before the adoption of SFAS No. 131 and the three years after the adoption, so a Difference-in-Differences analysis is conducted.

[Insert Table VI]

Results are shown in Table VI. Column (1) reports the regression results for the three-year sample when firms still adopt the old accounting rule (i.e., SFAS No. 14). The coefficient of the interaction term of *NET* and *Affected10K* is 1.636, which is statistically insignificant, while the coefficient of *NET* and *Unaffected10K* is -0.053, also statistically insignificant. This result suggests that under SFAS No. 14, there is either no significant difference in the anomaly returns between the two groups of firms, or that affected firms correct more mispricing than unaffected firms on 10-K filing days.

Column (2) reports the results for the three-year sample after firms adopt SFAS No. 131. While the coefficient of the interaction term of *NET* and *Affected10K* is 5.668 (statistically insignificant), the coefficient of *NET* and *Unaffected10K* increases to 8.158 with 1% significance. The difference between the two coefficients is 2.49, meaning that on 10-K filing days, an unaffected firm has expected returns of 7.47 basis points (18.82% annualized) higher than an affected firm, assuming both firms have a *NET* value of 0.03. The anomaly returns on 10-K filing days differ significantly between affected and unaffected firms after the adoption of SFAS No. 131, whereas no such difference is observed under the old standard. Under the assumption of parallel trends, these results suggest that the adoption of SFAS No. 131

caused affected firms to have lower anomaly returns on 10-K filing days. Since the adoption of the new standard improved the disclosure quality of the affected firms, we conclude a causal relationship: better disclosures decrease the ability to correct mispricing.

4.4 Mechanism

Following Goldstein and Yang (2017), we argue that low-quality public disclosures increase the marginal value of private information by contributing to a noisier information environment. In contrast, high-quality public disclosures may crowd out private information acquisition by reducing uncertainty and diminishing the incentive to seek additional insights. Since private information can play a critical role in enhancing price efficiency, this mechanism helps explain why more transparent disclosures are associated with a weaker correction of mispricing.

Our proposed mechanism suggests that the elevated anomaly returns observed on low-quality disclosure days are primarily driven by increased private information acquisition. To empirically test this prediction, we extend our baseline regression model (Eq 4). Specifically, within the subset of low-quality 10-K filings, we further classify the events based on the intensity of private information acquisition. We define two groups: *HighPriv10K* and *LowPriv10K*. Both groups contain only low-quality 10-K filings; however, *HighPriv10K* equals one if the level of private information acquisition around the filing is high, while *LowPriv10K* equals one if the intensity is low.

While private information acquisition cannot be directly observed, measuring it remains a significant challenge. Drawing inspiration from prior literature (Lee and Wang, 2015; Ryan, 2017; Lee and Watts, 2021, among others), which uses EDGAR search volume as a proxy for general information acquisition, we adapt this approach to specifically capture private information acquisition. We argue that investors can extract private information by conducting further analysis on existing public disclosures. Therefore, for firms with higher levels of private information acquisition, we expect investors to search for past filings on EDGAR around the release of new 10-K reports

Based on this hypothesis, we construct our proxy for private information acquisition as follows. First, we obtain the complete EDGAR search log from the SEC website and follow the filtering methodology in Ryan (2017) to exclude IP addresses associated with automated (machine) searches. Second, for each 10-K filing, we exclude search activity targeting the current 10-K document, thereby isolating searches for historical disclosures. Third, we calculate abnormal search activity by subtracting the average daily non-event search volume (measured over the 60 trading days prior to the event window, as suggested in the literature) from the average search volume during the 3-day event window surrounding the 10-K filing. This adjustment helps mitigate concerns that our measure reflects general investor attention or other unrelated firm characteristics.

Using this measure of non-current EDGAR search volume, we classify the intensity of private information acquisition. Within the subset of *LowQuality10K* filings, we assign *HighPriv10K* = 1 to filing days where non-current EDGAR search volume exceeds the cross-sectional median, and *LowPriv10K* = 1 otherwise.

Due to data availability—EDGAR search logs are only publicly accessible for the period from 1996 to mid-2017—we restrict this analysis to the 1996–2016 sample period.

[Insert Table VII]

The results are presented in Table VII. In Column (1), we observe that the interaction terms between *NET* and *MedianQuality10K* or *HighQuality10K* have small magnitudes and are statistically insignificant. This indicates that higher-quality 10-K filings do not contribute meaningfully to mispricing correction, which is consistent with our earlier findings.

Focusing on the *LowQuality10K* subsample, we further divide the observations into *HighPriv10K* and *LowPriv10K* groups based on the intensity of private information acquisition. While the interaction terms between *NET* and both *HighPriv10K* and *LowPriv10K* are statistically significant and positive, their magnitudes differ notably. For *HighPriv10K*, the interaction coefficient is 6.028, implying a 17.93 basis point return when *NET* equals 0.03. In contrast, for *LowPriv10K*, the coefficient is 3.285, corresponding to a return of 9.70 basis points under the same *NET* value.

In Column (2), the regression is conducted without control variables, and the results remain largely consistent.

These results suggest that the mispricing correction associated with low-quality 10-K filings is predominantly driven by firms with higher levels of private information acquisition. This finding provides further empirical support for our proposed mechanism: wherein low-quality disclosures create a noisy information environment that enhances the marginal value of private information.

4.5 Robustness

Our previous results rely on the measure of mispricing and disclosure quality. To ensure the robustness of our findings, we examine whether our results still hold with alternative measures.

4.5.1 Alternative Measure of Mispricing

As described in Section 3.2, we calculate our measure of mispricing, *NET*, by incorporating the 11 anomalies suggested by Stambaugh, Yu, and Yuan (2015). However, one might be concerned that the different effects of disclosure quality could be influenced by other characteristics not directly incorporated in the 11 anomalies, such as size. To address this, we further calculate the mispricing measure *NET97* using the same methodology as for *NET*, but incorporating the 97 anomalies from Mean and Pontiff (2016). We then re-run Eq. (4) using *NET97* instead of *NET*.

[Insert Table VIII]

In Table VIII, Column (1) reports results with control vairables. The interaction terms of *NET97* with *LowQuality10K* show a coefficient of 1.033, while the coefficients for *MedianQuality10K* and *HighQuality10K* are 0.954 and 0.301, respectively. Given that the coefficient for the interaction with *LowQuality10K* is three times larger than that with *HighQuality10K*, the patterns observed are very similar to our main results.

Similar results also hold for Column (2) in which control variables are excluded.

