What drives anomaly decay?

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Abstract

We develop a new variance decomposition to understand the economic channels of how anomalies predictability changes. Our decomposition isolates noise from information and partitions cash flow and discount rate news into market-wide and stock-specific information sources. We observe that the information environment changes over time and affects the profitability of the factor mimicking portfolios. Additionally, we investigate two potential explanations for anomaly decay: academic publication and liquidity recovery. Our findings indicate that both factors contribute to anomaly decay. Specifically, academic publications increase the market cash flow and private firm cash flow shares, while decimalization improves market quality by decreasing noise share. Anomalies not based on accounting information are more affected by academic publications, while those based on accounting information are more impacted by liquidity effects.

JEL classification: G11; G12; G14

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1. Introduction

Previous literature documents the evidence that anomalies deteriorate through time (e.g., Linnainmaa and Roberts, 2018; McLean and Pontiff, 2016, Green, Hand, and Zhang, 2017). It remains poorly studied what changes happen to the information environment of anomalies. Some researchers argue that the publication of anomalies "arbitrageurs' with increased computing power to attack mispricing (Brogaard and Zareei, 2022). In contrast, more recent studies suggest that most of the anomalies perform badly out-of-sample and are likely the fruit of data snooping (Linnainmaa and Roberts, 2018; Welch and Goyal, 2008). There are also researchers arguing that the rise of liquidity is the trigger for the attenuation of anomalies (Chordia, Subrahmanyam, and Tong, 2014). We focus on the effects of academic publication and liquidity recovery to depict the changes in the information components of anomalies across the years.

To address this range of unresolved issues, we develop a new variance decomposition method that can separate cash flow and discount rate information, while at the same time (i) removing noise so as to not contaminate the estimates, and (ii) partitioning each of these information types into a market-wide and idiosyncratic (stock-specific) component. We apply this decomposition to test whether there has been a rise in cash flow or discount rate information, and if so, what the implications of this structural trend are, including how it relates to the amount of mispricing and inefficiency in markets.

Changes in stock prices can be due to news about cash flow or news about the discount rate. However, cash flow/discount rate information plays a different role in mitigating mispricing. For example, passive investing overtook active investment in August 2018, and it stands at about 54% of the total U.S. equity market. However, the rise of passive investing has also generated some concerns regarding their impact on the information reflected in prices. For instance, funds that purchase stocks in baskets/bundles often tend to disregard the cash flow information of individual companies potentially causing that highly valuable (from a market efficiency perspective) information to decline in price. In contrast, discount rate information is unlikely to diminish as it is largely market-wide and therefore incorporated when investors trade in/out of baskets of stocks. The publication of anomalies raises new awareness of the mispricings that exist in the market and drives information movement and capital allocation. Therefore, we examine the role of cash flow/discount rate news in different information natures and further test how publication effect and liquidity improvement shift the information components of factor-mimicking portfolios.

We provide a unified framework to understand the essence of the information in the market by combining two prominent decomposition methods: the *nature* of the information (Hasbrouck 1991, Brogaard, Nguyen, Putnins, and Wu, 2021) and the *channel* of the information (Campbell and Shiller, 1988, Chen and Zhao, 2009). Previous literature assumes that cash flow news and discount rate news are homogenous among different information sources. Hence, the evidence for comparing cash flow news with discount rate news is incomprehensive or even misleading. This paper decomposes the stock return into three types of information: market-wide, public firm-specific, and private firm-specific (in addition to noise). Then we distinguish between two different economic channels of the innovation - information through cash flow news or information through discount rate news. We obtain seven variance components (three information components × two channels + noise) and examine how the varying components of the price process are the impetus of mispricings.

Firstly, we show there is time-serial trends in the information component and the profitability from the factor mimicking portfolios. Cash flow information shares tend dominate the discount rate information shares for hedge portfolios of anomalies. Over time, we note a gradual increase in the public firm cash flow news share, while the Private_CF share gradually becomes the second highest share. The combined shares of Public_CF and Private_CF account for 73% of the return variance, making firm-specific cash flow news highly influential. The noise share peaks show a decline over the years. Additionally, we find that the trend in profitability aligns with the phenomenon of "anomaly decay". Prior to 1998, the factor-mimicking portfolio generated mostly positive returns despite volatility, but after 1998, there were increasing years of losses.

Next, we re-examine the driving forces of the channels of cash flow news and discount rate news. Consistent with previous literature (Chen and Zhao, 2009; Campbell and Vuolteenaho, 2004, Chen, Da, and Zhao 2013), cash flow news is a bigger driver of stock return variance than discount rate news after we account for the contamination of noise. Discount rate news tends to be more systematic and market-wide than cash flow news, which is more idiosyncratic. We explore what drives the time-serial trends in the cash flow news versus discount rate news using high-frequency data. We focus on the role of market exposure (beta), market volatility, institutional ownership, algorithmic trading, and fragmentation. The results suggest that these market factors influence the information components differently, even within the same economic channel (cash flow or news discount rate news).

Lastly, we apply our approach to factor-mimicking portfolios to investigate the impact of the academic publication of anomalies and decimalization (liquidity recovery) in mitigating mispricings. Specifically, we aim to explain the fact that finds portfolio returns are significantly lower out-of-sample and deteriorate over time (Linnainmaa and Roberts, 2018; Mclean and Pontiff, 2016). We examine the informational channels through which the return-predictability of anomalies decays. We find consistent evidence that private firm-specific and market-wide cash flow information shares experience a jump near the year of publication. We establish that academic publications reduce the cost of identifying and correcting mispricing factors and therefore reduce mispricings by increasing the firm-specific and market-wide cash-flow information. The publication effect leads to an increase in the noise share as well. The publication effects suggest divergent evidence for different data categories of anomalies. On the contrary, decimalization, which significantly enhances stock liquidity and reduces trading costs, shows a similar effect on the information components, no matter how the subsamples are divided.

The main contributions of this paper are as follows: first, our paper unifies two prominent decomposition methods to study the heterogeneous effects of different types of information. The heterogeneity is not only in the ratio of the information transmitted through cash flow over that through discount rate is larger for firm-specific information and is smaller for market-wide information, but also in the explanatory power of mispricing measures. Secondly, we explore what drives the time-series trends in the cash flow news versus discount rate news based on high-frequency data. Lastly, we examine the implication of the rise of cash flow news and show how academic publication and enhanced liquidity alter the decomposed information components of hedge portfolios of anomalies.

There are two key distinctions between our paper and previous decomposition papers. First, we account for noise in stock prices to obtain more accurate measures of cash flow and discount rate news. Noise contaminates both discount rate and cash flow under the Campbell (1991) approach, as we calculate the cash flow news component as the residual of discount rate news (Chen and Zhao, 2009). This purifying process into seven components is particularly essential for our decomposition approach because noise shares are relatively larger in our method than that in Campbell decomposition (3-component). Second, we further partition the information into four categories: market-wide information, public firm-specific information, and private firm-specific information and noise. This allows us to understand the nature of the information that shifts the stock price away from its fundamental value. This partition provides a more granular characterization of cash flow and discount rate news.

We construct the seven-component decomposition using the following procedure. First, we decompose information, noise, and discount rate as in Brogaard et al. (2021), and further separate the information innovations w_t into three components (market-wide, public firm-specific, and private firm-specific). Second, we perform the Campbell decomposition (Campbell, 1991) to separate cash flow and discount rate news, but rather than using raw returns as are used in the Campbell decomposition, we use a de-noised discount rate and information from the first step. Then we project each of our three information components on the cash flow or discount rate returns to split each piece of information into a cash flow and discount rate part (six information components). Lastly, we compute the variances and covariances for each information component.

Overall, firm-specific cash flow information comprises the largest contribution to individual stock return variance, accounting for 63% of the return variance (26% for private firm-specific cash flow news and 37% for public firm-specific cash flow news). We see a significant drop in noise share over the years and a monotonically decreasing trend from low-price (low market capitalization) firms to high-price (high market capitalization) firms. This suggests that the information environment is more transparent for large firms and tends to improve over years. We observe the time-serial and cross-sectional variation of the decomposition in the sample. There exist disparities among the information shares across different periods, different firm characteristics subsamples, and among different industries.

In terms of the methodology, our approach combines two main branches in decomposition literature: on one hand, this paper is based on the four-component decomposition in Brogaard, Nguyen, Putnins, and Wu (2021) and the market-wide/firm-specific news decomposition in Morck, Yeung, and Yu (2020). On the other hand, we extend the model and further decompose the information components into cash flow and discount rate sub-components to relate the model to the long-standing area of the asset pricing literature components (Campbell and Shiller, 1988a, 1988b; Campbell, 1991). We overcome the noise-filtering limitations of the traditional decomposition method by relying on low-frequency data to reduce estimation errors. This also allows the variance decomposition to be performed at higher frequencies (e.g., annual decompositions of daily returns) and therefore allows researchers to examine time-series variation in the components of stock return variance.

Our methodology is related to Hasbrouck (1991a, 1991b, 1993), who decomposed the stock price into permanent and transient parts. We back out the unexpected noise to get cleaner information components, and then decompose these components into three types of information. We perform cash flow/discount rate information decomposition to determine the economic channel of the shocks, which is related to Campbell and Shiller (1988a, 1988b), Chen and Zhao (2009), Chen, Da, and Zhao (2013), and Campbell (1991). Our paper provides evidence of the relative importance of cash flow news and discount rate news in each information category (Chen, Da, and Zhao, 2013; Campbell, 1991; Campbell and Ammer, 1993; Vuolteenaho, 2001). The ratio of CF/DR news share of firm-specific news is almost double that of market-wide news. This is consistent with cash flow news being more diversifiable than discount rate news (Vuolteenaho, 2001; Chen et al, 2013), and the diversification effect being stronger with market-wide information.

This paper is also related to the literature on asset pricing anomalies. Researchers have published hundreds of anomalies to capture the predictability of characteristics-based factors (Green, Hand, and

Zhang, 2013, 2017; Hou, Xue, and Zhang, 2016). However, research has shown a loss in the predictive power of those anomalies in post-2003 and post-publication years (Green, Hand, and Zhang, 2017; Mclean and Pontiff, 2016). The essential role of arbitrage is emphasized in explaining the disappearance of anomalies. (Calluzzo, Moneta, and Topaloglu, 2019; Green, Hand, and Soliman, 2011; Chordia, Subrahmanyan, and Tong, 2014). Additionally, data snooping could be an explanation for the bad out-of-sample performance of anomalies (Linnainmaa and Roberts, 2016). We distinguish our paper from previous work by providing a more fine-grained decomposition method and directly examining the changes in information components. Our results suggest that post-2003, there is an increase in the share of firm-specific news (mainly in cash flow news). The result of a staggered difference-in-difference regression for the publication effect provides evidence that investors trade on firm-specific and market-wide cash flow news instead of public firm-specific news. The decimalization suggests an increase in marker-wide cash flow news but decreases in other components including noise share.

The paper is organized as follows. In section 2, we describe our model and elaborate on how to perform the decomposition methodologically. Section 3 presents the summary statistics for our sample. Section 4 presents the empirical results hedge portfolio of anomalies, and determinants of information components. Section 5 and Section 6 present the effect of publication and decimalization. Lastly, Section 7 concludes and offers the key insights of our paper.

2. Methodology

In this section, we highlight our variance decomposition approach by separating each of the information components of variance into cash flow and discount rate parts. One reason for doing so is that by accounting for noise, decompositions of cash flow / discount rate news can be performed at higher frequencies (traditionally, monthly returns are used to minimize concerns about noise), which allows examination of the time-serial and cross-sectional trends in those information components.

First, we review the standard approach for separating cash flow and discount rate news, developed by Campbell and Shiller (1988a, 1988b) and Campbell (1991) and subsequently used in many papers (Section 2.1). We then extend the standard approach by accounting for noise, noting how noise impacts the estimated cash flow and discount rate news (Section 2.2). Finally, we use cash flow / discount rate decompositions to produce the final version of our variance decomposition (Section 2.3).

2.1. The standard approach to separating cash flow and discount rate news

Campbell and Shiller (1988a, 1988b) and Campbell (1991) show, without having to make behavioral or preference assumptions, that an unexpected stock return, $\varepsilon_{r_{t+1}}$, is made up of two parts:

$$\begin{aligned}\varepsilon_{r_{t+1}} &= (\mathrm{E}_{t+1} - \mathrm{E}_t)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j} - (\mathrm{E}_{t+1} - \mathrm{E}_t)\sum_{j=1}^{\infty}\rho^j r_{t+1+j} \\ &= \varepsilon_{CASHFLOWS_{t+1}} + \varepsilon_{DISCOUNT_{t+1}}, \qquad (1)\end{aligned}$$

where $\varepsilon_{CASHFLOWS_{t+1}} = (\mathrm{E}_{t+1} - \mathrm{E}_t)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j}$ is cash flow news and $\varepsilon_{DISCOUNT_{t+1}} = -(\mathrm{E}_{t+1} - \mathrm{E}_t)\sum_{j=1}^{\infty}\rho^j r_{t+1+j}$ is discount rate news, d_t is the log dividend at time t, r_t is the log holding period return at time t, and $\rho \approx 0.96$ is a constant.

