What Drives Anomaly Decay?

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Abstract

We examine why asset pricing anomalies decay by decomposing the information in prices. We find that anomalies primarily decay around structural increases in market liquidity. The decomposition of information shows that anomaly decay at decimalization is mainly driven by a decrease in the noise share. We also find that for other types of anomalies, the decay drivers are different. For instance, risk-based anomalies are often the result of data snooping, which gets corrected through publication as investors are induced to trade on noisy signals. The results suggest that anomalies are primarily inefficiencies that get corrected through liquidity increases.

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, Dong, Li, Rapach, and Zhou, 2021). 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, other 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). Some researchers argue that the rise of liquidity drives the attenuation of anomalies (Chordia, Subrahmanyam, and Tong, 2014). We seek to disentangle these potential drivers of anomaly decay by decomposing the different types of information in prices and analyzing how those components change around anomaly publication events and liquidity shocks.

To address this range of unresolved issues, we develop a new variance decomposition method that separates 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 the market.

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 and liquidity shocks 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 *type* 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 types × two channels + noise) and examine how the varying components of the price process are the impetus of mispricings.

Firstly, we show there are time-serial trends in the information component and the profitability from the factor mimicking portfolios. Cash flow information shares tend to dominate the discount rate information shares for hedge portfolios of anomalies. Over time, we note a gradual increase in the public firm-specific cash flow news share, while the private firm cash flow 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 in 1993 and then shows a decline over the years. Additionally, we find that the trend in profitability aligns with the phenomenon of "anomaly decay". The monthly return of the anomaly hedging portfolio reaches its peak around the year 2000 and subsequently experiences a decline in the following two decades.

Next, we investigate the timing of anomaly decay. We explore various potential explanations, assessing whether anomalies predominantly decay as a result of their publication events or liquidity shocks (i.e., decimalization). Alternatively, the decay of anomalies may arise from a general time-series market trend, such as the market becoming more efficient, rather than discrete events like publication or liquidity shocks. Our findings suggest that anomalies primarily decay during the period of structural increases in market liquidity. Publication events and general market changes only explain a smaller proportion of anomaly decay.

Lastly, we apply our decomposition approach to factor-mimicking portfolios to investigate the mechanisms through which the academic publication of anomalies and decimalization (liquidity shocks) mitigate mispricings. Specifically, we aim to explain the fact that portfolio returns are significantly lower out-of-sample and deteriorate over time (Linnainmaa and Roberts, 2018; McLean and Pontiff, 2016). We establish that academic publications lead to an increase in the noise share, which is probably a result of data snooping anomalies. The publications of data snooping anomalies induce trading based on noise and exaggerate the role of noise, leading to worse market quality. The publication effects suggest divergent evidence for different data categories of anomalies. On the contrary, decimalization significantly enhances stock liquidity and reduces trading costs of correcting mispricings. Post-decimalization, we find an increase in market-wide information and a decrease in noise share, indicating a better market trading environment.

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 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. Lastly, we empirically test the mechanisms through which the publications and decimalization contribute to the reduction of anomaly hedging portfolios.

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 the years. We observe the time-serial and cross-sectional variation in the decomposition shares in the sample. There exist disparities among the information component shares across different periods, different firm characteristics subsamples, and among different industries.

There are two key distinctions between our methodology 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. 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.

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. While we are not the first paper to employ the decomposition method in anomaly hedging portfolios (Lochstoer and Tetlock, 2020), we are the first to utilize this method to investigate the mechanisms behind anomaly decay. Researchers have published numerous 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-1997, 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 noisy signals in the market. The decimalization suggests an increase in market-wide cash flow news but decreases in other components, such as 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 investigates the factors driving anomaly decay: publication, liquidity shock, or general market trend. Section 5 details the mechanism through which decimalization and publication impact the profitability of anomalies. Lastly, Section 6 concludes and provides 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, explaining 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:

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

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 $\varepsilon_{DISCOUNT_t}$.

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

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[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., $\varepsilon_{DISCOUNT_{t+1}} = -(\mathrm{E}_{t+1} - \mathrm{E}_t)\sum_{j=1}^{\infty}\rho^j r_{t+1+j} = \sum_{j=1}^{\infty}\rho^j \mathrm{E}_t\left[r_{t+1+j}\right] - \sum_{j=1}^{\infty}\rho^j \mathrm{E}_{t+1}[r_{t+1+j}]$.

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 1 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 by incorporating a time-varying discount rate following Brogaard et al. (2021). Consider the logarithm of the observed price at time t, p_t, as the sum of two components:

$$p_t = m_t + s_t \, , \tag{3}$$

where m_t is the efficient price and s_t is the pricing error. The transitory pricing error has no long-term impact on stock prices. The efficient price is:

$$m_t = m_{t-1} + \mu_t + w_t \, , \tag{4}$$

and the stock return becomes

$$r_t = p_t - p_{t-1} = \mu_t + w_t + \Delta s_t \, , \tag{5}$$

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 (w_t is unpredictable, and $\mathrm{E}_{t-1}[w_t] = 0$), 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

[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.

"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:

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

$$= \sum_{j=1}^{\infty}\rho^j \mathrm{E}_t\left[\mu_{t+1+j}\right] - \sum_{j=1}^{\infty}\rho^j \mathrm{E}_{t+1}\left[\mu_{t+1+j}\right]. \quad (6)$$

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:

$$\varepsilon_{CASHFLOWS_{t+1}} = w_{t+1} - \varepsilon_{DISCOUNT_{t+1}}. \quad (7)$$

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

[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.

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 (6) and (7). 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 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.

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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.

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 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:

$$w_t = \theta_{r_m}\varepsilon_{r_m,t} + \theta_x\varepsilon_{x,t} + \theta_r\varepsilon_{r,t} \ , \tag{8}$$

and thus we can rewrite the stock returns as

$$r_t = \underbrace{\mu}_{\text{discount rate}} + \underbrace{\theta_{r_m}\varepsilon_{r_m,t}}_{\text{market-wide info}} + \underbrace{\theta_x\varepsilon_{x,t}}_{\text{private info}} + \underbrace{\theta_r\varepsilon_{r,t}}_{\text{public info}} + \underbrace{\Delta s_t}_{\text{noise}} \ , \tag{9}$$

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:

$$r_{m,t} = \sum_{l=1}^{5} a_{1,l} r_{m,t-l} + \sum_{l=1}^{5} a_{2,l} x_{t-l} + \sum_{l=1}^{5} a_{3,l} r_{t-l} + \varepsilon_{r_{m,t}}$$

$$x_t = \sum_{l=0}^{5} b_{1,l} r_{m,t-l} + \sum_{l=1}^{5} b_{2,l} x_{t-l} + \sum_{l=1}^{5} b_{3,l} r_{t-l} + \varepsilon_{x,t} \quad (10)$$

$$r_t = \sum_{l=0}^{5} c_{1,l} r_{m,t-l} + \sum_{l=0}^{5} c_{2,l} x_{t-l} + \sum_{l=1}^{5} c_{3,l} r_{t-l} + \varepsilon_{r,t}$$

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. Following to Pastor and Stambaugh (2003), we use the product of price, volume, and the sign of the stock's daily return as a proxy for the signed dollar volume (x_t), given its minimal data requirements.

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:

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

$$\varepsilon_{CASHFLOWS_t} = \gamma_1 r_{A,t} + \gamma_2 r_{B,t} + \gamma_3 r_{C,t}, \quad (11)$$

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, $\widehat{\beta_3} r_{C,t}$

[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.

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 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]

3. Data

First, we describe the data used in our decomposition method and main tables in Section 3.1. Next, 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.

3.1. Variation of estimated shares

For the decomposition of individual stocks, 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. Our sample contains on average 4029 firms per year and a total of 16966 firms.

Insert Table 1 About Here

Table 1 reports the summary statistics of stocks' characteristics, decomposition components, drivers of components, etc.

[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.

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%).[10] 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 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 cash flow news remains

[10] 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.

relatively stable. Therefore, the variation of market cash flow 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 plots 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 firm-specific cash flow 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 peaks in 1993 and then starts going down after that.

3.2. Anomaly hedge portfolio returns

The 207 predictive firm-level characteristics are available from Chen and Zimmermann (2020)'s Open Source Asset Pricing website[11]. We follow Chen and Zimmermann (2020) to construct daily hedge 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. Our sample includes both the continuous anomalies and indicator anomalies and choose the port and weighting method as the original paper suggests. If the long-short portfolio is value-weighted, 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 $t-1$. 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 $t-1$.[12] The final sample ready for decomposition consists of 204 anomalies on a daily basis and 144,010 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 by Chen and Zimmermann (2020).

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[11] The data is downloaded directly from "Open Source Asset Pricing" website: https://www.openassetpricing.com/data/

[12] We construct the monthly anomalies data based on the public-available code on their "OSAP" website

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 results 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 co-move through time. However, the three cash flow ($Market\ CF$, $Private\ CF$, and $Public\ CF$) components show heterogeneous fluctuations across the years. We observe a gradual upward trend over time for the public firm-specific cash flow news share. The public firms-specific cash flow news of anomalies' hedge portfolio accounts for the highest variance share among the 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 market-related news share. Not surprisingly, the private firm-specific cash flow news share gradually grows 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 share is the lowest among the three cash flow news shares after 2000. The noise share peaks around 1986 and starts shrinking after.

