Anomaly Time

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ABSTRACT

We examine the timing of returns around the publication of anomaly trading signals. Using a database that measures 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.

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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 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 causes 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 a 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 at least partly due 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 an average of five months in the past. Motivated by the theoretical literature on underreaction and costly information processing (e.g., Blankespoor et al. (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 this, 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.

[Figure 1 about here.]

Our findings suggest 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 a 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 a look-ahead bias throughout our sample period from 1990 to present. 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's (SEC) EDGAR system in 1993, arbitrageurs would have to access financial statements by physically traveling 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 a considerable delay. After a financial statement was prepared, it would be physically mailed to the SEC, and it might take weeks (in some cases even months) before it was processed and made available to investors (Kothari et al. (2022)). 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 et al. (2010)). As a result, even though financial statements were publicly available, it took time for investors, and therefore 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 a look ahead bias, the academic literature has established a convention in which 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 this convention causes many analyses to rely on stale information and 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 this data to examine the precise timing of returns for a large number of anomalies. Using this data, we examine the timing of returns

[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. 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."

relative to information releases and test the implications of theories about costly information processing.

We start by identifying the set of anomalies that exclusively rely on information which arrives at infrequent and discrete points in time.[2] Specifically, we begin with the list of anomalies in McLean and Pontiff (2016), 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 then 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] Further, at the 90th 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 date and the FF92 date is relatively small (i.e., the 10th 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

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

[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.

[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. On the other hand, using the FF92 convention, this same stock would not be added to the anomaly portfolio until June 30, 2012, a delay of 396 days.

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 present). Even at the 90th 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 it 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, as well as 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. But over the first four months following an information release, the average daily abnormal return is just 4.69%, annualized, which implies the returns significantly dissipate 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 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 et al. (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 a reduction in information processing costs leads to faster arbitrage and shorter periods of return predictability.

Moreover, 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 et al. (2022)). As a consequence, our second prediction implies there should be more rapid trading on information signals in recent years. We find this is 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 rebalancing 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% more than the FF92-rebalancing approach on an annualized basis. Across a battery of additional tests that account for transaction costs, the impact of small firms, news days, and publication dates, we consistently find evidence that links predictable returns to the timing of information arrival. In sum, our evidence all 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 et al. (2016), Hou et al. (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 alphas are stationary. By explicitly considering timing, our tests avoid this issue.

Moreover, 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), Chen and Velikov (2023), Muravyev et al. (2022)). We find, like much of the literature, that anomalies do tend to vanish in recent periods (e.g., Chordia et al. (2014), McLean and Pontiff (2016)). However, we show that existing approaches form portfolios using information that is weeks, months, or even years old, which causes 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 (2019), Chen and Zimmermann (2021), and Jensen et al. (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 anomalies returns are related to information release dates. Section V then 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 et al. (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 created a competition about 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 present even after the launch of the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system in the mid-1990s which automated the submission and hosting of companies' financial filings. However, despite this and other advancements, 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; further, even the same 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. Further, anomaly-relevant information is increasingly released at the same time as other important pieces of information, such as management

[5]For additional details, see Gao and Huang (2020) and Kothari et al. (2022).

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

guidance, conference calls, analyst estimates, and the earnings releases of other firms (e.g., Hirshleifer et al. (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 and use it 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 et al. (2020), investors must (1) monitor for the release of new anomaly-relevant information (awareness), (2) expend effort in acquiring and extracting information from the release (acquisition), and (3) 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 to inhibit trading on the release of anomaly-relevant information. We refer to these collectively as *information processing costs*.

In order 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 et al. (2009) find that post-earnings 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.

Further, 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. Further, 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 et al. (2009)) and the particular signal needed by the investor could be buried deep within a 200-page financial filing. Moreover, increasingly financial statements are released around the same time as other important pieces of information, such as management guidance, conference calls, and analysts revisions (e.g., Rogers and Van Buskirk (2013)). Further, 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 including overconfidence (e.g., Daniel et al. (1998)) and representativeness (e.g., Barberis et al. (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 re-rank 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 upon 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 et al. (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 just discussed lead to a specific prediction in our context: if investors are unable to be attend, 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 towards 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 lowered information processing costs, including innovations related to disclosure regulation such as EDGAR, IFRS, and XBRL (Kothari et al. (2022)); automated information generation and dissemination, such as robojournalism (Blankespoor et al. (2018)), expanding sources of novel and 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 the anomaly and firm level – the earliest date at which anomaly-relevant information is publicly known.[7]

Our sample period begins January 1990 and goes through 2019. Snapshot data identifies 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 get daily prices, returns, volume, and shares outstanding from CRSP. We also obtain daily factors from the five-factor model (MKT-RF, HML, SMB, RMW, CMA) plus the daily momentum factor (MOM) from CRSP. In additional analyses, we use news data from RavenPack, NYSE size breakpoints from Kenneth French's database, and bid-ask spreads from TAQ.[8]

[7]For more details on Snapshot, see Appendix B. The Snapshot manual (Compustat Snapshot User Guide, July 24, 2023) can be accessed at https://wrds-www.wharton.upenn.edu/documents/925/compustat-snapshot-user-guide.pdf.

[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 (2022)). See

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 constantly changes, 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 are constantly changing, making it difficult to define the precise information release date for this anomaly. On the other hand, asset growth (Cooper et al. (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, 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 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]

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https://sites.google.com/site/chenandrewy/publications. Additional details on the data can be found in Appendix C.

[9]In order 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 as a way 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 Appendix A.

For each anomaly, we use Snapshot to identify the earliest date at which all information necessary to construct the anomaly variable is known, and we call this date the *information release date*.[12] Our dataset contains a panel of firm-by-year observations accompanied with 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.

[Table 1 about here.]

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 the decades. We focus on five distinct dates: the Fiscal Year-End (FYE), the Information release date (Info), the Earnings Announcement date (EA), the 10-K Filing date (10K), and the conventional June-rebalancing date (FF92).

[Table 2 about here.]

Table II displays results about the timing of information releases relative to key dates; columns 2 through 5 show the average distance (in calendar days) from the Fiscal Year-End

[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*.

to the other four dates; columns 6 through 8 show the average distance (in calendar days) between the information release date and other relevant dates.

Several insights 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.

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, the distance is less than two weeks. In other words, the time between the release of basic earnings information and the release of the full suite of financial statements and footnotes has declined dramatically in recent years.

Third, Info dates are now much nearer to the Fiscal Year-End. In the 1990s, there was an average of almost three months from the Fiscal Year-End to the Info date. By the 2010s, this distance decreased to less than two months. Put differently, the time between the production of information and the disclosure of information has declined dramatically over the sample period.[13]

Fourth, the FF92 date is also nearer the Fiscal Year-End 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 30th of year $t+1$ using information from Fiscal Year-End 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 Fiscal Year-End minimizes the distance between the Fiscal Year-End and FF92 dates, the average distance has decreased

[13] We show additional results about the timing of information releases by anomaly in Appendix D.

in recent years. Moreover, this implies that firms increasingly produce and release their financial information at similar times.

[Figure 2 about here.]

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 Announcement, 10K, 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 Info date occurred approximately one month after Earnings Announcement dates. But by the early 2010s, the distance was less than a week. At the same time that Info dates were getting closer to Earnings Announcement dates, 10-K dates were getting farther from Info dates. Why? Earnings announcements tend to reveal more financial information in recent years. In the late 2000s, firms began releasing a full set of financial statements in their earnings announcements instead of simply reporting earnings (D'Souza et al. (2010)). As a result, Earnings Announcement dates are the proper Info 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 EA, Info, 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.

[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.

[Figure 3 about here.]

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 thirty years ago when the convention originated, it can also induce a severe delay in portfolio formation.

First, Panel A shows the distance from the Info date to the 10-K date. The evidence in column 2 shows that, throughout the last thirty years, the 10-K date has been, on average, within a week of the true Info date (at the median, the 10K date has been equal to the Info date). In recent years, even at its worst, the 10-K date has occurred within a month of the Info 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 Info date, on average (column 2). Even at its best, the FF92 date still falls three months after the Info date (column 5). At its worst, the FF92 date is delayed by approximately a year (column 6). These results suggests that a substantial time gap occurs in which traders might trade on released information, but before academics often form portfolios.

[Table 3 about here.]

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

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

[Table 4 about here.]

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

Overall, these findings suggest 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 (2019), which is based on the original papers that identified each anomaly. For example, as in Cooper et al. (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 5-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 18th and information concerning the assets of firm B is released on November 2nd, our event-time approach would form long-short asset growth portfolios on June 19th and November 3rd, 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.

[Table 5 about here.]

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 five and twelve months post-information release, during which abnormal returns are just 1.99% (column 8). This relation is also evident when looking at the anomalies individually, where 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 ten months).

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

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

[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. (2021)). Thus, even with precise information releases, we acknowledge that our methods do not rule out long-run mispricing entirely.

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 instead we allow the portfolio to change as new information is released. We refer to the resulting strategy as the *Info-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 Info-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 that the Info-rebalancing strategy will outperform FF92-rebalancing as it can quickly trade on new information and will 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 Info and FF92 strategies.

[Table 6 about here.]

Panel A of Table VI shows that the average anomaly performs significantly better when new information is incorporated quickly, instead of waiting until June 30th. The average anomaly's annualized daily abnormal return is 3.07% when using the Info-rebalancing strategy which is 0.66 percentage points more than 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. Further, while 21 of the 28 anomalies show positive improvements using the Info rebalancing strategy relative to the FF92 approach, only 4 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 Info-rebalancing portfolios include stocks that have released information several months ago. In effect, the Info 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 Info and FF92 strategies, but focus on *when* the returns are generated. We do this by dividing the calendar into two periods. The first period includes February through April, which captures annual earnings season for most December fiscal year-end firms. We expect that, from February through April, the Info 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 that the returns to the two strategies will be approximately the same from May through January when new information is not being 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 Info-rebalancing strategy strongly outperforms the FF92-rebalancing strategy. During these months, the Info 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 Info and FF92 strategies generate returns that are quite similar. This difference is directly related to the findings in our event-time setting. The Info-rebalancing approach quickly incorporates new information released during annual earnings season and captures the high returns over the first couple of months post-information release. By July, both the Info and FF92 portfolios have incorporated all the same information and thus have very similar compositions and performance.

Figure 4 visually highlights 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 Info rebalancing versus FF92 rebalancing for many of the 28 anomalies we consider.

[Figure 4 about here.]

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 Info and FF92 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 Info strategy is better than FF92. We can reject the null hypothesis that Info and FF92 are equivalent as the probability of observing 10 or more positive differences is extremely small ($p < .001$).[16]

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

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[16]See Appendix E 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, however 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 Info-rebalancing strategy than the FF92-rebalancing strategy in the months from February through April. We again reject the null hypothesis that Info and FF92 are equivalent ($p < .001$).

[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.

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 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, however anomalies do predict returns if portfolios are formed immediately after information releases.

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, at least in part, the result of information processing costs which generate drift in prices. Specifically, Prediction 2 argues that changes in information processing costs may alter 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 entire 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, 8-Ks). This implementation directly reduced the costs of acquiring public filings.[18] The SEC rolled out the implementation of EDGAR in phases (Kothari et al. (2022)). 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 this, 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, then 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 the details of the staggered implementation while Panel B presents the anomaly returns before and after the implementation of EDGAR.

[Table 7 about here.]

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 four-month return. Similarly, columns 7-8 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 post-information release, the average anomaly earned 2.38%. Over

[18]As support for this, 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)).