The terms in Equation (1) can be estimated from a VAR in which one of the variables is the log stock return.[1] The typical approach is to use the VAR to estimate discount rate news because that does not require information on dividends and then obtain the cash flow news as the difference between the unexpected stock return and the discount rate news, $\varepsilon_{CASHFLOWS_{t+1}} = \varepsilon_{r_{t+1}} - \varepsilon_{DISCOUNT_{t+1}}$. The importance of cash flow news and discount rate news can be quantified by the variance or standard deviation of the two time-series: $\varepsilon_{CASHFLOWS_t}$ and $\varepsilon_{DISCOUNT_t}$.

[1] For example, once the VAR is estimated, one can obtain the time t expectations of returns at $t+2$, $t+3$ and so on (multi-step forecasts from the VAR) from which one can compute $\sum_{j=1}^{\infty}\rho^j \mathrm{E}_t[r_{t+1+j}]$. Repeating this process at time $t+1$ one obtains $\sum_{j=1}^{\infty}\rho^j \mathrm{E}_{t+1}[r_{t+1+j}]$. The difference gives the discount rate news at time $t+1$, i.e., $\varepsilon_{DISCOUNT_{t+1}} = -(\mathrm{E}_{t+1} - \mathrm{E}_t)\sum_{j=1}^{\infty}\rho^j r_{t+1+j} = \sum_{j=1}^{\infty}\rho^j \mathrm{E}_t\left[r_{t+1+j}\right] - \sum_{j=1}^{\infty}\rho^j \mathrm{E}_{t+1}[r_{t+1+j}]$.

2.2. Accounting for noise when separating cash flow and discount rate news

A limitation of the standard approach for separating cash flow and discount rate news is that it does not account for the noise in stock returns. Without accounting for noise, the cash flow / discount rate decomposition can only be reliably performed using low-frequency data such as monthly returns so that the ratio of noise to information remains within acceptable error tolerances. Therefore, the standard approach is limited in its ability to examine time-series variation in the cash flow / discount rate components. For example, with monthly returns and a minimum of 20 time-series observations in the VAR, one can obtain a single value of cash flow and discount rate variance every ten years. Accounting for noise, however, allows us to apply the decomposition to daily data and thereby estimate cash flow and discount rate news variances every year. This higher resolution reveals time-series trends in cash flow and discount rate news and enables us to further partition the information components in our baseline model.

To understand how noise manifests in a standard cash flow / discount rate decomposition and therefore how to approach the task of isolating noise in the decomposition, consider Figure 2 Panel A. A stock return is composed of a discount rate that captures the required or expected rate of return, noise, and information. Noise has an expected and an unexpected component. The expected component arises from reversals of pricing errors. For example, a positive pricing error is expected to reverse resulting in an expected negative return component.[2] The unexpected component of noise reflects random changes to the pricing errors. Thus, the expected return is made up of the discount rate and the return from the expected change in the pricing error.

Insert Figure 1 About Here

[2] There are several reasons why pricing errors can be inferred from past returns and their reversals are somewhat predictable. At the most basic level, bid-ask bounce (trade prices oscillating between the bid and the ask or offer quotes) creates negative serial correlation in returns and therefore a predictable "noise" component of returns (e.g., Roll, 1984). For example, if a stock's closing price is at the bid quote, its next close could be at the bid or the ask/offer, i.e., there is an expected positive noise return. However, negative serial correlation is also found in midquote returns of individual stocks and at longer horizons such as weekly and monthly returns (e.g., Jegadeesh, 1990; Lehmann, 1990; Hendershott and Menkveld, 2014). Reversals in returns at daily through to monthly horizons are driven by imperfect liquidity and the inability for the market to absorb order imbalances without temporarily deviating from efficient prices (e.g., Avramov et al., 2006; Hendershott et al., 2011; Nagel, 2012). The existence of predictable reversals in returns due to temporary price distortions from efficient prices is also supported by market microstructure theory (e.g., Stoll, 1978, Ho and Stoll, 1981; Kyle, 1985; Glosten and Milgrom, 1985).

The unexpected return is driven by information arrivals and shocks to pricing errors (unexpected noise). Therefore, in the standard cash flow / discount rate decomposition, noise contaminates the estimated discount rate news because the expected return reflects the discount rate *and* noise. Noise also contaminates the estimated cash flow news component because: (i) cash flow news is usually calculated as the difference between the unexpected stock return and the discount rate news, which is contaminated by noise; and (ii) part of the unexpected return, which goes into the cash flow news calculation, is noise. To resolve these issues, our modified cash flow / discount rate decomposition first removes noise from both the expected and unexpected returns, resulting in a method that is suitable for higher-frequency data.

First, we start our baseline model with allowing for a time-varying discount rate. The efficient price is:

$$m_t = m_{t-1} + \mu_t + w_t \,, \tag{2}$$

and the stock return becomes

$$r_t = p_t - p_{t-1} = \mu_t + w_t + \Delta s_t \,, \tag{3}$$

where the time-varying drift, μ_t, is the discount rate on the stock over the time t period, w_t is an innovation that reflects new information about the stock's fundamentals, and Δs_t is the change in pricing error. Noise has an expected component ($\mathrm{E}_{t-1}[\Delta s_t]$) and an unexpected component (ε_{s_t}), $\Delta s_t = \mathrm{E}_{t-1}[\Delta s_t] + \varepsilon_{s_t}$. The expected component comes from the fact that pricing errors are temporary and therefore tend to reverse, as discussed above. Consequently, the expected return ($\mathrm{E}_{t-1}[r_t]$) is made up of the discount rate and the expected change in the pricing error, $\mathrm{E}_{t-1}[r_t] = \mu_t + \mathrm{E}_{t-1}[\Delta s_t]$. Similarly, the unexpected return ($\varepsilon_{r_t} = r_t - \mathrm{E}_{t-1}[r_t]$) is made up of new information about the stock's fundamentals and unexpected changes in the pricing error (noise), $\varepsilon_{r_t} = w_t + \varepsilon_{s_t}$.

We empirically separate these components in three steps: (i) estimate the information in each shock similar to our baseline model, (ii) estimate the unexpected noise by subtracting information and expected returns from realized returns, and (iii) estimate the part of expected returns that is due to noise, resulting in an estimate of expected returns that is not driven by noise. The latter is a clean (de-noised) discount rate that is then used in the fourth step of partitioning the information in the first step into cash flow and discount rate components. Specifically, the information-driven innovation in the efficient price is the same as in our baseline model and is estimated from the VAR model shocks and long-run impacts of those shocks: $w_t = \theta_{r_m}\varepsilon_{r_m,t} + \theta_x\varepsilon_{x,t} + \theta_r\varepsilon_{r,t}$. The stock's expected return over the next period, $\mathrm{E}_{t-1}[r_t]$, is the one-period-ahead forecast of the return from the VAR, in the spirit of Campbell (1991). The unexpected noise (unexpected change in the pricing error) is the unexpected return that is not attributed to information: $\varepsilon_{s_t} = r_t - \mathrm{E}_{t-1}[r_t] - w_t$. The expected noise is the part of the expected return that is predicted by past unexpected changes in the pricing error: $\mathrm{E}_{t-1}[\Delta s_t] = \frac{Cov(\mathrm{E}_{t-1}[r_t],\varepsilon_{s_{t-1}})}{Var(\varepsilon_{s_{t-1}})}\varepsilon_{s_{t-1}}$.[3] The remainder of the expected return is the clean (de-noised) discount rate, $\mu_t = \mathrm{E}_{t-1}[r_t] - \mathrm{E}_{t-1}[\Delta s_t]$. Finally, the total change in the pricing error (sum of expected and unexpected parts) is $\Delta s_t = \mathrm{E}_{t-1}[\Delta s_t] + \varepsilon_{s_t} = r_t - \mu_t - w_t$.

Firstly, we break noise into expected and unexpected parts. Subtracting expected noise from the expected return gives the "clean" discount rate. The clean discount rate is similar to the discount rate in Campbell (1991) but purged of noise. Subtracting unexpected noise from the unexpected return gives the "clean" information. The clean information is similar to the cash flow and discount rate information in Campbell (1991) but purged of noise.

Next, we apply a cash flow / discount rate decomposition similar to Campbell (1991) but using the clean discount rate and the clean information. Using the de-noised expected return ($\mathrm{E}_t[\mu_{t+1}]$) in place of the standard expected return ($\mathrm{E}_t[r_{t+1}]$), we estimate discount rate news using the Campbell (1991) approach:

[3] This approach is equivalent to estimating the predictive regression, $\mathrm{E}_{t-1}[r_t] = a + b\varepsilon_{s_{t-1}} + e_{t-1}$, where the estimate of the coefficient b is given by $\hat{b} = \frac{Cov(\mathrm{E}_{t-1}[r_t],\varepsilon_{s_{t-1}})}{Var(\varepsilon_{s_{t-1}})}$ and the part of $\mathrm{E}_{t-1}[r_t]$ that is explained by $\varepsilon_{s_{t-1}}$ is $\hat{b}\varepsilon_{s_{t-1}}$. This approach picks up the first-order negative serial correlation in returns that occurs at daily frequencies due to bid-ask bounce and price pressures. We focus on correcting the first-order serial dependence of returns as their magnitude tends to be stronger than dependencies at further lags (e.g., Table 1 shows the first-order serial correlation of returns is twice as strong as the subsequent order serial correlations) and it helps keep the noise adjustment relatively simple. The serial dependence in returns beyond the first lag creates a conservative error in that we underestimate the variation in expected returns due to noise and thereby remove too little of the variation that would usually be attributed to the discount rate. Therefore, accounting for higher orders or serial dependence in pricing errors would merely strengthen our finding that after correcting for noise, there is considerably less discount rate information than cash flow information and less discount rate news than implied by traditional cash flow / discount rate decompositions that ignore noise.

$$\varepsilon_{DISCOUNT_{t+1}} = -(\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=1}^{\infty} \rho^j \mu_{t+1+j}$$

$$= \sum_{j=1}^{\infty} \rho^j \mathrm{E}_t\left[\mu_{t+1+j}\right] - \sum_{j=1}^{\infty} \rho^j \mathrm{E}_{t+1}\left[\mu_{t+1+j}\right]. \quad (4)$$

Also following Campbell (1991), but using the de-noised unexpected return instead of the standard unexpected return, we estimate the cash flow news at time $t+1$ as the informational part of the return that is not associated with discount rate news:

$$\varepsilon_{CASHFLOWS_{t+1}} = w_{t+1} - \varepsilon_{DISCOUNT_{t+1}}. \quad (5)$$

From the time series of the cash flow and discount rate news, we compute the variances $Var(\varepsilon_{CASHFLOWS_t})$ and $Var(\varepsilon_{DISCOUNT_t})$. We also compute the variance of the noise, $Var(\Delta s_t)$.[4] We then plot the cash flow news, the discount rate news, and the noise as shares of variance.

Figure 2 plots the time series of the cash flow news, discount rate news, and noise, expressed as shares of stock return variance.[5]

Insert Figure 2 About Here

Panel A reports results from the standard model that does not account for noise as represented in Equation (1), while Panel B is the model that accounts for noise and is described in Equations (4) and (5). In the model that does not account for noise, cash flow news is estimated to account for around 75% of stock return variance, while discount rate information makes up around 10%. The remaining variation is attributable to time-series variation in the discount rate itself (15%), which is different from discount rate

[4] The variance of noise differs slightly from our baseline model because we allow for a time-varying discount rate.

[5] In expressing the variance components as "shares" of variance, to make the results comparable to other models in the paper, we must also consider the covariance between cash flow and discount rate news. Given the total information in this model is the same as in the baseline model, to ensure the sum of the information component variances in this model is equal to the variance of information in the baseline model, we allocate a fraction α of $2Cov\left(\varepsilon_{DISCOUNT_t}, \varepsilon_{CASHFLOWS_t}\right)$ to the cash flow news variance and a fraction $(1-\alpha)$ to the discount rate news variance, where $\alpha = \frac{Var(\varepsilon_{DISCOUNT_t})}{Var(\varepsilon_{DISCOUNT_t}) + Var(\varepsilon_{CASHFLOWS_t})}$. Doing so does not change the ratio of cash flow news to discount rate news and, for consistency, we apply this covariance attribution to both the models that account for noise and those that do not.

news.[6] These results are consistent with Vuolteenaho (2002) who also performs a variance decomposition on individual stocks without accounting for noise and finds similar estimates.[7]

Other studies have performed similar decompositions on portfolios of stocks rather than individual stocks (e.g., Campbell, 1991; Campbell and Ammer, 1993). In portfolios, discount rate news plays a larger role, suggesting that cash flow news is more idiosyncratic than discount rate news. The dominance of cash flow information in our stock-level variance decomposition and the fact that cash flow information tends to be relatively idiosyncratic is also consistent with our baseline decomposition, which shows that idiosyncratic information is a far more important driver of individual stock returns than market-wide information.

