The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

THE JOURNAL OF FINANCE • VOL. LXXIX, NO. 5 • OCTOBER 2024

Anomaly Time

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ABSTRACT

We examine the timing of returns around the publication of anomaly trading signals. Using a database that captures when information is first publicly released, we show that anomaly returns are concentrated in the first month after information release dates, and these returns decay soon thereafter. We also show that the academic convention of forming portfolios in June underestimates predictability because it uses stale information, which makes some anomalies appear insignificant. In contrast, we show many anomalies do predict returns if portfolios are formed immediately after information releases. Finally, we develop guidance on forming portfolios without using stale information.

IN INFORMATIONALLY EFFICIENT CAPITAL MARKETS, investors compete to profit from asset-pricing anomalies before mispricing is arbitraged away. This competition creates a race to acquire and process information quickly, and this race begins as soon as information about an anomaly signal becomes public. Yet despite the importance of the timing of information releases for anomaly strategies, the academic literature largely ignores when anomaly returns occur and when they are arbitraged away. In fact, academic studies

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DOI: 10.1111/jofi.13372

often form portfolios using information that has been publicly available for weeks, months, or even years at the time of portfolio formation.

Using Compustat Snapshot, a relatively unknown database that precisely identifies the dates of important information releases, we study the timing of abnormal returns around release dates. We find that the timing of anomaly returns yields important insights about the relation between information and stock returns: anomaly returns are concentrated in the first month after anomaly-relevant information is first released, and the returns decay quickly thereafter. Moreover, we show that the academic convention of forming portfolios in June leads researchers to significantly underestimate return predictability, which makes some anomalies appear insignificant even though they do reliably predict returns in the days and weeks immediately after information is first released. We compare actual release dates to dates available in standard academic databases to develop guidelines for future research that show how to avoid using stale information without creating look-ahead bias. Overall, by examining *when* anomaly returns occur, we provide new information about *why* anomaly returns occur: our findings show that anomaly returns are due, at least partly, to delayed information processing by investors.

We first show that the literature's conventional portfolio rebalancing approach leads to anomaly portfolios that rely on stale information. Across the 28 anomalies we study, the academic convention of updating anomaly portfolios annually, at the end of June, relies on information that was released five months previously, on average. Motivated by the theoretical literature on underreaction and costly information processing (e.g., Blankespoor, deHaan, and Marinovic (2020)), we develop and investigate two predictions that are made possible because of the precise information release dates provided by Snapshot. First, if anomalies are the result of costly information processing, then return predictability should be strongest in the period immediately following the release of key information, and it should decay thereafter. Second, reductions in information processing costs should coincide with faster arbitrage and shorter periods of return predictability. Consistent with these predictions, we show that returns to many anomalies are concentrated in the first month after information releases, and these returns get weaker in the months that follow. Moreover, as shown in Figure 1, we document a strong time trend in this result: in recent years, the returns to anomaly strategies are increasingly earned in the first few weeks after information releases, consistent with technological improvements leading to lower processing costs.

Our findings suggest that the existing literature often dramatically underestimates anomaly returns because it relies on stale data. To correct this issue, we compare actual information release dates to dates available in commonly available databases and develop guidelines for how to study asset-pricing anomalies without using stale data or introducing look-ahead bias. If researchers do not have access to the actual information release date, we show that forming portfolios the day after the 10-K filing date in Compustat leads to very little staleness for most anomalies, and it never leads to look-ahead bias

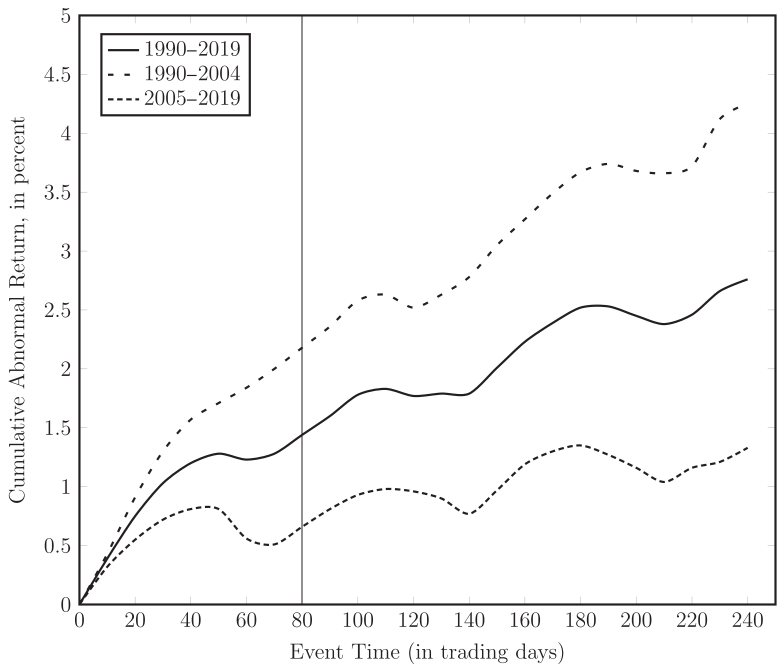

Figure 1. Anomaly returns in event time. The figure shows the profile of abnormal returns for the average anomaly (equally weighted) in event time. The figure shows the returns across the entire sample (1990 to 2019), across the early period of our sample (1990 to 2004), and across the recent years of our sample (2005 to 2019). The solid vertical bar at $t = 80$ trading days indicates when the FF92 rebalancing date occurs, on average.

over our sample period from 1990 to 2019. We also show that anomaly returns are much stronger using 10-K filing dates instead of June rebalancing.

Although it may seem that processing costs should be low for most anomalies, acquiring and processing data can be challenging. Prior to the full launch of the Securities and Exchange Commission (SEC)'s Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system in 1993, arbitrageurs interested in accessing financial statements had to physically travel to one of the SEC's reference rooms, which kept paper copies of financial statements on file. Moreover, these filings arrived in the reference rooms with considerable delay. After a financial statement was prepared, it would be physically mailed to the SEC, and it might take some weeks or even months before it was processed and made available to investors (Kothari, Zhang, and Zuo (2023)). Furthermore, this process created a production lag for data aggregators such as Standard & Poors, making it difficult for even well-connected traders to acquire timely information (D'Souza, Ramesh, and Shen (2010)). As a result, even though financial statements were publicly available, it took time for investors, and in turn prices, to update.

The challenges of accessing financial data remain even in the era of electronically available financial statements. We show that firms increasingly release some financial data prior to the release of their 10-K (often in earnings press releases or conference calls), so even 10-K information may contain stale data. Unfortunately, standard academic databases do not show when a particular information signal was first made public. As a result, to avoid introducing look-ahead bias, the academic literature has established a convention whereby anomaly portfolios are formed annually, typically in June, to ensure that financial statement information would be publicly available to traders at the time of portfolio formation (e.g., Fama and French (1992), hereafter the "FF92" convention).[1]

We find that this convention causes many analyzes to rely on stale information. We overcome this issue using a powerful but relatively unknown database: Compustat Snapshot. The Snapshot database contains the precise date on which accounting items were first made publicly available. Our study is the first to exploit these data to examine the precise timing of returns for a large number of anomalies. Using these data, we examine the timing of returns relative to information releases and test the implications of theories about costly information processing.

We start by identifying the set of anomalies that rely exclusively on information that arrives at infrequent and discrete points in time.[2] Specifically, we begin with the list of anomalies in McLean and Pontiff (2016). We then select the subset of anomalies that rely on information released in either earnings announcements or 10-K filings. Our study includes 28 anomalies.

We next examine the distance, in time, between information release dates and conventional portfolio formation dates. We find that the FF92 convention of annual rebalancing in June leads to many anomaly portfolios that are based on extremely stale information. Across our sample period, the FF92 convention forms portfolios, on average, between 160 and 180 calendar days after the information release date.[3] Furthermore, at the 90$^{\text{th}}$ percentile, the difference between the FF92 rebalancing date and the actual information release date is approximately one year. Even when the delay between the information release

[1] The portfolios are formed in June and returns are measured from July to June over the next 12 months. Because actual information release dates were not known, the June portfolio formation date was intended to be conservative to ensure that all relevant information would have been publicly available at the time of portfolio formation. As Fama and French (1992) state, "To ensure that the accounting variables are known before the returns they are used to explain, we match the accounting data for all fiscal year ends in calendar year $t-1$ with the returns for July of year t to June of $t+1$."

[2] We do not consider anomalies that include signals that are continuously updated, such as momentum (Jegadeesh and Titman (1993)), because the timing of their information release cannot be precisely identified. See Table I for a list of all 28 anomalies. Section I of the Internet Appendix contains additional information for each anomaly. The Internet Appendix may be found in the online version of this article.

[3] The median delay is approximately 120 calendar days, which corresponds to approximately 80 trading days. Indeed, Figure 1 highlights the fact that the typical FF92 rebalancing date arrives 80 trading days after the information release date.

date and the FF92 date is relatively small (i.e., the 10$^{\text{th}}$ percentile), the delay is still approximately 90 calendar days.[4]

In contrast, we show that portfolios formed immediately after 10-K filing dates are much closer to the true information release dates. On average, 10-K filing dates occur within a week of information release dates. Moreover, we show that the median delay between information release dates and 10-K filing dates is *zero* days and the 10-K filing date is *never* before the actual release date in our sample (from 1990 to 2019). Even at the 90$^{\text{th}}$ percentile, the difference between the information release date and the 10-K filing date is less than one month. As a result, our findings suggest a new convention: instead of forming portfolios annually in June, future researchers should form portfolios using the actual information release date from Snapshot or, if that is not available, they should use the 10-K filing date from Compustat for all years after 1994.

Next, we test two predictions motivated by the literature on costly information processing. First, if anomalies are the result of costly information processing, then return predictability should be strongest in the period immediately following the release of key information and should decay thereafter. Second, reductions in information processing costs should coincide with faster arbitrage and shorter periods of return predictability.

We test the first prediction using an event-study approach that lines up returns in event time around the publication of anomaly trading signals. Consistent with this prediction, we find that an event-time portfolio generates statistically positive returns in the first few months after an information release for the majority of anomalies, but these returns dissipate in subsequent trading periods. These results hold both for individual anomalies and for an "average anomaly" portfolio that trades on all 28 anomalies combined. For example, the daily abnormal return to the average anomaly portfolio is 9.84%, annualized, over the first month following the release of information. However, over the first four months following an information release, the average daily abnormal return is just 4.69%, annualized, which implies that the returns dissipate significantly after the first month. Finally, in the period after these first four months, the average daily abnormal return falls to 1.99%, annualized. Taken together, these findings show that abnormal returns are concentrated in the window immediately following the release of key data, consistent with theories of costly information processing. Moreover, since the FF92 approach leads to portfolios that are formed on average 160 to 180 calendar days after the true information release date, these results highlight the importance of revising the conventional portfolio formation methodology to avoid stale information.

