Anomaly Time*

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Abstract

We provide evidence that arbitrageurs face a complex signal processing problem that delays the elimination of mispricing. Using a powerful database containing the precise timing of information announcements, we find that returns to many anomalies are concentrated in the 30 days after announcements and disappear soon thereafter. We find that prices incorporate information more quickly when portfolio rebalancing is less complex. Moreover, anomaly profits vanish more quickly and arbitrageurs trade more quickly as signal processing costs decline. Our evidence shows the timing of anomaly returns yields important insights about their existence, magnitudes, and relation to computational costs.

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1 Introduction

For anomalies based on information releases, competition creates a race to profit from mispricing before it is arbitraged away – and this race begins when that information is first made public. Yet, despite the importance of timing for these anomaly strategies, the academic literature has largely ignored when anomaly returns occur and when they are arbitraged away. Using a powerful database to capture the exact date of information releases, we study the precise timing of abnormal returns for 28 prominent anomalies that rely exclusively on measurable information releases. We find that the timing of anomaly returns yields important insights about the role of processing costs and complexity in anomaly returns, their magnitudes following information releases, and the trends in their behavior in recent decades.

Our approach is motivated by the large theoretical literature on underreaction, limited attention, and information processing costs, which in turn generate drift in subsequent prices.[1] In response to this literature, we specifically examine whether return predictability from anomalies is related to information processing costs. Our results show that many anomalies are related to the cost of acquiring and processing key signals. We first show that anomaly returns exhibit a strong pattern in event time: returns are earned in the days and weeks immediately following the release of key accounting data, and they dissipate soon thereafter. We also find that anomaly returns are captured more slowly when information is more complex to process. Furthermore, as processing costs have fallen due to technological innovation, we find over our sample period that anomaly returns are being earned earlier.

Although it may seem that processing costs should be low for most anomalies, acquiring and processing data can be challenging, even in the era of algorithmic trading. For example, consider the asset growth anomaly, which uses the book value of assets to generate a trading

[1]For example, Hong and Stein (1999) develop a model of underreaction in which investors gradually receive signals about the fundamental value of an asset. Similarly, Hirshleifer and Teoh (2003) develop a model in which investors display limited attention, which can explain well-known phenomena like post-earnings announcement drift (Ball and Brown (1968)). Consistent with this approach, DellaVigna and Pollet (2009) develop a simple model in which a share of investors is distracted each period, which then leads to delayed responses to earnings announcements.

signal. We show that 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. Occasionally, even the same firm will switch the time when it reports this information. Thus, an investor trading on the asset growth anomaly, who needs to rank all stocks by asset growth, must essentially monitor every possible firm that *could* release information about the book value of assets each day. Moreover, since many other anomalies depend on accounting items, this issue applies to much of the information released in firm-level accounting statements. In practice, the release of many different signals by many different firms increases processing costs, and the fact that the release date of these signals is not perfectly predictable leads to a signal processing problem that grows dramatically in complexity. As a result of this complexity, information is incorporated with a delay. In other words, when new information arrives, investors update slowly, and so do prices.

While costly signal processing has been proposed as an explanation for individual anomalies, to date, it has not been examined as a unifying explanation for a large set of anomalies. Examining the connection between returns and the timing of information releases has been difficult for previous research because standard databases do not show when a particular accounting line item was first made public. As a result, over the past three decades the literature has established a convention in which anomaly portfolios are formed annually, typically in June, to ensure that financial statement information has been publicly released (e.g., Fama and French (1992)). A byproduct of this convention is that the precise timing of information signals has been largely ignored.

We overcome this issue by 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.

To test the costly signal processing explanation, we identify 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 in McLean and Pontiff (2016), then select the subset of anomalies that rely on information released in either earnings announcements or 10-K filings. For example, the asset growth trading strategy is determined solely by accounting data on a firm's current and past book value of assets, so we include the asset growth anomaly in our analyses. Our analyses include 28 well-known anomalies.[3]

The costly signal processing theory generates several testable predictions. First, if anomalies are the result of costly signal processing, then return predictability should be strongest in the period immediately following the release of key information. Second, if signal processing costs reduce the speed of adjustment, then prices should reflect information more slowly on days when signal processing is more complex. Finally, technological improvements that reduce signal processing time should coincide with faster arbitrage and shorter periods of return predictability.

We test the first prediction using an event-time approach. Consistent with the existing literature critiquing anomalies (e.g., Harvey et al. (2016), Hou et al. (2020)), we find that many anomalies do not generate strong return predictability in our sample when forming portfolios in June (the conventional strategy). However, when we use Snapshot data to form portfolios the day after the release of key information for each anomaly, we find that anomaly returns are significantly stronger. Consistent with the first prediction, we find that an event-time portfolio generates statistically positive returns in the first 30 trading days for the majority of anomalies and these returns dissipate dramatically in subsequent trading periods. For example, annualized daily abnormal returns to a "super portfolio" composed of all 28 anomalies are 14.79% over the first 30 trading days following information releases, whereas annualized daily abnormal returns over the next four- and six-month windows are

[2]We do not consider anomalies, such as momentum Jegadeesh and Titman (1993), that involve signals that are continuously updated because the information release timing can not be clearly identified.

[3]See Table 1 for a list of all 28 anomalies. Table IA1 in the Appendix contains additional information for each anomaly.

more modest at 9.72% and 3.99%, respectively.[4] In other words, abnormal returns are concentrated in the window immediately following the release of key data.

To test the second prediction and further explore the mechanism underlying delayed information processing, we split the super anomaly portfolio into two sub-portfolios based on how computationally difficult it would be for a hypothetical investor to acquire and process accounting information on that date. On some dates, an arbitrageur would need to rebalance hundreds of positions in their portfolio after the release of key accounting information, while other dates have few or no changes. On these more "complex" days, an arbitrageur would have to identify and read a large number of accounting statements and adjust their position weights in multiple assets. Consistent with the delayed information processing explanation, we find that anomaly returns update more slowly on complex days relative to non-complex days.

Finally, we test our third prediction that technological improvements over time coincide with faster price discovery following information releases. During the first two trading days following information releases, the proportion of earnings within our super portfolio's 30-day abnormal return amounted to 4% in the early years of our sample, compared with 14% in latter years. These results demonstrate that in recent years, mispricing is being arbitraged away more quickly .

Implicit in our third prediction is the notion that technological improvements over time should lead to more rapid trading on information signals. Our results support this notion. We show in Figure 5 that abnormal trading volume following information releases is inversely related to computing costs; in other words, abnormal trading volume has gotten higher as computing costs have gotten lower. Moreover, abnormal volume is increasingly concentrated in the days immediately following information releases, similar to the pattern we find with returns – Figure 4 shows significantly more trading volume occurring in the days immediately following information releases in more recent years compared to early years in our sample.

[4]In Section 4.2 we show that transaction costs from our information-rebalancing strategy reduce, but do not eliminate, the benefit from this strategy.

Importantly, these results account for the general trend of increased trading volume, and thus reflect a change in the speed with which arbitrageurs trade on information.

While our event-time approach 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 on information release dates instead of rebalancing once a year in June. When we compare our information-rebalancing approach to the June-rebalancing approach, we find significant gains. The spread between the super portfolio's daily abnormal return from the information-rebalancing approach relative to the June-rebalancing approach is 4.60% annualized. Further, on average, the annualized daily abnormal return to June-rebalancing is only 2.59%, while information-rebalancing yields 7.30%. We also examine the opportunity cost of waiting to rebalance in June by examining the returns to the information-rebalancing strategy as we move away from June. As we move farther from June, it is increasingly likely that the June-rebalancing strategy is relying on stale information while the information-rebalancing strategy is incorporating new information. Consistent with this notion, we find that the information-rebalancing strategy increasingly outperforms the June-rebalancing strategy as time passes. The results again suggest that anomaly returns are closely related to the arrival of key anomaly-relevant information.

In a series of corroborating analyses, we examine the effects of transaction costs, small stocks, and trader speed. Across a battery of tests, we consistently find evidence that links predictable returns to the timing of information arrival. When we examine transaction costs, we find that the returns to information-rebalancing easily exceed transaction costs. When we examine partitions of the sample based on firm size using NYSE breakpoints, we find that micro- or small-capitalization stocks do not drive our results. Similarly, our conclusions still hold when we form portfolios on a value-weighted basis (instead of an equal-weighted basis), even though the magnitudes are slightly reduced. We also examine hedge fund returns and find that hedge funds that appear to trade faster on anomaly variables earn predictably larger future returns, consistent with the notion that speed is key to capturing abnormal returns. In sum, across a wide variety of analyses, the evidence all points to the same conclusion: anomaly returns are related to the costs of acquiring and processing information about the underlying information signal.

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. We are the first to use a large set of anomalies to confirm the link between information processing costs and anomaly returns. Our approach would not have been possible for prior studies, as precise timing data have only recently become available.

Moreover, while our results may seem intuitive, they are surprising when viewed with the mounting evidence that anomalies are no longer in the data and/or are the result of data mining (e.g., Harvey et al. (2016), McLean and Pontiff (2016), Hou et al. (2020)). Schwert (2003) explains the debate in the existing literature: "Some interesting questions arise when perceived market inefficiencies or anomalies seem to disappear after they are documented in the finance literature: Does their disappearance reflect sample selection bias, so that there was never an anomaly in the first place? Or does it reflect the actions of practitioners who learn about the anomaly and trade so that profitable transactions vanish?"

We find, like much of the literature, that anomalies do tend to vanish. However, we find that those same anomalies remain strong in the period immediately following the release of key information. In addition, we find that anomaly profits are vanishing more quickly and arbitrageurs trade more quickly as signal processing costs decline. In sum, our evidence supports the conclusion that anomaly patterns can be explained by costly signal processing.

The rest of the paper proceeds as follows: Section 2 provides details about our sample and methodology. We present our main findings in Section 3 while Section 4 presents several corroborating analyses. Section 5 concludes.

2 Data and Methodology

2.1 Data

Our predictions rely on the notion that anomaly returns may be tied to the release of the information signals that determine long-short portfolio assignment. Information signals are released primarily from two sources, (*i*) earnings announcements and (*ii*) the filing of financial statements (in particular, SEC Form 10-K). However, the timing of information releases can vary substantially over time, across anomalies, and across firms. For example, in 2004 Gulfmark Offshore, Inc. included total assets in its 10-K report released on March 15$^{\text{th}}$, but not in its earnings announcement released on February 26$^{\text{th}}$. Yet, in 2018, Gulfmark Offshore included total assets in both its earnings announcement and its 10-K. To identify the precise date on which important information signals are publicly released, we use a powerful but relatively unknown database: Compustat Snapshot. This database enables us to address the considerable heterogeneity in the timing of information releases.

Historical context illustrates why forming long-short portfolios using conventional approaches may not be fully accurate. From 1995 through 2018, 53% of annual earnings announcements included a report of total assets, implying that 47% of the time, total assets were reported later on the 10-K filing (which, by mandate, includes a full balance sheet).[5] Over our sample, firms average 23 days between their annual earnings announcement and their 10-K filing, indicating that using the wrong portfolio assignment date would result, on average, in forming portfolios three weeks too early or three weeks too late. This potential measurement error from portfolio assignment has evolved substantially over time. First, beginning around 2008, firms increasingly include complete balance sheets and income statements with their annual earnings announcements: since 2008, 93% of annual earnings announcements report total assets. Second, the number of days between the average firm's annual earnings announcement and its 10-K filing has decreased over time (Arif et al. (2019)).

[5]For the 53% of annual earnings announcements that reported total assets, the vast majority released a balance sheet and income statement as part of the earnings release.

Taken together, these facts imply that it would often be inaccurate to assume total assets (and many other anomaly signals) were first reported in a 10-K filing; similarly, forming portfolios in June (as is the common convention in the literature) introduces substantial delays to portfolio formation.

Fortunately, the Snapshot database allows us to address these issues because it "creates a historical investment environment by showing the information that was available at that time in history."[6] For every line item on a financial statement (e.g., total assets), Snapshot identifies the date at which it is first reported. For example, following a March 1^{st} earnings announcement that releases only total revenue and net income, Snapshot recognizes and records that these two line items are first reported on March 1^{st}. If the remaining line items from the income statement and balance sheet are released with the firm's 10-K filing on March 25^{th}, then Snapshot recognizes that all other line items are first reported on this second date. As a counterexample, if the March 1^{st} earnings release contains a full income statement and balance sheet, then the line items from these statements are all recognized and recorded by Snapshot as being first reported on March 1^{st}. In short, the Snapshot database enables us to identify the precise date on which each accounting line item is first made publicly available.

We use the Snapshot data to precisely identify the first date at which anomaly signals are known. This allows us to form long-short anomaly portfolios immediately upon the release of new information. We combine the Snapshot data with information from the Center for Research in Security Prices (CRSP), Compustat, RavenPack, and Morningstar Center for International Securities and Derivatives Markets (CISDM) databases, as well from Kenneth French's website. From CRSP, we pull individual stock returns, retaining only common stocks (CRSP share codes of 10 or 11) and dropping those with prices of less than $5. From Compustat, we acquire firm-level financial statement data. From RavenPack, we acquire

[6]See the Compustat Snapshot North America User Guide, August 7, 2018 v 1.0.

media coverage for each firm. We use the Morningstar CISDM database to measure hedge fund performance. Finally, we use Kenneth French's database to acquire benchmark returns.