Insert Figure 4 About Here

Next, Figure 4 illustrates the time-series trend in the 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 monthly returns of the portfolio that mimic the factor. We subsequently average the monthly returns across the year. Finally, we compute the average monthly returns for all anomalies per year. Overall, we discover that the trend aligns with the "anomaly decay" phenomenon. Prior to 2000, the factor-mimicking portfolios generate mostly positive returns, despite of volatility in the returns. However, post-2000, we observe a significant decline, aligning with the timing of decimalization. Furthermore, the figure displays some intriguing periodical patterns. In particular, there are notable peaks in monthly returns during the years 2008 and 2021, indicating that the global financial crisis also contributed to significant profitability in the long-short portfolios of anomalies. There is a downward trend relative to the publication event, although the magnitude is smaller than the decline observed after the year 2000. Therefore, Figure 4 provides some illustrative support for the existing evidence in previous literature regarding the diminishing predictability of firm characteristics and profitability from the factor-mimicking portfolio.

4. What drives Anomaly Decay?

In this section, we provide empirical evidence of the timing of anomaly decay, which is consistent with previous literature. Firstly, we observe that the anomaly (monthly) returns reach their peak (slightly over 1.5%) in the year 2000, after which they begin to decline over the following two decades. This decay might be driven by a number of structural changes in the market, such as decimalization in 2001.

Additionally, we observe a much poorer performance of the anomaly hedging portfolio out-of-sample (McLean and Pontiff, 2016). Specifically, the out-of-sample performance is much weaker for the pre-period (sample frame prior to the in-sample period) and post-period (sample frame after the in-sample period) (Linnainmaa and Roberts, 2018). The mean of the in-sample monthly long-short portfolio return is about 0.60%, while the pre-period and post-period sample means are 33% and 22% lower, respectively, relative to the in-sample period. There are several possible explanations for the decay of asset pricing anomalies. We test whether anomalies primarily decay due to their publication events or liquidity shocks (i.e., decimalization). Alternatively, the anomaly decay may result from a general time-series market trend, such as the market becoming increasingly efficient/informative, rather than from discrete events like publication or liquidity shocks. In the following analysis, we attribute the proportion of anomaly decay to these three reasons and then study the mechanism of how these major changes lead to anomaly decay. We include the following models to capture the publication effect and decimalization effect, and then keep the residual as the effect of general market changes:

$$Return_{j,t} = \alpha + \beta_{Pub} \times Post_{publication_{j,t}} + \beta_{Dec} \times Post_{Decimalization_t} + \beta_{Liq} \times Liquidity_{j,t} + \varepsilon_{j,t} \tag{12}$$

Where j represents each anomaly, and t represents the year-month. We control the liquidity for factor-mimicking portfolios as the absolute value of signed dollar volume liquidity. The dependent variable is the monthly return of hedging portfolios. $Post\_publication$ is a dummy variable that indicates the observation after the publication year of the anomaly, while $Post\_decimalisation$ indicates the observation is after April 2001. We also include year fixed effect to account for common changes for all anomalies within the same year. Standard errors are clustered at the anomaly category level (following Chen and Zimmermann's signal document) and year-month level.

Insert Table 3 About Here

To assess the magnitudes of the publication and decimalization effects, we examine the notable decline in monthly returns from the peak (1.6% to 0.3%) over the past two decades to indicate the total decline. Table 3, Column (1), indicates that the publication of asset pricing anomalies leads to a 0.14% decline, after controlling for year fixed effects. The coefficient is statistically significant at the 5% confidence level. However, in contrast, decimalization leads to a 0.80% decline in monthly returns. This implies that the publication effect only accounts for 11% of the anomaly decay, while decimalization leads to 61% of the anomaly decay, and general structural changes in the market contribute to 28% of the anomaly decay. This makes decimalization the largest factor explaining the anomaly decay. In columns (2) and (3), we incorporate the absolute value of trading volume to account for additional liquidity variations over time. The results remain robust, whether we include or exclude anomaly fixed effects and control for other liquidity changes in the market over time.

From the perspective of partial correlation and partial R^2, $Post\_decimalization$ also shows the largest magnitude. Specifically, when controlling for the effects of other variables, the association between monthly return and the $Post\_decimalization$ dummy variable is the strongest among all. Additionally, partial R^2, quantifies the additive proportion of variance in the dependent variable that is explained by a specific independent variable, while controlling for the effects of other variables. Controlling for the anomaly and year fixed effect, the $Post\_decimalization$ dummy variable has increased the R^2 by 1 basis point, almost doubling the explanatory power of $Post\_publication$ and $Liquidity$. Hence, considering findings from both magnitudes and explanatory power, it appears that the primary driver behind the decay of the anomalies is decimalization.

5. Mechanisms of Potential Hypothesis

The anomaly decay is attributed to approximately 70% explained by the publication effect and decimalization event, with only 30% explained by general market changes. The next logical question is to understand the mechanisms through which these two factors contribute to the reduction of anomaly hedging portfolios. Therefore, in the following section, we focus our study on how decimalization and publication effects alter the information components.

5.1. What components are linked to anomaly return?

To comprehend the mechanism by which decimalization and publication contribute to anomaly decay, the first step is to understand the association between anomaly return and information components. We focus on the long-short anomaly portfolio returns, a commonly used indicator of cross-sectional mispricing in the literature (Dong, Li, Rapach, and Zhou, 2021). To ensure precision, we conduct VAR estimation on an annual basis and subsequently calculate variance components on a monthly basis[18]. The independent

[18] To avoid the mechanical issue of the shares summing to 100%, we do no use the shares of the information components. Consequently, an increase in one information share will automatically lead to a decrease in the other shares.

variables consist of the variance of information components at a monthly frequency. Long-short portfolio returns are derived by multiplying the monthly return of the hedge portfolio by the sign of the predictor, following the methodology outlined in the original published papers (as provided in Chen and Zimmermann's signal document).

We perform regression analysis at the monthly frequency, aligned with the monthly computation of variances and considering the relatively slow process of information dissemination and recovery of mispricings. All the regressions are contemporaneous and include factor fixed effects (γ_j) and year fixed effect (τ_t), with standard error clustered on anomaly category and year level. We introduce the following regression model:

$$Return_{j,t} = \alpha + \Sigma_i \beta_i \times VarComponent_{i,j,t} + \tau_t + \gamma_j + \varepsilon_{j.t} \quad (13)$$

Table 4 Panel A, Column (1) reports the result of the long-short portfolio. Table 3, Column (2), and Column (3) report the regression results of the long portfolio and the short portfolio of each anomaly. Firstly, the positive effect of noise on profitability is robust across the three columns. As the informational environment becomes more opaque, arbitrageurs have greater opportunities to trade and generate profits from trading on anomalies. Also, the long-short portfolio return is positively correlated with the variance of public firm-specific news components. Nevertheless, the return shows no correlation with market-wide news, and the association between anomaly return and private firm-specific information is insignificant as well.

Insert Table 4 About Here

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 news variance is negatively associated with the profitability of long/short portfolios, while the monthly return displays a positive relationship with both public and private firm cash flow information. Although the market information component and private firm-specific news components display significance in the one-sided (long or short) portfolio, they eventually cancel out when constructing the hedging portfolio. Therefore, we will only observe significance in the public firm information and noise variance estimations.

Due to the potential high correlation among variance components, we conducted additional univariate regression analyses, incorporating only one information component variance for each regression. Only the variance associated with market discount rate news emerges as statistically significant compared to the multivariate regression results. All other components exhibit similar results. In summary, the results indicate that only the noise share and public firm-specific information are significantly correlated with the returns of the anomaly long-short portfolios. For every 10% increase in the $Public\ DR$, $Public\ CF$, and $Noise$ variance, the dependent variable (anomaly monthly return) experiences approximately 1.04 basis points, 1.68 basis points, and 0.70 basis points growth, respectively.

These findings support our hypothesis that greater opacity in informational environments may lead to increased opportunities for arbitrage, consistent with the peak of anomaly return during the financial crisis in Figure 4. The informational cost and information asymmetry allow the investors with informational advantage to make a profit through trading on public firm-specific news.

5.2. Decimalization

5.2.1. Baseline Analysis

Some studies have shown that the improvement of liquidity causes the stock to be traded at a lower cost and mispricing to attenuate over time. So we test liquidity shock (decimalization) as an explanation for anomaly decay and to see whether liquidity shock reduced the cost of the market correcting mispricing.

Firstly, we use the absolute value of the signed trading volume as the $Liquidity$ measure[19]. The dependent variable in our analysis is the information shares obtained through our decomposition method. We start our analysis with OLS regression to examine the correlation between anomaly trading volume ($Liquidity$) and the share of the information component. We introduce the following model:

$$InforShare_{j,i,t} = \alpha_i + \beta_i \times Liquidity_{j,t} + \tau_t + \gamma_j + \varepsilon_{j,i,t} \tag{14}$$

where *j* represents each anomaly, *t* represents the year-month, and *i* represents each information component. We include year-month fixed effect τ_t and anomaly fixed effect γ_j. We normalize the liquidity measure to standard normal distribution for easier interpretation.