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 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 re-run our analyses to see *when* anomaly returns are earned in the first versus the second half of our sample.

[Table 8 about here.]

Table VIII presents the results, which show 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 (1990-2004) and lower in the latter half of the sample period (2005-2019).

[19] Appendix F discusses trends on information processing costs and provides some visual evidence that information processing costs have declined.

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 half 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 (1990-2004), returns in the first four months were not very concentrated after information release. The return over the first four months post-information 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 quite different in the latter half of the sample period (2005-2019), where fully 50% of the four-month return was earned in the first two weeks, 86% was earned over the first month, and over 100% was earned in the first two months. These results are consistent with Prediction 2: a decline in information processing costs coinciding with increased return concentration following information releases.

Panel C repeats the analyses in Table VI, but splits the sample period in half. Comparing our implementable Info-rebalancing strategy to the FF92-rebalancing strategy, we again find that anomaly returns have diminished in the latter half of the sample period and are more concentrated in the weeks immediately following information releases. In the early part of

[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 (2021).

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 Info-rebalancing approaches both generated nearly 3.50% on an annualized basis in the May through January months. Furthermore, the Info-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 2 of the 28 anomalies were significantly improved when traded using the Info 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 showed that anomaly returns have largely disappeared during periods distant from information release dates. In February through April, however, the Info-rebalancing approach still generates high returns while the FF92-rebalancing approach does not. Indeed, much of the outperformance of the Info-rebalancing strategy over FF92-rebalancing occurs in the recent period. This further indicates 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 became more concentrated over time as information processing costs generally 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, we measure trading volume in our event-time framework by averaging volume across all stocks in anomaly portfolios. Specifically, for each trading day post-information release, we take the ratio of volume that day to average daily volume over the first two-months post-information 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 relatively 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 about here.]

Figure 5 details our 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 post-information release. In more recent years, trading volume is much more concentrated, with more than twice the percentage of volume occurring within ten 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 analyses 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 Internet Appendix G. Together, they both support and provide nuance to our main results.

First, Table IX replicates the analysis in Table V while using different risk adjustments. The first row is a direct replica of the first row of Table V, where the Fama-French 5-factor model with momentum is used. The second row uses the Fama-French 3-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.

[Table 9 about here.]

Second, in Appendix G.1 we account for transactions costs and test whether quickly rebalancing on information release dates yields high returns *net* of costs. We find that, though the implementable Info-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 Appendix G.2, we show that our return results are distinct from the findings in Engelberg et al. (2018), who show that anomaly returns are primarily earned on days with news. We use our unique setting to test whether news days have higher predictive power than non-news 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 non-news days, which suggests our findings are distinct from the conclusions in Engelberg et al. (2018).

Fourth, in Appendix G.3, we show that the concentration of anomaly returns after information release dates is independent of 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 pre-publication years with the three post-publication years for our anomalies. The results show that returns are similarly concentrated in the first weeks after information release dates for pre-publication years and post-publication 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). Then, we 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 are the same in this period, regardless of whether the anomalies are "old" or "new."

Fifth, in Appendix G.4, we show that our event-time results do not depend on market capitalization. Indeed, whether focusing solely on large stocks, excluding micro-cap stocks, or even focusing on micro-cap stocks, the pattern holds: anomaly returns are highly concentrated in the weeks immediately following information releases.

Sixth, since the month of fiscal year-end determines the staleness the FF92-rebalancing strategy, in Appendix G.5 we test whether the Info-rebalancing strategy increasingly outperforms when the fiscal year-end is not near December. Our findings confirm this intuition by showing that the Info-rebalancing strategy outpaces the FF92 strategy when the fiscal year-end is earlier in the calendar year.

Finally, in Appendix G.6, we document the differences between the long and short legs of the hedge anomaly portfolio. These results demonstrate 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 should 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 electroni-

[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.

cally 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 thirty years, the median Info 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 a look-ahead bias throughout our sample period from 1990 to present.[22]

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

[Table 10 about here.]

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

[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 have provided SAS code in Appendix H 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. Third, based on concerns from 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.

[23]For reasons discussed in Section B, this study is limited to 28 anomalies. However, our recommendation – researchers should 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.

VI. Conclusion

We show 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 measures when information is first publicly released, we test two predictions that investigate the implications of costly information processing and under-reaction theories. We then develop guidelines for studying asset pricing anomalies without using stale data or introducing a 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, and we use this to examine the precise timing of returns for a large number of anomalies. We show 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 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 a look-ahead bias throughout our sample period from 1990 to present.

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

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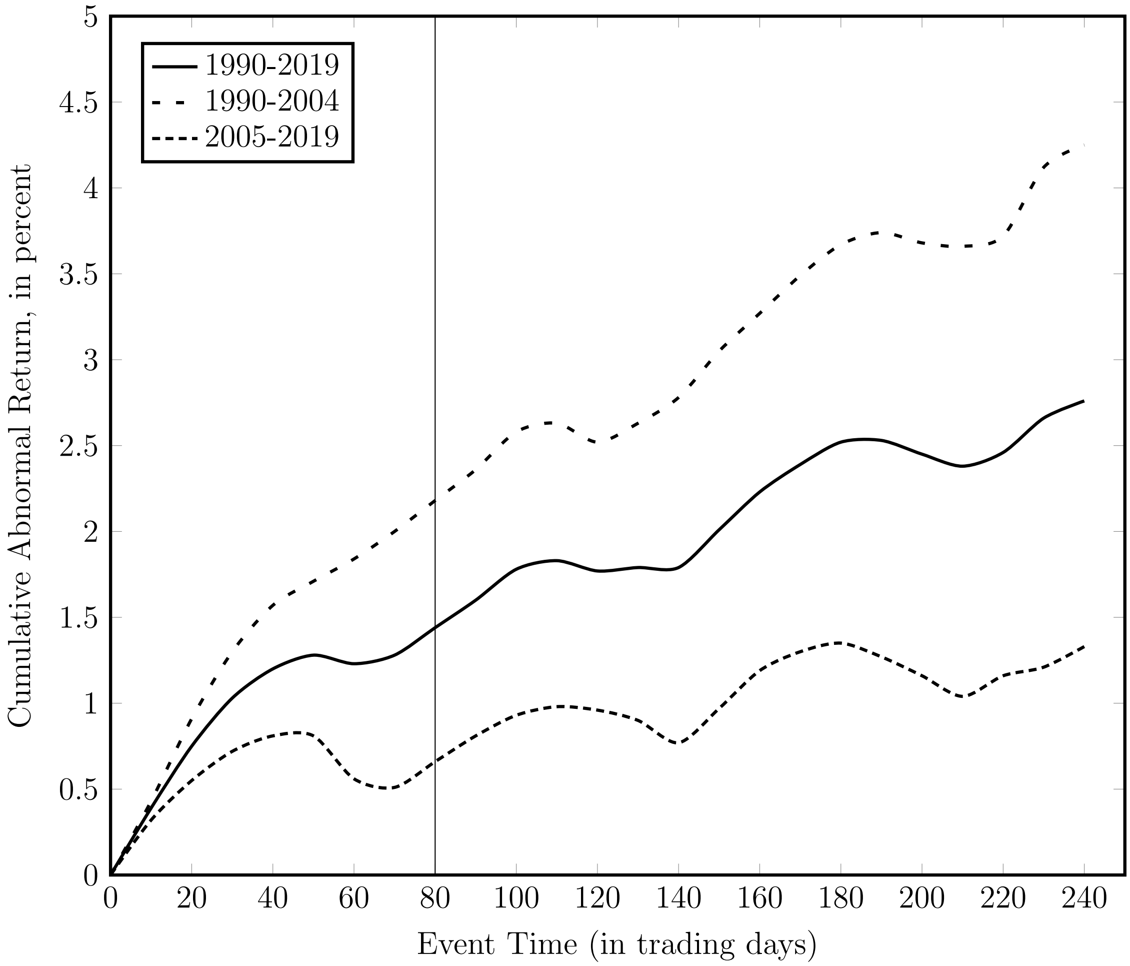

Figure 1. Anomaly Returns in Event Time. The figure shows the profile of abnormal returns for the average anomaly (equally-weighted) in event time. The figure shows the returns across the entire sample (1990-2019), across the early period of our sample (1990-2004), and across the recent years of our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

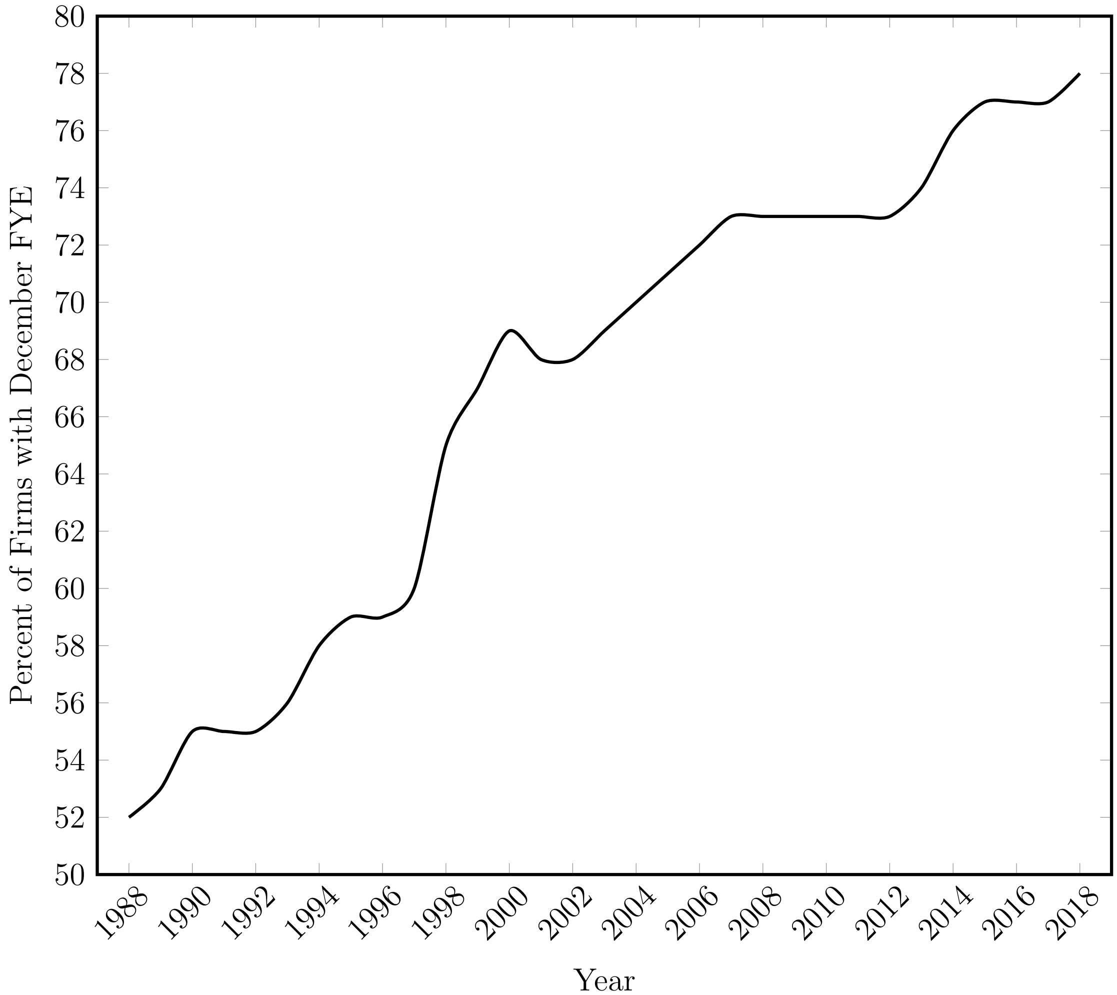

Figure 2. Percent of Firms with December Fiscal Year-End. The figure shows the percent of public U.S. firms with a December Fiscal Year-End for each year from 1988 through 2018.