2.2 Anomaly Calculations

We use a set of anomalies for which we can clearly examine the relation between returns and the release of important information. Our starting point is the set of 97 anomalies examined by McLean and Pontiff (2016). However, for many of these anomalies, the constantly changing nature of the underlying data on which the anomaly portfolio is based makes it difficult to establish a clean setting to test our anomaly timing hypotheses. For example, a commonly cited anomaly, the earnings-to-price ratio (Basu (1977)), requires two data points for each stock: earnings and price. While earnings data have clear information release dates, prices constantly change, making it difficult to define a precise information release date.[7] Accordingly, we use the following process to identify anomalies for our study.

From the list of 97 anomalies in McLean and Pontiff (2016), we focus on the anomalies that they identify as "event" or "fundamental" predictors.[8] This excludes anomalies based on market variables (e.g., momentum, size, trading volume) and valuation variables (e.g., market-to-book, earnings-to-price). The resulting list contains 60 anomalies. We further refine the list by requiring each anomaly to be based entirely on information that is publicly revealed in financial statements at a distinct point in time; this ensures that precise information release dates can be identified using the Snapshot database. For example, asset growth is an accounting signal included in our study since it is based entirely on the book value of assets; on the other hand, firm age is excluded from our sample because it is not based on a measurable signal that is publicly revealed via financial statements. These criteria leave us with the 28 anomalies shown in Table 1.

[Table 1 about here.]

[7] More specifically, an information rebalancing strategy for the earnings-to-price anomaly would need to re-rank all stocks every time any one of them experienced a price change.

[8] See the Internet Appendix to McLean and Pontiff (2016), Table IA.IV.

Each of the 28 anomaly variables is calculated in accordance with previous literature. First, we calculate the anomaly variable (e.g., asset growth, asset turnover, earnings consistency, etc.) using accounting data corresponding to the precise information release date provided by Snapshot. For example, if the amount of total assets for a firm is released on February 15$^{\text{th}}$, we then calculate asset growth as the percentage change in assets ($\frac{A_t - A_{t-1}}{A_{t-1}}$) on February 15$^{\text{th}}$. Second, we rank all stocks by the anomaly variable. Finally, we form long-short portfolios using these rankings.

For all anomalies, the long and short portfolios are based on relative rankings, which evolve through time as new information arrives. For example, in Cooper et al. (2008), the long leg of the asset growth portfolio is formed by selecting the bottom decile of stocks based on asset growth ratio. Since these rankings are relative, the change in one stock's asset growth ratio may affect the portfolio inclusion of other stocks. This gives rise to the possibility that some stocks will be near the inclusion cutoff, potentially jumping in and out of the portfolio frequently as information arrives throughout the year. If these stocks' returns are driving our main results, then it would be difficult to interpret our findings. To address this potential issue, we calculate portfolios for our event-time tests following a rule that stocks cannot jump out of the portfolio based on the release of future information pertaining to other stocks. Instead, stocks that enter the portfolio remain for one year or until their next annual filing. Our results are qualitatively similar with or without this restriction, indicating that it is rare for stocks to enter and exit the portfolio many times in the same year.

Although the 28 anomalies we examine are all derived from existing academic studies, the method to construct a long-short portfolio based on those anomalies is occasionally unclear. As Chen and Zimmermann (2020) point out, several of the original papers do not provide univariate tests, so it is unclear as to whether the anomaly positively or negatively predicts future returns.[9] To account for this issue, when presenting results for individual anomalies and when aggregating across anomalies, we multiply strategies that have negative in-sample returns by minus one so that all anomalies generate positive returns. Our tests thus examine whether our predictions lead to larger (i.e., more) positive returns for each anomaly.[10] Excluding these anomalies instead of multiplying them by minus one leaves all of our conclusions unchanged.

Finally, in many of our tests, we also examine a "super portfolio," generated as an equally-weighted combination of all 28 anomalies listed above. In other words, the super anomaly portfolio is an equally-weighted portfolio of all of the individual anomaly portfolios, similar to the Net variable in Engelberg et al. (2018).[11]

We examine primarily abnormal returns. We calculate daily abnormal returns for each stock based on the six-factor model (Fama and French (2015) and Carhart (1997)). Specifically, the abnormal return for a given stock is calculated using one year of past daily returns to estimate factor loadings, which are then used to estimate the next period's abnormal returns.

2.3 Descriptive Statistics

Table 1 provides summary statistics for the sample. Our sample includes approximately 10,500 stocks over the 24-year period from 1995 through 2018. Panel A displays firm-level characteristics, while Panel B provides summary statistics for each individual anomaly.

[9]For example, Soliman (2008) shows that *change in asset turnover* is positively related to future returns, however, his evidence consists of multivariate regressions that include between 8 and 17 variables. As such, it is unclear how *change in asset turnover* would relate to returns in a univariate setting.

[10]See Section IA1.1 of the Internet Appendix for more details on the construction of each anomaly.

[11]Our $superportfolio$ differs from the Net construction method in Engelberg et al. (2018) in that our approach weights the different anomalies equally, instead of using a long position in one anomaly portfolio to cancel a short position in another anomaly portfolio. Our approach allows us to examine the relation between an anomaly and future returns for *all* anomalies even if another anomaly contains contradictory information, which is important for testing whether information rebalancing is related to return predictability.

3 Main Results

Our analyses are motivated by the large theoretical literature on underreaction, limited attention, and information processing costs (e.g., Hong and Stein (1999), Hirshleifer and Teoh (2003), DellaVigna and Pollet (2009)). These models commonly predict that underreaction (due to limited attention and/or information processing costs) will generate drift in subsequent prices. This generates several testable predictions. First, if anomalies are driven by costly signal processing, then anomaly returns should be concentrated in the period immediately following the release of the information signal. The intuition is simple: if costly signal processing causes prices to update over time, then prices will drift starting at the information release date, and this drift will dissipate over time as more of the information is impounded into prices. Second, if costly signal processing reduces the speed of adjustment, then prices should reflect information more slowly on days when signal processing is more complex. Put differently, it should take longer for prices to reflect information on complex days. Third, as technological improvements reduce signal processing time, arbitrage should occur more quickly and return predictability should decline more rapidly.

3.1 Anomaly Returns in Event Time

To test the first prediction, we examine the abnormal returns to anomaly portfolios using an event-time approach. Using Snapshot, we define event dates as the annual information release date for each anomaly variable and for each stock in the sample. Using this approach, we use Snapshot to determine when an anomaly signal first becomes publicly available for each stock, as discussed in Section 2.

Table 2 reports the annualized average daily abnormal returns for all 28 anomalies and the super anomaly portfolio using this event-time approach. The table shows strong evidence of positive abnormal returns following information release dates. Columns 1 and 2 show the average daily abnormal returns earned over the first 30 trading days after information release dates. In these first 30 trading days, 21 of the 28 anomalies earn significantly positive returns. Over this same period, the super portfolio generates an annualized average daily abnormal return of 14.79%.

We also compare the immediate anomaly returns to those that occur several months later. Columns 3 through 6 show average daily abnormal returns for the 31-120 trading day period and the 121-240 trading day period. Compared to the first 30 trading days, the next 90 trading days generate a daily return that is much smaller. For example, the average daily abnormal return to the super portfolio is 9.72% in the 31-120 trading day period, which is only two-thirds of the average daily return earned in the first 30 trading days. Furthermore, in the 121-240 trading day period following information release, the super portfolio averages a return of 3.99%, which is approximately one-fourth of the return earned in the first 30 trading days.

These results show that anomaly returns are earned mainly in the weeks immediately after the anomaly signal becomes public, and returns diminish substantially thereafter. In the first half of the year following information releases (Columns 1 and 3), the super anomaly portfolio earns large and predictably positive abnormal returns. After the first 120 days, however, these returns are much smaller. These findings are consistent with our first prediction – anomaly returns are concentrated in the period immediately following important information releases – and provide evidence that anomaly returns are, at least in part, the result of costly signal processing.

[Table 2 about here.]

Figure 1 further summarizes our first result. It displays average daily abnormal returns for each of the 28 anomalies in the first 30 trading days compared to the 121-240 trading day period following information release. The top panel of the figure shows that many of the anomalies earn positive, large, and statistically significant returns on average in the first 30 trading days. The second panel, in contrast, shows much smaller returns and fewer statistically significant returns in the 121-240 trading day period following information release.

[Figure 1 about here.]

Figure 2 further highlights the diminishing returns to the super anomaly portfolio over time. The figure shows that abnormal returns consistently drop as we move away from the information release date, consistent with the resolution of mispricing as arbitrageurs overcome signal processing costs. This figure also helps resolve tension in the existing literature regarding the apparent disappearance of anomalies in the data. The prevailing academic approach of forming portfolios in June leads to stale portfolios that are rebalanced, on average, 85 trading days after new information is released. Put differently, the standard framework excludes the time period in which most of the potential return is earned (days 1-30 after the information event).

[Figure 2 about here.]

Overall, our event-time test shows a clear connection between information release dates and anomaly returns. This connection is consistent with the idea that anomaly returns are driven by costly signal processing.

3.2 Anomaly Returns and Signal Processing Complexity

To test the second prediction, we examine the complexity of processing signals on different dates. If costly signal processing reduces the speed of adjustment, then it should take longer for prices to reflect information on days that are more complex. For example, consider the difficulty faced by a hypothetical arbitrageur when acquiring and processing accounting information. An arbitrageur would have to pay attention every time information about any firm's assets might be revealed, re-rank all stocks every time even one firm releases new asset data, and then potentially rebalance her entire portfolio. Importantly, an arbitrageur may not be able to identify, ex ante, the precise date on which information will be first revealed. In sum, trading on information signals in real time is difficult because "investors face a high-dimensional prediction problem" (Martin and Nagel (2020)).

To empirically measure this complexity, we partition days into complex and non-complex days using an approach in the spirit of Hirshleifer et al. (2011). However, we modify the measure in that paper to capture the task complexity faced by arbitrageurs when they must acquire, process, and rebalance based on an influx of new information. On some days, our hypothetical investor faces severe task complexity as many firms release new accounting information that may require rebalancing of anomaly portfolios. On other days, the investor's job will be easy as no relevant information is released. We define "complex" days based on this idea. Specifically, if over the preceding two trading days the number of additions to anomaly portfolios falls in the top 10^{th} percentile of days in a given year, then the latter of these two trading days is considered a complex day.[12] Intuitively, a complex day is one where our hypothetical investor is busy identifying and processing a large number of accounting statements and adjusting position weights in a large number of investment securities.

[Table 3 about here.]

Table 3 shows that abnormal returns are significantly delayed for stocks entering anomaly portfolios on complex days. Stocks generate no statistically significant return in the first week after entering an anomaly portfolio on a complex day. In contrast, stocks that enter on non-complex days generate 34 basis points over the succeeding week. The same pattern holds when one considers only the first two trading days after information release: stocks entering on complex days generate no return while stocks entering on non-complex days have already generated 19 basis points. Furthermore, over the first two trading days, stocks entering on complex days generate zero percent of the 30 trading day return, compared with 11 percent generated by stocks entering on non-complex days. Indeed, the results of this test support the link between costly signal processing and anomaly returns: when there is more information to process, anomaly returns are earned more slowly.

[12] We also restrict the sample to include only those stocks that release financial information in January through April.

3.3 Trends in Anomaly Returns, Trading, and Computing Costs

Finally, we examine the third prediction: if anomaly returns are the result of costly signal processing, then technological improvements that reduce signal processing costs should result in faster arbitrage and declining return predictability. We test this prediction in our event-time setting by splitting our sample into two time periods: 1995-2007 and 2008-2018. With respect to information processing technology (i.e., computing), these two time periods are notably different. As shown in Figure 3, computing costs as measured in Wetterstrand (2021) decreased rapidly in the early 2000s. Thus, we compare the return predictability of anomaly strategies between two time periods with different signal processing costs.

[Figure 3 about here.]

[Table 4 about here.]

Table 4 shows that, when focusing on the first 30 trading days after information releases, return predictability for anomalies declines over time: after 30 trading days the super portfolio earns 1.88% in the 1995-2007 period, compared with only 1.38% in the 2008-2018 period. Indeed, in the latter period, where signal processing costs are much lower, anomaly returns are also lower.

The more notable feature in Table 4 describes *when* the anomaly returns are earned. While the 30-day return is higher in the earlier period (1995 - 2007), the 2-day and 5-day returns are higher in the latter period (2008 - 2017). To highlight this difference, Columns 4 and 5 present the percent of the 30-day return that is earned in the first two days and the first five days after information is released. In the early period, 4% of the super portfolio's total 30-day return was earned in the first two days and 15% in the first five days. By contrast, in the latter period, almost 14% of the super portfolio's 30-day return was generated in the first two days and 23% in the first five days. This finding shows that information is incorporated into prices more quickly in the latter part of our sample, when signal processing costs are much smaller.

The results of this test also relate to prior research. Several papers find evidence that many anomalies have lost significance in recent time periods (e.g., Green et al. (2011, 2017); McLean and Pontiff (2016)). Our results provide an explanation for these findings: costly signal processing, combined with the drastic decrease in computing costs over recent decades.