We use several tests to examine the second prediction that reduced information processing costs coincide with faster price discovery following information

[4] As an extreme example, for 2011 the Tax Expense anomaly portfolio would include the firm, IDTI, on May 31, 2011 using the actual information release date. In contrast, using the FF92 convention, this same stock would not be added to the anomaly portfolio until June 30, 2012, a delay of 396 days.

releases. First, we examine the staggered implementation of the SEC's EDGAR system as a shock to information processing costs (e.g., Gao and Huang (2020) and Goldstein, Yang, and Zuo (2022)). We find that the implementation of EDGAR leads to anomaly returns that are much more concentrated in the period immediately after information releases. In the pre-EDGAR period, only 41% of the four-month return is earned in the first two months after an information release, while in the post-EDGAR period, 85% of the four-month return is earned in the first two months. In effect, price discovery happens twice as fast after the implementation of EDGAR, relative to before. The results suggest that a reduction in information processing costs leads to faster arbitrage and shorter periods of return predictability.

While the advent of EDGAR represents one example of a decrease in information processing costs, information processing costs have fallen in general over the last three decades (e.g., Goldstein, Yang, and Zuo (2022)). As a consequence, our second prediction implies that there should be more rapid trading on information signals in recent years. We find that this is indeed the case—significantly more trading volume occurs in the days immediately following information releases in more recent years compared to early years in our sample. Importantly, these results account for the overall trend of increased trading volume in recent years, and thus reflect a change in the speed with which arbitrageurs trade on information.

Finally, we explore the economic significance of our findings for an investor who trades on information releases. While the event-time approach discussed above provides an intuitive way to examine whether anomaly returns are related to information release dates, the event-time strategy cannot be implemented in real time. Accordingly, we also examine an implementable calendar-time trading strategy. While the calendar-time approach is common in the existing literature, we make one key change: we rebalance the day after information release dates instead of once a year in June. When we compare our information-rebalancing approach to the FF92-rebalancing approach, we find significant gains. The average anomaly portfolio's daily abnormal return from the information-rebalancing approach is 4.60% larger than that for the FF92-rebalancing approach on an annualized basis. Across a battery of additional tests that account for transaction costs, firm size, news days, and publication dates, we consistently find evidence that links predictable returns to the timing of information arrival. In sum, our evidence consistently points to the same conclusion: anomaly returns are related to the costs of acquiring and processing information about the underlying signal, so it is crucial to measure the precise date on which the trading signal is first released.

Our paper contributes to a large literature on asset-pricing anomalies. Asset-pricing anomalies have been documented since at least Ball and Brown (1968), and for almost as long, there has been an active debate about the source of anomaly returns (e.g., Harvey, Liu, and Zhu (2016), Hou, Xue, and Zhang (2020)). We are the first to examine and confirm a link between the timing of information releases and anomaly returns for a large number of anomalies at once. That is, we show how time patterns in the release of information affect the dynamics of mispricing. Pénasse (2022) notes that if alphas decay after information releases, existing tests may be biased because they assume that alphas are stationary. By explicitly considering timing, our tests avoid this issue.

While our results may seem intuitive, they are surprising when contrasted with claims that anomalies are no longer in the data and/or are the result of data mining or unmeasured costs (e.g., McLean and Pontiff (2016), Muravyev, Pearson, and Pollet (2022), Chen and Velikov (2023)). We find, like much of the literature, that anomalies do tend to vanish in recent periods (e.g., Chordia, Subrahmanyam, and Tong (2014), McLean and Pontiff (2016)). However, we show that existing approaches form portfolios using information that is weeks, months, or even years old, which leads them to underestimate return predictability. When portfolios are formed immediately after the release of information, many anomalies are revived, consistent with several recent papers that argue anomalies are the result of real mispricing as opposed to data mining (e.g., Chen and Zimmermann (2020), Chen and Zimmermann (2022), and Jensen, Kelly, and Pedersen (2021)). Moreover, consistent with theories of costly information processing, we find that anomaly profits are vanishing more quickly and that arbitrageurs trade more quickly as information processing costs decline. In summary, our findings show that identifying when information is first released is crucial to accurately measuring anomaly returns.

The rest of the paper proceeds as follows. Section I discusses the literature on delayed information processing and develops our key predictions. Section II discusses our data and the construction of the anomaly variables. Section III shows that conventions in the existing literature lead to the use of extremely stale data, which prevents it from testing theories of delayed information processing. Section IV presents our main findings that anomaly returns are related to information release dates. Section V develops guidelines for future research to avoid the use of unnecessarily stale information. Section VI concludes.

I. Information Processing Costs

A. Background

While it has long been argued that investors should be able to acquire and trade on information in financial statements quickly and easily (e.g., Blankespoor, deHaan, and Marinovic (2020)), a number of papers note that real-world frictions can impede the ability of traders to acquire and trade on information, leading to delayed information processing.

Consider the problem of acquiring financial information in the days before the Internet, when financial filings were submitted to the SEC in paper form. In a *New York Times* article, Noble (1982) summarizes the key issues. After finalizing their financial statements, firms would physically mail them to the SEC in Washington DC. The SEC would review these filings, a process that could take several weeks. Once the review was complete, the SEC would place these filings in public reference rooms in New York, Washington DC, or Chicago; paper copies were stored for 30 days and then transferred to microfiche thereafter. Stunningly, there was typically just a single paper copy of public filings in each location, which led to competition with respect to who could view filings first. Moreover, these reference rooms were often crowded and disorganized, with observers noting that "…the place can be a zoo" and "…files are often misplaced or even stolen…" (Noble (1982)). Alternatively, interested parties could request their own paper copies of filings (via mail or delivery service), but this too would take substantial time for the SEC to fulfill.[5]

The challenges of accessing and processing data quickly remain even after the launch of the SEC's EDGAR system in the mid-1990s, which automated the submission and hosting of companies' financial filings. However, despite this and other advances, several challenges remain. We show that firms increasingly release some financial data prior to the release of their 10-K (often in earnings press releases or conference calls), so even 10-K information may contain stale data. Furthermore, financial information is not always released in the same form or on a consistent date. For example, consider the asset growth anomaly, which uses the book value of assets to generate a trading signal. For some firms, information about the book value of assets is first released in the earnings announcement, while for other firms, this information is first released in the 10-K filing—and a given firm might switch where it reports this information.[6]

Moreover, while EDGAR and modern computers make it easier to access financial statement data, real-time databases (such as the Snapshot database we use) are costly, as are skilled computer programmers. Furthermore, anomaly-relevant information is increasingly released at the same time as other important pieces of information, such as management guidance, conference calls, analyst estimates, and the earnings releases of other firms (e.g., Hirshleifer, Lim, and Teoh (2009), Rogers and Van Buskirk (2013)). All of these are examples of the larger challenge: while technological improvements make it easier to access financial information today relative to 30 years ago, it continues to be costly for investors to process information instantaneously.

Below we discuss the existing literature on costly information processing, which we draw on to motivate our key empirical predictions.

B. Theory and Practical Considerations

Investors face multiple tasks between the release of information and making a trading decision. Based on the three-step framework in Blankespoor, deHaan, and Marinovic (2020), investors must (i) monitor for the release of new anomaly-relevant information (awareness), (ii) expend effort to acquire and

[5] For additional details, see Gao and Huang (2020) and Kothari, Zhang, and Zuo (2023).

[6] For example, in 2004 Gulfmark Offshore, Inc. included total assets in their 10-K report released on March 15, but not in their earnings announcement released on February 26. However, in 2018 Gulfmark Offshore included total assets in both its earnings announcement and its 10-K.

extract information from the release (acquisition), and (iii) use the acquired information in modeling (integration). In our setting, in each of these steps—awareness, acquisition, and integration of information—significant costs can arise that inhibit trading on the release of anomaly-relevant information. We refer to these collectively as *information processing costs*.

To trade on the arrival of new information, investors must be *aware* that such information exists and has been released. Existing research has modeled some form of awareness costs since at least Merton (1987); in these models, awareness costs often lead to "inattention." Empirical support for these models is growing. For example, Hirshleifer, Lim, and Teoh (2009) find that postearnings announcement drift is larger on days with more earnings announcements, consistent with the idea that return drift occurs when investors are distracted. DellaVigna and Pollet (2009) show that market reactions to Friday earnings announcements are muted, consistent with inattention. Similarly, Cohen and Frazzini (2008) find that, owing to attention constraints, investors do not properly account for information about economically linked firms, which then leads to return predictability.

Furthermore, investors face costs in *acquiring* information. Despite recent regulatory advances and technological innovations, information acquisition costs remain. Computing power, subscriptions to data aggregating services, and models for algorithmic trading are costly. Furthermore, investors must bear significant costs to monitor and update these systems.

Just as important, cognitive frictions can inhibit information acquisition. Often, anomaly-relevant information is released around the same time as hundreds of other financial statements (e.g., Hirshleifer, Lim, and Teoh (2009)), and the particular signal needed by the investor could be buried deep within a 200-page financial filing. Moreover, financial statements are increasingly released around the same time as other important pieces of information, such as management guidance, conference calls, and analyst revisions (e.g., Rogers and Van Buskirk (2013)). Furthermore, data sources are growing at a rate that potentially outpaces investors' ability to process them all. As alternative, imprecise information becomes more abundant, it can crowd out the processing of more precise information (e.g., Dugast and Foucault (2018)). All of these frictions can impede or slow information acquisition.

Lastly, traders may face significant costs when *integrating* new information into existing models of expected returns. Several papers argue that investors face constraints integrating new information as a result of behavioral biases such as overconfidence (e.g., Daniel, Hirshleifer, and Subrahmanyam (1998)) and representativeness (e.g., Barberis, Shleifer, and Vishny (1998)). Moreover, there are several practical challenges to integrating new information. Following the release of information about a firm, traders must update their forecast of expected returns for that firm. For anomalies that are based on portfolio ranks, this may force investors to rerank all other firms that could possibly be in their portfolio. As a result, traders may need to recalculate their optimal holdings every time new anomaly information arrives about *any* firm.

B.1. Empirical Predictions

A growing literature draws on these potential information processing costs as a possible explanation for the link between return predictability and information (e.g., Hong and Stein (1999), Hirshleifer and Teoh (2003), DellaVigna and Pollet (2009), Barberis (2018), and Blankespoor, deHaan, and Marinovic (2020)). That is, information processing costs can explain the presence of predictable returns around publicly available information. For instance, in the model in DellaVigna and Pollet (2009)), information processing costs lead to a delayed response to information. As the fraction of inattentive investors increases, there is more subsequent drift in prices.

The innovation in our setting is *timing*. In particular, our tests condition on information release dates to see *when* anomaly returns occur. The theories and findings discussed above lead to a specific prediction in our context: if investors are unable to be aware of, acquire, and integrate all possible information released for all possible firms, then prices will not instantaneously respond to the release of anomaly signals. Instead, starting on the information release date, prices will begin to drift toward the correct value as in DellaVigna and Pollet (2009). Together, these arguments lead to the following testable prediction.

PREDICTION 1: *Return predictability should be strongest in the period immediately following the release of key information and should decay thereafter*.

In addition, recent changes to information processing costs motivate a second prediction. The last few decades have seen a number of technological innovations that have lowered information processing costs, including innovations related to disclosure regulation such as EDGAR, IFRS, and XBRL (Kothari, Zhang, and Zuo (2023)), automated information generation and dissemination such as robojournalism (Blankespoor, deHaan, and Zhu (2018)), expanding sources of novel or alternative data such as parking lot or foot traffic data (Zhu (2019)), improvements in technology and its applications such as AI and machine learning (Goldstein (2023)), and improvements in trading technologies to better capture new information such as algorithmic trading (Weller (2018)).