4.5.2 Alternative Measure of Disclosure Quality

While accrual quality (*AQ*) captures a key dimension of 10-K disclosure quality—namely, the opaqueness of earnings information—10-K filings encompass multiple other aspects that contribute to overall disclosure quality. To capture a broader range of these dimensions, we incorporate additional direct measures of 10-K quality, based on both numerical and textual features of the filings.

Building on the theoretical premise that more detailed disclosures improve transparency and reduce information asymmetry, Chen, Miao, and Shevlin (2015) argue that greater disaggregation in financial statements enhances disclosure quality. Following their approach, we adopt disaggregation quality (*DQ*) as our second measure of 10-K disclosure quality. Specifically, balance sheet and income statement items are organized hierarchically according to COMPUSTAT's balancing models. For each high-level "group" account, we calculate the ratio of the number of non-missing data items to the total number of items applicable to a given firm-year. The overall DQ measure is then constructed as a weighted average of these group-level ratios. Higher DQ values indicate greater numerical detail in the financial statements, serving as a proxy for higher-quality disclosure.

In addition to the quality of numerical disclosures, a growing body of literature highlights that textual complexity in financial statements can obscure information and reduce overall disclosure transparency. To complement our numerical measures of 10-K quality, we therefore incorporate a text-based measure of complexity and readability using established techniques from textual analysis. Numerous readability metrics have been developed in the literature—such as the Fog Index—that assess the linguistic difficulty of a document. However, relying on a single index may introduce measurement error or fail to capture the multidimensional nature of textual complexity. To address this, we follow the methodology of Guay et al. (2016) and Bonsall et al. (2017) by constructing a composite readability score (*ReadIndex*), defined as the first principal component of six widely used readability metrics: Flesch-Kincaid, Gunning Fog, RIX, ARI, SMOG, and LIX. These measures evaluate aspects such as sentence length and word complexity in 10-K filings. Higher values of *ReadIndex* correspond to greater linguistic complexity and lower readability, which we interpret as indicative of lower textual disclosure quality.

For both Disaggregation Quality (*DQ*) and *ReadIndex*, we re-estimate their interactions with mispricing using Eq. (4). Specifically, we divide 10-K filings into three groups based on the 30th and 70th percentiles of the DQ and ReadIndex distributions, allowing us to examine how varying levels of numerical disaggregation and textual readability affect the relationship between disclosure quality and mispricing.

[Insert Table IX]

Table IX reports the results. In Column (1), 10-K filings are grouped based on the value of Disaggregation Quality (*DQ*), while in Column (2), filings are grouped by *ReadIndex*. In both cases, a general decreasing pattern in the coefficients of the interaction terms between *NET* and the *Low/Median/HighQuality10K* indicators is observed. For *DQ*, the difference between the coefficients of interaction terms for *LowQuality10K* and *HighQuality10K* is 0.951 (equivalent to 1.96 basis points when NET equals 0.03), while for *ReadIndex*, the corresponding difference is 2.853 (5.89 basis points for *NET* equals 0.03). While *DQ*, and *ReadIndex* each capture distinct dimensions of disclosure quality, these findings consistently suggest that expected anomaly returns on 10-K filing days decline as the quality of disclosure improves. However, compared to *AQ*, the patterns for *DQ* and *ReadIndex* are less pronounced, likely due to greater measurement noise and the relatively lower salience of the specific quality aspects they capture.

In addition to direct measures of 10-K report quality and information environment proxies, we also incorporate an indirect measure of disclosure quality based on timeliness. Prior accounting research (Lambert, Brazel, and Showalter, 2017; Whittred, 1980; Brooks et al., 2023, among others) suggests that disclosure timeliness is closely related to disclosure quality. Specifically, firms engaging in greater earnings management often incur higher auditing costs, which tend to delay their earnings announcements and 10-K filings. Following Brooks et al. (2023), we measure timeliness by calculating *Diff*, defined as the number of days between the fiscal year-end and the 10-K filing date.

[Insert Table X]

Table X reports the averages and trends in the timing differences between fiscal period end dates, earnings announcement dates, and 10-K filing dates. On average, 10-K filings occur 72.7 days after the fiscal year-end, which is about 22.76 days after the year-end earnings announcement. Quarterly earnings announcements, in comparison, happen on average 35.63 days after the quarter-end. Notably, there is a clear downward trend in the lag between the fiscal year-end and 10-K filing dates. For instance, while 10-K filings occurred an average of 85.17 days after the fiscal year-end in 1995, this lag shortened to 58.26 days by 2019. This reduction is primarily driven by a significant decrease in the time gap between earnings announcements and 10-K filings, which fell from 40.53 days to 9.21 days over the same period. In contrast, the average delay between fiscal period end and earnings announcements remained relatively stable. These findings are consistent with the results documented by Bowles et al. (2023).

For 10-K filing days, we re-run Eq. (4), dividing the 10-K filings by the days' difference between fiscal year end and 10-K filing days.

[Insert Table XI]

Table XI reports the results for the regression models. Similar to previous regressions, the variable *Low*/*Median*/*HighDiff10K* equals 1 if the day falls within the event window of 10-K filings, and the days' difference between fiscal year end and 10-K filings is in the bottom 30%, middle 40%, or top 30%, respectively. The interaction terms of *NET* with *LowDiff10K*, *MedianDiff10K*, and *HighDiff10K* have coefficients of 1.493, 2.159, and 6.708, with t-statistics of 1.906, 2.403, and 3.010, respectively. Both the magnitude and significance of the coefficients show increasing patterns. Consistent with our main results, the findings show that anomaly returns increase as the days' difference increases, indicating that lower disclosure quality (i.e., higher days' differences) leads to higher anomaly returns.

The results show consistency, indicating that disclosures with less timeliness correct more mispricing. As we interpret timeliness as an indirect measure of disclosure quality, where more timeliness reflects better public disclosure quality, the tests involving the timeliness of public disclosure provide evidence that our previous results and hypothesis remain robust under this alternative measure of disclosure quality.

4.6 Earnings Announcements

Our study primarily focuses on public disclosure events related to 10-K filings due to the broad availability of disclosure quality measures for these reports. However, the implications of our research extend beyond 10-K filings alone. To generalize our argument regarding the causal impact of disclosure quality, we also examine earnings announcement events.

Measuring the quality of earnings announcements directly is challenging, as these disclosures typically provide a single piece of information—earnings—especially in earlier years. Nonetheless, variations in earnings announcement quality also affect the market environment, allowing our indirect market-based measures of disclosure quality (*abnQSPD* and *abnIVOL*) to be valid not only for 10-K filing days but for earnings announcement days as well. Similarly, we use the timeliness of earnings announcements, measured as the number of days between the fiscal quarter-end and the earnings announcement date (*Diff*), as an additional proxy for disclosure quality.