3.3.1 Trading Volume and Computing Costs

The results in the previous section highlight the link between costly signal processing and anomaly returns. The actions of investors are at the heart of this link. For instance, our predictions suggest that anomaly stocks should experience more arbitrage trading in the days and weeks immediately following information releases. Further, the predictions suggest that trading on information signals should be more concentrated in more recent periods as computing costs have declined.

To test these ideas, we examine the time series of abnormal trading volume in the days following information releases. We measure daily abnormal trading volume as the percent difference between daily trading volume and the average daily trading volume for a stock over the first 30 trading days after an information release. For example, abnormal trading volume of 10% means that volume on that day was 10% higher than the average daily volume over the first 30 trading days. That is, our measure of abnormal trading volume for a given day captures the daily proportion of 30 days worth of trading volume.

This measure is unique to the abnormal volume metrics used in the past and has two key empirical advantages. First, it holds total trading volume constant. This is important because trading volume has significantly increased over time due to the rise of high-frequency trading and other temporal trends. Second, the measure allows us to identify *when* relative volume occurs in a given window of time. Based on our predictions, we expect that trading volume, as a proportion of total volume, has accelerated over the sample period, with arbitrageurs trading much more quickly on information signals. Specifically, we test whether abnormal volume in the two weeks – 10 trading days – after information releases has changed over our sample period. The results are presented in Table 5.

[Table 5 about here.]

Table 5 shows a clear acceleration in information-based trading over the sample period. Specifically, the results show that abnormal (proportional) trading volume in the first 10 trading days after an information release has increased over our sample period. From 1995-2003, there is almost no difference in the proportion of abnormal trading volume over the first 10 trading days relative to the total 30-day window. This result indicates that in this period, trading volume was not concentrated in the period immediately following information releases. From 2004-2011, however, there is a gradual and significant increase in abnormal trading volume over the first 10 trading days. During this period, trading is increasingly concentrated in the two weeks following information releases. From 2011-2018, trading volume becomes highly concentrated over the first 10 trading days. The results from Table 5 are visually portrayed in Figures 4 and 5; the figure clearly depicts the acceleration in trading on information in more recent years, consistent with reductions in signal processing costs leading to faster arbitrage trading.

[Figure 4 about here.]

[Figure 5 about here.]

Overall, our results support the idea that costly signal processing drives anomaly returns – at least in part – and that the concentration of anomaly returns over the last twenty years is related to trading behavior and improvements in signal processing technology.

4 Corroborating Analyses

In this section, we provide additional evidence to corroborate our findings that show patterns of anomaly returns following information releases. First, we examine the returns to an implementable version of our event-time anomaly portfolios. Next, we test whether transaction costs eliminate anomaly returns in our setting. We also test whether the concentration of anomaly returns after information releases exists when dividing stocks based on size. Finally, we use hedge fund returns to infer whether traders benefit from trading quickly after the release of important information.

4.1 Information Rebalancing vs. June Rebalancing

Although the event-time approach provides an intuitive way to examine whether anomaly returns are related to information release dates, it is not implementable in real time. In this section, we develop an implementable version of our strategy to examine the economic significance of our findings. As a benchmark, we compare the returns from our strategy to those of the traditional academic strategy that rebalances in June.

Our implementable approach, which we call the information-rebalancing approach, continuously adjusts anomaly portfolios as new information arrives. This approach offers three significant benefits. First, it is both simple and implementable. Second, it avoids look-ahead bias: at each point in time we only condition on information that was publicly available. To avoid adding a look-ahead bias to our results, the portfolio is adjusted the day *following* the release of new anomaly-related information as indicated by the Snapshot data. Third, it minimizes transaction costs by rebalancing only when new information shifts the stocks in the extreme deciles of the anomaly variable.[13]

Table 6 shows the results comparing the information-rebalancing approach to the June-rebalancing approach. The results consistently show that information rebalancing outperforms June rebalancing. For the super portfolio, the annualized average daily abnormal return using June rebalancing is 2.59% (Column 1), whereas information rebalancing yields an annualized average daily abnormal return of 7.30% (Column 3). The difference between

[13] Because the rebalancing does not occur daily, but only when new information forces rebalancing, portfolio turnover is only 46% higher for information rebalancing than for June rebalancing. We further consider transaction costs in Section 4.2.

the two approaches of over 4.60% (Column 5) is both statistically and economically significant. Moreover, across the majority of the individual anomalies, the returns to information rebalancing exceed the returns to June rebalancing. Indeed, 21 of the 28 anomalies we consider show significant improvements using information rebalancing. Under the null hypothesis that information rebalancing should generate the same returns as June rebalancing, the probability of measuring statistically significant improvement in 21 of 28 anomalies is less than one percent, based on a binomial test. These results, also summarized in Figure 6, provide clear evidence that anomaly variables continue to generate large abnormal returns in the period immediately after the release of key accounting data.

[Figure 6 about here.]

[Table 6 about here.]

We use this same empirical approach to quantify the opportunity costs of waiting to rebalance in June and to further highlight the connection between anomaly returns and information release dates. This analysis addresses the question: how much is left on the table by failing to account for the continuous arrival of new information? We do this by examining returns over different parts of the calendar year. That is, we align both approaches (June rebalancing and information rebalancing) to begin on July 1st and then examine their returns during two separate periods over the subsequent year: the July 1st through December 31st period and the January 1st through June 30th period. The results in Table 7 show clear evidence of an increasing spread between the two approaches as time passes from July 1st.

In the first six months after June rebalancing, the difference between the two strategies is modest at an annualized difference of 1.11%. This is consistent with the idea that the two approaches rely on similar information sets during this period. As time passes, however, the information set underlying the June-rebalancing approach becomes stale, while the information set underlying the information-rebalancing approach is updated, as the majority of annual financial statements are released in the early part of the calendar year. Thus, we would expect a divergence between our two approaches in the January to June period. The results confirm this. Specifically, the spread between information rebalancing and June rebalancing grows from 1.11% through December 31st to 8.38% through June 30th.

Furthermore, only 3 of the 28 anomalies we study show significantly positive abnormal returns in the January through June period under the June-rebalancing approach, while 21 anomalies have positive and significant returns in the same period under the information-rebalancing approach. The information-rebalancing approach accounts for new information better than the June-rebalancing approach, thus it follows that the return difference between the two approaches comes almost entirely during the first half of the calendar year. Since the vast majority of firms release their annual earnings and financial reports between January and March, the difference between information rebalancing and June rebalancing is greatest during this period.

[Table 7 about here.]

Figures 7 and 8 highlight the results from Table 7. Figure 7 shows that the spread between information rebalancing and June rebalancing is generated primarily in the first half of the calendar year when new information is most frequently released via annual reports and earnings news. Figure 8 shows the average compound return earned by the super anomaly portfolio from July 1st through June 30th. This figure shows that it is after the financial reporting season (February-March) when new information is released that the June-rebalancing portfolio does poorly and the information-rebalancing portfolio continues to perform.

[Figure 7 about here.]

[Figure 8 about here.]

The results in Tables 6 and 7 provide consistent evidence that anomaly returns are tightly related to the release of important information. Again, our results are consistent with the idea that anomaly returns are related to costly signal processing. While our approach may seem intuitive, we note that it could not have been used in early academic work due to the lack of available data. The advent of the Snapshot data allows us to provide novel evidence on the precise relation between information releases and anomaly returns for a large number of anomaly variables.

4.2 Transaction Costs

While the information-rebalancing portfolio is implementable, one concern is that it may be practically infeasible, due to either transaction costs or excessive portfolio turnover (e.g., Novy-Marx and Velikov (2015)). Because our results provide insight into the relationship between anomalies and signal processing costs, our analysis is important even if transaction costs are high in the implementable strategy. Still, this subsection considers the after-trading-cost performance of our information-rebalancing strategy. To do so, we adjust abnormal returns based on the effective bid-ask spread as in Chen and Velikov (2019).[14] We replicate our analysis from Sections 3.1 and 4.1, assuming that a trader must pay half the bid-ask spread when a stock is either added to or subtracted from the event-time portfolio.

The results of adjusting for transaction costs are presented in Table 8. Although anomaly returns are lower, they are still positive and significant. Panel A uses the event-time approach to show that the super anomaly portfolio, even after paying half of the spread on day one and the other half on day 120, earns an annualized daily abnormal return of 4.75%. After the entire 240 trading days and adjusting for the bid-ask spread, the super anomaly portfolio still generates an abnormal return of 3.31%. Thus, anomaly returns are not simply a result of transaction costs.

Panel B of Table 8 uses the implementable, information-rebalancing approach to show that the super anomaly portfolio, even after paying half of the spread when a firm enters the portfolio and the other half when exiting the portfolio, earns an annualized daily abnormal

[14] Monthly measures of the bid-ask spread are available on Andrew Chen's website: https://sites.google.com/site/chenandrewy/

return of 4.16% using the information-rebalancing strategy. In contrast, the traditional June-rebalancing portfolio shows no return after accounting for transaction costs.

[Table 8 about here.]

4.3 Size Effects

We also examine whether the relation between anomaly returns and anomaly timing varies by firm size. Hou et al. (2020) show that anomaly returns for many anomalies cannot be replicated after excluding micro-cap stocks. To examine whether our findings are driven by micro- or small-cap stocks, we examine our results after splitting the sample into large, small, and micro subsamples using the methodology in Fama and French (2012). Importantly, we follow the same empirical event-time and information-rebalancing approaches used in Tables 2 and 6, respectively, except that we split the sample into terciles based on NYSE size breakpoints.[15] Large stocks are those with market capitalization greater than or equal to the 50$^{\text{th}}$ percentile of NYSE breakpoints, small stocks are those with market capitalization greater than or equal to the 20$^{\text{th}}$ percentile but less than the 50$^{\text{th}}$ percentile, and micro stocks are those with market capitalization below the 20$^{\text{th}}$ percentile.

The results are reported in Table 9. Panel A shows that in the event-time framework, anomaly returns to stocks in each size group display the same general pattern of return concentration we found in Table 2. That is, for stocks of all sizes (large, small, and micro-cap), abnormal returns are most prominent immediately following the release of information, with abnormal returns to anomalies diminishing as information becomes stale. Thus, while prior research finds evidence that anomaly returns are concentrated in micro-cap stocks, our results suggest that once timing is considered, anomaly returns are present across firms in all size groups. Panel B performs the same type of analysis in the implementable framework,

[15]NYSE size breakpoints are available on Kenneth French's website: `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

and again shows that the information-rebalancing approach leads to high anomaly returns even among large stocks.[16]

[Table 9 about here.]

Overall, the results in this section indicate that our main findings in Tables 2 and 6 are not driven by small or micro-cap stocks.

4.4 Implied Hedge Fund Speed and Future Fund Performance

Finally, we develop a measure of implied hedge fund speed to examine whether hedge funds that trade quickly on new anomaly information generate higher future returns. For this analysis, we use Morningstar data to measure monthly returns for each fund. We focus on approximately 2,500 funds operating from 1998 through 2018, and further limit our sample to funds denominated in U.S. Dollars and focusing on U.S. equities.[17] To be clear, the data do not contain individual trades, so we cannot measure reaction speed directly for a given trader. Instead, we infer trading speed as follows. For each fund j, we calculate implied hedge fund speed as the slope parameter estimate (β) from a rolling, fund-by-fund regression of fund j's return on the information-rebalancing return:

$$Return_{jt} = \alpha + \beta_{jt}(InfoRebalancingReturn_t) + \epsilon_{jt}, \tag{1}$$

where $Return_{jt}$ is the return for hedge fund j in month t and $InfoRebalancingReturn_t$ is the monthly abnormal return earned by the information-rebalancing approach's super portfolio.[18] The idea behind this approach is simple: on average, funds that perform well precisely when the information-rebalancing strategy performs well are more likely, all else

[16] Similarly, in the Appendix we show that our conclusions still hold when we form value-weighted (instead of equal-weighted) portfolios.

[17] Specifically, we include the following fund types: Convertible Arbitrage, Diversified Arbitrage, Equity Market Neutral, Event Driven, Fund of Funds (FoF) Equity, FoF Event, FoF Multistrategy, FoF Relative Value, Global Long/Short Equity, Long-Only Equity, Long-Only Other, Multistrategy, U.S. Long/Short Equity, and U.S. Small Cap Long/Short Equity.

[18] The information-rebalancing approach's super portfolio is described in Section 4.1.

equal, to be trading quickly on the release of anomaly information. The regression runs in a rolling fashion for each fund, j, over the previous 36 months. Thus, our measure of the implied fund speed for month t for fund j is the parameter estimate, β, from the rolling regression using fund and information-rebalancing returns from month $t-36$ to month $t-1$.

We then test whether implied hedge fund speed predicts future fund performance. To do so, we compute the fund's compound abnormal return looking forward 12 months as the alpha from a regression of the fund's abnormal 12-month-ahead return on the six factors used in Fama and French (2015) and Carhart (1997). We then test the relation between the fund's future 12-month performance ($AbnReturn_{j,t+1:t+12}$) and implied hedge fund speed ($\widehat{\beta_{jt}}$) using panel regressions of the form:

$$AbnReturn_{j,t+1:t+12} = \gamma_0 + \gamma_1 \widehat{\beta_{jt}} + \epsilon_{j,t+1:t+12}. \tag{2}$$

As shown in Table 10, across all specifications, the result is the same: a fund's implied trading speed is positively related to its future performance. Column 2 adds fund fixed effects to account for unobserved heterogeneity at the fund level, and Column 3 adds month-year fixed effects to account for time-varying aggregate heterogeneity. The fund fixed effect allows us to examine the relation on a fund-by-fund basis. Indeed, as a given fund increases its speed, we find an increase in future performance. When including all fixed effects, we see that a one unit increase in speed leads to an annual performance increase of 0.59% (of abnormal returns). Given that the standard deviation of hedge fund speed is 0.89, a one standard deviation increase in speed results in an annual performance increase of 53 basis points, once again suggesting that much of the return to anomalies is generated soon after information releases and that it is beneficial to trade quickly.