Figure 2, Panel B adjusts the standard cash flow / discount rate decomposition for noise and reveals some interesting differences. A striking result is that almost all the stock price variation associated with information is driven by cash flow news, with very little variation attributed to discount rate news. In fact, cash flow news is responsible for 72% of stock return variance in the full sample, whereas discount rate news accounts for a little over 3%. It is natural to expect that accounting for noise would decrease both information components as some of the variation labeled as information in the standard models is noise. The interesting observation is that they do not decrease by a similar amount. The decrease in estimated discount rate news is far greater, resulting in a substantial increase in the estimated ratio of cash flow news to discount rate news when accounting for noise.

The results suggest that much of what is usually labeled as discount rate news is actually noise. Why? Chen and Zhao (2009) and Chen, Da, and Zhao (2013) show that misspecification in modeling the discount

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[6] The time-varying discount rate, $\mathrm{E}_t[r_{t+1}]$ in the model that does not account for noise and μ_t in the model that does account for noise, gives rise to variation in returns directly by determining the average rates of return in different periods, whereas the discount rate *news* captures price changes that occur when expectations of the discount rate change and the stock is re-priced accordingly. Given our focus on information and noise, we do not report the time-varying discount rate variance share in the plots.

[7] To better compare with Vuolteenaho (2002), we also calculate the ratio of cash flow news variance to discount rate news variance over the period from 1960 to 1996. Despite differences in data frequency and the VAR model used, the ratio of cash flow news variance to discount rate news variance is about five times in our model, which is very similar to the ratio reported in Vuolteenaho (2002) for the same period of time.

rate can bias the decomposition. Based on our results we argue that at least part of the misspecification of the discount rate in the standard approach occurs because noise creates considerable return predictability, so expected returns are not good measures of discount rates. Noise creates return predictability because pricing errors are stationary, mean-reverting processes. Prices are drawn towards fundamental values in the long run, so a positive noise-driven return shock in one period leads to a negative expected return component over the next period and vice versa. The empirical consequence of pricing error reversals is the widely documented negative serial correlation in returns, which is observed at a wide range of frequencies from the classic monthly reversals anomaly (e.g., Jegadeesh, 1990) to weekly, daily, and intraday horizons (e.g., Roll, 1984). Without accounting for noise, variation in the discount rate is overestimated when the expected/forecast return is taken as an estimate of the discount rate, leading to a substantial overestimation of the discount rate news component.

Estimates of cash flow news are also affected by explicitly accounting for noise, but to a lesser extent due to two opposing effects. These effects are best illustrated by recognizing that cash flow news is the difference between estimated information and estimated discount rate news: $\varepsilon_{CASHFLOWS_t} = w_t - \varepsilon_{DISCOUNT_t}$. First, removing noise shrinks the estimated information shocks (w_t), which tends to decrease cash flow news. But second, as explained above, the estimated discount rate news ($\varepsilon_{DISCOUNT_t}$) is considerably smaller after accounting for noise and this effect tends to increase the estimated cash flow news. The opposing effects explain why the estimated magnitude of cash flow news is less affected by accounting for noise than the estimated magnitude of discount rate news.

An advantage of isolating noise is the ability to apply the decomposition over relatively short windows using high-frequency data. Unlike previous studies, this allows us to examine the time-series variation in the cash flow and discount rate news. Figure 2, Panel B shows that since the late 1990s, there has been a notable increase in the proportion of stock returns that are attributable to cash flow news, mirroring the decrease in noise during the same period. This trend matches our earlier decomposition that shows firm-specific information has become an increasingly important component of stock returns during the past two decades, consistent with the widely held view that financial markets are now more informationally efficient than in previous decades.

2.3. Extended variance decomposition

Armed with a method to separate cash flow and discount rate news at the daily frequency purged of noise, we further extend our baseline variance decomposition by splitting each information component into a cash flow part and a discount rate part. This extended decomposition of information is illustrated in Figure 1 Panel B. Note that the noise and time-varying discount rate components are not shown.

As Brogaard et al. (2021) shows that the random-walk innovations, w_t, can then be decomposed into three parts:

$$w_t = \theta_{r_m}\varepsilon_{r_m,t} + \theta_x\varepsilon_{x,t} + \theta_r\varepsilon_{r,t} \; , \tag{6}$$

and thus we can rewrite the stock returns as

$$r_t = \underbrace{\mu}_{\text{discount rate}} + \underbrace{\theta_{r_m}\varepsilon_{r_m,t}}_{\text{market-wide info}} + \underbrace{\theta_x\varepsilon_{x,t}}_{\text{private info}} + \underbrace{\theta_r\varepsilon_{r,t}}_{\text{public info}} + \underbrace{\Delta s_t}_{\text{noise}} \; , \tag{7}$$

where $\varepsilon_{r_m,t}$ is the unexpected innovation in the market return and $\theta_{r_m}\varepsilon_{r_m,t}$ is the market-wide information incorporated into stock prices, $\varepsilon_{x,t}$ is an unexpected innovation in signed dollar volume and $\theta_x\varepsilon_{x,t}$ is the firm-specific information revealed through trading on private information, and $\theta_r\varepsilon_{r,t}$ is the remaining part of firm-specific information that is not captured by trading on private information ($\varepsilon_{r,t}$ is the innovation in the stock price). And Δs_t is changes in the pricing error.

We estimate the components of Equation (7) using a structural vector auto-regression (VAR) with five lags to allow a full week of serial correlation and lagged effects:

$$\begin{aligned} r_{m,t} &= \textstyle\sum_{l=1}^{5} a_{1,l} r_{m,t-l} + \sum_{l=1}^{5} a_{2,l} x_{t-l} + \sum_{l=1}^{5} a_{3,l} r_{t-l} + \varepsilon_{r_{m,t}} \\ x_t &= \textstyle\sum_{l=0}^{5} b_{1,l} r_{m,t-l} + \sum_{l=1}^{5} b_{2,l} x_{t-l} + \sum_{l=1}^{5} b_{3,l} r_{t-l} + \varepsilon_{x,t} \\ r_t &= \textstyle\sum_{l=0}^{5} c_{1,l} r_{m,t-l} + \sum_{l=0}^{5} c_{2,l} x_{t-l} + \sum_{l=1}^{5} c_{3,l} r_{t-l} + \varepsilon_{r,t} \end{aligned} \tag{8}$$

where $r_{m,t}$ is the market return, x_t is the signed dollar volume of trading in the given stock (positive values for net buying and negative values for net selling), and r_t is the stock return.

The six information components in the extended decomposition are obtained from the following regressions of cash flow and discount rate news on each of the information components from our variance decomposition:

$$\varepsilon_{DISCOUNT_t} = \beta_1 r_{A,t} + \beta_2 r_{B,t} + \beta_3 r_{C,t}$$

$$\varepsilon_{CASHFLOWS_t} = \gamma_1 r_{A,t} + \gamma_2 r_{B,t} + \gamma_3 r_{C,t}, \qquad (9)$$

where the information components are market-wide information ($r_{A,t} = \theta_{r_m} \varepsilon_{r_m,t}$), firm-specific private information ($r_{B,t} = \theta_x \varepsilon_{x,t}$), and firm-specific public information ($r_{C,t} = \theta_r \varepsilon_{r,t}$).[8] From the fitted values, we obtain six sources of variance: market-wide discount rate and cash flow news, $\widehat{\beta_1} r_{A,t}$ and $\widehat{\gamma_1} r_{A,t}$, firm-specific discount rate and cash flow news incorporated through trading on private information, $\widehat{\beta_2} r_{B,t}$ and $\widehat{\gamma_2} r_{B,t}$, and firm-specific discount rate and cash flow news incorporated through public information, $\widehat{\beta_3} r_{C,t}$ and $\widehat{\gamma_3} r_{C,t}$, respectively. In expressing the variance components as variance shares, we add back the covariance between cash flow and discount rate news as before, preserving the total variance attributable to information.

Previous studies have also recognized the shortcomings of the traditional cash flow / discount rate variance decompositions. For example, Chen and Zhao (2009) and Chen, Da, and Zhao (2013) show that in the traditional variance decomposition, because cash flow news is effectively the residual after modeling the discount rate news, misspecification in the discount rate model can bias both the estimated discount rate news and also the estimated cash flow news. The bias can go in either direction depending on whether

[8] There are no error terms in these regressions because there are no omitted variables on the right side, unlike in most regressions that use an incomplete set of explanatory variables. Recall that (i) the estimated information in our baseline model is the same as the information estimated in this extended model, and (ii) both partitions of that information are complete, i.e., market-wide information plus private firm-specific information plus public firm-specific information equals total information, as does cash flow information plus discount rate information. Therefore, the right side of the regressions is a complete explanation of the left side with no unexplained component. For similar reasons, in the regression we get $\beta_i + \gamma_i = 1$ (preserving the total amount of each information type) because if we sum the two equations, the left side is total information and so too is the right side, which is made up of one unit of the estimated market-wide information, private information, and public information.

discount rate variation is underestimated (e.g., missing relevant state variables) or overestimated (e.g., capturing return predictability from sources other than discount rates, such as noise). For example, in Treasuries, where there should be no cash flow news, the traditional decomposition overestimates cash flow news (Chen and Zhao, 2009) whereas in equities the traditional decomposition underestimates cash flow news (Chen, Da, and Zhao, 2013).

The decomposition above in which we remove noise from returns before decomposing them into cash flow and discount rate news tackles the same problem that is identified by Chen and Zhao (2009) and Chen, Da, and Zhao (2013) but using a different approach. Chen, Da, and Zhao (2013) reduce the bias by using actual cash flow forecasts by analysts to identify the cash flow news and using changes in the implied cost of capital to identify the discount rate news. This additional information leads to better predictions of discount rates and cash flows and thereby reduces the bias. In contrast, our approach does not bring additional information into the decomposition but rather removes a substantial source of contamination in the inferred discount rate, that being the return predictability that is due to noise. This correction to the inferred discount rate also affects the estimated share of cash flow news, as one is the inverse of the other. Interestingly, despite the differences in the two approaches, they reach the same general conclusion that in equities, cash flow news is a more important driver of individual stock return variation than previously believed based on the traditional decomposition. Our approach has the advantage that it requires no additional data and is therefore widely applicable to a long period of time and on a global scale, whereas the approach of using analyst forecasts constrains the time period, the cross-section, and the markets in which the decomposition can be applied.[9]

[9] The two approaches to reducing the bias are complimentary in that neither subsumes the other and, potentially, they could be combined. In our decomposition that focuses on removing noise from returns, one could bring additional identifying information into the decomposition when it is available, like the earnings forecasts of analysts as per Chen, Da, and Zhao (2013). Similarly, in decompositions such as Chen, Da, and Zhao (2013) one could add an additional step of removing noise from returns to improve the decomposition as per our approach. Therefore, future work on cash flow / discount rate news might combine the two approaches.

3. Data

First, we describe the data used in our decomposition method and main tables in Section 3.1. Then in Section 3.2, we report the summary statistics of the variance components in the full sample and discuss the time-serial and cross-sectional variations of the estimated seven component shares. Next, in Section 3.3, we illustrate how we construct the hedge portfolios of anomalies, which we use to examine the changes in the information environment time-serially. We focus on two major events: publication of anomalies and decimalization.

3.1. Data

For the decomposition, we include all the common stocks listed on the NYSE, AMEX, and NASDAQ from 1956 to 2021. We obtained daily stock returns, market capitalizations, and volumes from the Center for Research in Security Prices (CRSP). We remove duplicate stock-day observations and observations with a missing return, missing volume, or missing price. We require at least 20 valid daily observations for each stock-year for our VAR estimation and remove stock-years in which any of the variance components are estimated to be zero. We use Hasbrouck pricing error ((lower bound) standard deviation) as our dependent variables in our empirical analysis. The data to calculate Hascrouck pricing error comes from TAQ covering the period from 1993 to 2020. In all regressions, we take the log of the variance of information components to eliminate the right skew (in discount rate variables)[10]. Then we winsorize our mispricing measures at 2.5% and 97.5% levels to ensure the quality of data. Our sample contains on average 4029 firms per year and a total of 16966 firms.

Then we investigate the key drivers for the six information components by constructing the following variables. We use the absolute value of beta (the coefficient of market excess return in Fama Frech 3-factor model regression based on a 3-month rolling window (66 trading days)) to measure the exposure to market risk. We download the CBOE S&P 500 Volatility Index from CRSP as the measure of market volatility[11].

[10] We also test the level of variance in the regression, the results still hold.
[11] Source: yahoo finance

We construct the Institutional Ownership and Concentration variables using Thomson-Reuters 13F data[12]: Institutional Concentration (IC) is captured by the Herfindahl-Hirschman Index that uses all institutional holdings of a particular security and Institutional Breadth (IB) simply represents the number of institutions owning the stock during the quarter[13]. We follow Weller's (2018) paper to construct the algorithmic trading variables (Cancel_to_Trade) and the fragmentation variable (Herfindahl-Hirschman Index of trading volume on different exchanges)[14].

Table 1 report the summary statistics of stocks' characteristics, mispricing measures, and decomposition components, drivers of components, etc.