After estimating disclosure quality for earnings announcements using these proxies, we analyze anomaly returns on earnings announcement days across different levels of *abnQSPD*, *abnIVOL*, and timeliness. To address concerns that the information content of earnings announcements might itself influence the market environment around these events (as documented in prior studies such as Dechow and Dichev, 2002; Burgstahler and Dichev, 1997; Bergstresser and Philippon, 2006), we include controls for standard unexpected earnings, their absolute values, and interactions between these earnings measures and our mispricing metric (*NET*) in our tests.

[Insert Table XII]

Results are presented in Table XII, where Panels A, B, and C report findings using the measures of *abnQSPD*, *abnIVOL*, and *Diff*, respectively. *LowQSPDEDays* (*LowIVOLEDays*, *LowDiffEDays*) indicates whether a given day falls within the three-day window of a firm's earnings announcement and the average *abnQSPD* (*abnIVOL*, *Diff*) for those days lies in the lowest 30th percentile across firms' earnings announcement days in that year. Similarly, *Median/HighQSPDEDays* (*Median*/*HighIVOLEDays*, *Median*/*HighDiffEDays*) correspond to the median and highest percentiles, respectively. *SUEonEDays* (|*SUE*|*onEDays*) denotes the standard unexpected earnings (and its absolute value) on earnings announcement days, calculated following Livnat and Mendenhall (2006), and equals zero on non-earnings announcement days.

In Panel A, Column (1) reports results without controlling for *SUEonEDays*. The coefficients of the interaction terms between *NET* and *Low*/*MedianQSPDEDays* are relatively small (1.710 and 1.234), whereas the coefficient for the interaction between *NET* and *HighQSPDEDays* is substantially larger and statistically significant (6.894).

This pattern suggests that only earnings announcement days characterized by high bid-ask spreads contribute meaningfully to correcting mispricing. Columns (2) and (3) include controls for *SUEonEDays* and |SUE|*onEDays*, respectively, and the results remain consistent in magnitude and significance, indicating that the observed effects are not driven by the information content of the earnings announcements.

In Panel B, a similar pattern emerges: the interaction coefficient of NET with *HighIVOLEDays* is notably larger than those for *MedianIVOLEDays* and *LowIVOLEDays*, although the distinction is less clear when information content controls are excluded (Column (1)). Panel C, which uses the timeliness measure Diff, reports comparable findings.

Overall, compared to 10-K filings, earnings announcements exhibit a similar pattern. This supports the broader conclusion that the negative correlation between disclosure quality and the correction of mispricing is not limited to 10-K filings but generally applies across different types of public disclosures.

4.7 Additional Tests

4.7.1 Existing Information on non-disclosure days

To examine the dynamics of the relationship between mispricing and disclosure quality, we conduct a dynamic analysis. Specifically, using our primary disclosure quality measure, accrual quality (*AQ*), we estimate regression Equation (4) on a rolling 5-year window throughout the entire sample period.

[Insert Figure I]

In Figure I, we plot the coefficients of the interaction terms between NET and

LowQuality10K (β_4) and between NET and HighQuality10K (β_8). On average, the coefficient β_4 for LowQuality10K is around 6, while β_8 for HighQuality10K is around 2. Despite fluctuations over time, β_4 consistently remains higher than β_8, reinforcing the robustness of our results.

The figure also reveals additional dynamics in these coefficients. Notably, there is a noticeable decline around the financial crisis period. Beyond this, we observe a general downward trend in the coefficients for both *LowQuality10K* and *HighQuality10K* over the sample period. This trend can be explained by two potential hypotheses: first, as suggested by McLean and Pontiff (2016), the predictive power of anomalies diminishes over time as investors recognize these patterns and arbitrage them away; second, as documented by Bowles et al. (2024), earnings announcements increasingly incorporate information previously disclosed in 10-K filings, leaving less incremental information in 10-Ks to correct mispricing.

4.7.2 Existing Information on non-disclosure days

An alternative explanation for the results showing that low-quality disclosure corrects more mispricing is that firms publishing high-quality 10-Ks tend to have consistently better disclosure. As a result, if a firm is about to file a high-quality 10-K, the prevailing information about the firm in the market should already be more precise and clearer. For these firms, the correction of mispricing could occur on non-disclosure days before the 10-K filing days. When the high-quality 10-K is finally published, the stock may already be fairly priced, meaning that there may be no mispricing left to correct for those high-disclosure-quality firms.

To rule out this alternative possibility, we estimate the following regression:

$$R_{i,t} = \beta_1 * NET_{i,t} + \beta_2 * NET_{i,t} * Median_{i,t} + \beta_3 * Median_{i,t} + \beta_4 * NET_{i,t} * High_{i,t} + \beta_5 * High_{i,t} + Controls + \mu_t + \varepsilon_{i,t} \quad (3)$$

This regression is run on a sample of non-disclosure days, that is, trading days that are neither earnings announcement days, 10-K filing days, nor 8-K or 10-Q filing days. $Median_{i,t}$ is a forward-looking indicator variable, and it equals 1 if firm i is expected to file a high-quality 10-K (i.e., the *AQ* of the 10-K is in the middle 40%) at the end of the fiscal year of day t, and vice versa for $High_{i,t}$. In this regression, β_1 captures the average abnormal returns for low-disclosure-quality firms on non-disclosure trading days, $\beta_1 + \beta_2$ captures average abnormal returns for median-disclosure-quality firms, and $\beta_1 + \beta_4$ captures average abnormal returns for high-disclosure-quality firms.

[Insert Table XIII]

In Table XIII, Column (1) shows the results. The coefficient of *NET*(β_1) is statistically insignificant, indicating that *NET's* predictive power for daily returns is weak on non-disclosure days for low-disclosure-quality firms. Also, the interaction terms of NET and *High*/*Median* are all insignificant. Column (2) shows the results of the sample excluding only earnings announcement days and 10-K filing days, and the patterns are similar as Column (1).

These results show that, for high/median-disclosure-quality firms, there is no significant higher abnormal return on non-disclosure days compared to low-disclosure-quality firms. This evidence further rejects the hypothesis that firms with high-quality 10-Ks correct their mispricing on non-disclosure trading days.

4.7.3 Overpricing vs Under pricing

Stambaugh, Yu, and Yuan (2015) argue that there is asymmetry in arbitrage, caused by the differences in the ease of buying and short selling. This leads to asymmetry in mispricing: overpricing tends to persist, while underpricing is quickly corrected. As a result, there is generally overpricing, but no significant underpricing. To ensure our results are consistent with Stambaugh, Yu, and Yuan (2015)'s theory, we conduct additional tests.