[Table 10 about here.]

5 Conclusion

By studying the concentration of anomaly returns after important information announcements, we provide novel evidence that anomaly returns are the result – at least in part – of costly signal processing. Indeed, we show that anomaly returns are concentrated in the days immediately following information releases. We also demonstrate that anomaly returns and abnormal trading have moved earlier in time (i.e., closer to information release dates) as computational costs have decreased. Finally, consistent with the idea that anomalies exist because of costly signal processing, we show that prices update more slowly on "complex" days, when information processing is more difficult.

In addition to supporting the link between anomaly returns and costly signal processing, the patterns we document also clarify recent results in the literature. For example, while the literature suggests that anomalies have disappeared in recent periods, our results offer an alternative explanation: that perhaps anomalies *appear* to have disappeared because researchers have not been looking in event time or in the period immediately following information releases.

Finally, our use of the Snapshot data to examine the returns to anomaly strategies in event time not only provides an approach for out-of-sample testing for many anomalies, it also provides a framework in which to examine other relations with anomalies. Indeed, we believe that the event-time approach to anomalies can help resolve some of the open questions in this literature.

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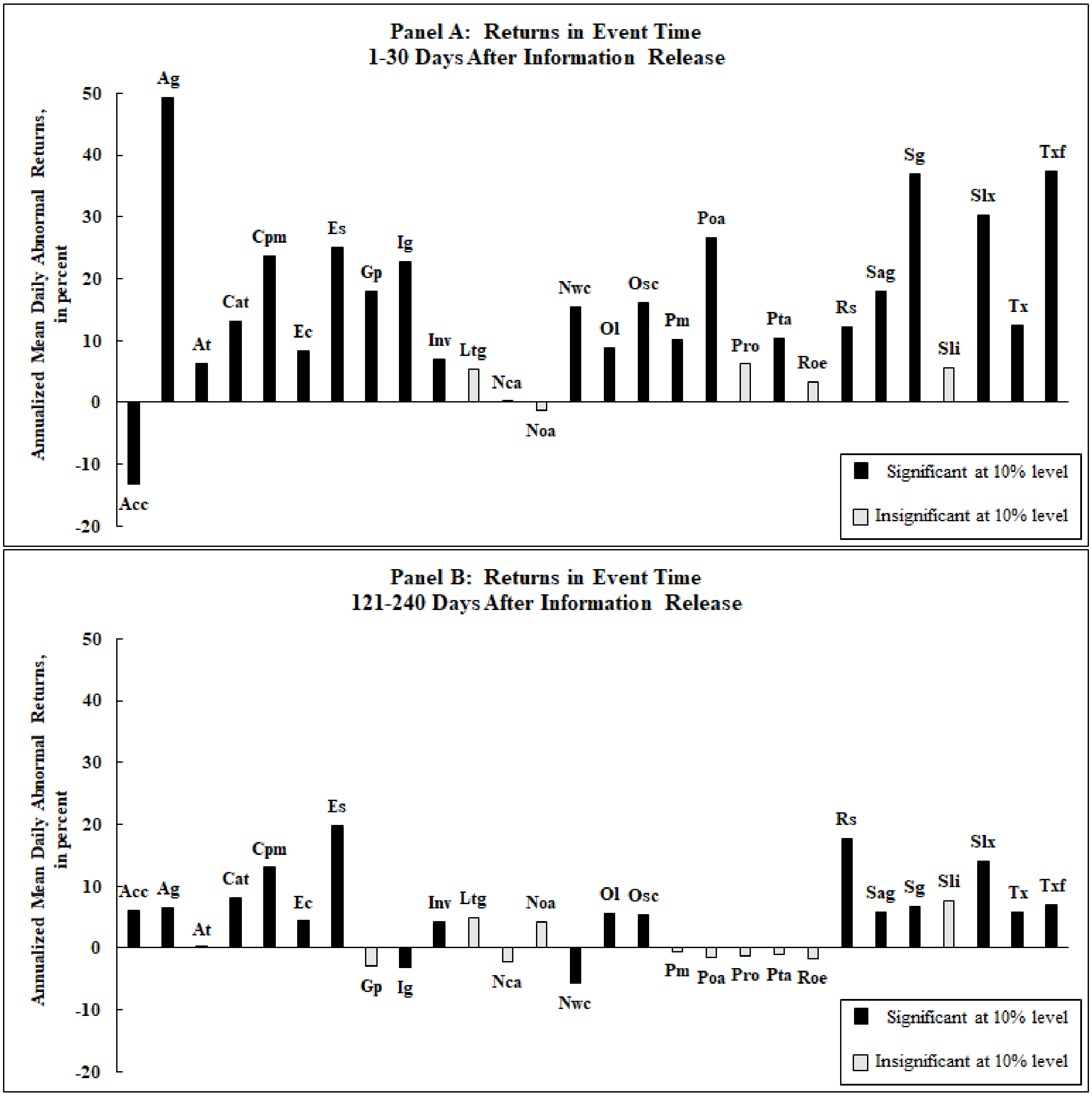

Figure 1: Anomaly Portfolio Returns in Event Time

The figure shows annualized mean daily abnormal returns in event time for the 28 anomalies considered. The first panel shows average abnormal returns over the the period 1-30 trading days following an information release. The second panel shows average abnormal returns over the period 121-240 trading days following an information release. The event date is determined by the release date of financial information about the anomaly conditioning variable(s), as identified in the Snapshot database. Abnormal returns for each anomaly are arranged in event time and are calculated using the six-factor model (Fama and French (2015) and Carhart (1997)). Statistical significance is indicated with by the fully shaded bars.

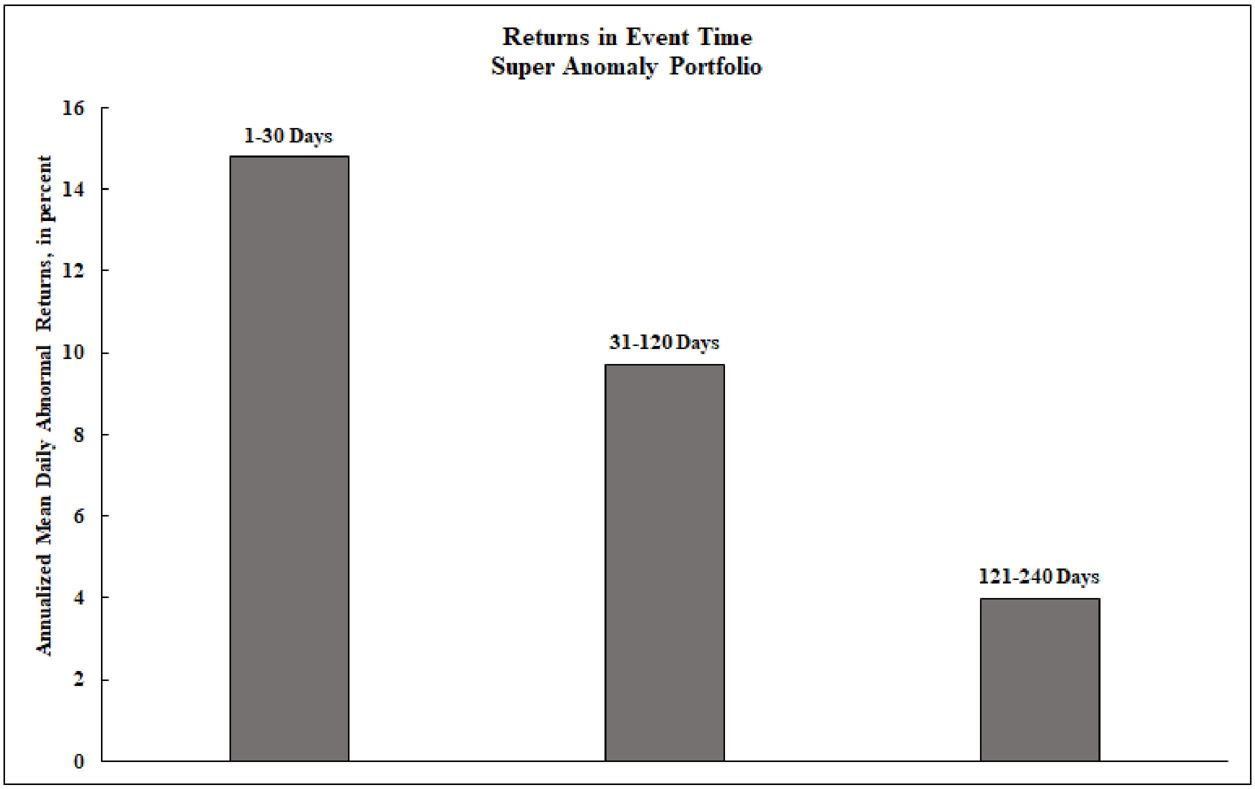

Figure 2: Anomaly Portfolio Returns in Event Time
The figure shows annualized mean daily abnormal returns in event time for the super anomaly portfolio. The super portfolio is constructed as the average across all individual anomaly portfolios. Returns for three distinct periods following an information release are presented in the figure: 1-30 trading days, 31-120 trading days, and 121-240 trading days. The event date is determined by the release date of financial information about the anomaly conditioning variable(s), as identified in the Snapshot database. Abnormal returns for each anomaly are arranged in event time and are calculated using the six-factor model (Fama and French (2015) and Carhart (1997)).

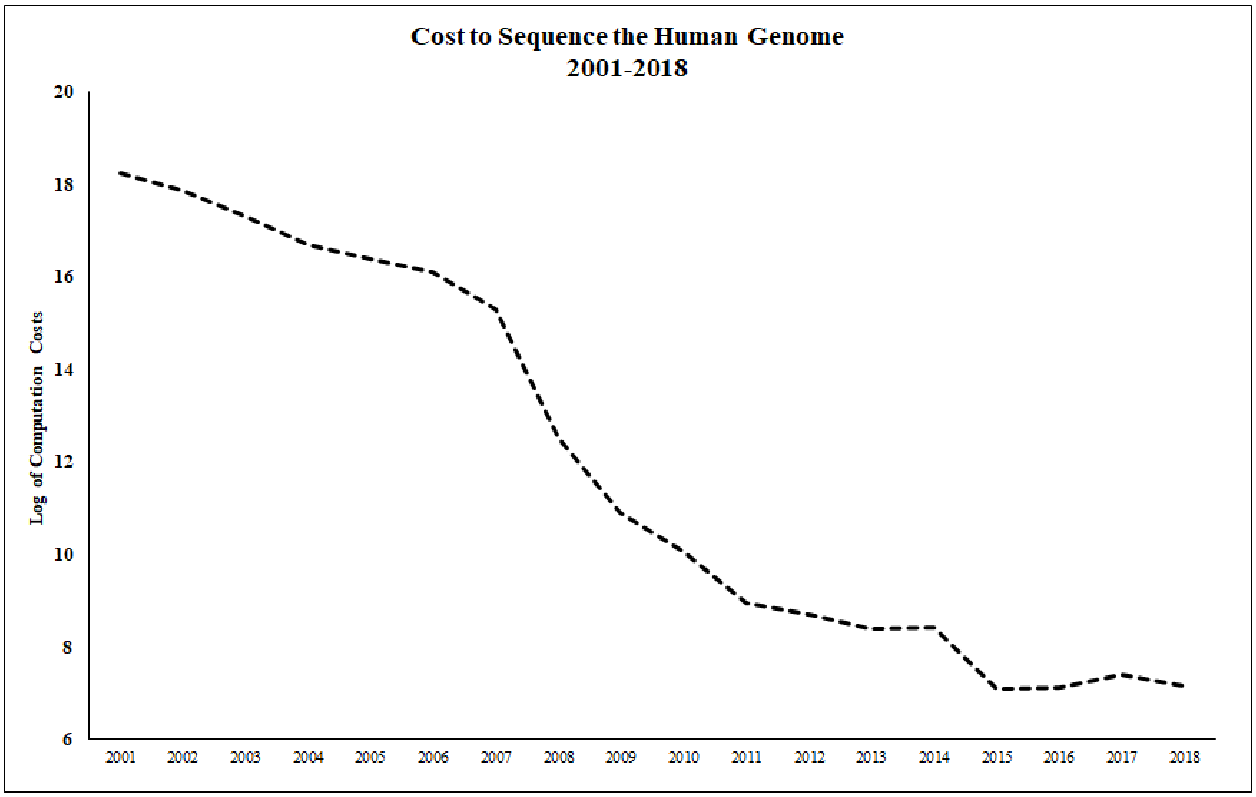

Figure 3: Computing Costs Over Time

The figure shows the time series of computing costs. Computing costs are measured as the log of the cost to sequence the human genome (Wetterstrand (2021)).