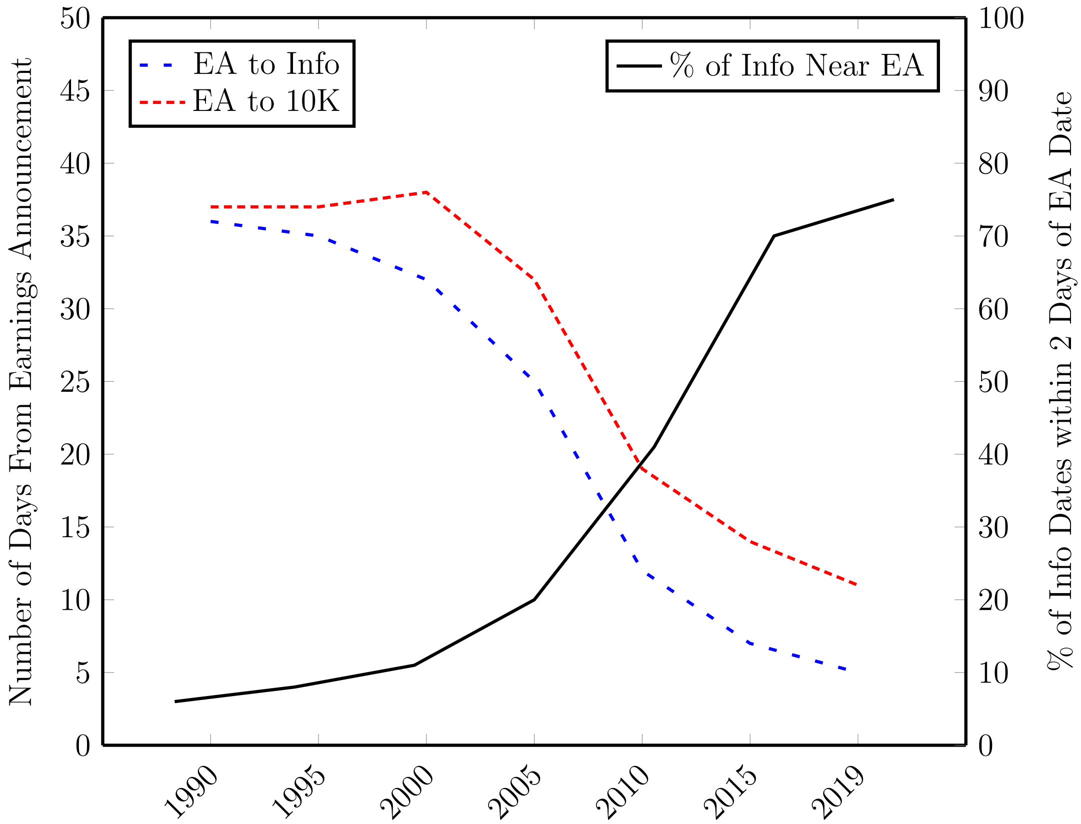

Figure 3. Information Releases Over Time. The figure shows the timing of information releases through time. The left-axis measures the mean number of days from the earnings announcement to either the information release date or the 10-K filing date. The right-axis measures the percent of observations where the information release date was within two days of the earnings announcement date.

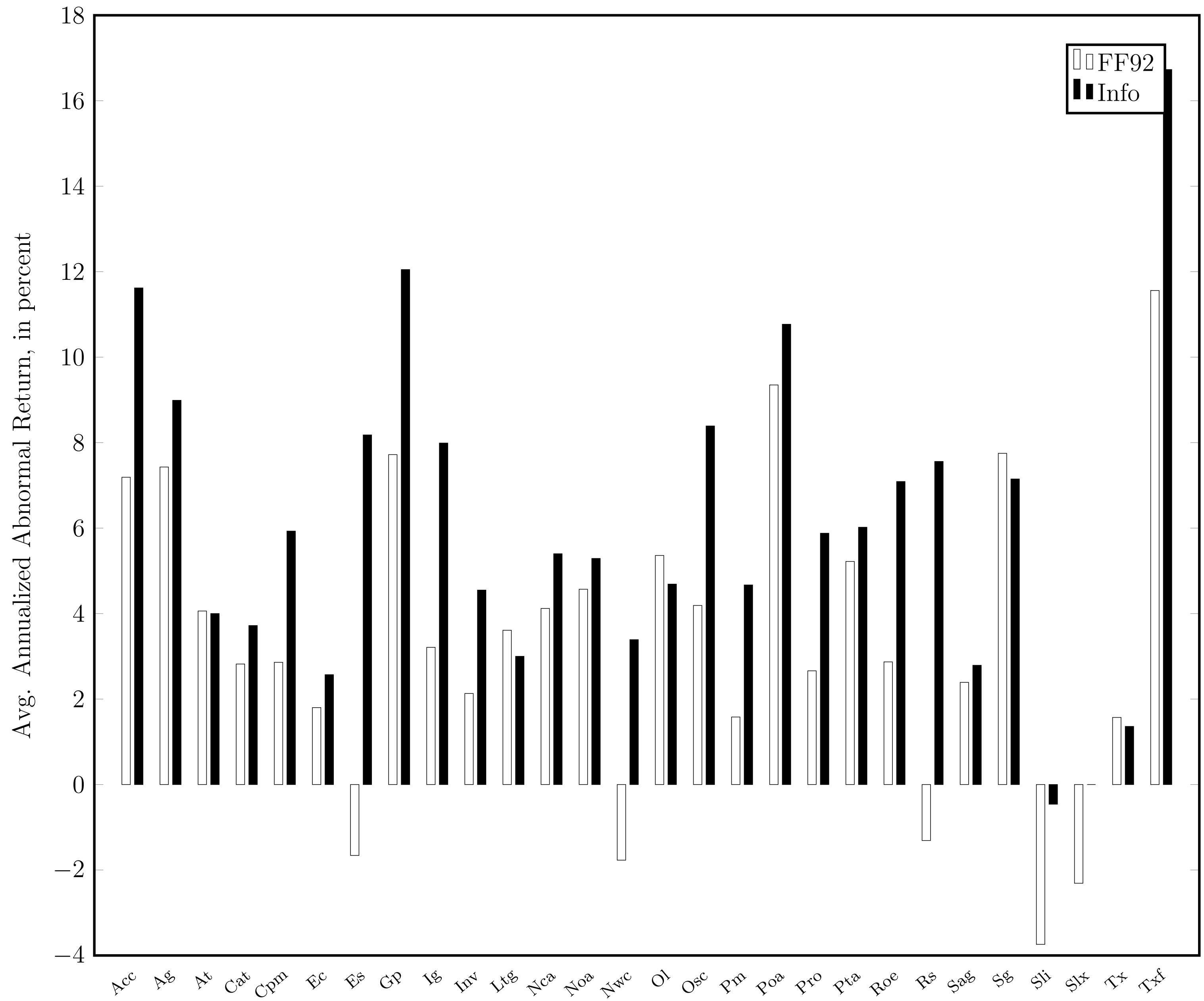

Figure 4. Info versus FF92 Rebalancing: February - April. The figure shows annualized mean daily abnormal returns from February through April for the 28 anomalies in our sample. For each anomaly, we form portfolios two different ways: Information rebalancing (solid black bar) and FF92 rebalancing (solid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

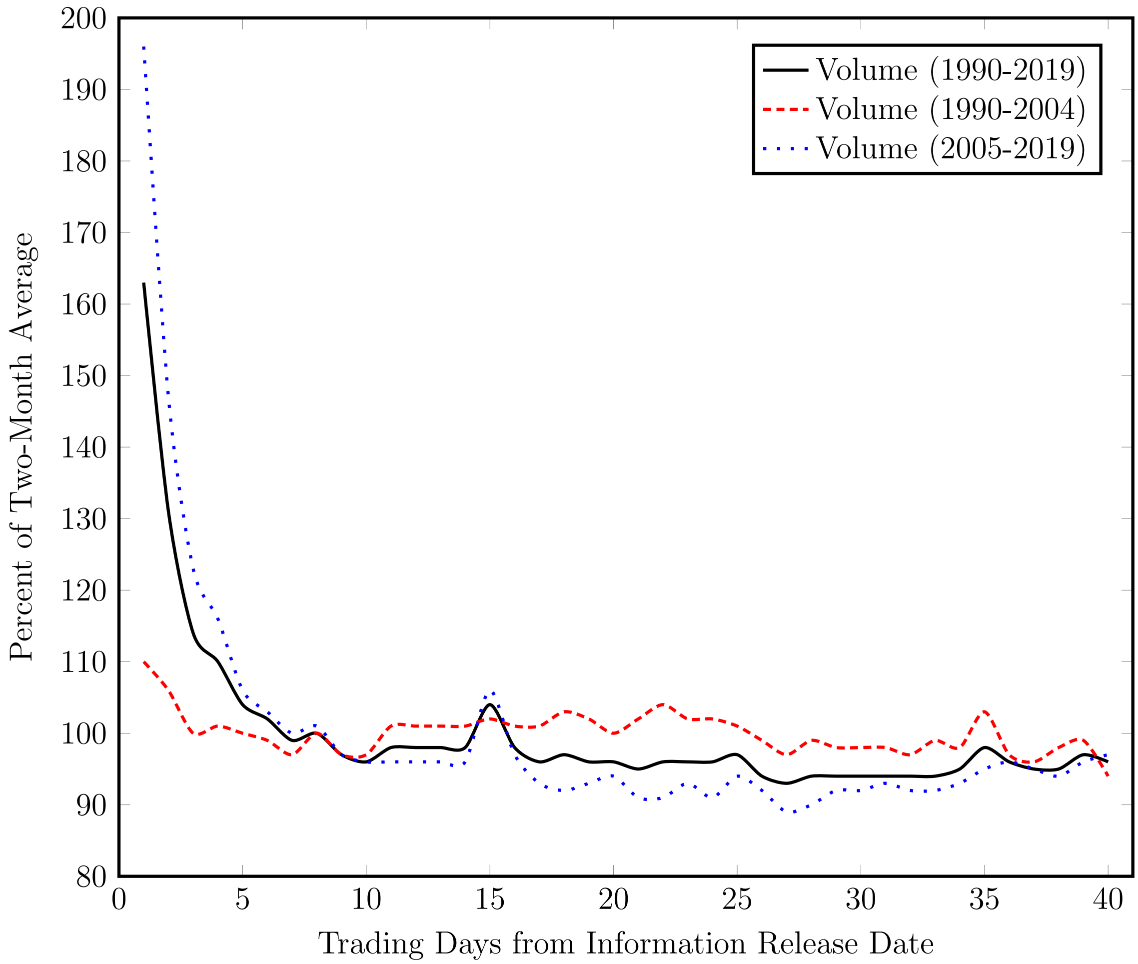

Figure 5. Trading Volume in Event Time. The figure shows trading volume for two months from the information release date and separates the analysis between the early and recent years in our sample. Volume is measured as share volume traded divided by shares outstanding; the data come from the CRSP database.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

Table I. Summary Statistics

The table provides summary statistics for our sample which covers 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
Non-Current 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

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

Table III. Comparison of 10K v. FF92 Updating

The table compares two rebalancing strategies: updating on the 10-K filing date versus updating on the FF92 date. The table shows summary statistics for the number of calendar days between the Info date and 10K date (Panel A) and the number of days between the Info date and 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.	10th pctl	90th 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.	10th pctl	90th 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

Table IV. The Timing of Information Releases: By Size and 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

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 ***, **, * 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 1 Month		First 2 Months		First 4 Months		Next 8 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)

Table VI. Info versus FF92 Rebalancing

The table reports mean daily abnormal returns to anomaly portfolios (annualized and in percent) for both the Info 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 ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by firm and date and are shown in parentheses.