As shown in Section 3.2, we construct the mispricing measure, *NET*, by summing the number of extreme portfolios to which the stocks belong. Higher *NET* values indicate a higher possibility that the stock return will increase. Positive *NET* values suggest that stocks are underpriced, while negative *NET* values indicate that stocks are overpriced. We divide our previous sample into two subsamples based on the sign of *NET*: the subsample with positive *NET* represents the underpriced group, and the negative *NET* represents the overpriced group. Then, we re-estimate Equation (5) on both subsamples.

[Insert Table XIII]

Table XIII, Column (1) reports results for the underpriced subsample. The coefficient for *NET* and the interaction term between *NET* and *EDays* is now insignificant, indicating that for underpriced stocks, *NET* no longer has predictive power for daily returns on earnings announcement days and non-earnings announcement/10-K filing days. Compared to the full sample results in Table IV, the interaction term between *NET* and *HighQuality10K* still shows a similar coefficient, between 1.0 and 2.0, but the interaction terms for *NET* with *MedianQuality10K* and *NET* with *LowQuality10K* have much less significant coefficients. Furthermore, the decreasing pattern of coefficients for the interaction terms between *NET* and *Low*/*Median*/*HighQuality10K* disappears.

Panel B reports results for the overpriced subsample. In contrast to the underpriced case, where results are weaker or insignificant, the overpriced subsample shows much stronger results. The coefficient of *NET* is 0.839, more than twice the value found in the full sample tests (0.398). For the interaction term between *NET* and *EDays*, the coefficient is 7.313, while in the full sample tests, it was 3.674. Focusing on the coefficients of interest, the interaction term between *NET* and *LowQuality10K* shows an increase of 47% compared to the full sample tests, from 4.247 to 6.191, while the interaction term between *NET* and *HighQuality10K* decreases from 1.508 to -0.981. In the overpriced subsample, the decreasing pattern of coefficients for the interaction terms between *NET* and *Low*/*Median*/*HighQuality10K* becomes stronger, with the difference between the coefficients for *LowQuality10K* and *HighQuality10K* widening from 2.739 to 7.172.

The subsample results indicate that the results are stronger in the overpriced subsample, while the patterns of our results almost completely disappear in the underpriced subsample. Consistent with Stambaugh, Yu, and Yuan (2015), these results can be explained by the asymmetrical predictability of underpricing and overpricing, further validating our results.

5. Conclusion

Traditionally, researchers have believed that disclosure transparency or quality improves price efficiency. However, recent theories, including Banerjee et al. (2018), challenge this view by analytically highlighting the potential negative impact of transparency. Our research provides empirical evidence supporting these theories. We find that anomaly returns are higher on firm public disclosure days when the quality of the disclosure is lower. This result is robust under different measures of disclosure quality, different types of disclosure, and various settings.

According to Engelberg et al. (2018), this suggests that only disclosure with low quality helps correct mispricing. Our findings reject the traditional view that disclosure transparency is beneficial to price efficiency, while aligning with recent theories. We argue that this is due to a crowding-out effect on private information acquisition caused by high-quality public disclosure. While investors' private information may be key to correcting mispricing, such an effect generates a negative causal relationship between disclosure transparency and price efficiency. We test this mechanism by demonstrating that public disclosure with higher information asymmetry and disagreement results in higher anomaly returns.

Our research is the first to explore the negative impact of public disclosure transparency on price efficiency in financial markets. This has important implications for regulators and should hopefully inspire further studies on the potential effects of public disclosure.

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Table I. Summary Statistics

Panel A. Daily Variables

Variable	N	Mean	Std	1%	25%	50%	75%	99%
RET	18,857,822	0.067	4.724	-11.628	-1.563	0.000	1.475	13.642
Volume	18,857,822	0.915	47.302	0.000	0.181	0.460	0.974	6.633
NET	18,857,822	0.003	0.029	-0.070	-0.010	0.000	0.020	0.060

Panel B. Yearly Variables

Variable	N	Mean	Std	1%	25%	50%	75%	99%
AQ	52,311	-0.561	2.433	-7.425	-0.385	-0.128	-0.044	-0.001

This table presents univariate statistics for key variables in the sample from 1996 to 2019. Panel A displays firm-day level variables, including *RET*, which denotes stocks' daily raw return in percentage, *Volume*, representing stocks' daily turnover (share volume divided by shares outstanding) also in percentage, and *NET*, the mispricing measure constructed with 11 anomalies, where higher values indicate a higher probability of being underpriced (construction of NET is described in Section 3.2). Panel B shows firm-year level variable (AQ) corresponding to individual 10-K filings, with definitions and construction methods outlined in Section 3.3.

Table II. Correlation

	RET	Volume	NET	AQ	DQ	Readability
RET	1.000	0.020	0.003	-0.007	0.004	-0.015
Volume	0.020	1.000	-0.002	-0.014	0.036	-0.044
NET	0.003	-0.002	1.000	0.015	0.083	-0.034
AQ	-0.007	-0.014	0.015	1.000	-0.109	0.096

This table presents the correlation of key variables in our sample, with firm-year variables matched to firm-day level variables on a calendar basis.

Table III. Anomaly Returns on Earnings Days and 10-K filing Days

	Dependent Variable: *RET*	
	(1)	(2)
NET	0.391	0.246
	(2.805)***	(1.828)*
NET * EDays	3.657	3.740
	(10.630)***	(10.970)***
EDays	0.06	0.042
	(5.763)***	(4.058)***
NET * 10KFilingDays	3.459	3.202
	(4.239)***	(4.030)***
10KFilingDays	-0.07	-0.065
	(-3.832)***	(-3.640)***
Control	Yes	No
Day Fixed Effect	Yes	Yes
N	18,239,677	18,288,983

This regression tests the effect of the mispricing score on earnings announcement days and 10-K filing days for the sample spanning 1996-2019. The dependent variable is daily stock returns. *NET* is the mispricing measure calculated at the end of the previous month, with a higher score indicating a higher likelihood of being underpriced. *EDays*/*10KFilingDays* are indicator variables for the corresponding three-day event windows. Control variables, as outlined by Engelberg et al. (2018), include a 10-day lag of daily return, the square of daily return, and daily turnover. All covariances are clustered by day, and t-statistics are shown in parentheses, with (*), (**) and (***) indicating significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table IV. Anomaly Returns on 10-K filing Day with Heterogeneous Accruals Quality