Insert Table 1 About Here

3.2. Variation of estimated shares

Table 2 reports the summary statistics of the seven variance components from our decomposition approach (six information components and a noise component, expressed as shares that sum to 100%).[15] The estimated variance components are winsorized at 5% and 95% each year. The pooled sample results are presented in Panel A. Panel B shows the results separately for the two subperiods, before and after 1997. Results for size, price, and industry subgroups are presented in Panel C, D, and E, respectively. Consistent with our earlier observation corroborating Chen, Da, and Zhao (2013) that cash flow news is a much larger

[12] The replication code are available from WRDS: https://wrds-www.wharton.upenn.edu/pages/support/applications/institutional-ownership-research/institutional-ownership-concentration-and-breadth-ratios/

[13] The institutional holding data are on a quarterly basis and other independent variables are on a daily basis

[14] The data are available from MIDAS (Market Information Data Analytics System): https://www.sec.gov/marketstructure/downloads.html

[15] The denominator of the shares is the sum of the information and noise components of variance, similar to our baseline variance decomposition model. To keep the baseline model parsimonious, we assumed the expected return was equal to the discount rate. In the extended model, we instead decompose the expected return into a "clean" or "denoised" discount rate and an expected change in the pricing error, which we add to the noise term. Therefore, while the baseline model assumes the changes in pricing errors (noise) are unpredictable and are captured by innovations in the VAR, the extended model allows for an additional predictable noise component in returns. This difference in modelling assumptions leads to a somewhat lower estimated noise share in the extended model compared to the baseline decomposition (24.79% vs 30.71% in the baseline model) and correspondingly the information shares are somewhat higher in the extended model.

driver of individual stock returns than discount rate news, we also find that the cash flow parts of the market-wide and firm-specific information components are much larger than the corresponding discount rate parts. Overall, firm-specific cash flow information comprises the largest contribution to individual stock return variance, accounting for 63% of the variance (the sum of the CF columns for $PrivateInfoShare$ and $PublicInfoShare$ in Table 2 Panel A).

Insert Table 2 About Here

Corresponding to improving market efficiency, there is an increase in cash flow news share: an increase in firm-specific cash flow news explains the time-serial variation (Panel B); while an increase in market cash flow news explains the cross-sectional variation (Panel C/D). Table 2 Panel B suggests that the noise share has significantly dropped post-1997, while we have seen the share shifts from noise to firm-specific cash flow information. Cross-sectionally, the decrease in noise share from small firms to large firms offset the increase in market-wide information. The combined firm-specific CF news remains relatively stable. Therefore, the variation of market CF news and noise explains the cross-sectional variation. The monotonically downward trend in the noise share from low-price (low market capitalization) firms to high-price (high market capitalization) firms in Panel C (Panel D) suggests that the information environment is better for larger firms. Correspondingly, we see an upward trend in Market_CF, Market_DR, Private_CF, Private_DR, and Public_DR information shares and a decreasing trend in Public_CF information shares from Q1 to Q4. Larger firms create a more effective information environment by closely connecting to market-wide information and revealing private firm-specific information via trading. Small-cap firms have a larger share of public cash flow news and a smaller share of private information disclosed via trading. The difference between the highest quartile and lowest quartile is significant at a 1% significance level for all seven components.

What is perhaps more interesting is that the ratio of cash flow to discount rate news differs across the three information components. The differences are consistent with the notion that cash flow news tends to be more idiosyncratic than discount rate news. For example, the ratio of cash flow news to discount rate news in firm-specific information is around 27 times, whereas in market-wide information it is around 12 times. We observe this relation in all price and size quartiles as well as industry groups. This finding helps reconcile differing results in the literature: when variance decompositions are performed on portfolios of stocks (e.g., Campbell, 1991; Campbell and Ammer, 1993), in which most of the firm-specific variation is canceled out through diversification, leaving predominantly market-wide information, discount rate news tends to play a larger role than when variance decompositions are performed on individual stocks (e.g., Vuolteenaho, 2002; Chen et al., 2013). The diversification effect is stronger with market-wide information than with firm-specific information.

Insert Figure 3A About Here

Figure 3A plot the trend of the seven decomposed components for an individual stock. As aligned with the table of summary statistics, cash flow news dominates discount rate news. We observe different trends of the cash flow components across time, while discount rate news shares are relatively flat. The trend of cash flow news illustrates the heterogeneity in the cash flow information of different information natures. Public_CF news accounts for the highest variance share among the seven components. There is a slight upward trend in the public cash flow news share and a downward trend in the market-wide cash flow news share over time. Surprisingly, we observe fluctuations in the private firm-specific cash flow news, but we are unable to identify any significant upward or downward trend. The noise share peaked in 1993 and then start going down after that.

3.3. Hedge portfolio returns of anomalies

The 204 predictive firm-level characteristics are available from Chen and Zimmermann (2020)'s Open Source Asset Pricing website[16]. We follow Green, Hand, and Zhang (2017) to construct daily hedge

[16] https://www.openassetpricing.com/data/

portfolio return and signed dollar volume based on the monthly anomalies variables. In addition to the anomaly data, we download the return and volume data from CRSP. We only focus on the continuous variables to construct the long-top-short-bottom decile portfolio (and ignore indicator portfolios). We deliberately make results more conservative by focusing on non-microcap stocks. The decile breakpoints are based on all-but-microcap stocks in NYSE to avoid overweighting microcaps (as in Green et al (2017)). The realized return/volume in the top/long and bottom/short deciles are value-weighted by the firms' market capitalization at the end of month $t-1$[17]. We assume that annual accounting data are available at the end of month $t-1$ if the firm's fiscal year ended at least six months before the end of month $t-1$ and that quarterly accounting data are available at the end of month $t-1$ if the firm's fiscal quarter ended at least four months before the end of month $t-1$.[18] The final sample ready for decomposition consist of 168 anomalies on a daily basis and 100,544 portfolio-month observations. We remove all the observations that have a missing value for realized return or signed dollar volume. Similarly, we winsorize the decomposed information components at 5% and 95% for each year. A description of the characteristics can be found in Table 2 in Chen and Zimmermann (2020).

Insert Figure 3B About Here

Figure 3B presents that the cash flow information shares also dominate the discount rate information shares for hedge portfolios of anomalies, like the result of individual stocks. The three discount rate news components (Market_DR, Private_DR, and Public_DR) only account for a small proportion of return variance and comove through time. However, the three cash flow components show heterogeneous fluctuations across years. We observe a gradual upward trend over time for the public firm cash flow news share. Public_CF news of anomalies' hedge portfolio accounts for the highest variance share among the

[17] We also constructed equally weighted portfolio as robustness check.
[18] We construct the monthly anomalies data based on the public-available code on their website: https://sites.google.com/site/jeremiahrgreenacctg/home

seven components and the percentage is on average higher than that of stocks. The diversifiability of idiosyncratic cash flow news in market-wide news is stronger in the constructed anomaly hedge portfolios, so we observe a lower maket-related news shares. Not surprisingly, the Private_CF gradually grow to be the second highest share, making firm-specific cash flow news 73% of the return variance (Public_CF and Private_CF shares combined). During the 1980s and 1990s, market-wide information share reaches its lowest point but begins to recover after 2000. As a result, the market-wide cash flow shares is the lowest among the three cash flow news shares. The noise share peaks around 1986 and starts shrinking after.

Insert Figure 3C About Here

Next, Figure 3C illustrates the time-series trend in profitability of the trading strategy that utilizes factor-mimicking portfolios of firm characteristics. Firstly, we restructure the long-short portfolio every month and compute the daily returns of the portfolio that mimics the factor. We subsequently aggregate the monthly returns from the daily returns. Finally, we average the monthly returns of each anomaly per year[19]. Overall, we discover that the trend aligns with the "anomaly decay" phenomenon. Prior to 1998, the factor-mimicking portfolio generates mostly positive returns, despite of volatility in the returns. However, after 1998, we observe a growing number of years with losses. Furthermore, the figure displays some intriguing periodical patterns. Specifically, there is a pronounced dip in monthly returns during the year 2008, suggesting that the global financial crisis also led to substantial losses in the long-short portfolios of anomalies. Considering the existing evidence in previous literature regarding the declining predictability of firm characteristics and profitability from the factor-mimicking portfolio, we examine alterations in the informational landscape of anomalies.

[19] We eliminate anomalies with excessive performance (monthly returns > 100%) to avoid the potential contamination of outliers.

4. Determinants of Profitability, Mispricing, and Information Components

4.1. Profitability

We focus on the long-short anomaly portfolio returns, often used as evidence of cross-sectional mispricing in the literature (Dong, Li, Rapach, and Zhou, 2021). The long-short portfolio returns are calculated as the monthly return of the hedge portfolio times the sign of predictor in the original published paper (provided in Chen and Zimmermann's signal document). We perform the VAR estimation on an annual basis to ensure the precision of estimation, then we calculate the variance components by month. The independent variables are the monthly variance of information components[20]. We perform the regressions on the monthly frequency as the information dissemination and recovery of mispricings is a relatively slow process, especially after the initial release of the anomalies. All the regressions are contemporaneous and include factor fixed effects (γ_j) and year fixed effect (τ_t), with standard error clustered on factor level. The return of the portfolio are calculated as value-weighted. We introduce the following regression model:

$$Ret_{j,t} = \alpha + \Sigma_j \beta_i \times VarComponent_{j,i,t} + \tau_t + \gamma_j + \varepsilon$$

Table 3, Column (1) reports the result of long-short portfolio. Table 3, Column (2) and Column (3) report the regression result of the long (high) and the short (low) portfolio of each anomaly. Firstly, the positive effect of noise on the profitability is robust across the three columns. As the informational environment becomes more opaque, arbitrageurs have greater opportunities to trade and generate profits from private information. Column (1) suggests that the long-short portfolio return is negatively correlated with the three discount rate news variance. Nevertheless, the return exhibits no correlation with the variance of cash flow news, which differs from the outcome in the long/short portfolios.

Insert Table 3 About Here

[20] We do not use the shares of the information components to avoid the mechanical issue that the shares sum to 100%

There are noteworthy differences in the correlation between the monthly returns and the variance components across the long portfolio of Column (2) and the short portfolio of Column (3) in contrast to Column (1). Specifically, market-wide cash flow news and public firm cash flow news variance are negatively associated with the profitability of long-short portfolios, while the monthly return displays a positive relationship with both the noise share and private firm cash flow information. Although the three cash flow components display significance in the one-side (long or short) portfolio, they eventually cancel out when constructing the hedging portfolio. Therefore, we will only observe significance in the discount rate estimations. Particularly, the significant positive estimation of Private_CF is primarily observed in the long side of the portfolio.

These findings support our hypothesis that greater opacity in informational environments leads to increased opportunities for arbitrage. Sophisticated investors, such as institutional investors, are more capable of taking advantage of the arbitrage opportunities in anomalies regarding firm-specific information. The informational cost and information asymmetry allow the investors with informational advantage to make a profit through trading on firm-specific news.

4.2. Mispricing

Next, we examine the relation between the return volatility and information variance components. We use the monthly return variance of factor-mimicking portfolio as the dependent variable and the variance of the information components as the independent variables. The following estimation is introduced:

$$Ret\_Variance_{j,t} = \alpha + \Sigma_j \beta_i \times VarComponent_{j,i,t} + \tau_t + \gamma_j + \varepsilon$$

Insert Table 4 About Here

The results presented in Table 4 exhibit consistency across the three columns. Nearly all six components' variances display a positive association with the return variance, with the exception of Public_DR in Column (1). The hedging effect of the information components between long portfolio and short portfolio is not as strong as observe in the monthly return regressions in Table 3. The noise component does not contribute to the return variance in any of the three portfolios. Interestingly, incorporating additional information does not increase the stability of the anomalies' hedge portfolio return. Instead, it amplifies the return volatility.

4.3. Drivers of Components

In the previous sections, our findings demonstrate a correlation between the information component and mispricing, as well as the profitability gained from trading on those mispricing factors. However, the forces that drive the information components' movement remain poorly understood. The mispricing can be a result of an absence of information (uninformed trading), aggressive informed trading (e.g., Grossman and Stiglitz, 1980; Kyle 1984, 1989; Collin-Dufresne and Fos, 2016), and uncompounded private information (Kyle, 1985; Glosten and Milgrom, 1985). Hence, it is equivalently important to understand the drivers of the information components before we investigate how academic publication and decimalization affect the information components. In this section, we bridge the external structural factors with mispricing through the information components - the intermediary variable. We provide indirect evidence on how the market structure changes shape the information environment by altering the information shares.

4.3.1. Exposure to market-wide risk

We test how the exposure to market-wide risk impacts the information components. In our hypotheses, Higher exposure to market risk will increase the market-wide news shares as a larger share of return variance is explained by the market-wide risk by definition. A higher exposure to market-wide risk/ a higher level of market risk increases the market-related shares and reduce other information component shares. We adopt two measures to gauge the sensitivity to market-wide risk: the first measure is the coefficient of market excess return (absolute value of beta) in the Fama French 3-factor model; the other one is the CBOE S&P 500 Volatility Index which measures the market volatility. The main result is displayed in the first two rows of Table 3.