Panel A. All Anomalies Across All Months

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	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 - January			February - 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

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 ***, **, * 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 4 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)			

Table VIII. Time Trends of Anomaly Returns

The table reports returns over our entire sample (1990-2019), over the early years of our sample (1990-2004), and over the recent years of our sample (2005-2019). 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 4-month return earned in earlier weeks. Panel C compares the implementable Info and FF92 strategies in both the early and recent periods. Indicators ***, **, * 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 1 Month	First 2 Months	First 4 Months	Next 8 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 4 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 - January			February - 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
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

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 3-factor model, DGTW-value weighted excess returns, DGTW-equally weighted excess returns, and raw returns. Indicators ***, **, * 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 1 Month	First 2 Months	First 4 Months	Next 8 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)

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 (1990-2019), the early years of our sample (1990-2004), and the recent years of our sample (2005-2019). 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 Info and FF92 strategies in both the early and recent periods, but in this analysis the Info strategy uses 10-K filing dates instead of actual information release dates. Indicators ***, **, * 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 1 Month	First 2 Months	First 4 Months	Next 8 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 - January			February - 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)

Internet Appendix for "Anomaly Time"

This internet appendix[1] provides additional empirical evidence to supplement the main text. Appendix A provides additional information about the construction of long-short portfolios. Appendix B provides additional information about the Compustat Snapshot Database. Appendix C provides detail on other data sources used in this paper that were not described in great detail in the text of the manuscript. Appendix D provides additional detail about the timing of information releases, extending the results from Section III. Appendix E provides an additional Binomial test to enhance the test discussed in Section B. Appendix F provides an additional figure showing the changes in technological availability and costs over the last three decades. Appendix G provides additional analyses referenced in Section D of the main text.

[1]Citation format: Bowles, Boone, Adam V. Reed, Matthew C. Ringgenberg, and Jacob R. Thornock, Internet Appendix to "Anomaly Time." Journal of Finance. Please note: The publisher is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the authors of the article.

A. Construction of Anomaly Variables

This appendix provides detail regarding the anomalies included in this paper. Each anomaly is listed, along with the paper originally citing the anomaly, a description of how frequently the original paper rebalanced the anomaly portfolios, and detail on anomaly construction.

Anomaly	**Paper**	**Original Rebalancing**	**Our Calculation**
Accruals (Acc)	Sloan (1996)	Firms are ranked into deciles based on accruals. Hedge returns for one year ahead are calculated beginning four months after the end of the fiscal year.	$ACC = \frac{WC_t - WCt-1}{\frac{1}{2}(A_t + A_{t-1})}$ WC = Working Capital A = Total Assets WC = current assets - cash and equivalents - current liabilities + debt in current liabilities + taxes payable - depreciation and amortization
Asset Growth (Ag)	Cooper et al. (2008)	Ranked into deciles at the end of June.	$AG = \frac{A_t - A_{t-1}}{A_{t-1}}$ A = Total Assets
Asset Turnover (At)	Soliman (2008)	Measures control variables from last fiscal year-end. Starts calculating monthly returns during the first month of the fiscal year.	$AT = \frac{Sales_t}{\frac{1}{2}(NOA_t + NOA_{t-1})}$ NOA = Net Operating Assets
Change in Asset Turnover (Cat)	Soliman (2008)	Measures control variables from last fiscal year-end. Starts calculating monthly returns during the first month of the fiscal year.	$CAT = AT_t - AT_{t-1}$ AT = Asset Turnover (defined previously)
Change in Profit Margin (Cpm)	Soliman (2008)	Measures control variables from last fiscal year-end. Starts calculating monthly returns during the first month of the fiscal year.	$CPM = PM_t - PM_{t-1}$ PM = Profit Margin (defined below)
Earnings Consistency (Ec)	Alwathainani (2009)	Consistency is based on the number of years in the preceding five years that the firm has had high earnings (low earnings), defined as falling within the top (bottom) 30th percentile. Portfolio returns are calculated beginning on either January or April first.	$EC = \frac{1}{5}(EG_t + EG_{t-1} + EG_{t-2} + EG_{t-3} + EG_{t-4})$ $EG = \frac{EPS_t - EPS_{t-1}}{(\frac{1}{2})EPS_{t-1} + EPS_{t-2}}$ // If EPS_t is opposite sign of EPS_{t-1} then don't include.

Anomaly	Paper	Original Rebalancing	Our Calculation
Earnings Surprise (Es)	Foster et al. (1984)	Earnings surprises are ranked into deciles quarterly.	$ES = \frac{EPS_t - EPS_{t-1} - Drift}{SD}$ $Drift$ = mean quarterly EPS over the preceding seven quarters. SD is the standard deviation of the difference between the preceding seven EPS values and the drift.
Gross Profitability (GP)	Novy-Marx (2013)	Ranked into quintiles at the end of June.	$GP = \frac{Sales_t - COGS_t}{A_t}$
Inventory Growth (Ig)	Thomas and Zhang (2002)	Ranked into deciles annually. Return calculations begin four months following fiscal year-end.	$INV = \frac{Inv_t - Inv_{t-1}}{(A_t + A_{t-1})/2}$ Inv = Inventory
Investments (Inv)	Titman et al. (2004)	Ranked into deciles annually. Return calculations begin four months following fiscal year-end.	$INV = \frac{CE_t}{(\frac{1}{3})(CE_{t-1} + CE_{t-2} + CE_{t-3})}$ $CE = \frac{CAPX}{Sales}$
Growth in Long Term Net Operating Assets (Ltg)	Fairfield et al. (2003)	Stocks are sorted into deciles based on growth in long-term net operating assets. Returns are calculated beginning in April after fiscal year-end.	$LTG = NOA_t - NOA_{t-1} - ACC_t$ NOA = receivables + inventory + other current assets + PP&E +intangible assets + other assets - accounts payable - other current liabilities - other liabilities all scaled by total assets. ACC is defined previously.
Non-current Operating Assets (Nca)	Soliman (2008)	Measures control variables from last fiscal year-end. Starts calculating monthly returns during the first month of the fiscal year.	$NCA = \frac{chgOA}{\frac{1}{2}(AT_t + AT_{t-1})}$ $OA = AT - ACT - IVAO - LT + DLC + DLTT$
Net Operating Assets (Noa)	Hirshleifer et al. (2004)	Stocks are sorted into deciles. Returns are calculated beginning 4 months after fiscal year-end	$NOA = \frac{OA_t - OL_t}{A_{t-1}}$ $OA_t = AT_t + CHE_t$ $OL_t = AT_t - DLTT_t - MIB_t - PSTK_t - CEQ_t$

Anomaly	Paper	Original Rebalancing	Our Calculation
Net Working Capital (Nwc)	Soliman (2008)	Measures control variables from last fiscal year-end. Starts calculating monthly returns during the first month of the fiscal year.	$NWC = \frac{NWC_t - NWC_{t-1}}{\frac{1}{2}(A_t + A_{t-1})}$ $NWC_t = ACT_t - CHE_t - LCT_t + DLC_t$
Operating Leverage (Ol)	Novy-Marx (2010)	Ranked into quintiles at the end of June.	$OL = \frac{COGS_t + SG\&A_t}{A_t}$
O-Score (Osc)	Dichev (1998)	Ranked into deciles. Returns are calculated beginning six months after fiscal year-end.	$OSC = -1.32 - 0.407(ln(A)) + 6.03(\frac{L}{A}) - 1.43(\frac{CA-CL}{A}) + 0.076(\frac{CL}{CA}) - 1.72I(L > A) - 2.37(\frac{NI}{A}) - 1.83(\frac{IO}{L}) + 0.285I(NI_t + NI_{t-1} < 0) - 0.521(\frac{NI_t - NI_{t-1}}{\lvert NI_t + NI_{t-1} \rvert})$ $A =$ total assets $L =$ total liabilities $CA =$ current assets $CL =$ current liabilities $NI =$ net income $IO =$ income from operations $I()$ is the indicator operator taking the value of one if true and zero otherwise.
Profit Margin (Pm)	Soliman (2008)	Measures control variables from last fiscal year-end. Starts calculating monthly returns during the first month of the fiscal year.	$PM = \frac{Sales - COGS}{Sales}$
Percent Operating Accruals (Poa)	Hafzalla et al. (2011)	Returns are calculated beginning four months after the end of the fiscal year.	$POA = \frac{IB_t - OANCF_t}{\lvert IB_t \rvert}$ $IB =$ Income before extraordinary items $OANCF =$ Net cash flow
Profitability (Pro)	Balakrishnan et al. (2010)	Measures profitability at date of earnings announcement and measures returns from earnings announcement date.	$PRO = \frac{Earnings_t}{Assets_{t-1}}$

Anomaly	Paper	Original Rebalancing	Our Calculation
Percent Total Accruals (Pta)	Hafzalla et al. (2011)	Returns are calculated beginning four months after the end of the fiscal year.	$PTA = NI + SSTKY - PRSTKCY - DVY - OANCFY - FINCFY - IVNCFY$ All scaled by absolute value of net income. NI = Income before extraordinary items $OANCFY$ = Net cash flow $SSTKY$ = Sale of common and preferred stock $PRSTKCY$ = Purchase of common and preferred stock DVY = Cash Dividends $FINCFY$ = Net cash from financing activities $IVNCFY$ = Net cash from investment activities
Return on Equity (Roe)	Haugen and Baker (1996)	"We assume a reporting lag of 3 months." We take this to mean they start 3 months after the fiscal year-end.	$ROE = \frac{NI_t}{BE_t}$ BE = Common Equity+Deferred Taxes NI = Net Income
Revenue Surprise (Rs)	Jegadeesh and Livnat (2006)	Revenue surprises are ranked into quintiles quarterly. Abnormal returns are measured from the earnings announcement date.	$RS = \frac{REV_t - REV_{t-1} - Drift}{SD}$ $Drift$ = mean quarterly REV over the preceding seven quarters. SD is the standard deviation of the difference between the preceding seven REV values and the drift.
Sales Growth (Sag)	Lakonishok et al. (1994)	Ranked into quintiles at the end of April.	$SAG = (5 \times R_t) + (4 \times R_{t-1}) + (3 \times R_{t-2}) + (2 \times R_{t-3}) + (1 \times R_{t-4})$ All scaled by 15. R = rank of sales growth as of earnings announcement.