If anomaly returns are related to information processing costs, then changes to processing costs should lead to changes in anomaly returns. This motivates our second testable prediction.

PREDICTION 2: *Reductions in information processing costs should correspond to reductions in return predictability and more rapid trading activity after information releases*.

II. Data and Anomaly Selection

A. Data

The key empirical hurdle for our study is to identify when anomaly-relevant information is first made available to investors. To overcome this hurdle, we rely on Compustat Snapshot (hereafter, "Snapshot"), a database that shows when accounting information about a firm was first publicly available. For each line item on every financial statement, Snapshot helps identify when the line item was first publicly released. For example, Snapshot identifies whether the book value of assets was revealed in the earnings announcement or at the 10-K filing date. Using Snapshot, we are able to determine—at both the anomaly level and the firm level—the earliest date at which anomaly-relevant information is publicly known.[7]

Our sample period begins in January 1990 and runs through 2019. Snapshot data identify information release dates beginning in the mid-1980s. However, we begin the sample in 1990 to allow for the measurement of several anomalies that use multiple years of data in their construction. We obtain daily prices, returns, volume, and shares outstanding from the Center for Research in Security Prices (CRSP). We also obtain daily factors for the five-factor model (MKT-RF, HML, SMB, RMW, and CMA) plus the daily momentum factor (MOM) from CRSP. In additional analyzes, we use news data from RavenPack, NYSE size breakpoints from Kenneth French's database, and bid-ask spreads from TAQ.[8]

B. Anomaly Selection and Calculations

We use a set of anomalies for which we can clearly study the relation between returns and the release of anomaly-relevant information. Our starting point is the set of 97 anomalies examined in McLean and Pontiff (2016). For many of these anomalies, however, the underlying data change constantly, making it difficult to establish a discrete information release date. For example, a commonly cited anomaly, the earnings-to-price ratio (Basu (1977)), requires two data points for each stock: earnings and price. While annual earnings data are released on clearly identified dates and generally remain unchanged for the year, prices change constantly, making it difficult to define the precise information release date for this anomaly. In contrast, asset growth (Cooper, Gulen, and Schill (2008)) is measured using only book assets, a value that is revealed at clear points in time. Accordingly, we focus on the subset of anomalies that depend entirely on information that has a precise revelation date.

From the list of 97 anomalies in McLean and Pontiff (2016), we focus on those categorized as "event" or "fundamental" predictors. This excludes anomalies based on market variables (e.g., momentum, size, and trading volume) and valuation multiples (e.g., market-to-book, earnings-to-price). The list contains 60 anomalies after these exclusions. We further refine the list by requiring each anomaly to be based entirely on information that is publicly revealed in annual financial statements or related releases (like press releases

[7] For more details, see Section II of the Internet Appendix.

[8] We are thankful to Andrew Chen and Mihail Velikov for providing low-frequency effective spread data and code to calculate spreads using high-frequency data (Chen and Velikov (2023)). See https://sites.google.com/site/chenandrewy/publications. Additional details on the data can be found Section III of the Internet Appendix.

around earnings announcement dates).[9] This ensures that information release dates can be identified using Snapshot.[10] The resulting sample contains 28 information-based anomalies.[11]

For each anomaly, we use Snapshot to identify the earliest date such that all information necessary to construct the anomaly variable is known. We call this date the *information release date*.[12] Our data set contains a panel of firm-by-year observations accompanied by the value of the anomaly variable and several important dates, especially the information release date. We extend the panel by incorporating daily returns, where each firm-by-trading day observation records the most recently released anomaly value.

Summary statistics for our sample are detailed in Table I.

III. Anomaly Timing

A. The Timing of Information Releases

We begin by examining *when* information is released, and how the timing of these releases has changed over our sample period. We focus on five distinct dates: the fiscal year-end (FYE), the information release date, the earnings announcement date, the 10-K filing date, and the conventional June-rebalancing date (FF92 date).

Table II displays results on the timing of information releases relative to key dates; columns (2) through (5) show the average distance (in calendar days) from the FYE to the other four dates, while columns (6) through (8) show the average distance (in calendar days) between the information release date and other relevant dates.

Several observations are worth noting. First, the average distance between the information release date and the typical rebalancing date used in prior research (June 30) is over 180 calendar days at the start of the sample period, and is still more than 160 calendar days by the end of the sample period. In other words, the time lag between the actual date of information release and the date used in prior research ranges between five and six months. This demonstrates the potential for using stale information if the researcher chooses to employ a single, static rebalancing date, such as June 30.

[9] To be consistent with the convention of annually rebalancing portfolios once a year on June 30, we focus on annual information release dates. Future research could examine quarterly information releases to further study information timing.

[10] For example, asset growth is included in our study since it is based entirely on book assets, while firm age is excluded as it is not publicly revealed via financial statements.

[11] For further details on these anomalies and their construction, see Section I of the Internet Appendix.

[12] For some composite measures based on multiple pieces of information, we use the latest information release date. For instance, to compute asset turnover, which requires sales, cash, long-term debt, short-term debt, common and preferred book equity, and minority interest, we use the latest information release date for those variables as the information release date for the anomaly. If sales is revealed on Monday in an earnings announcement but the other variables are not revealed until Wednesday in the 10-K filing, the anomaly variable cannot be calculated until Wednesday. Thus, for this example, Wednesday would be the information release date.

Table I

Summary Statistics

The table provides summary statistics for our sample which runs from 1990 through 2019. Panel A provides summary statistics for daily returns and market capitalization (in millions of USD) for all stocks in our sample. Panel B provides summary statistics for each of the anomaly variables.

(1)	(2)	(3)	(4)	(5)
Panel A: Daily Returns and Market Capitalization				
	Mean	Std. Dev.	Median	*N*
Daily raw returns	11 bps	347 bps	0 bps	28,856,905
Market cap.	\$3,586	\$18,168	\$364	28,867,029
Panel B: Anomaly Characteristics				
Anomaly (abbreviation)	Mean	Std. Dev.	Median	*N*
Accruals (Acc)	−0.04	0.12	−0.04	105,703
Asset growth (Ag)	0.18	4.48	0.06	126,554
Asset turnover (At)	3.46	47.59	1.70	121,828
Change in asset turnover (Cat)	0.04	39.03	0.00	103,246
Change in profit margin (Cpm)	−0.35	166.16	0.00	124,807
Earnings consistency (Ec)	0.02	1.56	0.07	56,123
Earnings surprise (Es)	−0.41	5.77	−0.03	83,300
Gross profitability (Gp)	0.31	1.13	0.28	149,700
Inventory growth (Ig)	0.01	0.06	0.00	124,284
Investments (Inv)	1.10	2.34	0.91	81,329
Growth in LT net operat. assets (Ltg)	0.03	1.74	0.03	99,048
Noncurrent operating assets (Nca)	0.01	4.13	0.00	126,560
Net operating assets (Noa)	0.58	3.03	0.59	118,180
Net working capital (Nwc)	−0.01	2.00	0.00	105,698
Operating leverage (Ol)	0.99	3.97	0.80	149,701
O-Score (Osc)	−0.76	4.94	−1.17	93,229
Profit margin (Pm)	−2.32	139.84	0.35	147,825
Percent operating accruals (Poa)	−1.09	23.91	−0.64	123,984
Profitability (Pro)	−0.02	1.19	0.03	126,514
Percent operating accruals (Pta)	2.02	36.33	0.35	112,346
Return on equity (Roe)	−0.38	104.10	0.09	149,681
Revenue surprise (Rs)	0.27	24.30	0.19	79,664
Sales growth (Sag)	1,157	575	1,102	68,777
Sustainable growth (Sg)	0.32	11.50	0.08	121,317
Sales growth less invest. growth (Sli)	−1.05	131.61	0.02	85,907
Sales growth less exp. growth (Slx)	0.03	5.84	0.00	91,947
Taxes (Tx)	1.13	21.89	0.99	109,359
Total external finance (Txf)	0.05	0.63	0.00	123,006

Second, 10-K dates more closely follow earnings announcement dates in recent years (e.g., Arif et al. (2019)). In the 1990s, 10-K dates were, on average, more than a month after earnings announcement dates. By the early 2010s, this distance is less than two weeks. In other words, the time between the release of basic earnings information and the release of the full

Table II

The Timing of Information Releases

The table examines the timing of information releases relative to important dates. Specifically, it reports the mean number of calendar days between important dates across all anomalies in our sample for each year. FYE is the fiscal year-end. EA is the earnings announcement date (item "rdq" from Compustat). 10K is the 10-K filing date. FF92 is the rebalancing date following the methodology in Fama and French (1992). Info is the actual information release date, which is the first date on which all information necessary to calculate an anomaly variable has been publicly revealed.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fiscal Year-End To:				Information Date To:		
Fiscal Year	Info	EA	10K	FF92	EA	10K	FF92
1990	84	49	86	266	−35	1	181
1991	84	48	86	266	−35	1	182
1992	84	49	86	266	−35	1	182
1993	85	49	86	269	−35	1	184
1994	85	49	86	267	−35	0	181
1995	85	48	86	261	−36	0	176
1996	80	46	84	251	−33	3	170
1997	76	46	84	255	−29	8	179
1998	76	46	86	251	−30	9	174
1999	78	47	85	245	−31	7	167
2000	79	48	86	240	−30	7	161
2001	77	48	84	239	−28	7	162
2002	74	48	83	240	−25	9	166
2003	68	47	76	242	−21	7	173
2004	68	49	76	240	−18	7	171
2005	66	50	74	238	−16	7	171
2006	64	50	71	236	−13	6	171
2007	63	51	69	235	−12	6	172
2008	62	51	68	234	−10	6	172
2009	59	51	66	234	−8	7	174
2010	58	50	65	233	−8	7	175
2011	58	50	65	234	−7	7	176
2012	57	50	64	233	−7	7	176
2013	56	49	64	232	−6	7	175
2014	56	50	63	229	−6	7	173
2015	56	50	63	228	−5	6	172
2016	56	50	62	227	−5	6	170
2017	57	51	62	226	−5	5	169
2018	57	51	62	225	−5	5	168

suite of financial statements and footnotes has declined dramatically in recent years.