Insert Table 5 About Here

The result of the regression of beta in Table 5 is consistent with our prior hypotheses: a higher exposure measure to market risk measured by beta increases the share of market-wide cash flow news and decreases the remaining shares. A higher beta implies a stronger exposure to systematic risk or market-wide risk and hence a larger share of the corresponding market-related information components. The result of VIX provides some complimentary but not contradictory evidence. Higher market volatility increases the shares of market-wide cash flow news as well as market-wide discount rate news. The result indicates that a more volatile market requires a higher market-wide discount rate to compensate the investors.

4.3.2. Trading Environment

Table 5 Row 3 to Row 6 respectively study the drivers including algorithmic trading (Row 3), fragmentation (Row 4), and institutional holdings (Row 5 and Row 6). Sophisticated investors traded more on firm-specific information if they possess an informational advantage over other investors. Trading is the information-revealing process to incorporate uncompounded information and mitigate information asymmetry. The variations in the trading environment should have a real impact on the information-transmission channels. Therefore, we investigate how the factors of trading environments affect information environments.

We construct an algorithmic trading (AT) index following the method in the codebook of SEC MIDAS and stick to thec Cancel_to_Trade variable[21]. Algorithmic trading (AT) *enhances market efficiency with respect to public information conditional on that information being revealed by other sources* (Weller 2018; Zhang 2017; Chakrabarty, Moulton, and Wang 2017). Public information can be both market-wide information and public firm-specific information. From the coefficient of the Cancel_to_Trade variable, we find a consistent result that AT enhances the shares of public firm information and market-wide information share and depresses the shares of private firm-specific cash flow information. Smart algorithmic trading

[21] We also perform regression on oddlot ratio and trade to order volume for robustness check, the general result holds.

provides more liquidity in the market to reduce the cost of trading and information transmission. In contrast, we find evidence that algorithmic trading harms the private firm-specific information revelation rather than boosts it.

Then we move to the effect of fragmentation on the information components. More fragmented stocks have lower transaction costs and fragmentation is associated with greater market efficiency (O'Hara and Ye, 2011). We calculate the Herfindahl-Hirschman Index (HHI) of trading volume on different exchanges on a daily basis. A higher HHI means that stock is more concentrated on one or several exchanges and therefore, lower fragmentation. More fragmented stocks are associated with a higher share of Market_CF and Private_CF but a lower share of Market_DR, Public_DR, Private_DR, and Public_CF. We are unable to establish the conclusion that fragmentation leads to great market efficiency. However, this does provide an additional layer of evidence that the (private) firm-specific cash flow news associated with fragmentation plays an essential role in improving market efficiency combined with our findings regarding publication effects of anomalies on firm-specific cash flow news share.

Lastly, we check how institutional holdings affect the information environments. Institutional investors are sophisticated investors, who can remove market anomalies and reveal information to the rest of the economy through active trading (Ye, 2012). We calculate the institutional Concentration (IC) and Institutional Breadth (IB) to measure the institution ownership (Chen, Hong, and Stein 2002). Table 5 suggests that the breadth of institutional investors has an impact on the private firm-specific information shares. More dispersed institutional investors (measured by lower HHI_inst) are also correlated with higher market-related and private firm-related information shares. The impact on public firm-specific information is the opposite sign. Passive institutional investors tend to trade on benchmark information and digest private firm information instead of public firm-specific information.

5. Publication Effect

Mclean and Pontiff (2016) show that the predictability decay post-publication and the publication effect account for more than 50% of the shrinkage in the long-short return. We calculate hypothetical value-weighted hedge portfolio return and signed dollar volume using the equity market value for month t-1. We aim to investigate which information components could directly explain the decay of the predictability of anomalies. We find that investors learn from publications, and reveal more firm-specific information through trading, but market efficiency by increasing noise share. We exploit the academic publication of these characteristics-based anomalies as the exogenous shock and see which factors contribute to the loss in the predictability of anomalies. Engelberg, Mclean, and Pontiff (2016) argue anomalies can be classified into three categories: risk (discount rate related), mispricing (cash flow related), and data snooping. Despite Engelberg, et al. (2016) providing evidence that the decay comes from biased investor expectations about cash flows, we also find the evidence to support not only biased expectation but also the risk-related hypothesis.

We adopt staggered diff-in-diff to consider that the causal impact of publication takes effect in different years for different anomalies. If the rollout is random for the publications of anomalies, we can approximately conclude that it gives us a causal relationship between the publication of anomalies and the shifts in these information component shares. We run the following regression, where j represents each anomaly and t represents the years.

$$InforShare_{j,t} = intercept_j + \beta_j * Post - Publication_{j,t} + \gamma_j + \theta_t + \varepsilon_{j,t} \tag{12}$$

Insert Table 6 About Here

The results of staggered difference-in-difference regressions also indicate that the private firm-specific cash flow and marker-wide cash flow information news shares expand in the post-publication period. We also see a significant reduction in the public firm-specific cash flow news share. We also find evidence for public risk-related anomalies as the public_DR share increase after publications. The result of staggered difference-in-difference regressions consolidates our statement that the publication of characteristics-based anomalies enhances the transmission of private firm-specific information and market-wide cash flow information. When we further decompose the long portfolio and short portfolio separately, we discovered a striking difference in the publication effect between long and short portfolio. Specifically, the effects on the two portfolios are almost opposite. In the long portfolio, there was a significant increase in firm-specific cash flow information shares and a corresponding decrease in the noise share. Conversely, the short portfolio experiences the opposite effect.

As the anomalies come from different data categories and own different information structures, the publication effect should also be heterogenous on different anomalies depending on the data source. Following Chen and Zimmermann (2020), we also divide the anomalies into two (but less granular) groups: Accounting-based anomalies and Non-Accounting-based anomalies. Table 7 Panel B – Panel C report the results of staggered diff-in-diff by subgroup. Interestingly, the results of our study of accounting-based anomalies reveal an increase in the noise share, which suggests that the publication of anomalies does not necessarily enhance market efficiency. The coefficients of Market_CF and Private_CF, on the other hand, remain largely unchanged. Given that accounting information is generally available before publication, anomalies based on accounting information may not benefit significantly from academic publication and may even harm market efficiency.

Insert Table 7 About Here

Non-Accounting-based Anomalies exhibits different patterns. Firstly, the information components undergo significant shifts since their publication. Market_CF share and Private_CF share increase, suggesting that revealing anomalies actually induce arbitrages to correct the market-wide and private firm-specific mispricings. The noise share shrinks, indicating that Non-Accouting anomalies benefit from the publication and improve the market efficiency. Also, the Public_CF share decreases, while Public_DR share decreases as well. The structural differences in different types of anomalies might reconcile the conflicting evidence on whether the anomaly decay is a result of academic publication or data mining. From the results in Table 7, non-Accounting-based anomalies are more likely to be true anomalies than Accounting-based anomalies, and the publication of non-Accounting-based anomalies improve the market quality by correcting the market and private firm mispricings.

6. Decimalization

Some researchers argue that the recovery of liquidity (measured by the inverse of effective spread) causes the stock to be traded at a lower cost and mispricing to attenuate over time. So we test liquidity as another explanation for anomaly decay. We use the Securities and Exchange Commission decimalization regulation as an exogenous shock to stock liquidity in 2001 (Brogaard, Li, and Xia, 2017; Fang, Tian, and Tice, 2014). Following their methodology, we construct the treatment group and control group for each portfolio of anomalies. We rank all firms based on their changes in liquidity (annual effective spread) before and after decimalization. We assign the firms experiencing changes above the median to the control group (lower improvement in liquidity) and assign the firms experiencing changes below the median to the treatment group (higher improvement in liquidity).

In Panel A, we report the result of the full sample. In Panel B, we create the treatment group and control group for both Long and Short portfolios of anomalies. And In Panel C, we perform diff-in-diff for subsample analysis depending on the data categories of anomalies.

$$InforShare_{j,t} = intercept_j + \beta_t * Treat_j + \beta_p * Post_t + \beta_j * Post * Treat_{j,t} + \varepsilon_{j,t} \qquad (13)$$

Insert Table 8 About Here

Firstly, for all the tables, we see the recovery of liquidity decrease the noise share. The lower the friction of trading, the higher the market efficiency. Correspondingly, in Panel A, we observe an increase in private firm cash flow and market-wide cash flow news shares and a decline in the private firm discount rate and public firm discount rate news shares. In Panel B, the Short portfolio has the most significance in the changes in the shares of public firm information and market-wide information, while the Long portfolio is most significant in the changes in private firm information. In Panel C, we observe a decrease in discount rate news share in almost every table. The conclusion is consistent with the main table (Panel A) except for some differences in the power.

Insert Table 9 About Here

Lastly, we perform the similar diff-in-diff analysis based on subsample: non-Accounting based anomalies and Accounting-based anomalies. The decimalization increases the shares of Market_CF and Private_CF but reduces the share of Private_DR, Public_DR, and Noise. The effect of decimalization is stronger in Accounting-based anomalies but the signs of the coefficients remain similar.

7. Conclusion

We provide a unified framework to understand the essence of the information in the market by combining two prominent decomposition methods: the nature of the and the economic channels. This paper decomposes the stock return into three natures of information: market-wide, public firm-specific, and private firm-specific (in addition to noise). Then we distinguish the economic channels of the innovation - information through cash flow news or discount rate news. Based on this, we re-examine the role of cash flow news and discount rate news among different information natures.

Then we explore what drives the time-series trends in the cash flow news versus discount rate news based on high-frequency data. We examine the role of market exposure (beta), market volatility, institutional holdings, algorithm trading, and fragmentation. The result suggests a change in the market factors will have different effects on information shares even within the same economic channels (cash flow or discount rate). We bridge the market trading environment with the information environment through the information shares as the intermediate variables.

Then we apply this decomposition to examine the drivers for the disappearance of mispricings. We examine the role of cash flow/discount rate news in different information natures, and further test how publication effect and liquidity improvement shift the information components of factor-mimicking portfolios. We find that academic publications recover firm-specific and market-wide information as well as increase noise share. The increase is most significant for accounting-based anomalies. The publication effects suggest different evidence for different types of anomalies. On the contrary, decimalization imposes similar effects on the information components, regardless of the data categories of the anomalies.

Overall, we examine the heterogeneity of CF / DR news among different natures of information through the lens of mispricing. The main distinction of our decomposition methods is obtaining the time series of different information component shares on a high-frequency level and deriving cleaner estimates of cash flow news and discount rate news. The high-frequency time-series data help depict the mechanism of mispricing, which normally reverses within several trading days. The more granular decomposition can be used to explain other major changes in the trading environment or study the policy impact on information disclosure, particularly useful in cases where an immediate effect is expected. Therefore, there is great potential for this approach to investigate the short-term impact of a disclosure requirement on the information/trading environment in the future.

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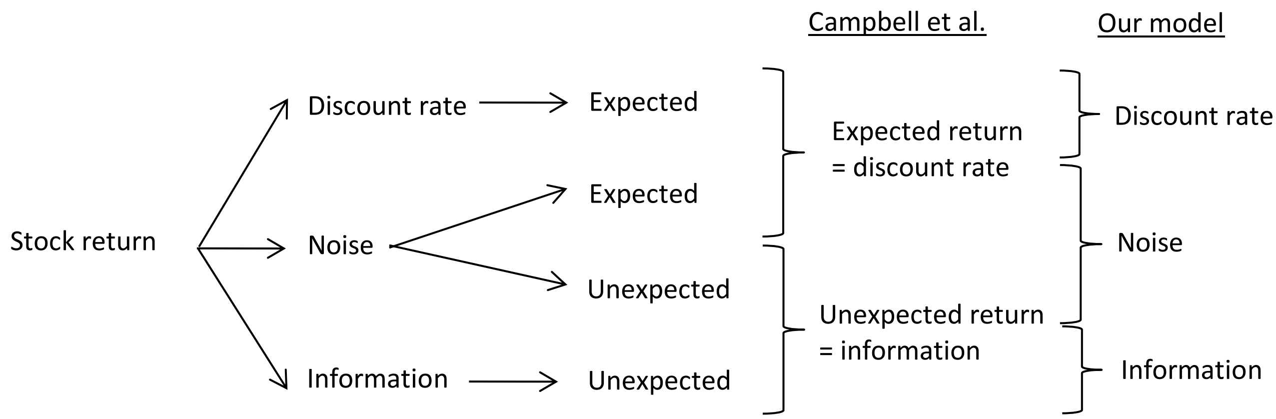
Panel A: Adjusting a standard cash flow / discount rate decomposition to account for noise