Anomaly	Paper	Original Rebalancing	Our Calculation
Sustainable Growth (Sg)	Lockwood and Prombutr (2010)	Ranked into deciles or quintiles at the end of June.	$SG = \frac{BE_t}{BE_{t-1}}$
Sales Growth Less Inventory Growth (Sli)	Abarbanell and Bushee (1998)	Anomaly variable measured from annual financial statements for December 31st fiscal-year-end firms. Returns are measured from April 1st to March 31st of following year.	$SLI = SAG - IVG$ $SAG = \frac{REV_t - \frac{1}{2}(REV_{t-1}+REV_{t-2})}{\frac{1}{2}(REV_{t-1}+REV_{t-2})}$ $IVG = \frac{INV_t - \frac{1}{2}(INV_{t-1}+INV_{t-2})}{\frac{1}{2}(INV_{t-1}+INV_{t-2})}$ INV = inventory.
Sales Growth Less Expenses Growth (Slx)	Abarbanell and Bushee (1998)	Anomaly variable measured from annual financial statements for December 31st fiscal-year-end firms. Returns are measured from April 1st to March 31st of following year.	$SLX = SAG - XG$ $SAG = \frac{REV_t - \frac{1}{2}(REV_{t-1}+REV_{t-2})}{\frac{1}{2}(REV_{t-1}+REV_{t-2})}$ $XG = \frac{XSGA_t - \frac{1}{2}(XSGA_{t-1}+XSGA_{t-2})}{\frac{1}{2}(XSGA_{t-1}+XSGA_{t-2})}$ $XSGA$ = selling and administrative expenses.
Tax (Tx)	Lev and Nissim (2004)	Anomaly variable is updated annually at the beginning of May.	$TX_t = \frac{TXFO_t + TXFED_t}{0.35 \times IB_t}$
Total External Financing (Txf)	Bradshaw et al. (2006)	Returns are calculated beginning four months after the end of the fiscal year.	$TXF = SSTKY - PRSTKCY - DVY + DLTISY - DLTRY$ Scaled by average of the preceding two years of total assets. $SSTKY$ = Sale of common stock. $PRSTKCY$ = Purchase of common stock. DVY = cash dividends. $DLTISY$ = Long term debt issuance. $DLTRY$ = Long term debt reduction.

B. Snapshot Details

Snapshot is a database within Compustat that provides fundamental information for firms and details when fundamental information was updated in the public record. From the Snapshot manual:[2]

> Compustat Snapshot North America ("Snapshot") is the premier historical analysis and backtesting database that provides fundamental financial data on publicly traded companies and shows all values obtained in the data collection process. The Snapshot database creates a historical investment environment by showing the information that was available at that time in history.
>
> Snapshot contains fundamental financial data from the reported annual and quarterly sources, retaining original values and all succeeding changes from the income statement, balance sheet, and cash flow statements. In addition, Snapshot provides both the preliminary data and final data with annual, quarterly and year-to-date periodicities known at user-specified observation dates. This information enables you to identify what item values have changed and when they changed.

Within Snapshot, perhaps the most salient variable is the *Effective Date*, which captures the date when a company's "fundamental data is captured from productions of the S&P Capital IQ's Compustat database." In other words, the effective date records that date that Compustat noticed that a new book assets or net income amount had been released to the public. Prior to December 2008, Compustat used weekly productions to record data. Beginning in 2008, Compustat uses intraday productions to record data changes.

Based on the Snapshot manual, the earliest effective date is December 14, 1986. This date applies to financial statements prior to 1986 as this was the date Compustat recorded the fundamental information. Obviously, information released in financial statements in 1976 or

[2]Compustat Snapshot User Guide, July 24, 2023

1984, for example, would have been public knowledge prior to December of 1986. However, the effective date is capturing *when* Compustat recorded the data, which, after 1986 took place weekly and after 2008 took place at least daily. As a result of this, we limit our sample to information releases beginning in 1990.

Finally, we utilize SAS code provided in the Snapshot manual to use the effective dates for fundamental information. In essence, we follow Snapshot's guidance to identify the date when information was updated via the release of new financial information.

C. Details on Other Data Sources

NYSE Size Breakpoints - Kenneth French's Database

We use the ME Breakpoints data provided by Kenneth French to classify stocks as micro, small, or large capitalization stocks. We define micro stocks as those in the bottom 20th percentile, small stocks as those between the 21st and 50th percentiles, and large stocks as those above the 50th percentile.

News Days - RavenPack

We use the RavenPack data – beginning in January 2000 – to identify *news days*. A news day is any day where news about the stock is published in the Wall Street Journal or over the Dow Jones Newswire. We require that the relevance of the news for the stock is at least 75 (relevance is determined by RavenPack), though our results hold if we do not require relevance of at least 75. If the news hit the newswire after hours, we count the next trading day as the news day.

Following Engelberg et al. (2018), we use the three-day window around the news day in our analysis and we include earnings announcement dates ("rdq" from Compustat) as a news day as well.

Effective Bid-Ask Spreads - TAQ and Chen and Velikov (2022)

To measure the effect of transaction costs on anomaly returns, we subtract the bid-ask spared (in percent) from stocks as they enter and leave anomaly portfolios. From 1990 through 2004, we use *low frequency effective spreads*. From 2005 through 2019, we use *high frequency effective spreads* calculated using the Trade and Quote (TAQ) and Intraday

Indicators by WRDS (IID) databases. To calculate high frequency effective spreads we utilize code generously provided by Andrew Chen and Mihail Velikov.[3]

Trading Volume - CRSP

In our anomaly-by-permno-by-date panel, we measure trading volume as the ratio of daily volume divided by shares outstanding. We then calculate the average trading volume in our event time framework across all of the stocks in anomaly portfolios. This means we have calculated average trading volume on the first day post-information release, the second day, the third day, and so forth. Finally, we measure daily abnormal trading volume as the ratio of daily average volume and the average of daily average volume over the first two months post-information release. In other words, abnormal trading volume is measured as the percent of the two-month average daily trading volume.

For example, abnormal trading volume of 110% means that volume on that day was 10% higher than the average daily volume over the first two months post information release.

[3]See Chen and Velikov (2022). The low frequency spread data and the high frequency spread code can be found at Andrew Chen's website, https://sites.google.com/site/chenandrewy/publications.

D. Timing of Information Releases: Extended

Table II from the main body of the text describes the timing of information over time. In Table AI, the timing of information releases is analyzed again, but results are now reported by anomaly while aggregating over the entire sample period.

[Table AI about here.]

E. Additional Binomial Test

The standard Binomial test assumes independent trials, requiring the independence of the 28 anomalies, but several of the 28 anomalies are correlated.[4] The average correlation coefficient between all 28 anomalies is 0.08. While this average correlation is not large, we nonetheless account for this by performing analyses similar to that reported in Panel B of Table VI, but condense the list of anomalies into six groups, based on the type of anomaly.[5] The six groups are the following: Investment, Accruals, Working Capital, Profitability, Sales Growth, and Surprises.[6]

As shown in Table AII, we find that four of the six groups generate significantly higher returns using the Info strategy than the FF92 strategy in the months from February through April.[7] Thus, we again reject the null hypothesis – that Info and FF92 are equivalent – as the probability of seeing four or more positive differences is extremely small ($p < .001$).[8]

[Table AII about here.]

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[4]For example, the correlation coefficient between the portfolio returns of Asset Growth and those of Investment Growth is 0.55.

[5]For example, Asset Growth and Sustainable Growth are very similar in construction and their return series are correlated with a coefficient of 0.84.

[6]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); Surprises (Es, Rs).

[7]These results – namely the negative relation between investment and profitability – confirm those in Kilic et al. (2022). Note that the investment anomalies (Ag, Sg, Txf, and Inv) take long positions in low investment and short positions in high investment while the profitability anomalies (At, Ec, Gp, Pm, Pro, Roe, Ol, Osc, and Tx) take long positions in high profitability and short positions in low profitability.

[8]Parameters for the Binomial test: $n = 6$, $K = 4$, $p = 0.05$. Further, it should be noted that all six groups generate high returns to Info Rebalancing in the February through April months.

F. Data on Information Processing Costs

Figure A1 shows scaled measures of technology adoption and costs over time. Varous technologies are included: PCs in homes, Internet use in homes, the cost to sequence the human genome, and the number of likely bots downloading financial data from EDGAR (machine downloads) and computer readability as in Cao et al. (2020) and Allee et al. (2018). Overall, the figure shows a sharp increase in technological availability in the 1990s and 2000s and a sharp drop in the cost of computation.

[Figure A1 about here.]

G. Additional Analysis

In this section, we provide further analysis of the relation between anomaly returns and the timing of information releases. To start, we examine the potential effects of transaction costs. In addition, we explore the potential impact of news events on the timing in anomaly returns, the potential effects of publication dates, variation in firm size, variation in fiscal year-ends for sample firms, and the long and short legs of the hedge portfolios.

G.1. Transaction Costs

Previous research argues that anomalies persist – even in recent years – because it is too expensive for arbitrageurs to capture the abnormal returns. Thus, the anomaly mispricing we document may be reduced or even eliminated in the presence of transactions costs. This may be especially true for our implementable Info-rebalancing strategy, which is potentially rebalanced every day that a new financial statement is released for any one firm.

In this section, we test whether trading quickly after information release dates generates high returns net of transaction costs. We do this in both our hypothetical event-time setting and with our implementable framework. In both cases, we employ a cost-mitigation strategy and account for transaction costs using effective bid-ask spreads calculated from TAQ (Chen and Velikov (2019)).

We employ a cost-mitigation strategy that limits turnover and only trades stocks with low bid-ask spreads. To the first point, instead of adjusting anomaly portfolios every time even one stock warrants portfolio admission upon the release of new financial statements, we follow two rules. First, stocks can only be added to the anomaly portfolio if it is the release of their own new financial statements that warrants their addition. Second, stocks are not removed from the portfolio when another firm releases information. When a stock is added to and removed from a portfolio, half of the effective bid-ask spread must be paid.

To the second point, instead of forming anomaly portfolios from the universe of stocks, we focus on stocks that are relatively inexpensive to trade. For each fiscal year, we rank stocks based on their effective bid-ask spread. This ranking is done within size deciles. Within each size decile, we then select the one-third of stocks with the lowest effective bid-ask spreads. We also remove all "micro-cap" stocks. The inexpensive stocks – at least inexpensive compared to stocks with similar market cap – make up the set of stocks we then rank according to anomaly variables in order to form the long and short portfolios.[9]

In addition to employing these cost-mitigation strategies, we also use the results from previous sections to inform enhanced return strategies for the average anomaly. To that end, we do the following: (*i*) exclude eight anomalies that do not perform well in our sample (Inv, Ltg, Noa, Sag, Sg, Sli, Slx, Tx.), (*ii*) in the event-time framework, we imagine holding stocks for only two months after information release dates, and (*iii*) for the implementable Info-rebalancing approach, we only hold the portfolios from February through April.

Table AIII reports the results for both the event time framework and for the implementable strategy and for the full sample period, the early period, and the more recent period. As can be seen in the table, transaction costs significantly depress anomaly returns, especially in the earlier period when transaction costs were higher. In Panel A the event-time approach shows that gross annualized returns of over 5% in the early period are completely erased by paying the bid-ask spread, which averaged 52 basis points over this period. In the more recent period, however, gross returns of over 6% were only slightly depressed, for a net return of 4.83%. This is largely the result of much smaller bid-ask spreads in recent years.

The same pattern holds in Panel B for the implementable Info-rebalancing approach. High bid-ask spreads erase returns in the early period, but returns survive in the more recent period when bid-ask spreads are much lower.

[Table AIII about here.]

[9]The size deciles are determined using French's NYSE size breakpoints. For convenience we also focus only on stocks with December fiscal year-ends. See Appendix C for further details and definitions for micro and small stocks.