Third, information release dates are now much nearer to the FYE. In the 1990s, the distance between the FYE and the information release date was almost three months. By the 2010s, this distance decreased to less than two

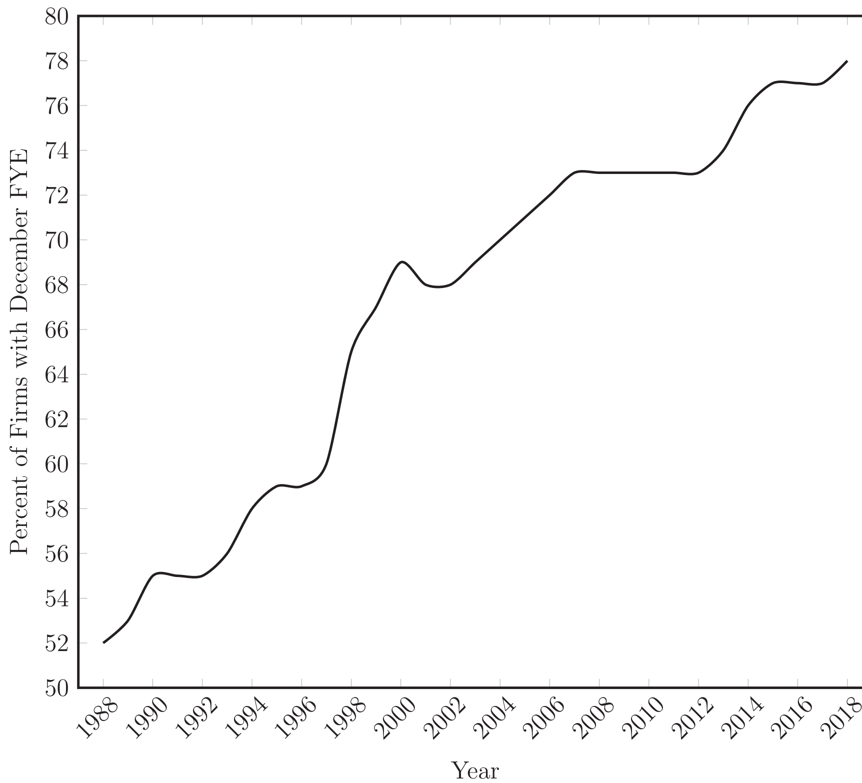

Figure 2. Percent of firms with December fiscal year-end. The figure shows the percent of public U.S. firms with a December fiscal year-end for each year from 1988 through 2018.

months. Put differently, the time between the production and the disclosure of information has declined dramatically over the sample period.[13]

Fourth, the FF92 date is also nearer the FYE date in recent years. On its face, this trend seems odd given that the FF92 convention uses the same date each year—it forms portfolios on June 30 of year $t + 1$ using information from the FYE of year t. However, the proportion of firms with December year-ends has increased substantially over our period, as can be seen in Figure 2. Since a December FYE minimizes the distance between the FYE and FF92 dates, the average distance has decreased in recent years. This implies that firms increasingly produce and release their financial information at similar times.

B. Measuring the Staleness of Information

We next present evidence on the time delay between the precise date when anomaly-relevant information is first released by the firm and the earnings an-

[13] We report additional results about the timing of information releases by anomaly in Section IV of the Internet Appendix.

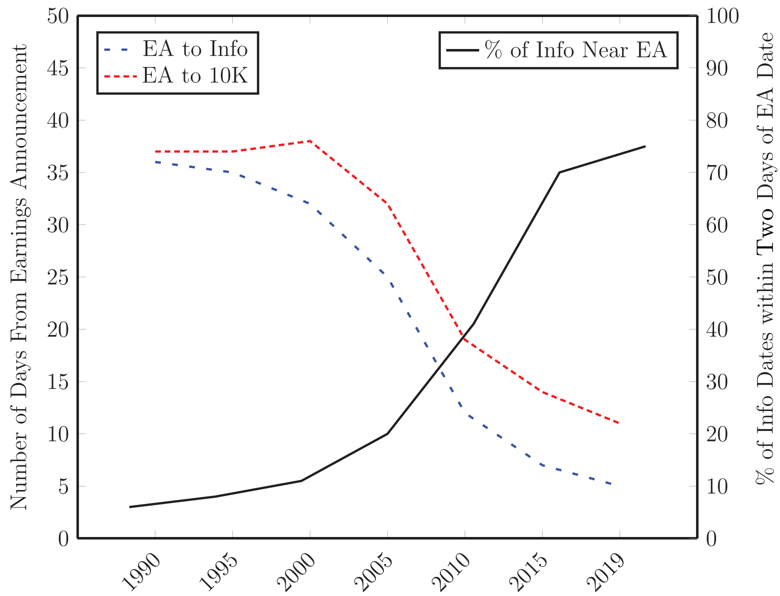

Figure 3. Information releases over time. The figure shows the timing of information releases over time. The left axis measures the mean number of days from the earnings announcement (EA) to either the information release date (Info) or the 10-K filing date (10K). The right axis measures the percent of observations in which the information release date was within two days of the earnings announcement date. (Color figure can be viewed at wileyonlinelibrary.com)

nouncement, 10-K, and FF92 dates. The results are presented in columns (6) through (8) of Table II. Two trends are clear. In the 1990s and early 2000s, the information release date occurred approximately one month after the earnings announcement date, but by the early 2010s, this distance was less than a week. At the same time that information release dates were getting closer to earnings announcement dates, 10-K dates were getting farther from information release dates. Why? Earnings announcements tend to reveal more financial information in recent years. In the late 2000s, firms started releasing a full set of financial statements in their earnings announcements instead of simply reporting earnings (D'Souza, Ramesh, and Shen (2010)). As a result, earnings announcement dates are the proper information release dates for many anomalies in recent years. Future researchers can have some confidence that, in more recent years, basic information from these financial statements was released on the earnings announcement date ("rqd" in Compustat). However, using the earnings announcement date as the information date could also lead to some look-ahead bias for some firms, especially prior to 2010.[14]

Figure 3 highlights these trends. The downward-sloping lines show that the distance (in calendar days) between the earnings announcement, information

[14] In Section V, we revisit this issue to develop recommendations on how to avoid using stale data while simultaneously avoiding a look-ahead bias.

Table III
Comparison of 10K versus FF92 Updating

The table compares two rebalancing strategies: updating on the 10-K filing date and updating on the FF92 date. The table shows summary statistics for the number of calendar days between the information release date and the 10-K date (Panel A) and the number of days between the information release date and the FF92 date (Panel B).

(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Information Release Date to 10-K Filing Date					
Fiscal Years	Mean	Median	Std. Dev.	10^{th} Pctl	90^{th} Pctl
1990–1994	1	0	7	0	0
1995–1999	6	0	15	0	35
2000–2004	7	0	16	0	36
2005–2009	6	0	12	0	28
2010–2014	7	0	12	0	27
2015–2018	5	0	10	0	22
Panel B: Information Release Date to FF92 Rebalancing Date					
Fiscal Years	Mean	Median	Std. Dev.	10^{th} Pctl	90^{th} Pctl
1990–1994	182	113	112	91	368
1995–1999	173	120	106	91	365
2000–2004	166	117	102	91	349
2005–2009	172	125	100	97	351
2010–2014	175	131	98	105	339
2015–2018	172	129	96	106	330

release, and 10-K dates has shrunk over time. At the same time, the upward-sloping line shows that the proportion of information releases that are very near earnings announcements has increased.

To further illustrate this point, we provide descriptive evidence on the lag between information release dates and conventional FF92 rebalancing dates. Table III provides direct evidence that the FF92 rebalancing strategy is very conservative. While this conservatism is understandable, especially 30 years ago when the convention originated, it can also lead to a severe delay in portfolio formation.

First, Panel A shows the distance from the information release date to the 10-K date. The evidence in column (2) shows that, over the last 30 years, the 10-K date has been, on average, within a week of the true information release date (at the median, the 10-K date has been equal to the information release date). In recent years, even at its worst, the 10-K date has occurred within a month of the information release date (column (6)).

In contrast to the delay using 10-K dates, Panel B shows the timeliness of the FF92 date. We find that it occurs over five months after the information release date, on average (column (2)). Even at its best, the FF92 date still falls three months after the information release date (column (5)). At

Table IV

The Timing of Information Releases: By Size and By FYE Month

The table examines the timing of information releases relative to important dates. Specifically, it reports the mean number of days between important dates across all anomalies in our sample. Panel A splits the sample by the market capitalization (size) of stocks. Panel B splits the sample according to the month of fiscal year-end. FYE is the fiscal year-end. EA is the earnings announcement date (item "rdq" from Compustat). 10K is the 10-K filing date. FF92 is the rebalancing date following the methodology in Fama and French (1992). Info is the actual information release date, which is the first date on which all information necessary to calculate an anomaly variable has been publicly revealed.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: By NYSE Size Breaks								
		Fiscal Year-End To:				Information Date To:		
Size	N	Info	EA	10K	FF92	EA	10K	FF92
Micro	1,435,536	77	58	81	251	−19	4	174
Small	589,399	66	43	72	242	−23	6	175
Large	590,349	59	34	67	233	−25	7	173
Panel B: By Month of Fiscal Year-End								
		Fiscal Year-End To:				Information Date To:		
Month	N	Info	EA	10K	FF92	EA	10K	FF92
Jan.	116,727	68	46	75	515	−21	6	446
Feb.	38,076	77	53	81	487	−23	4	409
Mar.	143,441	74	53	79	456	−21	4	381
Apr.	49,272	74	53	79	426	−21	4	351
May	48,932	73	50	78	395	−23	5	322
June	221,313	76	53	80	365	−23	4	288
July	45,303	76	57	79	334	−18	3	258
Aug.	43,766	74	53	78	303	−20	4	229
Sept.	194,549	71	49	76	273	−22	5	201
Oct.	63,515	73	49	79	242	−23	5	168
Nov.	30,611	77	54	80	212	−22	3	135
Dec.	1,960,224	69	48	75	181	−20	6	111

its worst, the FF92 date is delayed by approximately a year (column (6)). These results suggest that a substantial time gap occurs between when traders might trade on released information and when academics often form portfolios.

C. Cross-Sectional Splits and the Timing of Information Releases

Finally, we study the timing of information releases based on cuts of the data, in particular, by firm size and by FYE month. The results are shown in Table IV. When it comes to firm size (Panel A), larger stocks tend to have information release dates closer to the FYE date than smaller stocks. Earnings announcement and 10-K dates are also closer to the FYE date, consistent with larger firms finalizing financial statements more quickly. Microcap stocks have a time lag that is 18 days longer, on average, than large stocks between the FYE date and the information release date.

Panel B shows the average distance from the information release date to the FF92 date, sorting on FYE. For December FYE firms, this distance is just over four months. But for companies with a January FYE, the average gap between the information release date and the FF92 date is almost 450 days. In other words, a company with a January 2015 FYE would not be included in an FF92 portfolio until June 2016.

Overall, these findings suggest that the FF92 approach relies on potentially stale data. In the next section, we show that the use of stale information masks important patterns in the data.

IV. Anomaly Timing and Returns

Motivated by theories of delayed information processing, in this section we examine the timing of return patterns around information releases. We begin by testing Prediction 1 to see whether anomaly returns are stronger in the period immediately following the release of information about anomaly trading signals. We then turn our attention to Prediction 2 to see whether reductions in information processing costs result in faster arbitrage and shorter periods of return predictability.

Our basic methodology examines returns around the release of anomaly-relevant information. We form anomaly portfolios by taking long and short positions based on the relative rankings of the various anomalies following the methodology in Chen and Zimmermann (2020), which is based on the original papers that identified each anomaly. For example, as in Cooper, Gulen, and Schill (2008), the long leg of the asset growth portfolio is formed by selecting the bottom decile of stocks based on annual asset growth while the short leg selects the top decile. In all of our tests, we calculate abnormal returns to long-short anomaly portfolios using the Fama-French five-factor model with momentum (Fama and French (2015) and Carhart (1997)). We calculate standard errors clustered by firm and date.