Insert Table 5 About Here

Table 5 suggests that liquidity is negatively correlated with the noise share, and this relationship is significant at the 1% significance level. This finding aligns with evidence in the literature indicating that liquidity reduces the cost of trading on arbitrage opportunities and mitigates mispricing (Chordia, Subrahmanyam, and Tong, 2014). Additionally, trading volume is positively correlated with market-wide cash flow news and private firm-specific discount rate news at the 5% significance level. With lower trading costs, the long-short portfolio returns are more responsive to the market news and private stock-specific discount rate news. Surprisingly, we do not find a significant relation between liquidity and public firm-specific information. Overall, we find that liquidity improves market efficiency and attenuates mispricing. Considering the positive correlation between noise share and anomaly return, it appears that the reduction in noise share is the driver for anomaly decay.

[19] We use the signed trading volume as the liquidity measure since the variable can be directly derived from CRSP. This approach allows us to avoid losing a significant proportion of observations during the merging process and enables us to closely align with the long-short portfolio proposed by Chen and Zimmermann (2020).

5.2.2. Diff-in-Diff Analysis of Decimalization

Nevertheless, the relationship in OLS regressions could be endogenous. For example, a less noisy trading strategy might be more appealing to investors, consequently resulting in higher trading volumes. To tackle the endogeneity here, 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). Since 2004, the United States has mandated the transition of security prices from fractions to the decimal format. This change has caused a significant liquidity shock, particularly affecting securities with low stock prices. Within each port of the anomaly portfolio, securities with lower prices will be designated as the treatment group, while those with higher prices will be considered the control group. We exclusively focus on the six months preceding the initial phase of decimalization implementation as the pre-period and the six months following the completion of decimalization as the post-period. Throughout the brief event window, it is improbable for corporations to manipulate stock prices in reaction to decimalization.

We construct a double-sorting portfolio in the following steps. Firstly, we sort by signals based on Chen and Zimmermann (2020). Next, within each signal portfolio, we categorize stocks into quintiles based on their prices and designate the bottom price quintile as the treatment group (higher shocks in liquidity) and the top price quintile as the control group (lower shocks in liquidity). Last, we obtain long-short returns for both the treatment and control group we construct the treatment group and control group for each port of anomalies. The regression is as below:

$$InforShare_{i.j,t} = \alpha_i + \beta_t * Treat_{j,t} + \beta_p * Post_{j,t} + \beta_j * Post_{j,t} * Treat_{j,t} + \varepsilon_{i,j,t} \tag{15}$$

Insert Table 6 About Here

In Table 6, we report the result of the long-short portfolio sample. Firstly, we observe that the improvement in liquidity leads to a decrease in the noise share for the long-short portfolio. The lower the trading friction, the higher the market efficiency. Correspondingly, we also observe an increase in market-wide news shares (both cash flow news and discount rate news). This finding aligns with the OLS result in Table 5. Overall, the results from both OLS and Decimalization Diff-in-Diff suggest that improved liquidity decreases noise share and increases market-wide information.

5.2.3. Direct and Mediated Effects of Decimalization on Anomaly Decay

Given that liquidity shock is the main driver for anomaly decay, we employ a mediation model to establish a connection between liquidity shocks and anomaly decay, with information shares serving as the mediating variable as shown in Figure 5. The underlying hypothesis is that increased liquidity leads to a higher level of information and a lower level of noise, consequently resulting in anomaly decay. To assess the mediated relationship between liquidity shocks and the profitability of factor-mimicking portfolios, we adopt the mediation analysis steps outlined by Preacher and Hayes (2004). And we focus on the long-short anomaly portfolio returns.

Insert Figure 5 About Here

The mediation analysis is performed in the following steps. Firstly, we conduct a regression of the mediator variable (M, information shares) on the independent variable (X, $Post\_decimalization$) and save the coefficient as $a1$. Subsequently, we regress the dependent variable (Y, long-short portfolio return) on both the independent variable (X) and the mediator variable (M) with the coefficient on the mediator as $a2$. Finally, we regress the dependent variable (Y) on the independent variable (X) to obtain the coefficient c, representing the total effect. The proportion of the mediated effect (indirect effect $a1 \times a2$) is then calculated as $(a1 \times a2)/c$. [20]

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[20] We also use the liquidity measure as the independent variable for the robustness check. However, since security return serves as one of the inputs in calculating the signed dollar volume of the hedging portfolio, the regression of long-short portfolio return on the signed dollar volume may encounter mechanical issues. Therefore, we employ an alternative liquidity measure, namely the share-weighted percentage effective spread, utilizing interpolated quotes

Insert Table 7 About Here

Table 7 indicates that the total effect of decimalization on profitability is approximately -0.413, and the effect is significant at 1% level. Moreover, the negative correlation between the $Post\_decimalization$ dummy variable and the return of the long-short portfolio implies that higher liquidity is associated with lower profitability in the factor-mimicking portfolio. Notably, noise share carries the largest weight as the mediation pathway through which liquidity influences the profitability of the hedging portfolio. This consistency aligns with our findings in Tables 3 and 4, illustrating that liquidity enhances market efficiency by reducing the noise share. The combination of the seven components contributes to 18.5% of the mediated effect, which is economic significant considering that all moving parts in the economy might contribute to anomaly decay.

5.3. Publication Effect

5.3.1. Baseline Analysis

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 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

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from TAQ. We compute the weighted average of the effective spread measure within each anomaly portfolio and calculate the average between the long and short portfolios. Additionally, we introduce an additional filter: the composite stock in the hedge portfolio must have non-missing observations of effective spread, as we tend to lose a substantial portion of our observations during the merging process. But in the robustness analysis, we find the same result: noise share carries the largest weight as the mediator variable.

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 find that investors learn from publications of data snooping anomalies, trade on pure noise, and worsen the market efficiency by increasing noise share.

We adopt Bacon decomposition to establish a causal inference as the publications take effect in different years for different anomalies[21]. The Bacon decomposition not only compares the treated group and control group but also contrasts the early-treated and later-treated. This method does not necessitate a control group, which is non-existent in our setting. 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, *t* represents the year-month, and *i* represents each information component.

$$InforShare_{i.j,t} = \alpha_i + \beta_j * Post\_publication_{j,t} + \gamma_j + \theta_t + \varepsilon_{i,j,t} \tag{16}$$

Insert Table 8 About Here

The results of Bacon decomposition also indicate that the noise shares expand in the post-publication period. We also see a significant reduction in the private firm-specific cash flow and discount news share. The result of Table 8 consolidates our statement that the publication of characteristics-based anomalies induces investors to trade data-snooping anomalies and therefore pure noise in the market. This leads to an increase in the noise share. Moreover, following the publication of anomalies, investors become increasingly adept at using past returns to predict future returns - a facet considered public information in our VAR model. This shift renders the potential profitability of anomalies no longer private information.

[21] We also conducted a staggered diff-in-diff analysis for a robustness check, which yields the same result.

5.3.2. Data Snooping Anomalies

While previous literature argues that the publication of anomalies reveals arbitrage opportunities to investors, allowing them to trade on mispricing information, our findings present a surprising increase in the noise share. This could be attributed to the confusion in trading caused by data-snooping anomalies. We posit that the publication of data-snooping anomalies prompts investors to trade on "null information," leading to increased noise in stock returns within the market. To test this hypothesis, we divide our anomaly sample into "data-snooping anomalies" and "non-data-snooping anomalies" based on Linnainmaa and Roberts (2018). We classify anomalies that exhibit inferior performance in both the pre-period and post-sample as likely data-snooping anomalies. Specifically, we label anomalies falling into economic categories such as investment, profitability, sales growth, risk, default risk, and cash flow risk as such.

Insert Table 9 About Here

Table 9 reveals that the increase in noise share is only significant in the case of data-snooping anomalies, which tend to exhibit poorer performance in both pre-period and post-period samples. We observe no significant jump in non-data-snooping anomalies in Column (2). Additionally, in the full sample, we interact the $Post\_publication$ dummy variable with the $data\_snooping$ dummy variable, and the coefficient is positive and significant. This suggests that the publication effect on noise share is more pronounced in the data-snooping sample. This observation helps reconcile the puzzle of the deterioration in the profitability of anomalies after their publication. The significance of long-short portfolio returns might be sensitive to the selection of the sample period as well as the method of constructing the hedging portfolio.

5.3.3. Heterogeneous Publication Effects of Different Types of Anomalies

As anomalies originate from diverse data categories and possess distinct information structures, the publication effects are expected to vary among different anomalies depending on the data source. Following the categorization by Chen, Lopez-Lira, and Zimmermann (2023), we classify the anomalies into three broader groups: risk-based anomalies, mispricing-based anomalies, and agnostic anomalies. The results of the staggered diff-in-diff by subgroup are presented in Table 10, Panel A to Panel C.