G.2. News Days

Engelberg et al. (2018) shows that anomaly returns are primarily earned on days with news. That study defines *news days* at the stock-level as any day that a stock is included in news that hits the newswire. In many cases, these news days coincide with information release dates, such as the earnings announcement date or 10-K filing date. In other cases, they do not, as the news is simply a non-financial news article or a press release from the firm. Importantly, Engelberg et al. (2018) is not primarily concerned with the timing of financial statement releases and does not contemplate quickly updating anomaly portfolios upon these releases.

Nonetheless, we test whether news days have higher predictive power than non-news days when we account for the distance from information release dates. Table AIV shows returns over various types of days using the implementable Info-rebalancing strategy. Overall, the results show that news days and non-news days are very similar when we focus on the timing of information releases. In contrast to the main findings in Engelberg et al. (2018), we show significant returns on non new days, especially when trading quickly on new information in February through April.[10] In sum, these results suggest that our findings – that anomaly returns are closely tied to important information releases – are rather distinct from the conclusions in Engelberg et al. (2018).

[Table AIV about here.]

G.3. Publication Dates

Another recent paper (McLean and Pontiff (2016)) documents that anomaly returns are significantly diminished after publication of the anomaly in academic journals. It is worth noting that nearly all of the 28 anomalies we study were published inside our sample

[10]Given our sample of anomalies is primarily fundamental anomalies, the proper comparison should be with Table V from Engelberg et al. (2018), which shows that for fundamental anomalies, it is not clear that news days outperform non-news days.

period. Two points can be made about this. The first is that the relation between anomaly returns and information release may actually change based on academic publication of the anomaly. Using our event time approach, we examine returns in the six-year window around publication years. Then we compare the profile of anomaly returns from the three pre-publication years with the three post-publication years.[11] Figure A2 shows that the return profile for the average anomaly pre-publication is nearly identical to the return profile post-publication. In other words, the concentration of anomaly returns does not change around academic publication dates of the underlying anomaly.

[Figure A2 about here.]

The second point is more nuanced and is based on the fact that the amount of data in our sample that are out-of-sample relative to the original study vary by anomaly.[12] We can use this variation to test whether our results hold for anomalies that were discovered early in our sample and for anomalies that were discovered later in our sample. Further, and perhaps more importantly, we can use this variation to test whether data-mining is a primary driver of returns for this set of anomalies.

To see this, consider that under the data-mining hypothesis, anomalies that were discovered earlier in our sample would have more concentrated (and perhaps lower) returns than anomalies discovered more recently. This is because the early-discovered anomalies are more fully out-of-sample. Thus, the data from which these anomalies were selected – data that showed high returns – are less prominent in our sample. As a result, for early-discovered anomalies, we would expect more concentrated and lower returns under the data-mining hypothesis.

[11]For example, the Asset Growth anomaly was published in 2008 (Cooper et al. (2008)), so we focus our analysis on the three years before publication (2005-2007) relative to the three-year period after publication (2009-2011).

[12]For example, the return-on-equity anomaly was published early in our sample (Haugen and Baker (1996)) while the gross profitability anomaly was published much later (Novy-Marx (2013)).

Conversely, for the recently-discovered anomalies, the original sample is prominent in our sample. Again, under the data-mining hypothesis, our sample would be biased by featuring the data from which the anomalies were selected – data that showed high returns. Thus, for the recently-discovered anomalies, we would expect less concentrated and higher returns under the data-mining hypothesis.

To test this idea, we divide anomalies between those that are "old" (meaning they were discovered before 2000) and those that are "new" (discovered after 2009).[13] Then, we use our event-time approach to measure abnormal returns for each anomaly and for the average anomaly of both the old and new groups. Importantly, we only use the decade from 2000 through 2009. In this period, the old group is entirely out of sample from the original paper and the new group is entirely in sample. Comparing anomalies this way allows us to see whether the profile of anomaly returns in event time is different based on the publication date.

As can be seen in Table AV, there is little difference between these two sets of anomalies in the 2000-2009 period. On average, the old anomalies generate 16% (annualized) over the first month, 11% over the first two months, and 7% over the first four months with no significant return after the first four months. At the same time, the average of the new anomalies earned 17% over the first month, 13% over the first two months, 7% over the first four months, with nothing after that. Indeed, whether an anomaly was completely in sample or completely out-of-sample has no affect on the profile of anomaly returns.

[Table AV about here.]

[13]The old anomalies include Acc, Es, Osc, Roe, Sag, Sli, and Slx while the new anomalies are Gp, Ol, Poa, Pro, Pta, and Sg.

G.4. Size Cuts

We also examine whether the relation between anomaly returns and anomaly timing varies by firm size.[14] Hou et al. (2020) shows that anomaly returns for many anomalies cannot be replicated after excluding micro stocks. We examine whether our findings are driven by micro stocks. Table AVI reports results from our event-time framework when splitting the sample using stocks of all sizes (baseline), only large stocks, only non-micro stocks, and only micro stocks. The table also reports results over the entire sample period (1990-2019), over the early years (1990-2004), and over the recent years (2005-2019).

[Table AVI about here.]

The results show that, even when excluding micro stocks, anomaly returns are higher immediately following information releases, and over time anomaly returns have become more concentrated. In other words, these results show that our main findings are not driven by micro or small stocks.

G.5. Month of Fiscal Year-End

Given firms have different fiscal year-ends – many in December but some firms in other months – we investigate whether the month of the fiscal year-end, and the amount of lagging that would imply for the FF92 convention, affects the timing of anomaly returns. To study this, we use our implementable framework, but separate portfolios based on the month of firms' fiscal year-ends. Then we compare returns. Table AVII shows the results.

[Table AVII about here.]

The results show that returns to the FF92 convention using firms with fiscal year-ends near the end of the year (2.46%) are nearly twice as big as the returns from FF92 rebalancing using only firms with fiscal year-ends not near the end of the year (1.44%). When the lag

[14]For definitions of sizes – large, small, and micro – please refer to Appendix C.

between information releases and the FF92 rebalancing date is larger, returns are smaller. Furthermore, the benefit from trading quickly is also much larger when the lag is longer. For instance, the difference between Info and FF92 for firms with fiscal year-ends not near the end of the year is 1.11%, while there is little difference between Info and FF92 returns for firms with fiscal year-ends near the end of the year. We note, however, that in untabulated results, the difference between Info and FF92 for December fiscal year-end firms is large and positive in the February through April window, as was discussed in Section B.

Also, the number of firms with fiscal year-ends in December has grown steadily over the last thirty years. In the early 1990s, just over half of firms in our sample had fiscal year-ends occurring in December. By the mid-2000s the proportion had reached 70%, and as of 2019 approximately 80% of firms had their fiscal year-end in December. This change over time is shown in Figure 2.

G.6. Long and Short Legs

Figure A3 replicates Figure 1 from the paper, but focuses on the entire sample period and includes the returns for the long and short legs. Notice that this figure shows that the long leg earns high returns while the short leg earns relatively low returns. At first glance, this may appear to contradict previous work showing that anomaly returns are largely driven by the short-leg of anomaly portfolios (e.g., Stambaugh et al. (2012)). However, to do a one-for-one comparison of our results with previous work it is important to consider timing and the risk-adjustments. With regards to timing, the typical FF92 date arrives 80 trading days after the information release date (80 trading days corresponds to the median days from information dates to FF92 dates of 120 calendar days). Thus, one should compare our returns after the first 80 trading days. Also, we use the Fama-French 5-factor model with momentum while Stambaugh et al. (2012) uses the Fama-French 3-factor model. When we apply the 3-factor model to compute abnormal returns (see Figure A4) and focus on the period after the first 80 trading days we confirm the finding that the long-leg earns relatively low returns while the short-leg earns negative returns.[15]

[Figure A3 about here.]

[Figure A4 about here.]

[15]It is also important to note that our sample of anomalies and our time period is different from previous work. For example, Stambaugh et al. (2012) uses 11 anomalies while we study 28. Further, Stambaugh et al. (2012) uses a sample from the 1960s or 1970s (depending on the anomaly) until 2008. Our sample is from 1990 to 2019.

H. Code to obtain 10-K filing dates from COMPUSTAT

The following code, written in SAS, is used to obtain 10-K filing dates from the COMPUSTAT dataset.

```
/* Sign in to WRDS */
%LET wrds = wrds-cloud.wharton.upenn.edu 4016;
OPTIONS comamid=TCP remote=WRDS;
SIGNON username=_prompt_;
/* Set data library in WRDS */
LIBNAME comp remote '/wrds/comp/sasdata/naa/company' server=wrds;
/* Read in the company filing data from COMPUSTAT */
PROC SQL;
CREATE TABLE comp AS
SELECT DISTINCT
a.gvkey,
a.srctype,
a.filedatetime,
a.datadate,
a.filedate
FROM comp.co_filedate as a
WHERE year(a.datadate) >= 1994 and
year(a.datadate) <= 2020 and
a.srctype in ("10K")
ORDER BY a.gvkey,a.datadate;
QUIT;
```

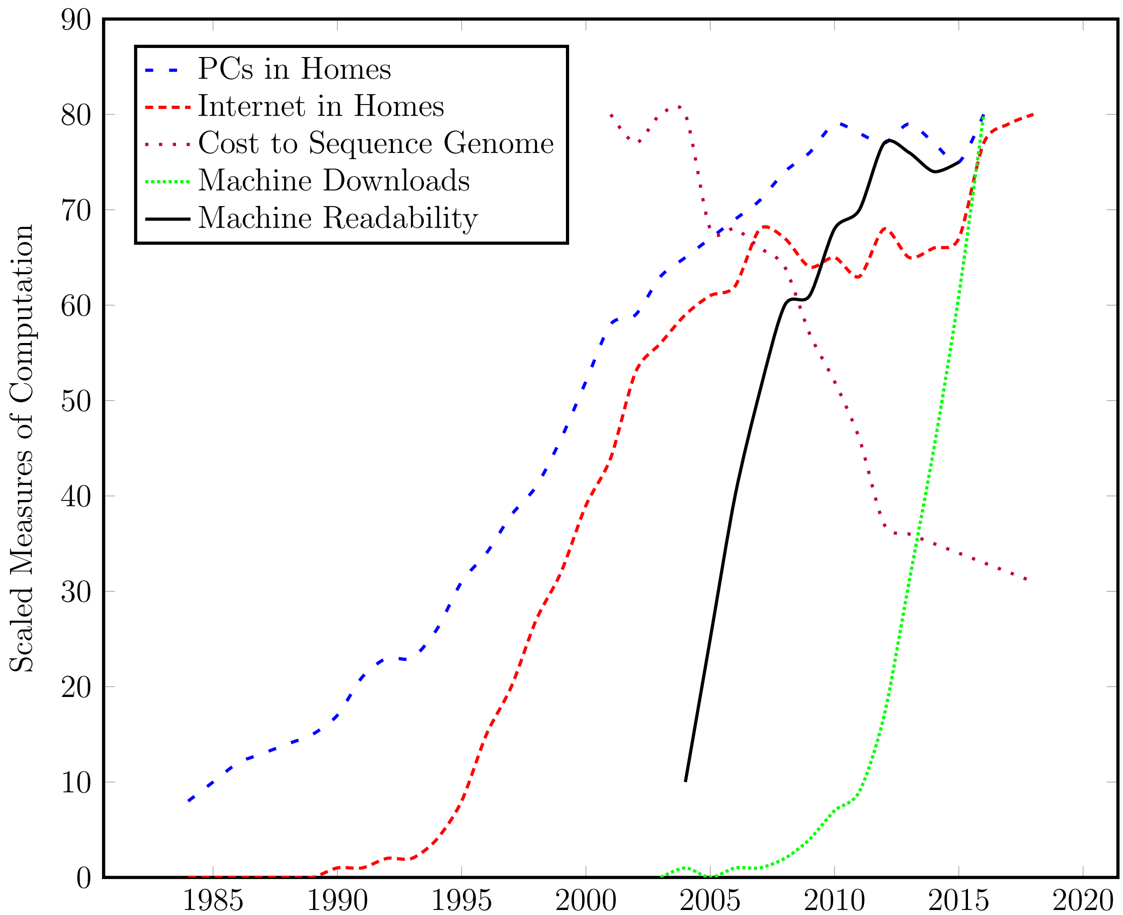

Figure A1. Technology Adoption and Costs Over Time. The figure shows scaled measures of technology adoption over time. The measures include: The percent of homes in the US with a PC, the percent of homes in the US with internet access, the logged cost to sequence the human genome, the number of likely bots downloading financial data from EDGAR (machine downloads), and the *computer readability* of filings uploaded to EDGAR (machine readability, Allee et al. (2018)).