In our baseline tests, we report results for each of the 28 anomalies in our sample. We also report results for the average anomaly, which is an equally weighted portfolio formed by averaging the returns of all of the anomalies. In our later tests, we present results only for the average anomaly in the interest of brevity.

A. Event-Time Approach

To test Prediction 1, our first empirical approach studies anomaly returns in event time. If an anomaly signal indicates that a firm should be in a particular anomaly portfolio, our approach adds the firm the day after the actual information release date and we then examine returns in event time over the next year focusing on horizons of one to eight months. For example, if information concerning the assets of firm A is released on June 18 and information concerning the assets of firm B is released on November 2, our event-time approach would form long-short asset growth portfolios on June 19 and November 3, respectively, and then examine average abnormal returns over four periods: (i) the first month after the information release date, (ii) the first two months after the information release date, (iii) the first four months after the information release date, and (iv) the next eight months after the information release date. The event-time results are shown in Table V.

Two important findings follow from Table V. First, abnormal returns earned by the average anomaly are highly concentrated in the months immediately after information releases. On average, anomalies generate an annualized abnormal return of 9.84% in the first month alone (column (2)). This is in stark contrast to the period between 5 and 12 months postinformation release, during which abnormal returns are just 1.99% (column (8)). This relation is also evident when looking at the anomalies individually—the majority of anomalies earn high returns in the first month but low or no returns in later periods.

Second, abnormal returns decay after the information release date. For the average anomaly, the first month's mean abnormal return is 9.84%, while the return across the first two months is 7.76% and the return across the first four months is 4.69%. This pattern holds for many of the individual anomalies as well and indicates that returns are initially quite high but dissipate quickly.[15]

Similar to Table V, the solid line in Figure 1 shows the returns (in event time) over the first year after an information release date across our entire sample. Supporting the findings in Table V, returns are high initially (approximately 1.25% in the first two months) before leveling off (total return of less than 1.75% over the next 10 months).

Taken together, these findings are consistent with Prediction 1. They suggest that anomaly returns concentrate in the weeks immediately following information releases and decay quickly thereafter.

B. Information-Rebalancing Approach

There are two caveats to our event-time approach. First, we assume that trades occur at the close of trading on the day after the information release date and the stock is rebalanced once per year. Second, to analyze anomaly returns in event time, we line up all information release dates at day zero (the event date) and we study the profile of returns earned over the next year. In other words, whether an information release date occurred early in our sample

[15] For most of the anomalies in this table, mispricing is greatly diminished as we move away from the information release. However, a handful of anomalies continue to show significant returns for 12 months following information release, consistent with other papers showing that anomalies predict returns long after sorting (e.g., Hirshleifer et al. (2004), Ball et al. (2015), van Binsbergen et al. (2023)). Thus, even with precise information releases, our methods do not rule out long-run mispricing entirely.

Table V

Anomaly Returns in Event Time

The table reports mean daily abnormal returns (annualized and in percent) to anomaly portfolios in event time over specific periods after the information release date. Even-numbered columns report mean returns while odd-numbered columns report the standard errors (clustered by firm and date). Indicators ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Annualized Mean Daily Returns							
	First One Month		First Two Months		First Four Months		Next Eight Months	
Anomaly	Return	StdErr	Return	StdErr	Return	StdErr	Return	StdErr
Average	9.84***	(1.22)	7.76***	(0.95)	4.69***	(0.71)	1.99***	(0.51)
Acc	13.76***	(3.86)	13.43***	(2.80)	6.86***	(2.06)	2.15	(1.56)
Ag	11.14***	(3.86)	8.31***	(2.91)	5.84**	(2.26)	6.00***	(1.46)
At	9.22***	(3.37)	7.35***	(2.47)	3.65*	(1.87)	3.96**	(1.52)
Cat	8.59***	(3.12)	5.50**	(2.28)	4.01**	(1.71)	−0.19	(1.32)
Cpm	12.71***	(3.33)	11.93***	(2.47)	5.50***	(1.83)	−1.56	(1.41)
Ec	10.48***	(3.58)	4.40	(2.71)	4.00*	(2.05)	1.08	(1.57)
Es	17.88***	(2.93)	13.43***	(2.22)	6.78***	(1.68)	0.88	(1.26)
Gp	20.76***	(4.46)	13.88***	(3.38)	6.53**	(2.53)	0.44	(1.85)
Ig	15.25***	(2.99)	11.79***	(2.21)	7.95***	(1.70)	5.69***	(1.21)
Inv	3.18	(3.02)	1.83	(2.18)	0.78	(1.56)	5.06***	(1.32)
Ltg	2.54	(3.75)	0.97	(2.63)	−1.55	(1.88)	−0.89	(1.41)
Nca	7.93**	(3.15)	8.02***	(2.24)	4.49***	(1.63)	4.96***	(1.20)
Noa	0.32	(4.17)	1.67	(3.19)	6.78***	(2.42)	15.42***	(1.85)
Nwc	14.20***	(3.55)	11.72***	(2.50)	5.26***	(1.74)	0.18	(1.24)
Ol	7.74**	(3.47)	1.30	(2.64)	−2.82	(2.00)	−2.45	(1.62)
Osc	15.78***	(5.63)	12.90***	(4.08)	7.48**	(2.87)	5.52**	(2.24)
Pm	8.09**	(3.75)	9.22***	(2.73)	8.33***	(1.98)	3.97**	(1.59)
Poa	17.65***	(2.67)	12.71***	(2.07)	9.30***	(1.52)	1.36	(1.28)
Pro	11.17**	(4.93)	7.97**	(3.86)	4.70*	(2.75)	−1.34	(1.99)
Pta	5.27*	(2.89)	5.05**	(2.20)	3.69**	(1.71)	0.95	(1.14)
Roe	10.98**	(4.28)	6.87**	(3.40)	5.02**	(2.51)	−2.76*	(1.71)
Rs	8.08**	(3.63)	10.79***	(2.56)	7.81***	(1.98)	−1.73	(1.40)
Sag	−1.03	(3.36)	−0.00	(2.45)	−2.39	(1.91)	1.44	(1.53)
Sg	0.57	(3.74)	2.56	(2.70)	2.36	(2.05)	4.97***	(1.40)
Sli	1.02	(3.07)	0.48	(2.25)	2.39	(1.67)	2.60**	(1.27)
Slx	0.33	(3.94)	0.94	(2.90)	−0.16	(2.23)	−3.73**	(1.62)
Tx	6.90	(4.34)	5.51*	(3.30)	4.90**	(2.44)	1.17	(1.85)
Txf	20.60***	(5.83)	16.59***	(3.93)	8.11***	(2.73)	3.32*	(1.75)

or late in our sample, we line them all up on day zero. As a consequence, this strategy is not implementable in real time.

Accordingly, we next examine an implementable calendar-time trading strategy. While the calendar-time approach is common in the existing literature, we make one key change: we rebalance on information release dates, instead of rebalancing once a year in June. In other words, we do not require that every stock be held for one year, but we instead allow the portfolio to change as new information is released. We refer to the resulting strategy as the *information-rebalancing* portfolio, and we contrast it with the conventional strategy in the literature, the *FF92-rebalancing* portfolio. When we compare our information-rebalancing approach to the FF92-rebalancing approach, we find significant gains.

The key advantage of the information-rebalancing approach is that it incorporates new, anomaly-relevant information right after it is released. Given the results from the event-time tests, we expect the information-rebalancing strategy to outperform FF92-rebalancing as it can quickly trade on new information and capture the returns earned in the weeks immediately following information releases. We find that it does.

Table VI reports the annualized mean daily abnormal returns earned by both strategies over our sample period as well as the differences between the returns of the information and FF92 strategies.

Panel A of Table VI shows that the average anomaly performs significantly better when new information is incorporated quickly, instead of waiting until June 30. The average anomaly's annualized daily abnormal return is 3.07% when using the information-rebalancing strategy, which is 0.66 percentage points higher than that of the FF92-rebalancing strategy (an increase of 27%).

While the improvement of 0.66 percentage points is statistically significant, the magnitude may appear small, especially relative to the impressive returns documented in the event-time results in Table V. Furthermore, while 21 of the 28 anomalies show positive improvements using the information-rebalancing strategy relative to the FF92 approach, only four are statistically different at the usual levels. This also seems low given the strong results from the event-time setting. Importantly, these results are the average of daily returns *across all months of the year*, even the summer and autumn months when the information-rebalancing portfolios include stocks that released information several months ago. In effect, the information-rebalancing strategy incorporates the high returns from the first four months shown in Table V, but also includes some of the low returns from the later months when new anomaly-relevant information is not being released.

Accordingly, we next compare the returns between the information and FF92 strategies, but focus on *when* the returns are generated. We do so by dividing the calendar into two periods. The first period includes February through April, which captures annual earnings season for most December FYE firms. We expect that from February through April, the information-rebalancing strategy will capture the high early returns documented in the event-time setting because new information is being released in this window. The second period covers May through January, months that correspond to the later period in the event-time setting. In light of our previous results, we expect the returns to the two strategies to be approximately the same from May through January when new information is not released for most firms.

The results confirm this intuition. Panel B of Table VI reports the annualized mean daily abnormal returns for the average anomaly for these two periods. We find that from February through April, the information-

Table VI

Info versus FF92 Rebalancing

The table reports mean daily abnormal returns to anomaly portfolios (annualized and in percent) for both the information- and FF92-rebalancing strategies and the difference between the two strategies. Panel A uses all daily returns. Panel B focuses on daily returns within different months. The final row of both panels counts the number of anomaly portfolios for which the mean daily abnormal return is positive and statistically significant. Indicators ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered by firm and date and are shown in parentheses.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: All Anomalies across All Months						
	FF92 Rebalancing		Info Rebalancing		Difference	
Anomaly	Return	StdErr	Return	StdErr	Return	StdErr
Average	2.40***	(0.43)	3.07***	(0.44)	0.66**	(0.27)
Acc	2.87**	(1.33)	4.56***	(1.34)	1.65	(1.02)
Ag	6.95***	(1.23)	7.74***	(1.35)	0.74	(1.19)
At	3.44***	(1.31)	3.64***	(1.28)	0.19	(0.72)
Cat	2.07*	(1.17)	1.20	(1.16)	−0.86	(0.98)
Cpm	0.87	(1.20)	0.44	(1.22)	−0.42	(1.02)
Ec	1.32	(1.49)	1.33	(1.52)	0.01	(1.17)
Es	−0.44	(1.24)	2.49**	(1.23)	2.94**	(1.17)
Gp	1.56	(1.57)	2.46	(1.64)	0.89	(0.76)
Ig	5.21***	(1.06)	7.37***	(1.10)	2.05**	(0.92)
Inv	3.81***	(1.26)	4.61***	(1.25)	0.77	(1.00)
Ltg	0.82	(1.24)	0.03	(1.26)	−0.78	(1.03)
Nca	3.29***	(1.06)	4.45***	(1.06)	1.13	(0.99)
Noa	12.57***	(1.55)	12.98***	(1.55)	0.36	(0.98)
Nwc	−0.12	(1.13)	2.02*	(1.16)	2.14*	(1.09)
Ol	−1.29	(1.38)	−1.93	(1.39)	−0.66	(0.54)
Osc	4.42**	(1.73)	4.96***	(1.87)	0.52	(0.98)
Pm	4.33***	(1.33)	4.69***	(1.37)	0.34	(0.66)
Poa	2.93***	(1.09)	4.09***	(1.10)	1.13	(0.78)
Pro	0.35	(1.51)	0.21	(1.69)	−0.15	(0.95)
Pta	2.53**	(1.05)	2.36**	(1.07)	−0.17	(0.89)
Roe	−0.94	(1.27)	−0.88	(1.40)	0.06	(0.90)
Rs	−2.75**	(1.21)	1.73	(1.27)	4.60***	(1.15)
Sag	0.36	(1.46)	−0.51	(1.45)	−0.87	(1.01)
Sg	5.34***	(1.23)	5.98***	(1.32)	0.61	(1.16)
Sli	1.69	(1.16)	2.52**	(1.19)	0.81	(0.97)
Slx	−3.11**	(1.36)	−2.88**	(1.49)	0.24	(1.16)
Tx	−0.52	(3.15)	1.56	(3.24)	2.09	(4.04)
Txf	4.71***	(1.47)	6.15***	(1.60)	1.37	(1.02)
No. > 0	14		16		4	