Insert Table 10 About Here

Interestingly, our study on risk-based anomalies reveals an increase in the noise share, suggesting that the publication of risk-based anomalies tends to prompt trading based on noise and may not necessarily enhance market efficiency. This finding aligns with Linnainmaa and Roberts (2018), indicating that risk-based anomalies are more likely to be data-snooping anomalies. For mispricing anomalies, we observe a reduction in the share of private firm-specific information components. The publication of anomalies allows investors to utilize past returns for predicting future anomaly returns, thereby correcting mispricing. For agnostic anomalies, there is a decline in $Market\ DR$ and $Public\ CF$ shares.

5.3.4. Subsample Analysis by Transaction Costs

In this section, we investigate whether transaction costs influence the magnitude of publication effects, particularly if investors react to anomaly publications by seeking new profitable opportunities. We categorize the anomalies into *liquid* and *illiquid* anomalies based on their trading volumes. An anomaly is labeled as a *liquid* anomaly if its trading volume is greater than the median for that year; otherwise, it is categorized as an *illiquid* anomaly.

Insert Table 11 About Here

Table 11, Panel A, suggests that *liquid* anomalies undergo an increase in the $Noise$ share and $Market\ CF$ share, similar to our findings in the full sample analysis. Additionally, we observe a decline in $Private\ CF$

share post-publication, indicating that the revealed anomalies are no longer private information. However, we do not detect any significant changes in the *illiquid* anomalies. Higher transaction costs dissuade investors from pursuing the factor-mimicking strategy for profit, resulting in notably weaker publication effects in anomalies characterized by elevated transaction costs.

6. Conclusion

We provide a unified framework to understand the essence of the information in the market by combining two prominent decomposition methods: the type of information 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.

We examine the timing of anomaly decay, empirically testing three potential explanations: publication events, liquidity shocks, or a general time-series market trend. Our findings indicate that anomalies predominantly (60%) decay during periods of structural increases in market liquidity. Publication events and general market changes explain only a smaller proportion (below 40%) of anomaly decay.

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 increase noise share. Academic publication of anomalies induces noise trading due to data snooping anomalies, leading to worse market quality. We use the decimalization event in 2001 as a liquidity shock to anomaly hedging portfolios and find liquidity contributes to anomaly decay. Based on mediation analysis, the mediated effects through information shares are economically non-trivial. Our findings suggest that liquidity is the main trigger for anomaly decay over time.

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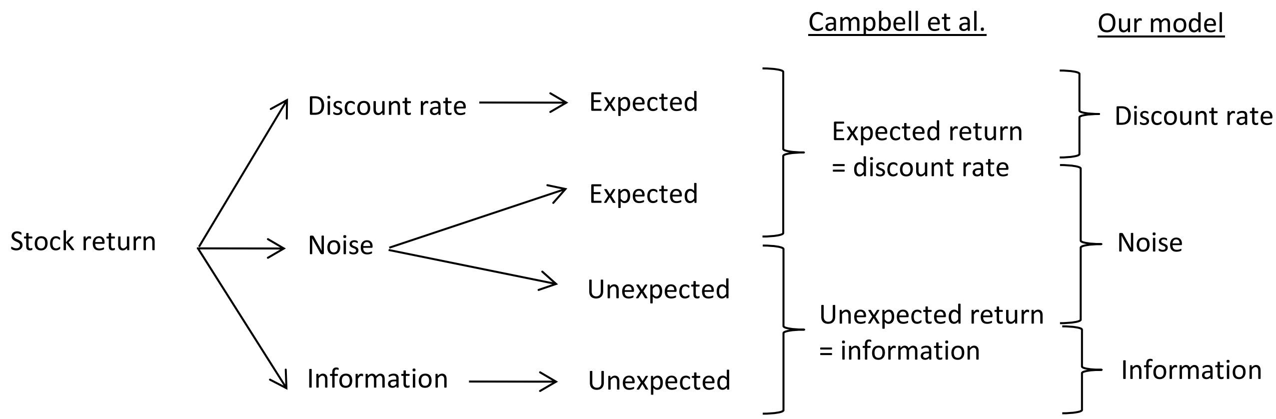
Panel A: Adjusting a standard cash flow / discount rate decomposition to account for noise



Panel B: Extended variance decomposition

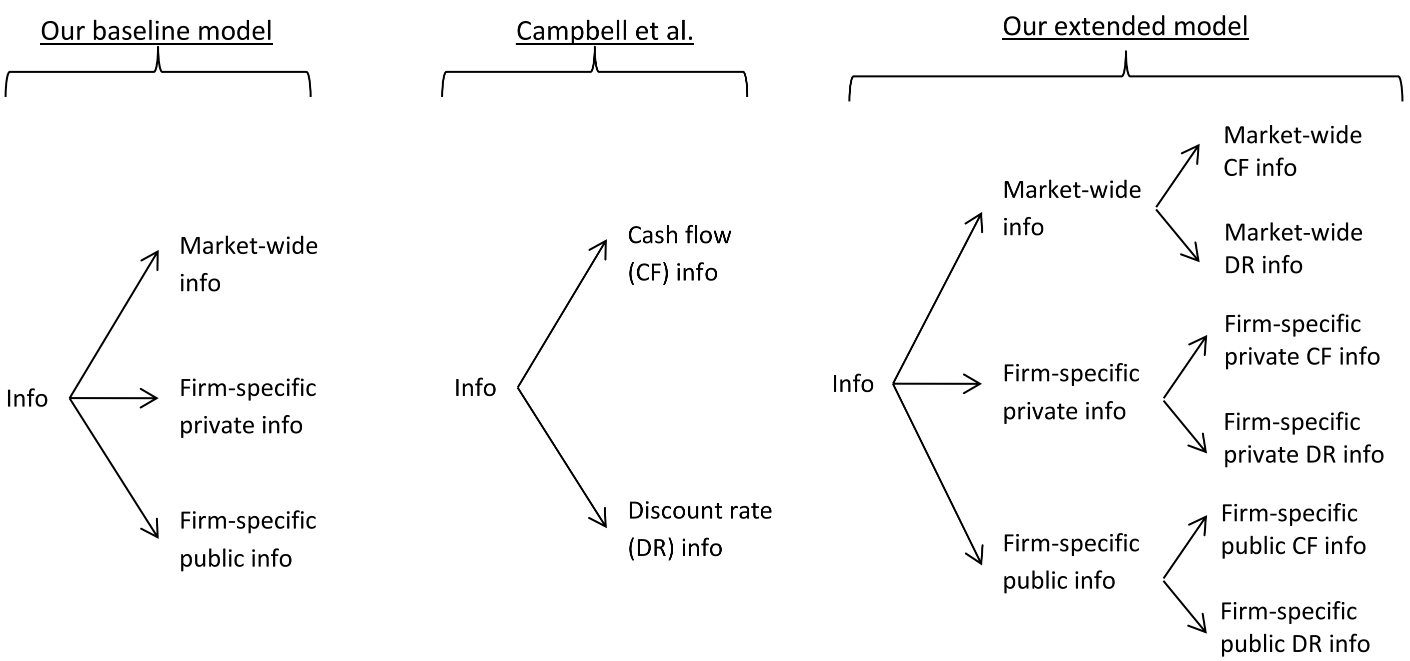
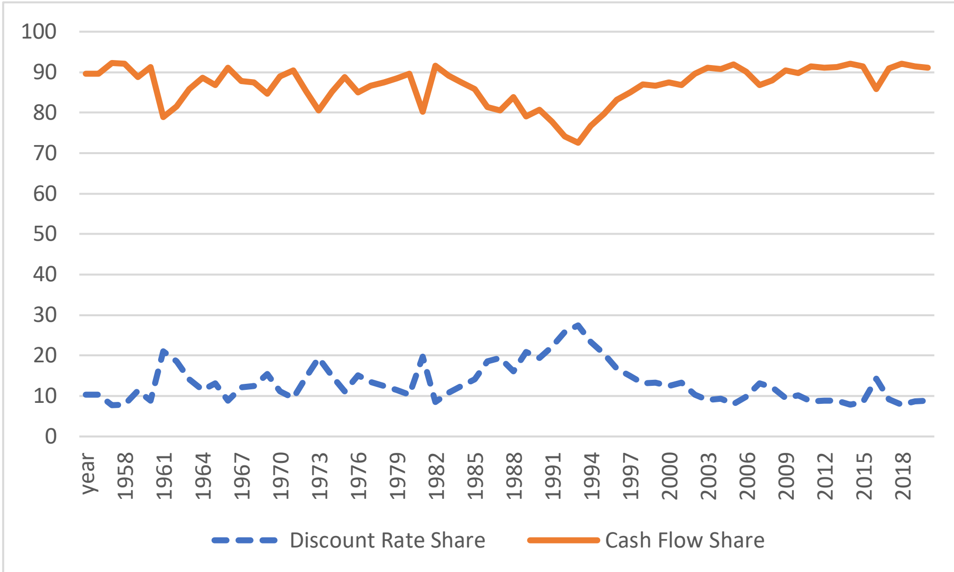