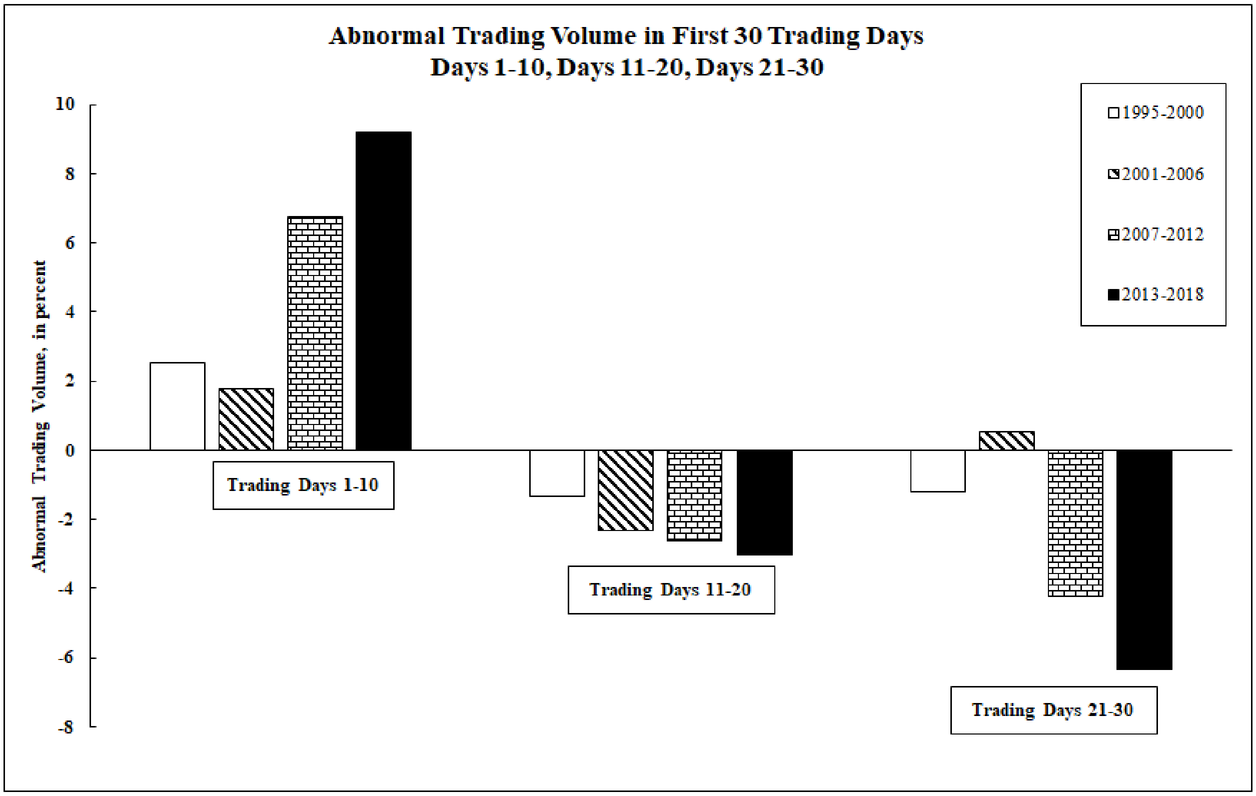

Figure 4: Trading Volume Over Time

The figure shows the change in the concentration of trading volume in the 30 trading days following information releases. Daily abnormal trading volume is the percent difference from the average daily trading volume (scaled by shares outstanding) over the first 30 trading days. Abnormal trading volume in the first ten trading days is the average of the daily abnormal trading volume measures over the first ten trading days. Abnormal trading volume in each successive ten trading days (days 11-20 and 21-30) is the average of the daily abnormal trading volume measures over their respective ten-day periods. The sample has been split among four time periods as shown.

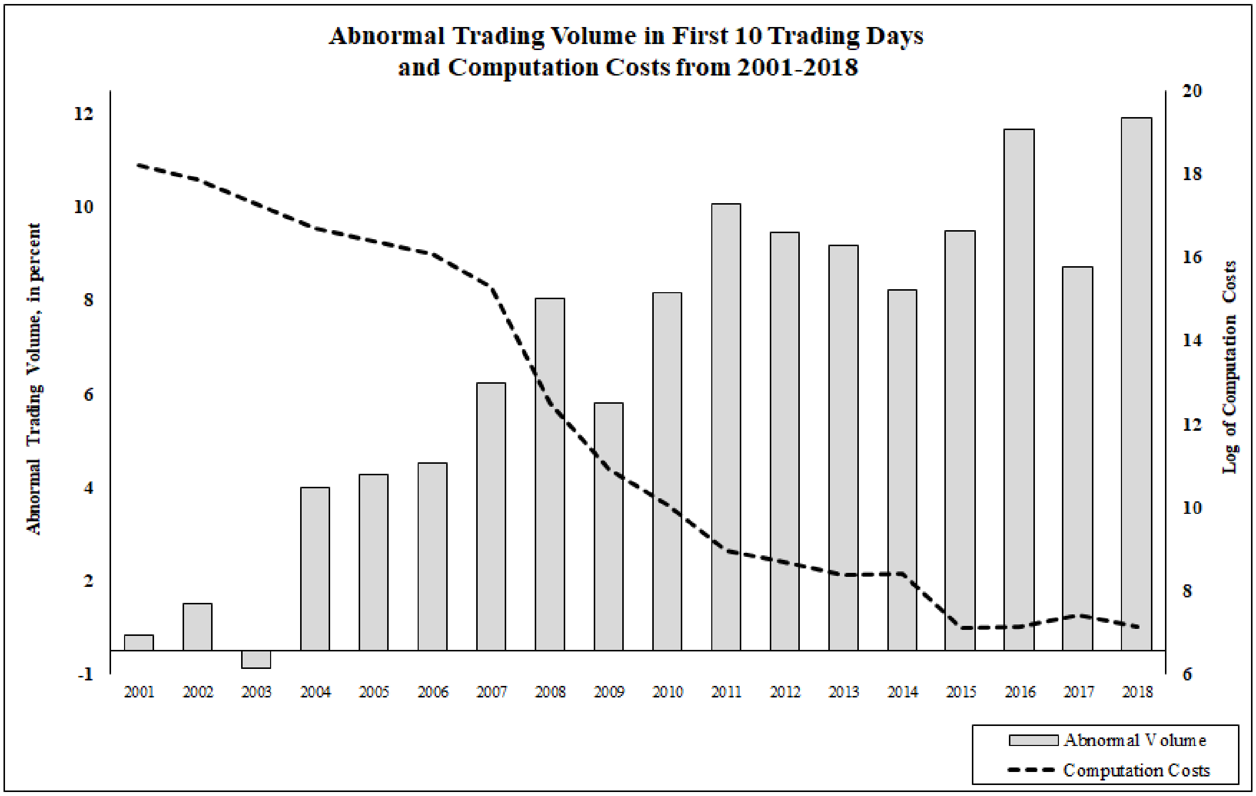

Figure 5: Trading Volume and Computing Costs

The figure shows the time series of computing costs (right axis) and abnormal trading volume (left axis). Computing costs are measured as the log of the cost to sequence the human genome (Wetterstrand (2021)). Daily abnormal trading volume is the percent difference from the average daily trading volume (scaled by shares outstanding) over the first 30 trading days. Abnormal trading volume in the first ten trading days is the average of the daily abnormal trading volume measures over the first ten trading days.

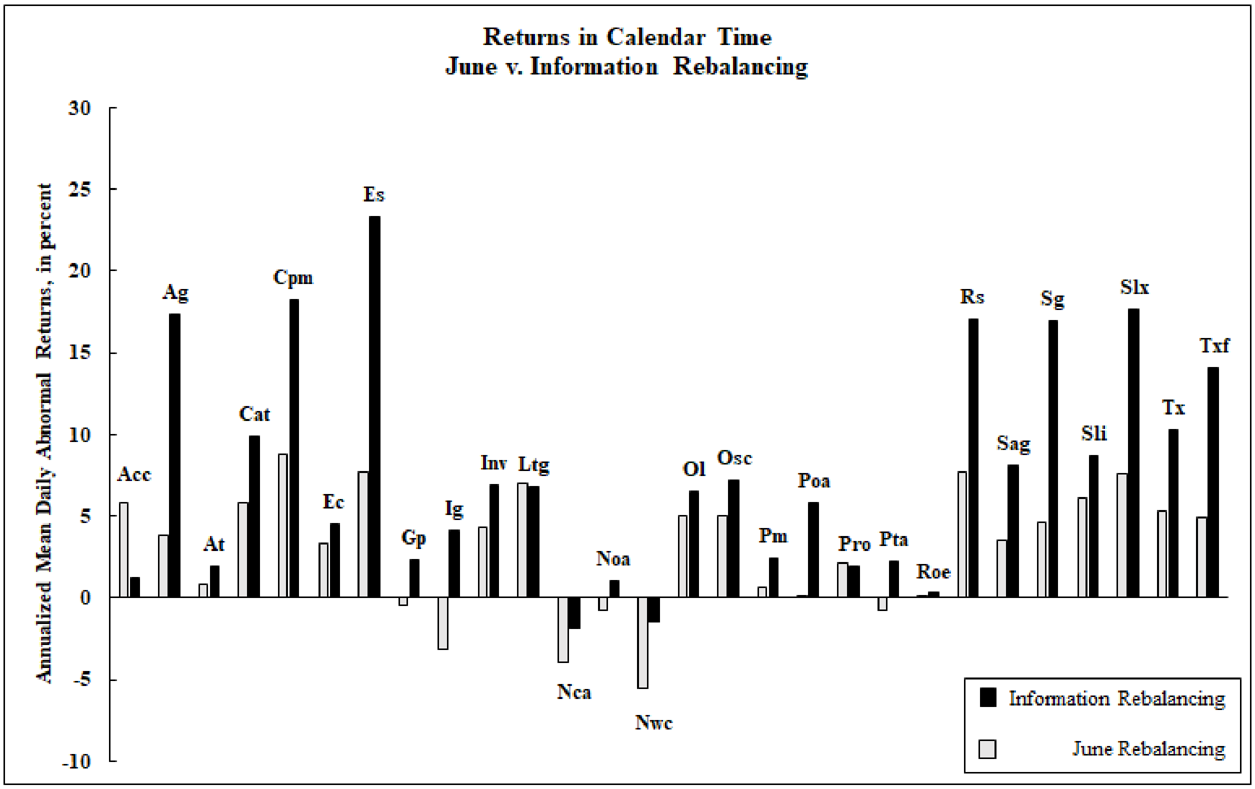

Figure 6: Anomaly Portfolio Returns in Calendar Time

The figure shows annualized mean daily abnormal returns in calendar time for the 28 anomalies considered. The dark bars show returns earned by the information rebalancing portfolios while the light bars show returns to the June rebalancing portfolios. Abnormal returns are calculated using the six-factor model (Fama and French (2015) and Carhart (1997)).

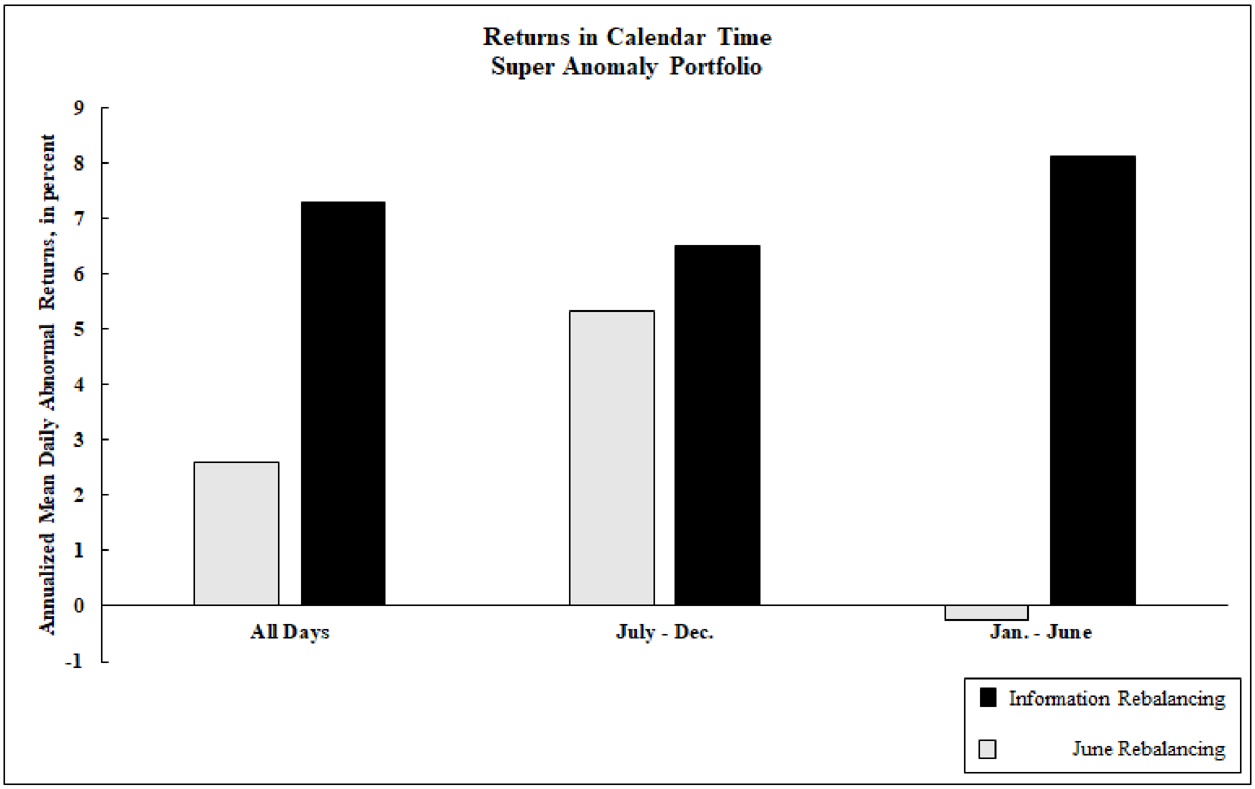

Figure 7: Super Anomaly Portfolio Returns in Calendar Time: Time of Year
The figure shows annualized mean daily abnormal returns in calendar time for the super anomaly portfolio, constructed as the average across all 28 individual anomaly portfolios. The dark bars show returns earned by the information-rebalancing portfolio while the light bars show returns to the June-rebalancing portfolio. Abnormal returns are calculated using the six-factor model (Fama and French (2015) and Carhart (1997)).