	Dependent Variable: *RET*			
	(1)	(2)	(3)	(4)
NET	0.391 (2.810)***	0.247 (1.833)*	0.561 (4.033)***	0.419 (3.119)***
NET * EDays	3.631 (10.568)***	3.710 (10.896)***		
EDays	0.062 (5.964)***	0.045 (4.339)***		
NET * LowQuality10K	4.283 (3.731)***	3.972 (3.521)***	4.619 (4.034)***	4.350 (3.866)***
LowQuality10K	-0.141 (-4.252)***	-0.131 (-4.041)***	-0.139 (-4.203)***	-0.131 (-4.058)***
NET * MedianQuality10K	1.969 (1.913)*	1.885 (1.849)*	2.234 (2.178)**	2.184 (2.149)**
MedianQuality10K	-0.026 (-1.028)	-0.027 (-1.074)	-0.024 (-0.938)	-0.027 (-1.055)
NET * HighQuality10K	1.530 (1.510)	1.361 (1.343)	1.707 (1.687)*	1.558 (1.540)
HighQuality10K	0.009 (0.330)	0.010 (0.349)	0.012 (0.439)	0.011 (0.408)
Control	Yes	No	Yes	No
Day Fixed Effect	Yes	Yes	Yes	Yes
N	18,231,753	18,315,195	18,231,753	18,315,195

These regressions test the effect of the mispricing score on high, median, and low disclosure quality in the sample from 1996 to 2019. The dependent variable is daily return. NET is the mispricing measure calculated at the end of the previous month, with a higher NET indicating a higher likelihood of being underpriced. EDays is the indicator for the three-day window around earnings announcements. High/Median/LowQuality10K are indicator variables for whether a trading day falls within the three-day window around a 10-K filing day, where the 10-K filing is categorized by disclosure quality based on the 30th and 70th percentiles of Accruals Quality of that calendar year. Column (1)(3) includes control variables of 10-day lag of daily return, the square of daily return, and daily turnover while Column (2)(4) exclude those variables.All covariances are clustered by day, and t-statistics are shown in parentheses, with (*), (**) and (***) indicating significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table V. Anomaly Returns on 10-K filing Day with Heterogeneous Market Outcome of Disclosure Quality

Panel A. Quoted Spread		Panel B. Intraday Volatility	
Dependent Variable: RET			
NET	0.144 (0.995)	NET	0.146 (1.003)
NET * EDays	3.45 (8.027)***	NET * EDays	3.423 (7.956)***
EDays	0.006 (0.464)	EDays	0.008 (0.592)
NET * LowQSPD10K	-2.044 (-1.319)	NET * LowIVOL10K	-2.155 (-1.338)
LowQSPD10K	0.193 (5.077)***	LowIVOL10K	0.153 (3.521)***
NET * MedianQSPD10K	0.33 (0.365)	NET * MedianIVOL10K	0.411 (0.453)
MedianQSPD10K	0.038 (1.456)	MedianIVOL10K	0.031 (1.200)
NET * HighQSPD10K	4.145 (3.551)***	NET * HighIVOL10K	3.753 (2.655)***
HighQSPD10K	0.01 (0.371)	HighIVOL10K	-0.223 (-5.916)***
Control	Yes	Control	Yes
Day Fixed Effect	Yes	Day Fixed Effect	Yes
N	9,961,781	N	9,961,781

These regressions test the effect of the mispricing score on the information environment around earnings announcements in the sample from 1996 to 2019. Panel A measures the noisiness of the information environment using abnormal bid-ask spreads, while Panel B measures it using abnormal intraday volatility. The dependent variable is daily return. NET is the mispricing measure calculated at the end of the previous month, with a higher NET indicating a higher likelihood of being underpriced. EDays is the indicator for the three-day window around earnings announcements. High/Median/LowQSPD10K and High/Median/LowIVOL10K are indicators of whether a trading day falls within the three-day window around earnings announcements, where the spread and intraday volatility are categorized into high, median, or low levels of noisiness in the information environment, based on the 30th and 70th percentiles of that calendar year. SUEonEDays (|SUE|onEDays) are the (absolute value of) standard unexpected earnings of that earnings announcement. Control variables include a 10-day lag of daily return, the square of daily return, and daily turnover. All covariances are clustered by day, and t-statistics are shown in parentheses, with (*), (**) and (***) indicating significance at the 0.1, 0.05, and 0.01 levels, respectively

Table VI. Anomaly Returns on 10-K filing Day under Different Accounting Standard

	Dependent Variable: RET	
	(1) Old Standard	(2) New Standard
NET	0.545 (2.450)**	0.844 (2.352)**
NET * EDays	2.976 (4.081)***	4.572 (5.043)***
EDays	0.131 (5.957)***	0.145 (4.623)***
NET * Affected10K	1.636 (0.672)	5.668 (1.491)
Affected10K	-0.012 (-0.166)	-0.116 (-1.218)
NET * Unaffected10K	-0.053 (-0.021)	8.158 (2.681)***
Unafffected10K	-0.02 (-0.324)	-0.350 (-4.743)***
Control	Yes	Yes
Day Fixed Effect	Yes	Yes
N	2,257,594	2,382,247

These regressions test the effect of the mispricing score on 10-K filings affected and unaffected by SFAS131 from 1996 to 2003. The dependent variable is daily return. *NET* is the mispricing measure calculated at the end of the previous month, following Engelberg et al. (2018), with a higher *NET* indicating a higher likelihood of being underpriced. *EDays* is the indicator for the three-day window around earnings announcements. Affected/Unaffected10K are indicator variables for whether a trading day falls within the three-day window around a 10-K filing, with firms classified as affected or unaffected by SFAS131. Column (1) runs on the sub-sample before SFAS131 adoption, while Column (2) runs after the adoption. Control variables include a 10-day lag of daily return, the square of daily return, and daily turnover. All covariances are clustered by day, and t-statistics are shown in parentheses, with (*), (**) and (***) indicating significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table VII. Anomaly Returns on 10-K filing Day with Heterogeneous Disclosure Quality and Private Information Acquisition Activity

	Dependent Variable: RET	
	(1)	(2)
NET	-0.051 (-0.336)	-0.072 (-0.472)
NET * EDays	3.527 (7.875)***	3.520 (7.929)***
EDays	0.045 (4.339)***	0.011 (0.837)
NET *HighPriv10K	6.028 (3.587)***	5.870 (3.493)***
HighPriv10K	-0.114 (-2.312)**	-0.107 (-2.258)**
NET * LowPriv10K	3.285 (2.574)**	3.143 (2.545)**
LowPriv10K	-0.084 (-2.147)**	-0.085 (-2.192)**
NET * MedianQuality10K	1.562 (1.295)	1.452 (1.211)
MedianQuality10K	-0.020 (-0.628)	-0.021 (-0.651)
NET * HighQuality10K	0.268 (0.215)	0.217 (0.174)
HighQuality10K	0.032 (0.972)	0.030 (0.903)
Control	Yes	No
Day Fixed Effect	Yes	Yes
N	9,618,727	9,618,727