Figure 1. Extension of variance decomposition to cash flow and discount rate information.
Panel A shows how noise is dealt with in a standard cash flow / discount rate news decomposition (e.g., Campbell, 1991) and in our modified cash flow / discount rate news decomposition. In the standard decomposition, 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

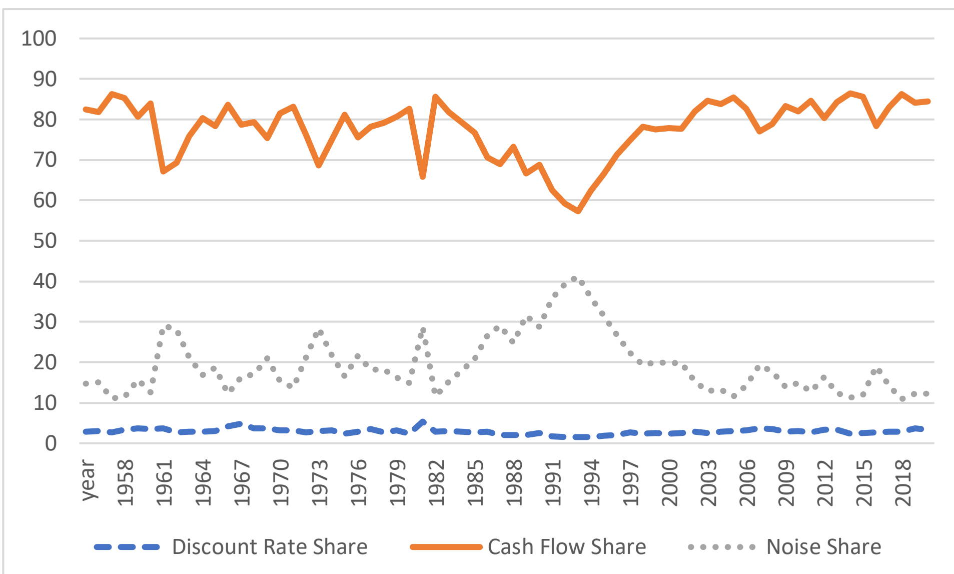


Figure 2. Cash flow news, discount rate news, and noise through time.
This figure shows the time-series trends in the percentage of stock return variance that is attributable to time-variation in the cash flow news ($Cash\ Flow\ Share$), discount rate news ($Discount\ Rate\ Share$), and noise ($Noise\ Share$) 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.

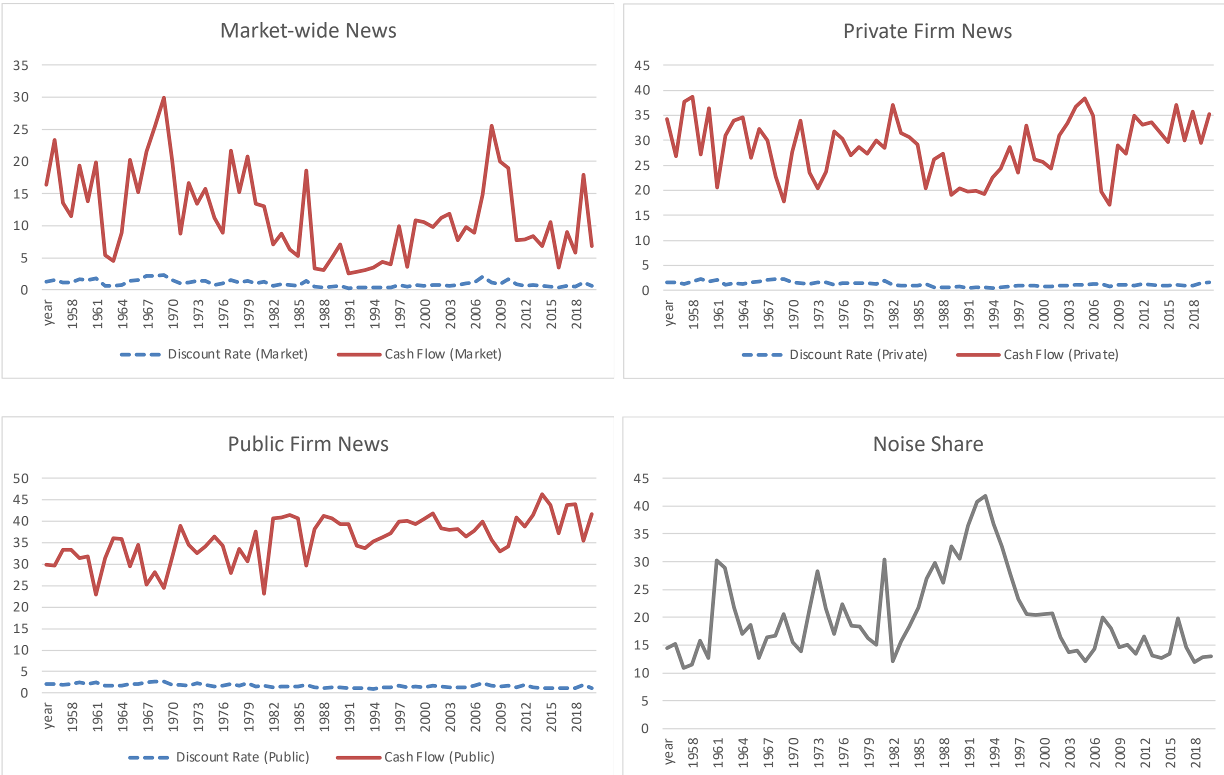


Figure 3A. Trend of the seven-components decomposition for individual stocks across time

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 2020. 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.

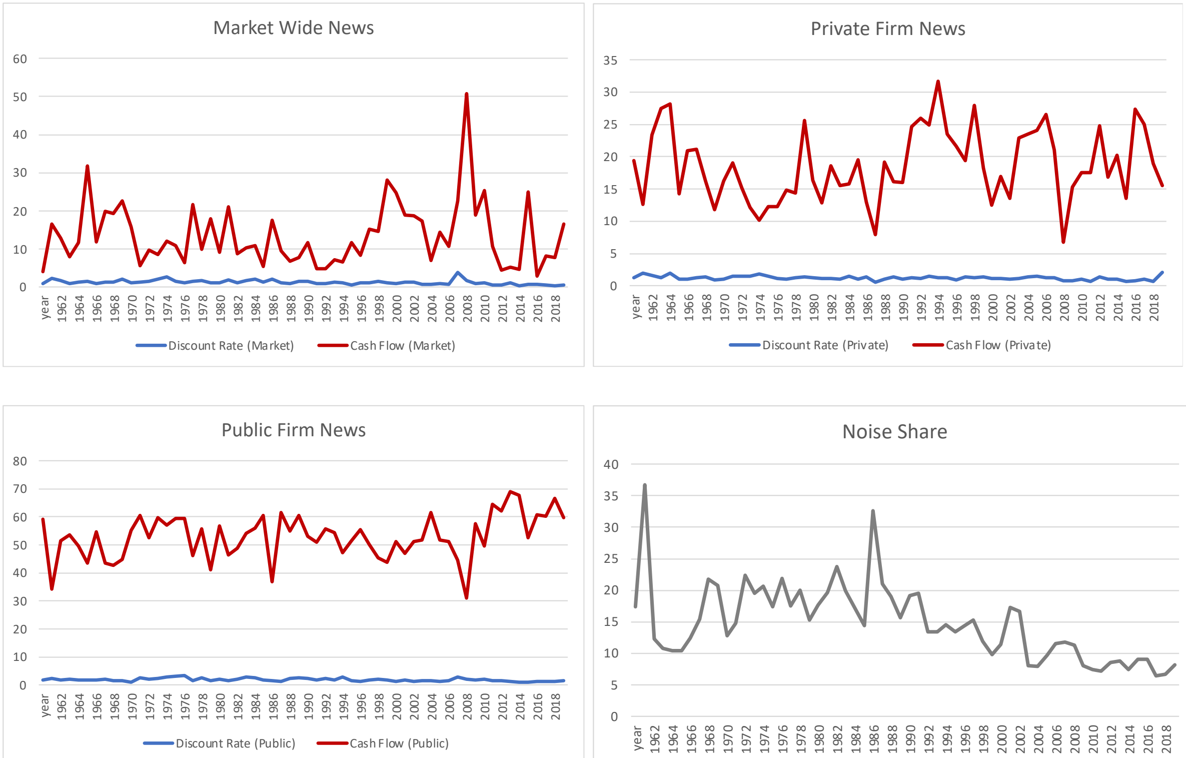


Figure 3B. Decomposed components of anomalies hedge portfolio across time

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). The variance components are calculated separately for each anomalies each year and then averaged across anomalies each year.