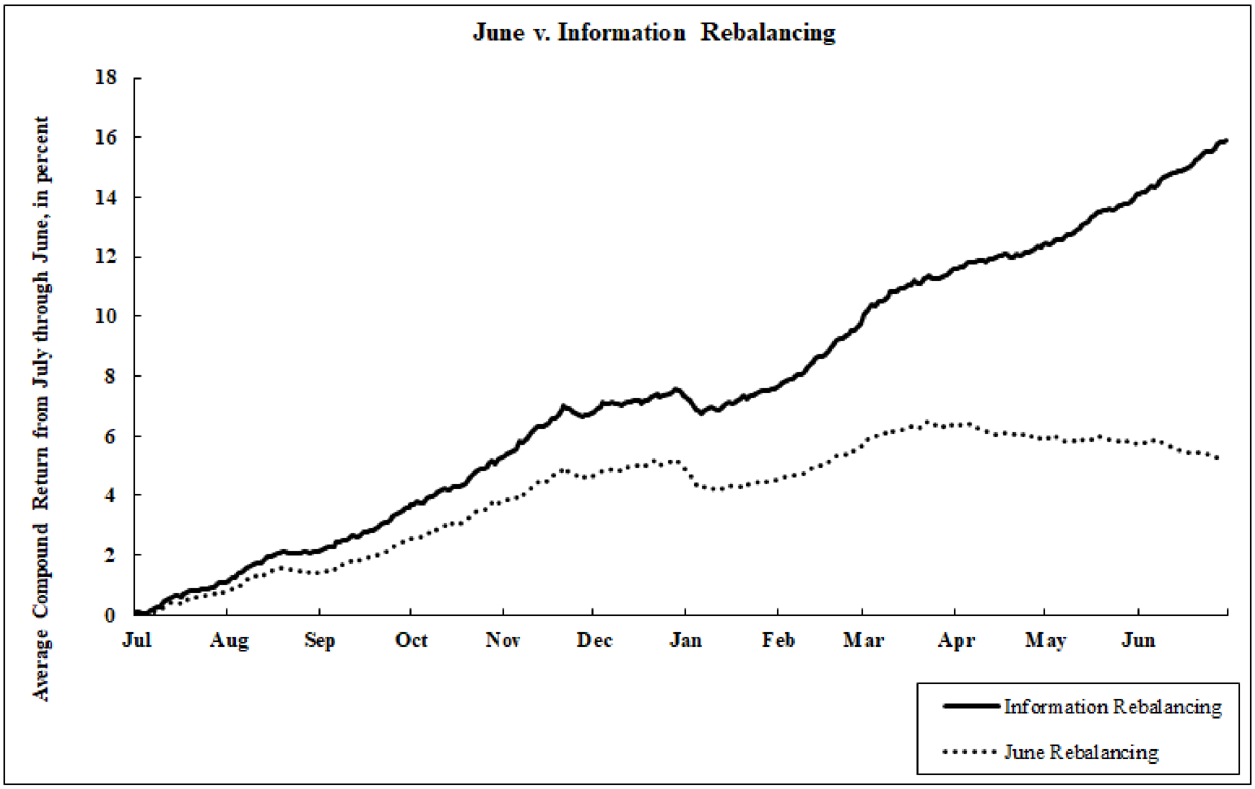

Figure 8: Super Anomaly Portfolio Returns in Calendar Time: Line Chart
The figure shows annualized mean daily abnormal returns in calendar time for the super anomaly portfolio, constructed as the average across all 28 individual anomaly portfolios. The dark line shows returns earned by the information-rebalancing portfolio while the dotted line shows returns to the June-rebalancing portfolio. Abnormal returns are calculated using the six-factor model (Fama and French (2015) and Carhart (1997)).

Table 1: Summary Statistics

The table provides summary statistics for our sample of firms. The sample covers 1995 through 2018, with approximately 10,500 firms. Panel A provides summary statistics for daily returns and market capitalization (in millions of USD) for all stocks in our sample. Abnormal returns are measured using the 6-factor model (Fama and French (2015) and Carhart (1997)). Panel B provides summary statistics for each of the anomaly variables. See Table IA1 in the appendix for detailed variable definitions.

Panel A: Daily Returns and Market Capitalization

	Mean	Std. Dev.	Median	N
Daily Raw Returns	11 bps	334 bps	0 bps	23,700,000
Market Cap.	\$1,185	\$5,844	\$172	10,540

Panel B: Anomaly Characteristics

Anomaly (abbreviation)	Mean	Std. Dev.	Median	N	Source Paper
Accruals (Acc)	0.00	0.11	0.00	62,524	Sloan (1996)
Asset Growth (Ag)	0.16	1.18	0.05	87,482	Cooper et al. (2008)
Asset Turnover (At)	1.34	213.15	1.47	75,243	Soliman (2008)
Change In Asset Turnover (Cat)	0.47	302.61	0.00	65,850	Soliman (2008)
Change In Profit Margin (Cpm)	-0.04	103.59	0.00	48,062	Soliman (2008)
Earnings Consistency (Ec)	0.00	1.96	0.08	32,134	Alwathainani (2009)
Earnings Surprise (Es)	-1.17	15.30	-0.12	59,100	Foster et al. (1984)
Gross Profitability (Gp)	0.27	0.67	0.25	61,116	Novy-Marx (2013)
Inventory Growth (Ig)	0.01	0.06	0.00	77,478	Thomas and Zhang (2002)
Investments (Inv)	1.58	66.47	0.93	36,223	Titman et al. (2004)
Growth In Long-Term Net Operating Assets (Ltg)	0.00	0.93	0.01	20,150	Fairfield et al. (2003)
Non-Current Operating Assets (Nca)	0.01	0.90	0.01	80,083	Soliman (2008)
Net Operating Assets (Noa)	0.50	1.26	0.51	67,497	Hirshleifer et al. (2004)
Net Working Capital (Nwc)	0.00	0.10	0.00	63,630	Soliman (2008)
Operating Leverage (Ol)	1.05	1.14	0.87	48,840	Novy-Marx (2010)
O-Score (Osc)	-0.67	5.11	-1.07	59,118	Dichev (1998)
Profit Margin (Pm)	-2.84	159.79	0.33	63,634	Soliman (2008)
Percent Operating Accruals (Poa)	-1.19	28.80	-0.70	60,584	Hafzalla et al. (2011)
Profitability (Pro)	-0.25	6.13	0.07	76,404	Balakrishnan et al. (2010)
Percent Operating Accruals (Pta)	1.14	31.34	0.16	52,402	Hafzalla et al. (2011)
Return On Equity (Roe)	-0.13	44.98	0.07	82,072	Haugen and Baker (1996)
Revenue Surprise (Rs)	0.53	15.64	0.45	57,199	Jegadeesh and Livnat (2006)
Sales Growth (Sag)	1182.59	434.11	1159.97	46,978	Lakonishok et al. (1994)
Sustainable Growth (Sg)	0.16	11.39	0.06	83,397	Lockwood and Prombutr (2010)
Sales Growth Less Investment Growth (Sli)	0.22	42.03	0.01	38,569	Abarbanell and Bushee (1998)
Sales Growth Less Expenses Growth (Slx)	0.50	85.69	0.00	43,009	Abarbanell and Bushee (1998)
Taxes (Tx)	1.10	18.74	0.87	58,370	Lev and Nissim (2004)
Total External Finance (Txf)	0.05	0.84	0.00	59,083	Bradshaw et al. (2006)

Table 2: Event-Time Anomaly Returns

The table shows abnormal returns to event-time portfolios formed for each of the anomaly portfolios as well as the super anomaly portfolio. The super portfolio is constructed as the average across all individual anomaly portfolios. The event date is determined by the release date of financial information about the anomaly conditioning variable(s), as identified in the Snapshot database. Abnormal returns for each anomaly are arranged in event time and are calculated using the six-factor model (Fama and French (2015) and Carhart (1997)). Column 1 shows the annualized average daily abnormal return (in percent) to an equally-weighted anomaly portfolio over the first 30 trading days following the release of financial information pertaining to the anomaly variable. Column 3 shows the annualized average daily return (in percent) earned during the period 31 to 120 trading days after information release. Column 5 shows the annualized average daily return (in percent) earned during the period 121 to 240 trading days after information release. Even-numbered columns show standard errors for daily returns, clustered by firm and date. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. The final three rows of the table count the number of anomaly portfolios for which the mean daily abnormal return is positive (negative) and statistically significant.

	Annualized Mean Daily Returns					
	Days 1 - 30		Days 31 - 120		Days 121 - 240	
	(1)	(2)	(3)	(4)	(5)	(6)
Anomaly	Return	Std. Error	Return	Std. Error	Return	Std. Error
Super	14.79***	(1.05)	9.72***	(0.72)	3.99***	(0.75)
Acc	-13.28***	(3.48)	-1.58	(2.40)	6.12***	(2.10)
Ag	49.29***	(4.05)	23.69***	(2.56)	6.62***	(2.11)
At	6.27*	(3.46)	2.27	(2.32)	0.01	(2.12)
Cat	13.25***	(3.21)	11.98***	(2.10)	8.10***	(1.89)
Cpm	23.78***	(3.82)	24.35***	(2.41)	13.04***	(2.41)
Ec	8.41*	(4.37)	2.14	(2.73)	4.38*	(2.27)
Es	25.02***	(2.58)	35.49***	(2.00)	19.80***	(2.12)
Gp	17.94***	(4.85)	2.35	(2.92)	-2.98	(2.69)
Ig	22.79***	(3.10)	8.76***	(2.12)	-3.14*	(1.74)
Inv	6.97*	(3.62)	10.63***	(2.28)	4.31**	(2.07)
Ltg	5.31	(5.43)	11.18***	(3.52)	4.99	(3.12)
Nca	0.26	(3.28)	-1.25	(2.07)	-2.23	(2.02)
Noa	-1.37	(4.79)	-0.58	(2.72)	4.28	(2.87)
Nwc	15.44***	(3.52)	0.50	(2.38)	-5.72***	(2.09)
Ol	8.89**	(4.30)	8.97***	(2.75)	5.64*	(2.94)
Osc	16.12***	(4.75)	6.53**	(2.76)	5.32*	(2.86)
Pm	10.19**	(4.21)	3.61	(2.30)	-0.49	(2.25)
Poa	26.72***	(3.11)	10.00***	(2.17)	-1.56	(1.98)
Pro	6.20	(4.63)	3.11	(3.01)	-1.25	(2.71)
Pta	10.40***	(3.10)	3.46	(2.12)	-1.14	(1.90)
Roe	3.32	(3.92)	0.38	(2.60)	-1.64	(2.46)
Rs	12.22***	(2.67)	20.35***	(1.93)	17.74***	(1.77)
Sag	17.97***	(3.38)	8.21***	(2.39)	5.81**	(2.23)
Sg	36.98***	(3.81)	26.05***	(2.39)	6.74***	(2.03)
Sli	5.70	(3.88)	10.89***	(2.63)	7.60***	(2.29)
Slx	30.28***	(4.36)	21.64***	(2.81)	14.03***	(2.42)
Tx	12.50***	(3.90)	15.01***	(2.64)	5.85**	(2.73)
Txf	37.44***	(4.16)	17.06***	(2.81)	6.90**	(2.90)
No. > 0	21		17		16	
No. < 0	1		0		2	
No. $= 0$	6		11		10	