Panel B: Average Anomaly across Specific Months						
	May to January			February to April		
	FF92	Info	Difference	FF92	Info	Difference
Abn. return	2.04***	2.05***	0.01	3.74***	6.40***	2.56***
Sharpe ratio	1.11***	1.11***	0.00	1.68***	2.30***	0.62***
No. > 0	11	11	1	9	20	10

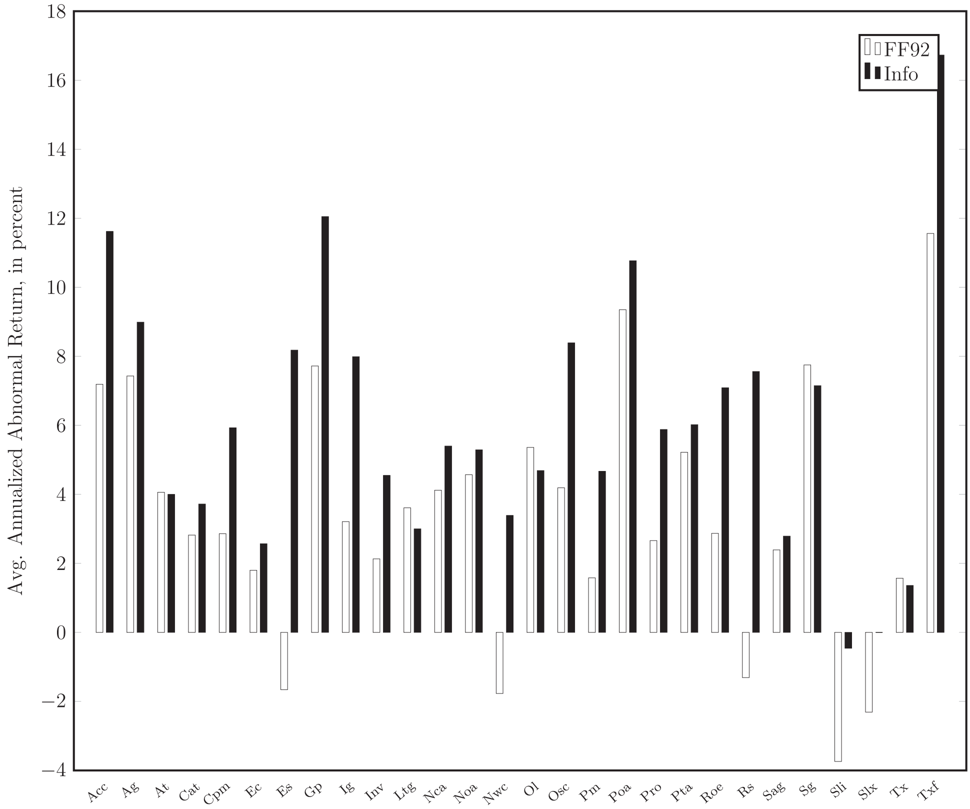

Figure 4. Info versus FF92 rebalancing: February to April. The figure shows annualized mean daily abnormal returns from February through April for the 28 anomalies in our sample. For each anomaly, we form portfolios two ways: information rebalancing (solid black bar) and FF92 rebalancing (solid white bar).

rebalancing strategy strongly outperforms the FF92-rebalancing strategy. During these months, the information-rebalancing strategy generates annualized abnormal returns of 6.40%, nearly twice as large as the 3.74% return generated by FF92. In contrast, from May through January, the information-rebalancing and FF92-rebalancing strategies generate returns that are quite similar. This difference is directly related to the findings in our event-time setting. The information-rebalancing approach quickly incorporates new information released during annual earnings season and captures the high returns over the first couple of months postinformation release. By July, both the information-rebalancing and FF92-rebalancing portfolios have incorporated the same information and thus have very similar compositions and performance.

Figure 4 depicts this temporal pattern in anomaly returns. This figure shows the February through April returns to both strategies for each anomaly.

The figure visually demonstrates the outperformance of the information-rebalancing strategy versus FF92-rebalancing for many of the 28 anomalies we consider.

Furthermore, Panel B of Table VI shows that of the 28 anomalies in our sample, 20 generate positive and significant abnormal returns from February through April. The return difference between the information-rebalancing and FF92-rebalancing strategies is positive and significant for 10 of the 28 anomalies. We use this finding (10 significantly enhanced anomalies out of a possible 28) and a standard Binomial test to further test whether the information-rebalancing strategy is better than FF92. We can reject the null hypothesis that the information-rebalancing and FF92-rebalancing strategies are equivalent as the probability of observing 10 or more positive differences is extremely small ($p < 0.001$).[16]

Finally, Panel B also reports Sharpe ratios for the two strategies. Similar to previous findings, the information-rebalancing and FF92-rebalancing strategies produce equivalent Sharpe ratios from May through January. But between February and April, the Sharpe ratios for the information-rebalancing strategy are significantly larger than for the FF92 strategy: the information-rebalancing strategy generates a Sharpe ratio of 2.30 while FF92 yields 1.68. The difference, 0.62, is statistically and economically significant.[17]

Taken together, the results from both the event-time and calendar-time frameworks demonstrate that anomaly returns are highly concentrated in the first weeks after information releases. These results provide strong evidence in favor of Prediction 1: return predictability is strongest in the period immediately following important information releases and decays quickly thereafter. Importantly, this finding also helps reconcile seemingly conflicting findings in the literature: while some recent papers argue that anomalies tend to vanish in recent periods, others argue that they are real and still present. We show that forming portfolios in June underestimates predictability because it uses stale information, which makes some anomalies appear insignificant, but anomalies do predict returns if portfolios are formed immediately after information releases.

[16] See Section V of the Internet Appendix for more on the binomial test. The standard binomial test assumes independent trials, requiring the independence of the 28 anomalies. The average correlation between all 28 anomalies is 0.08, but several anomalies are more highly correlated. We account for this by condensing the list of anomalies into six groups based on the type of anomaly: Investment (Ag, Sg, Txf, Inv), Accruals (Acc, Poa, Pta), Working Capital (Ig, Ltg, Nwc, Nca, Noa), Profitability (At, Ec, Gp, Pm, Pro, Roe, Ol, Osc, Tx), Sales Growth (Cat, Cpm, Sag, Sli, Slx), and Surprises (Es, Rs). Of these six groups, four generate significantly higher returns using the information-rebalancing strategy than the FF92-rebalancing strategy in the months from February through April. We again reject the null hypothesis that information-rebalancing and FF92-rebalancing are equivalent ($p < 0.001$).

[17] To test the differences in Sharpe ratios, we used a bootstrap method to obtain standard errors of the Sharpe ratio point estimates, and the 95% confidence interval for the point estimate of 0.62 is 0.22 to 1.02.

C. Testing Information Processing Costs

In this section, we turn our attention to Prediction 2 by testing an economic channel that helps explain the previous results. Motivated by a large theoretical literature, we test whether anomaly returns are driven, at least in part, by information processing costs, which generate drift in prices. Specifically, Prediction 2 argues that changes in information-processing costs may change the drift in prices: when information processing costs fall, prices should respond to new information more quickly.

To directly examine Prediction 2, we use two tests that capture changes in information processing costs: (i) the implementation of the SEC's EDGAR system in the mid-1990s and (ii) decreases in information processing costs over our full sample period.

C.1. EDGAR Implementation

We use the staggered implementation of the EDGAR system as a shock to information processing costs. In the mid-1990s, the SEC created EDGAR as an electronic repository for all digital SEC filings (e.g., 10-Ks, 10-Q, and 8-Ks). This implementation directly reduced the costs of acquiring public filings.[18] The SEC rolled out the implementation of EDGAR in phases (Kothari, Zhang, and Zuo (2023)). Firms were separated into 10 groups, with each group having a different date on which they were required to submit their filings via EDGAR. The filings were also made available online at various (staggered) dates between 1994 and 1996.

Using the staggered implementation of EDGAR, we test whether the return to anomalies became more concentrated in the weeks immediately following the release of key information. To do so, we use an event-time approach to examine the proportion of the four-month return that is earned in different windows following information releases: (i) the first two weeks, (ii) the first month, and (iii) the first two months. If information processing costs are related to anomaly returns, we expect returns to become more concentrated in the first few weeks after information releases once EDGAR is implemented. To test this, we compare the concentration of anomaly returns the year before EDGAR implementation relative to the year after EDGAR implementation. The results are shown in Table VII. Panel A presents details of the staggered implementation while Panel B presents the anomaly returns before and after the implementation of EDGAR.

In the pre-EDGAR period, anomaly returns are earned mostly in the middle to end of the first four months following information release. In these first four months (column (5)), the average anomaly earned 3.13%. Only 0.17% was earned over the first two weeks, which is only one-twentieth (5%) of the

[18] For instance, as support for this view, we note that the SEC closed the Chicago and New York reading rooms "Due to the success of electronic information dissemination through EDGAR and the Internet" (SEC (2000)).

Table VII

Anomaly Returns and EDGAR Implementation

The table compares mean daily abnormal returns to the average anomaly portfolio in event time between the year before EDGAR implementation and the year after EDGAR implementation. Indicators ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered by firm and date and are shown in parentheses. Panel A provides details on the implementation of EDGAR. Panel B displays the return results.

Panel A: Detail on EDGAR Implementation

(1)	(2)	(3)
Group	Online Date	Number of Stocks
CF-01	January 17, 1994	50
CF-02	January 17, 1994	273
CF-03	January 17, 1994	265
CF-04	January 17, 1994	350
CF-05	January 30, 1995	371
CF-06	March 6, 1995	240
CF-07	May 1,1995	170
CF-08	August 7, 1995	63
CF-09	November 6, 1995	51
CF-10	May 6, 1996	1,483

Panel B: Anomaly Returns Pre- and Post-EDGAR Implementation (Event Time)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Compound Returns Earned After Information Release				Percent of Four-Month Return Earned Over Span of:		
Period	2 Wks	1 Mo	2 Mos	4 Mos	2 Wks	1 Mo	2 Mos
Pre-EDGAR	0.17	0.66*	1.34***	3.13***	5%	21%	43%
	(0.20)	(0.28)	(0.43)	(0.67)			
Post-EDGAR	0.34*	0.98***	2.01***	2.38***	14%	41%	85%
	(0.17)	(0.25)	(0.40)	(0.60)			

four-month return. Similarly, columns (7) and (8) show that approximately one-fifth (21%) of the four-month return was earned in the first month while less than one-half (43%) of the four-month return was earned in the first two months.