These regressions test the effect of the mispricing score on high and low information acquisition activity within the low disclosure quality stocks in the sample from 1996 to 2019. The dependent variable is daily return. NET is the mispricing measure calculated at the end of the previous month, with a higher NET indicating a higher likelihood of being underpriced. EDays is the indicator for the three-day window around earnings announcements. High/Median/LowQuality10K are indicator variables for whether a trading day falls within the three-day window around a 10-K filing day, where the 10-K filing is categorized by disclosure quality based on the 30th and 70th percentiles of Accruals Quality. High/LowPriv10K are indicator variables for LowQuality10K and the non-current EDGAR searching volume is above/below the yearly median. control variables are 10-day lags of daily return, the square of daily return, and daily turnover while Column (2)(4) exclude those variables. All covariances are clustered by day, and t-statistics are shown in parentheses, with (*), (**) and (***) indicating significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table VIII. Anomaly Returns on 10-K filing Day with Heterogeneous Disclosure Quality with Alternative Measure of Mispricing

	Dependent Variable: RET	
	(1)	(2)
NET97	0.465 (7.754)***	0.413 (6.953)***
NET97 * EDays	1.584 (11.594)***	1.534 (11.241)***
EDays	0.082 (8.400)***	0.064 (6.608)***
NET97 * LowQuality10K	1.033 (2.430)**	1.031 (2.464)**
LowQuality10K	-0.12 (-3.851)***	-0.111 (-3.622)***
NET97 * MedianQuality10K	0.954 (2.606)***	0.908 (2.492)**
MedianQuality10K	-0.012 (-0.520)	-0.014 (-0.621)
NET97 * HighQuality10K	0.301 (0.836)	0.300 (0.833)
HighQuality10K	0.02 (0.880)	0.019 (0.812)
Control	Yes	No
Day Fixed Effect	Yes	Yes
N	18,252,670	18,288,862

These regressions test the effect of the mispricing score on High/Median/Low disclosure quality in the sample from 1996 to 2019. The dependent variable is daily return. *NET97* is the mispricing measure calculated at the end of the previous month, with a higher *NET97* indicating a higher likelihood of being underpriced. *EDays* is the indicator for the three-day window around earnings announcements. *High*/*Median*/*LowQuality10K* are indicator variables identifying whether a trading day falls within the three-day window around a 10-K filing day, where the 10-K filing is categorized by disclosure quality based on the 30/70 percentiles of Accrual Quality of that calendar year. Column (1) includes control variables of 10-day lags of daily return, the square of daily return, and daily turnover, and Column (2) excludes those variables All covariances are clustered by day, and t-statistics are shown in parentheses, with (*), (**) and (***) representing significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table IX. Anomaly Returns on 10-K filing Day with Heterogeneous Disclosure Quality with Alternative Measure of Quality

	Dependent Variable: RET	
	(1) DQ	(2) ReadIndex
NET	0.409 (2.933)***	0.39 (2.799)***
NET * EDays	3.73 (10.854)***	3.664 (10.660)***
EDays	0.058 (5.596)***	0.06 (5.772)***
NET * LowQuality10K	2.297 (1.740)*	3.964 (3.428)***
LowQuality10K	0.007 (0.205)	-0.073 (-2.755)***
NET * MedianQuality10K	2.975 (3.416)***	4.268 (4.620)***
MedianQuality10K	-0.014 (-0.536)	-0.098 (-4.018)***
NET * HighQuality10K	1.346 (1.149)	2.001 (1.587)
HighQuality10K	-0.06 (-1.656)*	-0.029 (-0.923)
Control	Yes	Yes
Day Fixed Effect	Yes	Yes
N	18,252,608	18,252,694

These regressions test the effect of the mispricing score on high, median, and low disclosure quality in the sample from 1996 to 2019. The dependent variable is daily return. *NET* is the mispricing measure calculated at the end of the previous month, with a higher *NET* indicating a higher likelihood of being underpriced. *EDays* is the indicator for the three-day window around earnings announcements. *High*/*Median*/*LowQuality10K* are indicator variables for whether a trading day falls within the three-day window around a 10-K filing day, where the 10-K filing is categorized by disclosure quality based on the 30th and 70th percentiles of various disclosure quality measures (Disaggregate Quality for Column (1), and Readability Index for Column (2)) of that calendar year. Control variables include a 10-day lag of daily return, the square of daily return, and daily turnover. All covariances are clustered by day, and t-statistics are shown in parentheses, with (*), (**) and (***) indicating significance at the 0.1, 0.05, and 0.01 levels, respectively.

Table X. Summary Statistics for the Timeliness of Public Disclosure

	Timeliness of 10K filing			Timeliness of Earnings Announcements	
Year	Number of 10K filings	Fiscal year end to 10K filing	Earnings Announcements to 10K Filing	Number of Earning Announcement	Quarter end to Earnings Announcement
1995	943	85.17	40.53	3,098	43.80
1996	2,097	84.94	39.82	14,677	32.04
1997	2,447	84.78	39.53	16,254	32.06
1998	2,285	85.42	40.03	16,495	32.18
1999	2,362	86.02	39.32	16,321	33.33
2000	2,376	85.96	38.48	16,711	33.27
2001	2,009	84.29	37.23	14,994	33.05
2002	2,976	83.08	36.51	13,723	33.14
2003	2,840	76.35	30.12	12,709	33.67
2004	2,799	77.45	27.09	12,521	35.25
2005	2,750	75.78	24.02	12,382	37.38
2006	2,742	74.72	20.23	12,145	39.64
2007	2,683	69.28	16.44	11,940	39.01
2008	2,567	66.86	14.46	11,360	37.56
2009	2,485	65.00	13.62	10,729	37.17
2010	2,436	64.48	13.97	10,469	36.68
2011	2,367	64.33	13.73	10,107	36.70
2012	2,291	63.69	13.36	9,700	36.55
2013	2,411	63.90	12.52	9,857	37.22
2014	2,505	63.22	11.53	10,283	37.73
2015	2,467	62.65	10.59	10,353	37.89
2016	2,432	62.55	9.80	10,075	38.16
2017	2,408	62.50	8.91	9,997	38.76
2018	2,319	62.35	8.84	10,107	38.96
2019	286	58.26	9.21	7,800	34.59
All	58,283	72.70	22.76	294,950	35.63

The table examines the timing of information releases relative to important dates, such as 10-K filings, earnings announcements, and fiscal period ends. Specifically, it reports the mean number of calendar days between these important dates for each year.