Table 3: Anomaly Returns and Complexity

The table examines the relation between anomaly returns and the complexity of the information environment when firms announce anomaly-relevant information. We split the super anomaly portfolio into two sub-portfolios based on how difficult it would be for a hypothetical investor to acquire and process accounting information on that date. We define "Complex" information days as those days in which the number of additions to anomaly portfolios on that day, plus the day before, fall in the top 10th percentile of all days in a given year. Non-complex information days are all other dates on which portfolio relevant information is released. The super portfolio is constructed as the average across all individual anomaly portfolios. Abnormal returns for each anomaly are lined up in event time and the event date is determined by the release date of financial information about the anomaly conditioning variable(s), as identified in the Snapshot database. For each subsample, the first three columns display mean compound returns over horizons of 2, 5, and 30 trading days, respectively. The fourth column displays the mean compound return over the horizon from 31 to 120 trading days. The last two columns display the percent of the total 30-day return earned over the 2- and 5-day horizons, respectively. Standard errors are clustered by firm and date and are shown below the returns in parentheses. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Compound Returns Earned After Information Release				Percent of 30-Day Return Earned Over Span of Days	
	(1)	(2)	(3)	(4)	(5)	(6)
Sub Sample	2 Days	5 Days	30 Days	31 - 120 Days	2 Days	5 Days
Not Complex	0.19***	0.34***	1.69***	2.92***	11	20
(s.e.)	(0.04)	(0.06)	(0.17)	(0.34)		
Complex	-0.06	0.10	1.06***	2.59***	0	10
(s.e.)	(0.11)	(0.14)	(0.29)	(0.56)		

Table 4: Trends in Anomaly Returns

The table examines trends in anomaly return timing by partitioning the sample into two sub-periods, 1995-2007 and 2008-2018, for the super anomaly portfolio. The super portfolio is constructed as the average across all individual anomaly portfolios. Abnormal returns for each anomaly are lined up in event time and the event date is determined by the release date of financial information about the anomaly conditioning variable(s), as identified in the Snapshot database. For each sub-period, the first three columns display mean compound returns over horizons of 2, 5, and 30 trading days, respectively, while the last two columns display the percent of the total 30-day return earned over the 2- and 5-day horizons, respectively. Standard errors are clustered by firm and date and are shown below the returns in parentheses. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Compound Returns Earned After Information Release			Percent of 30-Day Return Earned Over Span of Days	
	(1)	(2)	(3)	(4)	(5)
Time Period	2 Days	5 Days	30 Days	2 Days	5 Days
1995-2007	0.08**	0.28***	1.88***	4.3	14.9
(s.e.)	(0.04)	(0.06)	(0.18)		
2008-2018	0.19***	0.32***	1.38***	13.8	23.2
(s.e.)	(0.04)	(0.07)	(0.18)		

Table 5: Abnormal Volume Over Time

The table examines trends in the concentration of trading volume. Daily abnormal trading volume is the percent difference between daily trading volume and the average daily trading volume for a stock over the first 30 trading days after an information release. The results below test whether average daily abnormal volume in the first 10 trading days after an information release is different from zero for each year. For example, in 2018 daily volume in the first 10 trading days was 11% more than daily volume over the first 30 trading days. Standard errors are clustered by firm and date and are shown below the returns in parentheses. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Abnormal Volume Over First 10 Trading Days	
	(1)	(2)
Year	Coef.	Std. Error
1995	-0.01	(0.02)
1996	0.04*	(0.02)
1997	0.02	(0.02)
1998	0.03*	(0.02)
1999	0.01	(0.02)
2000	0.05*	(0.03)
2001	0.00	(0.02)
2002	0.01	(0.02)
2003	-0.00	(0.02)
2004	0.04*	(0.02)
2005	0.04**	(0.02)
2006	0.04**	(0.02)
2007	0.06***	(0.02)
2008	0.08**	(0.03)
2009	0.05***	(0.02)
2010	0.08***	(0.02)
2011	0.10***	(0.02)
2012	0.09***	(0.02)
2013	0.09***	(0.02)
2014	0.08***	(0.02)
2015	0.09***	(0.02)
2016	0.11***	(0.02)
2017	0.09***	(0.02)
2018	0.11***	(0.02)
Permno FE	Yes	
R-squared	0.224	
N	238,638	

Table 6: Calendar-Time Portfolio Returns: June versus Information Rebalancing

The table shows abnormal returns to calendar-time portfolios formed for each of the anomaly portfolios and the super anomaly portfolio. The super portfolio is constructed as the average return across all individual anomaly portfolios. We examine both June-rebalancing and information-rebalancing strategies. The June-rebalancing strategy mirrors the typical strategy of the original published papers, where each portfolio is rebalanced one time per year at the end of June. The information-rebalancing strategy updates the portfolio to account for new financial information about the anomaly variable, using the Snapshot database to determine the precise date on which information is first publicly released. This strategy potentially updates the portfolio daily. Column 1 shows annualized mean daily abnormal returns (in percent) for June-rebalanced portfolios. Column 3 shows annualized mean daily abnormal returns (in percent) for information-rebalanced portfolios. Columns 2 and 4 show the standard error of daily abnormal returns, clustered by firm and date. Column 5 shows the annualized mean daily difference in abnormal returns between information and June rebalancing (similar to Column 3 minus Column 1). Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. The final three rows of the table count the number of anomaly portfolios for which the mean daily abnormal return is positive (negative) and statistically significant.

	Annualized Mean Daily Returns					
	June Rebalancing		Information Rebalancing		Difference	
	(1)	(2)	(3)	(4)	(5)	(6)
Anomaly	Return	Std. Error	Return	Std. Error	Return	Std. Error
Super	2.59***	(0.51)	7.30***	(0.53)	4.60***	(0.29)
Acc	5.76***	(1.43)	1.21	(1.45)	-4.31***	(1.30)
Ag	3.84**	(1.47)	17.34***	(1.65)	13.01***	(1.32)
At	0.79	(1.44)	1.93	(1.48)	1.13	(0.91)
Cat	5.85***	(1.27)	9.93***	(1.32)	3.86***	(1.21)
Cpm	8.78***	(1.64)	18.24***	(1.58)	8.70***	(1.35)
Ec	3.37**	(1.56)	4.53***	(1.65)	1.12	(1.26)
Es	7.72***	(1.37)	23.35***	(1.34)	14.51***	(0.95)
Gp	-0.44	(1.90)	2.34	(1.98)	2.79***	(0.97)
Ig	-3.11**	(1.29)	4.12***	(1.29)	7.47***	(1.17)
Inv	4.28***	(1.42)	6.94***	(1.43)	2.55**	(1.26)
Ltg	7.03***	(2.13)	6.85***	(2.18)	-0.17	(2.02)
Nca	-3.90***	(1.34)	-1.83	(1.35)	2.15*	(1.12)
Noa	-0.72	(1.89)	1.04	(1.93)	1.78	(1.11)
Nwc	-5.57***	(1.40)	-1.48	(1.43)	4.33***	(1.27)
Ol	5.06**	(2.01)	6.53***	(1.96)	1.39*	(0.82)
Osc	5.01**	(1.92)	7.25***	(1.96)	2.13*	(1.17)
Pm	0.60	(1.51)	2.43	(1.55)	1.81**	(0.90)
Poa	0.10	(1.34)	5.85***	(1.36)	5.74***	(1.09)
Pro	2.12	(1.86)	1.96	(1.97)	-0.15	(1.16)
Pta	-0.80	(1.31)	2.27*	(1.27)	3.09**	(1.20)
Roe	0.08	(1.60)	0.30	(1.72)	0.22	(1.09)
Rs	7.72***	(1.24)	17.05***	(1.19)	8.67***	(0.95)
Sag	3.53**	(1.43)	8.11***	(1.53)	4.42***	(1.10)
Sg	4.61***	(1.41)	17.00***	(1.52)	11.85***	(1.22)
Sli	6.13***	(1.54)	8.71***	(1.57)	2.43*	(1.40)
Slx	7.65***	(1.71)	17.66***	(1.74)	9.30***	(1.45)
Tx	5.29***	(1.85)	10.32***	(1.79)	4.78***	(1.17)
Txf	4.91**	(1.97)	14.10***	(1.97)	8.76***	(1.16)
No. > 0	17		19		21	
No. < 0	3		0		1	
No. $= 0$	8		9		6	

Table 7: Calendar-Time Portfolio Returns: Time of Year Effect

The table examines abnormal returns to calendar-time portfolios in two different parts of the year. The super portfolio is constructed as the average return across all individual anomaly portfolios. We examine two portfolio formation strategies: (1) June rebalancing and (2) information rebalancing. The June-rebalancing strategy mirrors the typical strategy of the original published papers, where each portfolio is rebalanced one time per year at the end of June. The information-rebalancing strategy updates the portfolio to account for new financial information about the anomaly variable, using the Snapshot database to determine the precise date on which information is first publicly released. This strategy potentially updates the portfolio daily. All columns show the annualized mean daily abnormal returns (in percent) for the rebalancing strategy indicated. The first three columns display the annualized mean daily abnormal returns earned in the last six months of the calendar year (i.e., during the first six months after the June-rebalancing strategy has updated). The final three columns show the average returns earned during the first six months of the calendar year. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. The final three rows of the table count the number of anomaly portfolios for which the mean daily abnormal return is positive (negative) and statistically significant.

	Annualized Mean Daily Returns					
	July - December			January - June		
Anomaly	June (1)	Information (2)	Difference (3)	June (4)	Information (5)	Difference (6)
Super	5.34***	6.51***	1.11***	-0.24	8.12***	8.38***
Acc	4.71**	2.10	-2.49***	6.88***	0.30	-6.16***
Ag	5.64**	9.15***	3.32***	1.95	26.33***	23.91***
At	0.51	0.26	-0.25	1.09	3.66*	2.55
Cat	10.20***	11.25***	0.95	1.43	8.60***	7.07***
Cpm	12.39***	14.97***	2.30***	5.09**	21.66***	15.78***
Ec	4.95**	4.68*	-0.26	1.74	4.39*	2.61
Es	23.70***	29.24***	4.49***	-6.62***	17.58***	25.91***
Gp	-3.83	-3.60	0.24	3.28	8.76***	5.30***
Ig	-1.42	0.94	2.39***	-4.88***	7.48***	12.98***
Inv	7.95***	7.81***	-0.13	0.53	6.06***	5.50**
Ltg	7.74**	8.53***	0.73	6.28**	5.17*	-1.05
Nca	-2.63	-2.12	0.52	-5.23***	-1.53	3.90*
Noa	5.76*	6.00**	0.23	-7.16***	-3.77	3.66*
Nwc	-4.19**	-1.54	2.76***	-7.02***	-1.42	6.02**
Ol	11.46***	12.36***	0.81	-1.31	0.90	2.24
Osc	10.35***	10.23***	-0.11	-0.35	4.29	4.66**
Pm	1.58	2.01	0.42	-0.42	2.85	3.29*
Poa	0.33	2.25	1.91**	-0.14	9.65***	9.80***
Pro	3.69	2.46	-1.19	0.47	1.45	0.98
Pta	-1.48	-0.17	1.33	-0.09	4.81***	4.90**
Roe	0.21	-0.37	-0.58	-0.06	0.99	1.05
Rs	14.92***	18.31***	2.95***	0.75	15.79***	14.93***
Sag	4.72**	6.42***	1.63**	2.30	9.86***	7.39***
Sg	7.49***	10.92***	3.19***	1.64	23.55***	21.56***
Sli	9.16***	8.89***	-0.25	3.03	8.52***	5.34**
Slx	14.35***	17.04***	2.35***	0.98	18.30***	17.15***
Tx	10.22***	10.08***	-0.13	0.40	10.57***	10.14***
Txf	9.61***	12.23***	2.40***	0.16	16.04***	15.86***
No. > 0	18	17	11	3	19	21
No. < 0	1	0	1	5	0	1
No. $= 0$	9	11	16	20	9	6

Table 8: Anomaly Returns: Transactions Costs

The table displays anomaly returns in event time and calendar time, net of transactions costs for the super anomaly portfolio, and is comparable to Table 2 and Table 6. Abnormal returns are calculated using the 6-factor model (Fama and French (2015) and Carhart (1997)). Abnormal returns are adjusted for transactions costs by accounting for the effective bid-ask spread as in Chen and Velikov (2019). The super portfolio is constructed as the average return across all individual anomaly portfolios. Panel A shows the annualized mean daily abnormal returns earned in event time according to the time periods noted. Columns 1 through 3 shows the super anomaly portfolio abnormal return before considering transactions costs over the first 120 trading days (in event time), the second 120 trading days (days 121-240), and the first 240 trading days. Columns 4 through 6 show abnormal returns over the same time periods, net of transactions costs. Panel B shows the annualized mean daily abnormal returns according to the rebalancing strategies noted. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Returns in Event Time

	Annualized Mean Daily Returns					
	Zero Transactions Costs			Net Transactions Costs		
	(1)	(2)	(3)	(4)	(5)	(6)
Anomaly	1 - 120 Days	121 - 240 Days	1 - 240 Days	1 - 120 Days	121 - 240 Days	1 - 240 Days
Super	7.65***	3.81***	4.58***	4.75***	-0.49	3.31***
(s.e.)	(0.72)	(0.73)	(0.54)	(0.71)	(0.71)	(0.54)

Panel B: Returns in Calendar Time

	Annualized Mean Daily Returns					
	June Rebalancing		Information Rebalancing		Difference	
	(1)	(2)	(3)	(4)	(5)	(6)
Condition	Return	Std. Error	Return	Std. Error	Return	Std. Error
No Costs	2.59***	(0.51)	7.30***	(0.53)	4.60***	(0.29)
With Costs	0.27	(0.61)	4.16***	(0.53)	3.88***	(0.43)

Table 9: Anomaly Returns: Size Breaks

The table examines abnormal returns to the super anomaly, broken out into size subsamples using the breakpoints in Fama and French (2012). The super portfolio is constructed as the average return across all individual anomaly portfolios. Large stocks are those with market capitalization greater than or equal to the 50^{th} percentile of NYSE breakpoints from Kenneth French's website, small stocks are those with market capitalization greater than or equal to the 20^{th} percentile but less than the 50^{th} percentile, and micro stocks are those with market capitalization below the 20^{th} percentile. Panel A shows abnormal returns in event time across a variety of horizons (columns) and size portfolios (rows), with standard errors shown below the returns in parentheses, similar to Table 2. Panel B shows abnormal returns in calendar time for portfolios split by size, similar to Table 6. Within Panel B, Column 1 shows abnormal returns to a June-rebalancing strategy, Column 3 shows abnormal returns to the information-rebalancing strategy, and Column 5 shows the average daily difference between the two approaches. Standard errors are clustered by stock and date. ***, **, * indicates statistical significance at the 1%, 5%, and 10% level.