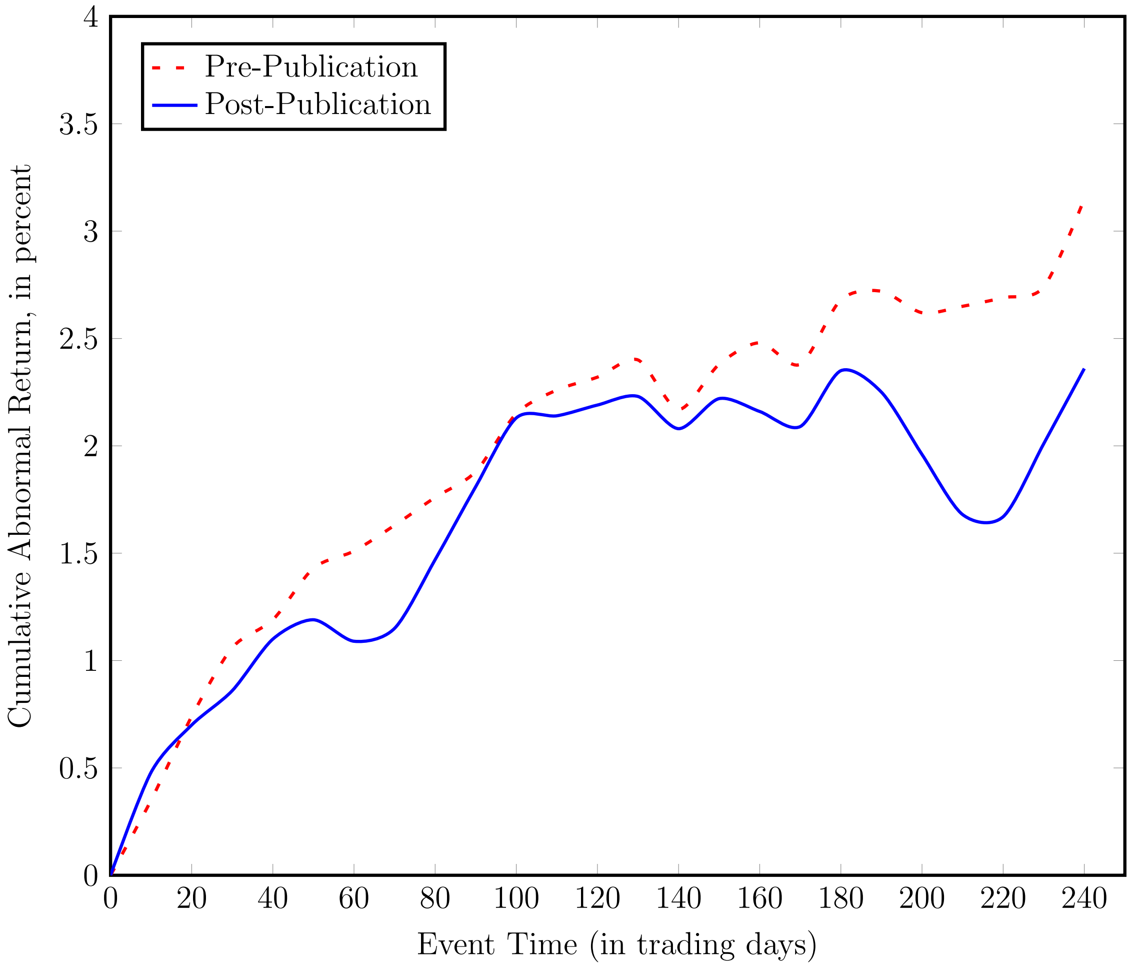

Figure A2. Anomaly Returns in Event Time: Pre- and Post-Publication. The figure shows the profile of abnormal returns to the average anomaly (equally-weighted) in event time. The pre-publication return uses three years before an anomaly was published. The post-publication return uses the three years after an anomaly was published.

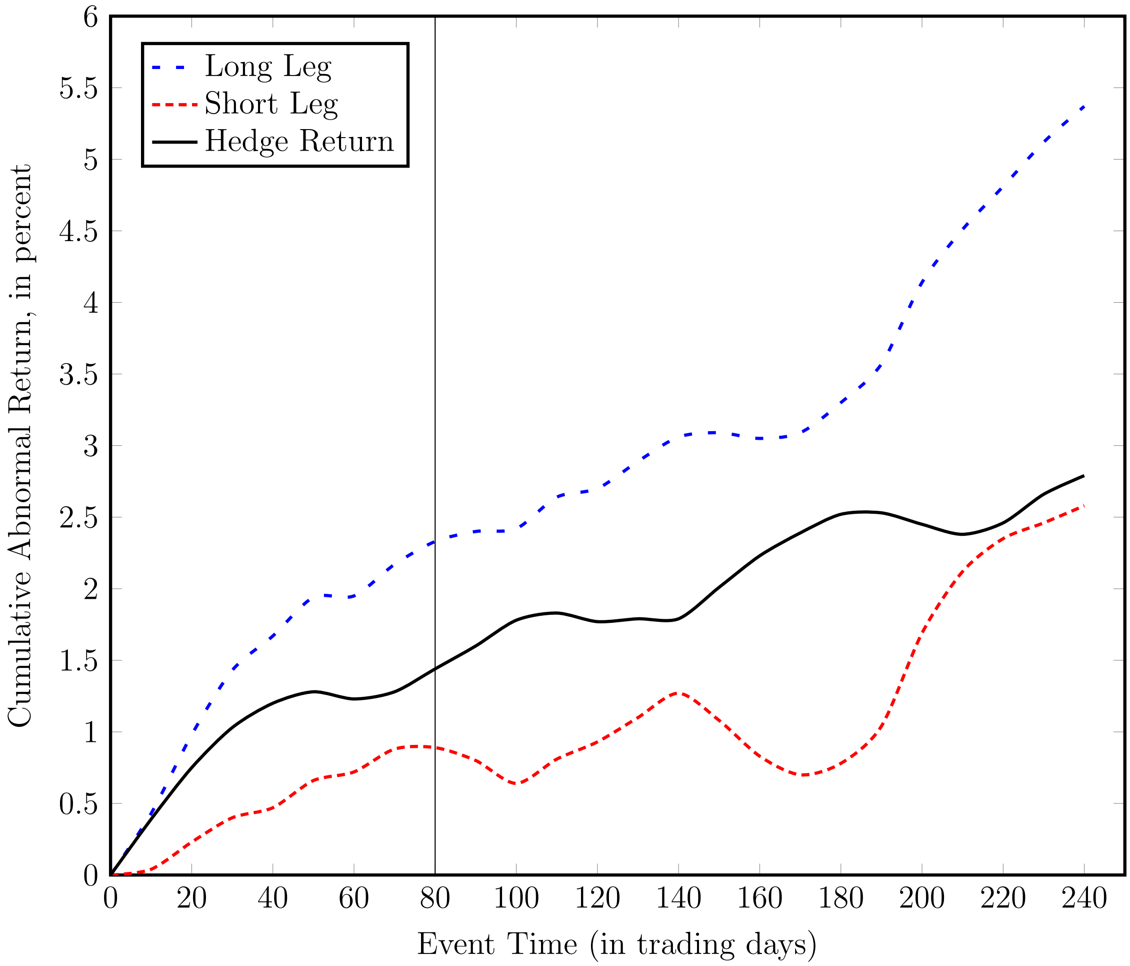

Figure A3. Anomaly Returns in Event Time: Long and Short Legs. The figure shows the profile of abnormal returns for the average anomaly (equally-weighted) in event time broken out by the long-leg (dashed blue line), short-leg (dashed red light), and hedge portfolio (solid black line). The solid vertical bar at t=80 trading days indicates when the FF92 rebalancing date occurs, on average.

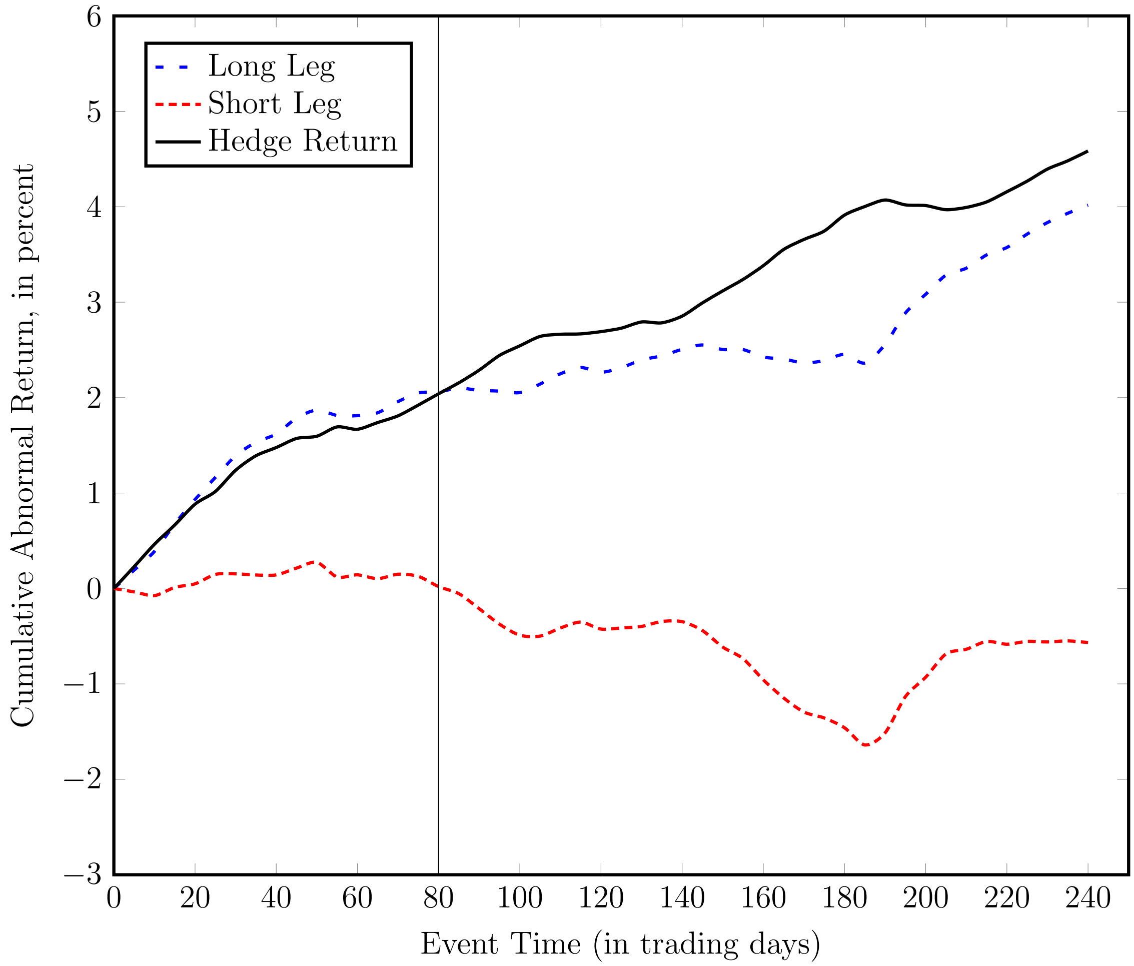

Figure A4. Anomaly Returns in Event Time: Fama-French 3-Factor Model. The figure shows the profile of abnormal returns for the average anomaly (equally-weighted) in event time broken out by the long-leg (dashed blue line), short-leg (dashed red light), and hedge portfolio (solid black line). The solid vertical bar at t=80 trading days indicates when the FF92 rebalancing date occurs, on average. Abnormal returns are calculated using the Fama-French 3-Factor Model.