Panel B: Extended variance decomposition

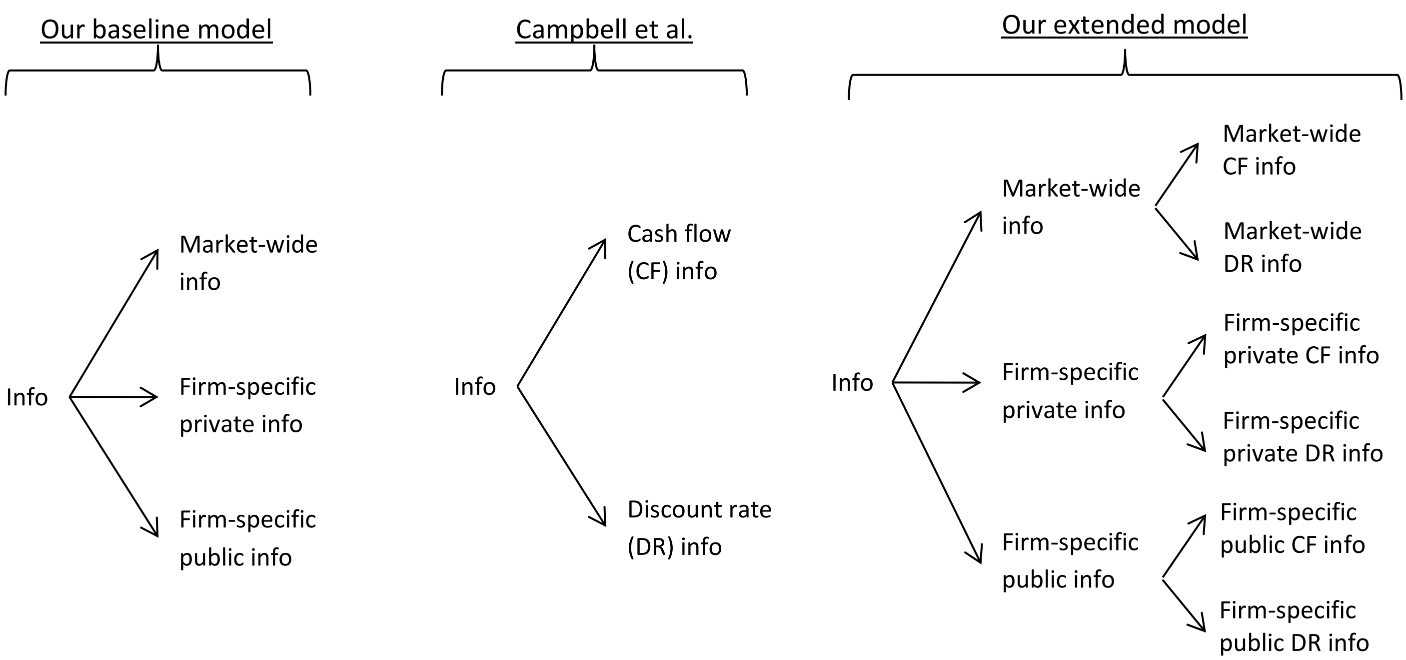
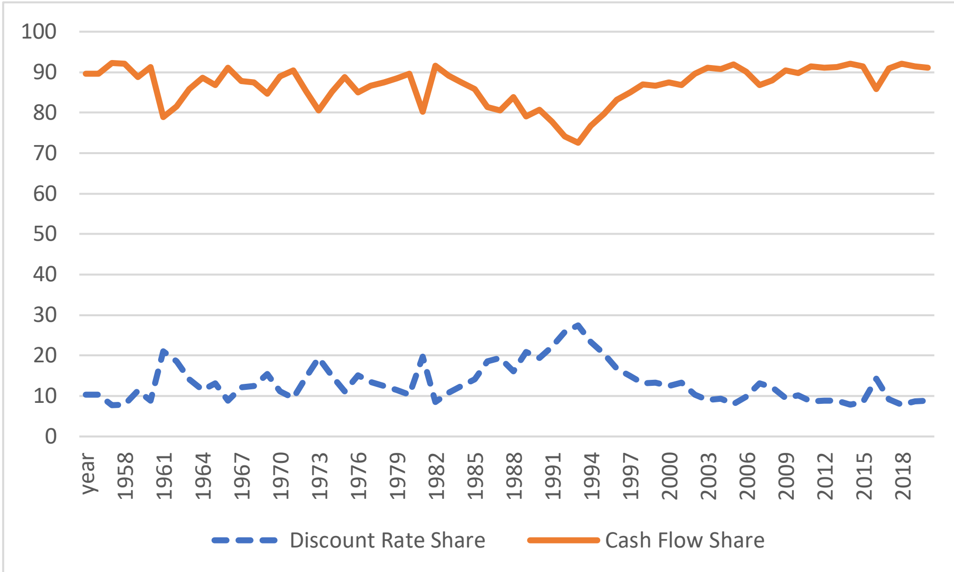


Figure 1. Extension of variance decomposition to cash flow and discount rate information.
Panel A shows how noise is dealt with in a standard cash flow / discount rate news decomposition (e.g., Campbell, 1991) and in our modified cash flow / discount rate news decomposition. In the standard decomposition, the expected changes in pricing errors contaminate the discount rate (expected return) and the unexpected changes in pricing errors contaminate the cash flow news. In our modified decomposition, noise is removed from both the discount rate and cash flow news. Panel B shows how our baseline variance decomposition is extended by splitting each of the baseline model's information components into a cash flow and discount rate part.

Panel A: Cash flow / discount rate decomposition not accounting for noise



Panel B: Cash flow / discount rate decomposition accounting for noise

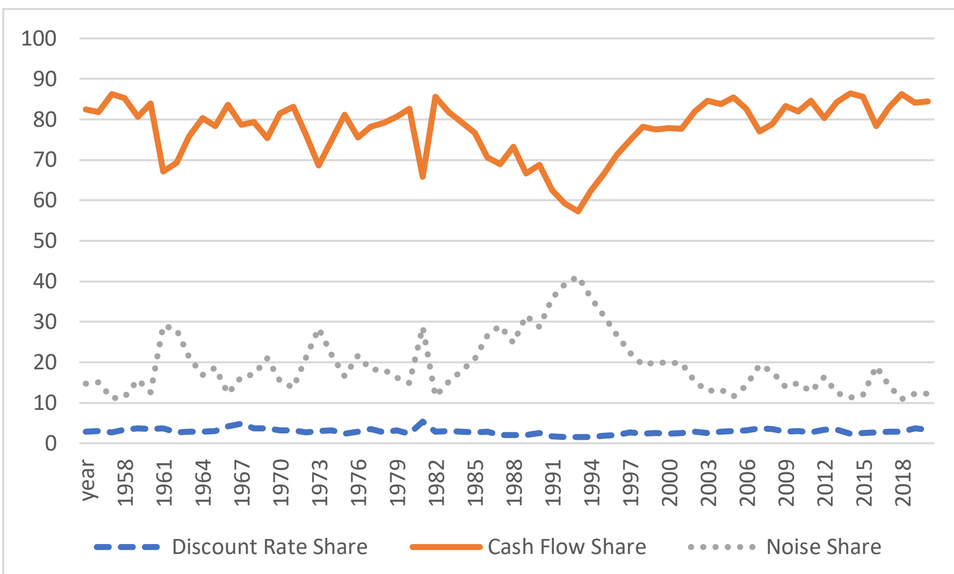


Figure 2. Cash flow news, discount rate news, and noise through time.

This figure shows the time-series trends in the percentage of stock return variance that is attributable to time-variation in the cash flow news ($Cash\ Flow\ Share$), discount rate news ($Discount\ Rate\ Share$), and noise ($Noise\ Share$) from 1956 to 202. Panel A shows the components estimated from a standard cash flow / discount rate news decomposition that does not account for noise. Panel B shows the components estimated from our modified cash flow / discount rate news decomposition that does account for noise. The variance components are calculated separately for each stock each year and then averaged across stocks each year.

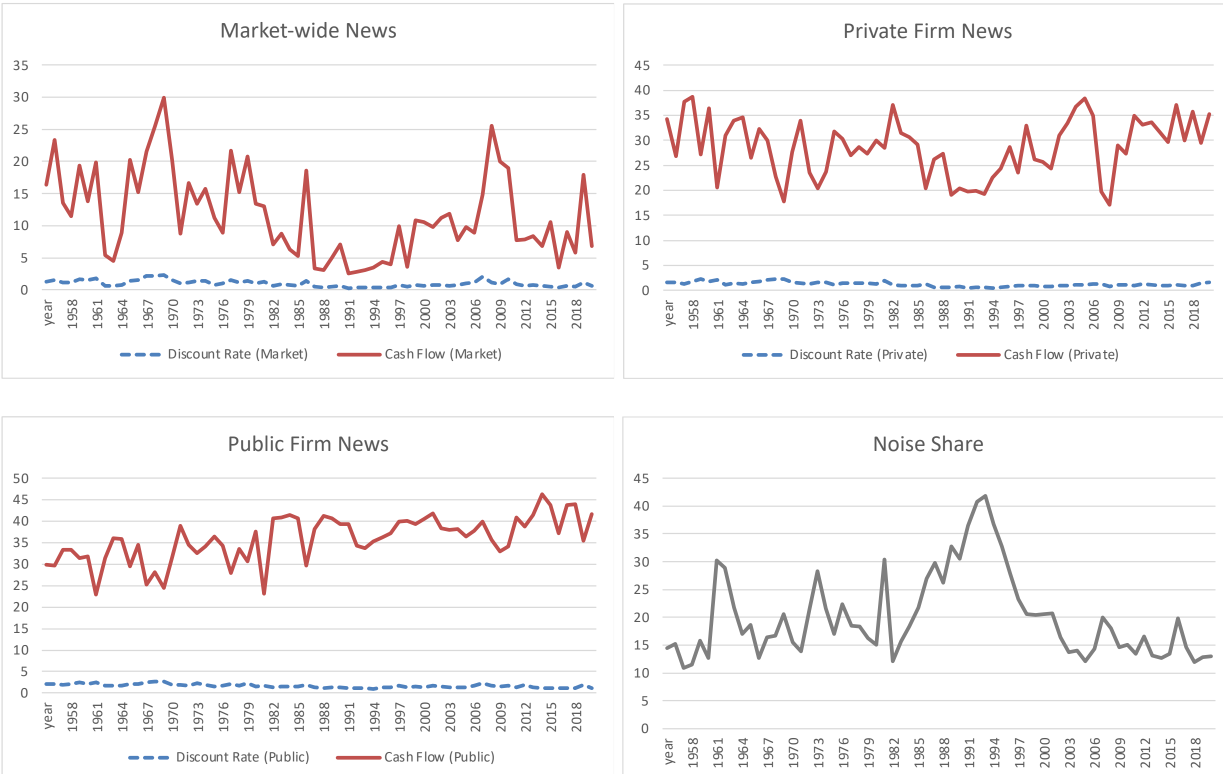


Figure 3A. Trend of the seven-components decomposition for individual stocks across time
This figure shows the time-series trends in the percentage of stock return variance that is attributable to time-variation in the *Market Discount Rate*, *Market Cash Flow*, *Public Discount Rate*, *Public Cash Flow*, *Private Discount Rate*, *Private Cash Flow*, and *Noise Share* from 1956 to 2021. The variance components are calculated separately for each stock each year and then averaged across stocks each year. The sample consists of stocks listed on NYSE, AMEX, and NASDAQ.

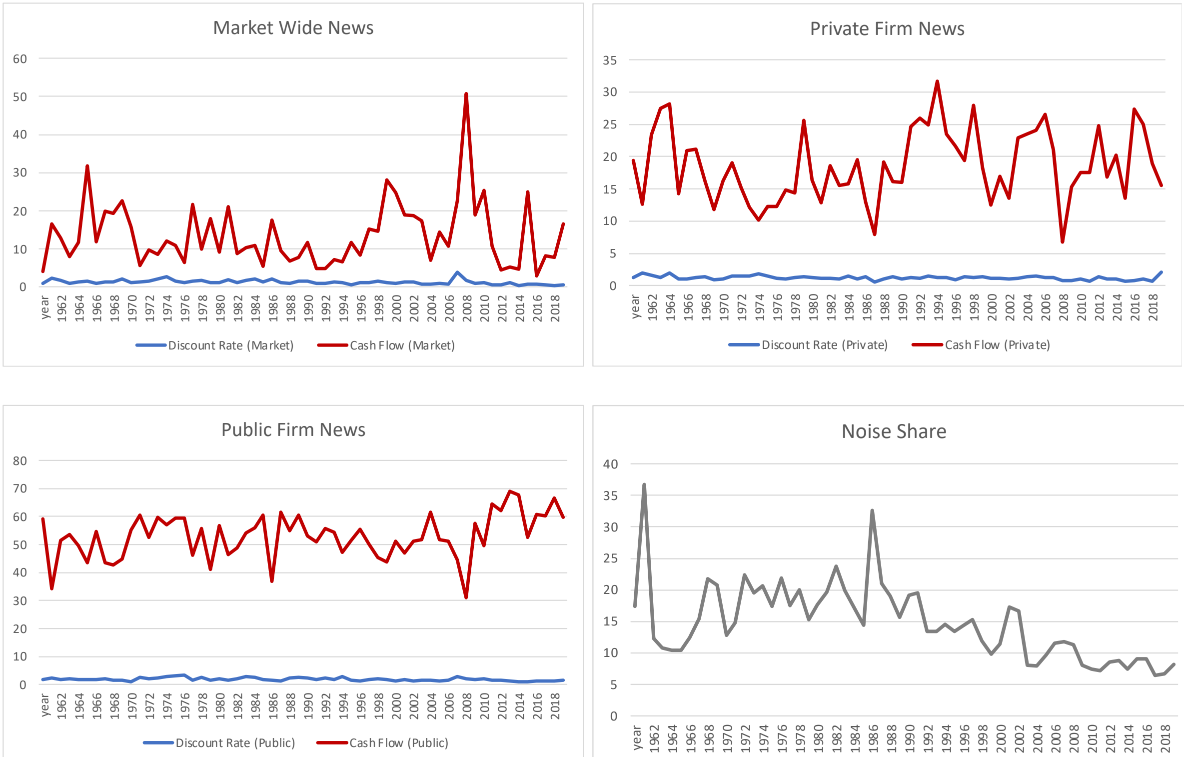


Figure 3B. Decomposed components of anomalies hedge portfolio across time
This figure shows the time-series trends in the percentage share of realized return variance of factor-mimicking portfolios for anomalies that is attributable to time-variation in the *Market Discount Rate*, *Market Cash Flow*, *Public Discount Rate*, *Public Cash Flow*, *Private Discount Rate*, *Private Cash Flow*, and *Noise Share* from 1961 to 2020. We go long on the top decile and short on the bottom decile to build the long-short portfolio.The firm charateristics are available from Chen and Zimmermann (2020). We deliberately make the results more conservative by eliminating micro-cap stocks. The variance components are calculated separately for each anomalies each year and then averaged across anomalies each year.