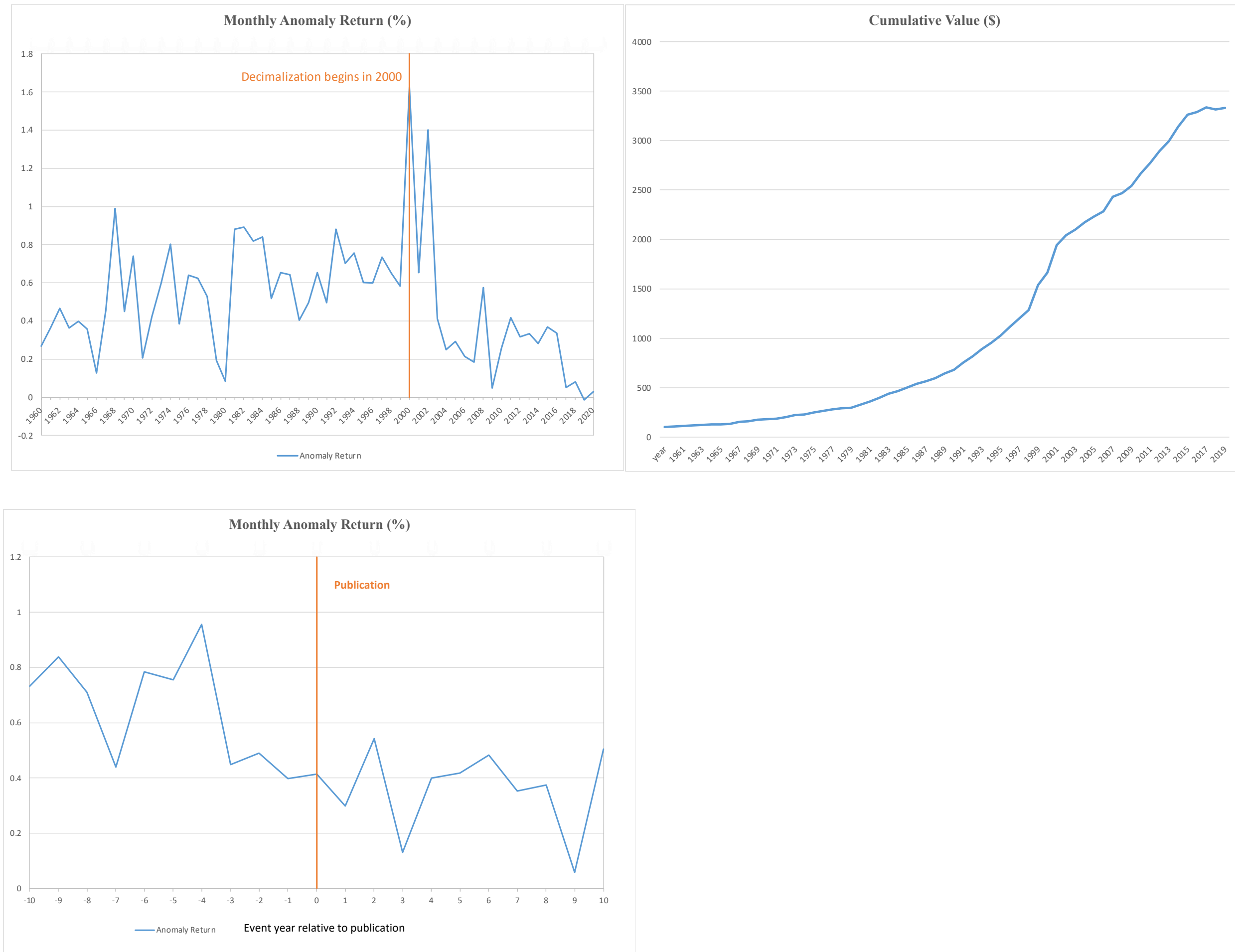


Figure 4. Monthly return of the anomalies portfolio

This figure shows the time-series trends of the realized annual returns for factor-mimicking portfolios of anomalies from 1960 to 2020. Monthly returns are averaged across anomalies each year. Cumulative value is calculated as the change in value of a one-dollar investment made at the beginning of 1960, assuming even investment across factor-mimicking portfolios. The monthly anomaly return is calculated as the average of the monthly return based on the anomaly and the event year in relation to the publication year.

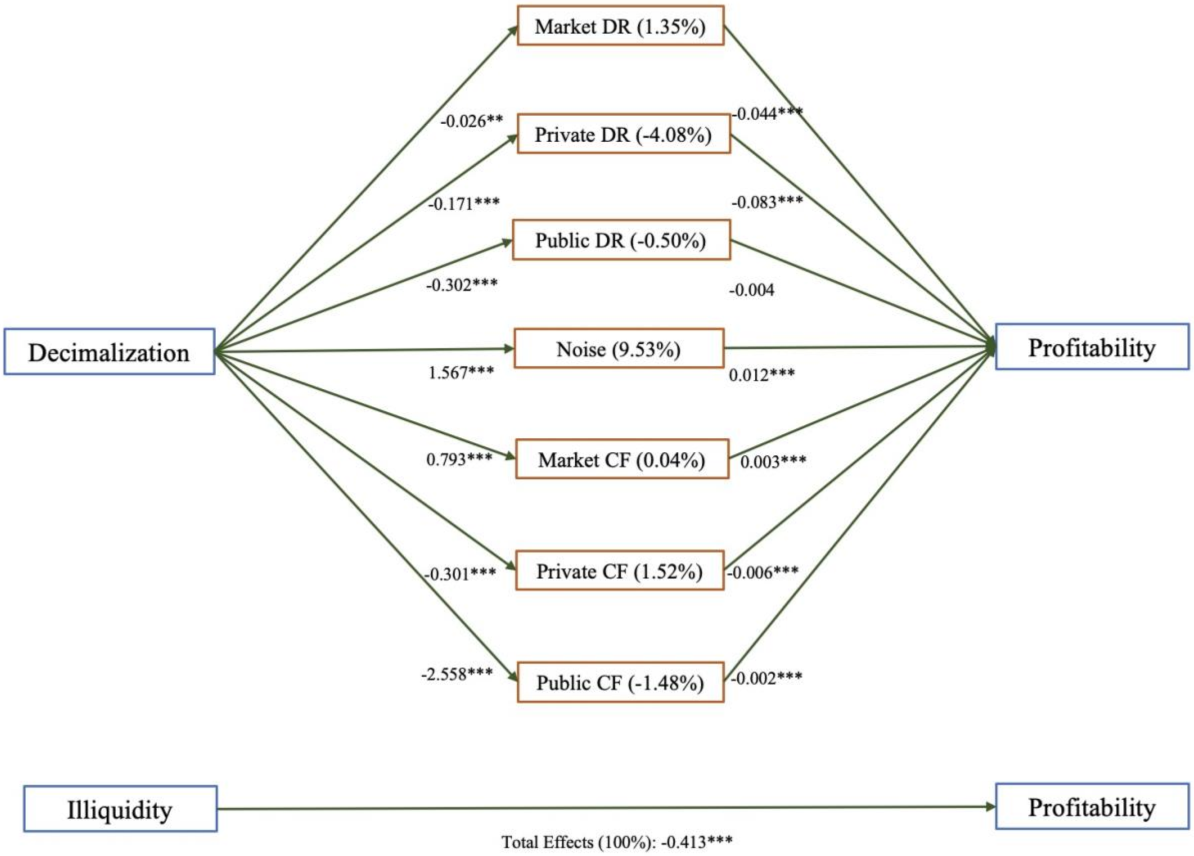


Figure 5. Direct and mediated effects of liquidity on profitability

This graph depicts the results from seven (separate) mediation analyses of the channels by which liquidity impacts the profitability of a factor-mimicking portfolio. The seven channels are $Market\ DR$, $Market\ CF$, $Private\ DR$, $Private\ CF$, $Public\ DR$, $Public\ CF$, and $Noise$. We perform the following set of panel regressions at factor-month observations:

$$InforShare_{j,i,t} = a_1 \times Post\_decimalization_t + \tau_t + \gamma_j + \varepsilon_{j,i,t}$$

$$Profitability_{i.j,t} = \beta_i \times Post\_decimalization_t + a_2 \times InforShare_{j,i,t} + \tau_t + \gamma_j + \varepsilon_{j,i,t}$$

$$Profitability_{i,j,t} = c \times Post\_decimalization_t + \tau_t + \gamma_j + \varepsilon_{j,i,t}$$

where $InforShare_{j,i,t}$ represents the information component share obtained from our decomposition method, $Post\_decimalization_{j,t}$ indicates the observation is after April 2001[23], and $Profitability_{i.j,t}$ denotes the returns of the long-short portfolio.

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[23] In mediation analysis, we also perform analysis using Illiquidity (effective spread) as the mediation.Noise also carries the largest mediation share (8%).

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). The variance variables are annualized for interpretation and winsorized at 5% and 95%. All other variables are winsorized at 1% and 99% levels to mitigate the effect of outliers.