Post-EDGAR, anomaly returns became more concentrated after information release dates. In the first four months postinformation release, the average anomaly earned 2.38%. Over the first two weeks, the average return was 0.34%, which is 14% of the four-month return. Similarly, 41% of the four-month return was earned in the first month, while fully 85% of the four-month return was earned in the first two months. Especially compared to the pre-EDGAR period, these results indicate a high level of concentration in the weeks immediately following information releases. Even after the implementation of EDGAR, however, we continue to observe return predictability for several months, suggesting that information processing costs were not completely eliminated.

Overall, these results show that information processing costs play a role in the timing of anomaly returns. When processing costs are lower, returns are earned more quickly.

C.2. Decreases in Processing Costs over the Sample Period

We also examine a second test of the information processing cost hypothesis. For this test, we rely on the intuition that information processing costs have fallen in general over the last three decades.[19] As information processing costs fall, we expect anomaly returns to become more concentrated in the period immediately after information releases. Our test is simple: we divide the sample in half and rerun our analyzes to see *when* anomaly returns are earned in the first versus the second half of our sample.

Table VIII presents the results. We find that abnormal returns are lower and more concentrated in the latter part of the sample period, consistent with Prediction 2. Panel A presents the results of an event-time test similar to that in Table V except it reports results for the average anomaly only and splits the sample period in half. When comparing the early and recent periods, it is clear that anomaly returns were higher in the first half of the sample period (1990 to 2004) and lower in the latter half of the sample period (2005 to 2019). For example, in the first month after information release, the average anomaly portfolio in the first half of the sample period earns annualized returns of over 12%, whereas the same portfolio in the latter half earns only 7% (column (2)). Panel A also shows that the average anomaly portfolio's returns were more concentrated in the latter half of the sample period as compared to the early period. In the early period, returns over the first four months are still high at 7.63%, and even returns over the next eight months are 3.12% (see columns (4) and (5)). In contrast, during the latter half of the sample period, returns are higher in the first two months before trailing off considerably.[20] This change in the return profile between the first and latter halves of the sample period can be seen in the dashed lines of Figure 1.

Both findings—lower returns and increased return concentration from the early period to the recent period—are also evident in Panel B of Table VIII, which details returns in the first four months after information releases. In the first half of the sample period (1990 to 2004), returns in the first four months were not very concentrated after information release. The return over the first four months postinformation release averaged 2.36%. Over the first two weeks, the average return was 0.45%, which is 19% of the four-month return. Similarly, 39% of the four-month return was earned in the first month while 67% of the four-month return was earned in the first two months. The results are

[19] Section VI of the Internet Appendix discusses trends in information processing costs and provides some visual evidence that information processing costs have declined.

[20] This finding also holds for many of the individual anomalies as well, including the earnings surprise anomaly, for which our findings and conclusions are similar to those in Martineau (2022).

Table VIII

Time Trends of Anomaly Returns

The table reports returns over our entire sample (1990 to 2019), over the early years of our sample (1990 to 2004), and over the recent years of our sample (2005 to 2019). Panel A reports event-time returns over the first year after each event. Panel B reports event-time returns within the first four months and calculates the percent of the four-month return earned in earlier weeks. Panel C compares the implementable information and FF92 strategies in both the early and recent periods. Indicators ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered by firm and date and are shown in parentheses.

Panel A: Event Time—across the Entire Year

(1)	(2)	(3)	(4)	(5)
	Annualized Mean Daily Returns			
Time Period	First One Month	First Two Months	First Four Months	Next Eight Months
1990–2019	9.84***	7.76***	4.69***	1.99***
	(1.22)	(0.95)	(0.71)	(0.51)
1990–2004	12.29***	10.47***	7.63***	3.12***
	(1.84)	(1.43)	(1.05)	(0.72)
2005–2019	7.09***	5.05***	2.02**	1.01
	(1.59)	(1.22)	(0.92)	(0.70)

Panel B: Event Time—Detail within the First Four Months

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Compound Returns Earned after Information Release				Percent of Four-Month Return Earned over Span of:		
Time Period	2 Weeks	1 Month	2 Months	4 Months	2 Weeks	1 Month	2 Months
1990–2019	0.39***	0.75***	1.19***	1.43***	27%	52%	83%
	(0.06)	(0.10)	(0.15)	(0.22)			
1990–2004	0.45***	0.92***	1.59***	2.36***	19%	39%	67%
	(0.09)	(0.14)	(0.23)	(0.33)			
2005–2019	0.32***	0.55***	0.78***	0.64**	50%	86%	122%
	(0.08)	(0.13)	(0.19)	(0.29)			

Panel C: Info versus FF92 Rebalancing

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Annualized Mean Daily Returns					
	May to January			February to April		
Time Period	FF92	Info	Difference	FF92	Info	Difference
1990–2019	2.04***	2.05***	0.01	3.74***	6.40***	2.56***
(s.e.)	(0.49)	(0.50)	(0.28)	(0.84)	(0.93)	(0.63)
No. > 0	11	11	1	9	20	10

(*Continued*)

Table VIII—*Continued*

Panel C: Info versus FF92 Rebalancing

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Annualized Mean Daily Returns					
	May to January			February to April		
Time Period	FF92	Info	Difference	FF92	Info	Difference
1990-2004	3.34***	3.41***	0.07	6.89***	8.69***	1.68
(s.e.)	(0.70)	(0.70)	(0.49)	(1.23)	(1.42)	(1.04)
No. > 0	13	15	2	14	13	2
2005-2019	0.77	0.73	−0.04	0.94	4.03***	3.06***
(s.e.)	(0.67)	(0.70)	(0.29)	(1.09)	(1.16)	(0.67)
No. > 0	3	5	3	3	10	9

quite different in the latter half of the sample period (2005 to 2019), where fully 50% of the four-month return was earned in the first two weeks, 86% over the first month, and over 100% in the first two months. These results are consistent with Prediction 2: a decline in information processing costs coincides with increased return concentration following information releases.

Panel C repeats the analyzes in Table VI but splits the sample period in half. Comparing our implementable information-rebalancing strategy to the FF92-rebalancing strategy, we again find that anomaly returns have declined in the latter half of the sample period and are more concentrated in the weeks immediately following information releases. In the early part of our sample, anomaly returns were strong not only in February through April, but also in the months that occurred well after important information releases. The FF92- and information-rebalancing approaches both generated nearly 3.50% on an annualized basis in the May through January months. Furthermore, the information-rebalancing strategy was not significantly better than FF92-rebalancing in February through April during the early part of our sample. Both strategies produced high returns and only two of the 28 anomalies were significantly improved when traded using the information-rebalancing strategy.

In the recent period, however, anomaly returns were insignificant for both strategies in the May through January months. This is unsurprising given the results in Panels A and B, which show that anomaly returns have largely disappeared during periods distant from information release dates. In February through April, however, the information-rebalancing approach still generates high returns while the FF92-rebalancing approach does not. Indeed, much of the outperformance of the information-rebalancing strategy over FF92-rebalancing occurs in the recent period. These results further indicate that anomaly returns have become more concentrated over time.

In sum, the evidence suggests that (i) anomaly returns became more concentrated after a decrease in information processing costs following the implementation of EDGAR, and (ii) anomaly returns gave become more concentrated over time as information processing costs have decreased. Overall, these results provide strong evidence in favor of Prediction 2.

C.3. Trading Volume

Another implication of Prediction 2 is that as information processing costs fall, trading should occur more quickly following the release of new information. To test this conjecture, we measure trading volume in our event-time framework by averaging volume across all stocks in anomaly portfolios. Specifically, for each trading day postinformation release, we take the ratio of volume that day to average daily volume over the first two months postinformation release. In other words, we compare trading volume each day to average trading volume in the first two months after an information release to see how much of the volume occurs on the first day. Prediction 2 implies that reduced information processing costs in the more recent sample period should coincide with more concentrated trading volume following the release of anomaly-relevant information.

Figure 5 shows the results. Consistent with Prediction 2, the figure shows that trading volume is initially high following information release dates, before returning to normal levels after a week. More importantly for our purposes, the figure also shows that in the more recent period, trading volume is much more concentrated immediately following the information release. Specifically, in the early part of our sample period, trading volume was only 10% higher than average in the first few days postinformation release, while in more recent years, trading volume is much more concentrated, with more than twice the percentage of volume occurring within 10 trading days following information releases as compared to the first half of the sample period. This finding corroborates our previous results and provides additional evidence on the importance of information processing costs.

D. Additional Analysis

In this subsection, we discuss several additional analyzes regarding the timing of information releases and the timing of anomaly returns. Apart from the first table shown below, these additional results are discussed in greater detail in Section VII of the Internet Appendix. Together, they both support and provide nuance to our main results.

First, Table IX replicates the analysis in Table V using different risk adjustments. The first row is a direct replica of the first row of Table V, where we use the Fama-French five-factor model with momentum. The second row uses the Fama-French three-factor model. The third and fourth rows use value- and equal-weighted DGTW returns (Daniel et al. (1997)). The last row uses raw returns. Overall, the results in Table IX show that risk adjustments are not the driving force behind our event-time results.

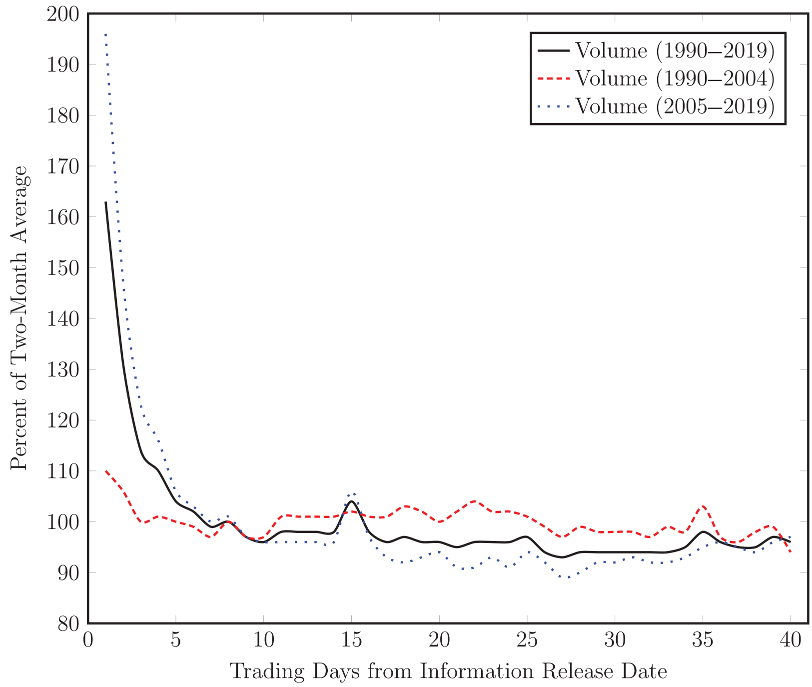

Figure 5. Trading volume in event time. The figure shows trading volume for two months from the information release date and separates the analysis between the early and recent years of our sample. Volume is measured as share volume traded divided by shares outstanding; the data come from the CRSP database. The vertical axis measures the percent of the two-month average that occurs on the given day postinformation release. For example, at Day 1, share volume was approximately 200% of the two-month average in the 2005 to 2019 period. (Color figure can be viewed at wileyonlinelibrary.com)

Second, in Section VII.A of the Internet Appendix we account for transactions costs and test whether quickly rebalancing on information release dates yields high returns *net* of costs. We find that although the implementable information-rebalancing strategy has higher turnover than the FF92 strategy, net returns are still high in the February through April months. This is especially true in recent years when transaction costs have been lower.