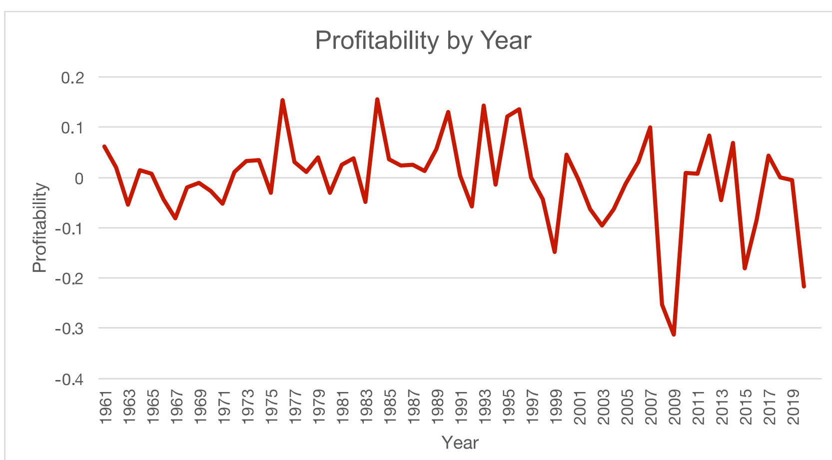


Figure 3C. Monthly return of the anomalies hedge portfolio
This figure shows the time-series trends in the realized monthly return of factor-mimicking portfolios for anomalies from 1961 to 2020. We calculate the monthly return compounded from daily return. Then monthly return are then averaged across anomalies each year.

Table 1. Stock characteristics and mispricing errors.

This table reports the characteristics and mispricing measures of common stocks. The three stock characteristic variables are obtained or derived from CRSP. We use the product of price, volume, and the sign of the stock's daily return as a proxy for the signed dollar volume, following Pastor and Stambaugh (2003). We take the logarithms of the variance variables. We use the absolute value of beta (the coefficient of market excess return in Fama Frech 3-factor regression based on a 3-month rolling window) to measure the exposure to market risk. We download the CBOE S&P 500 Volatility Index from CRSP as the measure of market volatility. We construct the Institutional Ownership and Concentration variables using Thomson-Reuters 13F data and follow Weller's (2018) paper to construct the algorithmic trading variables (Cancel_to_Trade) and the fragmentation variable (Herfindahl-Hirschman Index of trading volume on different exchanges). All variables are winsorized at 1% and 99% levels to mitigate the effect of outliers.

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	Std Dev	P01	P50	P99	N
Stock Characteristics						
Price	39.23	1887.10	0.22	14.00	113.50	209,426
Volume	449.36	4403.98	0.00	9.40	7679.01	206,580
Market Cap	1900.86	15068.67	1.27	79.48	33752.62	209,246
Anomaly Characteristics						
Var_Market_DR (log)	-13.09	1.23	-15.26	-13.04	-10.16	220,925
Var_Market_CF (log)	-9.55	1.09	-12.11	-9.59	-6.81	220,925
Var_Private_DR (log)	-13.20	1.16	-15.27	-13.19	-10.44	220,925
Var_Private_CF (log)	-12.17	1.41	-15.09	-12.17	-9.01	220,925
Var_Public_DR (log)	-13.07	1.18	-15.25	-13.02	-10.27	220,925
Var_Public_CF (log)	-11.26	1.45	-14.73	-11.21	-8.03	220,925
Var_Noise (log)	-11.54	1.397	-14.69	-11.51	-8.448	220925
Var_Return (log)	-9.40	1.07	-11.72	-9.49	-6.29	220,925
Return (%)	0.95	6.05	-16.53	1.18	16.06	220961
Drivers of Components						
Absulte Value of Beta	0.99	0.75	0.02	0.93	3.10	4,341,950
VIX	17.04	6.81	9.62	15.48	40.28	4,341,950
Cancel_to_Trade	0.30	0.35	0.06	0.20	1.99	4,225,027
HHI of Trading Volume	0.28	0.16	0.00	0.24	1.00	4,385,801
HHI of Institutional Holding	0.27	0.28	0.02	0.15	1.00	220,249
Breadth (Unit: hundred)	0.84	1.68	1.00	0.25	7.99	220,249

Table 2. Stock return variance components in the decomposition model.

This table reports mean variance shares (expressed as percentages of variance). Using an extended decomposition model, stock return variance is decomposed into market-wide information ($MktInfoShare$), private firm-specific information ($PrivateInfoShare$), public firm-specific information ($PublicInfoShare$), and noise ($NoiseShare$). The three information components are further decomposed into discount rate (DR) and cash flow (CF) related components. Panel A reports full sample averages. Panel B splits the sample into six sub-periods spanning from 1956 to 2021. Panels C and D group stocks into quartiles by price and size (market capitalization), respectively, with quartiles formed separately each year. Panel E groups stocks into major industry groups: the *Consumer* group comprises the industries of Consumer Durables, NonDurables, Wholesale, Retail, and some Services (Laundries, Repair Shops); the *Healthcare* group comprises the industries of Healthcare, Medical Equipment, and Drugs; the *Manufact* group comprises the industries Manufacturing, Energy, and Utilities; the *HiTech* group comprises the industries Business Equipment, Telephone, and Television Transmission; and the *Other* group comprises all other industries. The variance components are calculated separately for each stock in each year and then averaged across stocks within the corresponding quartile or group. We also report the differences in means for the post-1997 period minus the pre-1997 period (Panel B) and quartile 1 minus quartile 4 (Panels C and D) and corresponding t-statistics in parentheses. ***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels using standard errors clustered by stock and by year. The sample consists of stocks listed on NYSE, AMEX, and NASDAQ from 1956 to 2021 (an average of 4,029 stocks per year with a total of 16,966 stocks).

	$MktInfoShare$ (%)		$PrivateInfoShare$ (%)		$PublicInfoShare$ (%)		$NoiseShare$ (%)
	DR	CF	DR	CF	DR	CF	
Panel A: Full sample							
	0.72	8.39	0.94	25.57	1.42	37.35	25.60
Panel B: Sub-periods							
1956 - 1969	0.95	11.80	1.14	24.40	1.69	35.82	24.21
1970 - 1979	1.25	14.72	1.46	26.13	1.89	33.73	20.82
1980 - 1989	0.83	8.47	1.05	27.93	1.48	36.87	23.37
1990 - 1999	0.44	4.46	0.66	22.60	1.21	37.14	33.48
2000 - 2009	0.99	13.37	0.96	25.61	1.61	39.07	18.39
2010 - 2021	0.74	10.22	1.22	32.23	1.37	40.38	13.84
Difference	0.17	4.43	0.21	4.89	0.07	3.06	-12.82
(Post-Pre 2000)	(1.41)	(2.53)**	(2.15)**	(2.87)***	(0.65)	(2.71)***	(-6.67)***
Panel C: Quartiles by Price							
Q1=low	0.45	5.59	0.72	24.91	1.24	38.27	28.81
Q2	0.81	9.33	1.03	25.23	1.52	37.50	24.57
Q3	1.25	14.23	1.39	27.47	1.78	35.78	18.10
Q4=high	1.80	19.59	1.84	28.86	2.08	31.87	13.95
Difference	-1.35	-14.00	-1.12	-3.95	-0.84	6.40	14.86
(Q1-Q4)	(-13.34)***	(-14.77)***	(-15.31)***	(-2.58)**	(-11.08)***	(7.22)***	(9.15)***
Panel D: Quartiles by size (market capitalization)							
Q1=low	0.46	5.33	0.72	23.83	1.24	38.40	30.02
Q2	0.73	8.23	0.96	25.93	1.45	37.51	25.20
Q3	1.07	13.18	1.24	28.64	1.68	36.44	17.75
Q4=high	1.75	20.71	1.84	30.72	2.12	31.52	11.33
Difference	-1.29	-15.38	-1.12	-6.90	-0.88	6.88	18.68
(Q1-Q4)	(-13.63)***	(-14.29)***	(-15.23)***	(-3.85)***	(-10.92)***	(6.86)***	(9.13)***
Panel E: Industry groups							
Consumer	0.64	8.56	0.85	20.95	1.41	37.90	29.69
Healthcare	0.52	6.31	0.75	25.89	1.36	39.77	25.40
HiTech	0.60	8.09	0.81	26.38	1.29	37.88	24.94
Manufact	0.73	8.92	0.95	26.34	1.43	36.53	25.09
Other	0.74	7.97	0.98	24.49	1.44	38.04	26.34

Table 3. What component drives the monthly return (profitability) of factor-mimicking long-short portfolio. This table reports the result from the following regressions:

$$Return_{j,t} = \alpha + \Sigma_j \beta_i \times VarComponent_{j,i,t} + \tau_t + \gamma_j + \varepsilon$$

where monthly returns are used as the measure of the profitability of factor-mimicking portfolios and the variances of the information components are used as the independent variables. All the regressions include factor fixed effects (γ_j) and year fixed effect (τ_t), and i represents each variance component. Standard errors are clustered at the factor level. The return and signed trading volume of the portfolio are calculated as value-weighted. Column (1) reports the result of the long-short portfolio. Columns (2) and (3) report the results of the long portfolio and short portfolio respectively. The Table reports corresponding t-statistics in parentheses. ***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels.

	(1) VW (Long-Short) Monthly Return	(2) Long Portfolio Monthly Return	(3) Short Portfolio Monthly Return
Market DR	-0.158**	-0.410***	-0.439***
	(-2.24)	(-9.14)	(-10.26)
Market CF	-0.010	-1.537***	-1.403***
	(-0.58)	(-27.81)	(-20.04)
Private DR	-0.096**	-0.140**	-0.036
	(-2.05)	(-2.08)	(-0.61)
Private CF	-0.014	0.044***	0.033*
	(-0.71)	(2.68)	(1.84)
Public DR	-0.147**	-0.044	-0.156**
	(-2.50)	(-0.64)	(-2.42)
Public CF	0.021	-0.050**	-0.069***
	(0.35)	(-2.43)	(-2.80)
Noise	0.066**	0.112***	0.141***
	(2.54)	(4.97)	(5.13)
Constant	-4.900**	-20.011***	-19.701***
	(-2.59)	(-29.95)	(-27.82)
Factor FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R2	0.187	0.157	0.146
Observations	100,517	110,322	110,601

Table 4. What component drives the long-short return variance of factor-mimicking portfolio.
This table repeats the analysis of table 3 with return variance as the dependent variable:

$$Ret\_Variance_{j,t} = \alpha + \Sigma_j \beta_i \times VarComponent_{j,i,t} + \tau_t + \gamma_j + \varepsilon$$

where γ_j is the factor fixed effects, and τ_t is the year fixed effect. i represents each variance component. Standard errors are clustered at the factor level. The return and signed trading volume of the portfolio are calculated as value-weighted. Column (1) reports the result of the long-short portfolio. Columns (2) and (3) report the results of the long portfolio and short portfolio respectively. The Table reports corresponding t-statistics in parentheses. ***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels.

	(1) VW (Long-Short) Log (Return Variance)	(2) Long Portfolio Log (Return Variance)	(3) Short Portfolio Log (Return Variance)
Market DR	0.055***	0.087***	0.125***
	(4.92)	(6.46)	(12.17)
Market CF	0.059***	0.555***	0.510***
	(12.34)	(33.74)	(26.68)
Private DR	0.069***	0.123***	0.108***
	(8.01)	(10.96)	(10.26)
Private CF	0.099***	0.060***	0.069***
	(24.85)	(13.94)	(15.36)
Public DR	0.010	0.097***	0.119***
	(0.90)	(9.07)	(13.64)
Public CF	0.425***	0.106***	0.097***
	(33.63)	(21.21)	(19.44)
Noise	-0.011	-0.003	-0.003
	(-1.48)	(-0.40)	(-0.54)
Constant	-1.944***	1.819***	1.976***
	(-6.69)	(18.29)	(21.18)
Factor FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R2	0.804	0.810	0.813
Observations	100,517	110,322	110,601

Table 5. What drives the seven components shares.