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	Std Dev	P05	P50	P95	N
Stock Characteristics						
Price	39.234	1887.102	0.969	14.000	60.000	209,426
Volume	449.355	4403.984	0.000	9.400	1572.113	206,580
Market Cap	1900.864	15068.670	3.612	79.476	5406.387	209,246
Anomaly Characteristics						
Var (Market DR)	0.008	0.012	0.001	0.003	0.048	13,789
Var (Market CF)	0.094	0.167	0.001	0.018	0.640	13,789
Var (Private DR)	0.006	0.006	0.001	0.003	0.023	13,797
Var (Private CF)	0.064	0.089	0.002	0.024	0.326	13,797
Var (Public DR)	0.010	0.013	0.001	0.004	0.050	13,797
Var (Public CF)	0.332	0.364	0.028	0.182	1.374	13,797
Var (Noise)	0.108	0.163	0.003	0.036	0.637	13,797
Var (Return)	0.517	0.651	0.046	0.248	2.564	13,797
Return (%)	1.084	6.298	-8.263	1.118	9.763	1,141,481

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							
1960-1996	0.69	7.38	0.89	23.76	1.39	36.12	29.76
1997-2021	0.76	10.14	1.03	28.68	1.47	39.47	18.46
Difference	0.07	2.76	0.13	4.91	0.07	3.35	-11.30
(Post-Pre 1997)	(0.60)	(1.63)*	(1.32)	(3.32)***	(0.78)*	(3.20)***	(-5.12)***
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 drives anomaly decay?
This table reports the result from the following regressions:

$$Return_{j,t} = \alpha + \beta_{Pub} \times Post\_publication_{j,t} + \beta_{Dec} \times Post\_decimalization_t + \beta_{Liq} \times Liquidity_{j,t} + \varepsilon_{j,t}$$

Where j represents each anomaly, and t represents the year-month, the absolute value of signed dollar volume is used as the measure of liquidity for factor-mimicking portfolios, and the monthly return is used as the dependent variable. $Post\_publication_{j,t}$ is a dummy variable that indicates the observation after the publication year of the anomaly, while $Post\_Decimalization_{j,t}n$ indicates the observation is after April 2001. All the regressions include year fixed effects to control for time-varying market trends. Standard errors are clustered at the anomaly category level and year level.The Table reports corresponding t-statistics in parentheses. ***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels.

Panel A: Multivariate Regression			
	(1)	(2)	(3)
	Monthly Return	Monthly Return	Monthly Return
Post_publication	**-0.135****	**-0.134****	**-0.091****
	(-2.32)	**(-2.23)**	**(-1.99)**
Post_decimalization	**-0.802*****	**-0.800*****	**-0.800*****
	(-3.64)	**(-3.65)**	**(-3.63)**
Liquidity		0.037	0.033
		(0.60)	(0.56)
Constant	-0.127	-0.122	0.139
	(-1.06)	(-1.04)	(0.97)
Year FE	Yes	Yes	Yes
Anomaly FE	Yes	Yes	No
Adjusted R^2	0.012	0.012	0.005
Observations	163,729	163,729	163,729

Panel B: Partial Correlation and R^2		
	(1)	(2)
	Patial Correlation	Partial R^2
Post_publication	-0.007***	0.46 bp
Post_decimalization	-0.011***	0.94 bp
Liquidity	0.009***	0.64 bp

Table 4. What components are linked to anomaly return?
This table shows the association between anomaly monthly returns and variance components and reports the result from the following regressions:

$$Return_{j,t} = \alpha + \Sigma_i \beta_i \times Var\_Component_{i,j,t} + \tau_t + \gamma_j + \varepsilon_{j,t}$$

where j represents each anomaly, t represents the year-month, i represents each of the variance components, and the monthly return is used as the dependent variable. We take the logarithm of the monthly variance components to interpret the relative changes. All the regressions include year and factor fixed effects to control for time-varying market trends and time-invariant variation. Standard errors are clustered at the anomaly category level and year-month level. The Table reports corresponding t-statistics in parentheses. ***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels.

Panel A: Multivariate regression

	(1) Long-Short Portfolio Monthly Return	(2) Long Portfolio Monthly Return	(3) Short Portfolio Monthly Return
Market DR	0.005	0.106	0.187
	(0.15)	(1.07)	(1.29)
Market CF	-0.011	**0.313***	**0.264***
	(-0.73)	**(1.95)**	**(1.79)**
Private DR	-0.052	**0.168***	0.016
	(-1.36)	**(1.66)**	(0.21)
Private CF	-0.0267	**0.0777*****	0.0420
	(-1.53)	**(3.03)**	(1.60)
Public DR	**0.109****	**0.189***	0.092
	(2.41)	**(1.79)**	(0.89)
Public CF	**0.176*****	0.031	-0.022
	(4.28)	(0.91)	(-0.57)
Noise	**0.073****	**0.122*****	**0.112*****
	(2.16)	**(3.95)**	**(3.55)**
Factor FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.045	0.808	0.797
Observations	140,010	141,336	140,887

Panel B: Univariate regression

	(1) Market DR	(2) Market CF	(3) Private DR	(4) Private CF	(5) Public DR	(6) Public CF	(7) Noise
Variance	**0.091****	0.013	0.029	-0.001	**0.200*****	**0.263*****	**0.144*****
	(2.42)	(0.72)	(0.72)	(-0.07)	**(4.35)**	**(5.31)**	**(7.88)**
Constant	0.996***	0.525***	0.639**	0.465***	1.574***	0.949***	0.979***
	(4.66)	(7.38)	(2.76)	(6.31)	(6.25)	(10.91)	(16.95)
Factor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.036	0.035	0.035	0.035	0.037	0.037	0.037
Observations	140,010	140,010	140,010	140,010	140,010	140,010	140,010

Table 5. How does liquidity affects information components?
This table reports the result from the following regressions:

$$InforShare_{j,i,t} = \alpha_i + \beta_i \times Liquidity_{j,t} + \tau_t + \gamma_j + \varepsilon_{i,j,t}$$

where j represents each anomaly, t represents the year-month, i represents each of the variance components, and the monthly return is used as the dependent variable. Signed dollar volume is used as the measure of the liquidity of factor-mimicking portfolios. The decomposed information component shares are used as the dependent variables. All the regressions include factor fixed effects (γ_j) and year-month fixed effect (τ_t). Standard errors are clustered at the anomaly category level and year-month level. The return and signed trading volume of the portfolio are calculated as value-weighted. The Table reports 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
Liquidity	-0.001	**0.225****	**0.023****	-0.042	0.005	0.086	**-0.297*****
	(-0.10)	**(2.12)**	**(2.21)**	(-0.63)	(0.35)	(0.51)	**(-3.79)**
Constant	1.644***	11.96***	1.425***	11.88***	1.973***	57.74***	13.37***
	(3,743)	(815.7)	(899.4)	(1,428)	(966.1)	(2,247)	(1,196)
Adjusted R^2	0.325	0.378	0.438	0.261	0.222	0.352	0.261
Observations	139,803	139,803	139,803	139,803	139,803	139,803	139,803

Table 6: How decimalization (liquidity shock) affects information components?
The following table presents the results of the diff-in-diff regressions as below:

$$InforShare_{i,j,t} = \alpha_i + \beta_t \times Treat_{j,t} + \beta_p \times Post_{j,t} + \beta_j \times Post \times Treat_{j,t} + +\tau_t + \gamma_j + \varepsilon_{i,j,t}$$

Decimalization in 2001 allows for tighter spreads between bid and ask prices and the liquidity of the stock increases. This analysis follows Brogaard, et al (2017) and Fang et al. (2014) to construct the treatment and control group: we sort all sample firms based on their prices around the decimalization in 2001 and categorize them into five groups. The bottom quintile with the lowest stock prices is designated as the treatment group, while the top quintile is labeled as the control group. 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. All the regressions include factor fixed effects (γ_j) and year-month fixed effect (τ_t). Standard errors are clustered at the anomaly category level and year-month level. ***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels.

	(1) Market DR	(2) Market CF	(3) Private DR	(4) Private CF	(5) Public DR	(6) Public CF	(7) Noise
Treat	**-0.262****	-0.349	-0.152	**-1.285***	-0.044	1.197	0.895
	(-2.44)	(-0.42)	(-1.63)	**(-1.77)**	(-0.09)	(1.03)	(0.79)
Post * Treat	**0.199***	**1.420****	0.131	-1.153	-0.210	1.200	**-1.587*****
	(1.70)	**(2.38)**	(1.34)	(-1.05)	(-1.56)	(1.45)	**(-2.70)**
Adjusted R^2	0.320	0.369	0.214	0.207	0.202	0.278	0.261
Observations	5,124	5,124	5,124	5,124	5,124	5,124	5,124

Table 7. Direct and mediated effects of liquidity on anomalies profitability
This table reports the result from the following regressions:

$$InforShare_{j,i,t} = a_1 \times Post\_decimalization_t + \tau_t + \gamma_j + \varepsilon_{j,i,t}$$

$$Profitability_{i,j,t} = \beta_i \times Post\_decimalization_t + a_2 \times InforShare_{j,i,t} + \tau_t + \gamma_j + \varepsilon_{j,i,t}$$

$$Profitability_{i,j,t} = c \times Post\_decimalization_t + \tau_t + \gamma_j + \varepsilon_{j,i,t}$$

where $InforShare_{j,i,t}$ represents the information component share obtained from our decomposition method, $Post\_decimalization_{j,t}$ indicates the observation is after April 2001, and $Profitability_{i,j,t}$ denotes the returns of the long-short portfolio. The table reports bold numbers to indicate statistically significance at the 5% levels.