Panel A: Returns in Event Time

	Annualized Mean Daily Returns					
	Days 1 - 30		Days 31 - 120		Days 121 - 240	
	(1)	(2)	(3)	(4)	(5)	(6)
Size Category	Return	Std. Error	Return	Std. Error	Return	Std. Error
All Size	14.79***	(1.05)	9.72***	(0.72)	3.99***	(0.75)
Large	11.29***	(1.54)	7.42***	(0.95)	3.57***	(0.86)
Small	16.10***	(1.70)	9.88***	(1.16)	5.69***	(1.15)
Micro	15.25***	(1.39)	10.63***	(0.98)	3.03***	(0.90)

Panel B: Returns in Calendar Time

	Annualized Mean Daily Returns					
	June Rebalancing		Information Rebalancing		Difference	
	(1)	(2)	(3)	(4)	(5)	(6)
Size Category	Return	Std. Error	Return	Std. Error	Return	Std. Error
All	2.59***	(0.51)	7.30***	(0.53)	4.60***	(0.29)
Large	3.05***	(0.62)	5.92***	(0.66)	2.79***	(0.45)
Small	4.03***	(0.77)	8.29***	(0.81)	4.10***	(0.54)
Micro	1.31**	(0.64)	7.10***	(0.62)	5.71***	(0.48)

Table 10: Implied Hedge Fund Speed and Future Fund Performance

The table reports results from panel regressions of future hedge fund performance on implied hedge fund speed of the form:

$$AbnReturn_{j,t+1:t+12} = \gamma_0 + \gamma_1 \beta_{jt} + \epsilon_{j,t+1:t+12}.$$

AbnReturn is the 6-factor alpha (Fama and French (2015) and Carhart (1997)) and *Speed* is a monthly measure of implied hedge fund speed based on the relation between the fund's historical returns and the return on the information-rebalancing portfolio (see Table 6 and Equation (1)). We include fund and/or month-year fixed effects as indicated in the table. Standard errors are clustered by firm and month and are shown below the coefficient estimates in parentheses. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Dep. Variable = future alpha		
Ind. Variable	(1)	(2)	(3)
Speed	0.75***	1.22***	0.59**
(s.e.)	(0.18)	(0.28)	(0.28)
Fund FE	No	Yes	Yes
Month-Year FE	No	No	Yes
R-squared	.002	.146	.296
N	208,441	208,441	208,441

IA1 Internet Appendix

This internet appendix* provides additional empirical evidence to supplement the main text.

1. Section IA1.1 provides additional information about the construction of long-short portfolios.

2. Table IA1 provides detailed information about the calculation of each anomaly variable.

3. Table IA2 provides results from implementable portfolios formed using value-weighted returns.

4. Table IA3 shows anomaly returns using portfolios formed on news days relative to non-news days. We use RavenPack data to get news release data for each firm and date. The results show that it is not news, per se, that matters for anomalies, but rather news about the variable that determines portfolio assignment.

*Citation format: Internet Appendix for "Anomaly Time," 2021, Working paper.

IA1.1 Construction of Anomaly Variables

As discussed in the main text, the way to construct a long-short portfolio based on original source material is occasionally unclear for some anomalies. Several of the original papers do not examine univariate tests, so it is unclear as to whether the anomaly positively or negatively predicts future returns. For example, Soliman (2008) shows that *change in asset turnover* is positively related to future returns; however, his evidence consists of multivariate regressions that include between 8 to 17 variables. As such, it is unclear how *change in asset turnover* would relate to returns in a univariate setting.

Given this uncertainty, we assign stocks to long-short portfolios based on the following algorithm. First, we assign long-short portfolios based on the evidence from the original papers, even if the evidence is from a multivariate setting. We then replicate the original paper by constructing long-short anomaly portfolios that are rebalanced on June 30$^{\text{th}}$ and on which we calculate average daily returns. We calculate both raw returns and abnormal returns using the six-factor model (Fama and French (2015) and Carhart (1997)). Finally, if the raw and abnormal returns are not negative and statistically significant, we then use the methodology from the original paper. In contrast, if one of the returns is statistically negative and the other is also negative or not statistically positive, we then multiply the returns by minus one.

The last step uses the data to assign the direction of an anomaly, but only if there is *strong* evidence to overrule the original paper. For example, Soliman (2008) finds that *change in asset turnover* is positively related to future returns in a multivariate regression (i.e., after controlling for several other variables). However, our analysis shows that a hedged portfolio consisting of long positions in firms with high changes in asset turnover and short positions in firms with low changes in asset turnover will generate significantly *negative* abnormal returns and will not generate significant positive raw returns. As such, we multiply the returns by minus one, taking long positions in stocks with low *changes in asset turnover* and short positions in stocks with high *changes in asset turnover*.

Of the 28 anomalies in our study, this algorithm leads us to follow the methodology in the original papers for 21 of the anomalies, and we multiply by minus one for seven anomalies: *accruals*, *change in asset turnover*, *change in profit margin*, *investments*, *operating leverage*, *sales growth less investment growth*, and *sales growth less expenses growth*.[†] Excluding these anomalies instead of multiplying them by minus one leaves all of our conclusions unchanged. In fact, because our goal is to test whether information rebalancing improves the signal in anomaly strategies, this adjustment gives the null hypothesis the strongest possible chance of succeeding. Put differently, by making sure that these anomalies yield positive and significant returns when they are rebalanced annually, we make it more difficult for the information-rebalancing strategy to improve the performance.

[†]Four of these seven variables come from two papers: *change in asset turnover* and *change in profit margin* are both from Soliman (2008) while *sales growth less investment growth* and *sales growth less expenses growth* are both from Abarbanell and Bushee (1998). Both papers provide only multivariate evidence. Chen and Zimmermann (2020) also reports difficulty producing significantly positive long-short portfolio returns for these variables.

Table IA1: Anomaly Detail

The table provides detail regarding the anomalies investigated 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 how the anomaly is constructed.

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.

Table IA1: Anomaly Detail *continued*

The table provides detail regarding the anomalies investigated 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 how the anomaly is constructed.

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	$NOA = \frac{OA_t - OL_t}{A_{t-1}}$ $OA_t = AT_t + CHE_t$ $OL_t = AT_t - DLTT_t - MIB_t - PSTK_t - CEQ_t$

Table IA1: Anomaly Detail *continued*

The table provides detail regarding the anomalies investigated 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 how the anomaly is constructed.

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.	$PRO = \frac{Earnings_t}{Assets_{t-1}}$

Table IA1: Anomaly Detail *continued*

The table provides detail regarding the anomalies investigated 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 how the anomaly is constructed.

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.

Table IA1: Anomaly Detail *continued*

The table provides detail regarding the anomalies investigated 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 how the anomaly is constructed.

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.	$SLX = SAG - XG$ $SAG = \frac{REV_t - \frac{1}{2}(REV_{t-1}+REV_{t-2})}{\frac{1}{2}(REV_{t-1}+REV_{t-2})}$ $XG = \frac{XSGAY_t - \frac{1}{2}(XSGAY_{t-1}+XSGAY_{t-2})}{\frac{1}{2}(XSGAY_{t-1}+XSGAY_{t-2})}$ $XSGAY$ = 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.

Table IA2: Calendar-Time Portfolio Returns: Time of Year Effect - Value-Weighted

The table examines abnormal returns to calendar-time portfolios in two different parts of the year and considers each anomaly portfolio as being value-weighted. The super portfolio is constructed as the average return across all individual anomaly portfolios. We examine both June-rebalancing and information-rebalancing strategies. The June-rebalancing strategy mirrors the typical strategy of the original published papers, where each portfolio is rebalanced one time per year at the end of June. The information-rebalancing strategy updates the portfolio to account for new financial information about the anomaly variable, using the Snapshot database to determine the precise date on which information is first publicly released. This strategy potentially updates the portfolio daily. All columns show the annualized mean daily abnormal returns (in percent) for the rebalancing strategy indicated. The first three columns display the annualized mean daily abnormal returns earned in the last six months of the calendar year (i.e., during the first six months after the June-rebalancing strategy has updated). The final three columns show the average returns earned during the first six months of the calendar year. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. The final three rows of the table count the number of anomaly portfolios for which the mean daily abnormal return is positive (negative) and statistically significant.

	Annualized Mean Daily Returns					
	July - December			January - June		
Anomaly	June (1)	Information (2)	Difference (3)	June (4)	Information (5)	Difference (6)
Super	11.03***	10.89***	-0.12	6.74***	16.56***	9.20***
Acc	2.05	-1.20	-3.18	-1.07	-0.95	0.11
Ag	8.61**	9.75***	1.05	5.12	20.10***	14.25***
At	-7.54*	-5.54	2.17	-3.17	1.49	4.81
Cat	7.08	0.27	-6.37*	2.98	-5.54	-8.28
Cpm	11.19**	13.60***	2.17	6.00	23.64***	16.64***
Ec	7.44	4.21	-3.00	6.49	-2.44	-8.39
Es	8.16**	10.28***	1.96	-4.55	3.17	8.08**
Gp	1.56	2.29	0.72	5.86	4.70	-1.10
Ig	14.09***	16.89***	2.46	0.19	1.52	1.33
Inv	-1.37	0.31	1.71	6.84	24.58***	16.61*
Ltg	-5.39	0.47	6.20*	8.16*	4.79	-3.11
Nca	0.37	1.82	1.44	-0.90	3.09	4.02
Noa	9.80*	9.85*	0.05	-2.06	2.80	4.96
Nwc	2.30	-0.21	-2.45	-0.91	-1.98	-1.07
Ol	8.73	7.66	-0.99	0.91	3.06	2.13
Osc	26.69***	18.81***	-6.23**	12.51**	6.64	-5.21
Pm	8.16**	7.10*	-0.98	8.06**	2.31	-5.32*
Poa	-0.50	0.21	0.71	19.18***	19.81***	0.53
Pro	14.65***	16.54***	1.64	15.71***	20.13***	3.83
Pta	13.33**	9.39*	-3.49**	-4.01	1.53	5.77
Roe	10.49***	11.61***	1.01	13.27***	7.90**	-4.74
Rs	7.08**	8.33**	1.17	-2.15	7.34**	9.70***
Sag	13.95***	16.65***	2.37	-2.10	13.75***	16.19***
Sg	14.22***	13.58***	-0.56	-0.31	12.36***	12.71***
Sli	2.46	2.52	0.06	6.01	21.50***	14.62**
Slx	9.87*	16.60***	6.13**	10.32	19.06***	7.92
Tx	13.59**	13.04**	-0.48	0.49	5.81	5.30
Txf	33.27***	31.59***	-1.27	13.62***	31.96***	16.15***
No. > 0	16	16	2	7	12	9
No. < 0	1	0	3	0	0	1
No. $= 0$	11	12	23	23	16	18

Table IA3: Calendar-Time Portfolio Returns: News Days

The table examines abnormal returns to the super anomaly based on whether a given stock-day observation coincides with published news about the firm. The super portfolio is constructed as the average return across all individual anomaly portfolios. A news day is defined as a day in which news is published or an earnings announcement is released for a given firm. The table reports annualized mean daily abnormal returns over the entire sample, considering only stock-day observations that are *news days*, and considering only stock-day observations that are *non-news days*. Standard errors are clustered by stock and date. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Across the entire sample, approximately 40% of all days are news days. The sample for these tests begins in 2000, corresponding to the availability of news data from RavenPack.

	Annualized Mean Daily Returns					
	June Rebalancing		Information Rebalancing		Difference	
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Return	Std. Error	Return	Std. Error	Return	Std. Error
All Days	2.21***	(0.55)	6.84***	(0.57)	4.53***	(0.30)
News Days	2.10***	(0.79)	6.62***	(0.80)	4.42***	(0.44)
Non-News Days	1.69***	(0.59)	6.30***	(0.60)	4.54***	(0.34)
All Days (July-Dec.)	4.70***	(0.85)	5.75***	(0.86)	1.01***	(0.17)
News Days (July-Dec.)	4.92***	(1.26)	5.91***	(1.27)	0.94***	(0.27)
Non-News Days (July-Dec.)	3.90***	(0.85)	4.98***	(0.85)	1.04***	(0.21)
All Days (Jan.-June)	-0.27	(0.75)	7.94***	(0.77)	8.23***	(0.57)
News Days (Jan.-June)	-0.65	(1.02)	7.34***	(1.02)	8.04***	(0.83)
Non-News Days (Jan.-June)	-0.54	(0.80)	7.65***	(0.82)	8.23***	(0.64)