Table AI. Comparison of 10K v. FF92 Updating: By Anomaly

The table compares two rebalancing strategies: updating on the 10-K filing date versus updating on the FF92 date. The table shows summary statistics by anomaly for the number of days between the Info date and 10K date and between the Info date and FF92 date.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Info to 10K					Info to FF92				
Anomaly	mean	median	sd	10th pctl	90th pctl	mean	median	sd	10th pctl	90th pctl
Acc	2	0	7	0	4	176	123	106	91	367
Ag	6	0	14	0	30	173	127	102	91	364
At	5	0	12	0	22	172	124	103	91	365
Cat	5	0	12	0	24	173	126	103	92	365
Cpm	7	0	14	0	32	174	128	103	92	365
Ec	8	0	14	0	33	178	133	102	93	364
Es	22	21	19	0	49	187	146	100	108	366
Gp	6	0	13	0	29	172	125	102	91	364
Ig	6	0	13	0	28	173	126	103	91	365
Inv	2	0	8	0	11	175	124	104	92	366
Ltg	2	0	7	0	8	174	123	105	91	366
Nca	3	0	9	0	14	170	122	103	91	362
Noa	5	0	12	0	25	172	125	103	91	364
Nwc	5	0	11	0	22	179	128	107	91	367
Ol	5	0	13	0	27	171	124	103	91	364
Osc	2	0	7	0	8	175	123	106	91	367
Pm	7	0	14	0	31	173	127	103	91	365
Poa	2	0	7	0	6	169	121	103	91	364
Pro	6	0	14	0	30	173	127	102	91	364
Pta	1	0	7	0	1	169	121	103	91	364
Roe	5	0	13	0	28	171	124	102	91	364
Rs	19	18	18	0	48	186	142	102	106	367
Sag	8	0	14	0	32	178	132	102	93	365
Sg	3	0	10	0	18	171	123	103	91	365
Sli	6	0	13	0	29	180	131	106	92	367
Slx	7	0	14	0	32	181	133	106	92	367
Tx	0	0	1	0	0	170	120	105	91	366
Txf	1	0	6	0	0	170	121	104	91	365

Table AII. Info versus FF92 Rebalancing: Six Anomaly Groups

The table reports mean daily abnormal returns to anomaly portfolios for both the Info and FF92 rebalancing strategies and the difference between the two strategies. This table divides anomalies into six groups (discussed in the body of the paper) and calculates returns to the average anomaly within the group. Further, this table only presents the returns from February - April. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered by firm and date and are shown in parentheses.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Annualized Mean Daily Returns (Feb. - Apr.)					
	FF92 Rebalancing		Info Rebalancing		Difference	
Anomaly Group	Return	StdErr	Return	StdErr	Return	StdErr
Investment	7.53***	(1.79)	9.30***	(2.12)	1.65	(1.71)
Accruals	7.23***	(1.66)	9.24***	(1.73)	1.88	(1.42)
Working Capital	2.85**	(1.24)	5.18***	(1.31)	2.27*	(1.25)
Profitability	3.55*	(1.83)	6.10***	(1.96)	2.46**	(1.02)
Sales Growth	0.66	(1.24)	2.75**	(1.23)	2.07*	(1.24)
Surprises	-1.46	(1.90)	7.92***	(2.03)	9.52***	(2.46)

Table AIII. Anomaly Returns: Net of Transaction Costs

The table reports mean daily abnormal returns over the first two months in event time while accounting for transaction costs measured as the effective bid-ask spread. Panel A shows gross and net returns in the event time framework. Panel B shows gross and net returns for the implementable Info rebalancing strategy for the months of February through April. The sample is limited to December fiscal year-end firms, excludes micro-cap stocks, and only considers stocks in the lowest one-third by effective spread within size deciles. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered by firm and date and are shown in parentheses.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Event Time Framework						
	Annualized Mean Daily Returns					
	1990-2019		1990-2004		2005-2019	
	Gross	Net	Gross	Net	Gross	Net
Abn. Return	6.50***	2.75*	5.27***	-1.60	6.15***	4.83***
	(1.41)	(1.41)	(1.90)	(1.90)	(1.83)	(1.82)
Avg. Spread (bps)	0	28	0	52	0	10
Panel B. Implementable Framework with Info Rebalancing						
	Annualized Mean Daily Returns					
	1990-2019		1990-2004		2005-2019	
	Gross	Net	Gross	Net	Gross	Net
Abn. Return	5.83**	-0.50	4.48	-6.49*	7.04***	5.32***
	(2.25)	(2.29)	(4.02)	(4.15)	(1.97)	(1.96)
Avg. Spread (bps)	0	30	0	56	0	12

Table AIV. Anomaly Returns: News Days

The table reports daily abnormal returns for the average anomaly portfolio generated across all days, only news days, and only non-news days from the implementable Info strategy. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered by firm and date and are shown in parentheses.

(1)	(2)	(3)	(4)
	Annualized Mean Daily Returns		
Subset of Months	All Months	May - January	February - April
All Days	2.17***	1.14*	5.59***
	(0.57)	(0.62)	(1.31)
News Days	2.52***	1.39	6.40***
	(0.89)	(1.09)	(1.49)
Non-News Days	2.81***	2.04***	5.32***
	(0.70)	(0.74)	(1.52)

Table AV. Anomaly Returns: Publication Dates and Old versus New Anomalies

The table reports returns to anomaly portfolios in event time while separating anomalies based on whether they are "old" or "new". Old anomalies were discovered prior to 2000 while new anomalies were discovered after 2009. Only daily returns from 2000 through 2009 are used. Indicators ***, **, * 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)	(6)	(7)	(8)	(9)
	Annualized Mean Daily Returns							
	First 1 Month		First 2 Months		First 4 Months		Next 8 Months	
Anomaly	Return	StdErr	Return	StdErr	Return	StdErr	Return	StdErr
The 7 Old (pre-2000) Anomalies								
Average	16.07***	(3.48)	10.61***	(2.77)	7.19***	(2.02)	1.19	(1.28)
Acc	9.94	(7.15)	8.52*	(5.01)	1.82	(3.63)	-0.29	(2.67)
Es	26.58***	(5.22)	21.00***	(3.96)	13.14***	(2.93)	0.09	(2.17)
Osc	36.47***	(11.68)	22.99**	(8.83)	17.25***	(6.11)	14.83***	(4.26)
Roe	27.34***	(8.77)	15.31**	(7.45)	13.64**	(5.58)	1.10	(3.20)
Sag	-9.11*	(5.97)	-5.07	(4.37)	-5.45*	(3.41)	-4.80*	(2.68)
Sli	4.74	(5.04)	1.80	(3.86)	2.14	(2.91)	0.38	(2.05)
Slx	8.68	(7.03)	6.46	(5.15)	4.88	(3.96)	-1.92	(2.92)
The 6 New (post-2009) Anomalies								
Average	16.97***	(3.67)	12.60***	(2.88)	7.44***	(2.15)	0.89	(1.50)
Gp	40.68***	(8.38)	24.16***	(6.47)	14.01***	(4.81)	4.49	(3.23)
Ol	19.65***	(5.95)	8.03	(4.87)	3.14	(3.63)	-0.02	(2.93)
Poa	14.67***	(4.80)	13.39***	(3.82)	8.36***	(2.77)	-2.12	(2.29)
Pro	25.18**	(9.67)	19.07**	(8.09)	14.69**	(5.58)	2.87	(3.63)
Pta	7.31	(5.16)	4.59	(3.93)	2.11	(2.94)	-1.68	(1.98)
Sg	-6.73	(7.16)	2.11	(5.33)	-0.80	(4.13)	-0.42	(2.57)

Table AVI. Anomaly Returns: Size

The table reports mean daily abnormal returns (annualized and in percent) to the average anomaly portfolios in event time over specific periods after the information release date. The table replicates the earlier analysis while separating stocks by size and over the early and more recent time periods. Indicators ***, **, * 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			
Size Category (years)	First 1 Mo	First 2 Mos	First 4 Mos	Next 8 Mos
All Sizes (90-19)	9.84***	7.76***	4.69***	1.99***
	(1.22)	(0.95)	(0.71)	(0.51)
All Sizes (90-04)	12.29***	10.47***	7.63***	3.12***
	(1.84)	(1.43)	(1.05)	(0.72)
All Sizes (05-19)	7.09***	5.05***	2.02**	1.01
	(1.59)	(1.22)	(0.92)	(0.70)
Large Stocks (90-19)	5.37***	3.65**	1.30	1.29*
	(1.79)	(1.40)	(1.07)	(0.70)
Large Stocks (90-04)	4.23	4.08	0.69	2.23*
	(3.15)	(2.46)	(1.93)	(1.31)
Large Stocks (05-19)	5.18***	3.37***	1.51*	0.57
	(1.63)	(1.23)	(0.88)	(0.71)
Non-Micro Stocks (90-19)	8.89***	6.57***	3.13***	1.89***
	(1.52)	(1.17)	(0.89)	(0.95)
Non-Micro Stocks (90-04)	9.51***	8.27***	4.76***	2.99***
	(2.56)	(1.96)	(1.50)	(0.95)
Non-Micro Stocks (05-19)	7.80***	4.95***	1.56*	0.80
	(1.69)	(1.27)	(0.94)	(0.77)
Micro Stocks (90-19)	12.69***	10.04***	7.38***	2.91***
	(1.47)	(1.07)	(0.79)	(0.62)
Micro Stocks (90-04)	15.67***	12.68***	10.61***	4.64***
	(2.01)	(1.47)	(1.05)	(0.81)
Micro Stocks (05-19)	8.97***	7.22***	4.35***	1.61*
	(2.12)	(1.53)	(1.16)	(0.87)

Table AVII. Anomaly Returns: Month of Fiscal Year-End

The table shows returns to the Info and FF92 rebalancing strategies while separating portfolios based on the month of the FYE of firms. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered by firm and date and are shown in parentheses.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Annualized Mean Daily Returns					
	FF92 Rebalancing		Info Rebalancing		Difference	
Month of FYE	Return	StdErr	Return	StdErr	Return	StdErr
All Months	2.40***	(0.43)	3.07***	(0.44)	0.66**	(0.27)
Jan. - Sept.	1.44**	(0.60)	2.55***	(0.60)	1.11**	(0.44)
Oct. - Dec.	2.46***	(0.45)	2.84***	(0.48)	0.37	(0.30)