Table XI. Anomaly Returns on 10-K filing Day with Heterogeneous Timeliness

	Dependent Variable: RET
NET	0.391 (2.810)***
NET * EDays	3.623 (10.519)***
EDays	0.061 (5.896)***
NET * LowDiff10K	1.493 (1.906)*
LowDiff10K	-0.027 (-1.206)
NET * MedianDiff10K	2.159 (2.403)**
MedianDiff10K	-0.011 (-0.471)
NET * HighDiff10K	6.708 (3.010)***
HighDiff10K	-0.184 (-4.255)***
Control	Yes
Day Fixed Effect	Yes
N	18,250,279

These regressions test the effect of mispricing score on the timeliness of 10-K filings for the sample of 1996-2019. The dependent variable is the daily return. *NET* represents the mispricing measure calculated at the end of the previous month, with higher *NET* indicating a higher likelihood of underpricing. *EDays* is an indicator variable for whether a trading day falls within the 3-day window around earnings announcement days. *High/Median/LowDiff10K* are indicator variables for whether a trading day falls within the 3-day window around 10-K filing days, where the number of days difference between fiscal period end and the disclosure is categorized into high, median, or low days difference, representing disclosure timeliness based on the 30th and 70th percentiles in that calendar year. Control variables include a 10-day lag of daily return, square of daily return, and daily turnover. All covariances are clustered by days. T-statistics are shown in parentheses, with (*), (**) and (***) indicating significance levels of 0.1, 0.05, and 0.01, respectively.

Table XII. Anomaly Returns on Earnings Announcements Day with Heterogeneous Quality

Panel A. Quoted Spread (abnQSPD)

	Dependent Variable: RET		
NET	0.153 (1.057)	0.150 (1.034)	0.149 (1.033)
NET * LowQSPDEDays	1.710 (2.189)**	1.028 (1.127)	0.991 (1.086)
LowQSPDEDays	0.245 (10.646)***	0.192 (7.199)***	0.194 (7.293)***
NET * MedianQSPDEDays	1.234 (2.249)**	1.049 (1.810)*	1.042 (1.799)*
MedianQSPDEDays	0.068 (3.891)***	0.076 (4.095)***	0.078 (4.158)***
NET * HighQSPDEDays	6.894 (9.452)***	6.690 (8.044)***	6.710 (8.059)***
HighQSPDEDays	-0.288 (-13.607)***	-0.249 (-9.952)***	-0.250 (-10.007)***
NET *SUEonEDays		10.971 (3.756)***	
SUEonEDays		0.671 (4.627)***	
NET * |SUE|onEDays			-0.482 (-0.223)
|SUE|onEDays			-0.127 (-1.323)
Control	Yes	Yes	Yes
Day Fixed Effect	Yes	Yes	Yes
N	10,127,317	10,003,618	10,003,618

Panel B. IntradayVolatility (abnIVOL)

	Dependent Variable: RET		
NET	0.153 (1.055)	0.149 (1.030)	0.149 (1.030)
NET * LowIVOLEDays	2.159 (3.012)***	0.985 (1.222)	0.924 (1.150)
LowIVOLEDays	0.345 (17.178)***	0.344 (15.089)***	0.346 (15.266)***
NET * MedianIVOLEDays	0.900 (1.595)	0.754 (1.296)	0.763 (1.311)
MedianIVOLEDays	0.100 (5.565)***	0.100 (5.307)***	0.101 (5.352)***
NET * HighIVOLEDays	4.968 (6.505)***	4.461 (4.893)***	4.462 (4.888)***
HighIVOLEDays	-0.420 (-18.016)***	-0.438 (-15.892)***	-0.440 (-15.966)***
NET *SUEonEDays		10.513 (3.611)***	
SUEonEDays		0.656 (4.546)***	
NET * |SUE|onEDays			-0.032 (-0.015)
|SUE|onEDays			-0.112 (-1.178)
Control	Yes	Yes	Yes
Day Fixed Effect	Yes	Yes	Yes
N	10,127,317	10,003,618	10,003,618

Panel C. Timeliness (Diff)

	Dependent Variable: RET		
NET	0.426 (3.030)***	0.419 (2.981)***	0.419 (2.980)***
NET * LowDiffEDays	-0.826 (-1.144)	-0.779 (-1.025)	-0.776 (-1.020)
LowDiffEDays	0.228 (9.448)***	0.197 (7.510)***	0.198 (7.527)***
NET * MedianDiffEDays	2.733 (5.255)***	3.189 (5.748)***	3.179 (5.732)***
MedianDiffEDays	0.072 (5.222)***	0.045 (2.845)***	0.045 (2.899)***
NET * HighDiffEDays	6.846 (10.099)***	6.836 (7.161)***	6.778 (7.109)***
HighDiffEDays	-0.061 (-2.951)***	-0.104 (-4.100)***	-0.106 (-4.174)***
NET *SUEonEDays		6.506 (2.151)**	
SUEonEDays		0.476 (3.274)***	
NET * |SUE|onEDays			0.854 (0.530)
|SUE|onEDays			-0.077 (-1.080)
Control	Yes	Yes	Yes
Day Fixed Effect	Yes	Yes	Yes
N	18,739,401	18,464,252	18,464,252

These regressions test the effect of the mispricing score on disclosure quality of earnings announcements. Due to data availability, samples Panel A and Panel B are from 2003 to 2017 while Panel C expand from 1996 to 2019. Panel A measures disclosure quality using abnormal bid-ask spreads, while Panel B measures it using abnormal intraday volatility and Panel C using earnings announcements timeliness. The dependent variable is daily return. NET is the mispricing measure calculated at the end of the previous month, with a higher NET indicating a higher likelihood of being underpriced. High/Median/LowQSPDEDays, High/Median/LowIVOLEDays and High/Median/LowDiffEDays are indicators of whether a trading day falls within the three-day window around earnings announcements, where the spread, intraday volatility and earnings announcements timeliness are categorized into high, median, or low levels of noisiness in the information environment based on the 30th and 70th percentiles of that calendar year. SUEonEDays (|SUE|onEDays) represent the (absolute value of) standard unexpected earnings of that earnings announcement. Control variables include a 10-day lag of daily return, the square of daily return, and daily turnover. All covariances are clustered by day, and t-statistics are shown in parentheses, with (*), (**) and (***) indicating significance at the 0.1, 0.05, and 0.01 levels, respectively.