	Market DR	Market CF	Private DR	Private CF	Public DR	Public CF	Noise
Indirect Effect	-0.004	0.000	0.011	-0.004	0.001	0.004	-0.026
Direct Effect	-0.269	-0.272	-0.284	-0.268	-0.274	-0.276	-0.247
Total Effect	-0.272	-0.272	-0.273	-0.272	-0.273	-0.272	-0.273
% of Tot Eff mediated	**1.35%**	**0.04%**	**-4.08%**	**1.52%**	**-0.50%**	**-1.48%**	**9.53%**

Table 8. Publication effect – Bacon decomposition.
The table presents the results of the following regression:

$$InforShare_{i,j,t} = \alpha_i + \beta_i \times Post\_Publication_{j,t} + \gamma_j + \tau_t + \varepsilon_{i,j,t}$$

where j represents different anomalies, and t represents the year. $Post\_Publication_{j,t}$ takes the value 1 after the anomaly gets published, and 0 otherwise. Panel A report the result of Bacon decomposition for the long-short portfolio. We report corresponding t-statistics in parentheses. Standard errors are clustered at the anomaly category level[24].***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels.

	(1) Market DR	(2) Market CF	(3) Private DR	(4) Private CF	(5) Public DR	(6) Public CF	(7) Noise
Post_publication	0.041	0.535	**-0.087***	**-1.228***	-0.056	-0.794	**1.588****
	(0.32)	(0.67)	**(-1.79)**	**(-1.94)**	(-0.70)	(-1.06)	**(2.52)**
Constant	1.942***	12.591***	1.588***	11.689***	2.132***	56.645***	13.413***
	(62.97)	(62.49)	(157.07)	(80.47)	(111.55)	(340.53)	(90.36)
R-squared	0.303	0.358	0.541	0.293	0.236	0.386	0.292
Observations	13,797	13,797	13,797	13,797	13,797	13,797	13,797

[24] In staggered diff in diff, we cluster SE on both anomaly category level and year-month level, the result is still robust. But in Bacon decomposition, we can only cluster on one variable.

Table 9. Impact of data-snooping anomalies on noise share

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

$$NoiseShare_{j,t} = \alpha_i + \beta_i \times Post\_Publication_{j,t} + \gamma_j + \tau_t + \varepsilon_{j,t}$$

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. We divide our anomaly sample into "data-snooping anomalies" and "non-data-snooping anomalies" based on Linnainmaa and Roberts (2018). We classify anomalies that exhibit inferior performance in both the pre-period and post-sample as likely data-snooping anomalies. Specifically, we label anomalies falling into economic categories such as investment, profitability, sales growth, risk, default risk, and cash flow risk as such. Column (1) presents the results of staggered diff-in-diff analysis for data-snooping anomalies, while Column (2) reports the results for non-data-snooping anomalies. In Column (3), we introduce an interaction term between the $Post\_publication$ dummy variable and the $data\_snooping$ dummy variable. All the regressions include factor fixed effects (γ_j) and year-month fixed effect (τ_t). Standard errors are clustered at the anomaly category level and year-month level. We report corresponding t-statistics in parentheses. ***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels.

	(1) Data-Snooping	(2) Non-Data-Snooping	(3) Full Sample
Post_publication	**2.713*** **	1.168	1.167
	(4.00)	(1.57)	(1.57)
Post_publication * Snooping			**1.634** **
			(2.45)
R-squared	0.259	0.277	0.266
Observations	26,996	136,637	163,639

Table 10. Heterogenous publication effects of different types of anomalies
The table presents the results of the following staggered diff-in-diff:

$$InforShare_{i,j,t} = \alpha_i + \beta_i \times Post\_Publication_{j,t} + \gamma_j + \tau_t + \varepsilon_{i,j,t}$$

where j represents different anomalies, and t represents the year-month. $Post\_Publication_{i,j,t}$ takes the value 1 after the anomaly gets published, and 0 otherwise. We Follow the categorization by Chen, Lopez-Lira, and Zimmermann (2023 to classify the anomalies into three broader groups: risk-based anomalies, mispricing-based anomalies, and agnostic anomalies. All the regressions include factor fixed effects (γ_j) and year-month fixed effect (τ_t). Standard errors are clustered at the anomaly category level and year-month level. We report corresponding t-statistics in parentheses. ***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels.

Panel A:Risk Anomaly

	(1) Market DR	(2) Market CF	(3) Private DR	(4) Private CF	(5) Public DR	(6) Public CF	(7) Noise
Post_publication	0.037	-2.355	-0.009	0.540	**-0.446*** **	-0.104	**2.336** **
	(0.14)	(-1.38)	(-0.05)	(0.55)	**(-3.14)**	(-0.05)	**(2.48)**
Constant	1.945***	15.608***	1.550***	12.538***	2.007***	53.647***	12.704***
	(35.40)	(42.96)	(40.53)	(60.53)	(68.39)	(128.78)	(64.16)
Adjusted R^2	0.349	0.459	0.407	0.313	0.260	0.434	0.259
Observations	29,132	29,132	29,132	29,132	29,132	29,132	29,132

Panel B:Mispricing Anomaly

	(1) Market DR	(2) Market CF	(3) Private DR	(4) Private CF	(5) Public DR	(6) Public CF	(7) Noise
Post_publication	0.077	1.356	**-0.087***	**-1.969** **	0.085	-0.171	0.708
	(0.94)	(1.48)	**(-1.73)**	**(-2.43)**	(1.00)	(-0.16)	(1.43)
Constant	1.776***	10.848***	1.544***	11.119***	2.078***	59.395***	13.240***
	(70.93)	(38.65)	(102.39)	(45.05)	(80.80)	(180.47)	(88.50)
Adjusted R^2	0.355	0.336	0.529	0.253	0.263	0.324	0.281
Observations	87,567	87,567	87,567	87,567	87,567	87,567	87,567

Panel C:Agnostic Anomaly

	(1) Market DR	(2) Market CF	(3) Private DR	(4) Private CF	(5) Public DR	(6) Public CF	(7) Noise
Post_publication	**-0.294*** **	1.794	-0.087	-0.095	0.020	**-2.310***	0.973
	(-3.34)	(1.07)	(-1.20)	(-0.21)	(0.08)	**(-1.76)**	(1.15)
Constant	1.594***	12.301***	1.235***	12.595***	1.761***	56.343***	14.171***
	(79.91)	(29.94)	(69.79)	(120.15)	(29.12)	(177.48)	(69.19)
Adjusted R^2	0.290	0.354	0.309	0.297	0.161	0.368	0.308
Observations	43,029	43,029	43,029	43,029	43,029	43,029	43,029

Table 11. Does transaction costs influence the magnitude/significance of publication effects?
The table presents the results of the following staggered diff-in-diff:

$$InforShare_{i,j,t} = \alpha_i + \beta_i \times Post\_Publication_{j,t} + \gamma_j + \tau_t + \varepsilon_{i,j,t}$$

where j represents different anomalies, and t represents the year-month. We categorize an anomaly as $liquid$ if its signed dollar volume is greater than the median for that year. Panel A presents the results of staggered diff-in-diff analysis for liquid anomalies, while Panel B reports the results for illiquid anomalies. All the regressions include factor fixed effects (γ_j) and year-month fixed effect (τ_t). Standard errors are clustered at the anomaly category level and year-month level. We report corresponding t-statistics in parentheses. ***, **, and * indicate statistically significant differences at the 1%, 5%, and 10% levels.

Panel A: Liquid Anomaly

	(1) Market DR	(2) Market CF	(3) Private DR	(4) Private CF	(5) Public DR	(6) Public CF	(7) Noise
Post_publication	-0.011	**2.125*** **	-0.077	**-1.712*** **	-0.104	-1.153	**0.932* **
	(-0.09)	**(2.60)**	(-1.18)	**(-3.73)**	(-0.88)	(-1.02)	**(1.66)**
Constant	1.356***	12.081***	1.073***	13.402***	1.687***	56.233***	14.168***
	(37.69)	(51.93)	(56.80)	(195.35)	(48.65)	(182.39)	(94.06)
R-squared	0.251	0.438	0.280	0.311	0.173	0.397	0.338
Observations	70,494	70,494	70,494	70,494	70,494	70,494	70,494

Panel B: Illiquid Anomaly

	(1) Market DR	(2) Market CF	(3) Private DR	(4) Private CF	(5) Public DR	(6) Public CF	(7) Noise
Post_publication	0.120	-0.076	-0.045	-0.987	0.051	0.393	0.544
	(1.31)	(-0.13)	(-0.59)	(-0.95)	(0.39)	(0.32)	(1.19)
Constant	1.897***	11.261***	1.824***	11.196***	2.278***	59.540***	12.004***
	(76.64)	(90.37)	(81.96)	(37.92)	(58.88)	(172.18)	(109.49)
R-squared	0.406	0.364	0.495	0.254	0.280	0.340	0.220
Observations	69,765	69,765	69,765	69,765	69,765	69,765	69,765