Third, in Section VII.B of the Internet Appendix we show that our return results are distinct from the findings in Engelberg, McLean, and Pontiff (2018), who show that anomaly returns are earned primarily on days with news. We use our unique setting to test whether news days have higher predictive power than nonnews days when we account for the distance from information release dates. Overall, we find that the importance of timing continues to hold for both news days and nonnews days, which suggests our findings are distinct from the conclusions in Engelberg, McLean, and Pontiff (2018).

Fourth, in Section VII.C of the Internet Appendix, we show that the concentration of anomaly returns after information release dates is independent of

Table IX

Anomaly Returns: Different Risk Adjustments

The table reports mean daily abnormal returns (annualized and in percent) to anomaly portfolios in event time over specific periods after the information release date. The table replicates the earlier analysis while using different risk adjustments, including the Fama-French three-factor model, DGTW value-weighted excess returns, DGTW equally weighted excess returns, and raw returns. Indicators ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors are clustered by firm and date and are shown in parentheses.

(1)	(2)	(3)	(4)	(5)
	Annualized Mean Daily Returns			
Risk Adjustment	First One Month	First Two Months	First Four Months	Next Eight Months
FF5 plus Mom	9.84***	7.76***	4.69***	1.99***
	(1.22)	(0.95)	(0.71)	(0.51)
FF3	11.84***	9.73***	6.65***	3.93***
	(1.39)	(1.09)	(0.89)	(0.62)
DGTW_VW	9.87***	7.70***	5.37**	3.33***
	(1.26)	(0.96)	(0.67)	(0.54)
DGTW_EW	9.99***	7.75***	5.42***	4.10***
	(1.28)	(0.99)	(0.70)	(0.57)
Raw	11.34***	9.50***	6.36***	4.00***
	(2.01)	(1.50)	(1.05)	(0.74)

the anomaly publication date, as in McLean and Pontiff (2016). We show this in two ways. First, using our event-time setting, we visually compare the profile of anomaly returns from the three prepublication years with those from the three postpublication years for our anomalies. The results show that returns are similarly concentrated in the first weeks after information release dates for prepublication years and postpublication years. Second, we divide our sample of anomalies between those that were discovered early in our sample period (before 2000) and those that were discovered later (after 2009). We then use our event-time approach to compare abnormal returns for the "old" anomalies (i.e., those published before 2000) with the "new" anomalies (i.e., those published after 2009). Importantly, we only use the decade from 2000 through 2009 when the "old" anomalies are entirely out of sample and the "new" anomalies are entirely in sample. The results of this test show that the profile of anomaly returns is the same in this period, regardless of whether the anomalies are "old" or "new."

Fifth, in Section VII.D of the Internet Appendix we show that our event-time results do not depend on market capitalization. Indeed, whether focusing solely on large stocks, excluding microcap stocks, or even focusing on microcap stocks, the pattern holds: anomaly returns are highly concentrated in the weeks immediately following information releases.

Sixth, since the month of FYE determines the staleness the FF92-rebalancing strategy, in Section VII.E of the Internet Appendix we test whether the information-rebalancing strategy increasingly outperforms when the FYE is not near December. Our findings confirm this intuition by showing that the information-rebalancing strategy outpaces the FF92 strategy when the FYE is earlier in the calendar year.

Finally, in Section VII.F of the Internet Appendix we document the differences between the long and short legs of the hedge anomaly portfolio. These results demonstrate that the event-time return predictability occurs on both legs.

V. Recommendations for Future Research

The results above show that the existing literature often relies on stale information, which masks important patterns in anomaly returns. Accordingly, future researchers should endeavor to avoid the use of unnecessarily stale data when forming anomaly portfolios. We recommend that, whenever possible, researchers use the information release dates in Snapshot. However, because researchers may not have access to Snapshot, in this section we develop guidance on forming portfolios using standard academic databases.

If Snapshot is not available, we recommend that researchers update anomaly portfolios using the 10-K filing date.[21] The 10-K filing date can be accessed through Compustat without a Snapshot subscription and, by regulation, 10-K filings contain full, audited financial statements. Also, since the mid-1990s, these filings have been publicly available electronically and without delay. Thus, over the last three decades, all investors could reasonably access anomaly-relevant information on 10-K filings dates. As shown in Table II, the 10-K filing date leads to significantly less staleness than the FF92 date. Indeed, over the last 30 years, the median information release date is the 10-K filing date. Moreover, because 10-Ks, by regulation, must contain full audited financial statements, we find in Table II that this approach never leads to look-ahead bias over our sample period from 1990 to 2019.[22]

To establish the validity of this recommendation, in Table X, we replicate our main analyzes using the 10-K filing date (instead of the Snapshot date) as the rebalancing event.

Table X clearly shows that updating on 10-K filings dates is nearly as effective as updating on the information release dates. Given this evidence, we

[21] The Snapshot data and the 10-K filing date data are most readily available from the early 1990s when most firms began filing electronic statements with the SEC. Absent additional historical data, we do not make recommendations for the appropriate information dates prior to this time period.

[22] As of the date of publication, researchers can obtain 10-K filing dates from two sources. First, these dates are contained in a Compustat file named `Co_filedate` located on the WRDS-cloud at `/wrds/comp/sasdata/naa/company`. We provide SAS code in Section VIII of the Internet Appendix and on our author website(s) to assist others with acquiring these data from Compustat. Second, as of September 2023, these dates are also provided by the Notre Dame Software Repository for Accounting and Finance (SRAF) at https://sraf.nd.edu/data/augmented-10-x-header-data/, under the label of Augmented 10-X Header Data. We note that based on concerns of Bartov and Konchitchki (2017) regarding the accuracy of Compustat 10-Ks, we compared the 10-K dates in our sample from Compustat with the 10-K dates from the EDGAR master files. We found a 95% concordance between the two dates over our sample period, with a 99% concordance since 2005.

Table X

Anomaly Returns: Updating on 10-K Filing Dates

The table reports returns from updating on information release dates and from updating on 10-K filing dates. The table examines our entire sample (1990 to 2019), the early years of our sample (1990 to 2004), and the recent years of our sample (2005 to 2019). Panel A reports event-time returns after each event (where the event is either the information release date or the 10-K filing date). Panel B compares the implementable information release and FF92 strategies in both the early and recent periods, but in this analysis the information release strategy uses 10-K filing dates instead of actual information release dates. Indicators ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered by firm and date and are shown in parentheses.

Panel A: Event-Time Framework

(1)	(2)	(3)	(4)	(5)
	Annualized Mean Daily Returns			
Updating Date (years)	First One Month	First Two Months	First Four Months	Next Eight Months
Information date (90-19)	9.84***	7.76***	4.69***	1.99***
	(1.22)	(0.95)	(0.71)	(0.51)
10-K Filing date (90-19)	9.20***	7.02***	4.12***	2.17***
	(1.31)	(0.98)	(0.70)	(0.51)
Information date (90-04)	12.29***	10.47***	7.63***	3.12***
	(1.84)	(1.43)	(1.05)	(0.72)
10-K filing date (90-04)	12.58***	10.29***	7.00***	3.57***
	(2.12)	(1.51)	(1.05)	(0.72)
Information date (05-19)	7.09***	5.05***	2.02**	1.01
	(1.59)	(1.22)	(0.92)	(0.70)
10-K filing date (05-19)	5.73***	4.01***	1.64*	1.02
	(1.59)	(1.24)	(0.91)	(0.70)

Panel B: Implementable Framework with Info Rebalancing

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Annualized Mean Daily Returns					
	May to January			February to April		
Updating Date (years)	FF92	Info	Difference	FF92	Info	Difference
Information date (90-19)	2.04***	2.05***	0.01	3.74***	6.40***	2.56***
	(0.49)	(0.50)	(0.28)	(0.84)	(0.93)	(0.63)
10-K filing date (90-19)	2.04***	2.15***	0.11	3.74***	5.94***	2.20***
	(0.49)	(0.50)	(0.28)	(0.84)	(0.93)	(0.60)
Information date (90-04)	3.34***	3.41***	0.07	6.89***	8.69***	1.68
	(0.70)	(0.70)	(0.49)	(1.23)	(1.42)	(1.04)
10-K filing date (90-04)	3.34***	3.60***	0.26	6.89***	8.79***	1.90*
	(0.69)	(0.70)	(0.48)	(1.23)	(1.41)	(0.99)
Information date (05-19)	0.77	0.73	−0.04	0.94	4.03***	3.06***
	(0.67)	(0.70)	(0.29)	(1.09)	(1.16)	(0.67)
10-K filing date (05-19)	0.77	0.74	−0.03	0.94	3.19***	2.25***
	(0.67)	(0.70)	(0.29)	(1.15)	(1.16)	(0.65)

strongly recommend that researchers use 10-K filings dates to update anomaly portfolios when Snapshot data are unavailable.[23]

VI. Conclusion

We show that the conventional method of portfolio rebalancing used in financial research leads to anomaly portfolios that rely on information that can be severely outdated. Using a database that captures when information is first publicly released, we test two predictions that investigate the implications of theories on costly information processing and underreaction. We then develop guidelines for studying asset-pricing anomalies without using stale data or introducing look-ahead bias.

Our approach leverages the real-time data provided in the powerful but relatively unknown Compustat Snapshot database. This database contains the date on which accounting items were first made publicly available, which we use to examine the precise timing of returns for a large number of anomalies. We show that the convention of annual rebalancing in June leads to anomaly portfolios that are often based on extremely stale information. We then show that returns to many anomalies are concentrated in the first month after information releases, and these returns get weaker in the months that follow. The results support predictions based on theories of costly information processing, and suggest that the existing literature underestimates return predictability. Finally, we develop guidelines for future research. Specifically, we show that forming portfolios the day after the 10-K filing date in Compustat leads to very little staleness for most anomalies and never leads to look-ahead bias over our sample period from 1990 to 2019.

To date, the existing literature has largely studied anomalies from the perspective of annual buy-and-hold portfolios. Our approach suggests that this view leads to an incomplete picture as anomalies are based on events. Our event-based approach finds evidence that the anomaly zoo is alive and well in the information age, and future studies need to account for the fact that accounting statements are no longer sent by mail.

Initial submission: October 1, 2021; Accepted: July 10, 2023
Editors: Stefan Nagel, Philip Bond, Amit Seru, and Wei Xiong

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[23] For reasons discussed in Section II, this study is limited to 28 anomalies. However, our recommendation—that researchers update accounting information quickly using either Snapshot or 10-K filing dates—holds for other anomalies that are calculated, at least in part, using accounting information.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.