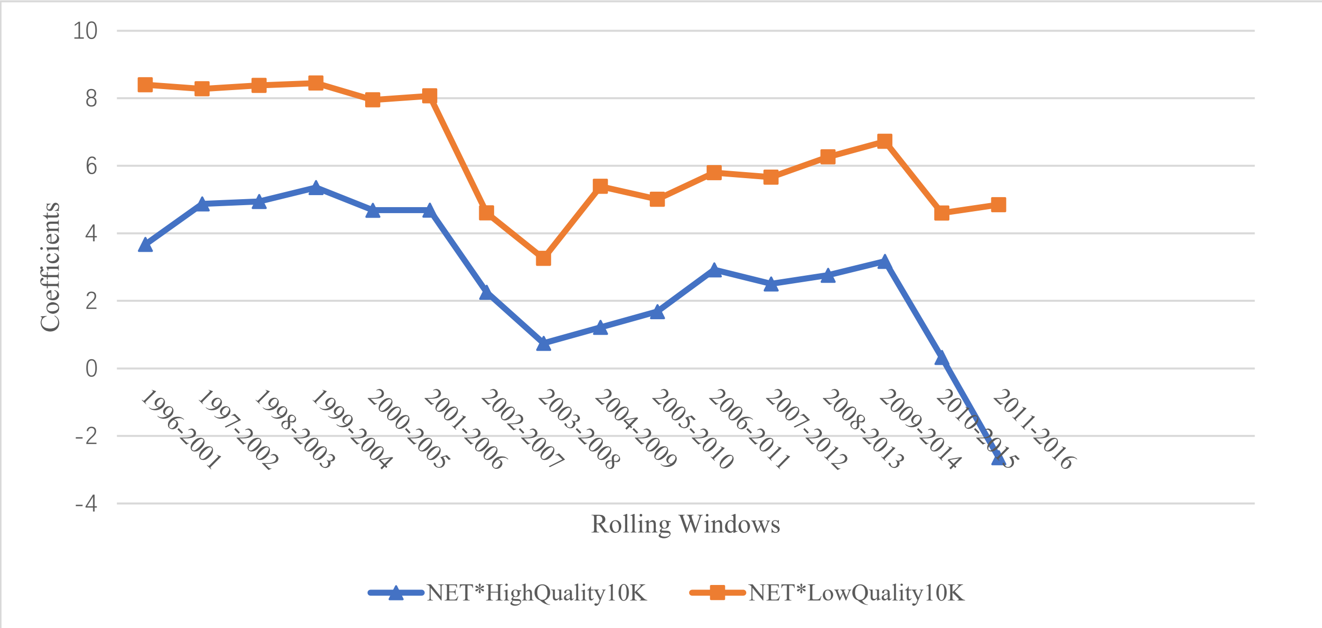

Figure 1. The figure plots the dynamic of the anomalies return on high/low quality 10-K filing days (The coefficients of *NET*HighQuality10K* and *NET*LowQuality10K* in regression model (4)).

Table XIII. Anomaly Returns on Non-disclosure Days Followed by Heterogeneous Quality 10-Ks

	Dependent Variable: RET	
	(1) Excluding EAs/10K/10Q/8K	(2) Excluding EAs/10K
NET	-0.035	0.053
	(-0.211)	(0.323)
NET * High	-0.054	-0.128
	(-0.378)	(-0.898)
High	-0.021	-0.016
	(-3.271)***	(-2.575)**
NET * Median	-0.053	-0.089
	(-0.412)	(-0.703)
Median	-0.016	-0.013
	(-3.599)***	(-2.917)***
Control	Yes	Yes
Day Fixed Effect	Yes	Yes
N	10,427,373	11,683,000

These regressions are run on the sample of non-disclosure days from 1996-2019, which includes days that are not earnings announcement days or important filing days. The dependent variable is the daily return. *NET* is the mispricing measure calculated at the end of the previous month, with a higher *NET* indicating a higher likelihood of underpricing. *High/Median/Low* are indicator variables denoting whether the firm files a high, median, or low-quality 10-K at the end of that year. The partition is based on different measures of Accrual Quality, with categorization based on the 30/70 percentile quantiles. Column (1) exclude earnings announcement days and 10-K/10-Q/8-K fling days while Column (2) exclude earnings announcement days and 10-K fling days. Control variables include a 10-day lag of daily return, square of daily return, and daily turnover. All covariances are clustered by days. T-statistics are shown in parentheses, with (*), (**) and (***) indicating significance levels of 0.1, 0.05, and 0.01, respectively.

Table XII. Anomaly Returns on 10-K filing Day with Heterogeneous Disclosure Quality under Underpricing/Overpricing Subsamples

	Dependent Variable: RET	
	(1) Positive *NET*	(2) Negative *NET*
NET	0.174 (1.513)	0.839 (3.728)***
NET * EDays	-0.334 (-0.598)	7.313 (7.744)***
EDays	0.145 (7.699)***	0.158 (5.499)***
NET * LowQuality10K	1.347 (0.981)	6.191 (2.056)**
LowQuality10K	0.003 (0.058)	-0.064 (-0.753)
NET * MedianQuality10K	0.183 (0.138)	2.933 (0.965)
MedianQuality10K	0.003 (0.062)	0.006 (0.075)
NET * HighQuality10K	1.969 (1.274)	-0.981 (-0.268)
HighQuality10K	-0.095 (-1.766)*	-0.07 (-0.760)
Control	Yes	Yes
Day Fixed Effect	Yes	Yes
N	8,876,129	6,498,859

These regressions test the effect of mispricing score on high/median/low disclosure quality in the sample from 1996-2019.Column (1) runs on the subsample with positive *NET*, while Column (B) runs on the subsample with negative *NET*. The dependent variable is the daily return. *NET* is the mispricing measure calculated at the end of the previous month, with higher *NET* indicating a higher likelihood of underpricing. *EDays* is the indicator for the 3-day window surrounding earnings announcements. *High/Median/LowQuality10K* are indicator variables denoting whether a trading day falls within the 3-day window around a 10-K filing, categorized by disclosure quality based on the 30th and 70th percentiles of various disclosure quality measures (Accrual Quality for Column 1, Disaggregate Quality for Column 2, and Readability Index for Column 3) of the calendar year. Control variables include a 10-day lag of daily return, square of daily return, and daily turnover. All covariances are clustered by days. T-statistics are shown in parentheses, with (*), (**) and (***) indicating significance levels of 0.1, 0.05, and 0.01, respectively.