The table reports the drivers of the time-series trends in cash flow news and discount rate news based on high-frequency data. The coefficients presented in the table reveal the impact of several factors, including market exposure (measured by the absolute value of beta, the coefficient of market excess return in Fama-French 3-factor regression), market volatility (as captured by the CBOE S&P 500 Volatility Index), algorithmic trading (quantified by cancel-to-trade, or the ratio of full or partial cancellations to the total number of trades), fragmentation (as measured by the Herfindahl-Hirschman Index of trading volume on different exchanges), and institutional holdings reflected by Breadth (the number of institutions that hold the stock during the quarter) and by Herfindahl-Hirschman Index of institutional ownership. The regressions include firm fixed effect and month fixed effect, and standard errors are clustered at firm and month levels. We report corresponding t-statistics in parentheses. ***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Market_DR	Market_CF	Private_DR	Private_CF	Public_DR	Public_CF	Noise
Beta	-0.087***	1.100***	-0.118***	-0.387**	-0.124***	-0.118	-0.266***
	(-7.11)	(6.39)	(-7.26)	(-2.44)	(-8.45)	(-0.94)	(-4.32)
VIX	0.007***	0.315***	-0.010***	-0.179***	-0.007***	-0.136***	0.010
	(2.64)	(5.07)	(-2.91)	(-3.37)	(-4.17)	(-4.62)	(0.94)
Cancel_to_Trade	0.055***	0.843***	-0.028**	-2.240***	0.070***	0.801***	0.499***
	(2.91)	(6.09)	(-2.16)	(-12.12)	(3.9)	(4.53)	(5.20)
HHI_Trade	0.958***	-1.001*	0.770***	-12.250***	1.225***	1.839**	8.455***
	(7.91)	(-1.67)	(6.30)	(-16.23)	(10.02)	(2.28)	(19.14)
Breadth	0.001	-0.323**	0.037*	1.030***	-0.008	-0.846***	0.111*
	(0.05)	(-2.31)	(1.98)	(5.14)	(-0.49)	(-5.84)	(1.80)
HHI_Institutional	-0.623***	-5.209***	-0.451***	-4.289***	0.053	7.178***	3.342***
	(-5.41)	(-5.95)	(-4.25)	(-3.33)	(0.34)	(5.06)	(5.18)
Constant	1.150***	11.530***	1.576***	35.670***	1.688***	42.010***	6.378***
	(15.22)	(9.30)	(18.89)	(32.13)	(25.33)	(59.73)	(21.72)
Adjusted R2	0.35	0.46	0.31	0.28	0.27	0.31	0.34
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,187,271	4,187,271	4,187,271	4,187,271	4,187,271	4,187,271	4,187,271

Table 6. Publication effect – Staggered diff-in-diff.

The table presents the results of the following staggered diff-in-diff:

$$InforShare_{j,t} = intercept_j + \beta_j \times Post\_Publication_{j,t} + \gamma_j + \theta_t + \varepsilon_{j,t}$$

where j represents different anomalies, and t represents the year-month. $Post\_Publication_{j,t}$ takes the value 1 after the anomaly gets published, and 0 otherwise. Panel A report the result of staggered diff-in-diff for the long-short portfolio. In Panel B and Panel C report the result from the long portfolio and short portfolio, seperately. We report corresponding t-statistics in parentheses. ***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels.

Panel A: all anomalies							
	(1) Market_DR	(2) Market_CF	(3) Private_DR	(4) Private_CF	(5) Public_DR	(6) Public_CF	(7) Noise
Post-Publication	-0.012	0.371***	-0.085***	0.622***	0.095***	-1.153***	0.163
	(-0.67)	(2.66)	(-4.08)	(3.15)	(3.80)	(-5.04)	(1.46)
Observations	100,517	100,517	100,517	100,517	100,517	100,517	100,517
Adjusted R2	0.13	0.25	0.05	0.14	0.05	0.12	0.21
Panel B: Long Portfolio (Top Decile)							
	(8) Market_DR	(9) Market_CF	(10) Private_DR	(11) Private_CF	(12) Public_DR	(13) Public_CF	(14) Noise
Post-Publication	0.012	-1.087***	0.036***	0.848***	0.096***	0.431***	-0.337***
	(0.66)	(-5.79)	(2.90)	(7.69)	(6.76)	(2.94)	(-3.93)
Observations	103,043	103,043	103,043	103,043	103,043	103,043	103,043
Adjusted R2	0.49	0.36	0.64	0.16	0.55	0.24	0.22
Panel C: Short Portfolio (Bottom Decile)							
	(15) Market_DR	(16) Market_CF	(17) Private_DR	(18) Private_CF	(19) Public_DR	(20) Public_CF	(21) Noise
Post-Publication	0.055***	1.231***	-0.070***	-0.766***	-0.110***	-0.599***	0.260***
	(3.30)	(7.21)	(-6.57)	(-8.01)	(-8.69)	(-4.65)	(3.54)
Observations	117,881	117,881	117,881	117,881	117,881	117,881	117,881
Adjusted R2	0.50	0.36	0.66	0.16	0.54	0.23	0.25

Table 7. Publication effect – Staggered diff-in-diff (by data category).
The table presents the results of the following staggered diff-in-diff:

$$InforShare_{j,t} = intercept_j + \beta_j \times Post\_Publication_{j,t} + \gamma_j + \theta_t + \varepsilon_{j,t}$$

where j represents different anomalies, and t represents the year-month. $Post\_Publication_{j,t}$ takes the value 1 after the anomaly gets published, and 0 otherwise. Panel A and Panel B, the anomaly sample was partitioned into two groups: anomalies based on accounting information, and anomalies not based on accounting information. We report corresponding t-statistics in parentheses. ***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels.

Panel A: Accounting-based Anomalies

	(1) Market_DR	(2) Market_CF	(3) Private_DR	(4) Private_CF	(5) Public_DR	(6) Public_CF	(7) Noise
Post-Publication	0.039*	0.226	-0.095***	0.500	0.169***	-1.727***	0.888***
	(1.65)	(1.14)	(-2.65)	(1.55)	(4.33)	(-4.78)	(5.64)
Observations	50,037	50,037	50,037	50,037	50,037	50,037	50,037
Adjusted R2	0.17	0.26	0.05	0.14	0.05	0.12	0.18

Panel B: Non-Accounting-based anomalies

	(8) Market_DR	(9) Market_CF	(10) Private_DR	(11) Private_CF	(12) Public_DR	(13) Public_CF	(14) Noise
Post-Publication	-0.065**	0.508**	-0.084***	0.789***	0.095***	-0.950***	-0.293*
	(-2.39)	(2.56)	(-3.52)	(3.20)	(2.98)	(-3.21)	(-1.84)
Observations	50,480	50,480	50,480	50,480	50,480	50,480	50,480
Adjusted R2	0.12	0.25	0.05	0.15	0.06	0.14	0.24

Table 8: How decimalization (liquidity) affects information components.
The following table presents the results of the diff-in-diff regressions as below:

$$InforShare_{j,t} = intercept_j + \beta_t \times Treat_j + \beta_p \times Post_t + \beta_j \times Post \times Treat_{j,t} + \varepsilon_{j,t}$$

Decimalization in 2001 allows for tighter spreads between bid and ask prices and the liquidity of the stock increase. This analysis follows Brogaard, et al (2017) and Fang et al. (2014) to construct the treatment and control group: we rank all sample firms based on their changes in liquidity (measured by Effective Spread) around the decimalization in 2001 and categorize them into two groups based on the median. The top half that experienced the most pronounced liquidity recovery is designated as the treatment group, while the bottom half is labeled as the control group.
Panel A presents the diff-in-diff regression based on whole samples in which we construct long-short portfolios, divide the treatment and control group, and then perform decomposition analysis. In Panel B1 and B2, we create the control and treatment groups within the long and short portfolios, respectively to test the effect of decimalization separately in the long portfolio and short portfolio. ***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels.

Panel A: All Samples							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Market_DR	Market_CF	Private_DR	Private_CF	Public_DR	Public_CF	Noise
Post	-0.642**	7.438***	-0.500**	-1.176	-0.430**	-2.474*	-2.216***
	(-2.61)	(3.52)	(-2.57)	(-1.21)	(-2.37)	(-1.69)	(-3.13)
Treat	0.258	-5.600***	0.378***	-0.425	0.388***	2.943***	2.058***
	(1.57)	(-6.00)	(2.86)	(-1.21)	(3.17)	(3.82)	(6.23)
Post*Treat	-0.196	3.078**	-0.364**	1.678*	-0.358**	-1.804	-2.034***
	(-1.03)	(2.19)	(-2.50)	(1.95)	(-2.59)	(-1.63)	(-4.48)
Observations	432,705	432,705	432,705	432,705	432,705	432,705	432,705
Factor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.07	0.17	0.10	0.04	0.07	0.13	0.10

Panel B1: Long Portfolio (Top Decile)							
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Market_DR	Market_CF	Private_DR	Private_CF	Public_DR	Public_CF	Noise
Post	-0.547**	8.830***	-0.430**	-1.754*	-0.344**	-3.122**	-2.633***
	(-2.31)	(4.03)	(-2.48)	(-1.73)	(-2.09)	(-2.05)	(-3.41)
Treat	0.383**	-6.107***	0.496***	-0.578	0.526***	3.026***	2.253***
	(2.19)	(-6.68)	(3.31)	(-1.41)	(3.81)	(4.17)	(6.49)
Post*Treat	-0.379*	3.449**	-0.521***	1.846**	-0.503***	-1.720	-2.172***
	(-1.89)	(2.55)	(-3.19)	(2.27)	(-3.31)	(-1.64)	(-4.54)
Observations	201,918	201,918	201,918	201,918	201,918	201,918	201,918
Factor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.11	0.22	0.15	0.04	0.12	0.14	0.16

Panel B2: Short Portfolio (Bottom Decile)

	(15)	(16)	(17)	(18)	(19)	(20)	(21)
	Market_DR	Market_CF	Private_DR	Private_CF	Public_DR	Public_CF	Noise
Post	-0.727***	6.260***	-0.565**	-0.684	-0.509**	-1.948	-1.827**
	(-2.78)	(2.94)	(-2.57)	(-0.70)	(-2.48)	(-1.32)	(-2.66)
Treat	0.148	-5.138***	0.275*	-0.293	0.265**	2.859***	1.884***
	(0.86)	(-4.87)	(2.00)	(-0.75)	(2.08)	(3.31)	(5.58)
Post*Treat	-0.0359	2.749*	-0.226	1.529	-0.231	-1.875	-1.910***
	(-0.18)	(1.76)	(-1.46)	(1.54)	(-1.53)	(-1.53)	(-4.07)
Observations	230,785	230,785	230,785	230,785	230,785	230,785	230,785
Factor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.13	0.22	0.16	0.065	0.11	0.19	0.10

Table 9: How decimalization (liquidity) affect information components (by anomaly category).
This table repeats the diff-in-diff analysis in Table 7**.** We split the anomalies into two categories: anomalies based on accounting information, and anomalies not based on accounting information. Panel A report the diff-in-diff regression based on accounting-based anomalies and Panel B report the result of non-accounting-based anomalies. ***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels.

Panel A: Accounting-based Anomalies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Market_DR	Market_CF	Private_DR	Private_CF	Public_DR	Public_CF	Noise
Post	-0.624**	8.129***	-0.459**	-1.585	-0.427**	-3.380**	-1.654**
	(-2.44)	(3.59)	(-2.34)	(-1.49)	(-2.31)	(-2.31)	(-2.05)
Treat	0.164	-5.933***	0.294**	-0.687*	0.312**	3.361***	2.489***
	(0.92)	(-5.67)	(2.20)	(-1.68)	(2.52)	(3.81)	(5.75)
Post*Treat	-0.136	3.431**	-0.307**	1.919*	-0.318**	-1.971	-2.618***
	(-0.65)	(2.21)	(-2.07)	(1.95)	(-2.23)	(-1.61)	(-4.52)
Factor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.0518	0.134	0.0660	0.0290	0.0531	0.0873	0.0729
Observations	201,139	201,139	201,139	201,139	201,139	201,139	201,139

Panel B: Non-Accounting-based Anomalies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Market_DR	Market_CF	Private_DR	Private_CF	Public_DR	Public_CF	Noise
Post	-0.974**	7.675***	-0.881***	-1.903**	-0.899***	-2.523*	-0.496
	(-2.71)	(3.21)	(-3.07)	(-3.04)	(-3.24)	(-1.86)	(-0.44)
Treat	0.266	-8.018***	0.515**	2.027**	0.465**	3.685**	1.060*
	(0.99)	(-4.12)	(3.01)	(3.03)	(2.56)	(2.58)	(1.96)
Post*Treat	-0.367	3.931	-0.576**	0.430	-0.505**	-0.396	-2.517**
	(-1.16)	(1.50)	(-2.84)	(0.38)	(-2.24)	(-0.22)	(-2.65)
Factor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.0875	0.189	0.124	0.0443	0.0796	0.151	0.118
Observations	19,749	19,749	19,749	19,749	19,749	19,749	19,749